On Taking the 'Alternative' Route: Risks, Rewards and Performance Persistence of Hedge Funds

Vikas Agarwal
Narayan Y. Naik*

Current Version: November 1999

JEL Classification: G11, G15, G24

---

* Corresponding author: Narayan Y. Naik, London Business School, Sussex Place, Regent's Park, London NW1 4SA, United Kingdom. E-mail: nnaik@lbs.ac.uk, Tel:+44-171-262 5050, extension 3579. Vikas Agarwal is the Fauchier Partner's Scholar in the PhD Programme (Finance) at the London Business School and Narayan Y. Naik is an Associate Professor of Finance and Citibank Research Fellow at the London Business School. We would like to thank Mark Britten-Jones, Stephen Brown, Elroy Dimson, William Goetzmann, David Hsieh, Fauchier Partners Limited, Thomas Schneeweis (the editor) and participants at the GAIM conference in Geneva in June 1999 for many helpful comments and constructive suggestions. Naik is grateful for funding from Inquire UK and the European Commission's TMR program (network ref. ERBFMRXCT 960054). Vikas Agarwal is grateful for the financial support from British Council's Chevening scholarship, Edward Jones', Frank Russell's and Fauchier Partner's scholarships during past three years in the PhD programme. We are grateful to Bob Potsic of Hedge Fund Research Inc., Chicago for providing us with the data. We are responsible for all errors.

On Taking the ‘Alternative' Route: Risks, Rewards and Performance Persistence of Hedge Funds

Abstract

This paper provides a comprehensive analysis of the risk-return characteristics, risk exposures, and performance persistence of various hedge fund strategies using a database on hedge fund indices and individual hedge fund managers. In a mean-variance framework, we find that a combination of alternative investments and passive indexing provides significantly better risk-return tradeoff than passively investing in the different asset classes. Using a broad asset class factor model, we find that the hedge fund strategies outperform the benchmark by a range of 6% to 15% per year. These abnormal returns are associated with an active risk ranging from 0.9% to 4.2% per month. Finally, using parametric and non-parametric methods, we examine persistence in the performance of hedge fund managers and find a reasonable degree of persistence. Since this seems to be attributable more to the losers continuing to be losers instead of winners continuing to be winners, it highlights the importance of manager selection in case of hedge funds.

On Taking the 'Alternative' Route: Risks, Rewards and Performance Persistence of Hedge Funds

I. Introduction

It is now well known that the traditional active strategies such as investing in mutual funds, on average, underperform passive investment strategies. The few mutual fund managers who successfully beat the passive strategies tend to move into the arena of 'alternative' investments and start their own hedge funds, often times putting their own money at stake[1]. In addition, hedge funds seek to deliver high absolute returns and typically have features such as hurdle rates, incentive fees with high watermark provision, which help in a better alignment of the interests of the managers and the investors. This has caused many investors following active-passive strategies to seriously consider replacing the traditional active part of their portfolio with alternative investment strategies.

Unfortunately, due to less stringent disclosure requirements (especially in the case of offshore hedge funds) and the short track record of a large number of hedge funds, there has been relatively little analysis of the true risk-return tradeoffs and the risk exposures of different types of hedge funds. Moreover, near-collapse of Long-Term Capital Management and liquidation of several hedge funds during the latter half of 1998 have left many investors demanding a better understanding of the different hedge fund strategies[2].

---

[1] See Appendix A for a general description of hedge funds.

[2] Hedge funds have mostly been shrouded in mystery although a new spate of legal regulations and obligations to disclose more portfolio information are being proposed and debated. This is being followed up by availability of real-time information on the performance and risk profiles of hedge funds through internet sites dedicated to hedge funds, e.g., Standard & Poor's and Ernst & Young, CSFB & Tremont Advisers, etc.

This paper employs a new database of indices compiled by Hedge Fund Research (HFR), which does not suffer from survivorship bias, to investigate the risk-return tradeoffs, estimate the degree of outperformance of hedge fund strategies over a portfolio of passive strategies. It extends our understanding of hedge funds in several ways. First, it examines the performance of several different types of hedge funds belonging to two broad categories: those that follow directional investment strategies and those that follow non-directional (opportunistic) investment strategies. Second, it conducts a mean-variance analysis to determine the extent to which one can improve the passive-only efficient frontier by optimally combining alternative and passive investment strategies. Third, using a multi-factor model, it estimates the factor loadings and 'alphas' of different types of hedge fund strategies vis-à-vis a broad range of asset classes. Finally, using a different database of *individual* manager returns, it examines the extent to which hedge fund managers exhibit persistence in their performance.

Our sample differs from that used in other studies with respect to the sample period, the extent of strategy coverage and the selection process of the funds. We examine data for the recent period from January 1994 to September 1998, which covers market ups and downs over stable and turbulent periods. We use HFR indices which do not suffer from survivorship bias and which cover over 1000 hedge fund managers with about $260 billion in assets under management. We use ten different HFR indices covering most commonly used hedge fund strategies including event driven, macro, short, etc. These ten indices are an equally weighted performance summary of 807 funds from the HFR database. For studying the issue of performance persistence, we employ a subset of 167 fund managers following the different investment strategies. For these managers, we confirm the reliability of the data by double checking the figures from several databases including those of TASS Management and Altvest.

For the multi-factor model, we use a broad range of indices to capture the different investment opportunities available to the hedge funds. For instance, we include Lehman high yield composite index to capture the interests of hedge fund strategies in distressed securities. We also include the Federal Reserve Bank trade weighted Dollar index to incorporate the currency bets taken by some of the hedge funds. Thus, our multi-factor model covering equities, bonds, currencies and commodities provides a richer characterization of different hedge fund styles and offers a better benchmark for estimating the extent of outperformance achieved by the hedge fund managers.

Our research complements and generalizes the recent literature on hedge funds in several ways. For instance, we extend the work of Fung and Hsieh (1997) by using a multi-factor model to investigate the value addition by hedge funds. We supplement Brown, Goetzmann, and Ibbotson's (1999) work on performance persistence by examining the performance of onshore fund mangers as well as that of offshore fund managers. We further the analysis of Ackermann, McEnally, and Ravenscraft (1999) and Liang (1999) by quantifying the extent to which the passive-only efficient frontier can be improved by the inclusion of alternative investments. We extend the work of Schneeweis and Spurgin (1998a) by benchmarking the different hedge fund strategies against a general asset class factor model consisting of passive positions in equities, bonds, currencies and commodities.

We find that hedge funds provide better opportunities for diversification by virtue of their low correlation with different indices. Based on the mean-variance analysis, we find that a portfolio comprising of passive asset classes and investment in mainly non-directional hedge fund strategies, provides better risk-return tradeoff than just investing passively. We observe from multi-factor analysis that the hedge funds outperform the benchmark consisting of a combination of the various asset classes by about 6% to 15% per year. These abnormal returns are associated with an active risk ranging from 0.9% to 4.2% per month. Finally, we control for the different investment styles of hedge funds and find a reasonable degree of persistence in their performance highlighting the importance of manager selection in case of hedge funds[3].

Rest of the paper is organized as follows. Section 2 classifies the sample into directional and non-directional hedge fund strategies and provides the summary statistics. Section 3 examines the risk-return characteristics of hedge funds. Section 4 analyses the improvement in the mean-variance frontier due to alternative investments. Section 5 provides the multi-factor model and abnormal returns analysis while Section 6 investigates the issue of performance persistence in hedge funds. Section 7 concludes.

II. Classification of Hedge Funds

Although the name 'hedge fund' originated from the equally long and short strategy employed by the managers, the new definition of hedge funds covers a multitude of

[3] This finding is in contrast to Brown et. al. (1999), who find little persistence in the performance of offshore hedge funds during 1989-1995. This may be because of the presence of onshore hedge funds

different strategies. Unlike the traditional investment arena, since there does not exist a universally accepted norm to classify the different strategies, we segregate them into two broad categories: ‘Non-Directional’ and ‘Directional’. Hedge fund strategies exhibiting low correlation with the market are classified as non-directional, while those having high correlation with the market are classified as directional. We further divide these two main categories into several popular sub-categories (see Appendix B for details).

