RISK MEASUREMENT FOR HEDGE FUND PORTFOLIOS

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Abstract

The purpose of this paper is to explore method to better quantify the risks associated with investing in hedge fund portfolios (a "fund of hedge funds"). More specifically, we measure the systematic and idiosyncratic risk of a sample hedge fund portfolio using eight different managers who invest across eight different trading styles/strategies. We employ two different measurement techniques, including Multivariate Regression analysis and Monte Carlo Value-at-Risk (VaR) to account for the volatility of returns and tail event risk, respectively. The Multivariate Regression approach utilizes a two-step process first suggested by Dor, Jagannathan, and Meier (2003). Our findings suggest that this two-step approach works well for hedge fund managers who follow a consistent strategy through time. Using this two-step approach resulted in increasing the predictive power of the regression and capturing non-linearity associated with hedge fund manager returns. Further research is needed to confirm these results using a larger sample of managers. Furthermore, future research is needed to identify ways to deal with manager who switch strategies or invest in multiple industries and asset classes.

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1. Industry Background

The hedge fund industry has grown dramatically over the last 10 years and is fast approaching one trillion dollars in assets under management (see Figure 1-1). This growth has been driven by the attractive risk-adjusted performance achieved by hedge funds as well as their ability to protect capital in negative equity markets as shown in Figure 1-2. Institutional investors have taken notice of hedge funds and are beginning to allocate significant amounts of capital to these investment vehicles. Several large institutions have received significant press lately for their planned investments into hedge funds. The California Public Employees' Retirement System, CalPERS, for example has committed to invest one billion dollars to hedge funds. Additionally, the $24 billion Pennsylvania State Employee's Retirement System is planning to allocate $2.5 billion or roughly 10% of its total portfolio to hedge funds.

The nature of the industry however, makes hedge fund investing difficult. First, many hedge fund strategies are complex and challenging to evaluate. Hedge fund managers, unlike mutual fund managers, have no rules or regulations limiting how or in what financial instruments they can invest. Secondly, because hedge funds are not required to register with the Securities and Exchange Commission (SEC), they cannot advertise or market their funds, which makes finding good hedge fund managers a challenging task. Third, because the industry is unregulated, many hedge fund managers are not required (and are very reluctant) to disclose details about their underlying investments and/or investment process. Managers believe that information about their trading strategies and underlying investment positions is highly proprietary and disclosure might compromise their financial returns.

As the industry becomes more institutionalized, hedge fund managers will face increased pressure to provide investors with better transparency to facilitate risk management. In fact, several recently performed surveys by Capital Market Risk Advisors, the Investor Risk Committee, and the Hennessee Hedge Fund Advisory Group indicate that hedge fund managers are growing aware of the importance of risk management practices (Jaeger, 2001). Institutional fiduciaries need to be able to explain investment decisions to their boards and comply with ERISA's prudent man rule both of which require understanding hedge fund strategies. This trend coupled with the highly publicized hedge fund failures (e.g., 'Long Term Capital Management', 'Manhattan', 'Granite and Lipper') have prompted strong reactions from many investors. Investors are beginning to demand more transparency and more sophisticated risk management systems. According to a survey conducted in May 2001 by *Investments & Pensions*, respondents believe that (i) lack of transparency and (ii) risk control are the two biggest issues facing the industry (Rahl, 2003). Although a gap still remains between managers and investors on the issue of transparency, it is clear that the events above have triggered an increased industry-wide focus on risk management.

2. Introduction

Risk Management is the science and art of understanding the nature of risks and managing portfolio exposures to provide expected return consistent with the risks taken. The goal of risk management is to minimize uncompensated and inappropriate risks. The process of risk management includes (i) identifying, (ii) measuring, and (iii) managing risk. A systematic process for identifying and measuring risks is necessary for effective risk control. Once potential risks have been identified, they can either be accepted, transferred, eliminated, or controlled (Jaffer, 2002).

Given the wide variety of hedge fund strategies, hedge fund managers and investors are exposed to many kinds of risk including market risk, interest rate risk, liquidity risk, credit risk, counterparty risk, fraud risk, etc. Within the context of a hedge fund portfolio, risk can be viewed from a pre and post-investment perspective. For example, pre-investment risk relates to the risks in properly selecting the managers (e.g., thorough quantitative and qualitative evaluation) and/or strategies that help meet fund objectives, and post-investment risk vis-à-vis risk monitoring to track both manager and portfolio level exposures (Jaeger, 2001). The scope of this paper is centered on the latter of these two that is, post-investment risk. More specifically, we focus on how a fund of funds manager might measure the risk of his/her portfolio.

The purpose of this paper is to explore and compare different ways of measuring risks associated with hedge fund portfolios. Challenges to measure risks that are particular to hedge funds include: 1) the relatively short time series of returns available from hedge fund managers, 2) the breath of investing strategies used by hedge fund managers, and 3) the non-linearity in returns exhibited by some hedge funds. This paper attempts to address these hedge fund specific challenges to measure risks.

Modern Portfolio Theory (MPT) suggests that the true measure of investor risk is the expected standard deviation on an investment portfolio. This risk can be further sub-divided into both “Market” and “Manager” related risks as shown in Equation (1):

$$\sigma_P^2 = \sigma_S^2 + \sigma_I^2 \quad (1)$$

where σ_p^2 = Portfolio risk, σ_S^2 = Systemic risk (or “Market” risk), and σ_I^2 = Idiosyncratic risk (or “Manager” risk)

However, traditional measures like ‘standard deviation’ are not always sufficient within the context of hedge funds. Many hedge fund strategies are dynamic and display option-like payoffs (Fung and Hsieh, 1997a), which can violate the normality and linearity assumptions of MPT. As such, we complement our volatility measure of risk with a technique known as Value-at-Risk (VaR). VaR measures the maximum loss one might expect from an adverse move within a specified confidence interval (over a given time period). In other words, VaR can provide some additional information about the risk in the extreme tails of a distribution, which would not be reflected in a standard deviation measure.

The remainder of the paper is organized in four sections: in section 3, we present an overview of the current academic literature. Section 4 provides the methodology of our study while section 5 provides the results. Section 6 concludes the paper by discussing the implications of our findings, addressing the limitations of our approach, and proposing areas for further research.

3. Literature Review

There are a considerable number of academic papers researching (and advocating) the integrity and persistence of hedge fund returns (Agarwal and Naik (2000), Fung and Hsieh (1997), Schneeweis (1998), Agarwal and Naik (1999), etc.) Others argue that the impressive risk-adjusted returns achieved by hedge funds in the 1990's should be viewed with skepticism because of measurement biases. Asness, Krail, and Liew (2001) and Getmansky, Lo, & Makarov (2003), for example, have cast doubt over the integrity of standard estimates of hedge fund betas (and alphas) due to stale pricing, or return smoothing (Barry, April 2002). Fung and Hsieh (1997) argue that even if one were to obtain 'holdings data' for hedge funds on a monthly basis, it would not provide a good picture of a hedge fund's risk due to the dynamic nature of their trading strategies. Agarwal and Naik (2001) highlight other biases resulting from the hedge fund return data such as the survivorship bias (resulting from non-inclusion of dead funds) and self-selection bias (resulting from the voluntary reporting by fund managers).

A majority of researches use some variation of the Jensen/Sharpe models to test hedge fund performance hypotheses. Jensen (1968) implemented an "innovative" technique, which regressed manager (i.e., mutual fund managers) returns on the market return and a risk free rate. This provided a means to decompose manager returns into manager "skill" and passive "market/style" components. Sharpe (1992) extended this single factor model to a multiple factor framework detailed in Equation (2) which provided good explanatory power in the case of mutual funds (i.e., buy and hold strategies). This decomposition into market/style (i.e., *asset class* mix) and skill (i.e., security selection) serves two purposes. First, for each manager, an investor can verify the source of the manager's performance and distinguish between performances based on security selection verses *asset class* mix. Second, for the portfolio, an investor can allocate investments across managers to achieve style (i.e., *asset class*) diversification (Fung and Hsieh, 1998).

$$R_t = \alpha + \sum_{i=1}^{N} \beta_{ij} F_{i,t} + \varepsilon_i \quad (2)$$

where $F_{i,t}$ is the risk factor, α and $\beta_{ij}^{'s}$ represent the intercept and slope coefficients, respectively, and the $\varepsilon^{'s}{}_i$ are the residuals.

The $\{ \sum_{i=1}^{N} \beta_{ij} F_{i,t} + \varepsilon_i \}$ term captures the "style" component or *asset class* mix, while the $\{ \alpha + \varepsilon'^{s}{}_i \}$ captures the "skill" of the manager.

Many academics question the value of return-based style analysis (i.e., the Sharpe (1992) model) for measuring hedge fund risk and performance. Dor, Jagannathan, and Meier (2003) state that return-based style analysis using traditional *asset class*es is unsuitable for determining the effective style of hedge funds due to their low correlations with returns on traditional *asset class*es. Fung and Hsieh (1998) argue that the Sharpe (1992) model does not extend to hedge fund managers who employ dynamic trading strategies (e.g., security shorting, actively moving money around, and use of derivatives). However, they do propose an extension to Sharpe's (1992) *asset class* factor model to allow a uniform treatment of buy-and-hold strategies, as well as dynamic trading strategies. Specifically, they include 'directional exposure', and 'leverage' as additional regression factors and are able to achieve R^2's of 85% for mutual funds and close to 40% for hedge funds.

Another significant area of the research is focused on the limitations of measuring hedge fund performance given the likely violation of the normality assumption. Brooks and Kat (2001) found that hedge fund index returns are not normally distributed. Many hedge fund indexes exhibit relatively low skewness and high kurtosis (especially in the case of funds investing in convertible arbitrage, risk arbitrage, and distressed securities). Brooks and Kat argue that in effect investors receive a better mean and a lower variance in return for more negative skewness and higher kurtosis. In other words, while some hedge funds may exhibit low standard deviations, this does not necessarily imply that they are less risky.

Others are working to overcome the non-normality issue, by adding option like variables which can account for this non-linearity effect. Glosten and Jagannathan (1994) suggested augmenting the return on style benchmark indexes with returns on selected options of the style benchmark indexes in order to capture the investment style of portfolio managers who employ dynamic trading strategies. More recently, Agarwal and Naik (2002) extend Fung and Hsieh's (1997a) dynamic *asset class* factor model to both option-based strategies and buy-and-hold strategies and found that the option-based factors significantly enhance the power of explaining hedge fund returns (see Fung and Hsieh (2001) and Mitchell and Pulvino (2001) for additional support).

Although many researchers criticize the Jensen/Sharpe models applied to hedge fund analysis (because of the previously mentioned weaknesses), a strong majority continue to use some form of these models in their work. In this paper, we build on the current literature and utilize multilinear regressions coupled with: 1) a two-step approach recently suggested by Dor, Jagannathan, and Meier (2003), 2) lags in *asset class* factors to account for possible stale price effect, and 3) option-like functions to capture the non-linearity in returns, to map hedge fund manager returns to *asset class* factors. Lastly, we perform Value-at-Risk analyses to help capture the risk caused from low probability but high consequence events.

4. Methodology Overview

Three different approaches to measure the risk of a sample hedge fund portfolio were used including 1) multivariate regression on manager returns (Method I), 2) VaR based on manager's return statistical models (Method II), and 3) VaR based on portfolio exposure (Method III). Our sample hedge fund portfolio includes eight different hedge fund managers who have on average a five year track record and represent eight different hedge fund styles (or strategies). Table 4-1 (and the Appendix) provides summary statistical data for the sample of hedge fund managers and their corresponding HFR index styles. Additionally, index information was gathered for a variety of investment sectors and styles (Table 4-2) as well as the Hedge Fund Research (HFR) indexes to serve as dependent variables in our regressions (See Table 4-3 for more descriptions on the HFR indexes strategies). Lastly, monthly return information summarized in Table 4-4 was assembled for a broad range of traditional *asset class*es such as equities, bonds, market volatility, credit spreads, etc. (currency and commodities were omitted because none of the eight managers invest in these *asset class*es). Our overall sample period for the manager returns, various indexes, and *asset class*es varied from 11-126 months, 160 months, and 160 months, respectively.

Method I – Two-step Multivariate Regression on Manager Returns

To circumvent the problems associated with the relative short return time series available for many hedge fund managers and the resulting poor regression explanatory power, Dor, Jagannathan, and Meier (2003) suggested a two-step multivariate regression approach for analyzing hedge fund performance using a return-based style analysis. The first step includes augmenting the traditional sector and strategy indexes with the manager specific HFR strategy indexes (as shown in Table 4-2). (Note: we refer to the dependent variables used in Step 1 as the *Risk Factors* as opposed to the dependent variables used in Step 2 which are referred to as *Asset Classes*.) For example, we added the HFRI Convertible Arbitrage index as a *risk factor* when analyzing the convertible arbitrage manager in the portfolio. An advantage of adding the HFR Indexes is that they potentially capture the non-linearity in return exhibited by hedge funds (Dor, Jagannathan, and Meier, 2003) and reported in the literature by Mitchell and Pulvino (2001), and Agarwal and Naik (2002), among others. This gives us an expanded set of dependent variables, F_{ij}, for our regression as shown in Equation (3) below:

(3) Step 1: $$r_{mi} = \alpha_i + \sum_j \beta_{ij} F_{ij} + \varepsilon_i$$

(4) Step 2: $$\sum_j \beta_{ij} F_{ij} = \alpha_i' + \sum_k \gamma_{ik} H_{ik} + \varepsilon_i'$$

(5) $$R_{mi} = (\alpha_i + \alpha_i') + \sum_k \gamma_{ik} H_{ik} + (\varepsilon_i + \varepsilon_i')$$

where α's are the regression intercepts; β's and γ's are the regression coefficients on the risk factors, F, and asset class factors, H, respectively. The residuals are represented by the vectors, ε.

