CONSTRUCTING MULTI-STRATEGY FUND OF HEDGE FUNDS

by

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ABSTRACT

This paper aims to develop a systematic allocation methodology to combine multi-strategy hedge funds within a structure of fund of funds in a risk-controlled manner. This is particularly important since the traditional mean-variance optimization proves ineffective in addressing hedge fund return distributions that are asymmetric in nature. Moreover, unstable correlations among various hedge fund strategies also pose a challenge to a meaningful optimization to combine various hedge fund strategies. This paper attempts to suggest some practical ways to overcome both these obstacles.

DEDICATION

To MATA for empowering me with her Shakti !

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1 INTRODUCTION

The poor performance of both traditional equity and fixed income markets in the recent past has brought alternative investments into the mainstream. The appeal of absolute returns and risk-controlled strategies with low correlation to traditional asset classes has made alternative investments a favoured asset class. As investors adopt more core and satellite asset allocation or a risk budgeting approach, hedge funds as an integral category within alternative investments find an easy acceptance into this new investing paradigm. As a result, the last decade has witnessed proliferating growth in the hedge funds industry.

The Hedge Funds Research Institute reports $866 billion invested in approximately 8,350 active hedge funds worldwide as of June 30, 2004. If leverage and proprietary trading are factored in, the figure could be as much as three to four times more. A big reality is that the metamorphic life cycle of hedge funds has given birth to various distinct strategies, from the conservative Market Neutral strategy to the more aggressive Global Macro style. Which strategy dominates over time, is anybody's guess and it is a challenge to determine from a top-down style approach, strategies that will outperform others to warrant integration into investment portfolios.

One alternative would be to allocate equal sums of money to each strategy to remain exposed to all styles all the time thus minimizing the guesswork. Private client portfolios, which are smaller in size compared to institutional portfolios, have led the industry in adopting perhaps a more practical approach by combining various hedge fund strategies in a fund of funds structure. Besides gaining exposure to a broad spectrum of strategies, the responsibility of due diligence in selecting strategies and managers, portfolio construction and risk management is transferred to the fund manager of the fund of funds structure. From a performance perspective fund of hedge funds with a correlation of 0.54 to the S&P 500, have outperformed the broad index in 59 out of 62 down months between Jan 1990 and Dec 2003.

It is little wonder, then, that about 20% of all money in hedge funds in recent times (Casey et al, 2001) has flowed into funds of hedge funds. With its growing popularity with an increasing number of wealthy individuals who tend to have an absolute return orientation, the proportion is likely to grow. Of late, registered fund of funds targeting the mass affluent have also started emerging on the investing landscape. Investable fund of fund indices (e.g. S&P, MSCI etc.) is yet another trend in the industry, which will add momentum to the growth of fund of funds. Many university endowments (some of which have allocated over 20% to hedge funds) and pension funds find themselves constrained by resources to conduct extensive due diligence on various hedge fund strategies and have begun adopting the fund of funds approach to gain exposure to hedge funds.

While much of the emphasis today is on qualitative top-down assessment to determine how and which strategies to combine, a lot remains desired in the absence of a systematic allocation methodology, which can scientifically combine diverse hedge fund strategies in a risk-controlled manner. Primary among the issues that have restrained the development of such methodology are survivorship bias, non-normal return distributions, and temporal variation in inter-strategy correlations.

A time-tested allocation tool is the mean-variance optimizer applied successfully if returns are normally distributed. To prescribe an allocation, expected returns, variance or risk measure and correlation are required as inputs. To apply it to hedge fund return distributions, the choice of an appropriate risk measure and establishing stable correlations would pose big challenges whereas expected returns is a matter of informed judgement surrounding various strategies. In addition, the static one-period consideration of a mean-variance model fails to recognize the dynamic trade-offs from one period to the next implicit in many hedge fund strategies.

Numerous studies have proved that the return distributions of many hedge fund strategies are non-normal i.e. they suffer from negative skewness and high kurtosis. This implies that the chances of suffering huge losses are big and extreme events are very likely, both suggesting that variance as a risk measure for hedge funds underestimates its risk. Thus arises the need for a method, which recognizes the downside risk in determining the risk-return trade-off i.e. optimization. The second problem facing the industry today as it adopts the fund of funds structure to combine various hedge fund strategies is the volatility or instability in the correlations among various pairs of hedge fund strategies. This tends to lower the confidence one would place on past correlation statistics as inputs in any optimization procedure. Hence, without considering skewness and kurtosis and without reducing the instability of inter-strategy correlations, our data set is not ready for optimization.