We use ten different HFR Performance Indices (HFRI) corresponding to the ten hedge fund strategies described above. These indices are constructed by equally weighting monthly net-of-fee returns of 807 onshore and offshore hedge funds. These indices incorporate funds that have ceased to exist and therefore do not suffer from survivorship bias. All HFR indices are re-weighted each month to incorporate new funds and eliminate defunct funds. Our sample period consists of 57 months from January 1994 to September 1998 and covers the recent period where most of the hedge funds did not perform well. We use these indices for conducting risk-return, mean-variance, multi-factor, and style analyses of the ten hedge fund strategies. To examine the issue of performance persistence, we use *individual* fund manager returns data from another source.

To get a general idea as to how the different hedge fund strategies have performed in bullish and bearish periods, we report in Table 1 the returns on different hedge fund strategies during seven large upturns and seven large downturns of the S&P500 composite index over the sample period. On average, we find that the non-directional

---

in our sample, and inference being based on quarterly returns over a more recent time period.

strategies perform worse than the S&P 500 index during market up-moves and vice-versa. Among the different non-directional strategies, although Equity Hedge and Event Driven strategies deliver higher returns during market up-moves relative to the rest, these strategies also lose more money during market down-moves. This suggests that the so-called non-directional strategies differ in terms of the extent of their market neutrality, Equity Hedge being least market neutral. In contrast, the directional strategies tend to move with the market, performing significantly better than the non-directional ones during market upturns and significantly worse during market downturns[4]. The only exception being the Short strategy which moves in direction opposite to that of the market.

III. Risk-Return Characteristics of Hedge Fund Strategies

We report the summary statistics for the HFR indices in Table 2. In general, we find that the non-directional strategies perform better than the directional ones based on various risk-return characteristics. For example, during the sample period, the average return on the non-directional strategies (0.94% per month) exceeds that on the directional strategies (0.71% per month). On different measures of variability of returns, again the non-directional strategies exhibit lower variability. We measure variability by the standard deviation of returns and find that the returns on non-directional strategies exhibit a standard deviation of about 1.7% per month while those on directional strategies equals 4.2% per month. We also measure variability in terms of the downside deviation (DD). Unlike the variance measure, which equally penalizes

[4] The performance of the non-directional strategies is more correlated with the broader equity indices like Russell 2000 as they have substantial investment in small stocks not captured by the S\&P 500

the good and the bad realizations, the downside deviation measure focuses entirely on return realization below a target rate. For the purpose of this analysis, we use the Eurodollar rate as the target rate and define downside deviation DD as[5]:

$$DD = \frac{\sum_{i=1}^{N} \Delta_i^2}{N+1} \; for\; i = 1,2,3,........,N, \;\; where \;\; \Delta_i = \{T_i - R_i \;\; for\; T_i > R_i \; ; 0 \; otherwise\}$$

N represents the total number of months, T_i is the target rate for month i (e.g., risk-free or LIBOR rate) and R_i is the return for a fund in month i.

We find that the downside deviation is lower for the non-directional strategies (0.5% per month) compared to that for the directional ones (1.9% per month). In terms of positive and negative realizations, the non-directional strategies show more positive returns (81%) than the directional ones (60%). In terms of Sharpe ratio as well, the non-directional strategies exhibit better risk-return trade-offs compared to the directional ones. For instance, the average Sharpe ratio for the non-directional strategies equals 0.3, almost the same as that of the S&P500 composite index, while that for the directional ones equals 0.1. Thus, during the sample period, overall the non-directional strategies seem to have delivered better risk-return trade-off compared to the directional strategies.

Having examined the risk-return characteristics of the various hedge fund strategies, we proceed with our mean variance efficient frontier analysis.

---

composite index.

[5] For a target rate of zero, the DD measure coincides with the semi-variance measure.

III. Mean Variance Efficient Frontier Analysis

In this section, we investigate the extent to which the efficient frontier generated by an investment strategy taking passive positions in equities, bonds, currencies and commodities can be improved by the addition of different alternative investment strategies.

We select a broad range of asset classes comprising of equities, bonds, currencies and commodities to effectively capture the investment opportunities available to a global investor. For the sake of parsimony, we restrict the passive-only strategy to eight indices belonging to four asset classes (see Table 3). To incorporate the exposure to global equities, we include the S&P 500 composite index, the MSCI world index excluding the US (developed markets besides the US), and the MSCI emerging markets index. To assess exposure to bonds, we use the Salomon Brothers (henceforth, SB) Government and Corporate Bond index, and the SB World Government Bond index[6] We also include Lehman High Yield composite index to incorporate returns available from investing in distressed securities. To account for returns arising from exposure to currencies and commodities, we include the Federal Reserve Trade-Weighted Dollar index and UK market price index for gold.

Table 4 shows the average returns, standard deviations and correlations among the eight indices. The low correlations suggest that a global investor may be able to achieve a reasonable level of diversification by following a passive-only strategy. Table

[6] We also use JP Morgan US government bonds and JP Morgan non-US government bond indices used by Fung & Hsieh (1997) and find qualitatively similar results (not reported).

5 shows the correlations among the ten hedge fund strategies and the eight indices. We can see that most of the hedge fund strategies exhibit a low correlation (less than 0.5) with the different indices suggesting opportunities for even higher diversification by using a mix of alternative and passive investment strategies.

Figure 1 shows the three different efficient frontiers generated by using passive-only, alternative-only and a combination of passive and alternative investment strategies. For this purpose, we use the Ibbotson Optimizer which characterizes the entire efficient frontier by a limited number of corner portfolios (henceforth CPs)[7]. The CP in the top-right hand corner denotes the maximum variance portfolio while the CP in the bottom-left hand corner corresponds to the minimum variance portfolio. As Figure 1 clearly shows, a combination of alternative and passive investment strategies offers significantly better risk-return trade-off compared to passive-only investment strategy.

For the passive-only efficient frontier, the CPs range from a 100% investment in S&P 500 composite index for the maximum variance portfolio to a mix of investments in the bond, currency, and commodity classes for the minimum variance portfolio. For the alternative-only efficient frontier, as we move from the maximum variance to minimum variance portfolio, the collective proportion of the directional strategies (i.e., Macro, Hedge-Long-Bias, Long, and Short) decreases monotonically. For the alternative and passive efficient frontier, there exist thirteen CPs (ranging from CP1, the maximum variance portfolio, to CP13, the minimum variance portfolio). Figure 2

[7] CPs are the places on the efficient frontier where an asset is either added or dropped. Every efficient portfolio is a linear combination of two adjacent CPs.

shows how the relative importance of passive and alternative components of the CPs change as one moves from maximum variance portfolio (σ =3.55% per month) to the minimum variance portfolio (σ =0.41% per month). Figure 3 further breaks up the passive and alternative components of each CP into equities, bonds, currencies and commodities, and into directional and non-directional strategies respectively.

These figures highlight several interesting points. The maximum variance portfolio consists of 100% investment in the S&P 500 composite index while the minimum variance portfolio comprises of about 60% investment in passive asset classes and about 40% in alternative investment strategies. As one moves towards the minimum variance portfolio, in the passive portion of the portfolio, the weight of the equity class decreases while that of the bond class (consisting mainly of non-US bonds) increases. In the alternative portion of the portfolio, the weight of the directional strategies falls while that of the non-directional strategies rises.

At first sight, the non-monotonicity of the passive and alternative components in Figure 2 appears surprising. However, this can be explained by the changes in weights on the different asset classes for the passive part and the changes in weights on the different hedge fund strategies for the alternative part of the portfolio. Figure 3 shows that the weights on the four asset classes belonging to the passive part change monotonically as one moves along the efficient frontier. The non-monotonicity of weights on directional and non-directional categories of hedge fund strategies can be attributed to the changes in weights on the different sub-categories, the weights of which change monotonically as one moves along the efficient frontier.

Having examined the risk-return tradeoffs and extent of improvement over passive-only strategy by the inclusion of alternative investment strategies, in the following section we evaluate the performance of different hedge fund strategies using a multi-factor model.