In Step 2, we aggregate the ("significant") beta-weighted factors from Step 1 and use it as our new dependent 'variable'. We use this new dependent 'variable' as a proxy for a 'longer-term' manager return stream. To capture the potential non-linearity inherent to hedge fund returns (e.g., Mitchell and Pulvino, 2001 and Fung anf Hsieh, 2001), we augment the traditional *asset class* factors with a collection of option-like functions on those related *asset class*es. These option-like functions are defined using the MIN and MAX functions: a) the call-like function is equal to the maximum of the asset class return minus the standard deviation of the asset class and zero; b) symmetrically, the short put-like function is the minimum of the asset class return plus the standard deviation of the asset class and zero. The choice of one standard deviation as a cut off value is arbitrary. A more accurate procedure would be to run a non-linear optimization to find the cut off value resulting in the best fit (i.e., maximum likelihood). Examples of these option-like functions are shown in Figure 4-1.

Finally, we regress the weighted factors from Step 1 (dependent variable) on the expanded set of *asset class* factors which includes the relevant option-like non-linear functions (represented above by R_{mi}) using historical data from January 1986 to April 2003 (Table 4-4). The length of the historical data available from the *asset class* monthly return time series is more than five times larger than for manager returns (e.g., 174 months vs. 29 months for manager SWIFT). The availability of longer time series increases the probability of encompassing tail events that play an important role in capturing the non-linearity effect and ultimately the total value at risk in the portfolio.

The results from Steps 1 & 2 are then combined and aggregated across all eight hedge fund managers (as shown in Equation 5). These results allow us to derive the portfolio variation for our sample hedge fund portfolio (See section 5 for more details).

Method II – VaR based on manager's return statistical models

We use Monte Carlo simulations to generate the return distribution for the portfolio based on the statistical regression models developed from Equation (5) for each manager. Sampling from each manager's historical return distribution could be done using either (i) the historical histogram or by (ii) smoothing the historical histograms into probability distribution functions. We used the software @Risk™ to develop probability density function for each basic *asset class* factor using monthly data from January 1986 to April 2003. Most *asset class* factors have a good statistical fit using the LogNormal, Logistic, Weibull, or Generalize Beta distributions. To fit the return of the option-like non-linear functions, we choose the triangular distribution fitted on the mode of the histogram. Normal distributions with zero mean presents the best fit to the residual vectors.

Monte Carlo simulations coupled with the Latin Hypercube sampling technique was used to generate the portfolio return distributions. Latin Hypercube is a stratified sampling technique that captures the tail of the distribution and minimizes the number of iterations to reach the convergence criteria. The correlation matrices between the basic *asset class* factors and the residual vectors were used to generate appropriate sampling sequences. The convergence coefficient was defined as being less than one percent change between iterations in the mean and standard deviation of the output distribution (e.g., portfolio return).

Note that additional approaches to risk measurement such as stress testing, scenario analysis, and sensitivity analysis of input variables are not discussed in this paper, but can easily be implemented using the framework developed in the paper.

Method III – VaR based on portfolio exposure

Method III used the current portfolio *asset class* exposures as of April 2003 shown in Table 4-5a. For each of the eight managers, we calculate gross exposure on the long and short side of equity, distressed, high yield, and the convertible bond asset classes. The weight (by dollar invested) for each manager in the portfolio is also presented. Combining all the managers, we are able to compute the portfolio net exposures to the basic *asset class* factors: equity, high yield, distress, and convertible bonds. Based on the portfolio exposure summarized in Table 4-5b and the return distribution for each basic *asset class*es (the MLHY index was used for both high yield and distress), we performed simulations to compute the portfolio return distribution. Notice that Method III does not take into account idiosyncratic risks. As an aside, the portfolio systematic risk could also be computed analytically following the methodology presented in Method I assuming no correlation between the *asset class*es or by adding the covariance terms to take into account the correlation. The simulation technique is, however, necessary to compute the VaR and capture the tail of the distribution.

5. Results

This section presents the results of the three proposed methods to evaluate hedge fund portfolio risks, including systematic and idiosyncratic risks as well as the maximum loss for a given probabilities (VaR).

Method I – Two-Step Multivariate Regression on Manager Returns

Step I Regression Model - Results

The results of Step 1 regressions are summarized in Tables 5-1 for the eight managers considered in this study. Different time periods of return were available for each manager as shown in Table 4-1. All the risk factors included in the models are statistically significant at 3 percent level (i.e., p-value less than 3%). Each regression was tested for normality of the residuals and heteroskedasticity using the Jarque-Bera non-normality and Breusch-Pagan heteroskedasticity tests. In the case where non-normality or heteroskedasticity arose, a robust regression based on the algorithm developed by Yohai and Zamar, 1998 was performed.

The coefficient of determination (R-square) for the model varies between 22 and 86 percent. The two managers (Swift and Bio) with R-square significantly less than 50 percent tend to either follow different strategies over time (Bio) or invest in several different industries (Swift). To improve the explanatory power of the regression model, we use sector and strategy specific indexes (e.g., Amex Disk Drive and Russell 1000 Growth). These indexes significantly improve the regression model for two managers, referred to as INT and NOVA in Table 5-1. Comparing Table 5-1 and 5-2, HFRI Indexes significantly improve the regression model for five managers. When an HFRI Index was statistically significant but did not add to the explanatory power of the regression (i.e., lower adjusted R-square), it was kept in the regression model because of the potential non-linearity embedded in the index.

Lag indexes (i.e., 1 and 2-month lags) for each significant risk factor index were then introduced to test for the possibility of "stale price" as described by Asness, Krail, and Liew, 2001. We found that the one-month lag on the Merrill Lynch Yield Index (MLHY Index) was statically significant for two managers, referred to as QUAD and FOUR (Table 5-1). In the case of manager FOUR, the MLHY one-month lag index effectively doubles the regression coefficient with respect to the Merrill Lynch High Yield index from -0.17 to -0.33. Table 5-3 illustrates the effect of introducing the lag index on R-Square. R-Square increases from 40 to 63 percent. Note that the p-value for the lag variable is zero percent showing the significance of this variable. We found that the lag variables are statically significant for managers who trade illiquid securities such as distressed bonds and convertible bonds. This result corroborates the hypothesis advanced by Asness et al., 2001, who attributed the presence of lag variable to "stale price" reported by fund managers trading in illiquid securities.

Step II Regression Model – Results

Results from Step II regressions are presented in Table 5-4. The reported R-squares vary between 4 and 95 percent. Four of the regressions have R-square greater than 60 percent. Four of the manager returns show a statistically significant correlation with basic *asset class*-derived nonlinear functions.

Figure 5-1 shows the non-linearity in return for the HFR Financial Index, where the HFRI Financial index monthly return is plotted versus the Russell 1000 Value (R1000V) monthly return for the periods from January 1992 to April 2003. Between -5% to +10% monthly returns on the Russell 1000V, the return on the HFRI Financial Index is linearly correlated with a slope of approximately 0.8. This slope, however, increase to about 1.2 in the -5% to -15% R1000V monthly return range. Table 5-5 illustrates the importance of using the two-step regression approach to pick up the non-linear functions as first advocated by Dor, Jagannathan, and Meier, 2003. In Step 1, manager NOVA monthly returns were regressed against the sector and strategy indexes including the HFR Financial Index and the Russell Mid-cap Value Index (RMVI). In Step 2, the weighted Index from Step 1 was regressed against the Russell 1000 Value Index and a non-linear function similar in form to a short put on the R1000V Index. Using the two-step regression approach the p-value for the regression coefficient on the non-linear function is one percent (i.e., statistically significant). Using the direct approach, regressing the manager return directly against the R1000V index and non-linear function, yields a p-value of 47.8%. Following the direct method would lead to dismiss the non-linear function as insignificant. The difference in result between the direct and two-step approaches is largely a result of the difference in the availability of historical data. The longer time series available for the traditional *asset class*es allows an increased likelihood of capturing tail events and eventually the non-linearity associated with such tail events. As previously mentioned, this non-linearity phenomenon has been investigated by some researchers (Mitchell and Pulvino, 2001) for certain well defined trading strategies such as merger arbitrage. However, this effect has not yet been clearly identified for most of the other trading strategies and may warrant further research.

Stationarity of the regression model

The stationary and stability of the regression models was tested by eliminating the last twelve and twenty four months of data and re-running the regressions. The results, presented in Table 5-1 and 5-4, indicate that all manager returns can be explained by a stable set of market risk factors through time. This method represents only a rough method to test for stationary as there may be other sub-periods exhibiting large variability.

Portfolio Construction

The portfolio return model was built by aggregating regression models from Steps 1 and 2 as mentioned in the Method's section. The weighting factors assigned to each manager return correspond to the proportion of the portfolio fund invested within each manager. Based on the expected monthly return regression equations developed for each manager (Equations 5), the expected portfolio monthly return would be written as:

(6) $$r_p = \sum_i \lambda_i(\alpha_i + \alpha_i^{'}) + \sum_i \lambda_i \sum_k \gamma_{ik} H_{ik} + \sum_i \lambda_i(\varepsilon_i + \varepsilon_i^{'})$$

where λ_i is the weight of each manager in the portfolio.

To draw conclusions about diversification and the proportion of systematic and idiosyncratic risks in the portfolio, we analyze the correlation structure between the residual vectors (ε and ε') for all managers. Table 5-6 & 5-7 and Figure 5-2 & 5-3 presents the Principal Component Analysis (PCA) matrices and the PCA circle plots for Step I and Step II regression, respectively. The correlation matrices show low correlation between the residual with only one correlation out of the forty eight pairwise correlations above thirty percent. Furthermore, several of the correlations are negative, which increase the diversification effect of the idiosyncratic risk. The PCA analyses reveal that the first two components accounts for about twenty eight percent of the variability. Ideally, these components would need to be extracted from the residuals and used as dependent variables in the Step 1 and 2 regressions. The lack of direct interpretation for these principle component factors represents, however, a limitation in interpreting the results of the risk analysis. Consequently, given the relatively small weights of these principle components and the results from simulations presented as part of Method II, we decided not to extract the principle components from the residual matrices.

Portfolio Systematic and Idiosyncratic Risks

Based on the portfolio return statistical model presented in Equation (6) and assuming that the residuals between managers are not correlated and the *asset class* factors also are not correlated between each others, the variance of the portfolio may be calculated as follow:

$$(7) \qquad \sigma_p^2 = \sum_i \sum_k \gamma_{ik}^2 \sigma_{Hik}^2 + \sum_i (\sigma_{\varepsilon_i}^2 + \sigma_{\varepsilon_i'}^2)$$

where σ_{Hik} is the historical variance of the market *asset class* indexes; and
σ_ε is the variance of the residual from Step I and II regression.

We computed the equally-weighted portfolio standard deviations for two cases. In the first case, the non-linear components of the return for each manager were "turned off". The resulting portfolio return is referred to as the "linear portfolio". In the second case, the non-linear components of the return for each manager were "turn on". In this latter case, the portfolio return is referred to as the "non-linear portfolio". Table 5-8 summarizes the results of the portfolio standard deviation split between systematic and idiosyncratic risk. For both scenarios, market risk represents about 30% of the portfolio risk, while idiosyncratic risk represents about 70% of the portfolio risk. The effect of the non-linear function is relatively small. This result may be explained by the fact that the non-linear functions affect mainly the tails of the return distribution. Consequently, we would expect the non-linear functions to have a greater impact on the value-at-risk analysis of the portfolio.

Method II - Value at Risk (VaR) based on Manager Return's Statistical Model

As for Method I, we ran two simulations to investigate the effect of the non-linear components: 1) "turning off" the non-linear components of manager's returns (linear portfolio); and 2) "turning on" the non-linear components of manager's returns (non-linear portfolio). The probability distribution functions for the linear and non-linear portfolio are presented in Figure 5-4. The effect of the non-linear functions is to thicken the left and right tails of the portfolio monthly return distribution. This is best illustrated in Table 5-9, where the 0.25, 1, 5, 10, 90, 95, 99, and 99.75 percentiles returns are reported for both the linear and non-linear portfolio. The non-linear effect is most pronounced in the tail ends of the distribution. The differences in return between the linear and non-linear portfolios are -0.3% and 0% at the 10 and 90 percentile, respectively. These differences increase to about -4% and +2% at the 0.25 and 99.75 percentile, respectively. Note that in this particular case, the non-linear function increase both the downside and upside return of the portfolio. For risk management, these non-linear effects are important as they account for a significant increase in the maximum loss under low probability events.

The simulation technique was also use to investigate the portfolio systematic and idiosyncratic risks. The advantage of using simulations is to account for the linear correlation between the different variables. Table 5-10 summarizes the results of the portfolio standard deviation split between systematic and idiosyncratic risk. By taking into account the residual correlation matrix, the standard deviation of the residual dropped from 3.3% (Table 5-8) to 1.04% (Table 5-10). Furthermore, market risk represents about 90% of the portfolio risk, while idiosyncratic risk represents only 10% of the portfolio risk. This result is significantly different from the results from Method I. From a risk management stand point, this is a significant result because based on finance theory, investors get compensated for systematic risk only as they theoretically could diversify the idiosyncratic risk away. Finally, similar to what we found with Method I, the effect of the non-linear function on the standard deviation is relatively small.

Method III - Value at Risk (VaR) based on Portfolio Exposure

Based on the current portfolio *asset class* exposures as of April 2003 shown in Table 4-5a, we used the probability density functions fitted on historical histogram for each *asset class* factor (see Section 4) to perform Monte Carlo simulations. The results of the simulations are presented in Table 5-11. The portfolio systematic risk monthly standard deviation is 0.82%. The reported 5 and 1 percentile are -1.02% and -2.8%, respectively.

6. Discussion and Future Research

Comparison of Method I, II, and III

Table 6-1 summarizes the results for the three methods using the portfolio weights and exposures presented in Table 4-5a and Table 4-5b. We re-run the analyses using Method I and II with the portfolio weights for each manager presented in Table 4-5a. Compare to Method II, which we believe to be the most "accurate" method because it captures both the correlation between variables and manager specific return distributions, Method I and II seems to underestimate systematic risk. Standard deviation for systematic risk from Method II is 1.5% versus 0.8% and 1.1% for Method III and I, respectively. The VaR results between Method II and III are within 1% of each other, with Method III predicting a slightly larger loss.

Interestingly, the idiosyncratic risk standard deviation is greater with Method II (1.35%) than with Method I (1.28%). This apparently contradicts the result presented in Table 5-10b, where we found out that the idiosyncratic risk was significantly lower using Method II. The rational was that Method II takes into account the correlation structure of the residual matrix and negative correlations enhance diversification. In the present case, the manager's weights in the portfolio are not equal. In fact, closer inspection of the correlation matrix (Table 4-6 & 4-7) reveals that compare to the equally weighted portfolio used previously, the weight associated with manager's residual that are negatively correlated, are smaller than in the equally weighted portfolio. Hence, the change in portfolio weights affects diversification and is captured by Method II. Thus depending on the allocation breakdown among the managers, Method I may underestimate or overestimate the degree of diversification.