In an attempt to overcome these concerns, Clifford De Souza and Suleyman Gokcan (2004) suggest organizing eight of the most commonly practiced strategies into four "Rational Strategy Groups" (RSG) or clusters. The plan is to keep the correlation between strategies within any RSG strong, while keeping the correlations between RSGs as weak as possible thus presenting them as favoured entities for optimization in a fund of funds structure. Once they prepare the data-set for optimization in terms of distinct clusters, they next optimize the four asset classes in a manner that considers the risk of the worst possible losses, which they term Conditional Value at Risk (CVaR). Therefore, instead of adopting a conventional mean-variance framework to optimize the four clusters, they recommend a mean-conditional CVaR method. Their tests resulted in portfolios with lower possibility of negative returns i.e. skewness and lower kurtosis suggesting less likelihood of extreme events.

This paper attempts to apply the intuition of the De Souza-Gokcan approach on a data set of HFRI indices extending from Jan 1990 to Dec 2003 and is not a replication of their study in its entirety. Since their tests for the effect of the Long Term Capital Management collapse, in the second half of 1998 did not suggest any significant impact on the risk adjusted performance of hedge funds, I have dispensed with that test. Moreover, De Souza and Gokcan conduct their entire study on the full time series (Jan 1990-Oct 2002) without excluding any period.

Secondly, they bring up the issue of serial correlation afflicting returns of some Event Driven strategies like Convertible Arbitrage and Distressed Securities which tend to understate their true volatility. They experiment with unsmoothing the data as a correction technique and find that on a mean-variance framework it tends to check unwarranted allocation biases as would result from smoothed data. However, they conclude that both smoothed and unsmoothed data result in identical RSGs- the premise for optimization in this study. Considering this and recognizing that mean-variance has little relevance in the hedge funds' context, I have conducted my tests with original HFR indices data.

Thirdly, De Souza and Gokcan use an optimizer for the mean-variance (MV) optimization and then re-map Conditional Mean-CVaR optimization onto a MV surface to show how accounting for higher moments results in portfolios with lower negative skewness. While an optimizer would have helped me optimize on the MV principle, it would not have been able to manage inputs of expected returns and variance-covariance matrix to produce the downside risk i.e. the conditional Value at Risk (CVaR). Hence, to pursue the same objective i.e. if factoring in downside risk produces better portfolios, I have instead used the intuition behind the optimizer by using the Sharpe Ratio and a Downside Risk Adjusted Return (reflecting CVaR) to determine allocations using some sample choice of weights.

The rest of this paper will be divided into the following sections. Section 2 will be a literature review encompassing perspectives on the importance of combining various hedge fund strategies and discussing ways to address non-normal distribution of returns. Section 3 will describe my data, the methodology and discuss my results. Section 4 discusses portfolio construction accounting for downside risk and Section 5 will conclude with the key findings of this study.

2 LITERATURE REVIEW

Given the accelerated capital flows into hedge funds in the last few years and the prevalence of a myriad of hedge fund styles, it would probably appear that at the very least even a simplistic dynamic strategy allocation is crucial. Martin (2001) stresses that proper style selection has immense benefits, which cannot be readily compensated by superior selection of hedge fund managers. This in a way is an echo of the old doctrine of the superiority of asset allocation to security selection (Brinson et al. 1987) in the traditional asset class sense.

Brown and Goetzmann (2003) in their study found that distinct styles of management account for about 20% of the cross-sectional variability in performance. Therefore, according to them appropriate style analysis and style management are crucial for investors looking to invest in hedge funds. They point out that stylistic differences exist across hedge funds and emphasize that the opportunity lies in the diversification that the varieties of hedge funds present.

To reap such benefits of diversification, Martin suggests beginning with an adequate system for classifying individual funds into groups that represent particular investment styles or strategies. While hedge fund managers may use trading techniques as the basis for classificatory schemes, Martin advocates that the technique most directly applicable is cluster analysis. Intuitively, cluster analysis attempts to group data to minimize intra-group variation while maximizing inter-group variation. According to him eight separate clusters on 21 indices, generate the most useful results.

The next big challenge is optimizing. Despite the perception that hedge funds are extremely risky, the absence of an appropriate risk measure for hedge funds often causes traditional mean variance optimizers to "plunge" into hedge funds. Amin and Kat (2002), and Brooks and Kat (2002) point out that hedge funds have negative skewness and high kurtosis whereas investors prefer to have positive skewness and low kurtosis. Mean-variance (MV) optimizers tend to ignore skewness and kurtosis thus making hedge funds look attractive, which is quite opposite to the case when these higher moments are considered. This implies that hedge funds can have large "single tail" events that can surprise investors in times of market stress. Hence, the use of traditional models such as the mean-variance is questionable.