IV. Asset Class Factor Model and Abnormal Returns

We construct an asset class factor model to evaluate the performance of hedge funds. In particular, we run the following regression:

$$R_t = \alpha + \sum_{k=1}^{K} b_k F_{kt} + u_t \qquad \textbf{(1)}$$

where,

R_t = Return on the HFR index for a particular strategy for period t,

α = abnormal return,

b_k = factor loading,

F_{kt} = return on k^{th} asset class factor (or index) for period t, (k=1,.......,8) and

u_t = error term.

As is evident from Table 4, the returns on some of the asset class factors (i.e., indices) are highly correlated which can result in misleading inference. We, therefore, use a stepwise regression technique where the variables are entered or removed from the model depending on the significance of the F value. The single best variable is chosen first; the initial variable is then paired with each of the other independent variables, one at a time, and a second variable is chosen, and so on[8].

Panel A of Table 6 shows the analysis for the full sample period of 57 months from January 1994 to September 1998. We note that the R-square values are higher for the four directional strategies (ranging from 0.49 to 0.83) and as expected, lower for non-directional strategies (ranging from 0.38 to 0.73), as the non-directional strategies are, by definition, less correlated with the market. As compared to the traditional mutual funds, the asset class factor model can explain a smaller fraction of the variance of returns on the hedge funds. Our low R-square values are consistent with those in Fung and Hsieh (1997) and reflect dynamic trading strategies employed by the hedge funds as opposed to the predominantly buy-and-hold strategies used by traditional mutual funds.

As can be seen, a large number of hedge fund strategies (directional as well as non-directional) show significant factor loadings on S&P500 composite index, on MSCI emerging market equity index and on Lehman High Yield index. In the non-directional strategies, the Fixed Income Arbitrage has negative factor loadings on both the SB bond indices indicating that these funds short the overvalued fixed income securities including government and corporate bonds in both US and non-US markets. The Event Driven and Equity Hedge strategies both exhibit positive factor loadings on the S&P 500 composite index and the MSCI emerging markets index. This is consistent

[8] Stepwise method involves entering the independent variables into the discriminant function one at a time, based on their discriminating power. The results are not sensitive to the order in which the variables are entered in the program. Same results are obtained after changing the order of different variables. For the sake of completeness, we also report results from general multivariate regression analysis (panel B of Table 6)

with the returns on these two non-directional strategies during large up moves and down moves in the US equity market (see Table 1). The Restructuring strategy has a positive coefficient on the Lehman high yield composite index and a negative coefficient of similar magnitude on SB Government Bond index indicating that these funds hedge out interest rate risk but retain credit risk of distressed firms undergoing bankruptcy or reorganization. It also exhibits small positive loading on the S&P500 composite index, which is consistent with the notion that the debt of distressed firms behaves partly like equity and partly like debt. Event Arbitrage strategies exploit market inefficiencies, which are likely to occur in the securities of the financially distressed firms, which may not be priced correctly and there may be arbitrage opportunities. Positive factor loadings for Event Arbitrage and Capital Structure Arbitrage strategies on the Lehman high yield composite index confirm this notion.

In the case of directional strategies, Macro funds show positive factor loadings on the S\&P 500 composite index, Federal Reserve Bank trade-weighted dollar index and the gold price index confirming that these funds follow a top-down global approach by investing in US equities, currencies and commodities. Hedge (long bias) funds are primarily having a net long market exposure and hence, show positive factor loadings on the S&P 500 composite and the MSCI emerging markets indices. Short funds have negative betas with respect to the S\&P 500 composite and MSCI emerging markets indices respectively, which reflects that these managers take positions against the markets.

The intercept term in the regression is positive and significant in all the cases as shown in Table 6. As the intercept can be interpreted as the unexplained return by the asset class factor model reflecting the skill of the managers, it proves that hedge funds exhibit superior market timing and/or security selection abilities which cannot be attributed to returns from passive portfolios. In addition, as our multi-factor model includes a wide range of asset classes to determine the level of outperformance, it mitigates to a large extent the problem of appropriate benchmark. In general, we find that all the hedge fund strategies earn significantly positive abnormal returns (from 0.53% to 1.25% per month), an evidence consistent with the massive growth in the investment in the alternative sector over the sample period. These alphas are also higher than the risk free rate over our sample period (0.4% per month), six of them being significantly greater than the risk free rate at 5% level.

Having noted that the different hedge fund strategies yield positive alphas and having observed that inclusion of alternative strategies significantly improves the risk-return tradeoff, it seems reasonable to allocate a part of the portfolio to hedge funds. However, question arises whether one should allocate funds to an individual fund manager or one should form a portfolio of funds pursuing a particular strategy. This leads us to examine the issue of persistence of performance of individual fund managers within a given strategy. We investigate this issue in the following section using returns data of *individual* fund managers.

V. Performance Persistence

We follow the approach of Brown & Goetzmann (1995) and Brown, Goetzmann and Ibbotson (1999) for determining the extent of persistence in the performance of onshore and offshore hedge fund managers over April 1995 to September 1998 period.

Although the performance of hedge fund managers is observed by the investment advisors on a monthly basis, monthly returns may have high volatility leading to spurious inference about persistence based on monthly returns. In contrast, using annual returns do not provide sufficient number of observations due to limited history of hedge funds, which can lead to lack of statistical robustness in the results. Hence, we examine the issue of persistence in performance using quarterly returns.

We know from Table 2 that different hedge fund strategies involve significantly different risk-return tradeoffs. Therefore, it is not prudent to compare the performance of a fund manager following a given strategy with another fund manager who is following a different investment strategy. We also know from Brown et. al. (1999) that the existence of 'style factor' can lead to reversals in the persistence phenomenon because of the differences in the levels of systematic risk across managers. This is especially relevant in the case of hedge funds, which are exposed to significantly different levels of risk depending on whether they follow directional or non-directional strategies. Even among the non-directional strategies, we know that Event Driven and Equity Hedge strategies exhibit significantly different risk-return tradeoffs compared to the other four strategies[9]. We, therefore, examine the issue of performance persistence *within* individual hedge fund strategies. Specifically, we compare the return of a fund manager following a particular strategy with the average return earned by all the fund managers pursuing that strategy. For this purpose, we follow Brown et. al. (1999) and define alpha as the return of a fund manager using a particular strategy minus the average return for all fund managers following the same strategy.

[9] See Brown and Goetzmann (1995) for the importance of relative risk adjustment. They find that the relative risk-adjusted performance of mutual funds persists from year to year but the absolute

It is well known that different hedge funds employ different degrees of leverage to scale up their alphas. However, this also scales up their return volatilities - a fact not captured by looking at the alphas of managers following a given strategy. The appraisal ratio (alpha divided by the residual standard deviation resulting from a regression of alpha on the average alpha) accounts for the differences in volatilities and is leverage-invariant. Therefore, we also investigate performance persistence using appraisal ratios.

To investigate the issue of persistence, we use both regression-based (parametric) and contingency-table-based (non-parametric) methods with respect to alphas as well as appraisal ratios. For the parametric method, we regress the alphas during a quarter on alphas during the previous quarter. A positive significant slope coefficient on past alpha suggests that fund managers who did well in a quarter do well in the subsequent quarter as well (and vice-versa). We repeat the regression by replacing alphas with the appraisal ratios.

For the non-parametric method, we construct a contingency table of winners and losers where a fund is a winner if the alpha of that fund is greater than the median alpha of all the funds in that quarter otherwise it is a loser. Persistence in this context relates to the funds, which are winners in two consecutive quarters, denoted by WW, or losers in two consecutive quarters, denoted by LL. Similarly, winners in first quarter and losers in the second quarter are denoted by WL and the reverse order is denoted by LW. Then, the ratio of the funds which show persistence in performance to the ones

---

performance measured by alphas does not.

which do not, is captured by the cross-product ratio (CPR), defined as *(WW*LL)/(WL*LW)*. The null hypothesis in this setting represents lack of persistence for which the CPR equals one. In other words, when there is no persistence, one would expect each of the four categories denoted by WW, WL, LW and LL to have 25% of the total number of funds. From Christensen (1990), we know that in large samples, the standard error of the natural logarithm of the CPR is given by $\sigma_{\ln(CPR)} = \sqrt[2]{\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}}$. As before, we repeat the non-parametric inference using the appraisal ratio instead of alpha.