Method I does not provide any information about VaR. We saw that the non-linearity functions have an impact on the VaR but did not have much impact of the standard deviation. Consequently, Method I by itself may not be appropriate to manage risk associated with hedge funds. Method III does not capture the idiosyncratic risk in the portfolio, which may represent a substantial proportion of the portfolio total risk, and consequently can not be used alone to manage portfolio risks.

In summary, neither Method I nor Method III alone is sufficient to properly manage risks in hedge fund portfolio. Method II seems to be the most appropriate as it capture the essential components for risk management, namely: a) idiosyncratic and systematic risk and b) VaR, leaving open the possibility to perform stress tests, scenario analysis, and sensitivity analysis on important model variables. But as illustrated by results in Table 6-1, Method I and II together also provide an approximation to Method II and represent an alternative to using the more sophisticated and time consuming Method II.

Summary and Future Research

First, this paper presented and compared three different approaches to measure risks associated with hedge fund portfolios. Comparing the three methods, we highlighted the need to capture all the major portfolio risk components (i.e., systematic, idiosyncratic, and tail event risks) to develop a meaningful portfolio risk management practice. Omitting any of the risk components would provide an incomplete picture that may severely underestimate or overestimate the true risk associated with the portfolio.

Second, the paper offered practical solutions to overcome the main challenges associated with measuring risks for fund-of-hedge funds. This is also the area where future research on hedge fund portfolio risk management is most needed:

1. As first recommended by Dor, Jagannathan, and Meier (2003), we used a two-step multivariate regression approach to circumvent the problems associated with the relative short return time series available for many hedge fund managers and the resulting poor regression explanatory power. Our finding suggests that this two-step approach works well for hedge fund managers who follow a consistent strategy through time. Using the two step approach resulted in increasing the predictive power of the regression and capturing non-linearity associated with hedge fund manager returns. Future research is needed to confirm these results using a larger sample of managers. Furthermore, future research is needed to

identify ways to deal with manager who switch strategies or invest in multiple industries and asset classes.

2. We captured the non-linearity associated with hedge-fund manager's return by augmenting the basic *asset class* factors with option-like non-linear functions following procedure presented in Mitchell and Pulvino (2001) and Agarwal and Naik (2000). We found that only some of the manager exhibited non-linear returns. More research would be needed to identify whether this result is an artifact of our small sample or can be generalized. Similar to the work by Mitchell and Pulvino (2001) on merger arbitrage, future research is also needed to identify the underlying phenomenon leading to non-linearity in returns for most of the other trading strategies.

3. We fit the option-like historical histograms with triangular probability distribution functions to perform the Monte Carlo simulations. Thus, stratified samples were chosen assuming triangular distribution for the option-like functions. Performing sensitivity analyses, we found out that the tail of the portfolio return probability distribution function is very sensitive to the choice of distribution function used to fit the option-like functions. One solution is not to fit any distribution and use the historical histogram for sampling purpose. This solution is, however, not ideal because it assumes that historical histogram captures all states of nature. Future research would be needed to investigate the use of extreme value theories to develop better estimates of the distribution functions associated with the option-like non-linear functions.

4. The majority of academicians researching hedge funds rely heavily on Hedge Fund Index data for their analyses. In our study, however, we used actual manager monthly return data. Further research should be conducted to understand the trade-offs between using index versus manager level return data. Interestingly, when we back-tested the sample hedge fund portfolio using actual historical data, the annualized portfolio standard deviation results were in line with those derived using our three methodologies Additional testing using out-of-sample data is needed to confirm these results.

5. We used Monte Carlo Value-at-Risk (VaR) to simulate the behavior of the underlying risk factors through random draws for the returns of the underlying risk factors. VaR measures the maximum loss one might expect from an adverse move within a specified confidence interval (over a given time period). VaR can provide some additional information about the risk in the extreme tails of a distribution, which would not be reflected in a standard deviation measure. However, VaR also has several weaknesses including (i) it does not tell you anything about the expected size of the loss, (ii) relies heavily on many modeling assumptions. VaR is the subject of considerable research and alternative forms of VaR analysis should be considered for use with hedge funds (e.g., Continuous VaR, Incremental VaR, and Conditional VaR).

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TABLES

TABLE 4-1

Statistic	Int (1)	Swift (2)	Bio (3)	Par (4)	Nova (5)	Quad (6)	Abr (7)	Four (8)	Average
Monthly Returns	58	30	112	126	48	11	50	83	65
Average Return	2.3%	1.5%	1.8%	1.1%	1.8%	1.1%	1.3%	1.3%	1.5%
Sample Variance	0.13%	0.04%	0.44%	0.20%	0.19%	0.12%	0.12%	0.02%	0.2%
Sample Standard Deviation	3.6%	2.0%	6.7%	4.5%	4.4%	3.5%	3.4%	1.5%	3.7%
Annualized Standard Deviation	12.5%	7.0%	23.0%	15.6%	15.3%	12.0%	11.9%	5.1%	12.8%
Miniumum	-4.5%	-1.6%	-10.7%	-10.8%	-7.3%	-6.5%	-10.0%	-3.9%	-6.9%
Maximum	18.0%	5.2%	38.1%	20.3%	10.8%	5.7%	7.0%	5.9%	13.9%
Range	22.6%	6.7%	48.8%	31.0%	18.1%	12.1%	17.0%	9.8%	20.8%
Median	1.3%	1.4%	1.5%	1.0%	1.0%	2.2%	1.2%	1.3%	1.4%
Mode	0.9%	n/a	4.0%	3.2%	0.1%	n/.a	1.2%	0.9%	1.7%
Confidence Interval, 99% lower	1.02%	0.44%	0.15%	0.02%	0.07%	-2.23%	0.03%	0.92%	0.1%
Confidence Interval, 99% upper	3.54%	2.46%	3.44%	2.12%	3.48%	4.36%	2.63%	1.77%	3.0%
Skewness	176.9%	30.3%	212.7%	60.9%	16.9%	-99.8%	-112.6%	-38.7%	30.8%
Kurtosis	536.0%	-83.9%	934.6%	234.1%	-2.2%	103.4%	281.4%	238.9%	280.3%

CORRESPONDING HFR INDEX:

Statistic	HFR Technology Index	HFR Equity Hedge	HFR Biotechnology	HFR Short-seller	HFR Financial	HFR Distressed Index	HFR Event Index	HFR Convertible Index	Average
Monthly Returns	148	160	124	160	136	160	160	160	65
Average Return	1.6%	1.4%	1.5%	0.5%	1.6%	1.2%	1.1%	0.9%	1.2%
Sample Variance	0.3%	0.1%	0.5%	0.4%	0.1%	0.0%	0.0%	0.0%	0.2%
Sample Standard Deviation	5.9%	2.7%	7.0%	6.5%	3.5%	1.8%	2.0%	1.0%	3.8%
Annualized Standard Deviation	20.4%	9.3%	24.2%	22.5%	12.2%	6.3%	6.8%	3.4%	13.1%
Miniumum	-15.2%	-7.7%	-17.7%	-21.2%	-18.7%	-8.5%	-8.9%	-3.2%	-12.6%
Maximum	21.6%	10.9%	42.2%	22.8%	11.5%	7.1%	5.1%	3.3%	15.6%
Range	36.7%	18.5%	59.9%	44.1%	30.1%	15.6%	14.0%	6.5%	28.2%
Median	1.6%	1.4%	1.2%	0.1%	1.6%	1.1%	1.3%	1.1%	1.2%
Mode	6.7%	2.5%	4.0%	0.1%	-0.5%	2.8%	1.7%	1.4%	2.3%
Confidence Interval, 99% lower	0.4%	0.9%	-0.1%	-0.8%	0.8%	0.8%	0.7%	0.7%	0.4%
Confidence Interval, 99% upper	2.9%	2.0%	3.2%	1.8%	2.4%	1.5%	1.5%	1.1%	2.1%
Skewness	27.1%	17.4%	185.6%	7.1%	-136.4%	-64.8%	-135.1%	-132.9%	-29.0%
Kurtosis	135.8%	118.6%	959.8%	114.2%	747.5%	546.3%	468.8%	319.6%	426.3%

TABLE 4 -2: "RISK FACTOR" LEGEND (STEP 1 REGRESSION)

Index Name	Abbreviation
Amex Biotechnology Index	ABI
Amex Computer Technology Index	ACTI
Amex Disk Drive Index	ADDI
Amex Gold BUGS Index	AMEXG
Amex North American Telecommunications	ANAT
CBOE Technology Index	TXX
CSFB Distressed Bond Index	CSFBD
CSFB High Yield Index	CSFBHY
Default Risk - Change in Credit spread (Baa - AAA)	DR
Gold (Spot)	GOLD
Goldman Sachs Composite Index	GTC
Goldman Sachs Hardware Index	GHA
Goldman Sachs Internet Index	GIN
Goldman Sachs Semiconductor Index	GSM
Goldman Sachs Software Index	GSO
HFR Distressed	HFRD
HFRFixed Income: High Yield	HFRFI
HFR Convertible Arbitrage	HFRCA
HFR Event Driven	HFRED
HFR Equity Hedge	HFREH
HFR Biotechnology	HFRB
HFR Short-seller	HFRSS
HFR Technology	HFRT
Lehman Aggregate Bond Index	LABI
Lehman Credit Bond Index	LCBI
Lehman High Yield Credit Bond Index	LHYCI
Lehman Intermediate Credit Index	LICI
Market Volatility Index	VIX
Market Volatility Index (Monthly Change)	VIXC
ML High Yield master	MLHY
Nasdaq 100 Index	NAS100
Nasdaq Composite Index	NAS
Philadelphia Bank Index	PBI
Philadelphia Gold/Silver Index	PGSI
PHLX Semiconducter Index	PHLX
PSE Technology Index	PSE
Risk Free Rate - (change in 3 month Tbill rate)	RFR
Russell 1000 Growth Index (DRI)	R1000G
Russell 1000 Index (DRI)	R1000
Russell 1000 Value Index (DRI)	R1000V
Russell 2000 Growth Index (DRI)	R2000G
Russell 2000 Index (PerTrac Indexes)	R2000
Russell 2000 Value Index (DRI)	R2000V
Russell 2500 Growth Index (DRI)	R2500G
Russell 2500 Index (DRI)	R2500
Russell 2500 Value Index (DRI)	R2500V
Russell 3000 Growth Index (DRI)	R3000G
Russell 3000 Index (DRI)	R3000
Russell 3000 Value Index (DRI)	R3000V
Russell Midcap Index (DRI)	RMI
Russell Midcap Value Index (DRI)	RMVI
Russell Top 200 Growth Index (DRI)	R200G
Russell Top 200 Index (DRI)	R200
Russell Top 200 Value Index (DRI)	R200V
S&P 100	SP100
S&P 500	SP500
SSB 10-Year Treasury Benchmark	10YEAR
SSB 1-Month Treasury Bill	1MONTH
SSB 1-Year Treasury Benchmark	1YEAR
SSB 30-Year Treasury Benchmark	30YEAR
SSB 5-Year Treasury Benchmark	5YEAR
SSB Banking Index	NASB
SSB Cable and Media	SSBC
SSB Consumer Products	SSBC
SSB Consumer Products	SSCP
SSB Corporate Index, BBB 10 year sector	BBB10
SSB Corporate Index, BBB sector	BBB
SSB Information/Data Technology Index	SSBI
SSB Life Insurance Index	SSBI
SSB Property and Casualty Index	SSBP
SSB Telecommunications	SSBT
SSFB Convertible Bonds Index	CB
Wilshire Target Large Cap 750 Universe	WTLC

TABLE 4 – 3: HFR Hedge Fund Index Definitions

Convertible Arbitrage	Convertible Arbitrage involves purchasing a portfolio of convertible securities, generally convertible bonds, and hedging a portion of the equity risk by selling short the underlying common stock. Certain managers may also seek to hedge interest rate exposure under some circumstances. Most managers employ some degree of leverage, ranging from zero to 6:1. The equity hedge ratio may range from 30 to 100 percent. The average grade of bond in a typical portfolio is BB-, with individual ratings ranging from AA to CCC. However, as the default risk of the company is hedged by shorting the underlying common stock, the risk is considerably better than the rating of the unhedged bond indicates.
Distressed	Distressed Securities strategies invest in, and may sell short, the securities of companies where the security's price has been, or is expected to be, affected by a distressed situation. This may involve reorganizations, bankruptcies, distressed sales and other corporate restructurings. Depending on the manager's style, investments may be made in bank debt, corporate debt, trade claims, common stock, preferred stock and warrants. Strategies may be sub-categorized as "high-yield" or "orphan equities." Leverage may be used by some managers. Fund managers may run a market hedge using S&P put options or put options spreads.
Equity Hedge	Equity Hedge investing consists of a core holding of long equities hedged at all times with short sales of stocks and/or stock index options. Some managers maintain a substantial portion of assets within a hedged structure and commonly employ leverage. Where short sales are used, hedged assets may be comprised of an equal dollar value of long and short stock positions. Other variations use short sales unrelated to long holdings and/or puts on the S&P 500 index and put spreads. Conservative funds mitigate market risk by maintaining market exposure from zero to 100 percent. Aggressive funds may magnify market risk by exceeding 100 percent exposure and, in some instances, maintain a short exposure. In addition to equities, some funds may have limited assets invested in other types of securities.

