Strategic Asset Selection Taxonomy: Fund of Hedge Funds

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1 Abstract

This thesis develops a logical methodology to be used to assess the hedge fund managers' return time series in comparison with their peers. This enables Fund of Hedge Funds portfolio manager to identify those with required factors to be included in a portfolio. The models that had been used as the industry standard for some time are derived on the assumption of normal distribution. Hence they use only mean and standard deviation to explain all data phenomenal attributes of time series. This study project uses higher order moments and some performance measures to rank order feasible portfolios of different hedge fund strategies based on their calculated metrics. Then determine the significance of t-Statistics, thus to observe the likelihood of achieving a particular return level relative to the downside associated with that target return and also on the behavioral hypothesis that investors prefer more to less. The study proposes and examines an alternative performance measures to facilitate the investment decision making. An indication of how this may be applied across a broad range of problems in hedge funds analysis. Some performance measures capture the higher order moments of the return distributions. This method makes intuitive sense since one of the key mandates of the hedge funds is to seek to capture most upside while protecting against downside.

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DEDICATION
Special dedication to my mother 'M'e 'Makaibe Mokoma, Mum you are a supermodel for the source of inspiration for me to strive to attain whatever I wish to acquire in life.

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This thesis serves as a documentation of my work during the academic Internship project at Blue Ink Investments, Financial Institution that specializes as the Fund of Hedge Funds, from April 2009 to October 2009. I wish to express my sincere gratitudes to Blue Ink Investments; Chief Investment Officer Thomas Schlebusch for his insightful guidance during the whole project and also I am more than gratified for the opportunity he accorded to me to do my thesis project with Blue Ink Investments. I am genuinely grateful to all Blue Ink Investments team that shared their office space with me, provided any form of assistance I needed. More especially I wish to convey my special gratifications to Eben Karsten, who had been more than willing to explain to the best of his knowledge any question I asked as was doing my research project.

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Contents

2 Introduction

The Hedge Funds have become an increasingly important investment asset class in recent years. This thesis develops the asset selection taxonomy that will facilitate the process of investment decision making by the Fund of Hedge Funds Manager in order to identify and select the best underlying Hedge Fund managers. Ineichen and Silberstein (2008) observed that the investment process into hedge funds industry is dynamic and can be classified into two selection processes (manager selection and portfolio construction) and two monitoring processes (manager review and risk management). This thesis will focus on the manager selection aspect. Initial and ongoing assessment and due diligence of the hedge fund managers is probably the single most important aspect of the investment process for all hedge fund investors. Portfolio construction and managing the risk of the hedge fund portfolio are also mission-critical in the hugely heterogeneous and dynamic hedge fund industry. Manager evaluation and monitoring has become more difficult despite increases in transparency and information flow, and it has become more labour-intensive. Investors with vast resources for research are likely to continue to have an edge over investors with little or no research capabilities. Manager identification and evaluation are one of the important things to be done correctly using either passive qualitative methods that search for, though not only limited to, the investment acumen skills, market-timing ability, regulatory framework compliance and track record, or using the actively data-intensive quantitative analysis methods that assess the returns time series to extract empirical trading success. The asset selection taxonomy that have been developed in this thesis uses the quantitative method. Having identified and evaluated worthy to invest with, then investor allocate capital to a manager or a group of managers, and then expects to utilise the skill of the managers more than just ordinarily participating in a particular investment strategy. The investor's expectation is to take advantage of inefficiencies and opportunities in the market where a skilled and experienced manager has a competitive advantage over the less skilled - that is, the rest of the market. In this thesis, the author develops the logical methodology to assess the hedge fund managers who possess skill to effectively and efficiently generate consistent alpha over time, and to protect and preserve the investors capital under all market conditions.

2.1 Thesis Structure

Thesis outline structure: 1. Abstract: provides an overview of the thesis. 2. Introduction: gives brief view on the hedge funds industry, some project specifics and how they address the challenges of this thesis. Background provides some brief literature review and some identified flaws that have to be taken into account. The motivation of this study and how the research goals are intended to be achieved. 3. Hedge Funds: provide some detailed descriptions and defines the business process in the hedge funds space. 4. Portfolio Construction Theory: gives the brevity of the Modern Portfolio Theory and the relevance of market data as the informationally efficient machinery. 5. Statistical Metrics in Modern Portfolio Theory; discussing the algorithms used to achieve strategic selection of hedge fund managers with desired attributes. 6. Alternative Performance Measurement; presents Financial Mathematics models that add to the logical algorithms used to assess the performance of hedge fund managers by means of traditional measures as well as those ones that incorporate higher moments. 7. Methodology: A detailed description of the project procedure. 8. Results and Data Analysis; discussion of the data results and their analytic interpretations. 9. Conclusion: summarizes the findings and observes how others interpreted their results. 10. Reference: citing the previous literatures. 11. Appendix: provide Tables of Results

2.2 Background

Some review of the finance literature in the hedge funds industry. The key investment philosophy for most hedge funds is to produce the risk-adjusted returns and preservation of capital against any financial loss. So the fund of hedge funds must be able to identify those who adhere to this principle.

In this subsection the intention is to elaborate briefly on the three points given below;

- cite brief history of the first hedge fund and how the industry evolved to its present status
- introduce the literature survey that is relevant to this dissertation
- highlight the preliminary asset selection process

Lhabitant and Learned (2000) narrates the origins of the evolution of 'hedge fund' industry. At about the same time Markowitz was publishing his portfolio diversification theory. Alfred Winslow Jones was working on exactly the opposite objective namely, the isolation of specific risk and the elimination of market risk. Jones was convinced that he had superior stock-selection ability, but no market-timing skills. Therefore, his strategy consisted of combining long positions in undervalued stocks with short positions in overvalued ones. This allowed him to make a (small) net profit in all markets, capitalizing on his stock-picking abilities while simultaneously reducing overall risk through lesser net-market exposure. To magnify his portfolio's returns, Jones added leverage, that is, he used the proceeds from his short sales to finance the purchase of additional long positions. This provided the basic principles for what was the first hedge fund.

More than half a century later, hedge funds have significantly evolved from the original model. Indeed, some of them do not actually hedge anything, the examples are Event-driven and distressed strategies. Nowadays, the term 'hedge fund' is applied somewhat indiscriminately and beyond the scope of its original meaning. It refers to any pooled investment instrument that is not a conventional investment fund - that is, any fund using a strategy or set of strategies other than investing long in bonds, equities, money markets, or a mix of these assets. Consequently, hedge funds are better identified by their common structural characteristics than by their 'hedged' nature. These characteristics include, but are not limited to, active management, long-term commitment of investors, use of incentive fees, leverage, broad discretion over the investment styles, asset classes, investment vehicles, gearing, etc.

Given the diversity of their strategies, hedge fund returns generally display moderate to low correlations with traditional equity and bond indices. In addition, hedge fund strategies have moderate to low correlations with each other. The idea of diversifying among loosely correlated funds is therefore very natural. The question however remains on which approach should to choose. Markowitz's, or naive? Intuitively, it appears that very few hedge fund portfolios are optimized along the lines of Markowitz's recommendations. The main reason could be attributed to the fact that hedge fund return distributions exhibit high moments above the second moment, and that renders the mean-variance framework almost inapplicable for their risk-return analysis. This makes the use of conventional methods of portfolio construction subject to question and necessitates the investigation of a more sophisticated approach to inform the construction of appropriate and efficient portfolio.

Bergh and van Rensburg (2008) compare and evaluate the results of two related optimisation procedures. First, the classic mean-variance portfolio optimisation of Markowitz and secondly, they use an approach suggested by Davies et al (2003) that is utilising Polynomial Goal Programming (PGP) to optimise the portfolios return distributions for higher moments to include mean, variance, skewness and kurtosis for a given set of investor preferences. This comparison can be presented in the context of both a fund-of-hedge-fund strategy allocation as well as asset allocation problem of what proportion to allocate to hedge fund in a balanced portfolio. They suggest that hedge funds offer the opportunity to reduce portfolio returns in economic environments in which traditional stock and bond investment offer limited opportunities. Bacmann and Scholz (2003) compared the various performance measures on the portfolios of equity, bonds and hedge funds, and find that higher moments matter when performance has to be evaluated. Getmansky (2004) explores what drives hedge fund returns, Models of Flows, Autocorrelation, Optimal Size, Limits to Arbitrage and Fund Failures. Mewasingh (2006) looks more into the Downside Risk Performance Measures and their effect on the portfolio of Hedge Funds.

During the recent past the emergence of hedge funds as an alternative investment class has spurred the proliferation of professionals interest and academic research. The vast majority of research has focused on portfolio diversification using the hedge fund in addition to traditional investments into portfolio of equity, bonds, cash. Black (2004) suggests that the main cost of hedge funds is the potential to increase the systemic risk. On the positive side, they note that hedge funds contribute to economic efficiency by enhancing price discovery and providing additional diversification.

Ingersoll (1987) asserts that the financial asset returns are in general not normally distributed. Strong empirical evidence against the normality of the returns has been reported in the past years by several authors. This evidence suggests that the probability distribution followed by the returns is often characterized by skewness and leptokurtic behaviour. This departure from the normal distribution usually exhibited by the returns of many financial assets is even more accentuated in the hedge fund environment. In this context, the returns distribution is strictly linked to the return generating process adopted by the fund manager and the strategy employed to exploit market opportunities is strongly affecting the return profile. In an asset allocation context, the presence of asymmetry and fat tails violates the assumption of elliptically distributed asset returns that underlies the traditional mean-variance analysis.

Benedetti (2004) recommends that in order to select the optimal portfolio, a preliminary assessment of the relevant beliefs about future performances of the available assets is needed. The method proposed by Markowitz (1952) is for addressing the selection of the optimal portfolio using as inputs, the parameters of the return distributions of the available assets. Since in general the true values for the parameters of the future returns distribution are not known, an estimate of these values must be used. This generates an estimation risk that must be included in the portfolio selection task. Previous studies had been trying to improve the precision of future estimation probability, and also to minimise the estimation risk, though they had attempted to resolve the estimation risk issue but remain in a mean-variance framework.

Borland *et al.* (2009) observed that financial time series represent an extremely rich and fascinating source of questions, for they store a quantitative trace of human activity, sometimes over hundreds of years. These time series, perhaps surprisingly, turn out to reveal a very rich and particularly non-trivial statistical texture, like fat tails and intermittent volatility bursts. Furthermore Borland *et al.* (2009) advance their view of how one is supposed to observe the data results, they say one of Mandelbrot's most important methodological messages is that one should look at data, charts and graphs in order to build one's intuition, rather than trust blindly or naively the result of statistical tests, often inadequate and misleading, in particular in the presence of non Gaussian effects. This visual protocol is particularly relevant when modelling financial time series, well chosen graphs often allow one to identify important effects, rule out an idea or construct a model.

2.3 Motivation

This subsection is going to discuss briefly the following points:

- Some shortcomings of traditional Markowitz portfolio selection that motivated the research into more viable alternatives
- The main objective of this thesis
- Give a brief view of how intend to achieve the objectives of the project.

The investment process into hedge funds as an asset class is a skilled search criterion to acquire talent that capitalizes on the inefficiency in capital markets. Thus, it constitutes an investment program whereby the portfolio manager seeks absolute returns by exploiting investment opportunities while protecting the principal from potential financial loss. Hence, it is essential for financial institutions (Fund of Hedge Funds) to be able to effectively identify and manage the risks associated with hedge fund investment in order to maintain the competitive edge and thus ensure survival. Since the hedge fund returns distribution does not follow a normal distribution as is the underlying key assumption in the Markowitz's formulations, this implies that Markowitz model is inappropriate in this case. Therefore, mean-variance analysis of portfolio construction is not only insufficient but is also likely to offer misleading interpretation of the actual existence of risk embedded in the higher moments. The model that incorporates higher moments becomes a necessity when analyzing the return time series of the hedge funds. However, the proper systematic utility function that uses the higher moments is not that easy to devise.

The primary aim of this thesis is the search for an appropriate methodological tool to be used to identify the hedge fund managers whose returns distribution offer the most desired results. Such desired results would be interpreted not only on the statistical significance of the parameters, but more also on the charts, graphs and depiction of what the historical data can provide.

To achieve the objective a thorough quantitative analysis is done on the hedge funds' actual returns, net of fees, as reported on a monthly basis. The algorithms suggested by Bowers et al (2003) are then applied to data in order to rank sorted managers to identify those with desired factors. Then using the mathematical models to do portfolio performance measurement as well as interpret the data based on which managers possess the most desirable investment benefits. With these methods of moments and Mathematical models the best hedge funds managers are identified, and those who are capable of attaining the investors i.e. Fund of Hedge Funds (FoHF) target returns with reasonably contained levels of risk that include higher moments, are chosen for portfolio construction.

3 Hedge Funds

In this chapter business activities and trading process within the hedge fund industry are considered. Some industry standards of hedge fund definitions and the strategies they employ are defined. Lastly the Funds of Hedge Funds (FoHF) that invest into the underlying hedge funds managers are also considered.

3.1 Definitions

While there might be some varied definitions of hedge funds, the one followed in this project will be that given by Ineichen and Silberstein(2008) in the Detailed RoadMaps to Hedge Funds. They define a hedge fund as an investment program whereby the managers or partners seek absolute returns by exploiting investment opportunities while protecting the principal from potential financial loss.

Brooks and Kat (2002) define the hedge fund investment as the pooled investment vehicle that is privately organised, administered by professional managers, and not widely available to the public. Due to their private nature, hedge funds have less restrictions on the use of leverage, short-selling, and derivatives than more regulated vehicles such as mutual funds. This allows for investment strategies that differ significantly from traditional non-leveraged, long-only strategies. Ineichen and Silberstein(2008) in their roadmaps to hedge funds dedicate the whole chapter on demystifying hedge funds [1]. They single out that Hedge funds are often portrayed as speculators, or worse, as gamblers. They state that many hedge funds do seek to hedge against various types of market risk in one way or another, making consistency and stability of return, rather than magnitude, their key priorities. Thus, some hedge funds are generally able to deliver consistent returns with lower risk of loss. Long/short equity funds, while somewhat dependent on the direction of markets, hedge out some of this market risk through short positions that provide profits in a market downturn to offset losses made by the long positions. Equity market-neutral funds that invest equally in long and short equity portfolios are not really correlated to market movements. That does not mean there is no directional risk. While this only means that there is no directional market risk, it would depend on some hedge fund strategy. As an example the Long-Short Equity Directional funds do bear some 'directional' market exposure with a calculated risk-reward trade-off. The 'directional' risk could manifest itself in being exposed to the divergence between value and growth stocks or small and large capitalisation stocks, as an example.

[1] (see http://www.aima.org, under research AIMA's Roadmaps to Hedge Funds)

3.1.1 Due Diligence

As part of the ongoing manager evaluation and management, due diligence is the key to keep all the checks in balance with hedge fund manager entrusted with responsibility to manage investors assets. Due diligence is the single most important aspect of the investment process for an investor investing in a hedge fund. Ineichen and Silberstein (2008) explain that due diligence includes quantitative excellence as well as qualitative judgement. Quantitative analysis of (imperfect) data is incomplete. Qualitative judgement is at least as important as quantitative analysis. Due diligence includes a thorough analysis of the fund as a business and a validation of manager information, and covers operational infrastructure, financial and legal documentation, affiliates, investment terms, investor base, reference checks and so on.

3.1.2 Manager Review

Manager review is a dynamic and iterative process. The due diligence process never ends. To truly understand a manager and a manager's value-added, a FoHF must first understand the sector in which they are operating. If it is believed that a manager would be successful in particular industry, they must be able to adapt to change and employ comprehensive risk management. However, the most important aspect of this research is the appreciation for the dynamic nature of both the markets and the strategies. This is not a single exercise, but rather a continual process of evaluation and review. Over time, the emphasis of importance may shift within the strategies from one factor to another, even to a newly developed factor.

The first step in manager evaluation and review is to determine the sources of risk and return in each strategy. This involves dissecting the strategies into their component parts and applying market knowledge to determine how a hedge fund operating within that strategy has the potential to make profits and what risks are being taken in order to achieve the returns. These points can be very subtle, particularly on the risk side of the equation as the most significant risks are often those not found in any textbook on the subject. In these cases, first-hand trading and risk management experience is invaluable in the assessment process.

The identification of the risk and return drivers also leads to establishing differentiating factors for comparing managers within a strategy. Certain aspects of these drivers will have more influence than others on the future performance of the manager and must be emphasized. Additionally, some of these factors will be conditional to a particular attribute of the market or fund manager, such as liquidity or asset levels. Therefore, the differentiating factors must be used in the proper context when applied to the manager selection process[2].

[2] for more details see AIMA's Roadmaps to Hedge Funds by Ineichen and Silberstein(2008) on www.aima.org

3.2 Hedge Funds Strategies

Hedge fund investment strategies tend to be quite different from the strategies followed by traditional money managers. In principle every fund follows its own proprietary strategy, which means that hedge funds are a very heterogeneous group. It is, however, customary to ask hedge fund managers to classify themselves into one of a number of different strategy groups depending on the main type of strategy followed.

The main differences with traditional long-only mutual funds are given by the differences in trading strategies and regulation. The freedom in the managing process and the lack of regulation are probably the main reasons for the heterogeneity and variety of characteristics of the hedge fund industry. Therefore, hedge funds can be classified on the basis of these key characteristics: asset class, market strategy, leverage and exposure. The asset class identifies the markets on which the funds are specialized or the financial instruments they mainly trade as an example equity or bond markets. The market strategy specifies the trading methods adopted by the managers and the kind of approach used to take advantage of market opportunities. Strategies can be based on exploiting arbitrage opportunities, assuming long and/or short positions in financial assets or adopting a trend following approach. Finally, hedge funds can be distinguished on the basis of the amount of leverage used and the amount exposure to the market:

Gross Exposure is the absolute total amount of long and short positions plus cash amount per fund's Net Asset Value (NAV):

$$\text{Gross Exposure} = \frac{Long + Cash + |Short|}{NAV} \tag{1}$$

Net Exposure is the difference between long positions and absolute value of short positions per unit NAV:

$$\text{Net Exposure} = \frac{Long - |Short|}{NAV} \tag{2}$$

In this classification, a traditional mutual fund can be characterised as operating in equity and/or bond markets, having a buy and hold strategy and no leverage. In the mutual fund universe, the location represents the only distinguishing element. Applying the same classification setup, any of the traditional hedge fund styles can easily be characterised. Hedge funds offer more variety and therefore the hedge fund universe is usually segmented in styles.

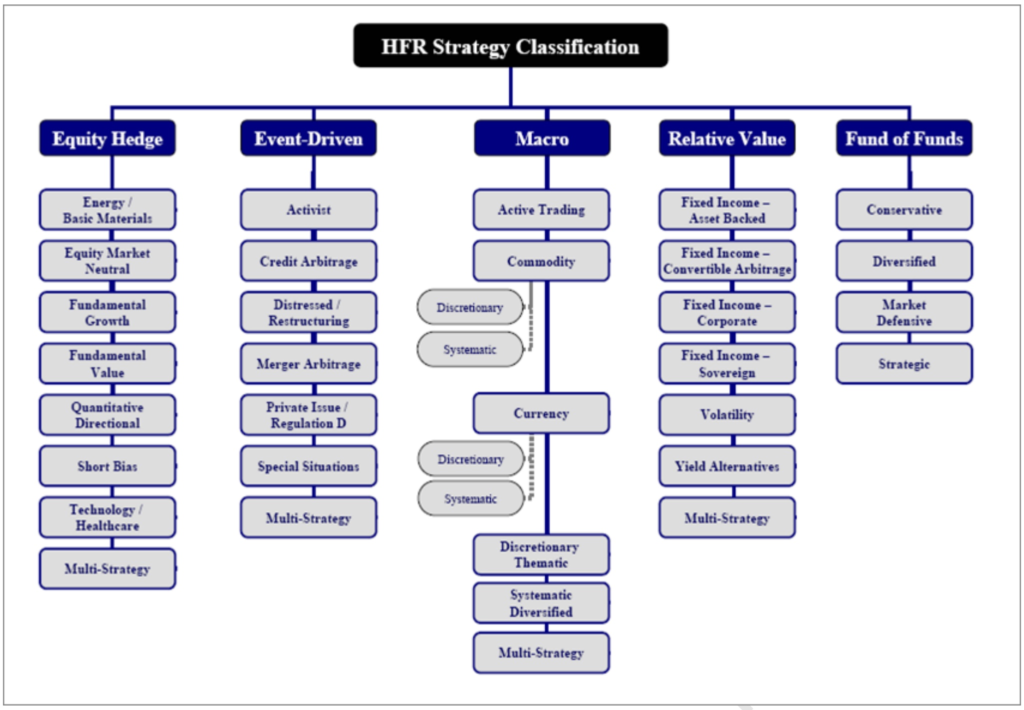

Figure 1: Offshore Hedge Fund Strategy Classification

Source: HFR Global Hedge Fund Industry Report 1^{st} *Quarter 2009*

In an effort to accurately reflect the dynamic evolution of the hedge fund industry and to continuously improve the quality of their products offerings, the Hedge Fund Database Administrators keep on reviewing the current strategy classification and continuously improve to supplement the existing strategy classification system with an enhanced version of the structure. The new structure allows database subscribers (include Funds of Funds, Risk Analyst, Professional Investors, etc.) to perform more specific, granular analysis of the hedge fund industry and allows Database Administrators to create new and exciting points of reference, some of which include Credit Arbitrage, Systematic Commodity, Volatility and Activist strategies[3].

Though some strategies may not be captured in the database of all available hedge funds managers in the South African industry. This thesis will offer some common hedge fund strategies as found in most academic literature on hedge funds.

[3] www.hedgefundresearch.com

3.2.1 Long-Short Equity Funds

This style seeks to anticipate movements on the equity markets from signals generated from statistical, fundamental and technical analysis. Long-Short (Directional) equity hedge funds both buy and sell stocks, with the ability to adjust their positions given their views on the direction of equity market. Ideally, these funds would have net long positions when stocks are rising, and net short positions when stock prices are in bear market. For managers with market-timing skill, long-short equity funds provide the strategy where they can best take advantage of their skill.

Long/Short (Non-Directional) Equity funds combine long as well as short equity positions. They can add value in both directions by selection of undervalued stocks to buy or overvalued stocks to sell. Thus, short positions are not only taken to hedge systematic risk but also to benefit from opportunities. These funds can adopt consistent or variable net long or net short exposure. They tend to build portfolios that are much more concentrated than traditional mutual funds, but with much minimised systemic risk. The Net and Gross position are generally lower than that of a Long/Short Directional fund.

3.2.2 Equity Market Neutral Funds

This investment strategy is designed to exploit equity market inefficiencies and usually involves being simultaneously long and short matched equity portfolios of the same size. Market neutral portfolios are designed to be beta neutral or currency neutral, i.e have a net exposure of zero. Well-designed portfolios typically control for industry, sector, market capitalization, and other exposures. Leverage is often applied to enhance returns.

Market-neutral funds separate stock picking from asset allocation decisions. A manager who only buys stocks can show positive returns simply because the stock market is rising. A market-neutral manager can only show positive returns when the stocks she buys outperform the stocks she sold. This means that a market-neutral fund manager can only be successful when she demonstrates skill in picking stocks.

In fact, some sectors are less lucrative than others for the market-neutral managers. In order for a manager to earn returns from market-neutral trades, there must be significant return difference between the top and bottom performing stocks in a sector. Typically, the market-neutral equity fund manager is matching the beta of the short positions to the beta of long positions to eliminate the influence of the return to equity market on a fund's returns.

3.2.3 Fixed Income Securities Funds

Many fixed-income arbitrage strategies require to have an intimate knowledge of the yield curve. Also called the *term structure of interest rates*, one can graph the yields to Treasury securities ordered by maturity. The shape and slope of this graph can be the basis of a number of different types of hedge fund trades. While many hedge fund managers will have no exposure to changes in the general level of interest rates, they may take massive bets based on an anticipated change in the yield curve.

An inverted yield curve is a relatively infrequent, but very important occurrence. When the short-term interest rates exceed long-term interest rates it is likely that the central bank is tightening the monetary policy. These restrictive actions are usually meant to slow down high levels of economic growth in order to control the level of price inflation. Inverted yield curves, therefore, usually precede significant economic slowdowns or recessions.

Specifically, the belief is that spreads in between yields on relative securities are mean-reverting. When yield spreads are wide relative to their history, traders will bet on the convergence of the spread. When yield spreads are narrow, fund managers can assume that the spread will widen toward historical levels. By tracking the differences between yields of different types of fixed-income securities, arbitrage managers attempt to capture small pricing anomalies, while maintaining a market-neutral position with respect to changes in the overall level of interest rates. This type of trading strategy is likely to be the most quantitatively sophisticated and data intensive strategy employed by the hedge funds. Not only does the manager need to track thousands of bonds worldwide, they must also understand credit risks, embedded options, liquidity and issuance schedules, and the strategies of government and corporate debt issues.
When a fixed-income fund is market-neutral, the funds seeks to have zero duration, which allows the fund to have returns that are uncorrelated to the direction of interest rates.

3.2.4 Event-Driven Strategy Funds

These are defined as the fund styles in which trading opportunities are created through changes in publicly traded companies, where hedge funds can take advantage of inefficiencies caused by corporate actions such as mergers, bankruptcies, and spin-offs.
The returns to event-driven strategies may be cyclical, as there may not be enough corporate actions in a given year to sustain the number of hedge funds dedicated to these trading styles.

Event driven strategies are put in place in order to take advantage of valuation disparities produced by corporate events. Within this style the Distressed Securities strategies invest in undervalued securities of companies experiencing financial distress. An approach adopted by the funds operating in these strategies is based on investing in equity or bonds of selected distressed firms that are expected to recover. Another approach is addressing firms in much more advanced distressed situation by buying a consistent portion of the firm's debt and trying to get rid of the shareholders in order to gain the control of the reorganization process. The Merger Arbitrage strategies rely on the identification and analysis of securities that can benefit from the occurrence of mergers and acquisitions. The funds operating within the Merger arbitrage style exploit the arbitrage opportunities created in these corporate events typically by buying stocks of the target company and shorting the stocks of the acquirer, trying to capture the merger spread. However, if the deal fails, the arbitrageur will face a loss that is usually much greater than the profits obtained in case of success of the strategy.

3.3 Funds of Hedge Funds

At the most general level, a fund of hedge funds manager is - as the name implies - a fund manager who creates and manages portfolios of hedge funds. A fund of funds simplifies the process of choosing hedge funds by blending together funds to meet a range of investor risk/return objectives while generally spreading the risks over a variety of funds to diversify idiosyncratic risks as well as the operational risks. This blending of different strategies aims to deliver a more consistent return than any of the individual funds. A fund of funds can be diversified broadly or highly concentrated to a fund, style or region.

3.4 Investment Process of Fund of Hedge Funds (FoHF)

As mentioned earlier, the hedge fund industry is heterogeneous when compared with the traditional long-only asset management industry. This heterogeneity allows one to pursue different strategies. The two extreme choices are to (1) minimise portfolio volatility or (2) maximise expected return. Most funds of funds will opt for a blend of this two extremes with a bias toward either directional or non-directional strategies.