For this analysis, we use the quarterly returns on the individual 167 hedge funds belonging to the ten different strategies. Table 8 provides the summary statistics for these funds. Comparing the figures with the summary statistics of the HFR indices in Table 2, we observe that the various statistics like mean, standard deviation, skewness etc. are similar to those of the HFR indices[10].

The results of parametric and non-parametric[11] methods are reported in Table 9 panel A (for alphas) and panel B (for appraisal ratios). Irrespective of whether we use alphas or we use appraisal ratios, we find identical results from both methods. In case of the parametric method, we find that the slope coefficients on lagged alphas and lagged appraisal ratios are positive and significant in 8 out of 13 regressions. In the case of non-parametric method, for alphas we find that the CPRs are significant in 6

[10] It may be noted that the data on individual fund managers that we use for investigating persistence in performance is not free from survivorship bias. Nevertheless, we conduct the analysis to indicate the importance of manager selection in case of hedge funds.
[11] We also employ Chi-square test statistic for the non-parametric test of persistence and find qualitatively similar results.

out of the 13 cases while for appraisal ratios the CPRs are significant in 7 out of the 13 cases. Overall, these results indicate a reasonable amount of persistence of performance among the 167 hedge fund managers[12].

Our result differs from that of Brown et. al. (1999) for offshore funds. This may be due to the presence of onshore funds in our sample and the analysis being based on quarterly returns as opposed to their analysis being based on annual returns. Also, we cover a more recent period till September 1998 where a large number of hedge fund strategies have performed badly which may be contributing to the overall level of persistence. However, our results are consistent with the previous findings where they find losers exhibiting more persistence than winners. In particular, we find that there are more LLs than WWs in every quarter, whether measured by the alphas or by the appraisal ratios. This suggests that the overall persistence results may be driven more by the losers who continue to be losers rather than winners who continue to be winners. Our results emphasize the importance of manager selection in case of hedge funds.

VI. Concluding Remarks

In this paper, we use a new and comprehensive database to examine the risk-return tradeoffs of investing in directional and non-directional hedge fund strategies. Our results provide strong support to allocating a significant part of the overall portfolio to hedge funds. We observe that, in general, the non-directional strategies

[12] Some of the persistence at the quarterly level may be driven by the fact that we examine net-of-fee

exhibit higher Sharpe ratios and lower downside risk as compared to the directional strategies. We find that the inclusion of hedge funds provides better opportunities for diversification. In particular, a mix of investment in hedge funds (mainly non-directional) and passive indexing offers a significantly better risk-return tradeoff compared to that achievable by passive-only investing. Using a multi-factor model covering a wide range of asset classes, we find that the hedge funds outperform the benchmark by 6% to 15% per year, a range much higher than that provided by the traditional active investments like the mutual funds. However, these abnormal returns are associated with an active risk ranging from 0.9% to 4.2% per month. Finally, we find a reasonable amount of persistence in the performance of various hedge fund strategies. However, this seems to be driven more by losers continuing to be losers rather than winners persisting to be winners indicating the importance of manager selection in case of hedge funds.

Taken together, these results significantly improve our understanding of the risk-return tradeoffs involved in allocating funds to alternative investment vehicles. Also, our empirical results provide the first exploration of the true risk-return characteristics of hedge fund strategies through an asset class factor model, a topic that needs more attention in the field of investment management.

---

returns. Hence, the imputation of incentive fees along with management and other fees may be contributing to the persistence.

References

Ackermann, Carl, Richard McEnally and David Ravenscraft, 1999, The Performance of Hedge Funds: Risk, Return and Incentives, *Journal of Finance* 54, 833-874.

Brown, Stephen J., and William N. Goetzmann, 1995, Performance Persistence, *Journal of Finance* 50, 679-698.

Brown, Stephen J., William N. Goetzmann, and Roger G. Ibbotson, 1999, Offshore hedge funds: Survival & Performance 1989-1995, *Journal of Business* 72, 91-117.

Brown, Stephen J., William N. Goetzmann, Roger G. Ibbotson, and Stephen A. Ross, 1992, Survivorship bias in performance studies, *Review of Financial Studies* 5, 553-580.

Brown, Stephen J., William N. Goetzmann, and James Park, 1999, Conditions for survival: Changing risk and the performance of hedge fund managers and CTAs, *Working Paper*, New York University.

Christensen, Ronald, 1990, Log-Linear Models, *Springer-Verlag*, New York.

Fung, William, and David A. Hsieh, 1997, Empirical characteristics of dynamic trading strategies: The case of hedge funds, *The Review of Financial Studies* 10, 275-302.

Liang, Bing, On the performance of Hedge Funds, 1999, *Financial Analysts Journal* 55, 72-85.

Schneeweis, Thomas, and Richard Spurgin, 1998a, Multifactor Analysis of Hedge Fund, Managed Futures, and Mutual Fund Return and Risk Characteristics, *Journal of Alternative Investments*, 1-24.

Schneeweis, Thomas, and Richard Spurgin, 1998b, Alternative Investments in the Institutional Portfolio, Alternative Investment Management Association.

Appendix A

Hedge funds refer primarily to the use of alternative investment strategies with the flexibility of investing in a broader spectrum of asset classes including currencies and distressed securities, where they can use short sales, leverage and derivatives in order to enhance their returns. In the last two years, the hedge fund industry with estimated 4,000 funds, domestic and offshore, and an asset base of more than $400 billion has experienced a breathtaking growth of $38 billion including an increase of 40% in the investor capital during 1997. They are largely unregulated and are usually structured as limited partnerships in which managers receive a substantial share of the profits. Minimum investments range from $100,000 to $20 million although the typical amount is around $1 million. Some of the funds have a lockup period of a few years providing the managers with the flexibility of investing from the long-term point of view. As the hedge funds are usually private investment partnerships, the SEC limits them to 99 investors, at least 65 of whom must be accredited, i.e. having a net worth of at least $1 million, excluding their home, or steady annual incomes of $200,000 or more. In order to encourage investments in hedge funds, in June 1997, the SEC allowed these funds to exceed the previous limit of 100 investors including the General Partner up to 499 limited partners without any registration and disclosure requirements. However, in this case each of the partners should have at least $5 million in invested assets. Hedge funds usually charge higher fees than the traditional active managers, a typical hedge fund charging 1% annual asset-management fee and an incentive fee amounting to 20% of the profits.

Appendix B

Non-directional Strategies: These strategies do not depend on the direction of any specific market movement and are commonly referred to as 'market neutral' strategies. These are usually designed to exploit short term market inefficiencies and pricing discrepancies between related securities while hedging out as much of the market exposure as possible. Due to the reduced liquidity inherent in many such situations, they frequently run smaller pools of capital than their counterparts following directional strategies. Included in this group are the following strategies:

1. <u>Fixed Income Arbitrage</u> - A strategy having long and short bond positions via cash or derivatives markets in government, corporate and/or asset-backed securities. The risk of these strategies varies depending on duration, credit exposure and the degree of leverage employed.
2. <u>Event Driven</u> - A strategy which hopes to benefit from mispricing arising in different events such as merger arbitrage, restructurings etc. Manager takes a position in an undervalued security that is anticipated to rise in value because of events such as mergers, reorganizations, or takeovers. The main risk in such strategies is non-realization of the event.
3. <u>Equity Hedge</u> - A strategy of investing in equity or equity-like instruments where the net exposure (gross long minus gross short) is generally low. The manager may invest globally, or have a more defined geographic, industry or capitalization focus. The risk primarily pertains to the specific risk of the long and short positions.
4. <u>Restructuring</u> - A strategy of buying and occasionally shorting securities of companies under Chapter 11 and/or ones which are undergoing some form of reorganization. The securities range from senior secured debt to common stock.

The liquidation of financially distressed company is the main source of risk in these strategies.

5. Event Arbitrage - A strategy of purchasing securities of a company being acquired, and shorting that of the acquiring company. The risk associated with such strategies is more of a "deal" risk rather than market risk.
6. Capital Structure Arbitrage - A strategy of buying and selling different securities of the same issuer (e.g. convertibles/common stock) seeking to obtain low volatility returns by arbitraging the relative mispricing of these securities.