Event Driven	Event-Driven is also known as "corporate life cycle" investing. This involves investing in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations and share buybacks. The portfolio of some Event-Driven managers may shift in majority weighting between Risk Arbitrage and Distressed Securities, while others may take a broader scope. Instruments include long and short common and preferred stocks, as well as debt securities and options. Leverage may be used by some managers. Fund managers may hedge against market risk by purchasing S&P put options or put option spreads.
HFR Biotechnology	Sector: Healthcare/Biotechnology funds invest in companies involved in the healthcare, pharmaceutical, biotechnology, and medical device areas.
Short-Seller	Short Selling involves the sale of a security not owned by the seller; a technique used to take advantage of an anticipated price decline. To effect a short sale, the seller borrows securities from a third party in order to make delivery to the purchaser. The seller returns the borrowed securities to the lender by purchasing the securities in the open market. If the seller can buy that stock back at a lower price, a profit results. If the price rises, however, a loss results. A short seller must generally pledge other securities or cash with the lender in an amount equal to the market price of the borrowed securities. This deposit may be increased or decreased in response to changes in the market price of the borrowed securities.
HFR Technology	Sector: Technology funds emphasize investment in securities of the technology arena. Some of the sub-sectors include multimedia, networking, PC producers, retailers, semiconductors, software, and telecommunications.

TABLE 4-4: '*Asset Classes*' used in the Asset Class Factor Model (Step 2)

Asset Class	Indice	Symbol	Dates
Equity	Russell 3000 Index	R3000	Feb 1991 - Apr 2003
Equity	Barra S&P 500	SP500	Feb 1991 - Apr 2003
Equity	Wilshire 5000 Index	W5000	Feb 1991 - Apr 2003
Distressed/High Yield	Merrill Lynch High Yield Index	MLHY	Feb 1991 - Apr 2003
Distressed/High Yield	Merrill Lynch High Yield Index - Lag 1 month	MLHY - L1	Feb 1991 - Apr 2003
Convertible Bond	CSFB - Convertible Bond Index	CB	Feb 1991 - Apr 2003
Equity Volatility	Market Volatility Index	VIX	Feb 1991 - Apr 2003
Credit Spreads	Baa Bonds - AAA Bonds	Default Risk	Feb 1991 - Apr 2003
Interest Rates	SSB 3-month T-Bill	RFR	Feb 1991 - Apr 2003
Bonds	Lehman Aggregate Bond Index	LABI	Feb 1991 - Apr 2003
Bonds	SSB Corporate Index, BBB Sector	SSB CORP BBB	Feb 1991 - Apr 2003

Note: Calls and Puts were created as well for all the asset classes above.

Table 4-5a: Method III - Manager Exposure and Weights as of April 2003

Manager	Percent	Gross Long Equity	Gross Short Equity	Gross Long Distressed	Gross Short Distressed	Gross Long High Yield	Gross Short High Yield	Converts Long	Converts Short	Volaility	Credit Spreads
Abrams**	17%	44.3%	0.0%	46.4%	-13.0%						
Quadrangle	17%	0.8%	-1.6%	56.2%	-0.2%	34.8%	-10.9%				
Intrepid	15%	90.4%	-57.9%								
Paradigm	12%	18.1%	-44.6%								
Swiftcurrent	10%	74.3%	-50.8%								
Biotechnology Value	16%	47.8%	-29.8%								
SuNova	8%	98.0%									
Fore Convertibles	5%		-142.5%					168.8%			

Total =	100%

Table 4-5b: Method III - Portfolio Net Exposure as of April 2003

NET ASSET CLASS EXPOSURES:	Net Exposure
Net Equity	14.90%
Net Distressed	15.14%
Net High Yield	4.01%
Net Convertibles	8.61%

Total =	43%

Table 5-1: Step I Regression Summary

	Manager Betas							
Strategy	L/S Tech.	L/S General	L/S Biotech.	L/S Short Biased	L/S Financials	Distressed	Event Driven	Convertible Arb
Manager	Int	Swift	Bio	Par	Nova	Quad	Abr	Four
Months =	58	30	112	126	48	11	50	83
Years =	4.8	2.5	9.3	10.5	4.0	0.9	4.2	6.9
Risk Factors	1	2	3	4	5	7	8	9
Amex Disk Drive Index	-0.17							
NASDAQ	0.16			0.56			-0.21	
Russell 3000 Growth Index					-7.28			
Russell 1000 Growth Index					6.33			
Russell Midcap Value Index					0.33			
Merrill Lynch High Yield Index							0.42	-0.17
Merrill Lynch High Yield Index - Lag 1 month						0.21		-0.16
SSB 1-Month Treasury Bill								
S&P 500							0.34	-0.07
HFRI Technology	0.24							
HFRI Market Neutral Index		1.15						
HFRI Sector: Health Care/Biotechnology Index			0.49					
HFRI Sector: Short Selling Index				0.30				
HFRI Sector Financial Services Index					0.68			
HFRI Distressed						0.99		
HFRI Event Driven							0.99	
HFRI Convertible Arb								1.35

Total Time R^2 =	50%	22%	28%	65%	77%	86%	61%	47%
Time - 1 year R^2 =	48%	22%	30%	70%	n/a	n/a	39%	51%
Time - 2 years R^2 =	49%	21%	32%	68%	n/a	n/a	42%	48%

Table 5-2: Step I Regression w/o HFR Index Summary

	Manager Betas							
Strategy	L/S Tech.	L/S General	L/S Biotech.	L/S Short Biased	L/S Financials	Distressed	Event Driven	Convertible Arb
Manager	Int	Swift	Bio	Par	Nova	Quad	Abr	Four
Months =	58	30	112	126	48	11	50	83
Years =	4.8	2.5	9.3	10.5	4.0	0.9	4.2	6.9
Risk Factors	1	2	3	4	5	7	8	9
ADDI								
Lag 2M								
PSE	0.11							
Lag 1M								
Lag 2M								
GIN	0.05							
TXX	0.08							
Lag 2M								
ABI			0.37					
NAS				0.44				
R1000G				7.92				
R3000G				-8.98				
RMVI					0.76			
CSFB - Distressed								
SSB Corporate Index, BBB								
Merrill Lynch High Yield Index						0.33	0.64	0.98
Merrill Lynch High Yield Index - Lag 1 month						0.27	0.30	0.12
SSB 1-Month Treasury Bill						-34.21		
S&P 500							0.19	-0.14

Total Time R^2 =	34%	0%	18%	60%	63%	78%	52%	5%
Time - 1 year R^2 =	36%	0%	16%	61%	63%	n/a	28%	5%
Time - 2 years R^2 =	36%	0%	14%	59%	62%	n/a	29%	4%

Table 5-3: Example of the Effect of Adding Lag Variables

A- Regression NOT Including LAG Variable:

The regression equation is

QUAD = 0.0122 + 0.448 MLHY + 0.367 CallW5000 + 0.197 CallVIX

Predictor	Coef	SE Coef	T	P
Constant	0.012165	0.001444	8.42	0.000
MLHY	0.44832	0.06468	6.93	0.000
CallW500	0.3672	0.1028	3.57	0.000
CallVIX	0.19749	0.04560	4.33	0.000

S = 0.01450   R-Sq = 47.2%   R-Sq(adj) = 46.1%

B- Regression Including LAG Variable:

The regression equation is

QUAD = 0.00933 + 0.342 MLHY + 0.420 MLHY - L1 + 0.417 CallW5000 + 0.113 CallVIX

Predictor	Coef	SE Coef	T	P
Constant	0.009329	0.001249	7.47	0.000
MLHY	0.34189	0.05527	6.19	0.000
MLHY - L	0.42041	0.05192	8.10	0.000
CallW500	0.41721	0.08551	4.88	0.000
CallVIX	0.11313	0.03926	2.88	0.005

S = 0.01203   R-Sq = 63.9%   R-Sq(adj) = 62.8%

Table 5-4: Step II Regression Summary

	Manager Betas							
Strategy	L/S Tech.	L/S General	L/S Biotech.	L/S Short Biased	L/S Financials	Distressed	Event Driven	Convertible Arb
Manager	Int	Swift	Bio	Par	Nova	Quad	Abr	Four
Months =	58	30	112	126	48	11	50	83
Years =	4.8	2.5	9.3	10.5	4.0	0.9	4.2	6.9
Risk Factors	1	2	3	4	5	7	8	9
NASDAQ	0.158			0.460				
Russell 1000 Value			-0.261		0.789			
Russell 1000 Growth			-5.345	8.013				
Russell 3000 Growth			5.740	-9.111				
Put Russell 1000 Value					0.283			
Merrill Lynch High Yield Index						0.342	0.637	
Merrill Lynch High Yield Index - Lag 1 month						0.420	0.169	
Call W5000						0.417		
Russell 3000 Index							0.207	
Call Russell 3000 Index							0.293	
Call Lehman Aggregate Bond Index								0.982
Call VIX						0.113		0.083
Risk Free Rate								-0.033
W5000		0.052						-0.122
Convertible Bond Index								0.166

Total Time R^2 =	40%	4%	37%	95%	87%	63%	77%	20%
Time - 1 year R^2 =	37%	6%	34%	94%	85%	61%	72%	18%
Time - 2 years R^2 =	42%	18%	33%	95%	88%	67%	71%	17%

Table 5-5: Why Two Steps Regression Approach to Capture Non-Linearity?

A - Proposed Two-Step Approach: Does Capture Non-Linearity:

Step I:

Regression: NOVA

	constant	RMVI	HFRI Sector: Financial Index
coefficient	0.01021987	0.335487042	0.67471684
std error of coef	0.00322902	0.102948243	0.122861362
t-ratio	3.1650	3.2588	5.4917
p-value	0.2781%	0.2134%	0.0002%
beta-weight		0.3491	0.5883
standard error of regression		0.021184845	
R-squared		77.83%	
adjusted R-squared		76.85%	

Step II:

NOVA INDEX = 0.335*RMVI + 0.675*HFRI Financial Index (from Step I)

Regression: NOVA INDEX

	constant	Russell 1000 Value	"Put" on R1000V
coefficient	0.0053218	0.788604283	0.282751347
std error of coef	0.00125787	0.035037146	0.108158612
t-ratio	4.2308	22.5077	2.6142
p-value	0.0044%	0.0000%	1.0015%
beta-weight		0.8717	0.1012
standard error of regression		0.012949235	
R-squared		87.22%	
adjusted R-squared		87.02%	

B - Direct Approach: Does Not Capture Non-linearity

Regression: NOVA

	constant	R1000V	"Put" on R1000V
coefficient	0.02014483	0.65635194	0.30675085
std error of coef	0.00448602	0.11053486	0.428725032
t-ratio	4.4906	5.9380	0.7155
p-value	0.0049%	0.0000%	47.7999%
beta-weight		0.7037	0.0848
standard error of regression		0.02951536	
R-squared		56.97%	
adjusted R-squared		55.06%	

Table 5-6: Step I Regression Residual Correlation and PCA Analysis

Correlations matrix :

	Swift	Bio	Par	Nova	Acq	Abr	Four
Swift	1	0.1793	-0.0314	-0.1223	0.0287	-0.0120	-0.2194
Bio	0.1793	1	0.1793	0.1267	0.3340	0.1901	-0.3192
Par	-0.0314	0.1793	1	-0.1363	0.5191	0.0943	0.1049
Nova	-0.1223	0.1267	-0.1363	1	-0.0541	0.2856	-0.5062
Acq	0.0287	0.3340	0.5191	-0.0541	1	0.2915	-0.0428
Abr	-0.0120	0.1901	0.0943	0.2856	0.2915	1	-0.1303
Four	-0.2194	-0.3192	0.1049	-0.5062	-0.0428	-0.1303	1

Eigenvalues and eigenvectors (based on the correlations matrix) :

Eigenvalue.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Value	1.9628	1.6505	1.1741	0.7860	0.6375	0.4391	0.3500
% of variability.	0.2804	0.2358	0.1677	0.1123	0.0911	0.0627	0.0500
Cumulated %	0.2804	0.5162	0.6839	0.7962	0.8873	0.9500	1.0000
Vectors :	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Swift	0.1451	-0.0599	0.7855	0.4059	-0.3190	-0.1453	0.2661
Bio	0.4981	0.0298	0.2666	-0.2399	0.7444	-0.2517	0.0691
Par	0.2838	0.5521	-0.0799	-0.2864	-0.4425	-0.5441	-0.1854
Nova	0.3204	-0.5137	-0.3624	-0.1594	-0.2468	-0.2225	0.6052
Acq	0.4555	0.4530	-0.0627	-0.0135	-0.1011	0.6887	0.3142
Abr	0.4130	-0.0268	-0.3715	0.7671	0.0849	-0.1356	-0.2769
Four	-0.4118	0.4700	-0.1798	0.2858	0.2644	-0.2781	0.5902

Table 5-7: Step II Regression Residual Correlation Analysis

Correlations matrix :

	Swift	Bio	Par	Nova	Quad	Abr	Four
Swift	1	0.3691	0.0274	0.2287	0.0998	0.2417	0.0843
Bio	0.3691	1	-0.1828	0.1029	0.2439	-0.0132	-0.0696
Par	0.0274	-0.1828	1	-0.1300	-0.1519	-0.0454	0.0564
Nova	0.2287	0.1029	-0.1300	1	0.1546	0.2900	0.0165
Quad	0.0998	0.2439	-0.1519	0.1546	1	0.2985	0.4339
Abr	0.2417	-0.0132	-0.0454	0.2900	0.2985	1	0.4252
Four	0.0843	-0.0696	0.0564	0.0165	0.4339	0.4252	1

Eigenvalues and eigenvectors (based on the correlations matrix) :

Eigenvalue.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Value	2.0376	1.3770	1.0650	0.9810	0.6622	0.4700	0.4073
% of variability.	0.2911	0.1967	0.1521	0.1401	0.0946	0.0671	0.0582
Cumulated %	0.2911	0.4878	0.6399	0.7801	0.8747	0.9418	1.0000
Vectors :	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Swift	0.3636	0.3588	0.5397	-0.1570	-0.3694	-0.4362	-0.3107
Bio	0.2705	0.5954	-0.0433	-0.4466	0.1339	0.3889	0.4493
Par	-0.1515	-0.3300	0.7212	-0.2892	0.4730	0.2014	-0.0046
Nova	0.3432	0.2083	0.1631	0.6911	0.5056	-0.1745	0.2203
Quad	0.4875	-0.1220	-0.3664	-0.2886	0.4634	-0.0368	-0.5603
Abr	0.4941	-0.2768	0.1483	0.2747	-0.3740	0.6572	-0.1007
Four	0.4149	-0.5225	-0.0624	-0.2366	-0.1083	-0.3928	0.5736