The ability to identify and understand risk characteristics is one of the most important issues when investing in hedge funds. The fund of funds manager will assess potential drawdowns for each manager in each strategy irrespective of ones historical track record. This assessment will allow the fund of funds manager to get a feel for the risk of the overall fund when a certain specified percentage of managers experience a drawdown at the same time.

One question a hedge fund manager is often asked by evaluators is how much of his own money is in the fund. As an example a manager with 20 years of savings in the fund is, everything else held equal, superior to a manager who puts only last year's bonus at risk. The argument is that interests between manager and investor are aligned when both have their funds at risk. The alignment of interests is obviously also relevant between a fund of funds manager and an investor. It is possible that business models in investment management in the future will require the agent to invest alongside their investors. In the absolute return world, this is already the case.

4 Portfolio Construction Theory

Bodie *et al.* (2003) splits the investment process into two broad tasks. One task is security and market analysis, by which to assess the risk and expected-return attributes of the entire set of possible investment vehicles. The second task is the formation of an optimal portfolio of assets. This task involves the determination of the best risk-return opportunities available from feasible investment portfolios and the choice of the best portfolio from the feasible set. They start their formal analysis of investments with portfolio theory. They then introduce three themes in portfolio theory, all centering on risk. The first is the basic tenet that investors avoid risk and demand a reward for engaging in risky investments. The reward is taken as a risk premium, the difference between the expected rate of return and that available on alternative risk-free investments.

The second theme allows the quantification of investors' personal tradeoffs between portfolio risk and expected return. To do this Bodie *et al.* (2003) introduce the utility function, which assumes that investors can assign a welfare or 'utility' score to any investment portfolio depending on its risk and return. Finally, the third fundamental principle is that risk of an asset cannot be evaluated separately from the portfolio of which it is a part. That is, the risk of an individual asset must be measured in relation to the impact on the volatility of the entire portfolio of investments.

As the work of Bodie *et al.* (2003) is founded on the assumption of normal distribution of the time series, the Markovitz mean-variance framework still holds. In this section it is shown how the Markowitz theory can only be applied to traditional investments, but lacks the practical relevance for the Alternative Investments.

Traditional investment asset classes, such as long-only investments in stocks, equity, indices and bonds, hold the vast majority of investor assets. Alternative investment asset classes include hedge funds, venture capital and private equity, real estate, managed futures, and commodity funds, among others. Alternative investments are however growing rapidly, and taking portfolio share from traditional investments, especially among institutional investors. The traditional investors aim for relative returns with respect to that of the market or the standing of their returns in relation to the level of market returns. When market benchmark rises they expect to perform better than the market and on the way down they wish to be least hit by downside returns in comparison to the market. However, for the alternative investment the mindset focus is on absolute returns, especially those who hold both long and short positions. Alternative investment asset managers have a specified target or threshold percentage they aim to achieve each year, regardless of the direction of the market. Often alternative investment returns are less volatile than returns to traditional asset classes because many alternative investment strategies have the ability to profit when the stock and bond prices are declining. Black (2004) cautions on the comparative studies on hedge fund industry versus the traditional investments in that while one could have over 100 years of U.S. stock market data, hedge fund databases may provide only ten years of historical data. Alternative investments such as hedge fund returns have therefore not been tracked during all types of market environments. For this thesis any comparisons made between hedge fund industry and the traditional investments of equity, bonds, cash, index securities, is done within the identical time periods.

The three main traditional criteria for choosing investments are the annual return, the risk as measured by the standard deviation of annual returns, and the correlations to other asset classes. Government Treasury Bills are often referred to as risk-free asset, as the central government debt is assumed to have no default risk. However, most fixed-income investments have a risk to inflation, where the future purchasing power of the investment declines as inflation increases. As alternative investment have a mandate to make money and protect or preserve the investors' assets against potential financial loss. They invest across a broad array of available opportunities including 'non-linear' instruments such as the derivatives. The heterogeneous trading strategies can never be adequately captured by only quadratic moments. That is, they induce extreme levels of skewness and kurtosis in their return distribution, that warrant being taken into account when assessing the impact of their risk on potential financial loss. Thus, this study incorporates the effect of higher moments and analyze their impact on the returns distribution.

4.1 Capital Asset Pricing Model (CAPM)

The theory of Markowitz gave a framework for deciding how best one could go about selecting investments, it does not provide anything about what price one should be willing to pay for the investment. Markowitz theory is a theory on asset choice, not a theory of asset pricing.
The CAPM was developed independently by following subsequent finance literature authors: Sharpe (1964), Litner (1965), Mossin (1966)

Bodie, *et al* (2003) refers to CAPM as a centrepiece of modern financial economics. The model gives a precise prediction of the relationship that should be observed between risk (as measured only with standard deviation) of an asset and its expected return. This relationship serves two vital functions. First, it provides a benchmark rate of return for evaluating possible investments. Second, the model helps to make an educated guess as to the expected return on assets that have not yet been traded in the marketplace. Although the CAPM does not fully withstand the scrutiny of empirical tests, it is widely used because of the insight it offers.

The Expected Return

The return a rational investor would expect from an investment in a risky asset must clearly be greater than an investment with no risk such as a savings account at a bank. In other words if one invests in a risky asset one expects to make the risk-free rate of return plus some extra compensation for bearing the risk.

Hence:

$$E(R_i) = R_{rf} + \text{extra return for risk compensation}$$

where $E(R_i)$ is the expected return on risky asset 'i'; and R_{rf} is the return on the risk free asset and is the compensation for the time delay in receiving return at some later date.

The risk associated with a security or a portfolio can be thought of as a measure of the uncertainty of the expected return. Numerous quantitative methods of measuring risk have been used, namely variance, semi-variance, the mean absolute deviation, the coefficient of variation, and others that incorporate higher moments. From the literature, it appears that variance is widely used measure of risk.

The Market Model

The model can be briefly summarized as follows: Symbolically the relationship between the return on the i^{th} security and the return on the market from period $t-1$ to period t can be written as:

$$r_{it} = \alpha_i + \beta_i r_{mt} + e_{it} \tag{3}$$

where r_{it} is the returns on the i^{th} security in the t^{th} period:
α_i and β_i are the parameters unique to security i
e_{it} is the disturbance or error term for security i and is assumed to have zero expectation and to be independent of all e_{ts}, $s \neq t$.

The α and β parameters can be estimated using standard regression analysis procedures. The return on the market is generally computed using some overall market index.

The Beta Coefficient

The β parameter has been used exclusively as a measure of the risk of the specific security in relation to the market. Where

$$beta = \beta_i = \frac{COV(R_{market}, R_i)}{\sigma_{R_{market}}} \tag{4}$$

where β_i is the beta coefficient for security i;
$COV(R_{market}, R_i)$ is the covariance between the returns on security i and the market returns;
$\sigma_{R_{market}}$ is the variance of returns on the market index.

The value of β_i indicates the volatility of security $i's$ rate of return by comparison with the market.

If the security's β is greater than one, then when the market rises, the return on the security will rise more rapidly than the return on the market. On the other hand, if the market falls, the return on the security will fall more rapidly than the return on the market. However, if the security's β is less than one, then in a rising market, the security will rise more slowly than the market, and in the falling market, the security will fall less than the market. Therefore, the securities having $\beta's$ greater than one are regarded as being more volatile and hence more risky than the market, while the securities having $\beta's$ less than one are regarded as being less risky than the market.

4.2 Arbitrage Pricing Theory

The exploitation of security mispricing in such a way that risk-free economic profits may be earned is called *arbitrage*. It involves the simultaneous purchase and sale of equivalent securities in order to profit from discrepancies in their price relationship. The concept of arbitrage is central to the theory of capital markets. This concept just offers brief overview of the nature and use of arbitrage opportunities by the hedge fund investors, especially those who participate in the fixed-income securities. Their key to business success is to identify arbitrage opportunities and how they will take the largest possible positions in arbitrage portfolios. Perhaps the most basic principle of capital market theory is that equilibrium market prices are rational in that they rule out (risk-free) arbitrage opportunities. Pricing relationships that guarantee the absence of arbitrage possibilities are extremely powerful. If actual security prices allow for arbitrage, the result will be strong pressure to restore equilibrium. Only a few investors need to be aware of arbitrage opportunities to bring about a large volume of trades, and these trades will bring prices back into balance. The CAPM gives the security market line, a relationship between expected return and risk as measured by beta, β. Arbitrage pricing theory, or APT, also stipulates a relationship between expected return and risk, but it uses different assumptions and techniques.

4.3 Efficient Market Hypothesis (EMH)

In more generic terms, an efficient market is a market in which all information is reflected in current stock prices. In a perfectly efficient market, investors cannot earn excess returns without bearing extra risk, and portfolio managers, therefore, cannot create alpha. In an efficient market, stock prices move randomly. If one looked at the historical prices of any stock in an efficient market, the day-to-day changes would show no discernible pattern. When stock prices do move in some predetermined fashion, then presumably an investor can make money by trading around the pattern, which means that there is an inefficiency in the market. Not even near-arbitrage opportunities exist in a perfectly efficient market.

EHM have different Efficiency levels: *Weak Form Efficiency* claims all past prices of a stock are reflected in today's stock price. Therefore, technical analysis cannot be used to predict and beat a market. *Semi-Strong Form Efficiency* implies all public information is calculated into a stock's current share price. Meaning that neither fundamental nor technical analysis can be used to achieve superior gains. *Strong Form Efficiency* states all information in a market, whether public or private, is accounted for in a stock price. Not even insider information could give an investor the advantage.

Soros (1987)'s theory of reflexivity suggests that in certain cases the activity of the financial markets driven by participant bias can influence the fundamentals that the market prices are supposed to represent. This results in disequilibrium causing the markets to behave differently than assumed by an efficient market hypothesis.

Bin (2007) argues that in the financial industry, the prevalent method for pricing products with future uncertainty is the so-called market implied approach. It assumes the current market prices to be as the relevant information source and a minimal prediction error between mathematical model and these market prices as the objective function.
This procedure for searching the statistically significant model metrics or factors is based on the assumption that a trader, who chooses and calibrates the model, agrees with the view that the market prices are fully consistent with the true, but a-priori unknown, mathematical process for the underlying asset. The market, on the other hand, is assumed to be a perfect informational machine, which absorbs all the relevant information about the unknown stock process, and produces consistent prices.

Lo (2001) says this concept of informational efficiency has a wonderfully counter-intuitive and seemingly contradictory flavour to it: the more efficient the market, the more random the sequence of price changes generated by such a market must be, and the most efficient market of all is one in which price changes are completely random and unpredictable. This, of course, is not an accident of nature but is the direct outcome of many active participants attempting to profit from their information.

This extreme version of market efficiency is now recognized as an idealization that is unlikely to hold in practice. In particular, market frictions such as transactions costs, borrowing constraints, costs of gathering and processing information, and institutional restrictions on shortsales and other trading practices do exist, and they all contribute to the possibility of serial correlation in asset returns which cannot easily be 'arbitraged' away precisely because of the presence of these frictions. From this perspective, the degree of serial correlation in an asset's returns can be viewed as a proxy for the magnitude of the frictions, and illiquidility is one of most common forms of such frictions.

5 Statistical Metrics in Modern Portfolio Theory

The algorithms used to define appropriate analysis of how factors could be interpreted to explain a desirable attribute in order to identify best hedge fund managers to be included in a portfolio.

The unique character that distinguishes one hedge fund manager from the rest is the time series of return distributions, which would be referred to it as data quite often in this chapter. Press *et al.* (1992) emphasise the importance of numerical data as follows: "The data consist of numbers, of course. But these numbers are given to the computer, not produced by it. These are numbers to be treated with considerable respect, neither to be tampered with, nor subjected to a computational process whose character one does not completely understand. It is advisable to acquire a reverence for data." The analysis of data inevitably involves some trafficking with the field of statistics, so this chapter is discussing all the statistical metrics applied in this study. Moreover, one will repeatedly encounter the following paradigm, usually called a t-stats or statistically significant or p-value test. So the definition of each paradigm will be given.

The following sequential order is normally followed when analyzing data, though not strictly binding:

- apply some formula to the data to compute 'a statistic'
- compute where the value of that statistic falls in a probability distribution that is computed on the basis of some 'null hypothesis'
- if it falls in a very unlikely spot, way out on a tail of the distribution, conclude that the null hypothesis is false for your data set.

The parameters that are extracted from data during analysis are model-independent, thus, include so-called descriptive statistics that characterize a data set in general terms: its standard deviation, skewness, kurtosis and so on. Also calculate statistical tests that seek to establish the 'sameness' or 'differentness' of two or more data sets, or that seek to establish and measure a degree of correlation between two data sets.

In order to determine which investment best fits the needs, one must analyse the historical return and risk of each hedge fund style. There are many ways to compute both statistics, and the method of calculation often change conclusions.

5.1 Effect of Hedge Fund Trading Strategies on Performance Analysis

Much of the current finance literature have been based on the Mathematical models that were derived on the assumption of normal distribution of the underlying time series data. However,

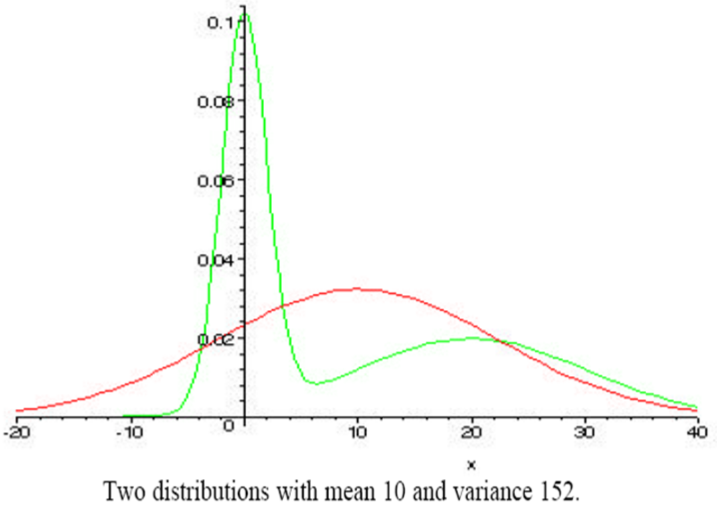

Figure 2: Two Distributions with same mean and Standard Deviation but differing in higher moments

Source: Keating and Shadwick, 2002, 'A Universal Performance Measure', The Journal of Performance Measurement

there is a rich empirical finance literature (Bergh and van Rensburg (2008), Davies, Kar, and Lu (2003), Lhabitant and Learned (2000), Fung and Hsieh (1999), Stutzer (2000)) that have discovered that the hedge fund returns distribution display non-normal distribution. Stutzer (2000) states that historical financial time series deviate from the normal due to large absolute values of skewness and/or kurtosis. This nature of time series renders the theoretical foundation based on normality to be inapplicable. Such non-normalities in a portfolio may arise from large asymmetrical economic shocks, investments in options and other derivative securities with inherently asymmetrical returns, limited liability (bankruptcy) effects on asset returns, or other causes. Optimal portfolio construction methodologies will therefore have to adjust with empirical discoveries as time goes on.

Hedge funds have an ultimate goal to make money and protect capital against losses. The capital protection obtained through hedging strategies and particular investment styles produces asymmetric return distributions. Hedge funds' frequent employment of dynamic trading strategies, compounded by highly leveraged positions, create significant skew and kurtosis in their return distributions. This accentuates the inadequacy of mean-variance portfolio analysis, justifying the applicability of higher moments beyond quadratic [4] in portfolio analysis and risk management.

5.2 Methods of Moments

Decomposition of portfolio distribution moments forms the building blocks to the portfolio analysis used in this study. It enables one to trace true return determinants of portfolio diversification, and actually highlights the relative importance of each factor in the process. In addition, it can be conveniently integrated into utility analysis and substantially facilitate the optimization process by virtue of its model-free nature. For each portfolio consisting of hedge fund managers the following are considered:

- 1^{st} Moment = an asset's return
- 2^{nd} Moment = asset's variance (standard deviation = $\sqrt{Variance}$)
- 3^{rd} Moment = an asset's skewness; and
- 4^{th} Moment = an asset's kurtosis

5.2.1 Returns

Though much of the theoretical foundations of the method of moments define this first moment as the mean or average value, when a set of values has a sufficiently strong central tendency, that is, a tendency to cluster around some particular value. Then it may be useful to characterize the set by a few numbers that are related to its moments, the sums of integer powers of the values.

The time series data $x_0, x_2, ..., x_n$, i.e.

$$\bar{x} = \frac{1}{N} \sum_{j=0}^{N-1} x_j \tag{5}$$

However, the industry standard to compute the hedge funds monthly returns, r_i, is the geometric compounded product from the initial date of interest, will denote as t_1 to the terminal month denoted as t_N that wish to calculate how the fund performed within that duration, the formula is as follows:

[4] The first two moments are referred to as quadratic or the first moment and the second moment, any other moment above the second is referred to as the higher moment

$$\langle r \rangle = \prod_{i=1}^{N} (1 + r_i) - 1 \tag{6}$$

which estimates the value around which the realised returns had compounded over the duration under observation. This formula gives the precise idea of how investors' capital had accrued over the period of time from month t_1 to month t_N, hence the preference is to have high value for this result.

5.2.2 Standard Deviation

Investors in the traditional investments typically use the standard deviation as the primary risk measure. Standard deviation (σ) is the square root of the squared differences of each return relative to the mean return, divided by the number of observations minus 1.
Standard deviation works best as a risk measure for return distributions that closely approximate the normal distribution. Portfolios that contain derivatives may not follow normal distribution. The typical difference between portfolios with and without derivatives is that buyers of options have the ability to truncate the distributions of returns.

$$\text{Std Dev} = \sigma = \sqrt{\frac{\sum_{i=1}^{N-1} (r_i - \bar{r})^2}{N-1}} \tag{7}$$

Using equation (7) to calculate the Standard Deviation as a measure of riskiness assumes that all volatility in portfolio returns is risky. But investors consider upside and downside deviations from mean return to have very different qualities. Investors can earn large returns from upside volatility, so this 'risk' is seen as very different from the downside risk volatility that causes investor losses.

5.2.3 Skewness

The skewness or third moment characterizes the degree of asymmetry of a distribution around its mean. While the mean, standard deviation are dimensional quantities, that is, have the same units as the measured quantities r_i, the skewness is conventionally defined in such a way as to make it non-dimensional. It is a pure number that characterizes only the shape of the distribution. The definition given below is also used by Microsoft Office Excel Function called *skew*().

$$Skewness = \frac{n}{(n-1)(n-2)} \sum \left(\frac{(r_i - \bar{r})}{\sigma} \right)^3 \tag{8}$$

Any set of N measured values is likely to give a non-zero value for equation (8), even if the underlying distribution is in fact symmetrical (has zero skewness). For equation (8) to be meaningful, an estimate of standard deviation is needed. Unfortunately, this would depend on the shape of the underlying distribution, and rather critically on its tails! For the idealized case of a normal (Gaussian) distribution, the standard deviation of (8) is approximately $\sqrt{\frac{15}{N}}$. In real life it is good practice to believe in skewness only when they are several or many times as large as this. Press *et al* (1992). Skewness is used to rank order the feasible portfolios based on the behavioural hypothesis of investors expectation as given below.

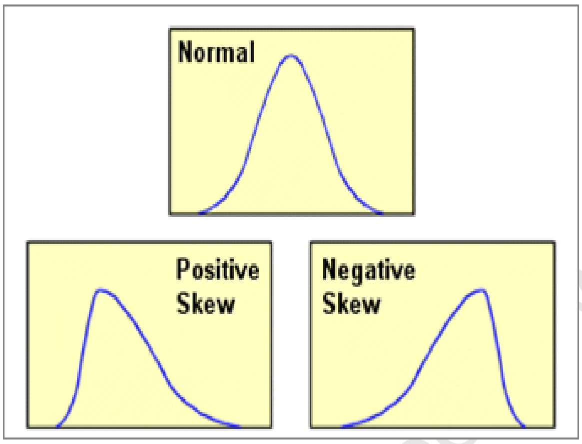

Figure 3: General Forms of Skewness Display

Investors desire positive skewness, where the probability of positive returns is higher than if the distribution were truly normal. Positive skewness can often come from the purchase of call or put options, from a fund manager that has market-timing skill. Investors may wish to avoid funds with negative skewness, where the probability of negative returns is higher than those implied by normal distribution. Negative skewness can arise from funds that are sellers of options or those that assume significant event risk. Black (2004).

5.2.4 Kurtosis

The kurtosis or fourth moment is also a non-dimensional quantity. It measures the relative peakedness or flatness of a distribution. Relative to a normal distribution. A distribution with positive kurtosis is termed leptokurtic, one with negative kurtosis is termed platykurtic, and of course, an in-between distribution is termed mesokurtic, see Figure(9). The conventional definition of the kurtosis given below is also what the Microsoft Office Excel Function called *kurt*() uses to compute kurtosis.

$$Kurtosis = \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{(r_i - \bar{r})}{\sigma} \right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)} \qquad (9)$$

The standard deviation of (9) as an estimator of the kurtosis of an underlying normal distribution is $\sqrt{\frac{96}{N}}$. However, the kurtosis depends on such a high moment that there are many real-life distributions for which the standard deviation of equation (9) as an estimator is effectively infinite. Press et al (1992)

A distribution with positive kurtosis has a much higher than normal probability of extremely large or small returns. Financial markets often have leptokurtic distributions, characterized by 'fat tails', where the probability of crashes is much larger than implied by normal distribution. Dramatic evidence of 'fat tails' occurs with regularity in financial markets, demonstrated by negative earnings surprises, corporate takeover announcements, stock market crashes, and currency devaluations.

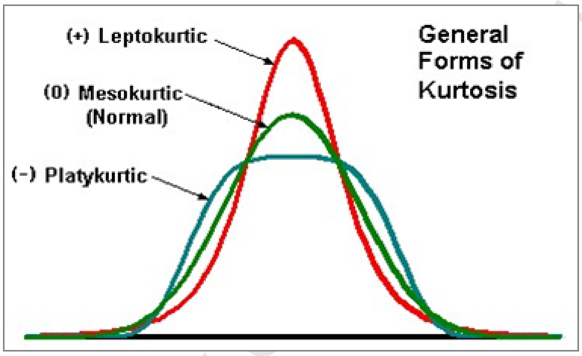

Figure 4: General Forms of Kurtosis Display

Black (2004) using the CSFB/Tremont database of hedge fund indices, finds that hedge funds with the largest Sharpe Ratios often have negative skewness and large kurtosis. If these values are large, the benefits of investing in hedge funds may be largely offset by the risk of extreme losses that result from investing in funds with negative skewness and 'fat tails' as measured by kurtosis. Indeed, many hedge fund strategies are based on accepting the event and liquidity risks that other investors choose to sell. If the hedge funds regularly accept event, liquidity, and 'fat tail' risks, their past history of risk and return may overstate the portfolio benefits of investing in these strategies.

Investors normally prefer odd-numbered moments, i.e. the mean and skewness to be positive and large. Whilst they desire that the even-numbered moments, that is variance and kurtosis, be small.

5.2.5 Negative Correlation Score

Negative Correlation Score defines the association between assets, namely their covariance. This measure describes how a particular asset compares to the 'crowd'. Whether it is an outlier that has precious diversification potential, or is it complementary to the 'herd' and, thus runs the risk of exacerbating a negative portfolio performance in response to unforeseen contagion? Bowers *et al.* (2003), help to define how the measure forces the inclusion of some risk association within the asset allocation taxonomy. By taking a snap-shop of the covariance matrix across a given asset universe and scaling all the negative elements for each respective asset array are able to illustrate just how diversified a particular asset is relative to its peers. The greater this negative covariance score, the more valuable a given asset is in terms of diversification potential relative to the remainder of the portfolio.

How is Covariance Measured?
Covariance is the degree to which alternate assets influence each other as measured by the co-movement of excess returns above their respective mean. It is defined as

$$Cov(R_{Asset(X)}, R_{Asset(Y)}) = \sum_{allX} \sum_{allY} (R_X - \mu_X)(R_Y - \mu_Y) \tag{10}$$

where:
$R_{Asset(X)}$ = Return on Asset X
$R_{Asset(Y)}$ = Return on Asset Y
μ_X = Mean Return for Asset X
μ_Y = Mean Return for Asset Y

How is 'Negative Covariance Score' Derived?
Firstly, take the mean level of negative covariance for a given asset array within the covariance matrix by setting all positive covariances to zero in the chosen array. This negative average is then multiplied by the number of negative elements. The absolute value of this final score is a measure of negative covariance - obviously, the higher the score the greater the diversification potential of the chosen asset.

$$\text{Negative Covariance Score} \cong |n * \overline{\mu}|$$
$$\text{where } \overline{\mu} = \text{mean of the negative Covariance elements;}$$
$$n = \text{number of negative Covariance observations;}$$

In order to measure the stability of the negative correlation score over time, consider the standard deviation of negative correlation score.

5.2.6 Stability of Negative Correlation

This standardized 'stability condition' measure of the negative correlation should be useful in exploring the efficacy of a particular asset in one's portfolio from a diversification point of view. If such diversification benefit is highly time variant, then the potential candidate is not really a candidate at all.

Correlation measures the degree to which alternate assets influence each other as expressed by a numeric between -1 and +1. In essence, correlation is the standardized measure of covariance and is defined as

$$Correlation = \rho_{XY} = \frac{Cov(R_{Asset(X)}, R_{Asset(Y)})}{\sigma_{Asset(X)}\sigma_{Asset(Y)}} \tag{11}$$

Then, take the Standard Deviation measure of this Correlation Measure through time as an Assessment of Covariance Stability

$$\text{Standard Deviation of Correlation} = \sqrt{\frac{n\sum_{t=1}^{T}\rho_{xy}^2 - (\sum_{t=1}^{T}\rho_{xy})^2}{n(n-1)}} \tag{12}$$

A simple arithmetic average of this measure for each correlation coefficient in the final array - each being measured against the other components in the portfolio - is then used to form overall assessment of covariance stability for the chosen asset.

5.3 t-Statistics Test for Significance

The t-statistic is a measure of how extreme a statistical estimate is. This statistic is computed by subtracting the hypothesized value from the statistical estimate and then dividing by the estimated standard error. In most cases the hypothesized value would be zero.

The t-test statistics takes the form $T = Z/s$, where Z and s are functions of the data. Typically, Z is designed to be sensitive to the alternative hypothesis (i.e. its magnitude tends to be larger when the alternative hypothesis is true), whereas s is a scaling parameter that allows the distribution of T to be determined.

Student's t-statistic is employed to ascertain whether the difference between two time series data is significantly different from zero. The X_i denotes the difference of each corresponding data elements of the two time series at each time step i up to the last element n, then take mean average of all $X_i's$ to have $\overline{X}$ as in the equation below:

$$t = \frac{\sqrt{n}\overline{X}}{\sigma} \tag{13}$$

where $\overline{X}$ is the sample mean of the data, n is the sample size, and σ is the population standard deviation of the data; s in the one-sample t-test, i.e. $\widehat{\sigma}/\sigma$, where $\widehat{\sigma}$ is the sample standard deviation.