Directional Strategies: These strategies hope to benefit from broad market movements. Some popular directional strategies are:

1. Macro - A strategy that seeks to capitalize on country, regional and/or economic change affecting securities, commodities, interest rates and currency rates. Asset allocation can be aggressive, and leverage and derivatives may be utilized. The method and degree of hedging can vary significantly.
2. Long - A strategy which employs a "growth" or "value" approach to investing in equities with no shorting or hedging to minimize inherent market risk. These funds mainly invest in the emerging markets where there may be restrictions on short sales.
3. Hedge (Long Bias) - A strategy similar to equity hedge with significant net long exposure.
4. Short - A strategy that focuses on selling short over-valued securities, with the hope of repurchasing them in the future at a lower price.

Table I. Performance of different hedge fund strategies during large upturns and downturns in the US equity market

This table shows the returns on ten different hedge fund strategies during the seven large up and down moves of the S&P 500 Composite index during January 1994 to September 1998.

Panel A: S&P 500 Composite Index: 7 Large Up Moves

	Nov-96	Jul-97	Jan-97	Sep-97	May-97	Mar-98	Sep-96	Mean
S&P 500 Composite	7.68	6.45	6.39	6.37	6.16	5.90	5.88	6.40
Non-directional Strategies								
Fixed Income Arbitrage	0.37	0.58	1.43	0.51	0.34	1.34	0.52	0.73
Event Driven	2.03	2.72	2.84	3.59	4.36	2.93	1.97	2.92
Equity Hedge	1.66	5.50	2.78	5.69	5.04	4.54	2.18	3.85
Restructuring	0.88	2.11	1.88	2.84	1.74	2.17	1.82	1.92
Event Arbitrage	1.38	1.60	1.04	2.31	1.92	1.05	0.81	1.42
Capital Structure Arbitrage	1.40	1.61	1.01	1.11	1.40	1.58	1.23	1.33
Directional Strategies								
Macro	4.72	5.90	5.14	3.05	1.83	5.05	2.01	3.96
Long	2.85	4.64	7.83	0.61	3.80	2.94	1.38	3.44
Hedge (Long Bias)	2.96	5.56	3.39	6.36	8.98	3.98	3.97	5.03
Short	-2.95	-2.94	-1.02	-2.58	-8.23	0.06	-7.53	-3.60

Panel B: S&P 500 Composite Index: 7 Large Down Moves

	Aug-98	Aug-97	Mar-97	Nov-94	Mar-94	Jul-96	Jul-98	Mean
S&P 500 Composite	-10.52	-4.91	-4.34	-3.93	-3.78	-3.63	-3.03	-4.88
Non-directional Strategies								
Fixed Income Arbitrage	-1.18	0.40	0.54	0.76	0.93	1.30	1.69	0.63
Event Driven	-8.87	0.52	-0.53	-1.27	-0.55	-0.50	-0.57	-1.68
Equity Hedge	-7.69	1.35	-0.73	-1.48	-2.08	-2.87	-0.67	-2.02
Restructuring	-8.55	1.08	0.22	-1.71	-0.93	0.21	-0.40	-1.44
Event Arbitrage	-6.09	1.04	1.05	-0.22	1.37	0.81	-0.57	-0.37
Capital Structure Arbitrage	-3.11	1.14	0.59	-0.79	-2.11	-0.37	0.49	-0.59
Directional Strategies								
Macro	-3.94	-1.25	-1.24	0.39	-3.43	-3.04	0.23	-1.75
Long	-20.98	-2.08	1.48	-2.81	-4.38	-2.65	-0.30	-4.53
Hedge (Long Bias)	-13.31	0.86	-5.04	-2.43	-3.07	-6.79	-2.87	-4.66
Short	19.53	-1.77	6.75	4.70	11.32	9.00	3.04	7.51

Table II. Summary Statistics of different hedge fund strategies

The table below shows the mean returns, standard deviations, downside deviations, medians, skewness, kurtosis, minimum and maximum realizations, proportion of positive realizations and Sharpe Ratios for ten different hedge fund strategies during January 1994 to September 1998. The Sharpe Ratio is calculated assuming a risk-free rate of 5% p.a.

Hedge fund strategy[#]	No.	Mean	SD	DD	Median	Skewness	Kurtosis	Min.	Max.	NP	SR
Non-Directional											
Fixed Income Arbitrage	15	0.53	1.40	0.42	0.71	-3.44	17.13	-7.28	2.49	82	0.08
Event Driven	67	1.14	2.07	0.41	1.45	-2.32	11.69	-9.56	5.01	77	0.35
Equity Hedge	212	1.32	2.31	0.71	1.35	-0.72	2.45	-7.41	5.69	72	0.39
Restructuring	36	0.90	1.74	0.37	1.15	-3.19	16.36	-8.74	3.82	82	0.28
Event Arbitrage	27	0.98	1.25	0.23	1.29	-3.96	22.35	-6.49	2.47	86	0.45
Capital Structure Arbitrage	56	0.76	1.13	0.61	1.11	-1.51	2.30	-2.79	2.32	84	0.31
Average	**69**	**0.94**	**1.65**	**0.46**	**1.18**	**-2.52**	**12.05**	**-7.05**	**3.63**	**81**	**0.31**
Directional											
Macro	53	0.96	2.47	1.32	0.57	-0.23	0.57	-6.40	5.90	67	0.22
Long	126	0.13	4.65	1.51	0.61	-1.45	4.75	-19.73	7.87	56	-0.06
Hedge (Long Bias)	201	1.28	3.69	1.49	1.68	-1.04	3.07	-13.08	8.98	67	0.23
Short	14	0.45	5.85	3.27	0.06	0.97	2.24	-9.96	22.11	51	0.01
Average	**99**	**0.71**	**4.17**	**1.90**	**0.73**	**-0.44**	**2.66**	**-12.29**	**11.22**	**60**	**0.10**

[#]The HFR indices corresponding to these strategies are: Fixed Income Arbitrage; Event Driven; Equity Hedge; Distressed Securities; Merger Arbitrage; Convertible Arbitrage; Macro; Emerging Markets (Total); Equity Non-Hedge and Short Selling.

No.: Number of funds in the HFR index
SD: Standard deviation
DD: Downside deviation defined as $\frac{\sum_{i=1}^{N}\Delta_i^2}{N+1}$ for i = 1,2,3,……..,N, where
$\Delta_i = \{T_i - R_i \;\; for \; T_i > R_i \; ; 0 \; otherwise\}$, N represents the total number of months, T_i is the target rate (Eurodollar rate) for month i and R_i is the return for a fund in month i.
NP: Percentage of months with positive returns
SR: Sharpe ratio

Table III. Various asset classes and the corresponding indices used for Mean-Variance Analysis, Asset Class Factor Model and Generalized Style Analysis

Asset Class	Indices
Equity	S&P 500 Composite Index
Equity	MSCI World Equity Index excluding US*
Equity	MSCI Emerging Markets Index
Bond	Salomon Brothers World Government Bond Index
Bond	Salomon Brothers Government & Corporate Bond Index
Bond	Lehman High Yield Composite Index
Currency	Federal Reserve Bank Trade-Weighted Dollar Index#
Commodity	UK Market Price Index for Gold

Source: Datastream

* Morgan Stanley Capital International (M.S.C.I.) World Equity index excludes the US and the emerging markets.

The Federal Reserve Bank Trade-Weighted Dollar index is calculated by weighting each country's dollar exchange rate by that country's share of total U.S. trade (exports plus imports).

Table IV. Means, Standard Deviations and Correlation Coefficients for the eight indices

The following table reports the means, the standard deviations and the correlation coefficients for the eight indices: S&P 500 composite index, MSCI world index excluding US, MSCI emerging markets index, Salomon Brothers government and corporate bond index, Salomon Brothers world government bond index, Lehman high yield composite index, Federal Reserve Bank trade-weighted dollar index and UK market price index for gold during January 1994 to September 1998. The figures in the parentheses indicate p-values. All the correlation coefficients greater than 0.5 in magnitude are expressed in bold face. Asterisk indicates that the correlation coefficients are significant at 5% level (one-tailed) while hash shows that they are significant at 10% level (one-tailed).