Table 5-8: Method I - Portfolio Monthly Standard Deviation

	Total Risk	Idiosyncratic Risk	Systematic Risk
Equally Weighted Linear Portfolio	4.0%	3.3%	2.3%
Equally Weighted Non-Linear Portfolio	4.3%	3.3%	2.8%
Manager Bio (Highest Std. Dev)	6.7%	5.8%	3.3%

Table 5-9: Value-at-Risk on Monthly Return Summary

	0.25 Percentile	1 Percentile	5 Percentile	10 Percentile
Equally Weighted Linear Portfolio	-5.7%	-5.1%	-3.4%	-2.2%
Equally Weighted Non-Linear Portfolio	-9.5%	-6.0%	-4.1%	-2.5%

	99.75 Percentile	99 Percentile	95 Percentile	90 Percentile
Equally Weighted Linear Portfolio	11.5%	9.5%	7.35%	6.0%
Equally Weighted Non-Linear Portfolio	13.3%	11.2%	7.6%	6.0%

Table 5-10a: Method II - Portfolio Monthly Standard Deviation

	Total Risk	Idiosyncratic Risk	Systematic Risk
Equally Weighted Linear Portfolio	3.27%	1.04%	3.10%
Equally Weighted Non-Linear Portfolio	3.39%	1.04%	3.23%
Manager Bio (Highest Std. Dev)	6.65%	5.80%	3.25%

Table 5-10b: Method I & II - Portfolio Monthly Standard Deviation

		Total Risk	Idiosyncratic Risk	Systematic Risk
Method II	Equally Weighted Linear Portfolio	3.27%	1.04%	3.10%
	Equally Weighted Non-Linear Portfolio	3.39%	1.04%	3.23%
Method I	Equally Weighted Linear Portfolio	4.00%	3.30%	2.30%
	Equally Weighted Non-Linear Portfolio	4.30%	3.30%	2.80%

Table 5-11: Method III – Portfolio Monthly Standard Deviation

	Total Risk	Idiosyncratic Risk	Systematic Risk.	5 Percentile	1 Percentile
Method III	N/A	N/A	0.82%	-1.02%	-2.8%

Table 6-1: Method I, II, and III – Portfolio Monthly Standard Deviation

	Total Risk	Idiosyncratic Risk	Systematic Risk.	5 Percentile	1 Percentile
Method I	1.78%	1.28%	1.12%	N/A	N/A
Method II	2.02%	1.35%	1.5%	-.9%	-2.4%
Method III	N/A	N/A	0.82%	-1.02%	-2.8%

FIGURES

FIGURE 1-1: HISTORICAL GLOBAL HEDGE FUND GROWTH

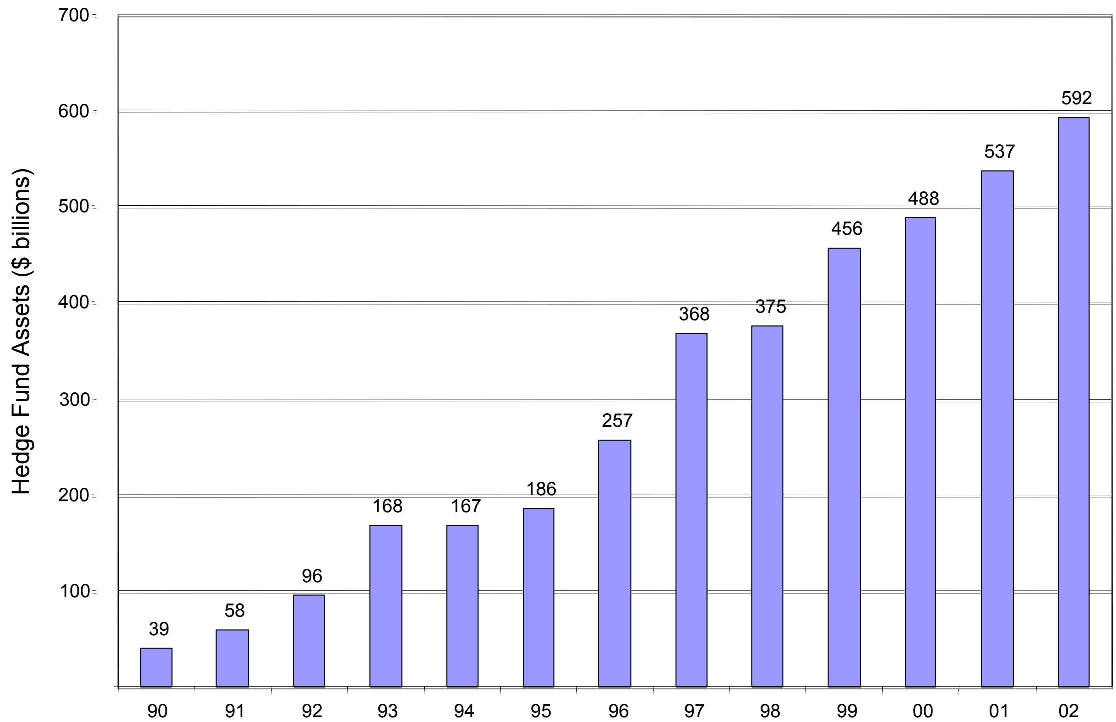
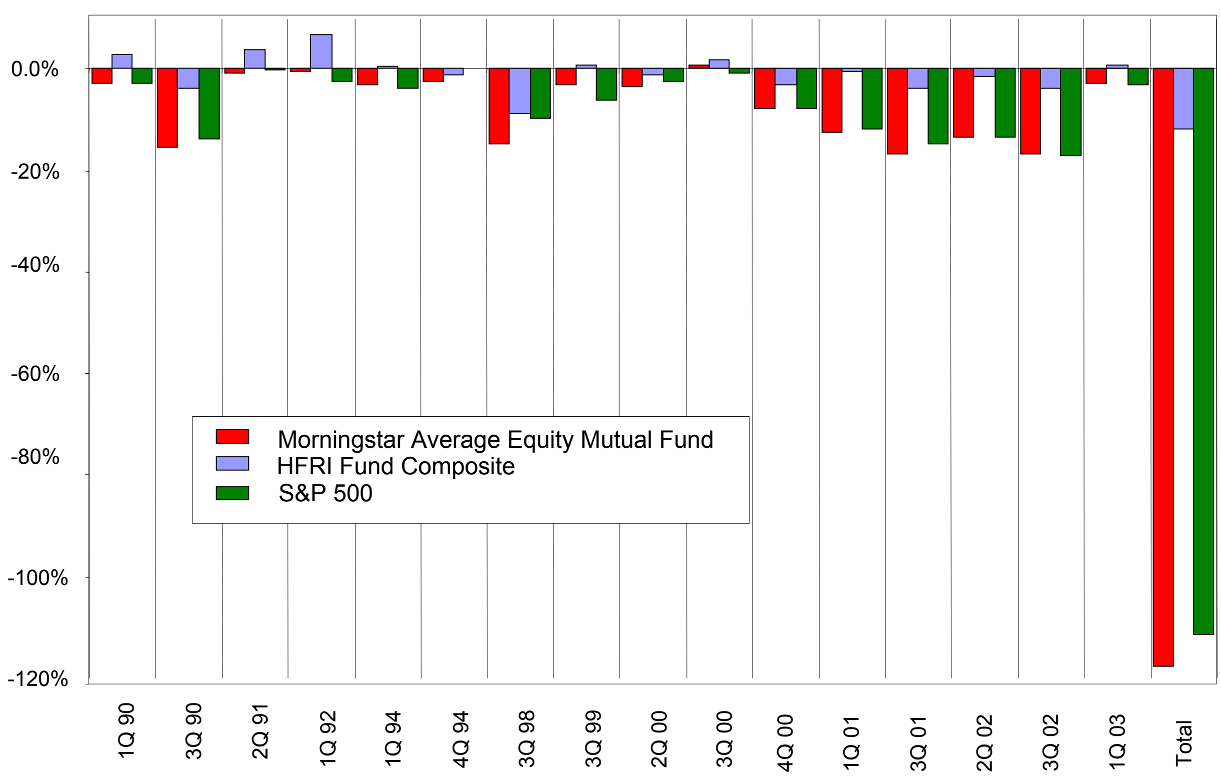


Figure 1-2: Hedge Fund and Mutual Fund Performance in Down S&P 500 Quarters (Jan 90 – March 03)



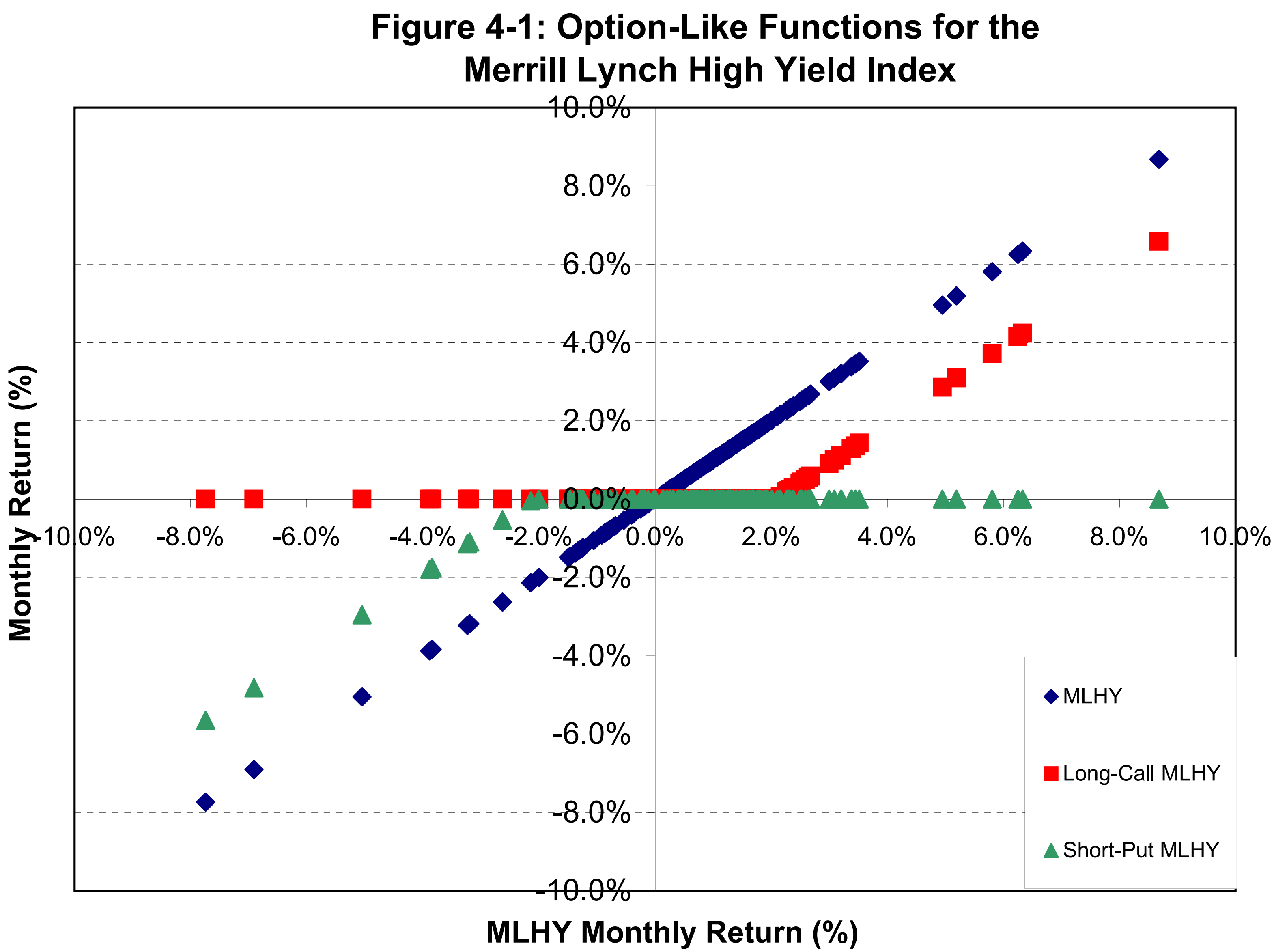


Figure 4-1: Option-Like Functions for the
Merrill Lynch High Yield Index
10.0%
8.0%
6.0%
4.0%
2.0%
0.0%
-2.0%
-4.0%
-6.0%
-8.0%
-10.0%
-10.0%
-8.0%
-6.0%
-4.0%
-2.0%
0.0%
2.0%
4.0%
6.0%
8.0%
10.0%
Monthly Return (%)
MLHY Monthly Return (%)
MLHY
Long-Call MLHY
Short-Put MLHY