The Visual Basic for Applications (VBA) program code below define equation (13):

```
Public Function Student_TTest(FirstArray As Variant, SecondArray As Variant)
    Dim i, j, strddev, result, N, U, RowCnt1, RowCnt2, maxVal As Integer
    Dim DiffArray()
    On Error Resume Next
    RowCnt1 = Application.Count(FirstArray)
    RowCnt2 = Application.Count(SecondArray)

    maxVal = Application.Max(RowCnt1, RowCnt2)
    ReDim DiffArray(maxVal)

    For i = 1 To maxVal
        DiffArray(i) = FirstArray(i) - SecondArray(i)
    Next i

    strddev = Application.StDev(DiffArray)
    result = Application.Average(DiffArray)

    Student_TTest = Sqr(maxVal) * result / strddev
End Function
```

The VBA function above takes two arrays as its parameter input list, then gets the length or the dimension of each array input, then compares the array sizes to take the maximum size of the two. Commencing from first entry of each array element the code calculates the difference between the numerical values held at each corresponding array index, then stores those differences into another array referred to as the DiffArray, then the Standard Deviation and the mean average of the DiffArray are calculated to compute the t-stats as given by equation (13).

t-Test: Two-Sample Assuming Unequal Variances

To supplement programmed t-stats function, Microsoft Excel in-built function is used that computes the t-stats, and decided to assume Unequal sample sizes, unequal variance so that when a program is running will dynamically cater for varying sample sizes and the variances treated as different. The t-statistic to test whether the means are different can be calculated as follows:

$$t = \frac{\overline{X_1} - \overline{X_2}}{s_{\overline{X_1} - \overline{X_2}}} \tag{14}$$

where

$$s_{\overline{X_1} - \overline{X_2}} = \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}} \tag{15}$$

Where s^2 is the unbiased estimator of the variance of the two samples, n = number of participants, 1 = group one, 2 = group two. For use in significance testing, the distribution of the test statistic is approximated as being an ordinary Student's t-distribution with the degrees of freedom calculated using:

$$D.F. = \frac{(s_1^2/n_1 + s_2^2/n_2)^2}{(s_1^2/n_1)^2/(n_1 - 1) + (s_2^2/n_2)^2/(n_2 - 1)} \tag{16}$$

This is called the Welch-Satterthwaite equation. Note that the true distribution of the test statistic actually depends (slightly) on the two unknown variances.

6 Alternative Performance Measurement

This chapter describes the portfolio performance measures that are implemented to develop a systematic methodology to assist the Fund of Hedge Funds manager to identify outstanding hedge funds that have the potential to create wealth and preserve capital. The Mathematical formulas are presented of these models, then offer some underlying assumptions that were used on derivations of such models, and how the results from the models could be interpreted and used to facilitate the process of investment decision making.

Bacmann and Scholz (2003) suggest that the measurement of performance is the cornerstone of the evaluation of an investment. Since the advent of the modern finance theory, this task has been performed within the risk-return framework. While the return is easy to define, the notion of risk is much more complex. The most used measure, namely the Sharpe Ratio, assumes that the standard deviation of the return distribution provides the full description of risk. However, risk averse investors tend to strongly dislike negative returns and large drawdowns. They would even prefer to partly sacrifice positive returns in order to avoid drawdowns. This asymmetric behaviour is not captured by the Sharpe ratio.

As an alternative, the Sortino ratio has been advocated by several authors (Stutzer (200), Bacmann and Scholz (2003), Bergh and van Rensburg (2008))as being a viable option to capture the asymmetry of the return distribution. It replaces the standard deviation in the Sharpe ratio by the downside deviation which captures only the downside risk. However, higher moments are incorporated only implicitly.

6.1 Sharpe Ratio

Since such transcendent setting publication by Sharpe (1964), the reward-to-variability or return-to-volatility ratio as it was originally known, the reward per unit of risk taken ratio is by far the most popular portfolio performance measure and had been industry standard for ages. The ratio is computed by dividing the return to the fund in excess of the risk-free rate by the standard deviation of returns.

$$\text{Sharpe Ratio} = \frac{R_{Actual} - r_{rf}}{\sigma_{actual-returns}} \tag{17}$$

where by

R_{Actual} is the actual returns (for this study it is actual hedge fund monthly returns)

r_{rf} is the risk-free rate

and $\sigma_{actual-returns}$ is the standard deviation of the actual returns

The Sharpe ratio is derived from the capital asset pricing model, which is frequently used as a test for the market efficiency. If the market is efficient, the CAPM predicts that each security will generally be fairly priced, and it will be difficult for active managers to outperform their benchmark or for market-neutral managers to have positive Sharpe ratio.

The Sharpe ratio declines as the volatility of return increases, which assumes that the fund should be penalized for all standard deviation in returns, whether this deviation is positive or negative.

6.2 Sortino Ratio

The Sortino ratio, calculated as the returns in excess of the risk-free rate divided by the downside deviation of returns (semi-variance), penalizes for losses and downside risks. The Sortino ratio will have higher values than Sharpe ratio, as only a portion of the total risk is included in the calculation of Sortino ratio. Funds with large volatilities can be more easily found through the use of the Sortino ratio than by the Sharpe ratio, so investors searching for funds with higher levels of 'good volatility' would choose funds based on the Sortino ratio.

$$\text{Sortino Ratio} = \frac{R_{Actual} - r_{rf}}{\sigma_{donwside-returns}} \tag{18}$$

where by

$\sigma_{donwside-returns}$ is the standard deviation of the portfolio return time series that are below target return.

Other variables have been defined in equation (17).

In essence the Sortino ratio measures whether the portfolio's return in excess of specified benchmark is sufficient to cover the downside risk inherent in the investment. It is therefore an indicator of capital preservation in nominal terms. The benchmark return can also be equated to the inflation benchmark so that the ratio then indicates whether real returns were sufficient to cover the risk of under-performing inflation. This is an important indicator of a fund's ability to match inflation-adjusted liabilities.

As mentioned earlier that the higher moments effects are not explicitly incorporated into the Sortino ratio, even though it provides much desired alignment with the investors views. There are performance measures available in finance literature that accommodate the higher order moments.

6.3 Omega Function

The Omega measure suggested by Keating and Shadwick (2002) incorporates all the moments of the distribution, as it is a direct transformation of it. This measure splits the return universe into two sub-parts according to a threshold. The 'good' returns are above this threshold and the 'bad' returns below. Very simply put, the Omega measure is defined as the ratio of the gain with respect to the threshold and the loss with respect to the same threshold,

$$\Omega(r) = \frac{\int_L^b [1 - F(r)]dr}{\int_a^L F(r)dr} \tag{19}$$

where the cumulative distribution F is defined on the interval (a,b).

According to Keating and Shadwick (2002), this performance measure is a natural feature of the returns distribution. In fact its construction from a returns distribution is entirely canonical, requiring no choices and admitting no ambiguity which is not already present in the data. As such it may be regarded as an extension of the notion of the cumulative distribution. It is a function that may be evaluated at any value in the range of possible returns, so that it allows performance comparisons with respect to any 'risk' threshold in this range. The use of a function of returns rather than a single number to measure performance is essential.

6.4 Maximum Drawdown Measure

The maximum drawdown is loosely defined as the transition from the peak to the trough of the fund performance flow. Black (2004) defines the maximum drawdown as the maximum percentage loss from the high-water mark. Hedge funds investors often request the fund to disclose the size of their largest drawdown, as they may feel that the mean and standard deviation of returns are not sufficient to fully understand the risk of the fund. To find the largest drawdown, calculate the difference between the high-water mark, which is the highest monthly closing NAV, and the subsequent lowest monthly closing NAV. Typically, month-end values are used in this calculation, so larger drawdowns will not be disclosed if they occur at a time other than month end. A related statistic is the time, measured in months, that it takes to move from the point of the largest drawdown to regain the losses and set a new high-water mark.

- **High WaterMark** refers to the highest value that the portfolio has ever been valued at. No performance fees can ever be charged if the fund is not above the high watermark and high watermark can never reset.

- **Hurdle rate** refers to the rate of return that must be achieved before performance fees can be charged. The fund manager is then only paid performance fees on return above the hurdle. Black (2004)

$$Drawdown = \frac{\text{recent High WaterMark} - \text{lowest Subsequent Monthly Close}}{recent \text{ HighWater Mark}} \tag{20}$$

Another statistic that is used by absolute-return strategies is the percentage of the months that a fund posts gains. The percent of winning month statistic is calculated by dividing the number of months that the fund posted positive returns by the numbers of months the fund has been invested.

$$\text{Percent Winning Months} = \frac{No. \text{ Months with Positive Returns}}{total \text{ No. of Months Invested}} \tag{21}$$

Low-volatility funds, especially market-neutral funds, are more likely to have a higher percentage of winning months, while higher-volatility strategies, especially those that are correlated to equity markets, are likely to have a lower percentage of winning months, especially when stocks enter a bear market.

7 Methodology

Data

Since the hedge fund industry operates in an unregulated environments, they are not obliged to publish their performance returns periodically as do other traditional investment asset classes. Such data is therefore only made available to professional risk managers acting on behalf of investors or funds of hedge funds. As this thesis project is industry based. The data was acquired through the risk management team who have direct access to the relevant hedge fund managers monthly returns reporting. The data starts from January 1999 (when first hedge fund manager in South Africa recorded monthly returns) to July 2009, it is the monthly returns, that is net of management fees, incentives or any other possible deductions.

As in any quantitative approach to risk management, historical data is used to some extent. Risk management for hedge funds is no exception. There is however one aspect of hedge-fund data that make this endeavour particularly challenging: namely survivorship bias. Few hedge-fund databases maintain histories of hedge funds that have shut down. In the few cases where databases do contain 'dead' as well as active funds, studies have concluded that the impact of survivorship bias can be substantial; (Lo (2003)). Another documented data bias is: backfill bias, whereby managers only start reporting their returns once they have achieved a respectable initial track record, and then these past positive results are 'backfilled' into the database together with the current results. Though, these data biases are found in some Offshore Hedge Fund databases, this is not the case for the data used in this study. The data used has every hedge fund manager who ever existed in the South African industry, without exclusion of some blown-ups, or others with extremely negative returns as low as -65% on a single month.

Algorithmic Model Description

This factor model uses the following Statistical metrics or factors; Returns, Standard Deviation, Skewness, Kurtosis, Negative Correlation, Reliability of Negative Correlation. It has been built to do extensive quantitative analysis of the hedge fund return distributions. In addition to these Statistical metrics, a model also implements the Mathematics of Financial Models (α-alpha, β-beta, Sharpe Ratio, Sortino Ratio, Omega Function, Maximum Drawdown) to assess the performance of hedge fund managers based on their return distributions. The factor model helps to make robust quantitative methodology to facilitate investors (Fund of Hedge Funds manager) in making good investment selection decisions. The factor model gives the quantitative portfolio manager a good idea of what (s)he can expect the portfolio to earn in the particular investment strategy.

A sound model begins with good planning. The preliminary work of the portfolio manager is to make a series of decisions that could serve as a blueprint for construction of the model. Other preliminary decisions determine the shape of the data set (including the nature of the hedge fund returns, the time interval between data points, and the overall time horizon of data) and the scope of hedge funds strategy to consider for the portfolio. Two other interrelated questions also affect the quality of the data set: i.e. what time interval should be used, and what overall time horizon should the data set cover? Ideally, the time interval should reflect the investment horizon (i.e. rebalancing frequency). If the portfolio is rebalanced every six months, then a semi-annual interval should be used. If portfolio is rebalanced every year, an annual interval should be used.

A model is not usually an exact description of reality, only the a good approximation of it. In statistics, shortcomings in the model are called specification errors. One should strive to build models that reflect persistent and stable patterns.

In this study a model-independent methodology that makes no parameter estimation is used. Only the empirical data set is used without any implicit parameters approximation. The statistical algorithms together with the Mathematical equations that are used as the building blocks of this multi-factor model, have been designed to be robust and dynamic enough to cater for sparse input data. For other hedge fund strategies the results might be different compared to other strategies whilst using the same factor to assess their ranks and generate the simulated portfolios.

Procedure for factor/metric modeling

Using the algorithms mentioned or discussed above, the statistical metrics are calculated for each hedge fund manager for every month starting from n-months specified as the duration/horizon of 'looking backward' from the initial date. Then retain that 'look back' duration as the rolling window period to 'move forward' every month until the end of the database is reached. Having done the calculation of that particular factor, then for every rebalancing period of months 'moving forward', fetch hedge fund managers that contain data to align them together, so that could be sorted, then fragment them into four equally spaced quartiles based on their numeric calculation of that certain factor that has been chosen. Having sorted them in order, the hedge funds' names only are passed to an array in the order that they had attained positions on the quartile ranking, thus pass their names only to an array leaving out the numerical calculations that was used to rank them.

This array of quartile rankings is now going to be used as sequential reference to search the actual returns from the raw data for each and every fund name in the array. These actual returns form the portfolio components for the four equally weighted portfolios. Then hold these quartiles of equally weighted portfolios to move forward each month for the period of the rebalancing frequency. When get to the end of rebalancing frequency, the portfolios are rebalanced from scratch still using the same factor to rank them and split into quartiles. Then from there get the quartiles into an array to search for their corresponding actual returns from the raw data. Hold that equally weighted portfolios for the duration of the rebalancing frequency. Then process keeps on recurring like that till the end of time horizon is reached. Finally portfolio returns or average of the simulated portfolios in each quartile are calculated every month from the beginning of the specified period under consideration to the terminal period. Using these simulated portfolios, make a hypothetical initial investment and then calculate the cumulative returns accrual from that initial period to the last date of the simulated portfolios. These hypothetical investments are best put on the graphs to depict clearly the point that trying to make here.

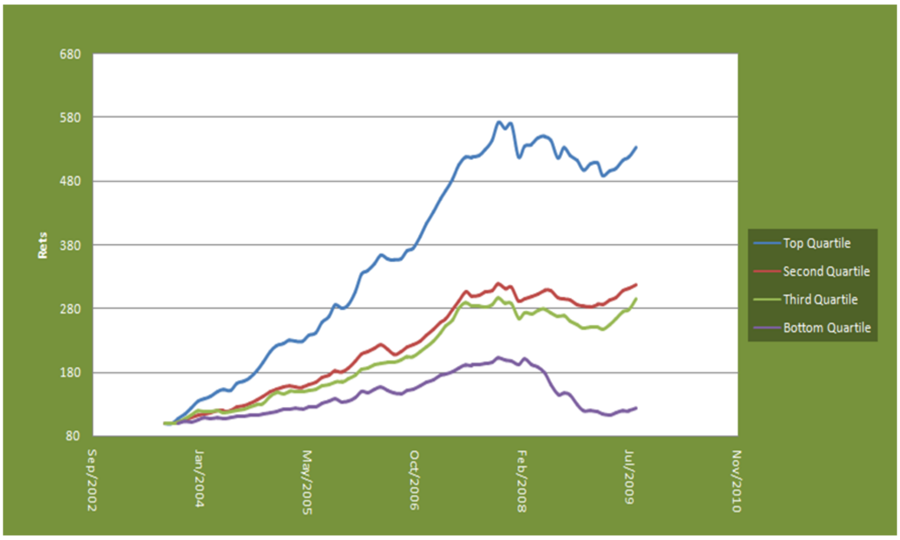

Figure 5: Quartile Ranking Simulated Portfolios

Figure (5) shows the four equally weighted portfolios simulated from the quartile ranking of fund managers by the returns factor. It also shows how the hypothetical initial investment of ZAR100 would have accrued for each quartile. The Top Quartile clearly would have accumulated more wealth in access of 300% from Dec. 2003 to Jul. 2009, as for the Bottom Quartile investors' assets could have barely made only 19% from Dec. 2003 to Jul. 2009 or worst still investors' assets could have suffered financial loss due to such portfolio propensity to have negative performance.

The second and third quartiles grow quite moderately upwards, and making 196% and 184% respectively over the same period of Dec. 2003 to Jul. 2009. These quartile portfolios were determined using the first moment, thus asset's returns to sort them in order of that calculated metric. Then rank them descending according to those who have best returns as first to those with lowest as the last. The 'look back' period of past 12 months and 'rebalancing frequency' of every 6 months were randomly chosen to make this example. Other factors such as Standard Deviation, Skewness, Kurtosis, Negative Correlation, Stability of Negative Correlation, alpha, beta, Sharpe ratio, Sortino ratio, Omega Function and the Maximum Drawdowns could have been used or selected and the logic is just similar even though the ranking might differ, because a manager who ranks number 1 for returns could rank differently for any metric under consideration.

The categorization of the HF managers into quartiles enables to build a hypothetical portfolios of HF managers; i.e. the Top Quartile Portfolio, Second Quartile, Third Quartile and Bottom Quartile Portfolio. The main focus has been put on top and bottom quartiles. Using t-stats compare the top versus bottom quartiles portfolios to determine if the results are significant and different from zero. The significance level of 95% is applied or rather any *p-value* greater than 5% is deemed to be insignificant.

A Fund of Hedge Funds is expected to perform somewhere along the mid-way between the Top and Bottom of any arbitrary classification of the underlying hedge funds. In order to establish a solid identification of the average return of the best fund managers in the top quartile are compared against the average return of the worst performing ones in the bottom quartile. The time series for the Top Quartile Portfolio minus the Bottom Quartile Portfolio returns is comparable to a hypothetical hedge fund going long of the Top Quartile portfolio and going short of the Bottom Quartile Portfolio.

For all the data analysis no assumptions were made concerning the practical market frictions such as transactions cost, tax or fees incurred during the rebalancing.

The Objectives of this Quantitative Analysis and Definition of 'Desirable' Factor

The primary intention of using all these metrics is to identify hedge fund managers whose return distributions best align with the investors' aspirations, or else who possess the desired statistical metrics that could be attributed to the good outstanding performance. The desirable aspects that investors would be looking for are, though not limited to, high values for the odd numbered moments, i.e. high values for hedge fund's returns and skewness, but low values for the even numbered moments thus very minimum standard deviation and kurtosis. The hedge fund managers who have highest score for the negative correlation as that indicates good diversification potential, and the lowest volatility of stability of negative correlation as that implies reliable diversification benefits. For the performance measures investors aspire to have in their portfolio assets that have good rewards for every unit of risk undertaken. That is they try to identify hedge fund managers with high values of alpha, Sharpe & Sortino ratios, Omega Function, however they desire for low values for the Maximum Drawdowns and the moderately low value for beta. The key issue to search for here is the statistically significant t-statistics calculated between the two portfolios consisting of the top and bottom quartile managers. If any factor under consideration could provide significant t-stats, then such a particular factor could be attributed as an important factor to assist the identification of good hedge fund managers who possess desired attributes in their distributional characteristics.

The program code below written in Visual Basic for Applications (VBA) is a generic model of how all the program codes for various factors considered have been programmed to follow a certain logical methodology when doing the factor calculation.

The Program Code Description

Most of the programming codes that have been developed are user interactive and there are common inputs to most of the functions. These user interactive inputs have their own corresponding functions to initialize them, so that they could just be dynamically called by other various program functions at run-time. Hence, few of the programmed functions have a list of parameters inputs between their parenthesis. The function below begins with declaration of variables list that is going to be used along the program, also the arrays declaration. The function named CountNumberofRows_onRawData() whose output is stored in a variable N, counts how many months does the database have so that could inform the code when end the of time horizon has been reached. The function named CountNumberofColumns_onRawData() then referenced from there by variable U, basically counts the number of hedge fund managers that are going to be considered in the ongoing calculation.

There is a source for raw data that contain all the hedge fund managers' strategies together with actual monthly returns data. So every time calculation is done such source is referenced to be the default one unless the user specifies the hedge fund trading strategy that wishes to be considered or analyzed. If the trading strategy has been chosen, the hedge fund managers of that particular strategy only are uniquely selected from the whole universe in raw data, all other logics still remain the same.

Having counted the number of months and number of the hedge fund managers, could as well as re-dimension the array indexes. The 'looking backward' window period is specified on the user interactive form and the input values or options chosen are catered for by the piece of code within the function named GetUserFormInputs_LookBackPeriod() which is then referenced within this function as the WindowPeriod, and the 'rebalancing frequency' is taken care of by the piece of code under the function named GetUserFormInputs_RollBy() and within this function is then referred to as the RollBy onwards. More additional program description is given after this code below:

```
Public Function StatsMetricsCalcs()

    Dim ColName, MsgBxTitle As String
    Dim i, j, a, ColNum, K, Counter, U, N As Integer
    Dim RollBy, WindowPeriod As Integer
    Dim RollingPeriodReturns(), GetEffectiveDate(), GetHF_ManagerNames() As Variant
    Dim SheetName As String

    N = CountNumberofRows_onRawData()
    U = CountNumberofColumns_onRawData()

    SheetName = "Raw Data"
    ColNum = 1
    If managerselectionstrategy.optbtnSelectStrategy.Value = True Then
       SheetName = "DataByStrategy"
       Do While ((IsEmpty(Sheets(SheetName).Range("B1").Cells(1, ColNum))) = False)
            ColNum = ColNum + 1
        Loop
        U = ColNum + 1
        N = N + 1
    Else
        SheetName = "Raw Data"
    End If

    MsgBxTitle = "Hedge Fund Managers Returns"

    ColName = GetColName(U + 1) 'returns columns label for the last column
     'of the data considered

    ReDim RollingPeriodReturns(N, U), GetEffectiveDate(N), GetHF_ManagerNames(U)
```

```
RollBy = GetUserFormInputs_RollBy
WindowPeriod = GetUserFormInputs_LookBackPeriod

ReDim Arr_Managers(N, U), Array_Test(N, U), RollingPeriodReturns(N, U)
For x = 1 To U
    For y = FirstDate To LastDate
        Arr_Managers(y, x) = Sheets(SheetName).Range("B2").Cells(y, x)
    Next y
Next x

For j = 1 To U
    For i = FirstDate To LastDate  'FirstDate To LastDate
      Array_Test(i, j) = Arr_Managers(i, j)
    Next
    For i = FirstDate To LastDate
        Counter = 0
        If i >= WindowPeriod Then
            For a = i To i - (WindowPeriod - 1) Step -1
                If Not (IsEmpty(Array_Test(a, j))) And _
                                            IsNumeric(Array_Test(a, j)) Then
                    Counter = Counter + 1
                End If
            Next a
        Else
        End If

        'Thats where calculate the annualised returns
        If Counter >= WindowPeriod Then
            RollingPeriodReturns(i, j) = "=PRODUCT('" & SheetName _
                                            & "'!R[" & (-WindowPeriod) & "]C:RC+1)-1 "
        End If
    Next i
    'Just clears the current array so that
        'on the next loop it contains fresh unique data
    For i = FirstDate To LastDate
        Array_Test(i, j) = ""
    Next i
```

```
    Next j
    'Print the calculated rolling window returns on
    'the entire space starting from A2 to number columns of data
    Range("A1", ColName & N).FormulaArray = RollingPeriodReturns

End Function
```

For the sake of brevity, some portions of the code have been excluded and only the areas that explain the main concept are highlighted.

The first 'for loop' acquire all numeric raw data from the source prior to performing any calculations,thus

```
    For x = 1 To U
        For y = FirstDate To LastDate
            Arr_Managers(y, x) = Sheets(SheetName).Range("B2").Cells(y, x)
        Next y
    Next x
```

the second iterated 'for loop' is essentially where the program code does the actual inspection to check if there is enough data for each individual hedge fund manager before could calculate the metric concerned, or else 'whoever' does not have sufficient data under that 'looking backward' period is excluded when doing the calculations for the factor under consideration.

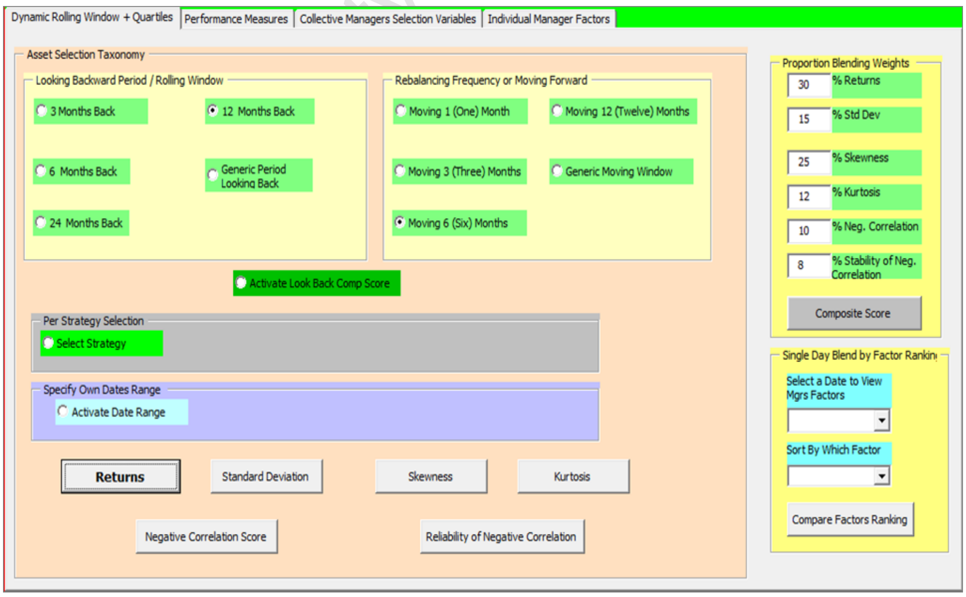

Figure 6: Our Asset Selection Taxonomy Model System Overview

Figure (6) shows the parameters setting overview to specify inputs for the system for any calculation chosen. The program above calculates the returns and contain all the calculated values in an array:- $RollingPeriodReturns(i, j)$ so that when finished calculating could just put the contents of that array to the destination.

The cross sectional view of the userform presented on Figure(6) represents an overview of the how project have been developed in order to come up with a systematic methodology to use when making the investment decision on how to select the best underlying Hedge Fund Managers who display the desired characteristics.