	Mean	SD	S&P 500 Composite Index	MSCI World Excluding US Index	MSCI Emerging Markets Index	Salomon Brothers Govt. and Corporate Bond Index	Salomon Brothers World Govt. Bond Index	Lehman High Yield Composite Index	Federal Reserve Bank Trade-Weighted Dollar Index	UK Market Price Index for Gold
S&P 500 Composite Index	1.57	3.54	1.00	**0.66*** (0.00)	**0.55*** (0.00	0.39* (0.00)	-0.03 (0.41)	**0.73*** (0.00)	0.30* (0.01)	0.05 (0.34)
MSCI World Excluding US Index	0.54	3.84		1.00	**0.66*** (0.00)	0.02 (0.44)	0.08 (0.27)	**0.58*** (0.00)	-0.05 (0.37)	0.14 (0.15)
MSCI Emerging Markets Index	-0.85	6.62			1.00	0.00 (0.50)	-0.14 (0.16)	**0.51*** (0.00)	0.17# (0.10)	0.14 (0.15)
Salomon Brothers Govt. and Corporate Bond Index	0.64	1.72				1.00	0.46* (0.00)	0.46* (0.00)	0.09 (0.26)	0.18# (0.09)
Salomon Brothers World Govt. Bond Index	0.64	1.32					1.00	0.08 (0.28)	**-0.77*** (0.00)	0.18# (0.09)
Lehman High Yield Composite Index	-0.16	1.60						1.00	0.18# (0.09)	0.05 (0.35)
Federal Reserve Bank Trade-Weighted Dollar Index	0.00	2.13							1.00	-0.09 (0.24)
UK Market Price Index for Gold	-0.46	1.99								1.00

Table V. Correlation coefficients among the ten hedge fund strategies and the eight indices

This table shows the correlation coefficients between the different hedge fund strategies and the eight indices during January 1994 to September 1998. The ten hedge fund strategies are: Fixed Income Arbitrage, Event Driven, Equity Hedge, Restructuring, Event Arbitrage, Capital Structure Arbitrage, Macro, Long, Hedge (Long Bias) and Short. The eight indices are: S&P 500 composite index, MSCI world index excluding US, MSCI emerging markets index, Salomon Brothers government and corporate bond index, Salomon Brothers world government bond index, Lehman high yield composite index, Federal Reserve Bank trade-weighted dollar index and UK market price index for gold. The figures in the parentheses indicate p-values. All the correlation coefficients greater than 0.5 in magnitude are expressed in bold face. Asterisk indicates that the correlation coefficients are significant at 5% level (one-tailed) while hash shows that they are significant at 10% level (one-tailed).

	S&P 500 Composite Index	**MSCI World Excluding US Index**	**MSCI Emerging Markets Index**	**Salomon Brothers Govt. and Corporate Bond Index**	**Salomon Brothers World Govt. Bond Index**	**Lehman High Yield Composite Index**	**Federal Reserve Bank Trade-Weighted Dollar Index**	**UK Market Price Index for Gold**
Fixed Income Arbitrage	0.10 (0.24)	0.34* (0.01)	0.20# (0.07)	-0.41* (0.00)	-0.43* (0.00)	0.15 (0.14)	0.22* (0.05)	-0.10 (0.23)
Event Driven	**0.71*** (0.00)	**0.60*** (0.00)	**0.63*** (0.00)	0.06 (0.33)	-0.23* (0.05)	**0.66*** (0.00)	0.28* (0.02)	-0.07 (0.29)
Equity Hedge	**0.66*** (0.00)	**0.57*** (0.00)	**0.61*** (0.00)	0.07 (0.29)	-0.07 (0.31)	**0.58*** (0.00)	0.14 (0.15)	0.05 (0.35)
Restructuring	**0.67*** (0.00)	**0.66*** (0.00)	**0.62*** (0.00)	-0.03 (0.42)	-0.23* (0.04)	**0.71*** (0.00)	0.20# (0.07)	-0.07 (0.31)
Event Arbitrage	**0.56*** (0.00)	0.49* (0.00)	**0.59*** (0.00)	0.04 (0.38)	-0.11 (0.21)	**0.54*** (0.00)	0.08 (0.29)	-0.10 (0.22)
Capital Structure Arbitrage	**0.52*** (0.00)	0.43* (0.00)	0.42* (0.00)	0.16 (0.12)	-0.08 (0.28)	**0.64*** (0.00)	0.22* (0.05)	-0.05 (0.35)
Macro	**0.63*** (0.00)	0.42* (0.00)	**0.52*** (0.00)	0.41* (0.00)	-0.16 (0.11)	**0.51*** (0.00)	0.51* (0.00)	0.21# (0.06)
Long	**0.57*** (0.00)	**0.57*** (0.00)	**0.87*** (0.00)	-0.06 (0.34)	-0.32* (0.01)	**0.55*** (0.00)	0.32* (0.01)	0.02 (0.44)
Hedge (Long Bias)	**0.72*** (0.00)	**0.62*** (0.00)	**0.67*** (0.00)	0.06 (0.32)	-0.06 (0.34)	**0.61*** (0.00)	0.13 (0.17)	0.05 (0.35)
Short	**-0.63*** (0.00)	**-0.52*** (0.00)	**-0.61*** (0.00)	-0.11 (0.22)	0.00 (0.49)	**-0.61*** (0.00)	-0.07 (0.31)	0.00 (0.49)

Table VI. Analysis of abnormal returns using Asset Class Factor Model

This table shows the results for the following regression for January 1994 to September 1998: $R_t = \alpha + \sum_{k=1}^{K} b_k F_{kt} + u_t$ where R_t =Return on the HFR index for a particular strategy for period *t*, α = abnormal return, b_k =factor loading, F_{kt} =return on the kth asset class factor (or index) for period *t*, (k=1,.......,8) and u_t =error term. The ten hedge fund strategies are: Fixed Income Arbitrage, Event Driven, Equity Hedge, Restructuring, Event Arbitrage, Capital Structure Arbitrage, Macro, Long, Hedge (Long Bias) and Short. The eight indices are: S&P 500 composite index, MSCI world index excluding US, MSCI emerging markets index, Salomon Brothers government and corporate bond index, Salomon Brothers world government bond index, Lehman high yield composite index, Federal Reserve Bank trade-weighted dollar index and UK market price index for gold. Panel A shows the results for the stepwise regression, a technique which involves entering or removing variables depending on the significance of their F-values. The single best variable is chosen first; the initial variable is then paired with each of the other independent variables, one at a time, and a second variable is chosen, and so on. We note that the results are not sensitive to the order in which the variables are entered in the program. Same results are obtained after changing the order of different variables. For the sake of completeness, we also report results from general multivariate regression analysis in panel B that involves using all the explanatory variables together at the same time. Asterisk indicates that the values are significant at 5% level while hash shows that they are significant at 10% level.

Panel A

Strategy	α	S&P 500 Composite Index	MSCI World Excluding US Index	MSCI Emerging Markets Index	Salomon Brothers Govt. & Corporate Bond Index	Salomon Brothers World Govt. Bond Index	Lehman High Yield Composite Index	Federal Reserve Bank Trade-Weighted Dollar Index	UK Market Price Index for Gold	R^2
Fixed Income Arbitrage	0.81*		0.14*		-0.28*	-0.28*				0.38
Event Driven	0.76*	0.30*		0.11*						0.58
Equity Hedge	0.95*	0.30*		0.12*						0.52
Restructuring	1.12*	0.19*			-0.63*		0.71*			0.73
Event Arbitrage	1.09*			0.08*			0.26*			0.43
Capital Structure Arbitrage	0.83*						0.45*			0.41
Macro	0.53*	0.35*						0.44*	0.27*	0.56
Long	1.06*			0.52*		-0.62*	0.58*			0.83
Hedge (Long Bias)	0.65#	0.52*		0.22*						0.62
Short	1.25#	-0.69*		-0.34*						0.49

Table VI (contd.). Analysis of abnormal returns using Asset Class Factor Model

This table shows the results for the following regression for January 1994 to September 1998: $R_t = \alpha + \sum_{k=1}^{K} b_k F_{kt} + u_t$ where R_t =Return on the HFR index for a particular strategy for period *t*, α = abnormal return, b_k =factor loading, F_{kt} =return on the kth asset class factor (or index) for period *t*, (k=1,.......,8) and u_t =error term. The ten hedge fund strategies are: Fixed Income Arbitrage, Event Driven, Equity Hedge, Restructuring, Event Arbitrage, Capital Structure Arbitrage, Macro, Long, Hedge (Long Bias) and Short. The eight indices are: S&P 500 composite index, MSCI world index excluding US, MSCI emerging markets index, Salomon Brothers government and corporate bond index, Salomon Brothers world government bond index, Lehman high yield composite index, Federal Reserve Bank trade-weighted dollar index and UK market price index for gold. Panel A shows the results for the stepwise regression, a technique which involves entering or removing variables depending on the significance of their F-values. The single best variable is chosen first; the initial variable is then paired with each of the other independent variables, one at a time, and a second variable is chosen, and so on. We note that the results are not sensitive to the order in which the variables are entered in the program. Same results are obtained after changing the order of different variables. For the sake of completeness, we also report results from general multivariate regression analysis in panel B that involves using all the explanatory variables together at the same time. Asterisk indicates that the values are significant at 5% level while hash shows that they are significant at 10% level.