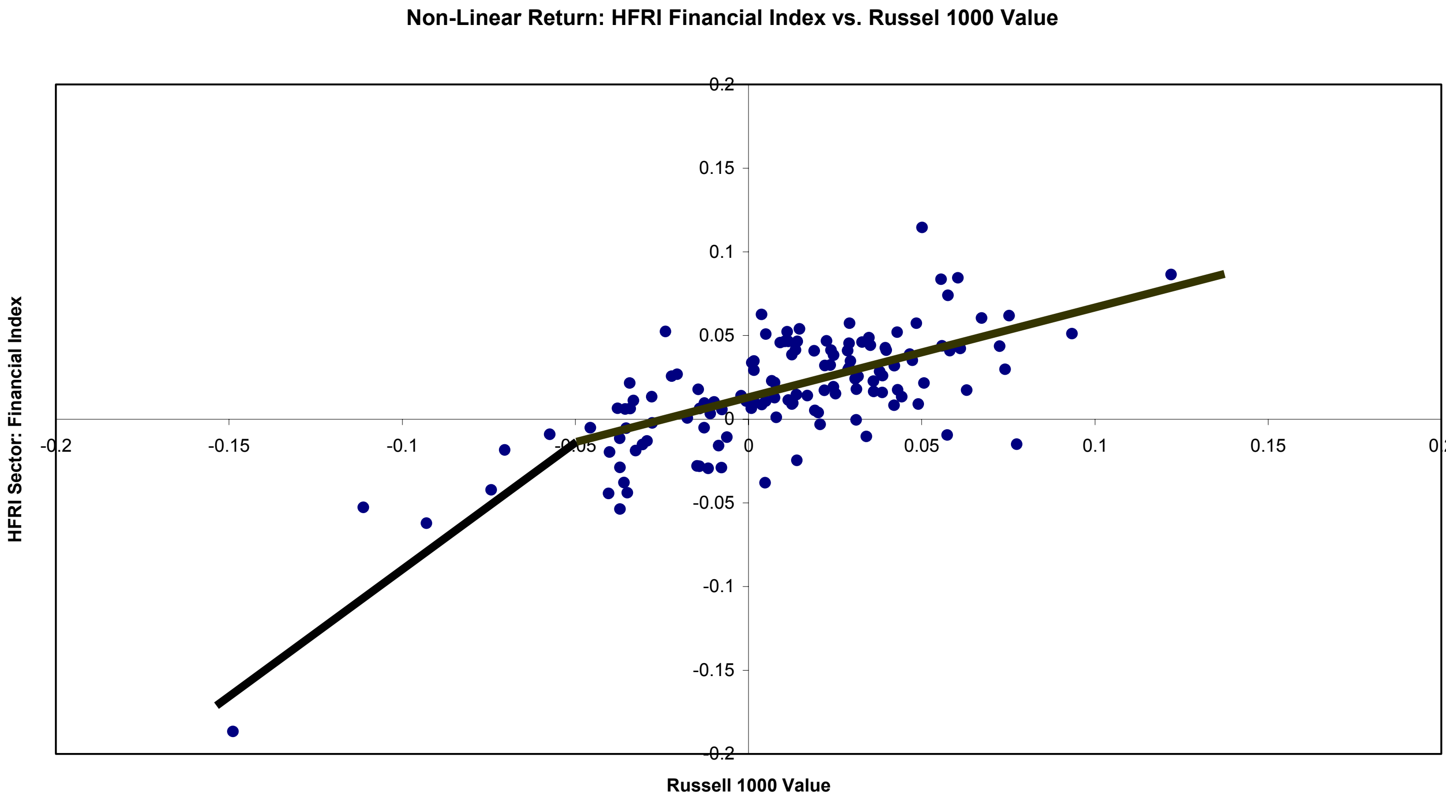


Figure 5-1: Non-Linearity in Monthly Return Exhibited by HFRI Financial Index from Jan 92 to April 03

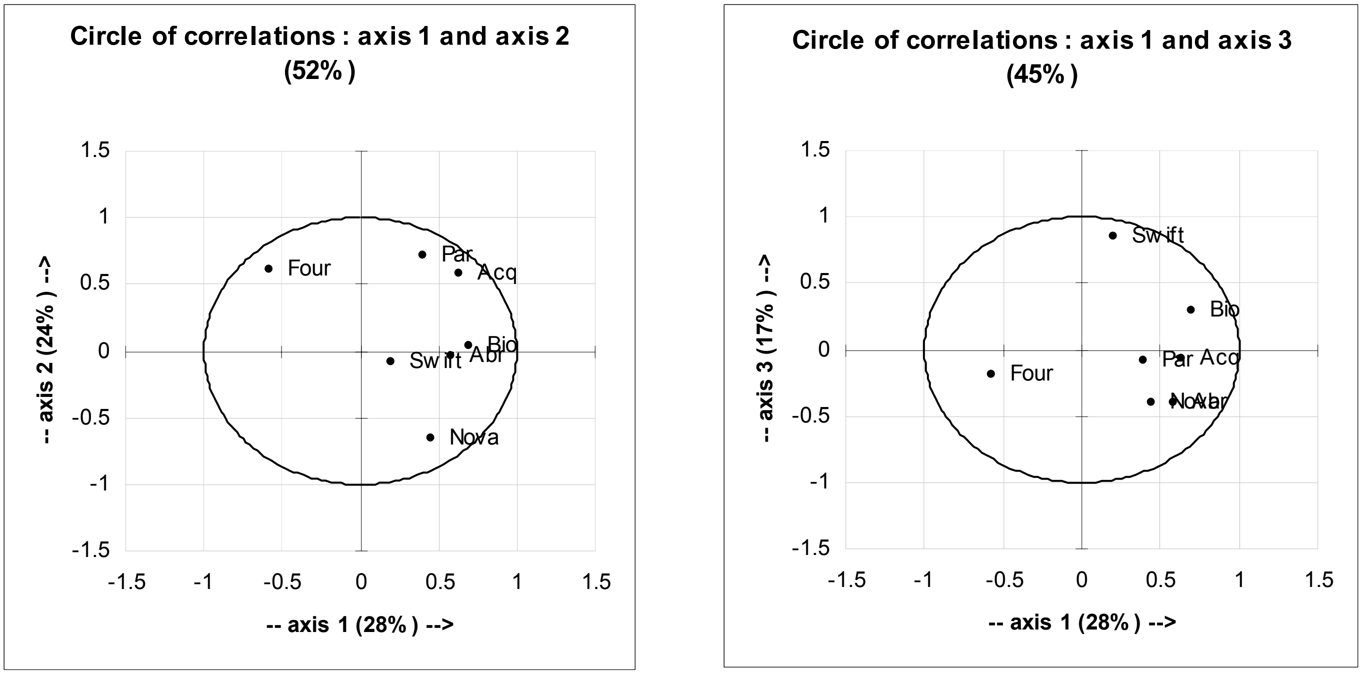


Figure 5-2: PCA Analysis for Residual from Step I Regression

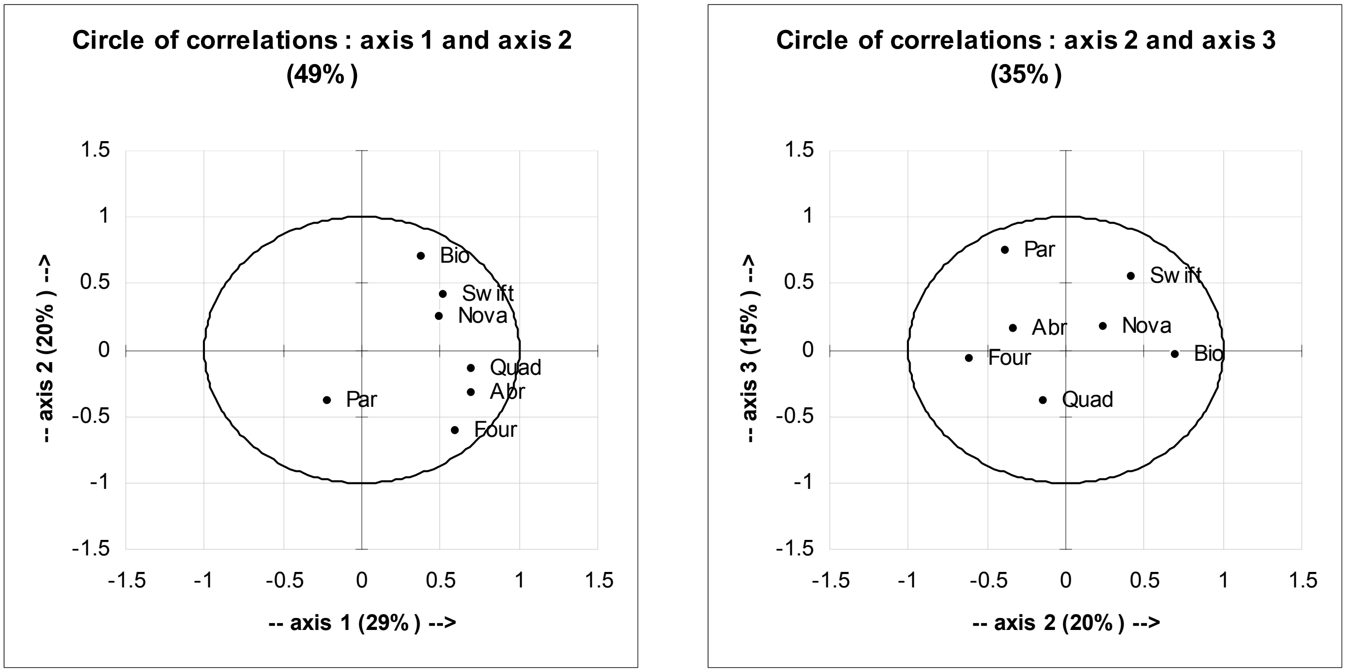


Figure 5-3: PCA Analysis for Residual from Step II Regression

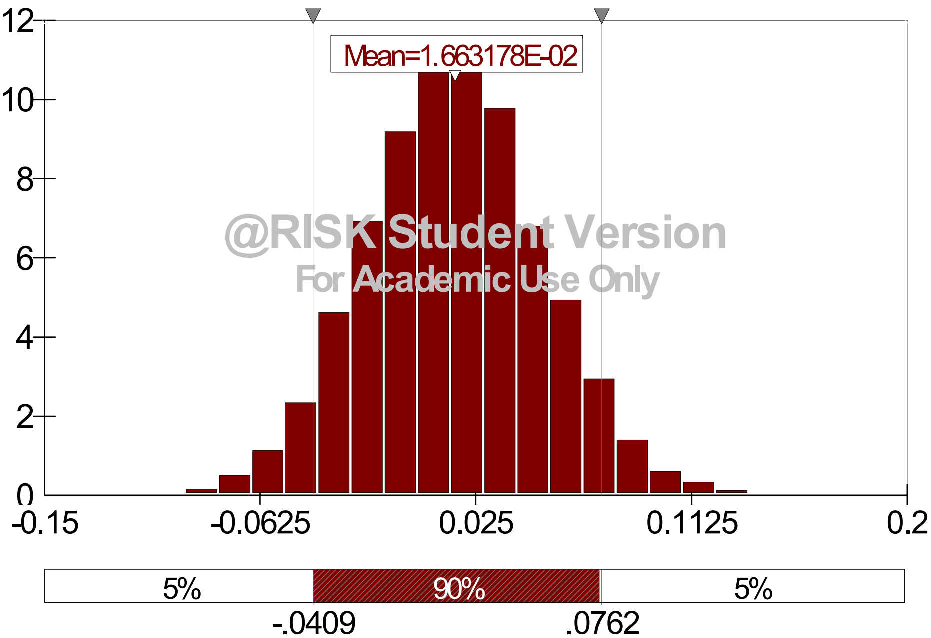


Figure 5-4a: Non-Linear Portfolio Return Distribution

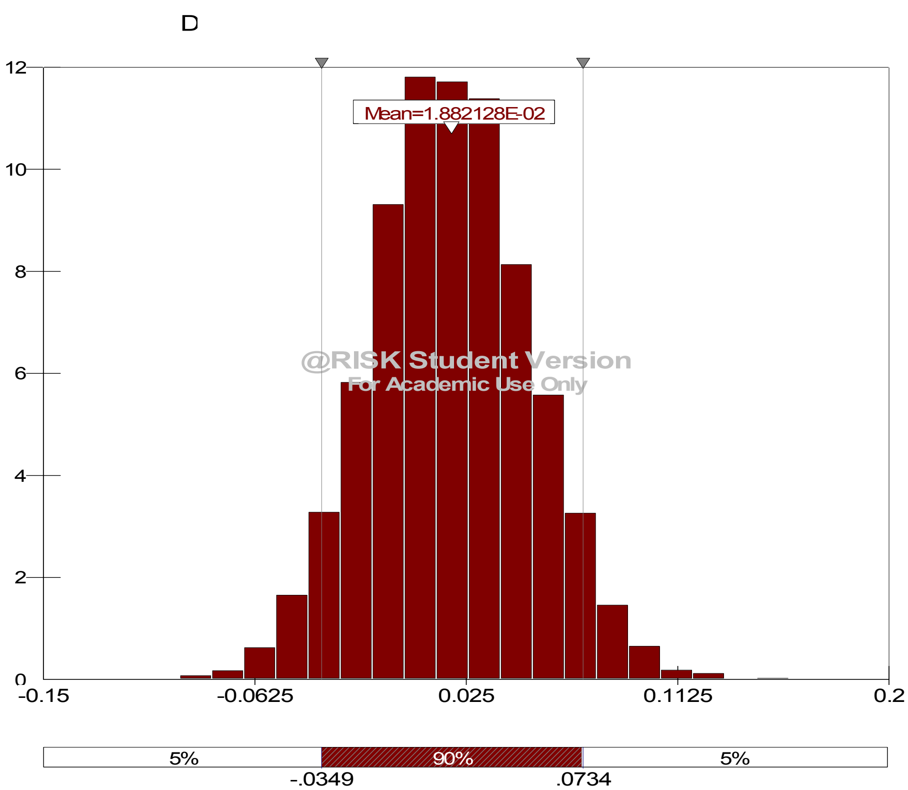


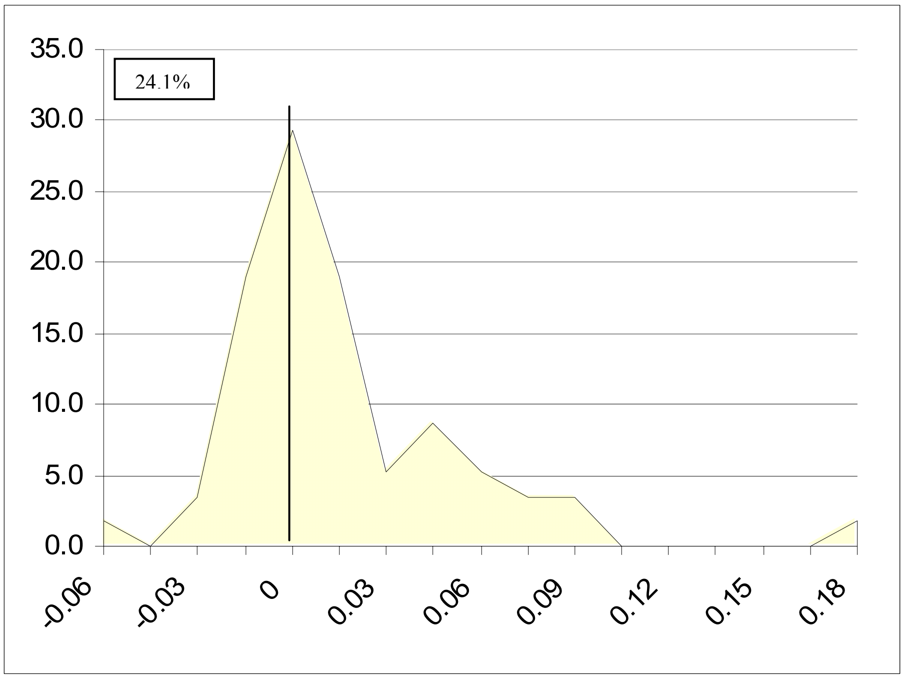
Figure 5-4b: Linear Portfolio Return Distribution