The generic function name FetchOrderSortBreakIntoQuartiles() below first searches for the month being considered and gets all the fund names and their corresponding calculated metric values, and then filters out the empty ones, from there sorts the non-empty list into descending order and then fragment the list of fund names into quartiles and put those names into an array and then that array would be used by another function to fetch the actual returns from the raw data source.


```
Public Function FetchOrderSortBreakIntoQuartiles()

'Retrieve the exact match of the dates from the available database
For i = 1 To N
Get_Array(i) = Sheets("ReturnsCalcs").Range("A1").Cells(i, 1)
SelectedDateCheck = Get_Array(i) Like SelectedDate
 If SelectedDateCheck = True Then
    SrtDate = i - 1
    srt = 1
    Exit For
End If
Next


If srt < 1 Then
Exit Function
MsgBox "Please check the valid dates, _
        " & SelectedDate & " was not found", vbExclamation, MsgBxTitle

End If
```

```
'Get the compounded returns from the row that corresponds with selected date
For a = 1 To U
 MovingReturns(a) = Sheets("ReturnsCalcs").Range("B2").Cells(SrtDate, a)
Next

init = 0
'Filter out the empty spaces from the captured
'managers from that row of selected date
For a = 1 To U
If (Not (IsEmpty(MovingReturns(a)))) And IsNumeric(MovingReturns(a)) Then
    init = init + 1
    MovingReturns(init) = MovingReturns(a)
    ManagersList(init) = ManagersList(a)
End If
Next

If init < 1 Then
Exit Function
End If
'Clear the cells from A1 to C _columnNo. to make a room
'for newly captured returns
Sheets("MovingWindowQuartiles").Activate
Range("A" & 1, "B" & U).Select
Selection.ClearContents

'Print the newly captured returns on the space cleared above
For j = 1 To init
Sheets("MovingWindowQuartiles").Range("B1").Cells(j, 1) = _
            ManagersList(j)
Sheets("MovingWindowQuartiles").Range("A1").Cells(j, 1) = _
            MovingReturns(j)
Next

'This is where doing the sorting using MS EXCEL
'inbuilt function to sort in descending order
Range("A1:B" & init + 50).Select
ActiveWorkbook.Worksheets("MovingWindowQuartiles").Sort.SortFields.Clear
ActiveWorkbook.Worksheets("MovingWindowQuartiles").Sort.SortFields.Add Key:= _
```

```
Range("A2"), SortOn:=xlSortOnValues, Order:=xlDescending, DataOption:= _
xlSortNormal
With ActiveWorkbook.Worksheets("MovingWindowQuartiles").Sort
.SetRange Range("A1:B" & init + 50)
.Header = xlNo
.MatchCase = False
.Orientation = xlTopToBottom
.SortMethod = xlPinYin
.Apply
End With

'Contain the sorted returns into an array so that
'could be able to quantise the printing area
For j = 1 To init + 1
MovingReturns_Sorted(j) = _
    Sheets("MovingWindowQuartiles").Range("A1").Cells(j, 1)
Next
Dim QC1, QC2, QC3, QC4 As Integer
Range("E2:J" & 4 * U).Select
Selection.ClearContents

'Fragment or split or segment total value into quartiles
QC1 = Application.RoundDown(0.25 * (init + 1), 0)
QC2 = Application.RoundDown(0.5 * (init + 1), 0)
QC3 = Application.RoundDown(0.75 * (init + 1), 0)
QC4 = init + 1
qij = 1

CQ1 = Application.RoundDown(0.25 * (U + 1), 0)
CQ2 = Application.RoundDown(0.5 * (U + 1), 0)
CQ3 = Application.RoundDown(0.75 * (U + 1), 0)
CQ4 = U + 1

a = 0
b = 0
c = 0
d = 0
```

```
If init < 4 Then
Exit Function
Else

 'Fragment the sorted data into quartiles and print them in ranks
 For i = 1 To QC1
     a = a + 1
     Sheets("MovingWindowQuartiles").Range("G2").Cells(a, 1) = _
                              MovingReturns_Sorted(i)
     Sheets("MovingWindowQuartiles").Range("F2").Cells(a, 1) = _
                 "=IfError(VLookup(RC[1], MovingWindowSldDate, 2, False), """")"
 Next
 For i = QC1 + 1 To QC2
     b = b + 1
     Sheets("MovingWindowQuartiles").Range("G" & CQ1 + 10).Cells(b, 1) = _
                              MovingReturns_Sorted(i)
     Sheets("MovingWindowQuartiles").Range("F" & CQ1 + 10).Cells(b, 1) = _
                 "=IfError(VLookup(RC[1], MovingWindowSldDate, 2, False), """")"
 Next
 For i = QC2 + 1 To QC3
     c = c + 1
     Sheets("MovingWindowQuartiles").Range("G" & CQ2 + 21).Cells(c, 1) = _
                              MovingReturns_Sorted(i)
     Sheets("MovingWindowQuartiles").Range("F" & CQ2 + 21).Cells(c, 1) = _
                 "=IfError(VLookup(RC[1], MovingWindowSldDate, 2, False), """")"
 Next
 For i = QC3 + 1 To QC4 + 1
     d = d + 1
     Sheets("MovingWindowQuartiles").Range("G" & CQ3 + 32).Cells(d, 1) = _
                               MovingReturns_Sorted(i)
     Sheets("MovingWindowQuartiles").Range("F" & CQ3 + 32).Cells(d, 1) = _
                 "=IfError(VLookup(RC[1], MovingWindowSldDate, 2, False), """")"
 Next

End If

End Function
```

The program codes provided above by VBA Functions :- StatsMetricsCalcs() and FetchOrder-

SortBreakIntoQuartiles() represent the generic flow of almost all the programming coded for every Statistical Metrics as detailed in theory of the chapter (5), and even though the programming style would definitely differ but it also represents how the Alternative Performance Measures have been coded of the chapters (4 & 6).

Van Rensburg and Robertson (2003 (b))employed a methodology that adopts both a one-way and two-way sorting procedure to create simulated portfolios. For the one-way sort procedure, stocks are ranked each month in descending order of the attribute under consideration. Quintile breakpoints are then inserted in the ranking, allowing all stocks to be assigned to one of five groups. Using the stocks in each quintile at the end of each month, an equally-weighted portfolio is constructed and rolled forward to the end of the following month. In this way, a time series of monthly returns is generated for each of the five portfolios. An aggregate post-ranking beta is then calculated for each simulated portfolio.

A two-way sort procedure allows two attributes to be examined concurrently. Stocks are first sorted in each month into quintiles by ranking on the first attribute under consideration. Then, within each quintile, stocks are ranked in descending order of the second attribute being investigated thereby creating twenty-five groups of stocks. This creates independent variation in each of the attributes thereby allowing the influence of one attribute to be examined while holding the other constant. As with the one-way sort procedure, a post-ranking beta is then estimated for each of the twenty-five simulated portfolios.

For this thesis, there is single factor approach that is used to observe how its influence could be used to explain the fund's performance, the logical methodology has been explained above. Also there is a combined composite score that uses all the factors as the ranking tool to simulate feasible portfolios, the details of this composite score ranking are given below.

Composite Score Ranking

The Composite Score Ranking consolidates all the factors considered up to this point. Then goes on to investigate how each collective combination of them all contributes to the determination of the best hedge fund managers. Firstly, run concurrently all the factors, with the same input parameters of the 'looking backward' window rolling every month forward and the 'looking forward' window or Rebalancing Frequency, then rank order hedge fund managers on each of these factors independently. Such that for each and every hedge fund manager name there is a corresponding metric factor used to rank them. The numerical rank position such particular hedge fund attains with respect to their peers in that category is recorded. Then blend up a consolidated matrix of how each hedge fund manager rank based on each of these factors. Using that numerical rank position on any particular factor as its score and consolidate them all in one table with hedge fund managers names making rows down the table and the column headings being the factors, then for each rows-columns intersection is the numerical score that particular manager along that row has been ranked on that factor along that column in comparison with others in the universe.

Just tentatively treating those numerical rank scores for each factor as the normal assets, then 'allocate' percentage weightings for each numeric rank score and multiply that numeric score with its own 'allocated' percentage to produce a consolidated score. Then sum up those products (score multiplied by 'allocated' percent) to the last column as the value obtained by individual hedge fund. When looking at all the composite score rankings together and having produced a single consolidated score value for the 'allocated' percentage multiplied by its numeric score attained on each factor, then could observe their influence on identification of best performance.

Then, they are sorted by the descending order of consolidated score, ranked and fragment into quartiles, and hold that as the four equally-weighted portfolios going forward for the period of the specified rebalancing frequency, after that a new rebalance of the consolidated score ranking is revisited, then sorted, rank into quartiles, hold portfolios going forward, and so on until the end of period. Just like for the single factor, if one fund gets blown up within the duration of holding the simulated portfolio forward, it is discarded from portfolio and re-arrange quartile rankings and re-distribute again to go forward with live data.

Calculate monthly returns for the portfolios, and then make initial equal hypothetical investment, calculate compounded returns, and generate graphs and observe how their illustration of performance look like, then investigate the significance of t-stats between the top and bottom quartiles portfolios

Initially the percentage are just 'allocated' equally or just randomly for each factor. However, equal percentage 'weighting' for the factors might not be optimal. So search for optimal percentage 'weightings' by varying the 'allocations' in steps of 10% to find out those that give the best significant t-stats. The optimal percentage 'weighting' had to go with the best combination of the 'looking backward' period versus the 'rebalancing frequency'. Then having found that optimal combination of the optimal percentage 'weighting' and the best 'looking backward' period versus the 'rebalancing frequency', the main objective behind this thesis project would have been achieved. This optimal combination could be per strategy or the whole universe even though hardly could any single investor distribute all her/his assets across all the universe, but the observation of the strategy that delivers good results is the key search for the fund of hedge funds manager primary goal to identify the best fund managers.

In Table (1), an example of the consolidated factor rankings is illustrated. The second last column shows the abbreviated manager names. Note that some managers do have empty spaces for `RelNgCr` (Reliability of Negative Correlation) as sufficient data to calculate that metric for that 'looking backward' period might not have been available. As such that factor is bypassed and is left empty. The code system only picks up the non-empty values, and the empty spaces in Table(1) are treated as zero to be multiplied by the percentage 'allocation' for the metric factor concerned. Highest scores are the ones with the highest calculated value for the factor considered. Thus HF Manager 1 has best annualized returns and skewness than the rest of other 26 HF Managers but does not score well for other factors. HF Manager 19 who happens to have the best overall score has good scores for higher moments like skewness, kurtosis, negative correlation and reliability of negative correlation. When the percentage 'allocated' for that metric is multiplied by the numeric rank attained and sum up altogether, then sort them descending to find out those who have the best composite ranking when all factors are considered together, from there segment them into quartiles, then construct quartile portfolios till rebalancing period, and re-loop the process again till the investment horizon duration has been reached.

Table 1: Hedge Fund Managers: Composite Score Ranking

HF Mgr Name	Ret	StdDv	Skew	Kurt	NegCor	RelNgCr	CompScore	Sorted Descending	
	20%	20%	20%	20%	10%	10%		HF Name	Score
HF Manager 1	27	13	27	4	7	6	15.5	HF Mgr 19	19
HF Manager 2	26	18	5	16	10	10	15	HF Mgr 5	18
HF Manager 3	25	7	13	23	27		16.3	HF Mgr 12	17.7
HF Manager 4	24	2	15	21	13	19	15.6	HF Mgr 13	17
HF Manager 5	23	23	22	10	24		18	HF Mgr 3	16.3
HF Manager 6	22	15	26	5	19	5	16	HF Mgr 6	16
HF Manager 7	21	3	21	22	17		15.1	HF Mgr 4	15.6
HF Manager 8	20	12	16	13	15	9	14.6	HF Mgr 1	15.5
HF Manager 9	19	1	9	26	1	1	11.2	HF Mgr 7	15.1
HF Manager 10	18	14	19	20	4	4	15	HF Mgr 14	15.1
HF Manager 11	17	4	6	9	12	13	9.7	HF Mgr 10	15
HF Manager 12	16	26	25	19	2	3	17.7	HF Mgr 2	15
HF Manager 13	15	5	17	25	26	20	17	HF Mgr 8	14.6
HF Manager 14	14	17	24	18	3	2	15.1	HF Mgr 22	14.3
HF Manager 15	13	19	12	24	6		14.2	HF Mgr 15	14.2
HF Manager 16	12	10	14	12	16	16	12.8	HF Mgr 21	13.6
HF Manager 17	11	6	18	7	22	15	12.1	HF Mgr 16	12.8
HF Manager 18	10	20	7	8	8	8	10.6	HF Mgr 27	12.6
HF Manager 19	9	16	20	27	25	21	19	HF Mgr 17	12.1
HF Manager 20	8	11	11	6	20		9.2	HF Mgr 26	11.5
HF Manager 21	7	22	8	17	11	17	13.6	HF Mgr 9	11.2
HF Manager 22	6	8	23	14	23	18	14.3	HF Mgr 18	10.6
HF Manager 23	5	25	1	1	5	7	7.6	HF Mgr 11	9.7
HF Manager 24	4	9	2	2	14	11	5.9	HF Mgr 20	9.2
HF Manager 25	3	21	3	3	9	12	8.1	HF Mgr 25	8.1
HF Manager 26	2	24	10	11	21		11.5	HF Mgr 23	7.6
HF Manager 27	1	27	4	15	18	14	12.6	HF Mgr 24	5.9

8 Results and Data Analysis

The overriding goal of this project has been to develop a quantitative asset selection methodology that would facilitate for fund of hedge funds to identify the optimal hedge fund managers from the pool of available in the industry. The analysts need a meaningful yet practical way to rank-order feasible portfolios. Hence the developed model ought to extract sufficient metrics to offer the utmost tangible portfolio construction for onwards management. Various results are presented in this chapter and analyzed as well.

Figure(7) shows the two separate pictures for the graphs of the simulated portfolios for the top and bottom quartiles and also the mid-average between the two, and the calculated statistical tests measures during the running of the program.

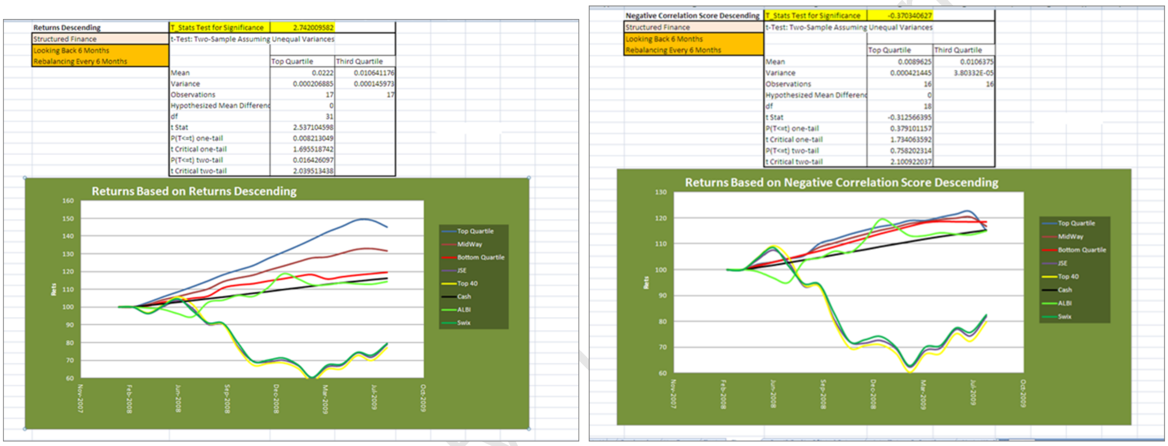

Figure 7: Structured Finance Strategy: Quartile Graphs, ranked based on Returns (LHS) and Negative Correlation (RHS), are above Cash (STEFI) when major Benchmark Indices were down

The portfolio simulated by ranking hedge funds using returns (the left side graph of Figure(7)) and negative correlation (right side of graphs of Figure(7)), have done relatively well during the turmoil market conditions of late 2008 and early 2009. So for any investor's assets under the Structured Finance strategy would have been insured against financial loss when the stock market crashed. As Borland *et al.* (2009) have warned of the danger of relying solely on statistical tests and also provided an alternative that one should look at data, charts and graphs in order to build one's intuition. Therefore, on top of t-stats results one has to observe how the time series graph looks like and how steady it seems to continuously grow in order to generate wealth, to preserve capital and prevent potential financial loss.

Figure(8) illustrates a graphical depiction of how the hedge fund universe had performed over the recent past years, in comparison with the major indices in the South African financial stock market (JSE). It is visually clear that the top performing hedge fund managers or those who fall within the Top Quartile in this categorization methodology, had consistently outperformed the market.

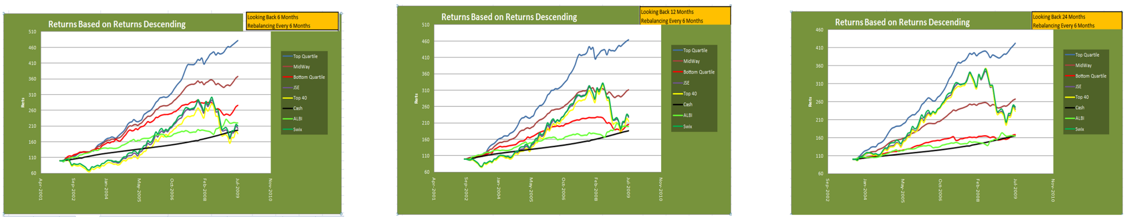

Figure 8: Graphs of HF Returns together with major South African Benchmark Indices

Fung and Hsieh (1999) argues that hedge fund investing could never be advocated on superior performance over the traditional investment, but rather on the effect of diversification they add to the portfolio that also include traditional asset classes. Nevertheless, results suggest that the hedge funds outperform the traditional investment into equity, bond, cash and indices, as shown on charts in Figure (8).

On Figure(8), the 'rebalancing frequency' is 6 months for three different 'looking backward' periods. Note that on the left most graph, the shorter the 'looking backward' period considered to calculate the metric or factor to rank order the simulated portfolios, then even the bottom quartile portfolio graph 'goes' above or is almost at par with the market (JSE) and other major indices (SWIX, TOP40). As the 'look back' period prolongs the top quartile portfolio consistently seems to outperform the market and the bottom quartile seem to outperform the bonds market and the risk-free rate (STEFI:- Cash). So for the fund of hedge funds manager, who are more rationally expected to be well diversified and taking well calculated risks, are more likely to operate at the middle of these two extreme levels of quite aggressive managers who chase to outbeat the market and those who produce absolute returns by taking moderate positions on more risk-averse and beta β-neutral securities.

It is also important to observe optimal hedge fund managers, not necessarily those who show outstanding performance, but also those who bring diversification benefits to the well-balanced Fund of Hedge Funds (FoHF). So that when FoHF decides to invest with would have made thorough assessment on the variety of attributes. If were to refer back to Figure(1), then would see that Fund of Hedge Funds portfolios must be conservative, diversified, market defensive and strategic. Such kind of classification necessitates FoHF portfolio managers to have quite a broad view of the industry and robust enough asset selection methodology to identify whom to include in the absolute return or more conservative portfolio, how to construct a more market defensive strategy to get the best out of any market conditions.

Note that the graphs on Figure(8) have been based on the first moment, i.e. returns. The numbers have been run for other moments as well and investigated how each one of them influence the hedge funds' return distributions. How much that attribute could be used to define the return distributions, on each graph generating process there is also the search for t-stats significance. The findings are provided in Table (2) below. The different 'looking back' periods versus different 'forward looking' or rebalancing frequencies are also shown together with t-stats and the corresponding p-value for each encounter.

Discussion of the Results in Table (2)

The values that are in **bold face** in Table (2) are statistically significant at 95% significant level. As could be seen that on the first sub-table of returns every combination of 'Look Back' versus 'Rebalancing Frequency' has a significant t-stats that means returns are more significant factor to look at when assessing hedge funds return distributions. The Standard Deviation sub-table shows that for 'look back' of 12 or more months one can find significant t-stats, though when 'looking back' 12 months one should not rebalance frequently, as in every 3 months. However for 24 months 'look back' there is a significant t-stats for 3 months rebalancing, but rebalancing annually is not bearing significant t-stats. For the skewness it is only when one calculates annualized skew and rebalance annually that could reap significant difference between the top quartile portfolio against the bottom quartile one. Although investors would be keen to have fund managers with high positive skewness it seems that such metric or factor should not be deemed that much to explain desirable attributes to be considered when assessing hedge funds universe. However, it would be seen when analyzing per individual strategy that it is still important attribute to some specific trading strategies, though its not for the whole universe of hedge funds.

For kurtosis sub-table, could only get the significant t-stats for 24 months 'look back' when rebalancing annually or every 12 months. The negative value means that those with lower kurtosis are the ones who have good outstanding performance. Moreover, 7 out of 9 t-stats values are negative even though other six are not significant but this reveals very valuable lesson to be looked at when searching for factors to consider to assess universe of hedge funds returns. Such a revelation is that low kurtosis return distributions offers a better performance than high values of kurtosis. The tables of results after Table (2), kurtosis sorting order has been changed from descending to ascending. So for some tables in the appendix, especially Table (5), table of

Table 2: Hedge Fund Universe: Descriptive Statistics (R.F. means Rebalancing Frequency)

RETURNS						
	6 M Look Back		12 Look Back		24 Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**1.71394**	**0.04415**	**2.94173**	**0.00187**	**3.88748**	**0.00009**
6m R.F.	**1.71695**	**0.04391**	**2.93763**	**0.00190**	**4.24586**	**0.00002**
12m R.F.	**1.91799**	**0.02854**	**2.91179**	**0.00212**	**2.51580**	**0.00671**
STANDARD DEVIATION						
	6 M Look Back		12 Look Back		24 Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.33809	0.09208	1.39986	0.08255	**1.83914**	**0.03493**
6m R.F.	1.62968	0.05328	**1.68267**	**0.04799**	**1.98292**	**0.02552**
12m R.F.	1.37619	0.08602	**1.96429**	**0.02644**	1.20640	0.11589
SKEWNESS						
	6 M Look Back		12 Look Back		24 Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-1.15047	0.12584	1.19097	0.11771	1.41578	0.07956
6m R.F.	-0.39429	0.34694	1.06955	0.14325	1.44422	0.07552
12m R.F.	-0.46271	0.32210	**1.94483**	**0.02687**	1.33272	0.09257
KURTOSIS						
	6 M Look Back		12 Look Back		24 Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-1.41227	0.07990	-0.96549	0.16789	-1.21827	0.11259
6m R.F.	-0.94021	0.17426	0.05243	0.47913	-1.16829	0.12235
12m R.F.	-0.77663	0.21923	0.29790	0.38314	**-1.70091**	**0.04589**
NEGATIVE CORRELATION SCORE						
	6 M Look Back		12 Look Back		24 Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.20767	0.41789	1.22576	0.11103	-0.03985	0.48414
6m R.F.	-0.31637	0.37606	0.83698	0.20194	-0.49445	0.31089
12m R.F.	-0.15482	0.43859	1.11151	0.13406	-0.17390	0.43113
STABILITY OF NEGATIVE CORRELATION						
	6 M Look Back		12 Look Back		24 Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.38721	0.08377	0.52756	0.29935	-0.14448	0.44278
6m R.F.	**1.69491**	**0.04709**	0.30327	0.38108	-0.10838	0.45702
12m R.F.	0.40194	0.34415	0.79668	0.21378	-1.54147	0.06447

results for Long/Short Equity Non-Directonal's kurtosis imply a direct opposite meaning to that of the whole universe when all hedge funds are considered together. In the sense that return distributions with high value of kurtosis do show good performance better than those with low values of kurtosis. For all the descriptive statistics tables in the appendix kurtosis factor had been of ascending order.

As for the Negative Correlation Score there is no single combination of 'look back' against 'rebalancing frequency' period that gives significant t-stats, however this factor could also be of important consideration when looking at individual strategies. The Stability of Negative Correlation requires one to 'look back' every six months, hold ranked portfolios, 'moving forward' three months before rebalancing. Other combinations could not satisfy the 95% conventional threshold. Even though the higher order moments seem not to offer that much statistically significant values, but when looking at more manageable single strategy will find some results with significant t-stats.

Discussion of the Results in Table (3)

The values in **bold face** in Table (3) are statistically significant at 95% significant level, though some are significant at 99% as well. Most of the alternative performance measures for various combinations of 'backward looking' versus the 'rebalancing frequency' had significant t-stats with the exception of the Maximum Drawdown. Only when one 'looks back' for the past 6 months 'moving forward' every 3 months prior to rebalancing, one can find significant t-stats for Maximum Drawdown sub-table The Alpha sub-table results shows that there is wide difference between those who generate high values of alpha and those who realize low values of alpha. As in the traditional investment space where alpha is commonly used as the measure of the fund manager's skill, this observation is also noted in the alternative investment side as well.

The top quartile portfolio consisting of fund managers with the highest alphas, is significantly different from the bottom quartile, which is composed of those managers with low values of alpha. The simulated portfolios made of the actual returns based on the ranking determined by alpha is more likely to help fund of funds manager to identify those funds with good outstanding performance. The Sharpe ratio still remains the industry standard to measure portfolio performance or rather reward for every unit of risk undertaken profile of the portfolio. Its sub-table in Table (3) shows that for 'looking backward' at least 12 months or 24 months could get fund manager who show good performance, but not for 12m 'back' and 12m 'forward'.

The beta sub-table also offers some significant t-stats, though it gives none for any 12 months rebalancing versus any 'look back' period. The Sortino ratio sub-table is bold face for all the

Table 3: Alternative Performance Measure: Whole Universe of HF Managers

ALPHA						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**1.9061021**	**0.0291427**	**3.1843774**	**0.0008681**	**4.1462721**	**3.23E-05**
6m R.F.	**1.8730648**	**0.031425**	**2.7306617**	**0.0035082**	**3.9543735**	**6.681E-05**
12m R.F.	1.5309526	0.0640108	**2.2461549**	**0.0131654**	**2.735378**	**0.0036376**
SHARPE RATIO						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.5214881	0.0651728	**3.1324452**	**0.0010343**	**2.9262438**	**0.0020044**
6m R.F.	1.5039398	0.0673568	**2.6110461**	**0.0049451**	**2.3184532**	**0.0109471**
12m R.F.	1.249271	0.1066623	1.4092627	0.0805726	**1.7214168**	**0.0438345**
BETA						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.9477797	0.1722857	**1.8702158**	**0.0318428**	**2.1995816**	**0.015106**
6m R.F.	0.349975	0.363388	1.3605092	0.087968	**2.2878894**	**0.0122176**
12m R.F.	0.1492328	0.4407704	0.2970206	0.3834822	0.6308876	0.2646775
Sortino Ratio						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**1.8758818**	**0.031178**	**2.8887227**	**0.0022057**	**2.582459**	**0.0054181**
6m R.F.	**1.8170956**	**0.0355487**	**2.6798863**	**0.004094**	**2.264265**	**0.0125472**
12m R.F.	**2.3826668**	**0.0092855**	**3.1280808**	**0.001086**	**1.9289038**	**0.0280048**
Omega Function						
	6 M Look Back		12 M Look Back		24 M Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**2.823168**	**0.0029081**	**1.9849375**	**0.025133**	**2.0927018**	**0.019926**
6m R.F.	**1.8790161**	**0.0317041**	**1.9059594**	**0.0299599**	**2.147882**	**0.0175212**
12m R.F.	1.4715063	0.0722296	**1.9160015**	**0.0293244**	0.5252015	0.3005173
Max Drawdown						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-0.1664398	0.4340555	-0.0127295	0.494935	0.0775643	0.4691524
6m R.F.	0.0775643	0.4691524	0.2700635	0.3938549	0.6518401	0.2582354
12m R.F.	**2.4471794**	**0.0077803**	-0.3131629	0.377449	0.0292452	0.4883728

combinations, that means those with lowest downside risk or high ratio of the portfolio returns over and above risk-free rate per unit of downside standard deviation could be identified as the best to be selected for the construction of the portfolio of hedge funds.

The Omega Function had been derived on the theoretical foundations that concerns over the existence and accuracy of estimated values of higher moments that render other approaches based upon the individual moments questionable to be relevant with Omega Function. Although all of the information on higher moments is encoded in the formulation of Ω, it is obtained through the cumulative distribution and hence there is no need to know any of the individual moments in order to observe their effect in total. The Ω Function sub-table results show that most combinations except two (6m 'look back' vs 12m 'rebalance' and 24m 'look back' vs 12m 'rebalance') have significant t-stats, and taking from the formulaic derivation of the Ω Function then one could see how higher order moments could be used to explain the identification or selection of the best fund managers.

The maximum drawdowns have just only one combination with significant t-stats. This could be accounted for, by the fact that those managers with high transition from peak to trough, does not necessarily mean that those who experienced worst drawdowns are poor performers. As that could occur for managers who take quite geared risk aiming to gain most if the market goes according to their predictions or analysis. Table (3) results show that maximum drawdowns is least influential to funds return distributions assessment than other performance measures.