Panel B

Strategy	α	S&P 500 Composite Index	MSCI World Excluding US Index	MSCI Emerging Markets Index	Salomon Brothers Govt. & Corporate Bond Index	Salomon Brothers World Govt. Bond Index	Lehman High Yield Composite Index	Federal Reserve Bank Trade-Weighted Dollar Index	UK Market Price Index for Gold	R^2
Fixed Income Arbitrage	0.98*	-0.10	0.18*	-0.04	-0.34	-0.26	0.27#	0.05	-0.01	0.44
Event Driven	1.16*	0.23*	0.01	0.07#	-0.24	-0.22	0.47*	-0.08	-0.10	0.69
Equity Hedge	1.24*	0.31*	-0.05	0.10#	-0.48	0.12	0.37	-0.01	0.02	0.56
Restructuring	1.15*	0.12#	0.06	0.03	-0.24	-0.36#	0.60*	-0.21	-0.06	0.76
Event Arbitrage	1.02*	0.13#	-0.04	0.07*	0.06	-0.33	0.21	-0.30*	-0.10	0.54
Capital Structure Arbitrage	0.84*	0.03	-0.01	0.01	-0.24	0.14	0.44*	0.13	-0.03	0.46
Macro	0.44	0.11	0.11	0.10*	0.45	0.21	-0.09	0.62*	0.16	0.65
Long	1.10*	0.11	-0.14	0.54*	-0.45	-0.39	0.71*	0.03	-0.09	0.84
Hedge (Long Bias)	1.08#	0.61*	-0.14	0.19*	-0.99*	0.34	0.57#	0.00	0.03	0.68
Short	0.45	-0.74*	0.36	-0.32*	1.19	-0.35	-1.36*	0.30	0.17	0.58

Table VII. Summary Statistics of individual fund managers using different hedge fund strategies

This table shows the mean returns, standard deviations, downside deviations, medians, skewness, kurtosis, minimum and maximum realizations, proportion of positive realizations and Sharpe Ratios for the 167 fund managers using ten different strategies during April 1995 to September 1998. The Sharpe Ratio is calculated assuming a risk-free rate of 5% p.a.

Hedge fund strategy	P	Size	Mean	SD	DD	Median	Skewness	Kurtosis	Min.	Max.	NP	SR
Non-Directional												
Fixed Income Arbitrage	42	$0.59 bn	0.96	1.26	0.92	1.31	-2.62	9.93	-4.68	3.02	88	0.44
Event Driven	42	$0.36 bn	1.14	1.61	1.20	1.33	-3.50	17.78	-7.24	3.29	91	0.45
Equity Hedge	42	$0.27 bn	1.06	1.27	0.77	1.42	-1.64	6.17	-4.21	3.37	81	0.52
Restructuring	42	$0.18 bn	0.94	2.05	1.59	1.55	-2.89	12.18	-8.83	3.67	53	0.26
Event Arbitrage	42	$0.12 bn	1.11	0.97	0.60	1.22	-2.26	10.20	-3.36	2.65	95	0.72
Capital Structure Arbitrage	42	$0.10 bn	0.94	1.36	0.85	1.16	-1.12	1.81	-3.44	3.14	81	0.39
Average	**42**	**$0.27 bn**	**1.03**	**1.42**	**1.48**	**1.33**	**-2.34**	**9.68**	**-5.29**	**3.19**	**82**	**0.46**
Directional												
Macro	42	$1.48 bn	1.56	3.05	1.74	1.61	-0.49	0.29	-5.60	6.79	74	0.38
Long	42	$0.22 bn	-0.13	7.37	3.53	0.98	-1.55	2.93	-24.76	11.29	62	-0.07
Hedge (Long Bias)	42	$0.18 bn	1.48	3.29	6.27	2.17	-1.27	3.46	-10.85	6.54	71	0.33
Short	42	$0.05 bn	0.22	5.84	2.13	-0.59	1.24	2.42	-8.53	20.65	45	-0.03
Average	**42**	**$0.48 bn**	**0.78**	**4.89**	**3.42**	**1.04**	**-0.52**	**2.28**	**-12.44**	**11.32**	**63**	**0.15**

P: Number of funds in the HFR index

SD: Standard deviation

DD: Downside deviation defined as $\frac{\sum_{i=1}^{N} \Delta_i^2}{N+1}$ for i = 1,2,3,……..,N, where

$\Delta_i = \{T_i - R_i \;\; for\; T_i > R_i\; ; 0\; otherwise\}$, N represents the total number of months, T_i is the target rate (Eurodollar rate) for month i and R_i is the return for a fund in month i.

NP: Percentage of months with positive returns

SR: Sharpe ratio

Table VIII. Performance persistence results

The table below shows the results for both the parametric (regression-based) and non-parametric (contingency-table-based) methods after adjusting for the risk according to the different strategies pursued by 167 hedge fund managers from April 1995 to September 1998. The results are based on the persistence in the alphas and the appraisal ratios of the hedge fund managers. Alpha is defined as the return of the fund manager using a particular strategy minus the average return on all the funds using the same strategy while the Appraisal Ratio is defined as the alpha divided by the standard errors of the residuals from the regression of the fund return on the average return of all the funds following that strategy. The second column in panel A (panel B) reports the slope coefficients and their p-values resulting from regressing current alphas (appraisal ratios) on past alphas (appraisal ratios). Bold face indicates that the slope coefficient is significant at 5% level. For the contingency table, Winners and Losers are determined on the basis of comparison of alphas and appraisal ratios of individual fund managers to those of the median manager within each strategy in each quarter. WW and LL denote winners and losers in two consecutive quarters, LW denotes Losers in the first quarter and Winners in the second quarter and WL denotes the reverse of this order. Cross-product ratio (CPR) is defined as *(WW*LL)/(WL*LW)*. The log of the CPR is asymptotically normally distributed with mean zero and a standard error of $\sqrt[2]{\frac{1}{WW}+\frac{1}{WL}+\frac{1}{LW}+\frac{1}{LL}}$. The Z-statistic is defined as the CPR divided by its standard error. Bold face indicates that the CPR is significant at 5% level.