APPENDICES

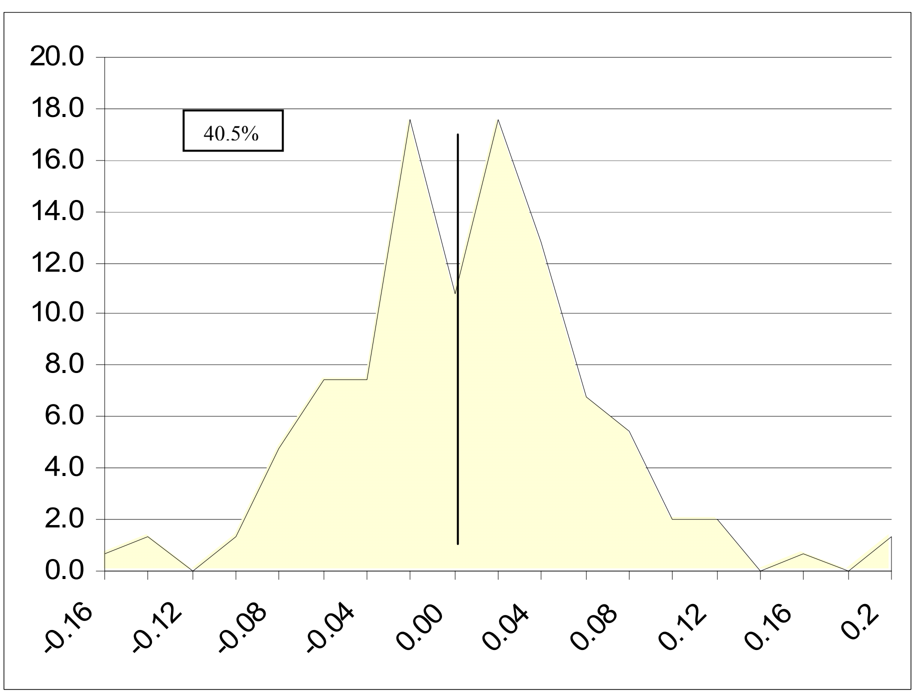
APPENDIX: Distribution of Monthly Returns (by Mgr/HFR Index)

(Text Box = Cumulative Frequency Less than Zero)

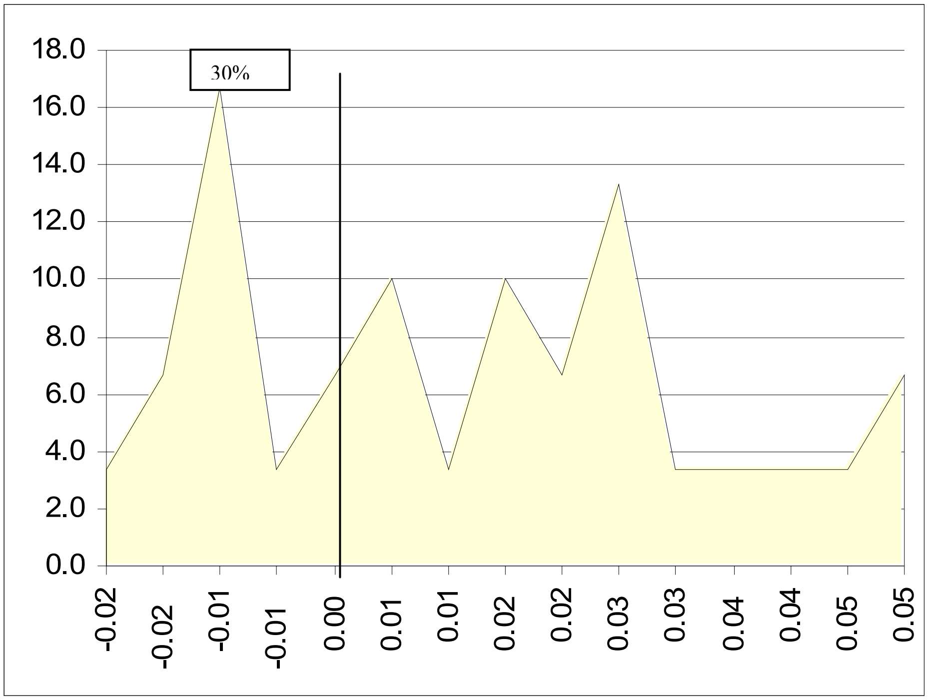
Manager #1 – Long/Short Technology



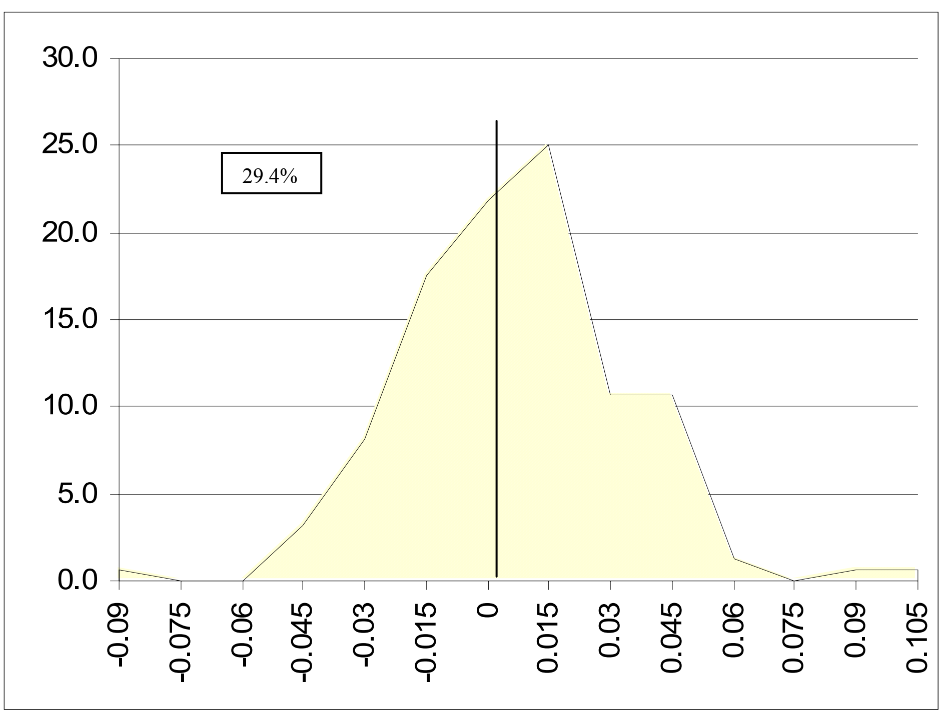
HFR Technology (Mrg #1)



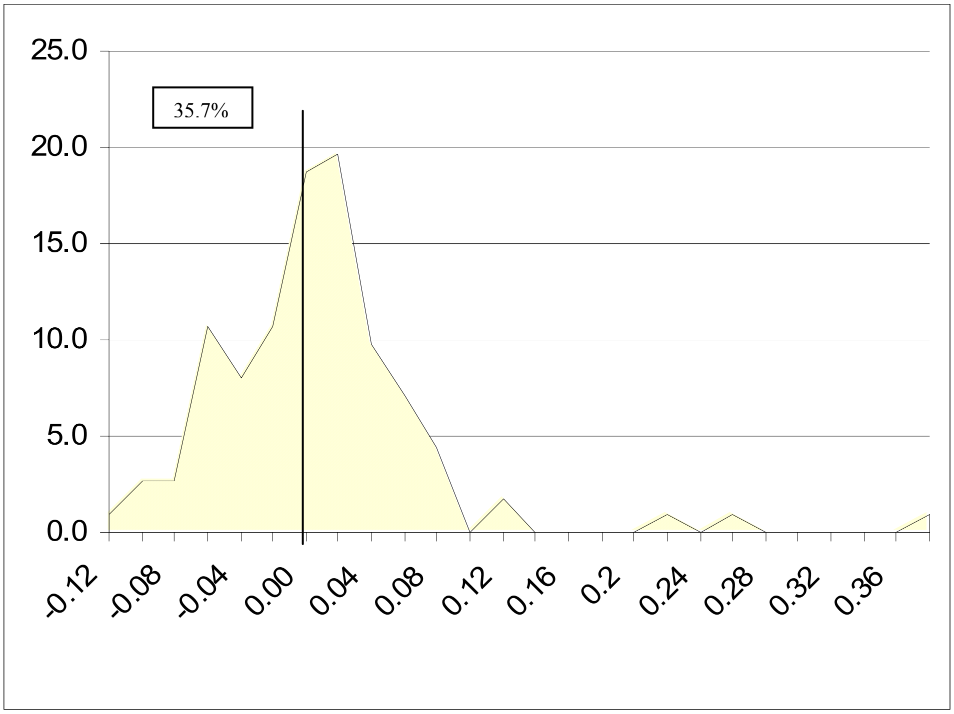
Manager #2 – Long/Short Generalist



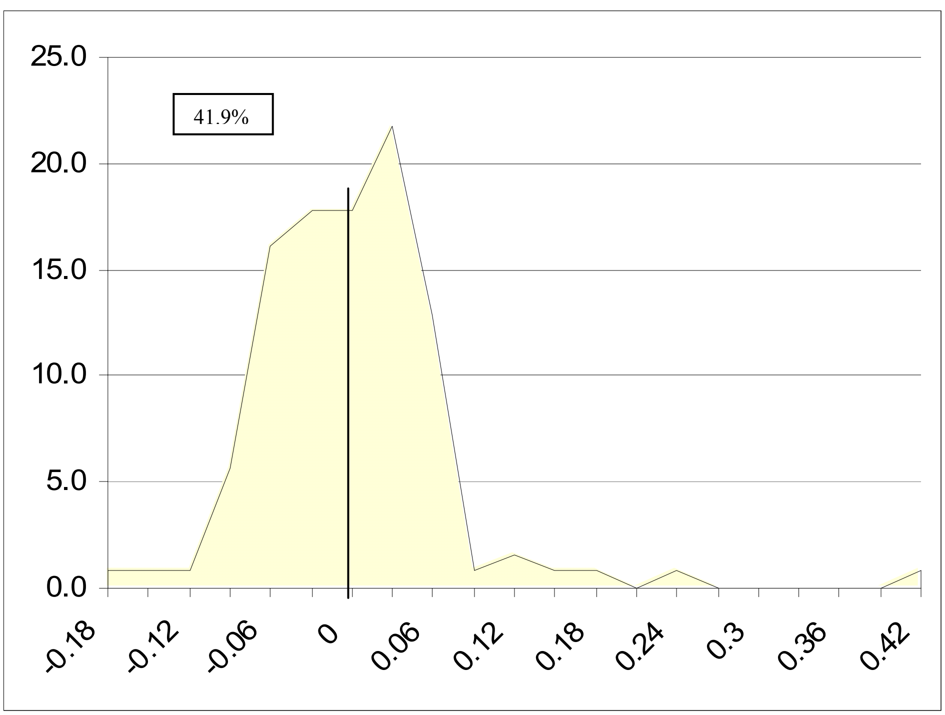
HFR Equity Hedge (Mrg #2)



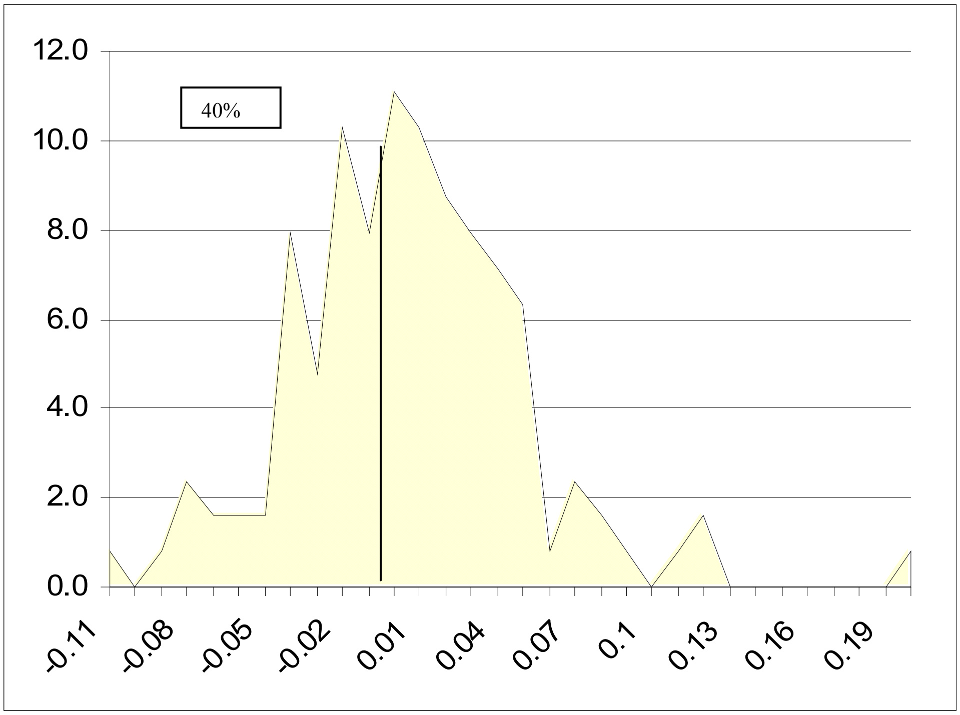
Manager #3 – Long/Short Biotechnology



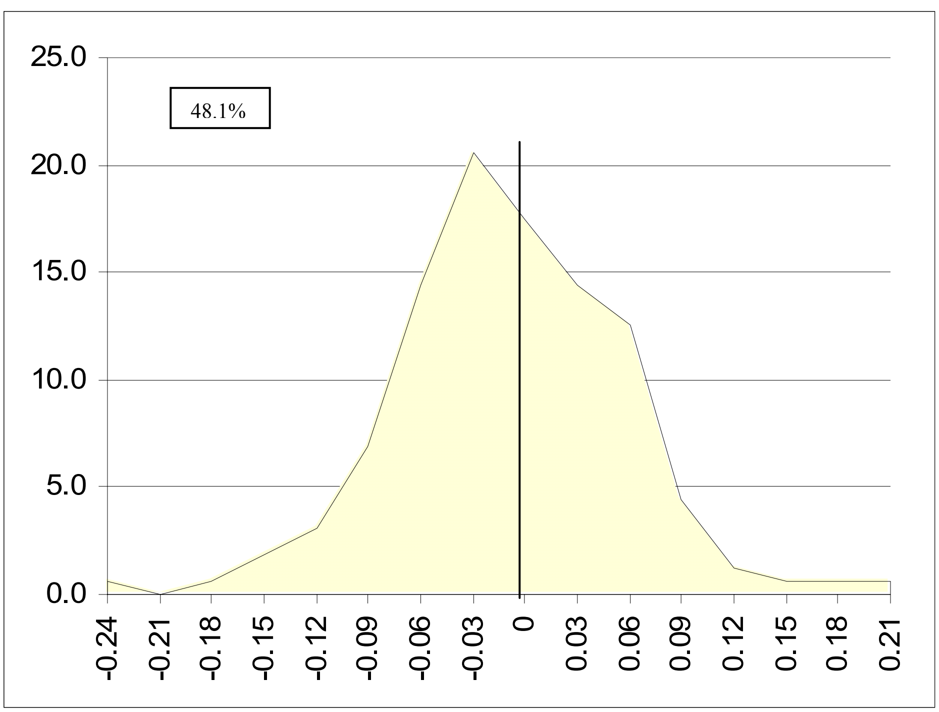
HFR Biotechnology (Mrg #3)