Many risk metrics and optimization approaches have been proposed as solutions, none of which have gained universal acceptance, yet. Lamm (2003) compares various optimization techniques applied to hedge fund portfolio construction. He employs Duarte's (1999) general model to exploit six optimization methodologies. Besides MV, he discusses two other squared deviation approaches namely mean semivariance (MSV) which admits the lower half of the bell-shaped distribution and Mean Downside risk (MDR) where downside deviations are calculated to a minimum acceptable return. In fact, Harlow (1993) also advocated the MDR where he viewed risk as the probability of shortfall below some benchmark level of return. MSV also finds another advocate in Estrada (2003) who concludes that semivariance seems more plausible than variance as a measure of risk.

Lamm's other group of techniques corresponding to each of the three squared deviation approaches, consist of absolute deviation measures where deviations are weighted equally. Since deviations are assigned no special penalty and squared deviations penalize large deviations more severely, he rejects the absolute measures in favour of the squared deviation measures. Of his selected batch, MV assumes normality (ignoring quadratic utility) and is rejected further, leaving MSV and MDR as the two possible optimization alternatives. On testing, both these approaches, which recognize downside risk yield similar results with less allocation to Event Driven like strategies like Distressed Debt and more allocation to Directional Strategies like Global Macro. As a result, MSV and MDR portfolios exhibit positive skew and much lower kurtosis.

However, none of these approaches embeds skew and kurtosis directly in the optimization process. Though Value at Risk (VaR) offers immediate gratification to this end, it lacks analytical tractability. To improve efficacy of VaR, Favre and Galeano (2002) propose the use of a Corner- Fisher (CF) expansion, which endeavours to minimize VaR by making explicit forecasts of skew and kurtosis. Lamm (2003) tested CF on his data set to reveal that it significantly improves the results of his MSV and MDR portfolios by minimizing negative skewness.

Going beyond VaR, Davies, Kat and Lu (2004) have developed a Polynomial Goal Programming (PGP) optimization model within a mean-variance-skewness-kurtosis framework. The PGP optimal portfolios contain hardly any allocation to Event Driven Distressed Securities and on the other hand, it allocates heavily to Global Macro funds, which tend to enhance portfolio skewness. From an economic perspective, none of this is surprising since Global Macro funds tend to take views on macro economic events and tend to perform best when markets become volatile as was evidenced in the recent bear market. On the other hand, a continued downturn in the economy and weak markets takes its toll on Distressed Securities, which could possibly lead to big losses.

Besides the other approaches, Favre and Galeano (2002) refer to various working papers that are considering GARCH models, conditional VAR models and the use of an Omega approach. The Omega measure suggested by Keating and Shadwick (2002) incorporates all the moments of the distribution, while integrating a return threshold parameter into the equation. The Omega measure is merely the ratio of the probability of being above a given return to the ratio of being below that given return. Keating and Shadwick's introduction of the Omega statistic seems to be an extension of the "Safety First" principle documented by Elton and Gruber (1991). In their model, the main purpose is to limit the risk of bad outcomes. The best portfolio is the one that has the smallest probability of producing a return below some specified level. Hence, their Safety First model is analogous to analysing risk below a certain threshold, like the Omega. Consequentially, Omega may in fact not be a new measurement in itself, as its implications are the same as Elton and Gruber's Safety First model. Since the proposal of the Omega measure by Keating and Shadwick, this Omega statistic has become the new buzzword in hedge fund analysis.

While much has been written about the non-normality of certain hedge fund strategies and its implication for optimization, instability of inter-strategy correlations is proving to be a new area of research attracting a lot of attention. It is increasingly felt that overlooking unstable correlations could lead to allocation results detrimental to risk budgets adopted by many institutional investors. This has long-term implications for relatively new entrants to the fund of hedge funds world, like pension funds who as fiduciaries have mandates, defined to manage risk beyond a singular, "total returns" focus acceptable to some other investors. Brooks and Kat (2002) investigated the stability of correlations between hedge fund strategies and found correlations to be higher than generally believed. However, practitioners like Andrew Lo (2004) and De Souza and Gokcan (2004) are gradually recognizing that correlations between hedge fund strategies are "unstable". Lo recommends a phase-locking risk model, which suggests factoring in the probability of crisis events when calculating correlations. De Souza and Gokcan like Martin, suggest cluster analysis to reduce the instability of correlations. Taking a cue from these practitioners, I address this issue in this study.

The literature review presented here provides a useful reference in guiding me to consider downside risk in the choice of an optimization technique for hedge fund strategy allocation as well as it helps me in identifying and addressing a problem concerning unstable correlations, which seems to be gradually surfacing on the horizon.