The results analysis of per funds strategy

Having tested all performance criteria for t-statistics significance, then move to find important combination of 'backward looking' period versus the 'forward period' or 'rebalancing frequency' that deliver superior performance results in Table (4) to Table (13) of individual strategies in the Appendix.

The search for the best optimal proportions of percentage 'weightings' into the composite ranking scores will offer the well desired results for the metrics to be utilized for assets selection. As it has been highlighted in the methodology chapter that all these metrics have been blended together, and varied the percentage proportions to each, and incrementally varying in steps of 10% to 100% to investigate how each factor influence the return distributions. Tabulated results are presented in the Appendix:- from Table (15) to Table (25).

General Discussion of the Tables (from Table 4 to Table 25) in the Appendix

The first pages in the Appendix present the results tables for various combinations of 'backward looking' period versus the 'Rebalancing Frequency' (R.F.). Whilst the last pages contain the tables for the results gotten on alterations of percentage 'weightings' to search for the optimal composite proportions one could possibly make on each factor. The values that are in bold face are statistically significant at the conventional threshold of 95%, and some might be significant at 99% and that would really help Fund of Hedge Funds manager to focus on them more closely when doing the asset selection analysis. Some factors could have significant t-stats at 90% level and would signal that some factors could not completely be ruled out.

Analysis of the sub-strategies using tables in the Appendix

For the **Long/Short Equity- Directional**; lets consider Table 4 in conjunction with Tables 9, 16 & 21, then it seems the returns offer the significant t-stats for all combinations of 'look back' against the 'rebalancing frequency'. Kurtosis gives some significant t-stats for 'look back' periods of 12 months or longer except only for 12m 'look back' vs 6m R.F. There is only one significant t-stats in the Negative Correlation sub-table. For the *alternative performance measures*: Alpha, Sharpe Ratio and Sortino Ratio do really give good t-stats. The Omega Function for 3 months 'rebalancing frequency' do provide the significant t-stats. As for the Beta none do seem to offer anything of significant difference and so are the other moments except the first (returns) and the fourth (kurtosis). This implies that there are some factors that are more influential than others when assessing the returns times series to identify the best out of available in the long/short directional strategy.

`Composite Score Search for Optimal weighting analysis: Equity Directional`
Table (16) further confirms findings that more weight has to be given to the returns (100 to 30) and could vary percentage 'allocations' slightly amongst other moments. Moreover Table (21) shows that its when 'over allocated' to either beta or maximum drawdowns that won't get significant t-stats, other performance measures have significant contribution to be considered when analyzing the long/short equity-directional return distributions.

For the **Long/Short Equity- Non-Directional**; consider Tables 5, 10, 18 & 23. For the moments, it seems like only returns and kurtosis sub-tables of Table (5) do provide some significant t-stats. There is negative yet significant t-stats values of kurtosis and thus can be accounted as follows, i.e. simply put it is to reverse the order of sorting or take those with high values of kurtosis to offer good performance and should be taken as the best.

`Composite Score Search for Optimal weighting analysis: Equity Non-Directional`
Lets survey results in Table (18), the 'overweighting' to kurtosis gives significant t-stats. That

means those with high values of kurtosis in the Non-Directional strategy do have good returns over those with low values of kurtosis. Scrutinize it further then one would observe from Table (18) top quartile portfolios do show some negative values or relatively small positive skewness (undesirable) together with moderately small values of kurtosis close to zero (desirable). There is really a paradoxical combinations of the factors for this strategy when searching for optimal metric 'weighting' to give best composite score. Also get significant t-stats when 'overweighting' (60% to 80%) to standard deviation whilst 'allocating' slightly to skewness and kurtosis, and zero 'weights' for returns, Negative Correlation & Reliability of Negative Correlation. Such combinations do give negative significant t-stats with the relevant portfolios having relatively small positive values for skewness and also high positive for kurtosis thus present fund manager with quite undesirable attributes. Nevertheless for the first two moments please observe that bottom quartile portfolio has higher mean return than the top quartile, and yet at the same time lower standard deviation. With these results one is more reasonably tempted to identify those hedge fund managers who scored lowest consolidated ranking to be the best, that is those with low values for standard deviation and skewness, and high values of kurtosis.

For the **Market Neutral Equity**; consider Tables 6, 11, 17 & 22. For the six sub-tables or components of Table (6) could only find two entries that give significant t-stats, thus one for skewness and one for Negative Correlation factors, and on Table (11) only one entry for Alpha. The scarcity of significant t-stats when considering single factors somehow suggests that hardly could one find the optimal weightings on the tables that search for optimal percentage proportions that could be 'allocated' to each metric.

`Composite Score Search for Optimal weighting analysis:  Market Neutral`

In Table (17), observe that when 'overweighting' Reliability of Negative Correlation and nothing for Kurtosis & Negative Correlation and some slight proportions for Standard Deviation & Skewness and little bit more for returns do give the significant t-stats. Though Alpha as a single metric gave one good t-stats, but in Table (22) when 'overweighting' is done to alpha, then that generates top quartile portfolios with high negative values for skewness and high positive values of kurtosis, which is an undesirable condition. When compared with relatively small positive for skewness and small positive kurtosis for the bottom quartile, however the ones that gave good t-stats, 70% α, 20% β & 10% Sharpe ratio, has the positive skew with high positive kurtosis. So in order to identify best fund managers in the Market Neutral Equity strategy 'overweight' to Alpha, 'look back' six months and rebalance every 6 months, for the statistics metrics 'over allocate' percentage proportion for Reliability of Negative Correlation and slight for 2^{nd} and 3^{rd} moments, almost zero for the 4^{th} and 5^{th} moments.

For the **Fixed Income Securities**; consider Tables 7, 12, 19 & 25. The statistics metrics on

Table (7) for every sub-table, except one for standard deviation, there is at least one entry for good t-stats. As for the alternative performance measures in Table (12) do get good t-stats only for two sub-tables:- one in the Sortino ratio and quite few on the Omega Function. The 'look back' vs rebalancing could clearly be seen that gave good t-stats. This reveals an important observation for the fixed Income Securities is that those fund managers with relatively low downside volatility and high upside potential, have good returns or have a potential of generating significant wealth.

`Composite Score Search for Optimal weighting analysis: Fixed Income`

Well, even though could not really identify good t-stats on Table (19), but could observe that all the top quartile portfolios have negative skewness and high values of positive kurtosis which is an undesirable condition. However when 'over allocates' to Kurtosis and Negative Correlation and slightly for Reliability of Negative Correlation and almost nothing for the first three moments, do get positive t-stats values and relatively low values for kurtosis and improved negative skewness. For the performance measures proportions do get top quartile portfolio with negative skewness and high kurtosis. Though when 'overweighting' on Sortino ratio & Omega Function gives good t-stats at 90% even though does not satisfy the threshold of 95%, but provide some insight that those two performance measures which penalize fund managers downside risk do have a significant role to play when identifying best Fixed Income Securities fund managers.

Also provide table results for other hedge funds strategies, some of them could have just only one or two hedge funds trading or using that particular strategy as their major one for full business operability. The tables of their results are classified as the other strategies to consolidate them all together those with few managers practicing such particular strategies. Tables 8, 13, 24 present findings when considering them together under the generic name of other strategies. The bold face numbers in the tables are significant at 95%. The 12m or 24m 'look back' combined with 3m or 6m 'rebalancing frequency' provide good significant t-stats when using returns, Sharpe & Sortino ratio.

9 Conclusion

A systematic model has been successfully developed that can to be used as an industry standard by the Fund of Hedge Funds Manager to identify and select the best performing hedge fund managers based on a diverse array of performance characteristics. Some detailed observations and interpretations of results are presented in the results and data analysis section.

Based on the results of Tables (2) & (3) can conclude that one has to consider returns, together with Alpha, Sortino ratio and Omega Function to assess the hedge fund return distributions. These metrics produce significant t-stats for any combination of 'look back' period versus 'balancing frequency'. Other metrics provide significant t-stats for only certain combinations of 'look back' and 'rebalancing frequency'. So that identified pattern could be used to select fund managers and also informs fund of funds manager which duration or time horizons should be careful about.

Stutzer (2000) suggests that the fund manager may have sensible reasons to be averse to earning a time-averaged portfolio return that is less than the average return of some trustee-designated benchmark and, therefore, will choose a portfolio with a positive expected excess return over the benchmark. The Strategic Asset Selection Taxonomy that incorporates diverse performance evaluation criteria, presents the robust and broadly versatile measurement scale to minimize the possibility of choosing and including into a portfolio a fund managers that does not exceed designated benchmark index. This model would be utilized by Fund of Hedge Funds to identify desired factors from the hedge fund return distributions and then select the appropriate hedge funds to invest with, also could be used even by single strategy hedge fund manager to assess their own in-house performance.

As concluded by Bacmann and Scholz (2003) that higher moments matter when performance has to be evaluated. When using the Sharpe ratio, some investments may mistakenly appear better or worse than they are, because all the potential risk characteristics are not taken into account. This study therefore advocates the use of new performance measures, namely the Sortino Ratio, Omega Function and the Stutzer index. Moreover, these measures can be applied in order to generate a better asset allocation among hedge fund styles. So for the second phase of this project that used the alternative performance measures, the results show that the models that accommodate the investor's preference like Sortino Ratio and Omega Function are good to rank order feasible portfolios in matched alignment with investors expectation and provide empirical evidence for the preference of more to less. For models that incorporate higher moments like Omega Function revealed important findings that fund managers with minimal downside risk provide good results.

Mewasingh (2006) makes the following concluding remarks, with the increasing use of financial instruments with asymmetric pay-offs incorporated into trading or portfolio management strategies, investment returns distributions are increasingly predisposed to be asymmetric. Hedge funds have traditionally fallen in this category and will continue to be because of their key mandates. Hence, investors and advisers need to understand and use the performance measures that help to select and reward not only managers who produce higher returns, but also those who produce asymmetric distributions of value-added above benchmark with enhanced upside and curtailed downside. This project has found that for some Hedge Funds Strategies some performance measures reflect valuable information about effects of higher order moments. This observation necessitates the Fund of Hedge Funds portfolio manager to apply relevant analysis for each strategy of which factors to be given more weight of consideration when assessing the returns distribution of hedge funds. The graphs, charts, tables of matrix combinations also provide useful information to identify not only managers who produce good returns but also those who have potential to produce asymmetric returns and preserve capital.

The generalized discussions on all the tables of results do provide the key findings for the optimal combinations of 'backward looking' window period versus the 'rebalancing frequency'. Furthermore, when using the composite score ranking of all the factors considered together for their influence on the investment return distributions, do get how much 'weightings' could one 'allocate' to each factor to identify the best fund managers and also give preference to those who produce asymmetric distributions of value-added above benchmark with enhanced upside and curtailed downside.

The process of making correctly valid investment decisions involves quite alot of both qualitative view and quantitative analysis whilst also keeping abreast with time constraints that market dynamics do constantly change, and adaptability is the longevity for survival. This thesis has presented different measures that could be utilized when assessing the hedge funds returns distributions, however as the results have shown no single risk measure deserve to be viewed in isolation. Otherwise, one runs costly risk of relying on erroneous model risk. Though the past performance is not an assurance of the future, but for one to construct a quantitative view of the data times series has to make some statistically justifiable assumptions on the methodology to use for asset selection process. Such methodology must have the smallest possible prediction error whenever projecting those who are currently the best performing top quartile to retain the good performance till rebalancing periodicity.

10 Reference

Amin, G. S. and Kat, H. M. (2003), Hedge Fund Performance 1990-2000, Journal of Financial and Quantitative Analysis, Vol. 38, No. 2, pp. 1-24

Bacmann, J.F. and Scholz, S. (2003), Alternative Performance Measures for Hedge Funds, AIMA Journal, Vol. 1, pp. 1-9

Benedetti, S. M. (2004), Hedge Fund Portfolio Selection with Higher Moments, MSc Thesis, University of Zurich

Bergh, G. and van Rensburg, P. (2008), Hedge Funds and Higher moment portfolio selection, Journal of Derivatives and Hedge Fund, Vol. 14, No. 2, pp. 102-126

Bin C. (2007), Calibration of the Heston Model with Application in Derivative Pricing and Hedging, Technical University of Delft, MSc Thesis

Black, H. K.,(2004), Managing a HEDGE FUND: A Complete Guide to Trading, Business Strategies, Risk Management, and Regulations, McGraw-Hill

Black, F. and Scholes, M.,(May/June 1973), The Pricing of Options and Corporate Liabilities, Journal Political Economy, Vol. 81, No. 3, pp. 637-654

Bodie, Kane, and Marcus, (2003), Investments, McGraw-Hill Primis, 5th Ed,

Borland, L., Bouchaud, J.P., Muzy, J.F and Zumbach G. (2009), The Dynamics of Financial Markets - Mandelbrot's Multifractal Cascades, and Beyond, Wilmott Magazine

Bowers, D., Molinas, C. and Dowling B. (2003), Assest Allocation Almanac, Merrill Lynch

Boyle, P. and Liew S.S. (2007), Asset Allocation with Hedge Funds on the Menu, North American Actuarial Journal, Vol.11, No.4, pp.1-22

Bradfield, D. and Kgomari, W. (2004), Concentration - Should We be Mindful of it?, CADIZ Financial Strategies, Quantitative Rearsch

Bradfield, D. and Munro, B. (2006), The Quality of Risk: The Good, The Bad and The Ugly, CADIZ Financial Strategies, Quantitative Rearsch

Brooks, C. and Kat, H., (2002), The statistical properties of hedge fund index returns and their implications for investors, Journal of Alternative Investments Vol. 5, No. 2, pp. 26-44

Chincarini, L.B. and Kim, D. (2006), Quantitative Equity Portfolio Management: An Active Approach to Portfolio Construction and Management, McGraw-Hill

Davies, R., Kar,H. and Lu, S. (2003),Higher Moment Portfolio Analysis with Hedge Funds, Discussion Paper, ISMA Centre, University of Reading

Fung, W., and Hsieh, D. A. (1999), Is mean-variance analysis applicable to hedge funds, Economic Letters Vol. 62, No. 1, pp. 53-58

Getmansky, M., (2004), What Drives Hedge Fund Returns? Models of Flows, Autocorrelation, Optimal Size, Limits to Arbitrage and Fund Failures, PhD Thesis, Massachusetts Institute of Technology (MIT)

Ineichen, A. and Silberstein, K (2008), AIMA'S [5] ROADMAP TO HEDGE FUNDS , AIMA Journal

Ingersoll, J. E. Jr., (1987), Theory of Financial Decision Making, Baltimore: Rowman and Littlefield.

Keating, C. and F. Shadwick, (2002), A Universal Performance Measure, The Journal of Performance Measurement, Vol. 6, No. 3, pp. 10-22

Lhabitant, F. and Learned, M. (2000), Hedge Fund Diversification: How Much is Enough, Journal of Alternative Investments, Vol. 5, No. 3, pp. 23-49

Litner, J. (Feb, 1965), The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, Review of Economics and Statistics, Vol. 47, No. 1, pp. 13-37.

Lo, A. W. (2001); 'Risk Management for hedge Funds': Introduction and Overview, Financial Analysts Journal, Vol. 7, No. 6, pp. 16-33

Markovitz, H. (1952), Portfolio Selection, The Journal of Finance, Vol. 7, No. 1, pp. 77-91

[5] AIMA stands for Alternative Investment Management Association,

Markovitz, H. (1959), Portfolio Selection, Efficient Diversification of Investments, (New York: John Wiley and Sons, Inc.),Vol. 7, No. 1, pp. 77-91

Merton, R. (Spring 1973), Theory of Rational Option Pricing, Bell Journal of Economics and Management Science, Vol. 4, No. 1, pp. 141-183

Mewasingh, V. (2006), Downside Risk Performance Measures and Hedge Funds, MBA Thesis, Simon Fraser University

Mossin, J. (October 1966), 'Equilibrium in a Capital Asset Market.' Econontetrica, Issue 34, pp. 768-83.

Press, W. H., Teukolsky, S. A., Vetterling, W. T. and Flannery, B. P. (1992) Numerical Recipes in Fortran 77: The Art of Scientific Computing, 3rd Ed, Cambridge University Press.

Sharpe, W. F. (1964), Capital Asset Prices: A Theory on Market Equilibrium under the Conditions of Risk, The Journal of Finance, Vol. 19, Issue 3, pp. 425-442

Soros, G. (1987), The Alchemy of Finance, John Wiley & Sons. ISBN 0-471-04206-4, New York City

Stutzer, M (2000), A Portofolio Performance Index, Financial Analysts Journal, Vol. 56, No. 3, pp. 52-61

van Rensburg, P. and Robertson, M. (2003 (a)), Style Characteristics and the Cross-Section of JSE returns, Investment Analyst Journal, No. 57, pp. 7-15

van Rensburg, P. and Robertson, M. (2003 (b)), Size, Price-to-Earnings and Beta on the JSE Securities Exchange, Investment Analysts Journal, Issue 57, pp. 7-16

van Rensburg, P. and Robertson, M. (2003 (c)), The Interaction Between Sectors, Styles and JSE Securities Exchange Returns, Journal of Studies in Enonomics and Ecnometrics, Vol. 27, No. 1, pp. 75-94

11 Appendices

Table 4: Long/Short Equity Directional: Descriptive Statistics

	RETURNS					
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**2.5620**	**0.0057**	**3.6782**	**0.0002**	**2.5677**	**0.0058**
6m R.F.	**1.9927**	**0.0241**	**3.6790**	**0.0002**	**2.9556**	**0.0019**
12m R.F.	**2.9618**	**0.0018**	**3.2994**	**0.0006**	**2.5706**	**0.0058**
	STANDARD DEVIATION					
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.1380	0.1289	1.3999	0.0826	-0.0984	0.4409
6m R.F.	1.6297	0.0533	0.7229	0.2357	-0.0053	0.4979
12m R.F.	-1.2564	0.1058	0.0472	0.4812	-0.7210	0.2367
	SKEWNESS					
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-0.0777	0.4691	0.4832	0.3148	0.0798	0.4683
6m R.F.	-0.1933	0.4235	0.4433	0.1291	-0.0532	0.4788
12m R.F.	0.1556	0.4383	-0.0764	0.4696	0.4822	0.3154
	KURTOSIS					
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.6867	0.2466	**1.7891**	**0.0380**	**2.5415**	**0.0062**
6m R.F.	1.3004	0.0977	1.1705	0.1220	**1.9863**	**0.0247**
12m R.F.	0.7953	0.2119	**1.8369**	**0.0343**	**2.5921**	**0.0055**
	NEGATIVE CORRELATION SCORE					
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.2652	0.3956	-0.5203	0.3022	-0.2538	0.4012
6m R.F.	-0.0937	0.4628	**-2.1122**	**0.0195**	0.1463	0.4422
12m R.F.	0.6509	0.2544	-1.6162	0.0631	0.8897	0.1916
	STABILITY OF NEGATIVE CORRELATION					
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.3280	0.3732	-0.3472	0.3646	0.1215	0.4518
6m R.F.	0.8396	0.2015	-0.2483	0.4022	0.0063	0.4974
12m R.F.	-0.1482	0.4412	-0.5388	0.2957	0.8625	0.1961

Table 5: Long/Short Equity - Non-Directional: Descriptive Statistics

RETURNS						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**1.8079**	**0.0364**	**1.7236**	**0.0436**	0.8231	0.2063
6m R.F.	0.8196	0.2069	0.7249	0.2350	0.5207	0.3020
12m R.F.	1.0685	0.1437	1.2596	0.1051	-0.5235	0.3009
STANDARD DEVIATION						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-0.3962	0.3463	-0.5460	0.2930	-0.8799	0.1907
6m R.F.	-1.2430	0.1080	-1.1236	0.1317	-0.8339	0.2034
12m R.F.	-0.1975	0.4219	-1.3028	0.0976	-0.8615	0.1957
SKEWNESS						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.4065	0.3425	-0.2442	0.4037	-0.4703	0.3195
6m R.F.	-0.5347	0.2969	0.1447	0.4426	-0.0073	0.4971
12m R.F.	0.7797	0.2185	1.1914	0.1179	0.5514	0.2913
KURTOSIS						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.0946	0.4624	**-2.2737**	**0.0123**	**-1.8877**	**0.0309**
6m R.F.	0.3119	0.3778	**-2.6289**	**0.0048**	-1.5281	0.0648
12m R.F.	-0.0952	0.4621	**-2.3584**	**0.0099**	-0.4608	0.3230
NEGATIVE CORRELATION SCORE						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-0.5004	0.3088	0.0110	0.4956	-0.7493	0.2341
6m R.F.	0.4015	0.3445	0.9241	0.1792	-1.7201	0.0567
12m R.F.	-1.2436	0.1089	0.7865	0.2170		
STABILITY OF NEGATIVE CORRELATION						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-0.2818	0.3893	0.5782	0.2822	-0.2285	0.4101
6m R.F.	0.8434	0.2003	0.7950	0.2142	0.0295	0.4883
12m R.F.	0.7519	0.2268	0.6367	0.2629	-0.7024	0.2427

Table 6: Market Neutral Equity: Descriptive Statistics

RETURNS						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.7864	0.2166	0.6213	0.2678	1.0296	0.1529
6m R.F.	0.9467	0.1729	-0.8158	0.2084	0.9126	0.1819
12m R.F.	-1.1754	0.1214	0.6906	0.2458	0.1306	0.4482
STANDARD DEVIATION						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-0.6466	0.2600	0.3192	0.3753	1.0579	0.1469
6m R.F.	-0.8827	0.1902	0.3292	0.3716	0.4541	0.3257
12m R.F.	0.8766	0.1919	-0.4255	0.3360	0.1634	0.4354
SKEWNESS						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-1.3706	0.0867	0.1884	0.4254	0.4092	0.3417
6m R.F.	-0.7717	0.2211	-1.3103	0.0967	0.3583	0.3605
12m R.F.	**-1.6939**	**0.0464**	0.8124	0.2093	1.6089	0.0558
KURTOSIS						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.9045	0.1837	-0.5736	0.2837	-0.8045	0.2115
6m R.F.	1.3980	0.0823	-0.3607	0.3595	-0.9447	0.1736
12m R.F.	-0.1128	0.4552	0.2799	0.3901	-0.6665	0.2536
NEGATIVE CORRELATION SCORE						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**1.7348**	**0.0426**	1.1372	0.1293	0.4625	0.3228
6m R.F.	0.6371	0.2627	0.7840	0.2179	0.9116	0.1834
12m R.F.	0.7159	0.2380	1.4597	0.0746	1.0493	0.1498
STABILITY OF NEGATIVE CORRELATION						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.0838	0.1403	0.1863	0.4264	-0.4422	0.3306
6m R.F.	1.1435	0.1276	0.1276	0.4495	1.0460	0.1524
12m R.F.	1.6494	0.0516	-0.5861	0.2803	-0.2381	0.4067

Table 7: Fixed Income Securities: Descriptive Statistics

RETURNS						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**1.7254**	**0.0435**	1.5090	0.0671	0.6559	0.2570
6m R.F.	-0.0978	0.4611	-0.6358	0.2632	-0.3867	0.3501
12m R.F.	0.5097	0.3057	-0.4031	0.3439	-0.0985	0.4609
STANDARD DEVIATION						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-0.1397	0.4446	0.8385	0.2021	-1.1649	0.1238
6m R.F.	1.0953	0.1382	0.5575	0.2892	-0.9328	0.1770
12m R.F.	0.0810	0.4678	0.5090	0.3060	-0.2888	0.3868
SKEWNESS						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**-2.0520**	**0.0212**	-0.5985	0.2755	-0.4776	0.3172
6m R.F.	-0.4582	0.3239	-0.4582	0.3239	-0.8458	0.2002
12m R.F.	0.0538	0.4786	-1.1269	0.1312	-1.0246	0.1548
KURTOSIS						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-1.1732	0.1215	-1.1727	0.1222	-1.2709	0.1042
6m R.F.	-0.9628	0.1688	-0.9967	0.1606	0.0073	0.4971
12m R.F.	-1.1511	0.1266	1.0070	0.1582	**1.7279**	**0.0453**
NEGATIVE CORRELATION SCORE						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.0060	0.4976	0.2686	0.3945	0.4659	0.3214
6m R.F.	0.4719	0.3192	-0.3364	0.3687	0.0152	0.4940
12m R.F.	0.0152	0.4940	**-1.6701**	**0.0495**	-0.5657	0.2870
STABILITY OF NEGATIVE CORRELATION						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-1.5215	0.0659	0.3814	0.3520	-1.4026	0.0942
6m R.F.	-0.6200	0.2686	1.1925	0.1187	-1.4026	0.0942
12m R.F.	**-1.8326**	**0.0349**	**1.8103**	**0.0395**	0.1047	0.4608

Table 8: Other Strategies: Descriptive Statistics

RETURNS						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.4092	0.3416	**2.4895**	**0.0073**	**2.8244**	**0.0031**
6m R.F.	0.3657	0.3577	**2.2679**	**0.0129**	**1.8432**	**0.0348**
12m R.F.	-0.0920	0.4635	1.5814	0.0590	-0.5006	0.3093
STANDARD DEVIATION						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.5960	0.2763	1.2224	0.1127	**1.8106**	**0.0380**
6m R.F.	0.1085	0.4569	0.9462	0.1734	**3.0894**	**0.0015**
12m R.F.	-0.4385	0.3310	0.9475	0.1737	0.8892	0.1891
SKEWNESS						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-0.2785	0.3906	-1.2915	0.0999	-0.8196	0.2077
6m R.F.	0.8276	0.2049	-1.2983	0.0988	-1.0672	0.1448
12m R.F.	**1.9282**	**0.0283**	**-2.6970**	**0.0043**	-1.5707	0.0609
KURTOSIS						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.0285	0.1531	-1.0594	0.1465	-0.7017	0.2429
6m R.F.	-0.8409	0.2012	-0.3647	0.3582	-0.9757	0.1666
12m R.F.	-1.0368	0.1512	-0.5455	0.2935	-0.4630	0.3226
NEGATIVE CORRELATION SCORE						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.1048	0.1361	**2.2151**	**0.0147**	1.5728	0.0615
6m R.F.	0.8540	0.1977	**2.1868**	**0.0157**	1.0532	0.1503
12m R.F.	**1.9328**	**0.0285**	**2.9414**	**0.0022**	0.5730	0.2867
STABILITY OF NEGATIVE CORRELATION						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.0368	0.1512	-0.4395	0.3311	1.4025	0.0871
6m R.F.	1.2551	0.1065	0.0679	0.4731		
12m R.F.	**2.1859**	**0.0159**	-0.4663	0.3218		