Panel A

Quarter	Coefficient	p-value	R^2	WWs	WLs	LWs	LLs	CPR	Z-statistic
Q1-Q2	**0.33**	0.00	0.11	43	38	38	48	1.43	1.15
Q2-Q3	**0.25**	0.00	0.08	49	32	32	54	**2.58**	2.98
Q3-Q4	-0.03	0.59	0.00	45	36	36	50	1.74	1.76
Q4-Q5	**0.17**	0.03	0.03	47	34	34	52	**2.11**	2.38
Q5-Q6	0.09	0.16	0.01	41	40	40	46	1.18	0.53
Q6-Q7	**0.43**	0.00	0.10	46	35	35	51	**1.92**	2.07
Q7-Q8	**0.22**	0.03	0.03	43	38	38	48	1.43	1.15
Q8-Q9	**-0.28**	0.00	0.08	39	42	42	44	0.97	-0.09
Q9-Q10	**0.43**	0.00	0.11	51	30	30	56	**3.17**	3.58
Q10-Q11	-0.07	0.25	0.01	43	38	38	48	1.43	1.15
Q11-Q12	-0.15	0.06	0.02	37	44	44	42	0.80	-0.71
Q12-Q13	**0.37**	0.00	0.18	39	42	42	44	0.97	-0.09
Q13-Q14	**0.52**	0.00	0.09	49	32	32	54	**2.58**	2.98
Total				572	481	481	637	**1.57**	5.25

Panel B

Quarter	Coefficient	p-value	R^2	WWs	WLs	LWs	LLs	CPR	Z-statistic
Q1-Q2	**0.30**	0.00	0.09	46	35	35	51	**1.92**	2.07
Q2-Q3	**0.31**	0.00	0.13	48	33	33	53	**2.34**	2.68
Q3-Q4	**0.17**	0.03	0.03	43	38	38	48	1.43	1.15
Q4-Q5	**0.34**	0.00	0.12	47	34	34	52	**2.11**	2.38
Q5-Q6	0.08	0.17	0.01	40	41	41	45	1.07	0.22
Q6-Q7	**0.37**	0.00	0.11	47	34	34	52	**2.11**	2.38
Q7-Q8	**0.21**	0.03	0.03	45	36	36	50	1.74	1.76
Q8-Q9	-0.03	0.69	0.00	39	42	42	44	0.97	-0.09
Q9-Q10	**0.55**	0.00	0.19	50	31	31	55	**2.86**	3.28
Q10-Q11	-0.10	0.14	0.01	39	42	42	44	0.97	-0.09
Q11-Q12	**-0.20**	0.01	0.05	36	45	44	41	0.73	-1.02
Q12-Q13	0.04	0.58	0.00	37	44	44	42	0.80	-0.71
Q13-Q14	**1.08**	0.00	0.25	52	29	29	57	**3.52**	3.87
Total				569	484	484	634	**1.54**	5.00

Figure 1: Efficient Frontiers using hedge fund strategies & passive investment strategies

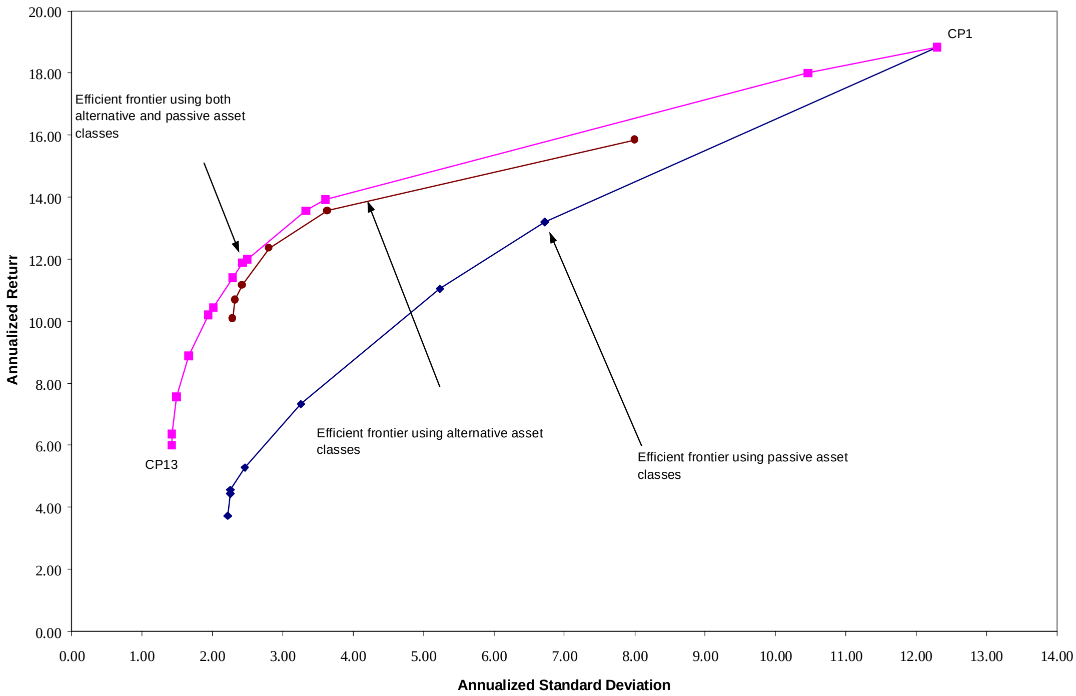
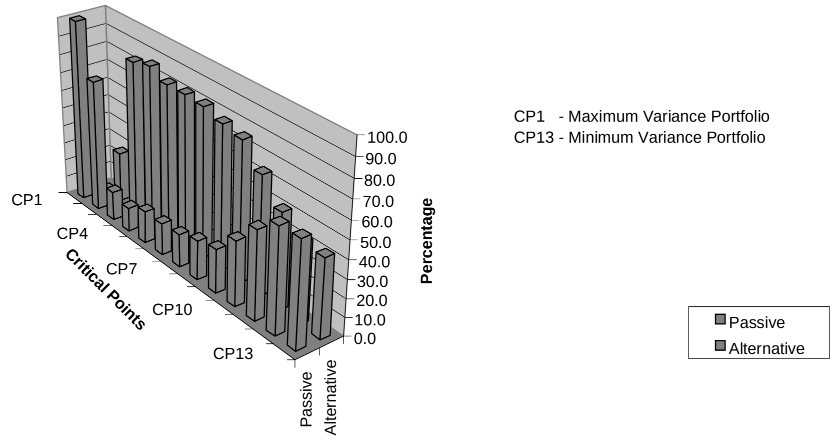
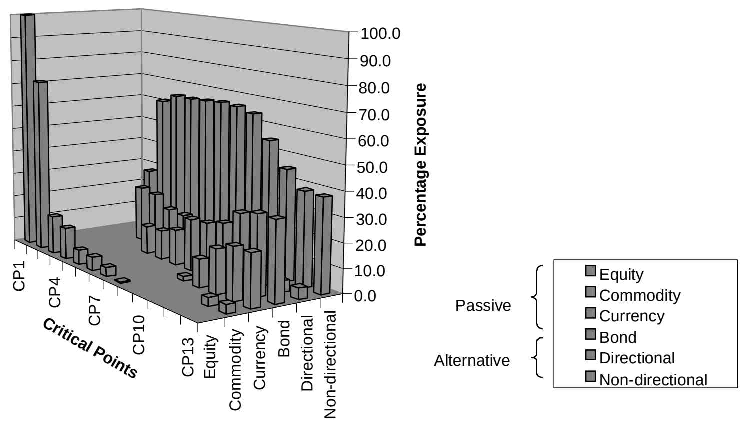


Figure 2: Proportions of Alternative and Passive investment strategies along the efficient frontier



	CP1	CP2	CP3	CP4	CP5	CP6	CP7	CP8	CP9	CP10	CP11	CP12	CP13
Passive	100.0	72.3	15.8	13.1	17.6	17.5	18.2	21.6	23.8	35.5	48.2	57.0	57.4
Alternative	0.0	27.7	84.2	86.9	82.4	82.5	81.8	78.4	76.2	64.5	51.8	43.0	42.6
Mean	18.84	18.00	13.92	13.56	12.00	11.88	11.40	10.44	10.20	8.88	7.56	6.36	6.24
Std. Dev.	12.30	10.46	3.60	3.33	2.49	2.43	2.29	2.01	1.94	1.66	1.49	1.42	1.42

Figure 3: Composition of Alternative and Passive investment strategies along the efficient frontier



	CP1	CP2	CP3	CP4	CP5	CP6	CP7	CP8	CP9	CP10	CP11	CP12	CP13
Equity	100.0	72.3	15.8	13.1	6.0	5.5	3.7	0.4					
Commodity												3.4	3.6
Currency									1.9	11.4	17.9	21.3	21.4
Bond					11.6	12.0	14.5	21.2	21.9	24.1	30.3	32.3	32.4
Directional			23.1	22.2	17.7	17.2	15.9	12.8	12.2	9.7	6.7	4.6	4.5
Non-directional		27.7	61.1	64.7	64.7	65.3	65.9	65.6	64.0	54.8	45.1	38.4	38.1