3 DATA, METHODOLOGY AND RESULTS

3.1 Statistical Properties of Hedge Fund Strategy Indices

My starting point in this study is an examination of the statistical properties of the various hedge fund strategies. For this study, I have used the Hedge Fund Research Institute (HFR) indices for the following reasons:

- The HFR indices are composed of equal weighted composites of the performance of funds of hedge funds representing 1500 funds across eight strategies. Unlike the asset-weighted CSFB/Tremont (i.e. my other alternative) which has only 340 funds, the HFR does not require minimum assets nor a minimum track record in order to qualify for classification, while the CSFB/Tremont requires minimum assets to be $10 million and minimum track record to be 1 year or $500 million in assets. Hence, the HFR presents more robust performance statistics.
- The HFR index data retains the performance characteristics of liquidated funds thus mitigating survivorship bias for the period after 1994.
- Funds are assigned to individual indices based on the descriptions in their offering memorandums. The return data are therefore representative of strategy returns and not individual manager biases. Thus the choice of HFR indices mitigates the problem of "self-definition"

- For the most part (about 90% of the funds), the performance numbers are net-of-fees data.

- The only caveat is that some of the funds in the index use additional leverage which can skew the results upwards.

Using the HFR indices, I performed a study on thirteen years of data from Jan 1990 to Dec 2003. The performance statistics are summarized in Table 1. As observed from Table 1. the historical return and risk profiles of hedge fund strategies vary substantially. Equity Long/Short and Global Macro have significantly higher returns higher standard deviations, positive skewness and low kurtosis. Statistical Arbitrage, Market Neutral, Equity Long/Short and Global Macro have broadly normal distributions with minimal skewness and kurtosis. On the other hand Convertible Arbitrage, Distressed securities, Merger Arbitrage and Fixed Income Arbitrage display both negative skewness ranging from -0.69 to -2.78 as well as high kurtosis (greater than 3 for a normal distribution) ranging from 5.36 to 22.72

Having isolated the characteristics of individual strategies, I now examined the inter-strategy correlations, as presented in Table 2. While most correlations are low, there is the occasional larger correlation i.e. Convertible Arbitrage - Distressed securities (0.57), Statistical Arbitrage -Market Neutral (0.53) Distressed Securities-Equity Long/Short (0.58) and Equity Long/Short-Global Macro (0.58). However, since all correlations are less than perfect i.e average of 0.30, they offer good prospects for diversification when combined in a fund of funds structure.

Essential to all allocation methodologies i.e. optimization techniques, is that the correlation structure remain stable over time. I therefore performed an analysis of the time stability of the correlations between all possible pairs of strategies. I analyzed the spread between the maximum and minimum 12-month rolling correlations, the results of which are in Table 3. The results show that the average spread is 0.99, which implies that the correlations have varied, for example, from -0.09 to 0.90. This large spread indicates the instability of the correlations among hedge fund indices. Therefore, lack of perfect correlation (Table 2) among most hedge fund strategies make the beginnings of a strategy allocation methodology realistic provided we can mitigate the effects of correlations changing over time.

Thus, the effect of skewness and kurtosis as well as unstable inter-strategy correlations, are two key issues questioning the viability of applying a mean-variance optimization to combine various hedge fund strategies.

3.2 Rational Strategy Groups and Cluster Analysis

My solution to the issue of varying inter-strategy correlations raised in the previous section is to employ a technique to construct or identify groups of the underlying strategies that over time display a large degree of internal similarity and thus higher correlation while maintaining low correlation between the groups themselves. I have called these groups of strategies, Rational Strategy Groups (RSGs) just as De Souza and Gokcan had named them in their study.

The first step in the process is determining the RSGs. To deal with this type of return data that correctly considers the time varying nature of the correlation structure, I used "cluster analysis" to isolate similar elements. Intuitively, this statistical technique attempts to group data to minimize intra-group variation while maximizing inter-group variation.

For clustering strategies, I used variable clustering procedure (proc varclus) in SAS statistical software. The assignment of variables occurs in two phases. The first is the nearest component-sorting phase where iteratively the cluster components are computed and each variable is assigned to one and only one component (disjoint clusters) with which it has the highest squared correlation (r-squared). The second phase involves a search algorithm where each variable in turn is tested to see if assigning it to a different cluster increases the amount of the variance explained.

Table 4 presents the results of the cluster analysis where I selected to group the eight strategies into four clusters as adopted by De Souza and Gokcan in their study. Based on the groups produced by SAS, I named the clusters as follows:

Event Driven Plus: Consisting of Convertible Arbitrage, Distressed Securities and Merger Arbitrage

Equity Arbitrage: Consisting of Statistical Arbitrage and Market Neutral

Fixed Income Arbitrage: A strategy by itself, and

Discretionary: Consisting of Equity Long/Short and Global Macro

Of interest, is the similarity among strategies within a group as expressed by the r-squared statistic, the lowest being 0.617. As desired, the correlation of a strategy with the next closest cluster is low, the highest being 0.365. The two statistics are collectively reflected in the last column, $(1-R^2_{own})/(1-R^2_{nearest})$ where low values as resulted above depict the formation of clusters with a high degree of internal consistency as well as a high degree of "separateness" among clusters.