Table 9: Long/Short Equity -Directional: Alternative Performance Measures

ALPHA						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**2.6110**	**0.0050**	**3.4062**	**0.0004**	**2.2565**	**0.0130**
6m R.F.	**2.2239**	**0.0139**	**3.4443**	**0.0004**	**2.7183**	**0.0039**
12m R.F.	**3.0824**	**0.0013**	**3.3304**	**0.0006**	**2.7984**	**0.0031**
SHARPE RATIO						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**1.8681**	**0.0320**	**2.9172**	**0.0021**	**2.2762**	**0.0125**
6m R.F.	**1.8009**	**0.0370**	**3.0884**	**0.0012**	**2.7530**	**0.0036**
12m R.F.	**3.4353**	**0.0004**	**3.1059**	**0.0012**	**3.0976**	**0.0013**
BETA						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.3077	0.3794	1.2784	0.1017	-0.5812	0.2812
6m R.F.	0.0306	0.4878	0.7135	0.2385	-1.0274	0.1533
12m R.F.	-0.3130	0.3774	0.8971	0.1857	-0.5654	0.2865
Sortino Ratio						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**1.7025**	**0.0454**	**2.4670**	**0.0074**	**2.0062**	**0.0239**
6m R.F.	**1.7058**	**0.0451**	**2.6888**	**0.0041**	**2.2775**	**0.0126**
12m R.F.	**2.2715**	**0.0124**	**3.3426**	**0.0005**	**2.3765**	**0.0098**
Omega Function						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**1.3780**	**0.0856**	**1.6311**	**0.0531**	**1.8246**	**0.0356**
6m R.F.	0.8250	0.2056	0.9222	0.1794	1.1268	0.1315
12m R.F.	-0.2474	0.4026	-0.6007	0.2747	0.7420	0.2300
Max Drawdown						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.8338	0.2030	**1.9858**	**0.0247**	1.4592	0.0739
6m R.F.	0.6056	0.2730	1.6226	0.0537	1.3648	0.0879
12m R.F.	**2.6145**	**0.0050**	1.2555	0.1059	1.3354	0.0926

Table 10: Long/Short Equity -Non-Directional: Alternative Performance Measures

ALPHA						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**1.9637**	**0.0258**	**1.8574**	**0.0329**	0.8354	0.2029
6m R.F.	1.4607	0.0732	0.8883	0.1881	0.6588	0.2559
12m R.F.	1.5618	0.0604	1.3359	0.0920	-0.3745	0.3544
SHARPE RATIO						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**2.2111**	**0.0144**	**1.9009**	**0.0299**	1.0651	0.1450
6m R.F.	1.3565	0.0886	1.4498	0.0748	0.6092	0.2720
12m R.F.	1.2572	0.1055	1.4870	0.0698	-0.3600	0.3599
BETA						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.3252	0.0936	0.3994	0.3452	-1.1290	0.1308
6m R.F.	-0.0314	0.4875	0.0740	0.4706	-1.1153	0.1337
12m R.F.	**-2.1394**	**0.0171**	-1.1839	0.1193	**-1.8691**	**0.0322**
Sortino Ratio						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.6354	0.0521	0.6067	0.2727	0.4489	0.3273
6m R.F.	0.2950	0.3842	0.1720	0.4319	0.1621	0.4358
12m R.F.	1.0197	0.1549	0.6219	0.2676	-0.0553	0.4780
Omega Function						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.8533	0.1975	0.6390	0.2620	-0.6990	0.2431
6m R.F.	-1.4673	0.0723	-1.3120	0.0960	-1.8716	0.0322
12m R.F.	-0.5094	0.3057	**-1.8177**	**0.0358**	-1.2537	0.1065
Max Drawdown						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.2712	0.1029	1.2611	0.1048	0.8230	0.2063
6m R.F.	0.8068	0.2106	0.9278	0.1777	**1.6913**	**0.0470**
12m R.F.	**2.5934**	**0.0053**	1.1040	0.1359	1.3560	0.0892

Table 11: Market Neutral Equity: Alternative Performance Measures

ALPHA						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.6196	0.0540	0.3022	0.3815	0.5659	0.2864
6m R.F.	**1.6612**	**0.0497**	-0.9769	0.1656	1.0878	0.1398
12m R.F.	-1.2438	0.1083	0.4694	0.3200	0.4694	0.3200

SHARPE RATIO						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.3938	0.0829	0.5805	0.2814	0.8134	0.2098
6m R.F.	0.6935	0.2448	-0.4420	0.3299	0.8389	0.2027
12m R.F.	-1.2653	0.1048	0.9719	0.1669	0.8707	0.1943

BETA						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.0395	0.4843	1.5747	0.0592	-1.1422	0.1292
6m R.F.	-0.1557	0.4383	1.5875	0.0579	-1.4266	0.0795
12m R.F.	1.3512	0.0901	0.9661	0.1682	-0.1308	0.4482

Sortino Ratio						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.0664	0.1442	-0.0552	0.4780	1.0730	0.1440
6m R.F.	1.2255	0.1114	-0.5166	0.3033	0.8567	0.1977
12m R.F.	-0.8380	0.2020	1.5357	0.0638	0.6223	0.2683

Omega Function						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-0.1307	0.4482	0.4237	0.3366	0.7935	0.2152
6m R.F.	-0.0072	0.4971	0.9434	0.1745	0.3918	0.3481
12m R.F.	-0.1755	0.4305	0.1795	0.4290	0.6609	0.2553

Max Drawdown						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.5808	0.2814	0.6246	0.2671	0.6527	0.2581
6m R.F.	0.2403	0.4053	0.0688	0.4727	0.7273	0.2348
12m R.F.	0.3937	0.3474	1.3312	0.0933	0.5585	0.2893

Table 12: Fixed Income Securities: Alternative Performance Measures

ALPHA						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.3607	0.0881	0.9897	0.1623	0.5494	0.2923
6m R.F.	-0.0927	0.4631	-0.5711	0.2846	-0.1280	0.4493
12m R.F.	0.2770	0.3912	-0.4031	0.3439	-0.0985	0.4609
SHARPE RATIO						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.8974	0.1857	-0.1076	0.4573	1.1093	0.1353
6m R.F.	0.4424	0.3295	-0.2505	0.4014	0.8295	0.2047
12m R.F.	-0.3878	0.3495	-0.9489	0.1725	-0.2058	0.4187
BETA						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-0.2768	0.3913	-0.2446	0.4037	-0.2983	0.3833
6m R.F.	-0.0602	0.4761	-0.3121	0.3779	0.0643	0.4745
12m R.F.	0.9636	0.1691	-0.2618	0.3971	1.0209	0.1564
Sortino Ratio						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.8503	0.1985	0.0360	0.4857	1.5131	0.0672
6m R.F.	-0.2580	0.3984	-0.8282	0.2047	1.5630	0.0614
12m R.F.	0.3792	0.3527	-0.6341	0.2637	**2.1737**	**0.0164**
Omega Function						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	1.5858	0.0581	0.8626	0.1953	0.3655	0.3580
6m R.F.	1.5423	0.0629	1.0367	0.1512	**1.7236**	**0.0451**
12m R.F.	1.3239	0.0945	**1.7795**	**0.0393**	**-2.2665**	**0.0133**
Max Drawdown						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.7378	0.2311	0.1975	0.4219	1.1128	0.1349
6m R.F.	-0.4020	0.3442	0.9520	0.1717	0.6432	0.2613
12m R.F.	0.6736	0.2510	0.5848	0.2800	0.3546	0.3620

Table 13: Other Strategies: Alternative Performance Measures

ALPHA						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.2158	0.4148	2.3174	0.0114	2.6546	0.0049
6m R.F.	0.4110	0.3410	2.0415	0.0221	2.0841	0.0205
12m R.F.	-0.1204	0.4522	2.3970	0.0094	0.3805	0.3525
SHARPE RATIO						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.2379	0.4062	**2.1457**	**0.0173**	**2.3858**	**0.0104**
6m R.F.	0.5021	0.3084	**2.3811**	**0.0098**	**2.2506**	**0.0142**
12m R.F.	0.4351	0.3323	1.5535	0.0623	**1.6693**	**0.0505**
BETA						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-0.3248	0.3730	0.4652	0.3215	-1.3102	0.0974
6m R.F.	-0.1959	0.4225	0.1583	0.4373	-0.8954	0.1871
12m R.F.	0.8947	0.1865	0.6435	0.2610	0.6119	0.2719
Sortino Ratio						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	-0.1825	0.4278	**1.9205**	**0.0291**	**1.9497**	**0.0277**
6m R.F.	0.8734	0.1922	**2.2210**	**0.0144**	**2.1282**	**0.0185**
12m R.F.	0.1581	0.4374	1.4055	0.0819	1.3610	0.0896
Omega Function						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	0.9886	0.1626	0.9842	0.1640	0.9073	0.1838
6m R.F.	0.3904	0.3485	1.2601	0.1057	0.6545	0.2575
12m R.F.	0.3672	0.3571	1.1441	0.1283	0.1179	0.4533
Max Drawdown						
	6m Look Back		12m Look Back		24m Look Back	
	t-stats	p-value	t-stats	p-value	t-stats	p-value
3m R.F.	**1.8137**	**0.0364**	1.1270	0.1315	0.4284	0.3349
6m R.F.	0.7266	0.2347	0.0453	0.4820	-0.4136	0.3404
12m R.F.	0.3382	0.3680	-0.4283	0.3348	0.2830	0.3893

Table 14: Key to the Abbreviations

Shorthand codes to optimize space

Abbreviation	Description		Abbreviation	Description
Rets	Returns		Top($\bar{x}$)	Top Quartile Mean
StdDv	Standard Deviation		Top(σ)	Top Quartile Std Dev
Skw	Skewness		Bttm($\bar{x}$)	Bottom Quartile Mean
Krt	Kurtosis		Bttm(σ)	Bottom Quartile Std Dev
NegCor	Negative Correlation		SkwTop	Top Quartile Skewness
Rel	Reliability of Negative Correlation		KrtTop	Top Quartile Kurtosis
Calc t	Formula t-stats		SkwBttm	Bottom Quartile Skewness
Excel t	t-stats given by Excel		KrtBttm	Bottom Quartile Kurtosis
p-val	Probability Value		MaxDD	Maximum Drawdowns

Table 15: Whole Universe: Search for Optimal Metric/Factor Weights Combination

Rets	StdDv	Skw	Krt	NegCor	Rel	Calc t	Excel t	p-val	Top($\bar{x}$)	Top(σ)	Bttm($\bar{x}$)	Bttm(σ)	SkwTop	KrtTop	SkwBttm	KrtBttm
100	**0**	**0**	**0**	**0**	**0**	**3.76**	**2.94**	**0.002**	**0.019**	**0.023**	**0.009**	**0.019**	**-0.43**	**3.69**	**-0.17**	**3.35**
90	**10**	**0**	**0**	**0**	**0**	**3.95**	**3.10**	**0.001**	**0.019**	**0.023**	**0.009**	**0.018**	**-0.23**	**2.60**	**-0.02**	**3.57**
80	**10**	**10**	**0**	**0**	**0**	**4.87**	**3.69**	**0.000**	**0.019**	**0.022**	**0.008**	**0.017**	**-0.06**	**2.13**	**-1.14**	**2.84**
70	**10**	**10**	**10**	**0**	**0**	**4.68**	**3.64**	**0.000**	**0.019**	**0.022**	**0.008**	**0.016**	**0.18**	**1.70**	**-1.09**	**2.90**
60	**10**	**10**	**10**	**10**	**0**	**3.56**	**2.86**	**0.002**	**0.017**	**0.023**	**0.009**	**0.015**	**-0.92**	**5.22**	**-1.13**	**3.42**
50	**10**	**10**	**10**	**10**	**10**	**4.45**	**3.35**	**0.001**	**0.019**	**0.024**	**0.009**	**0.013**	**-0.44**	**4.15**	**-0.70**	**1.70**
40	**20**	**10**	**10**	**10**	**10**	**3.99**	**3.24**	**0.001**	**0.019**	**0.026**	**0.009**	**0.010**	**0.12**	**2.18**	**-0.78**	**3.72**
30	**30**	**20**	**10**	**10**	**0**	**2.83**	**2.32**	**0.011**	**0.017**	**0.027**	**0.010**	**0.009**	**0.11**	**1.37**	**0.43**	**3.84**
20	**40**	**30**	**10**	**0**	**0**	**2.60**	**2.24**	**0.014**	**0.017**	**0.027**	**0.010**	**0.007**	**0.26**	**1.14**	**0.00**	**0.29**
10	**50**	**40**	**0**	**0**	**0**	**2.59**	**2.27**	**0.013**	**0.019**	**0.030**	**0.011**	**0.008**	**0.65**	**2.46**	**1.18**	**4.03**
0	60	10	30	0	0	1.42	1.30	0.099	0.015	0.027	0.011	0.006	-0.44	0.88	-0.81	3.49
0	70	20	10	0	0	1.62	1.48	0.072	0.016	0.029	0.011	0.006	-0.07	0.69	-0.14	1.17
0	**80**	**20**	**0**	**0**	**0**	**2.11**	**1.96**	**0.027**	**0.017**	**0.029**	**0.011**	**0.006**	**-0.12**	**0.56**	**-0.47**	**1.74**
0	90	10	0	0	0	1.70	1.57	0.060	0.016	0.029	0.010	0.006	-0.19	0.86	-0.20	1.22
0	**100**	**0**	**0**	**0**	**0**	**1.81**	**1.68**	**0.048**	**0.016**	**0.029**	**0.010**	**0.006**	**-0.06**	**0.46**	**-0.11**	**0.78**
10	**10**	**50**	**10**	**10**	**10**	**2.99**	**2.36**	**0.010**	**0.017**	**0.024**	**0.010**	**0.013**	**0.93**	**1.94**	**-1.03**	**3.54**
0	**0**	**60**	**20**	**10**	**10**	**2.29**	**1.80**	**0.037**	**0.015**	**0.019**	**0.010**	**0.015**	**0.01**	**2.20**	**-0.81**	**3.36**
0	**0**	**70**	**10**	**20**	**0**	**2.02**	**1.67**	**0.049**	**0.015**	**0.019**	**0.010**	**0.013**	**0.39**	**2.87**	**-1.06**	**3.34**
20	**0**	**80**	**0**	**0**	**0**	**2.68**	**2.04**	**0.022**	**0.016**	**0.018**	**0.011**	**0.014**	**0.72**	**2.54**	**-0.41**	**1.05**
10	**0**	**90**	**0**	**0**	**0**	**2.39**	**1.79**	**0.037**	**0.017**	**0.021**	**0.012**	**0.014**	**1.17**	**2.33**	**-0.31**	**1.21**
0	0	100	0	0	0	1.36	1.07	0.143	0.015	0.019	0.012	0.015	1.24	3.57	-0.68	2.20
0	0	0	40	50	10	0.55	0.50	0.309	0.014	0.022	0.012	0.016	-0.92	3.47	0.85	4.50
0	0	10	50	30	10	0.93	0.77	0.222	0.014	0.021	0.012	0.018	-0.53	2.38	0.27	3.75
0	0	0	60	40	0	0.37	0.31	0.379	0.014	0.021	0.013	0.020	-0.75	2.97	1.23	3.80
0	0	0	70	20	10	0.46	0.36	0.359	0.014	0.019	0.013	0.018	-0.25	1.57	0.87	3.79
10	0	0	80	10	0	0.13	0.10	0.462	0.013	0.019	0.012	0.019	-0.68	2.26	0.64	3.39
0	0	10	90	0	0	0.24	0.18	0.430	0.013	0.018	0.013	0.019	-0.34	1.34	0.67	3.23
0	0	0	100	0	0	0.02	0.01	0.495	0.013	0.018	0.013	0.019	-0.32	1.25	0.70	3.37
0	0	0	0	60	40	1.54	1.44	0.077	0.015	0.022	0.011	0.016	-0.73	2.39	0.23	5.64
30	**0**	**0**	**0**	**70**	**0**	**2.07**	**1.66**	**0.050**	**0.017**	**0.021**	**0.012**	**0.012**	**-0.75**	**4.20**	**0.34**	**2.35**
0	0	10	0	80	10	0.78	0.73	0.234	0.014	0.020	0.013	0.014	-0.67	4.48	1.33	5.74
10	0	0	0	90	0	1.06	0.97	0.168	0.015	0.020	0.012	0.015	-0.36	2.85	1.02	5.38
0	0	0	0	100	0	1.10	1.00	0.159	0.015	0.019	0.012	0.019	-0.41	3.03	0.09	3.30
20	**20**	**20**	**0**	**20**	**20**	**3.15**	**2.67**	**0.004**	**0.018**	**0.026**	**0.010**	**0.008**	**-0.06**	**1.26**	**0.12**	**-0.24**
20	**10**	**10**	**10**	**20**	**30**	**2.91**	**2.57**	**0.006**	**0.018**	**0.025**	**0.010**	**0.010**	**-0.26**	**1.06**	**-0.27**	**2.54**
10	**0**	**0**	**10**	**30**	**50**	**2.29**	**2.07**	**0.020**	**0.016**	**0.022**	**0.010**	**0.013**	**-0.25**	**0.47**	**1.50**	**10.14**
20	**10**	**10**	**0**	**0**	**60**	**2.37**	**1.92**	**0.028**	**0.017**	**0.023**	**0.011**	**0.010**	**-0.41**	**0.57**	**0.07**	**1.80**
10	0	10	0	10	70	1.49	1.18	0.120	0.015	0.023	0.011	0.015	-0.40	0.40	0.87	6.20
0	10	0	10	0	80	0.97	0.69	0.245	0.015	0.023	0.013	0.013	-0.30	0.16	1.62	8.74
10	0	0	0	0	90	1.78	1.30	0.097	0.015	0.023	0.011	0.014	-0.38	0.37	1.33	6.30
0	0	0	0	0	100	-0.92	-0.77	0.222	0.015	0.022	0.018	0.034	-0.30	0.25	-1.30	4.60

Table 16: Long/Short Directional: Search for Optimal Metric/Factor Weights Combination

Rets	StdDv	Skw	Krt	NegCor	Rel	Calc t	Excel t	p-val	Top($\bar{x}$)	Top(σ)	Bttm($\bar{x}$)	Bttm(σ)	SkwTop	KrtTop	SkwBttm	KrtBttm
100	**0**	**0**	**0**	**0**	**0**	**5.31**	**3.04**	**0.001**	**0.025**	**0.035**	**0.007**	**0.034**	**-0.39**	**0.59**	**-1.23**	**3.21**
90	**10**	**0**	**0**	**0**	**0**	**5.17**	**2.98**	**0.002**	**0.025**	**0.034**	**0.008**	**0.032**	**-0.29**	**0.60**	**-1.13**	**3.63**
80	**10**	**10**	**0**	**0**	**0**	**5.16**	**3.06**	**0.001**	**0.025**	**0.034**	**0.008**	**0.034**	**-0.30**	**0.41**	**-1.27**	**3.56**
70	**10**	**10**	**10**	**0**	**0**	**5.32**	**2.96**	**0.002**	**0.025**	**0.035**	**0.008**	**0.030**	**-0.54**	**1.00**	**-0.85**	**2.39**
60	**10**	**10**	**10**	**10**	**0**	**4.81**	**2.65**	**0.004**	**0.024**	**0.037**	**0.009**	**0.030**	**-0.65**	**1.09**	**-0.88**	**2.43**
50	**10**	**10**	**10**	**10**	**10**	**5.11**	**2.65**	**0.005**	**0.024**	**0.036**	**0.010**	**0.028**	**-0.49**	**1.15**	**-0.71**	**2.59**
40	**20**	**10**	**10**	**10**	**10**	**4.85**	**2.50**	**0.007**	**0.024**	**0.037**	**0.011**	**0.024**	**-0.53**	**1.27**	**-0.27**	**0.62**
30	**30**	**20**	**10**	**10**	**0**	**4.49**	**2.72**	**0.004**	**0.024**	**0.036**	**0.011**	**0.022**	**-0.47**	**0.80**	**-0.29**	**0.54**
20	40	30	10	0	0	2.21	1.45	0.076	0.020	0.040	0.013	0.021	-0.76	2.15	-0.06	-0.03
10	50	40	0	0	0	1.53	1.07	0.144	0.020	0.045	0.014	0.020	-0.74	2.96	0.00	-0.27
0	60	10	30	0	0	0.84	0.58	0.280	0.018	0.047	0.015	0.020	-0.93	1.88	-0.44	1.24
0	70	20	10	0	0	0.49	0.35	0.362	0.017	0.050	0.015	0.021	-0.68	1.26	-0.42	1.01
0	80	20	0	0	0	0.39	0.27	0.393	0.018	0.049	0.016	0.020	-0.59	0.82	-0.05	-0.00
0	90	10	0	0	0	0.63	0.43	0.333	0.019	0.046	0.016	0.020	-0.50	1.14	0.00	0.07
0	100	0	0	0	0	0.59	0.41	0.341	0.018	0.047	0.016	0.019	-0.46	0.91	-0.03	0.22
10	10	50	10	10	10	2.95	1.57	0.059	0.019	0.033	0.011	0.028	-0.23	0.25	-0.80	2.92
0	0	60	20	10	10	0.95	0.57	0.286	0.018	0.032	0.015	0.031	-0.14	0.30	-0.53	1.88
0	0	70	10	20	0	1.25	0.74	0.230	0.019	0.032	0.015	0.030	-0.32	0.67	-0.33	1.10
20	0	80	0	0	0	1.82	1.01	0.158	0.021	0.031	0.015	0.033	0.13	0.73	-0.57	1.31
10	0	90	0	0	0	1.97	1.10	0.137	0.021	0.030	0.015	0.031	0.32	0.60	-0.67	2.89
0	0	100	0	0	0	1.92	1.04	0.150	0.020	0.032	0.014	0.032	-0.07	1.17	-0.58	1.66
0	0	0	40	50	10	1.09	0.61	0.272	0.016	0.035	0.013	0.029	-0.42	1.76	-0.05	1.50
0	0	10	50	30	10	1.36	0.77	0.221	0.016	0.037	0.012	0.025	-1.02	3.44	0.11	2.14
0	0	0	60	40	0	0.78	0.47	0.319	0.015	0.039	0.012	0.026	-1.25	4.41	-0.08	1.84
0	0	0	70	20	10	0.63	0.36	0.361	0.015	0.037	0.013	0.026	-0.98	3.25	0.06	1.67
10	0	0	80	10	0	1.64	0.90	0.184	0.016	0.036	0.012	0.027	-0.97	3.27	-0.10	1.79
0	0	10	90	0	0	1.43	0.83	0.205	0.016	0.036	0.012	0.027	-0.94	3.22	-0.14	2.00
0	0	0	100	0	0	1.34	0.77	0.221	0.016	0.036	0.012	0.027	-0.94	3.18	-0.12	1.80
0	0	0	0	60	40	1.34	0.77	0.221	0.017	0.038	0.023	0.034	-0.83	1.76	-0.30	0.74
30	0	0	0	70	0	2.03	1.19	0.118	0.020	0.039	0.014	0.022	-0.57	0.67	0.48	1.03
0	0	10	0	80	10	-0.86	-0.47	0.320	0.016	0.042	0.019	0.027	-0.79	2.41	0.32	-0.22
10	0	0	0	90	0	0.80	0.53	0.299	0.018	0.042	0.015	0.020	-0.78	1.29	0.73	1.45
0	0	0	0	100	0	-2.61	-0.88	0.190	0.020	0.043	0.026	0.035	-0.72	1.22	-0.17	0.60
20	20	20	0	20	20	2.12	1.54	0.064	0.023	0.043	0.014	0.019	-0.89	2.10	0.09	0.30
20	10	10	10	20	30	1.76	1.16	0.125	0.020	0.040	0.013	0.021	-0.88	2.05	0.04	0.24
10	0	0	10	30	50	0.68	0.43	0.333	0.018	0.040	0.015	0.025	-0.80	1.51	1.23	5.52
20	10	10	0	0	60	1.74	0.89	0.188	0.018	0.040	0.013	0.028	-0.60	0.37	0.26	1.25
10	0	10	0	10	70	-0.45	-0.22	0.414	0.016	0.037	0.017	0.031	-0.79	1.74	0.63	1.46
0	10	0	10	0	80	-0.80	-0.44	0.331	0.016	0.038	0.019	0.028	-0.66	1.56	0.70	2.76
10	0	0	0	0	90	0.77	0.38	0.354	0.017	0.038	0.015	0.031	-0.67	1.48	0.54	1.82
0	0	0	0	0	100	-1.79	-1.11	0.135	0.017	0.038	0.024	0.042	-0.71	1.53	-1.09	2.07

Table 17: Market Neutral Equity: Search for Optimal Metric/Factor Weights Combination

Rets	StdDv	Skw	Krt	NegCor	Rel	Calc t	Excel t	p-val	Top($\bar{x}$)	Top(σ)	Bttm($\bar{x}$)	Bttm(σ)	SkwTop	KrtTop	SkwBttm	KrtBttm
100	0	0	0	0	0	0.97	0.91	0.182	0.011	0.016	0.008	0.015	0.28	4.61	0.28	-0.10
90	10	0	0	0	0	0.89	0.81	0.209	0.010	0.016	0.008	0.015	0.25	4.31	0.23	-0.21
80	10	10	0	0	0	0.56	0.47	0.318	0.009	0.017	0.008	0.015	0.18	3.18	0.25	-0.14
70	10	10	10	0	0	1.42	1.16	0.124	0.009	0.017	0.006	0.013	0.15	3.15	-0.03	-0.25
60	10	10	10	10	0	0.71	0.59	0.277	0.008	0.020	0.007	0.011	-0.92	5.55	0.11	-0.35
50	10	10	10	10	10	1.21	0.97	0.167	0.009	0.020	0.006	0.012	-0.78	4.15	-0.02	-0.16
40	20	10	10	10	10	0.98	0.92	0.181	0.012	0.036	0.008	0.009	0.05	10.45	-0.26	0.70
30	30	20	10	10	0	1.41	1.34	0.092	0.013	0.030	0.008	0.007	2.45	11.15	0.61	0.63
20	40	30	10	0	0	1.26	1.21	0.115	0.013	0.031	0.008	0.008	2.05	9.27	0.38	0.21
10	50	40	0	0	0	1.03	0.99	0.164	0.013	0.032	0.009	0.007	1.90	8.35	0.16	-0.07
0	60	10	30	0	0	-0.27	-0.24	0.406	0.008	0.022	0.009	0.007	-0.19	0.79	0.28	0.12
0	70	20	10	0	0	0.49	0.50	0.310	0.012	0.032	0.009	0.007	1.96	8.34	0.25	-0.20
0	80	20	0	0	0	0.55	0.54	0.295	0.012	0.033	0.010	0.007	1.63	7.20	0.45	0.39
0	90	10	0	0	0	0.04	0.04	0.485	0.009	0.038	0.009	0.007	0.03	7.78	0.49	0.89
0	100	0	0	0	0	0.00	0.00	0.500	0.009	0.038	0.009	0.007	0.04	7.77	0.50	0.95
10	10	50	10	10	10	0.65	0.61	0.273	0.010	0.016	0.009	0.010	-0.82	2.79	0.63	1.57
0	0	60	20	10	10	1.25	1.19	0.119	0.011	0.012	0.008	0.011	0.22	1.57	-0.43	3.25
0	0	70	10	20	0	1.10	0.93	0.176	0.011	0.015	0.008	0.021	-0.74	2.43	-4.54	28.37
20	0	80	0	0	0	0.66	0.64	0.261	0.011	0.014	0.009	0.010	-0.83	3.35	0.90	1.81
10	0	90	0	0	0	0.88	0.80	0.213	0.011	0.014	0.009	0.010	-0.77	3.18	0.90	2.57
0	0	100	0	0	0	0.85	0.80	0.212	0.011	0.014	0.009	0.010	-0.88	4.09	0.86	2.42
0	0	0	40	50	10	1.77	1.65	0.051	0.011	0.011	0.007	0.014	0.14	-0.34	-1.64	9.89
0	0	10	50	30	10	1.31	1.21	0.114	0.010	0.011	0.008	0.011	0.08	-0.28	-0.43	5.15
0	0	0	60	40	0	0.92	0.85	0.200	0.010	0.012	0.008	0.021	0.07	-0.60	-5.18	35.05
0	0	0	70	20	10	1.05	0.89	0.187	0.011	0.012	0.009	0.011	-0.09	-0.07	0.40	0.58
10	0	0	80	10	0	0.56	0.46	0.324	0.010	0.014	0.009	0.010	-0.51	0.80	0.23	0.54
0	0	10	90	0	0	0.33	0.29	0.385	0.011	0.013	0.010	0.011	0.03	-0.05	-0.12	1.51
0	0	0	100	0	0	0.50	0.44	0.331	0.011	0.014	0.010	0.010	-0.39	0.64	-0.24	1.35
0	0	0	0	60	40	0.65	0.59	0.279	0.011	0.009	0.009	0.017	-0.29	-0.29	0.47	1.81
30	0	0	0	70	0	0.59	0.55	0.293	0.011	0.010	0.009	0.025	-0.27	-0.46	-3.71	21.44
0	0	10	0	80	10	1.35	1.24	0.109	0.010	0.009	0.006	0.023	-0.33	-0.72	-4.19	26.01
10	0	0	0	90	0	0.39	0.36	0.358	0.010	0.009	0.008	0.026	-0.38	-0.54	-2.95	17.09
0	0	0	0	100	0	0.54	0.49	0.314	0.010	0.009	0.008	0.017	-0.30	-0.57	0.03	2.51
20	20	20	0	20	20	1.72	1.66	0.051	0.015	0.028	0.008	0.008	2.98	14.41	0.02	0.87
20	10	10	10	20	30	1.52	1.48	0.071	0.015	0.033	0.008	0.009	-0.37	16.83	0.40	1.87
10	0	0	10	30	50	0.94	0.91	0.183	0.010	0.022	0.007	0.011	-4.64	30.19	0.16	-0.40
20	**10**	**10**	**0**	**0**	**60**	**1.89**	**1.86**	**0.034**	**0.014**	**0.033**	**0.006**	**0.009**	**-0.15**	**15.37**	**-0.51**	**0.44**
10	0	10	0	10	70	1.40	1.30	0.098	0.010	0.023	0.005	0.018	-5.22	35.77	-0.47	2.82
0	10	0	10	0	80	1.42	1.36	0.088	0.011	0.025	0.006	0.012	-4.24	27.99	-1.55	5.00
10	0	0	0	0	90	1.01	0.95	0.172	0.010	0.024	0.007	0.015	-4.36	30.36	-0.59	1.56
0	0	0	0	0	100	0.28	0.27	0.393	0.010	0.021	0.008	0.040	-4.08	26.45	0.89	6.52
20	10	20	0	0	50	1.66	1.63	0.054	0.015	0.032	0.007	0.010	-0.16	16.89	-0.47	0.33
20	10	10	10	10	40	1.42	1.42	0.081	0.015	0.033	0.008	0.008	-0.31	16.91	0.12	0.31
30	20	20	0	0	30	0.98	0.94	0.175	0.012	0.036	0.007	0.008	-0.01	9.50	-0.24	1.03