De Souza and Gokcan's study showed the lowest R^2 within groups to be 0.615; this study has produced equally cohesive groups with the lowest R^2 being 0.617. However, while their study showed separateness between groups, with the squared correlation with the next closest group, to be as high as 0.4173, the highest squared correlation in this study of a strategy with the next closest group is 0.365. Overall, these results are very consistent with De Souza and Gokcan's study in terms of the grouping, degree of self-similarity within groups and low correlations between strategies.

3.3 Statistical Properties of Rational Strategy Groups

With the components for each cluster now known, I weighted the respective strategies equally within their cluster to arrive at four RSGs. For example, the Event Driven Plus cluster consists of 33% to Convertible Arbitrage, 33% to Merger Arbitrage and 34% to Distressed Securities. Next, I examined the statistical properties of the four RSGs just as I had done for the eight individual strategies in 3.1. The results are presented in Table 5. The results show that Equity Arbitrage and Discretionary clusters are both normal with no negative skew and low kurtosis whereas Event Driven Plus strategies and Fixed Income arbitrage have both negative skew and very high kurtosis. As also concluded by Martin (2001), Event Driven Plus is the least stable classification, which should compel the investor seeking to include such funds in her portfolio to question their performance in the future especially during times of market stress. However, these measures are relatively reduced (e.g. compare Merger Arbitrage skewness -2.78 and Kurtosis 22.72 with -1.84 and 16.31 respectively for Event Driven Plus strategies) from the levels at the granular strategy level.

Finally I analyze inter-cluster correlations the results of which are in Table 6. As desired, the results show low correlations with an average of 0.28 making the clusters attractive for portfolio diversification. This is also slightly lower than the average correlation of 0.30 obtained at the individual strategies level. Hence clustering has helped reduce the correlations to a slight extent.

But the true test of clustering lies in reducing the instability of the correlations between strategies. As before, I tested for the spread between the maximum and minimum 12 month rolling spreads for each RSG pair and obtained the results as shown in Table 7.

With clustering, we have successfully reduced the average spread from 0.99 for independent strategies to 0.91 for clusters. This however, is less than the magnitude drop from 1.30 (independent strategies) to 0.89 (clusters) registered by De Souza and Gokcan in their study.

In summary, the data would have us conclude that structurally the similarity (high r-squared for inter-strategy correlations and low r-squared for intra-strategy correlations) and the stability (lower spread of min-max moving average correlations) theoretically warrants allocation i.e. optimization at this level where the RSGs would define the equivalent of asset classes within the hedge fund universe.

4 PORTFOLIO CONSTRUCTION CONSIDERING DOWNSIDE RISK

With the RSGs acting as our asset classes, we can define a hedge fund efficient frontier. However, we know from the test results obtained in Table 5 that the return distribution of some RSGs is non-normal in that they suffer from negative skewness and kurtosis. Hence applying a conventional mean-variance optimization, which considers normality would be misplaced in this regard. Nonetheless, as a starting point I conducted a mean-variance optimization and then sought to improve my results by factoring in skewness. The purpose here was to determine and contrast if in fact considering the skewness inherent in the return distribution of RSGs yielded better portfolios such that the overall skewness and kurtosis are reduced as compared to the portfolios obtained using a mean-variance approach.

To execute this, I assumed four weights 10%, 20%, 30% and 40% and constructed portfolio sets using unique permutations for the four RSGs, constraining the use of a particular weight to only once in a portfolio i.e. no two RSGs could have the same weight in a given portfolio set. For the resulting 24 unique portfolios, I calculated the Sharpe Ratio (encompassing only mean and standard deviation) from high to low and selected three portfolios representing my conservative, moderate and aggressive portfolios. The results are displayed in Table 8.

Conservative portfolios allocate away further from the discretionary RSG due to its high-gain, high-risk profile and its proportion increases with risk tolerance. Event Driven Plus enjoys a prominent allocation given its highest risk-adjusted return among all RSGs.

The overall results show negative skewness and high kurtosis attributable to the preponderance of Event Driven Plus strategies, which have significant negative skewness, -1.84 and high kurtosis 16.31 as indicated in Table 5. This is not surprising as the Sharpe [(Mean Return-Risk Free Rate)/ Standard Deviation], a risk adjusted measure of the mean-variance framework ignores the higher moments, skewness and kurtosis when optimizing portfolios.

Mean-Variance analysis is appropriate when asset returns are normally distributed. At a 95% confidence level the variance is a good measure capturing the value at risk (VaR) However, when returns as in the case with RSGs are non-normally distributed, the first two moments are insufficient for risk assessment. Higher moments, skewness and kurtosis, must be considered. In other words, the true risk measure is the possibility of the worst possible returns or the expectation of losses exceeding VaR, which is termed as the conditional value at risk (CVaR), which is the mean of the worst 5% returns in a month. Since it concentrates on the tail risk, it is a more appropriate measure of risk for negatively skewed distributions.

Led by this notion, I calculated the worst 5% returns for each of my 24 portfolios formed above across the entire time series. The average of these 5% worst returns was my CVaR representing my downside risk in a month. I used CVaR to substitute the standard deviation in a typical Sharpe Ratio to calculate a Downside Risk Adjusted Return (DRAR). Just as I had ranked my 24 portfolios on Sharpe in the mean-variance framework, I ranked my portfolios again but this time on the DRAR measure. I again selected three portfolios representing my conservative, moderate and aggressive portfolios approximating similar returns as in the mean variance model. The results are shown in Table 9.

The results show a sharp reduction in skewness and kurtosis compared to the mean variance portfolios, mainly due to the dominance of positively skewed Discretionary Strategies at the expense of negatively skewed Event Driven Plus strategies. Positively skewed Equity Arbitrage strategies retain their big allocations, which more than offset the slight increase in negatively skewed Fixed Income strategies. Also, the Sharpe Ratios for Mean-CVaR portfolios are much lower than those obtained for the MV portfolios. On comparison, one might get tempted to select the MV portfolios with higher Sharpe Ratios, little knowing that those portfolios are fraught with higher chances of losses (i.e. skewness) and extreme events (i.e. kurtosis).

For example, for a return of say 13 %, an investor could be enticed to select the aggressive portfolio on a Sharpe Ratio basis over the moderate portfolio offering similar returns in the Mean- CVaR space. However, a similar probability of loss, say 5%, results in a much bigger CVaR (monthly loss) of 1.46% in the MV world compared to a 1.33% loss if the moderate portfolio is selected in the Mean-CVaR universe. This is because the skewness in the latter case is 93% (-0.59 vs. -0.04) lower compared to the MV portfolio. The difference in the risk between the mean-variance efficient frontier and the mean-CVaR efficient frontier for the same rate of return when skew is accounted for in the optimization process is termed as the "skew gap". This is depicted in Figure 1. It shows how when assets with significant negative skew, like Event Driven Plus strategies are included in a portfolio, MV tends to underestimate the riskiness.

It is interesting to note that the overall volatility (standard deviation) in the Mean-CVaR allocations has gone up. In these two portfolios, the volatility has increased by 15 bps when the skew risk has declined by 93% (-0.59 vs. -0.0.4) and the kurtosis is down almost 72% (4.51 vs. 1.25). Hence, 15 bps would be a fair price to pay for a reduction in the possibility of losses and big surprises.

The results are consistent with De Souza and Gokcan's study, which showed a bigger allocation to Discretionary strategies over Event Driven strategies in the Mean Conditional CVaR optimization and a slight drop in CVaR in the latter case. The results in Table 9 are also in agreement with Lamm's (2003) findings that optimal hedge fund portfolios should have upto 30% smaller allocation to Event Driven strategies like Distressed Debt than symmetric models indicate since the downside risk i.e. skewness is unusually large for such strategies. Instead, systematic Macro strategies i.e. Discretionary strategies occupy a greater proportion producing more positively skewed portfolios.

The results point to the importance of such a methodology for structuring a fund of multi-strategy hedge funds. Given RSGs as variables, an infinite variety of hedge fund portfolios with stable customized, risk, return and correlation characteristics can be constructed within a mean-CVaR framework. This approach results in significantly more stable and risk-transparent final portfolios. However, the approach needs to be modified to allow for the inclusion of hedge fund strategies not considered in this study and to address the issue of unequal strategy weightings within the RSGs.

5 CONCLUSION

The data and analysis contained in this study make us acutely aware of the skewness and kurtosis present in most hedge fund strategies. Also evident is the instability of correlations that strategies have among them. Both these aspects render currently available methods like the traditional mean-variance approach to produce efficient portfolios, ineffective.

Organizing distinct strategies into clusters or rational strategy groups such that they represent cohesiveness within a cluster yet maintain low correlation with other clusters is one suggested approach to lower the instability of correlations. More research is being conducted in this area since overlooking unstable correlations could give misleading allocation results detrimental to the risk management objectives of fiduciaries like pension plans. By addressing this concern, the fund of funds world could potentially gain by attracting more institutional investors like pension funds who could catalyze the growth of this segment of the hedge funds industry.

To prepare the data for optimization, a risk measure that looks beyond variance and considers higher moments, specifically skewness and kurtosis should be considered given the non-normality of the return distributions of the RSGs. I have demonstrated that instead of the standard variance, a downside risk measure such as a Conditional Value at Risk, should be considered. The DRAR i.e. mean-CVaR optimization would yield portfolios significantly lower in skewness and kurtosis since the optimizer would lean towards those clusters, which have positive skewness and lower kurtosis, something that it tends to plunge into, in the simple mean-variance framework. While this study provides a framework to develop allocation methodologies to combine multi-strategy hedge funds in a proliferating industry for fund of hedge funds, it calls for investigating the next sequential step of integrating multi-managers in a multi-strategy structure.