Table 18: Long/Short Equity- Non-Directional: Search for Optimal Metric/Factor Weights Combination

Rets	StdDv	Skw	Krt	NegCor	Rel	Calc t	Excel t	p-val	Top($\bar{x}$)	Top(σ)	Bttm($\bar{x}$)	Bttm(σ)	SkwTop	KrtTop	SkwBttm	KrtBttm
100	0	0	0	0	0	2.14	1.35	0.090	0.012	0.017	0.007	0.023	−0.14	1.83	−0.77	1.10
90	10	0	0	0	0	1.70	1.13	0.129	0.012	0.017	0.008	0.023	−0.14	1.83	−0.84	1.18
80	10	10	0	0	0	1.65	1.06	0.145	0.012	0.017	0.008	0.021	−0.14	1.83	−0.31	0.37
70	10	10	10	0	0	0.56	0.36	0.359	0.012	0.017	0.011	0.020	−0.16	1.86	0.34	2.11
60	10	10	10	10	0	0.17	0.11	0.454	0.012	0.017	0.012	0.020	−0.06	1.37	0.37	1.85
50	10	10	10	10	10	0.21	0.14	0.445	0.012	0.017	0.012	0.020	−0.08	1.09	0.37	1.85
40	20	10	10	10	10	0.92	0.61	0.272	0.012	0.017	0.010	0.020	0.14	0.26	0.04	2.46
30	30	20	10	10	0	0.02	0.01	0.495	0.012	0.018	0.012	0.018	−0.30	1.24	0.43	3.69
20	40	30	10	0	0	−0.50	−0.35	0.365	0.012	0.019	0.013	0.017	−0.62	1.89	0.35	3.88
10	50	40	0	0	0	0.32	0.21	0.418	0.013	0.018	0.012	0.018	−0.32	0.78	0.46	3.40
0	**60**	**10**	**30**	**0**	**0**	**-3.25**	**-2.45**	**0.008**	**0.005**	**0.022**	**0.014**	**0.016**	**-0.35**	**-0.17**	**0.65**	**5.98**
0	**70**	**20**	**10**	**0**	**0**	**-2.36**	**-1.69**	**0.047**	**0.007**	**0.021**	**0.013**	**0.017**	**-0.23**	**-0.21**	**0.44**	**4.95**
0	**80**	**20**	**0**	**0**	**0**	**-2.38**	**-1.71**	**0.045**	**0.007**	**0.022**	**0.013**	**0.019**	**-0.40**	**0.06**	**0.25**	**3.39**
0	90	10	0	0	0	−2.28	−1.61	0.055	0.007	0.023	0.013	0.019	−0.47	0.16	0.31	3.55
0	100	0	0	0	0	−2.25	−1.61	0.055	0.007	0.023	0.013	0.019	−0.36	−0.05	0.31	3.55
10	10	50	10	10	10	−0.13	−0.09	0.466	0.014	0.016	0.014	0.018	0.13	1.00	0.45	3.76
0	0	60	20	10	10	−0.92	−0.61	0.272	0.012	0.018	0.014	0.017	−0.26	0.63	0.46	4.17
0	0	70	10	20	0	−0.80	−0.55	0.292	0.013	0.018	0.014	0.018	−0.47	1.65	0.43	3.86
20	0	80	0	0	0	0.12	0.07	0.471	0.013	0.016	0.013	0.019	0.10	1.08	0.23	2.84
10	0	90	0	0	0	−1.27	−0.86	0.195	0.012	0.018	0.015	0.017	−0.24	1.18	0.99	2.90
0	0	100	0	0	0	−1.11	−0.75	0.228	0.013	0.017	0.015	0.017	−0.15	0.84	0.99	2.90
0	**0**	**0**	**40**	**50**	**10**	**-3.27**	**-2.51**	**0.007**	**0.007**	**0.019**	**0.015**	**0.017**	**0.08**	**0.61**	**0.44**	**4.44**
0	**0**	**10**	**50**	**30**	**10**	**-3.36**	**-2.49**	**0.007**	**0.007**	**0.019**	**0.015**	**0.017**	**-0.01**	**0.71**	**1.13**	**3.63**
0	**0**	**0**	**60**	**40**	**0**	**-3.89**	**-3.06**	**0.001**	**0.008**	**0.018**	**0.017**	**0.015**	**-0.08**	**0.87**	**1.07**	**4.30**
0	**0**	**0**	**70**	**20**	**10**	**-4.31**	**-3.20**	**0.001**	**0.007**	**0.019**	**0.017**	**0.016**	**0.10**	**0.57**	**1.31**	**4.35**
10	**0**	**0**	**80**	**10**	**0**	**-4.12**	**-3.04**	**0.001**	**0.007**	**0.018**	**0.016**	**0.016**	**0.10**	**0.58**	**1.37**	**4.27**
0	**0**	**10**	**90**	**0**	**0**	**-4.12**	**-3.04**	**0.001**	**0.007**	**0.018**	**0.016**	**0.016**	**0.10**	**0.58**	**1.37**	**4.27**
0	**0**	**0**	**100**	**0**	**0**	**-4.43**	**-3.27**	**0.001**	**0.007**	**0.018**	**0.017**	**0.016**	**0.10**	**0.58**	**1.32**	**4.34**
0	0	0	0	60	40	−0.45	−0.28	0.391	0.012	0.018	0.013	0.015	0.26	0.31	0.50	1.65
30	0	0	0	70	0	2.24	1.63	0.053	0.013	0.018	0.008	0.023	−0.25	1.78	−0.86	1.41
0	0	10	0	80	10	−0.29	−0.19	0.425	0.012	0.018	0.013	0.017	−0.17	1.33	0.87	3.31
10	0	0	0	90	0	2.02	1.41	0.080	0.013	0.017	0.008	0.019	−0.37	1.98	−0.30	0.50
0	0	0	0	100	0	−0.19	−0.09	0.464	0.012	0.018	0.012	0.017	−0.33	2.05	0.03	1.12
20	20	20	0	20	20	0.87	0.59	0.278	0.014	0.018	0.012	0.017	0.13	0.17	0.70	4.02
20	10	10	10	20	30	−0.27	−0.18	0.430	0.012	0.018	0.012	0.018	0.29	0.05	0.42	2.96
10	0	0	10	30	50	−1.22	−0.76	0.224	0.012	0.018	0.014	0.017	0.41	0.28	0.95	3.07
20	10	10	0	0	60	0.54	0.35	0.363	0.013	0.018	0.012	0.018	0.27	−0.03	0.61	2.45
10	0	10	0	10	70	0.20	0.15	0.441	0.013	0.018	0.012	0.017	0.28	−0.06	0.85	3.09
0	10	0	10	0	80	−2.06	−1.61	0.055	0.009	0.019	0.014	0.016	0.20	−0.15	1.10	4.34
10	0	0	0	0	90	0.49	0.34	0.367	0.012	0.018	0.011	0.017	0.31	0.18	0.03	0.43
0	0	0	0	0	100	−0.16	−0.10	0.459	0.012	0.018	0.013	0.019	0.33	0.12	−1.39	6.18

Table 19: Fixed Income Securities: Search for Optimal Metric/Factor Weights Combination

Rets	StdDv	Skw	Krt	NegCor	Rel	Calc t	Excel t	p-val	Top($\bar{x}$)	Top(σ)	Bttm($\bar{x}$)	Bttm(σ)	SkwTop	KrtTop	SkwBttm	KrtBttm
100	0	0	0	0	0	-0.253	-0.230	0.409	0.997%	0.012	1.044%	0.009	-1.356	4.524	0.301	1.317
90	10	0	0	0	0	-0.253	-0.230	0.409	0.997%	0.012	1.044%	0.009	-1.356	4.524	0.301	1.317
80	10	10	0	0	0	-0.253	-0.230	0.409	0.997%	0.012	1.044%	0.009	-1.356	4.524	0.301	1.317
70	10	10	10	0	0	-0.712	-0.739	0.231	0.960%	0.010	1.120%	0.012	-0.897	4.902	1.504	5.047
60	10	10	10	10	0	-0.833	-0.843	0.201	0.947%	0.010	1.111%	0.010	-0.970	5.355	0.450	0.831
50	10	10	10	10	10	-1.068	-1.181	0.120	0.947%	0.010	1.173%	0.009	-0.970	5.355	0.733	1.348
40	20	10	10	10	10	-0.914	-0.993	0.162	0.929%	0.010	1.127%	0.010	-0.913	5.221	0.686	1.090
30	30	20	10	10	0	-0.350	-0.406	0.343	0.929%	0.012	1.014%	0.009	-1.618	10.624	0.995	1.912
20	40	30	10	0	0	-0.283	-0.290	0.386	1.030%	0.012	1.099%	0.012	-1.659	10.327	1.286	4.751
10	50	40	0	0	0	-0.089	-0.093	0.463	1.076%	0.012	1.099%	0.012	-1.446	9.584	1.286	4.751
0	60	10	30	0	0	-0.074	-0.073	0.471	1.067%	0.012	1.090%	0.019	-1.766	10.728	1.397	10.819
0	70	20	10	0	0	0.893	1.015	0.156	1.114%	0.012	0.914%	0.008	-1.706	10.953	0.890	2.524
0	80	20	0	0	0	0.170	0.200	0.421	0.975%	0.012	0.938%	0.006	-1.607	10.320	1.062	4.045
0	90	10	0	0	0	0.277	0.324	0.373	0.998%	0.012	0.938%	0.006	-1.578	9.931	1.062	4.045
0	100	0	0	0	0	0.277	0.324	0.373	0.998%	0.012	0.938%	0.006	-1.578	9.931	1.062	4.045
10	10	50	10	10	10	-0.170	-0.136	0.446	1.108%	0.012	1.140%	0.013	-1.891	13.232	0.386	3.449
0	0	60	20	10	10	-0.855	-0.724	0.235	0.991%	0.008	1.144%	0.013	-1.066	5.979	0.240	2.975
0	0	70	10	20	0	-0.946	-0.923	0.179	0.990%	0.008	1.175%	0.012	-1.164	3.013	0.418	3.899
20	0	80	0	0	0	0.161	0.119	0.453	1.155%	0.011	1.127%	0.013	-1.925	14.177	0.279	2.983
10	0	90	0	0	0	-0.080	-0.064	0.475	1.131%	0.008	1.144%	0.013	-0.603	3.596	0.240	2.975
0	0	100	0	0	0	-0.080	-0.064	0.475	1.131%	0.008	1.144%	0.013	-0.603	3.596	0.240	2.975
0	0	0	40	50	10	0.134	0.112	0.455	0.944%	0.007	0.925%	0.010	-0.507	1.147	-0.079	0.729
0	0	10	50	30	10	0.072	0.052	0.479	0.969%	0.010	0.958%	0.012	-0.974	5.944	-0.432	4.179
0	0	0	60	40	0	0.356	0.314	0.377	1.048%	0.010	0.991%	0.009	-1.069	5.396	0.229	0.328
0	0	0	70	20	10	0.313	0.280	0.390	0.999%	0.010	0.945%	0.010	-0.851	5.423	-0.357	0.519
10	0	0	80	10	0	0.333	0.304	0.381	0.986%	0.010	0.928%	0.010	-0.750	4.647	-0.332	0.614
0	0	10	90	0	0	0.333	0.304	0.381	0.986%	0.010	0.928%	0.010	-0.750	4.647	-0.332	0.614
0	0	0	100	0	0	0.333	0.304	0.381	0.986%	0.010	0.928%	0.010	-0.750	4.647	-0.332	0.614
0	0	0	0	60	40	0.362	0.354	0.362	1.056%	0.006	0.999%	0.010	-0.433	0.395	-0.159	2.167
30	0	0	0	70	0	0.334	0.372	0.355	1.152%	0.007	1.090%	0.010	-0.658	7.803	1.771	5.963
0	0	10	0	80	10	0.204	0.220	0.413	1.115%	0.006	1.084%	0.008	-0.605	2.907	0.846	0.966
10	0	0	0	90	0	0.269	0.291	0.386	1.115%	0.006	1.074%	0.008	-0.605	2.907	0.838	0.872
0	0	0	0	100	0	-0.405	-0.425	0.336	1.089%	0.006	1.152%	0.009	-0.603	2.091	0.995	1.353
20	20	20	0	20	20	-0.152	-0.174	0.431	0.917%	0.014	0.958%	0.009	-1.368	7.686	1.055	1.631
20	10	10	10	20	30	-0.118	-0.104	0.459	1.002%	0.010	1.022%	0.010	-1.251	5.629	0.596	1.238
10	0	0	10	30	50	-0.003	-0.003	0.499	1.012%	0.009	1.012%	0.011	-1.521	5.453	0.283	0.863
20	10	10	0	0	60	-1.049	-0.912	0.182	0.906%	0.015	1.131%	0.010	-2.327	8.729	0.540	2.188
10	0	10	0	10	70	-0.626	-0.626	0.266	1.013%	0.009	1.126%	0.009	-1.579	5.571	0.218	2.484
0	10	0	10	0	80	-0.281	-0.273	0.393	0.995%	0.009	1.042%	0.009	-1.439	6.342	0.441	3.151
10	0	0	0	0	90	-0.430	-0.399	0.345	1.057%	0.009	1.131%	0.010	-1.696	7.319	0.517	2.048
0	0	0	0	0	100	-0.133	-0.121	0.452	1.066%	0.009	1.085%	0.007	-1.533	6.055	-0.462	0.987

Table 20: Whole Universe : Search for Optimal Performance Weights Combination

α	β	Sharpe	Sortino	Omega	MaxDD	Calc t	Excel t	p-val	Top($\bar{x}$)	Top(σ)	Bttm($\bar{x}$)	Bttm(σ)	SkwTop	KrtTop	SkwBttm	KrtBt
100	0	0	0	0	0	3.99	2.73	0.004	0.018	0.019	0.010	0.018	-0.05	0.53	-0.37	0.90
90	10	0	0	0	0	3.89	2.64	0.005	0.018	0.019	0.011	0.017	-0.04	0.39	-0.43	1.38
80	10	10	0	0	0	3.80	2.76	0.003	0.019	0.019	0.011	0.017	-0.03	0.39	-0.14	1.04
70	10	10	10	0	0	3.65	2.71	0.004	0.018	0.019	0.011	0.017	-0.11	0.49	-0.09	0.90
60	10	10	10	10	0	4.62	3.50	0.000	0.020	0.021	0.010	0.014	0.30	1.46	-0.34	1.21
50	10	10	10	10	10	4.71	3.40	0.000	0.021	0.022	0.011	0.016	0.14	1.41	-0.04	1.40
40	20	10	10	10	10	4.19	3.12	0.001	0.020	0.022	0.011	0.017	0.10	1.55	0.78	4.46
30	30	20	10	10	0	4.15	3.37	0.000	0.021	0.024	0.010	0.015	-0.25	1.84	1.21	6.98
20	40	30	10	0	0	3.64	2.91	0.002	0.020	0.023	0.010	0.018	-0.21	2.09	0.43	3.78
10	50	40	0	0	0	4.13	3.29	0.001	0.020	0.024	0.009	0.018	-0.39	2.67	0.68	4.64
0	60	10	30	0	0	2.98	2.51	0.007	0.019	0.027	0.010	0.016	-0.33	0.63	1.19	5.71
0	70	20	10	0	0	2.52	2.17	0.016	0.017	0.028	0.009	0.017	-0.50	1.09	0.63	4.57
0	80	20	0	0	0	1.96	1.71	0.045	0.016	0.029	0.010	0.017	-0.36	0.76	0.54	4.58
0	90	10	0	0	0	1.79	1.57	0.059	0.015	0.028	0.010	0.017	-0.46	0.52	0.57	4.99
0	100	0	0	0	0	1.55	1.36	0.088	0.015	0.028	0.010	0.017	-0.45	0.58	0.52	4.70
10	10	50	10	10	10	3.91	3.07	0.001	0.019	0.020	0.010	0.018	-0.41	2.93	-0.83	2.83
0	0	60	20	10	10	3.55	2.64	0.005	0.018	0.019	0.010	0.021	-0.14	2.75	-0.50	1.61
0	0	70	10	20	0	3.97	3.21	0.001	0.019	0.020	0.010	0.017	-0.27	3.37	-0.48	1.95
20	0	80	0	0	0	3.37	2.61	0.005	0.019	0.018	0.011	0.021	0.09	3.28	-0.48	0.97
10	0	90	0	0	0	3.42	2.62	0.005	0.018	0.018	0.010	0.021	-0.14	3.94	-0.51	1.05
0	0	100	0	0	0	3.40	2.61	0.005	0.018	0.018	0.010	0.021	-0.14	3.94	-0.53	1.11
0	0	0	40	50	10	3.84	3.41	0.000	0.019	0.024	0.010	0.009	0.14	1.15	-0.63	4.26
0	0	10	50	30	10	3.64	2.89	0.002	0.018	0.024	0.009	0.016	0.02	0.98	-1.13	5.45
0	0	0	60	40	0	3.61	3.03	0.001	0.019	0.025	0.010	0.010	-0.08	1.04	-1.19	5.41
0	0	0	70	20	10	3.15	2.52	0.006	0.019	0.025	0.011	0.016	-0.12	1.30	-0.61	5.28
10	0	0	80	10	0	3.66	2.91	0.002	0.018	0.024	0.009	0.016	-0.09	1.18	-1.16	4.29
0	0	10	90	0	0	3.49	2.71	0.004	0.018	0.024	0.010	0.017	-0.11	1.29	-1.36	5.24
0	0	0	100	0	0	3.42	2.66	0.004	0.018	0.024	0.010	0.017	0.02	1.07	-1.34	5.23
0	0	0	0	60	40	3.78	3.18	0.001	0.019	0.023	0.010	0.013	-0.04	2.16	-0.29	6.02
30	0	0	0	70	0	2.89	2.65	0.005	0.018	0.025	0.010	0.006	0.17	0.94	1.05	3.97
0	0	10	0	80	10	2.33	2.28	0.013	0.017	0.029	0.010	0.005	0.35	1.91	0.66	0.88
10	0	0	0	90	0	2.31	2.06	0.021	0.017	0.028	0.011	0.005	0.61	2.05	1.29	4.99
0	0	0	0	100	0	2.11	1.91	0.030	0.017	0.028	0.010	0.005	0.68	1.75	1.34	5.29
20	20	20	0	20	20	4.57	3.89	0.000	0.021	0.021	0.009	0.019	0.14	1.53	0.34	3.77
20	10	10	10	20	30	4.41	3.59	0.000	0.019	0.021	0.009	0.017	0.12	1.82	-0.62	1.40
10	0	0	10	30	50	4.34	3.39	0.000	0.018	0.017	0.008	0.021	-0.12	1.74	-0.69	1.64
20	10	10	0	0	60	2.53	1.90	0.030	0.015	0.012	0.009	0.024	-0.34	2.21	0.12	1.43
10	0	10	0	10	70	2.51	1.95	0.027	0.015	0.013	0.009	0.024	0.78	4.02	-0.49	1.22
0	10	0	10	0	80	1.05	0.87	0.194	0.014	0.009	0.011	0.028	-1.04	5.26	0.36	1.41
10	0	0	0	0	90	1.50	1.22	0.113	0.013	0.009	0.010	0.026	-0.05	1.21	-0.03	0.72
0	0	0	0	0	100	1.21	1.01	0.158	0.013	0.008	0.010	0.026	-0.35	2.05	-0.04	0.57

Table 21: Long/Short Equity-Directional : Search for Optimal Performance Weights Combination

α	β	Sharpe	Sortino	Omega	MaxDD	Calc t	Excel t	p-val	Top($\bar{x}$)	Top(σ)	Bttm($\bar{x}$)	Bttm(σ)	SkwTop	KrtTop	SkwBttm	KrtBt
100	0	0	0	0	0	5.45	3.22	0.001	0.024	0.034	0.005	0.035	-0.42	1.01	-1.70	4.56
90	10	0	0	0	0	5.50	3.31	0.001	0.024	0.033	0.005	0.034	-0.41	1.04	-1.74	4.97
80	10	10	0	0	0	5.73	3.40	0.000	0.025	0.033	0.005	0.035	-0.42	0.96	-1.66	4.58
70	10	10	10	0	0	5.57	3.34	0.001	0.024	0.034	0.005	0.035	-0.45	1.02	-1.79	5.45
60	10	10	10	10	0	5.21	3.13	0.001	0.023	0.035	0.005	0.035	-0.57	1.55	-1.68	4.51
50	10	10	10	10	10	5.21	3.01	0.002	0.024	0.036	0.006	0.035	-0.60	1.42	-1.37	3.83
40	20	10	10	10	10	6.27	3.41	0.000	0.025	0.034	0.005	0.034	-0.49	1.29	-1.12	2.35
30	30	20	10	10	0	4.73	3.10	0.001	0.025	0.034	0.006	0.040	-0.68	2.17	-1.49	3.95
20	40	30	10	0	0	5.38	3.29	0.001	0.024	0.030	0.005	0.036	-0.36	1.57	-1.09	2.19
10	50	40	0	0	0	5.14	3.25	0.001	0.024	0.032	0.005	0.036	-0.28	1.77	-1.10	2.12
0	60	10	30	0	0	3.49	2.44	0.008	0.020	0.027	0.006	0.038	0.27	0.12	-1.03	1.98
0	70	20	10	0	0	2.36	1.59	0.057	0.018	0.026	0.010	0.038	-0.13	0.38	-0.89	2.48
0	80	20	0	0	0	2.12	1.35	0.090	0.018	0.027	0.010	0.037	-0.19	0.14	-0.91	2.61
0	90	10	0	0	0	1.09	0.69	0.246	0.016	0.026	0.012	0.038	-0.19	0.19	-1.01	2.81
0	100	0	0	0	0	1.09	0.70	0.244	0.016	0.026	0.012	0.037	-0.19	0.13	-0.97	2.88
10	10	50	10	10	10	5.96	3.54	0.000	0.025	0.032	0.004	0.036	-0.67	1.76	-1.00	2.22
0	0	60	20	10	10	4.91	2.98	0.002	0.022	0.031	0.006	0.032	-0.70	1.73	-0.82	2.87
0	0	70	10	20	0	4.63	2.89	0.002	0.021	0.034	0.005	0.032	-0.99	2.67	-1.06	2.62
20	0	80	0	0	0	5.54	3.41	0.000	0.021	0.030	0.003	0.035	-0.76	1.69	-1.65	3.54
10	0	90	0	0	0	4.81	2.93	0.002	0.021	0.029	0.006	0.034	-0.74	1.72	-0.89	2.03
0	0	100	0	0	0	5.04	2.98	0.002	0.021	0.030	0.005	0.035	-0.82	1.96	-0.91	1.88
0	0	0	40	50	10	5.13	3.10	0.001	0.025	0.034	0.008	0.029	-0.16	1.34	-1.44	6.03
0	0	10	50	30	10	4.81	3.04	0.001	0.021	0.031	0.005	0.032	-0.65	2.37	-1.22	2.86
0	0	0	60	40	0	4.37	2.88	0.002	0.022	0.030	0.006	0.035	-0.58	2.25	-1.99	7.59
0	0	0	70	20	10	4.59	2.83	0.003	0.020	0.030	0.005	0.033	-0.63	2.26	-1.84	7.20
10	0	0	80	10	0	4.40	2.76	0.003	0.020	0.029	0.005	0.033	-0.63	2.17	-1.74	6.58
0	0	10	90	0	0	5.08	2.92	0.002	0.020	0.030	0.005	0.033	-0.66	2.21	-1.22	2.87
0	0	0	100	0	0	4.91	2.86	0.002	0.020	0.030	0.005	0.033	-0.65	2.23	-1.26	3.08
0	0	0	0	60	40	2.71	1.81	0.037	0.019	0.032	0.011	0.024	-0.34	1.28	0.18	1.38
30	0	0	0	70	0	2.51	1.83	0.035	0.019	0.035	0.010	0.022	-1.06	4.84	-0.31	1.07
0	0	10	0	80	10	2.00	1.45	0.075	0.017	0.037	0.010	0.022	-1.11	3.93	-0.36	1.16
10	0	0	0	90	0	1.73	1.25	0.108	0.017	0.037	0.010	0.022	-0.92	3.54	-0.35	1.06
0	0	0	0	100	0	1.75	1.26	0.104	0.017	0.038	0.010	0.023	-1.14	4.37	-0.59	1.12
20	20	20	0	20	20	5.68	3.52	0.000	0.024	0.035	0.004	0.035	-0.62	2.33	-1.41	3.13
20	10	10	10	20	30	5.90	3.59	0.000	0.025	0.032	0.005	0.035	-0.46	1.35	-1.05	2.99
10	0	0	10	30	50	6.02	3.18	0.001	0.023	0.029	0.007	0.031	-0.40	1.01	-0.58	1.50
20	10	10	0	0	60	4.70	2.63	0.005	0.021	0.027	0.005	0.042	-0.75	1.92	-0.69	1.97
10	0	10	0	10	70	3.59	2.11	0.018	0.021	0.027	0.009	0.038	-0.61	1.20	-0.09	1.03
0	10	0	10	0	80	3.58	2.21	0.014	0.021	0.027	0.007	0.042	-0.77	1.63	-0.60	1.85
10	0	0	0	0	90	3.73	2.27	0.013	0.021	0.027	0.008	0.042	-0.58	0.95	-0.60	1.89
0	0	0	0	0	100	3.46	2.14	0.017	0.020	0.026	0.007	0.043	-0.48	1.27	-0.60	1.70