Table 1. Summary Statistics of Hedge Fund Strategy Indices

	Convertible Arbitrage	Distressed Securities	Merger Arbitrage	Fixed Income Arbitrage	Statistical Arbitrage	Market Neutral	Equity L/S	Global Macro
Compound Rate of Return	11.51%	15.36%	10.87%	8.64%	9.08%	9.72%	18.35%	17.17%
Annualized Standard Deviation	3.38%	6.26%	4.35%	4.47%	4.00%	3.23%	9.11%	8.61%
Skewness	-1.27	-0.69	-2.78	-1.70	-0.10	0.13	0.14	0.27
Kurtosis	5.36	10.11	22.72	17.73	0.91	0.41	2.41	0.70

Table 2. Correlation Analysis of Hedge Fund Strategies

	Convertible Arbitrage	Distressed Securities	Merger Arbitrage	Fixed Income Arbitrage	Statistical Arbitrage	Market Neutral	Equity Long/Short	Global Macro
Convertible Arbitrage	1.00	0.57	0.44	0.12	0.18	0.15	0.44	0.38
Distressed Securities		1.00	0.50	0.35	0.27	0.16	0.58	0.46
Merger Arbitrage			1.00	-0.02	0.34	0.19	0.47	0.29
Fixed Income Arbitrage				1.00	0.09	0.06	0.06	0.13
Statistical Arbitrage					1.00	0.53	0.34	0.21
Market Neutral						1.00	0.33	0.22
Equity Long/Short							1.00	0.58
Global Macro								1.00

Table 3. Spread Between Maximum/Minimum 12-Month Moving Average Correlations: HFRI Hedge Fund Strategy Indices

	Convertible Arbitrage	Distressed Securities	Merger Arbitrage	Fixed Income Arbitrage	Statistical Arbitrage	Market Neutral	Equity Long/ Short	Global Macro
Convertible Arbitrage	-	0.96	0.80	0.87	0.66	0.89	1.18	0.92
Distressed Securities		-	0.82	0.82	0.97	1.05	0.68	0.93
Merger Arbitrage			-	1.26	1.07	0.94	1.10	0.87
Fixed Income Arbitrage				-	1.05	1.05	1.15	1.11
Statistical Arbitrage					-	1.22	1.20	1.10
Market Neutral						-	1.29	0.83
Equity Long/Short							-	0.79
Global Macro								-

Table 4. Principal Component Cluster Analysis

Cluster	HF Strategy	R-Squared with Own Cluster	R-Squared with Next Closest Cluster	$1-R^2$ Ratio
Event Driven Plus	Convertible Arbitrage	0.675	0.209	0.411
	Distressed Securities	0.722	0.340	0.421
	Merger Arbitrage	0.617	0.181	0.468
Equity Arbitrage	Statistical Arbitrage	0.761	0.097	0.265
	Market Neutral	0.761	0.097	0.265
Fixed Income Arbitrage	Fixed Income Arbitrage	1.000	0.036	0.000
Discretionary	Equity Long/Short	0.789	0.365	0.332

Table 5. Summary Statistics of RSGs

	Event Driven Plus	Equity Arbitrage	Fixed Income Arbitrage	Discretionary
Compound Return	12.61%	9.42%	8.64%	17.85%
Annualized Standard Deviation	3.86%	3.16%	4.47%	7.87%
Skewness	-1.84	0.10	-1.70	0.18
Kurtosis	16.31	0.43	17.73	0.88

Table 6. Correlation Analysis of RSGs

	Event Driven Plus	Equity Arbitrage	Fixed Income Arbitrage	Discretionary
Event Driven Plus	1.00	0.31	0.22	0.61
Equity Arbitrage		1.00	0.09	0.36
Fixed Income Arbitrage			1.00	0.11
Discretionary				1.00

Table 7. Spread Between Maximum/Minimum 12-Month Moving Average Correlations: RSGs

	Event Driven Plus	Equity Arbitrage	Fixed Income Arbitrage	Discretionary
Event Driven Plus	-	1.00	0.96	0.85
Equity Arbitrage		-	0.87	0.99
Fixed Income Arbitrage			-	0.82
Discretionary				-

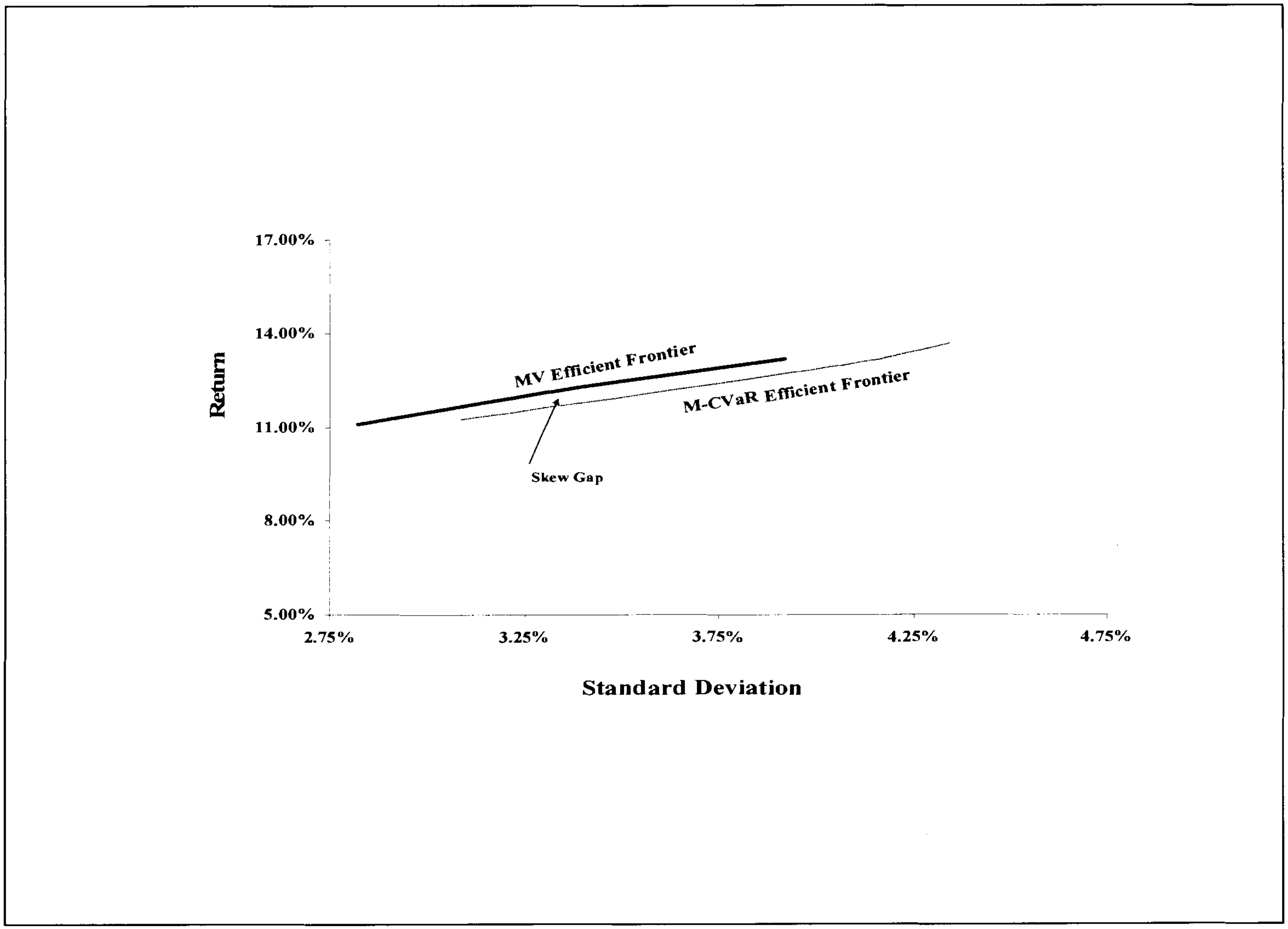
Table 8. Mean-Variance Proposed Portfolio Allocations

	Event Driven Plus	Equity Arbitrage	Fixed Income Arbitrage	Discretionary	Annualized Return	Standard Deviation	Skewness	Kurtosis	Sharpe r=2%	CVaR
Conservative	30%	40%	20%	10%	11.10%	2.82%	-0.72	5.33	3.23	-1.08%
Moderate	40%	30%	10%	20%	12.33%	3.39%	-0.77	5.78	3.04	-1.27%
Aggressive	40%	20%	10%	30%	13.17%	3.92%	-0.59	4.51	2.85	-1.46%

Table 9. Mean-CVaR Proposed Portfolio Allocations

	Event Driven Plus	Equity Arbitrage	Fixed Income Arbitrage	Discretionary	Annualized Return	Standard Deviation	Skewness	Kurtosis	Sharpe r=2%	CVaR
Conservative	10%	40%	30%	20%	11.24%	3.09%	-0.28	2.38	2.99	-1.07%
Moderate	10%	30%	20%	40%	12.99%	4.07%	-0.04	1.25	2.70	-1.33%
Aggressive	30%	20%	10%	40%	13.69%	4.34%	-0.31	2.73	2.69	-1.44%

Figure 1. Mean-Variance vs. Mean-CVaR Efficient Frontier



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