Table 22: Market Neutral : Search for Optimal Performance Weights Combination

α	β	Sharpe	Sortino	Omega	MaxDD	Calc t	Excel t	p-val	Top($\bar{x}$)	Top(σ)	Bttm($\bar{x}$)	Bttm(σ)	SkwTop	KrtTop	SkwBttm	KrtBttm
100	0	0	0	0	0	1.031	0.908	0.183	0.010	0.024	0.006	0.014	-3.403	20.665	0.151	1.111
90	10	0	0	0	0	1.012	0.894	0.187	0.010	0.024	0.006	0.014	-3.441	20.932	0.147	1.087
80	10	10	0	0	0	0.865	0.783	0.218	0.009	0.024	0.006	0.016	-3.534	21.410	0.572	2.565
70	10	10	10	0	0	0.888	0.801	0.213	0.009	0.024	0.006	0.014	-3.545	21.464	0.207	1.116
60	10	10	10	10	0	0.913	0.804	0.212	0.009	0.024	0.006	0.014	-3.449	21.260	0.254	0.737
50	10	10	10	10	10	1.116	0.995	0.161	0.010	0.024	0.006	0.014	-3.488	21.432	0.347	1.137
40	20	10	10	10	10	0.910	0.820	0.207	0.009	0.024	0.006	0.013	-3.355	19.967	−0.148	0.191
30	30	20	10	10	0	0.159	0.137	0.446	0.007	0.023	0.007	0.013	-3.922	22.328	−0.254	0.715
20	40	30	10	0	0	1.577	1.356	0.089	0.009	0.014	0.006	0.014	−0.959	5.040	0.017	0.470
10	50	40	0	0	0	1.296	1.213	0.114	0.008	0.011	0.005	0.016	0.066	1.888	−0.561	0.902
70	20	10	0	0	0	1.783	1.644	0.051	0.011	0.015	0.007	0.014	0.201	6.355	−0.065	0.150
0	60	10	30	0	0	1.061	0.958	0.170	0.009	0.013	0.007	0.016	0.002	0.885	−0.815	0.912
0	70	20	10	0	0	1.271	1.248	0.108	0.013	0.027	0.008	0.013	3.410	17.463	−0.804	0.686
0	80	20	0	0	0	1.043	0.993	0.162	0.013	0.029	0.008	0.014	2.738	12.109	−0.728	0.766
0	90	10	0	0	0	0.962	0.940	0.175	0.013	0.027	0.009	0.014	3.443	17.729	−0.701	0.760
0	100	0	0	0	0	1.148	1.101	0.137	0.013	0.027	0.008	0.014	3.348	17.258	−0.707	0.704
10	10	50	10	10	10	−0.094	−0.089	0.465	0.010	0.013	0.011	0.027	−0.881	6.350	3.423	16.771
0	0	60	20	10	10	0.223	0.209	0.418	0.011	0.013	0.010	0.029	−1.009	6.567	2.930	14.489
0	0	70	10	20	0	−0.214	−0.197	0.422	0.011	0.013	0.012	0.027	−0.808	6.050	3.444	16.742
20	0	80	0	0	0	0.314	0.296	0.384	0.011	0.013	0.010	0.028	−1.039	6.678	3.206	15.410
10	0	90	0	0	0	0.245	0.231	0.409	0.011	0.013	0.010	0.028	−1.019	6.659	3.225	15.587
0	0	100	0	0	0	0.245	0.231	0.409	0.011	0.013	0.010	0.028	−1.019	6.659	3.225	15.587
0	0	0	40	50	10	1.028	0.848	0.199	0.011	0.017	0.009	0.009	0.204	4.320	0.332	2.752
0	0	10	50	30	10	−0.029	−0.027	0.489	0.011	0.016	0.011	0.027	0.147	5.043	3.704	18.865
0	0	0	60	40	0	−0.557	−0.510	0.306	0.011	0.017	0.013	0.025	0.069	4.609	4.206	22.598
0	0	0	70	20	10	0.045	0.042	0.483	0.012	0.017	0.011	0.026	0.025	4.157	3.826	19.388
10	0	0	80	10	0	−0.019	−0.018	0.493	0.011	0.015	0.011	0.028	0.336	5.601	3.249	15.337
0	0	10	90	0	0	−0.042	−0.039	0.485	0.011	0.015	0.011	0.027	0.362	5.370	3.477	17.214
0	0	0	100	0	0	−0.028	−0.026	0.490	0.011	0.015	0.011	0.027	0.351	5.353	3.477	17.214
0	0	0	0	60	40	−0.578	−0.498	0.310	0.009	0.013	0.010	0.009	−0.200	2.081	−0.235	−0.314
30	0	0	0	70	0	−1.030	−0.978	0.166	0.004	0.041	0.010	0.006	−4.978	32.617	−0.458	2.150
0	0	10	0	80	10	−1.528	−1.288	0.101	0.007	0.019	0.010	0.006	−2.084	10.254	−0.473	2.031
10	0	0	0	90	0	−1.559	−1.324	0.095	0.007	0.017	0.010	0.007	−0.830	3.353	−0.454	1.657
0	0	0	0	100	0	−1.352	−1.155	0.126	0.007	0.016	0.010	0.007	−1.057	4.140	−0.383	1.552
20	20	20	0	20	20	0.430	0.415	0.340	0.009	0.012	0.008	0.013	−1.095	4.698	0.226	0.238
20	10	10	10	20	30	−0.462	−0.425	0.336	0.010	0.017	0.012	0.027	−1.639	10.751	3.623	18.374
10	0	0	10	30	50	−0.136	−0.128	0.449	0.011	0.010	0.012	0.027	−1.048	6.038	3.611	18.310
20	10	10	0	0	60	0.388	0.367	0.357	0.012	0.007	0.010	0.028	0.145	0.624	3.176	15.435
10	0	10	0	10	70	0.791	0.757	0.226	0.012	0.008	0.008	0.031	0.080	0.192	2.131	10.835
0	10	0	10	0	80	0.636	0.605	0.274	0.012	0.008	0.009	0.029	−0.014	0.112	2.803	13.095
10	0	0	0	0	90	0.935	0.898	0.186	0.012	0.007	0.008	0.031	0.206	0.489	2.246	10.603
0	0	0	0	0	100	0.706	0.678	0.250	0.012	0.007	0.009	0.030	0.206	0.489	2.634	12.539

Table 23: Long/ShortEquity Non-Directional : Search for Optimal Performance Weights Combination

α	β	Sharpe	Sortino	Omega	MaxDD	Calc t	Excel t	p-val	Top($\bar{x}$)	Top(σ)	Bttm($\bar{x}$)	Bttm(σ)	SkwTop	KrtTop	SkwBttm	KrtBtt
100	0	0	0	0	0	2.38	1.48	0.071	0.012	0.017	0.007	0.023	-0.31	2.16	-0.97	2.13
90	10	0	0	0	0	2.58	1.59	0.057	0.012	0.017	0.006	0.024	-0.31	2.16	-1.18	2.84
80	10	10	0	0	0	2.58	1.59	0.057	0.012	0.017	0.006	0.024	-0.31	2.16	-1.18	2.84
70	10	10	10	0	0	2.60	1.59	0.057	0.012	0.017	0.007	0.023	-0.31	2.16	-0.97	2.22
60	10	10	10	10	0	2.66	1.56	0.061	0.012	0.017	0.007	0.021	-0.31	2.16	-0.66	1.18
50	**10**	**10**	**10**	**10**	**10**	**2.83**	**1.67**	**0.049**	**0.012**	**0.017**	**0.007**	**0.021**	**-0.31**	**2.17**	**-0.63**	**1.24**
40	20	10	10	10	10	1.13	0.67	0.252	0.012	0.016	0.009	0.020	-0.27	2.93	-0.05	2.41
30	30	20	10	10	0	0.62	0.36	0.362	0.011	0.016	0.010	0.020	-0.01	2.55	0.10	2.56
20	40	30	10	0	0	0.54	0.32	0.376	0.011	0.016	0.010	0.019	0.12	1.82	-0.42	1.01
10	50	40	0	0	0	1.01	0.59	0.279	0.011	0.015	0.009	0.022	0.12	2.67	-1.12	2.77
0	60	10	30	0	0	-0.28	-0.20	0.421	0.010	0.016	0.010	0.020	0.12	1.28	-0.39	0.86
0	70	20	10	0	0	-1.22	-0.83	0.205	0.009	0.018	0.012	0.020	0.18	0.52	-0.63	1.44
0	80	20	0	0	0	-0.86	-0.61	0.273	0.010	0.018	0.012	0.020	0.14	0.26	-0.76	1.33
0	90	10	0	0	0	-1.54	-1.01	0.156	0.009	0.017	0.012	0.019	0.38	0.24	-0.59	1.05
0	100	0	0	0	0	-1.38	-0.89	0.187	0.009	0.018	0.012	0.019	0.32	0.14	-0.58	1.05
10	**10**	**50**	**10**	**10**	**10**	**2.38**	**1.70**	**0.046**	**0.013**	**0.016**	**0.007**	**0.019**	**0.05**	**1.62**	**-0.20**	**0.44**
0	**0**	**60**	**20**	**10**	**10**	**2.58**	**1.81**	**0.037**	**0.013**	**0.016**	**0.007**	**0.020**	**-0.17**	**2.72**	**-0.47**	**1.21**
0	0	70	10	20	0	1.79	1.30	0.098	0.012	0.017	0.008	0.018	-0.38	2.12	-0.19	0.38
20	**0**	**80**	**0**	**0**	**0**	**2.87**	**1.99**	**0.024**	**0.013**	**0.016**	**0.007**	**0.020**	**-0.01**	**1.63**	**-0.52**	**1.14**
10	**0**	**90**	**0**	**0**	**0**	**2.87**	**1.99**	**0.024**	**0.013**	**0.016**	**0.007**	**0.020**	**-0.01**	**1.63**	**-0.52**	**1.14**
0	**0**	**100**	**0**	**0**	**0**	**2.87**	**1.99**	**0.024**	**0.013**	**0.016**	**0.007**	**0.020**	**-0.01**	**1.63**	**-0.52**	**1.14**
0	0	0	40	50	10	-1.49	-0.97	0.168	0.012	0.017	0.015	0.017	-0.34	2.70	1.06	3.55
0	0	10	50	30	10	1.42	0.97	0.166	0.013	0.017	0.010	0.021	-0.01	1.06	-0.25	2.66
0	0	0	60	40	0	0.22	0.16	0.439	0.013	0.019	0.012	0.019	-0.29	1.68	0.41	2.50
0	0	0	70	20	10	0.06	0.04	0.482	0.011	0.017	0.011	0.020	-0.48	0.15	0.45	1.85
10	0	0	80	10	0	0.24	0.17	0.433	0.011	0.017	0.011	0.020	-0.50	0.27	0.47	1.87
0	0	10	90	0	0	0.06	0.05	0.481	0.011	0.017	0.011	0.020	-0.42	0.09	0.46	1.76
0	0	0	100	0	0	0.06	0.05	0.481	0.011	0.017	0.011	0.020	-0.42	0.09	0.46	1.76
0	0	0	0	60	40	-0.85	-0.66	0.255	0.011	0.018	0.013	0.016	0.15	0.77	1.25	5.02
30	0	0	0	70	0	-1.21	-0.77	0.221	0.012	0.018	0.014	0.016	0.25	0.38	1.11	4.31
0	0	10	0	80	10	-1.20	-0.77	0.221	0.012	0.017	0.014	0.016	0.40	0.38	1.10	4.27
10	0	0	0	90	0	-2.03	-1.40	0.083	0.010	0.018	0.014	0.016	0.14	-0.03	1.09	4.27
0	0	0	0	100	0	-2.12	-1.52	0.066	0.009	0.019	0.014	0.016	-0.11	0.44	1.11	4.31
20	20	20	0	20	20	1.53	0.90	0.186	0.012	0.015	0.009	0.021	0.00	2.00	-0.21	2.72
20	10	10	10	20	30	1.26	0.76	0.223	0.012	0.015	0.009	0.022	0.09	2.28	-0.62	3.20
10	0	0	10	30	50	0.81	0.49	0.314	0.011	0.016	0.010	0.020	-0.14	2.08	-0.13	3.05
20	10	10	0	0	60	2.10	1.31	0.096	0.012	0.015	0.008	0.021	0.15	2.26	-0.33	0.73
10	0	10	0	10	70	1.96	1.18	0.121	0.012	0.016	0.008	0.021	-0.04	2.06	-0.32	0.72
0	10	0	10	0	80	1.78	1.13	0.130	0.012	0.016	0.008	0.021	-0.40	3.46	-0.32	0.72
10	0	0	0	0	90	1.78	1.13	0.130	0.012	0.016	0.008	0.021	-0.40	3.46	-0.32	0.72
0	0	0	0	0	100	1.69	1.05	0.148	0.012	0.017	0.008	0.021	-0.45	3.30	-0.32	0.72

Table 24: Other Strategies: Search for Optimal Performance Weights Combination

α	β	Sharpe	Sortino	Omega	MaxDD	Calc t	Excel t	p-val	Top($\bar{x}$)	Top(σ)	Bttm($\bar{x}$)	Bttm(σ)	SkwTop	KrtTop	SkwBttm	KrtBt
100	**0**	**0**	**0**	**0**	**0**	**2.59**	**2.83**	**0.003**	**0.024**	**0.038**	**0.004**	**0.032**	**-0.25**	**0.26**	**-0.76**	**1.87**
90	**10**	**0**	**0**	**0**	**0**	**2.59**	**2.84**	**0.003**	**0.024**	**0.038**	**0.003**	**0.033**	**-0.25**	**0.26**	**-0.71**	**1.78**
80	**10**	**10**	**0**	**0**	**0**	**2.54**	**2.79**	**0.003**	**0.024**	**0.038**	**0.004**	**0.032**	**-0.25**	**0.26**	**-0.76**	**1.87**
70	**10**	**10**	**10**	**0**	**0**	**2.59**	**2.83**	**0.003**	**0.024**	**0.038**	**0.004**	**0.032**	**-0.25**	**0.26**	**-0.76**	**1.87**
60	**10**	**10**	**10**	**10**	**0**	**2.53**	**2.76**	**0.004**	**0.024**	**0.038**	**0.004**	**0.034**	**-0.25**	**0.26**	**-0.91**	**2.61**
50	**10**	**10**	**10**	**10**	**10**	**2.18**	**2.39**	**0.009**	**0.020**	**0.034**	**0.003**	**0.034**	**-0.46**	**0.59**	**-0.88**	**2.52**
40	**20**	**10**	**10**	**10**	**10**	**1.83**	**1.89**	**0.031**	**0.017**	**0.035**	**0.003**	**0.034**	**-0.25**	**0.28**	**-0.85**	**2.41**
30	30	20	10	10	0	1.06	1.02	0.155	0.014	0.042	0.006	0.029	-0.26	0.41	-0.48	1.86
20	40	30	10	0	0	1.03	0.93	0.176	0.016	0.040	0.009	0.031	-0.24	0.66	1.33	6.07
10	50	40	0	0	0	1.03	0.90	0.186	0.016	0.037	0.009	0.033	-0.24	1.18	1.03	4.62
0	60	10	30	0	0	-0.75	-0.71	0.239	0.010	0.045	0.017	0.037	-0.39	0.26	0.83	1.74
0	70	20	10	0	0	-1.09	-1.01	0.157	0.010	0.045	0.019	0.039	-0.39	0.26	0.67	1.07
0	80	20	0	0	0	-0.44	-0.45	0.326	0.010	0.045	0.014	0.038	-0.39	0.26	0.06	-0.21
0	90	10	0	0	0	-0.57	-0.56	0.288	0.010	0.049	0.015	0.036	-0.51	0.45	0.07	0.16
0	100	0	0	0	0	-0.57	-0.56	0.288	0.010	0.049	0.015	0.036	-0.51	0.45	0.07	0.16
10	10	50	10	10	10	1.47	1.53	0.064	0.017	0.035	0.005	0.039	-0.25	0.32	-0.21	5.07
0	**0**	**60**	**20**	**10**	**10**	**1.82**	**1.94**	**0.028**	**0.021**	**0.039**	**0.005**	**0.039**	**-0.07**	**0.05**	**-0.21**	**5.07**
0	0	70	10	20	0	1.59	1.46	0.074	0.021	0.039	0.010	0.033	-0.07	0.05	1.12	5.21
20	**0**	**80**	**0**	**0**	**0**	**1.91**	**2.00**	**0.024**	**0.021**	**0.039**	**0.004**	**0.040**	**-0.07**	**0.05**	**0.20**	**3.35**
10	**0**	**90**	**0**	**0**	**0**	**1.82**	**1.91**	**0.030**	**0.021**	**0.039**	**0.005**	**0.038**	**-0.07**	**0.05**	**-0.14**	**5.52**
0	**0**	**100**	**0**	**0**	**0**	**1.82**	**1.91**	**0.030**	**0.021**	**0.039**	**0.005**	**0.038**	**-0.07**	**0.05**	**-0.14**	**5.52**
0	0	0	40	50	10	1.18	1.05	0.149	0.018	0.040	0.010	0.030	-0.20	0.98	-1.14	3.91
0	0	10	50	30	10	1.60	1.57	0.060	0.017	0.041	0.004	0.034	-0.43	0.81	-0.66	2.30
0	0	0	60	40	0	1.11	0.93	0.177	0.016	0.041	0.009	0.031	-0.37	0.68	-1.03	3.40
0	0	0	70	20	10	1.59	1.55	0.062	0.017	0.035	0.005	0.039	-0.26	0.25	0.35	3.23
10	0	0	80	10	0	1.62	1.61	0.055	0.018	0.040	0.005	0.039	0.10	-0.06	0.37	3.19
0	0	10	90	0	0	1.55	1.50	0.068	0.018	0.040	0.005	0.043	0.10	-0.06	-0.14	2.55
0	0	0	100	0	0	1.55	1.50	0.068	0.018	0.040	0.005	0.043	0.10	-0.06	-0.14	2.55
0	**0**	**0**	**0**	**60**	**40**	**2.35**	**2.09**	**0.020**	**0.022**	**0.035**	**0.008**	**0.030**	**0.99**	**1.60**	**-0.12**	**0.94**
30	0	0	0	70	0	1.04	0.82	0.209	0.017	0.045	0.011	0.024	0.06	1.25	-0.48	4.60
0	0	10	0	80	10	0.81	0.60	0.276	0.018	0.049	0.013	0.023	-0.07	1.16	0.65	2.21
10	0	0	0	90	0	0.63	0.44	0.331	0.016	0.047	0.013	0.024	-0.10	1.62	0.48	1.89
0	0	0	0	100	0	0.63	0.44	0.331	0.016	0.047	0.013	0.024	-0.10	1.62	0.48	1.89
20	**20**	**20**	**0**	**20**	**20**	**1.81**	**1.85**	**0.034**	**0.021**	**0.044**	**0.007**	**0.026**	**-0.27**	**0.34**	**-0.03**	**1.34**
20	**10**	**10**	**10**	**20**	**30**	**1.89**	**1.97**	**0.026**	**0.019**	**0.036**	**0.004**	**0.033**	**-0.00**	**0.21**	**-0.71**	**2.68**
10	0	0	10	30	50	1.43	1.47	0.072	0.019	0.034	0.010	0.025	0.08	0.36	0.51	0.08
20	10	10	0	0	60	1.37	1.45	0.076	0.014	0.034	0.004	0.032	0.09	0.61	-0.69	2.94
10	0	10	0	10	70	1.30	1.21	0.114	0.017	0.035	0.008	0.038	-0.09	0.30	-0.46	2.20
0	10	0	10	0	80	2.12	1.58	0.058	0.018	0.032	0.007	0.038	0.28	0.20	-0.41	2.32
10	0	0	0	0	90	2.12	1.58	0.058	0.018	0.032	0.007	0.038	0.28	0.20	-0.41	2.32
0	0	0	0	0	100	2.12	1.58	0.058	0.018	0.032	0.007	0.038	0.28	0.20	-0.41	2.32

Table 25: Fixed Income Securities: Search for Optimal Performance Weights Combination

α	β	Sharpe	Sortino	Omega	MaxDD	Calc t	Excel t	p-val	Top($\bar{x}$)	Top(σ)	Bttm($\bar{x}$)	Bttm(σ)	SkwTop	KrtTop	SkwBttm	KrtBttm
100	0	0	0	0	0	-0.93	-0.88	0.190	0.009	0.013	0.010	0.009	-1.39	4.03	0.33	0.85
90	10	0	0	0	0	-0.93	-0.88	0.190	0.009	0.013	0.010	0.009	-1.39	4.03	0.33	0.85
80	10	10	0	0	0	-0.93	-0.88	0.190	0.009	0.013	0.010	0.009	-1.39	4.03	0.33	0.85
70	10	10	10	0	0	-0.93	-0.88	0.190	0.009	0.013	0.010	0.009	-1.39	4.03	0.33	0.85
60	10	10	10	10	0	-0.93	-0.88	0.190	0.009	0.013	0.010	0.009	-1.39	4.03	0.33	0.85
50	10	10	10	10	10	0.37	0.38	0.353	0.011	0.013	0.010	0.009	-0.80	4.88	0.33	0.85
40	20	10	10	10	10	1.17	1.11	0.135	0.012	0.013	0.009	0.009	-1.01	6.01	0.12	0.27
30	30	20	10	10	0	0.34	0.31	0.378	0.012	0.010	0.011	0.010	-0.95	10.21	0.20	0.46
20	40	30	10	0	0	0.56	0.44	0.329	0.012	0.010	0.011	0.012	-0.91	10.69	-0.20	0.78
10	50	40	0	0	0	-0.66	-0.59	0.278	0.010	0.006	0.011	0.010	0.48	4.13	0.01	-0.09
0	60	10	30	0	0	-0.66	-0.56	0.287	0.010	0.006	0.011	0.012	0.52	3.14	-0.52	3.19
0	70	20	10	0	0	-0.46	-0.43	0.335	0.010	0.006	0.010	0.012	0.96	3.50	-0.28	3.07
0	80	20	0	0	0	-0.50	-0.46	0.324	0.010	0.006	0.011	0.013	0.95	3.34	-1.08	6.36
0	90	10	0	0	0	-0.01	-0.01	0.496	0.010	0.006	0.011	0.013	0.10	0.48	-1.07	6.29
0	100	0	0	0	0	-0.01	-0.01	0.496	0.010	0.006	0.011	0.013	0.10	0.48	-1.07	6.29
10	10	50	10	10	10	-0.00	-0.00	0.499	0.012	0.013	0.012	0.010	-1.00	6.26	0.10	0.56
0	0	60	20	10	10	0.04	0.04	0.484	0.012	0.013	0.012	0.010	-1.02	6.16	0.10	0.56
0	0	70	10	20	0	-0.00	-0.00	0.499	0.012	0.013	0.012	0.010	-1.00	6.26	0.10	0.56
20	0	80	0	0	0	-0.00	-0.00	0.499	0.012	0.013	0.012	0.010	-1.00	6.26	0.10	0.56
10	0	90	0	0	0	-0.22	-0.22	0.415	0.011	0.013	0.012	0.010	-0.94	6.41	0.10	0.56
0	0	100	0	0	0	-0.22	-0.22	0.415	0.011	0.013	0.012	0.010	-0.94	6.41	0.10	0.56
0	0	0	40	50	10	-0.83	-0.92	0.179	0.008	0.012	0.010	0.008	-1.47	4.47	0.57	0.86
0	0	10	50	30	10	-0.96	-0.92	0.180	0.008	0.012	0.010	0.009	-1.52	4.65	0.33	0.85
0	0	0	60	40	0	-1.49	-1.62	0.054	0.008	0.013	0.011	0.009	-1.32	3.51	0.71	1.22
0	0	0	70	20	10	0.09	0.08	0.467	0.011	0.014	0.010	0.009	-0.73	4.07	0.33	0.85
10	0	0	80	10	0	0.19	0.18	0.427	0.011	0.013	0.010	0.009	-0.79	4.21	0.33	0.85
0	0	10	90	0	0	0.19	0.18	0.427	0.011	0.013	0.010	0.009	-0.79	4.21	0.33	0.85
0	0	0	100	0	0	0.19	0.18	0.427	0.011	0.013	0.010	0.009	-0.79	4.21	0.33	0.85
0	0	0	0	60	40	-1.39	-1.44	0.077	0.009	0.008	0.012	0.009	-1.95	4.88	0.22	0.77
30	0	0	0	70	0	-0.54	-0.60	0.275	0.009	0.011	0.010	0.009	-1.04	3.42	0.91	1.59
0	0	10	0	80	10	-1.15	-1.21	0.115	0.008	0.012	0.010	0.009	-2.45	8.43	0.91	1.59
10	0	0	0	90	0	-1.15	-1.21	0.115	0.008	0.012	0.010	0.009	-2.45	8.43	0.91	1.59
0	0	0	0	100	0	-1.15	-1.21	0.115	0.008	0.012	0.010	0.009	-2.45	8.43	0.91	1.59
20	20	20	0	20	20	-0.08	-0.07	0.472	0.012	0.011	0.012	0.010	-0.94	9.86	0.04	1.01
20	10	10	10	20	30	0.49	0.48	0.317	0.012	0.013	0.011	0.010	-1.06	6.55	0.18	0.84
10	0	0	10	30	50	0.18	0.15	0.440	0.012	0.013	0.011	0.010	-1.01	6.31	0.17	1.03
20	10	10	0	0	60	-0.46	-0.43	0.334	0.010	0.011	0.011	0.010	-0.55	8.66	0.11	0.57
10	0	10	0	10	70	-0.16	-0.16	0.438	0.011	0.011	0.011	0.010	-0.61	9.28	0.11	0.57
0	10	0	10	0	80	-0.01	-0.01	0.496	0.011	0.011	0.011	0.010	1.73	8.75	0.11	0.57
10	0	0	0	0	90	-0.01	-0.01	0.496	0.011	0.011	0.011	0.010	1.73	8.75	0.11	0.57
0	0	0	0	0	100	-0.01	-0.01	0.496	0.011	0.011	0.011	0.010	1.73	8.75	0.11	0.57

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TO WHOM IT MAY CONCERN

I have checked the corrections to the M Sc thesis of Kaibe Mokoma. I am satisfied that they comply with the requirements of the examiners.

Professor Ronald Becker