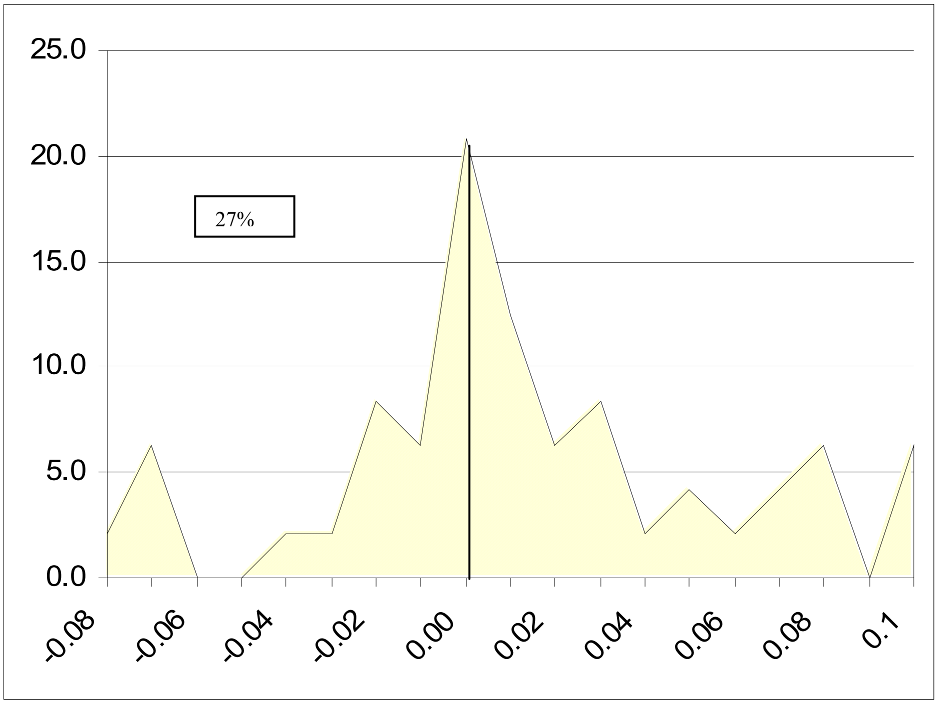
Manager #4 – Long/Short Generalist (Short-Bias)



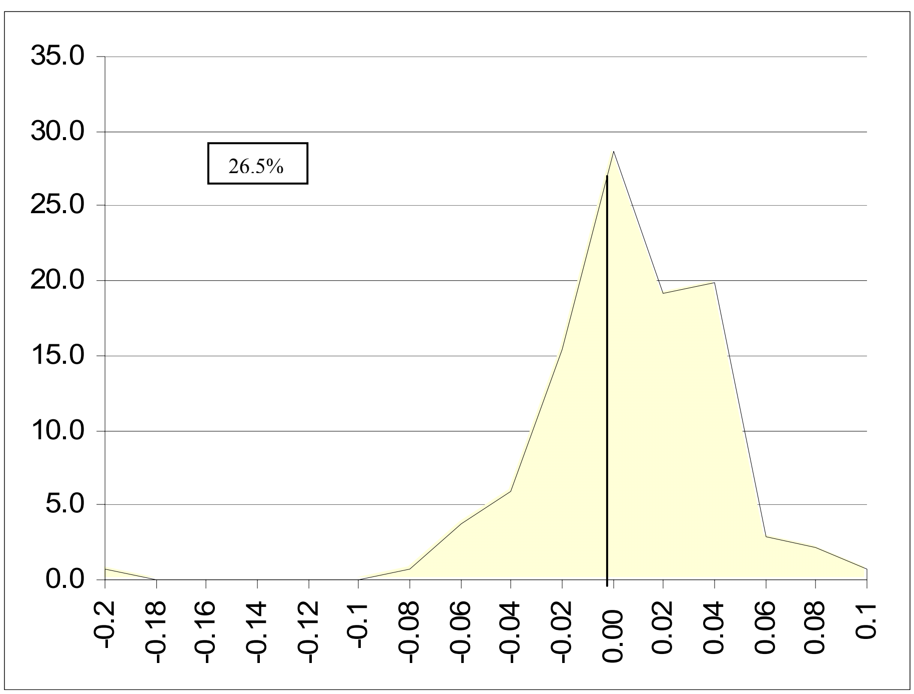
HFR L/S Short-Biased (Mrg #4)



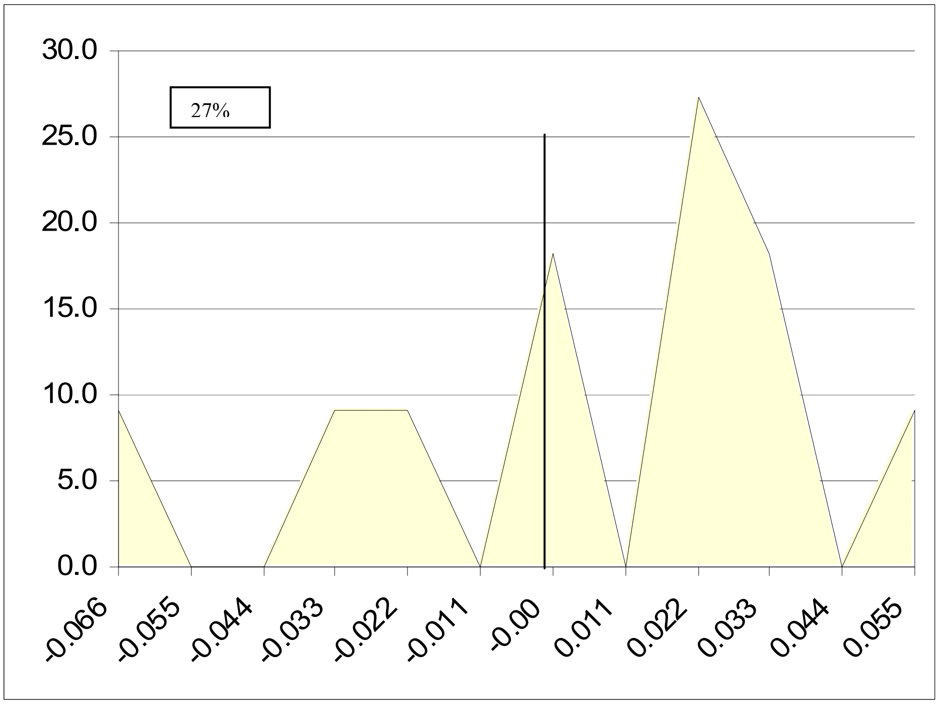
Manager #5 – Financial Long-Bias



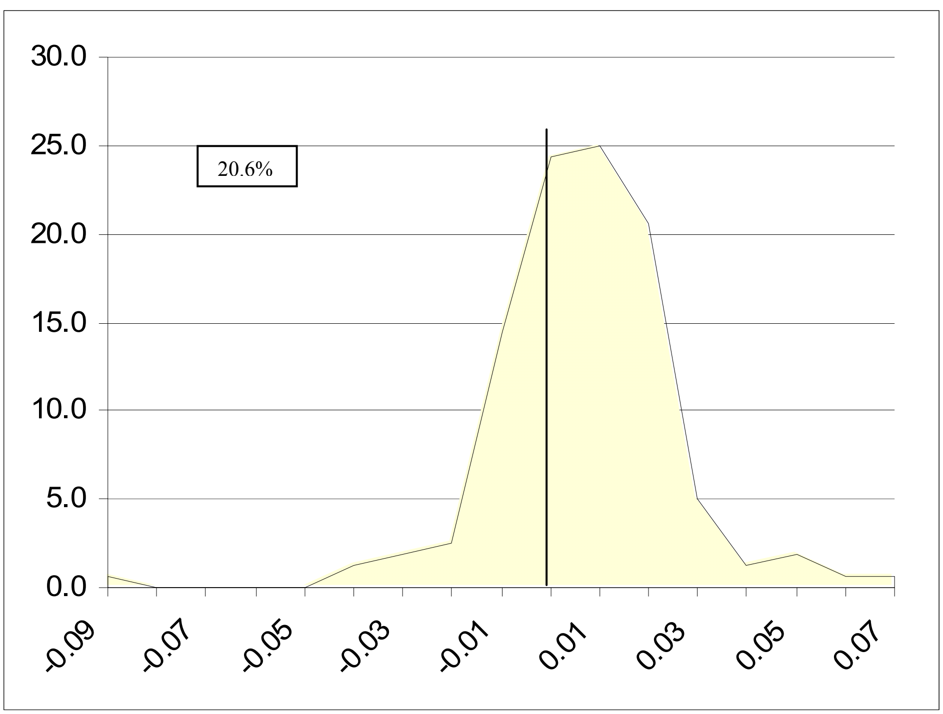
HFR Finance (Mrg #5)



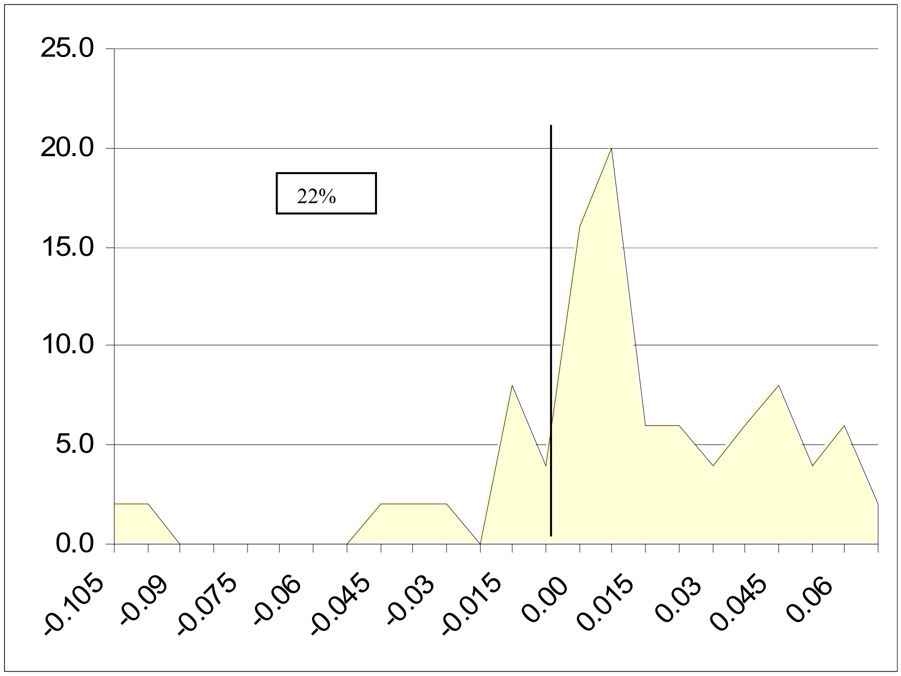
Manager #6 – Distressed



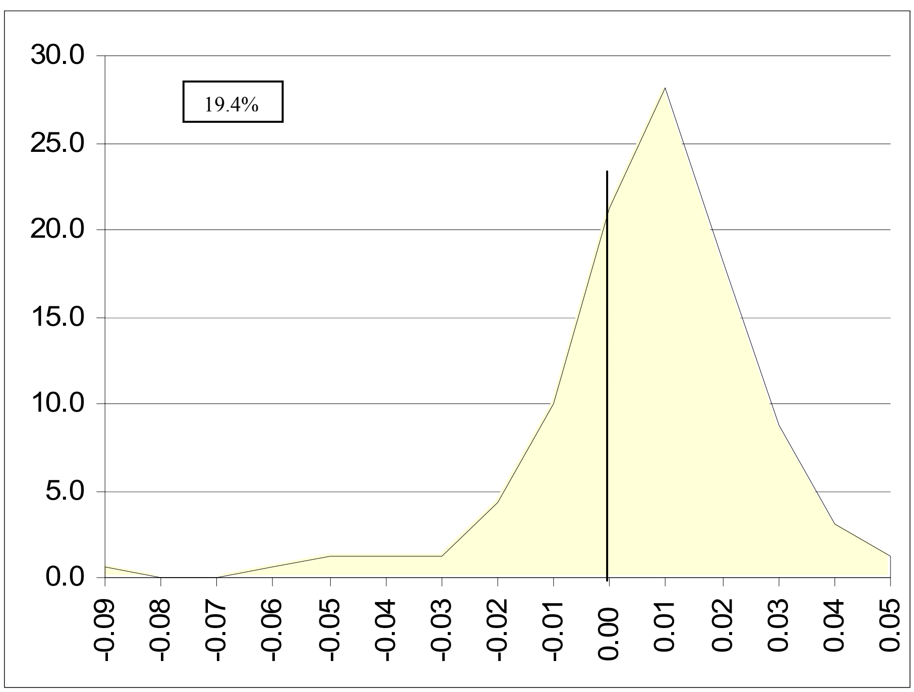
HFR Distressed (Mrg #6)



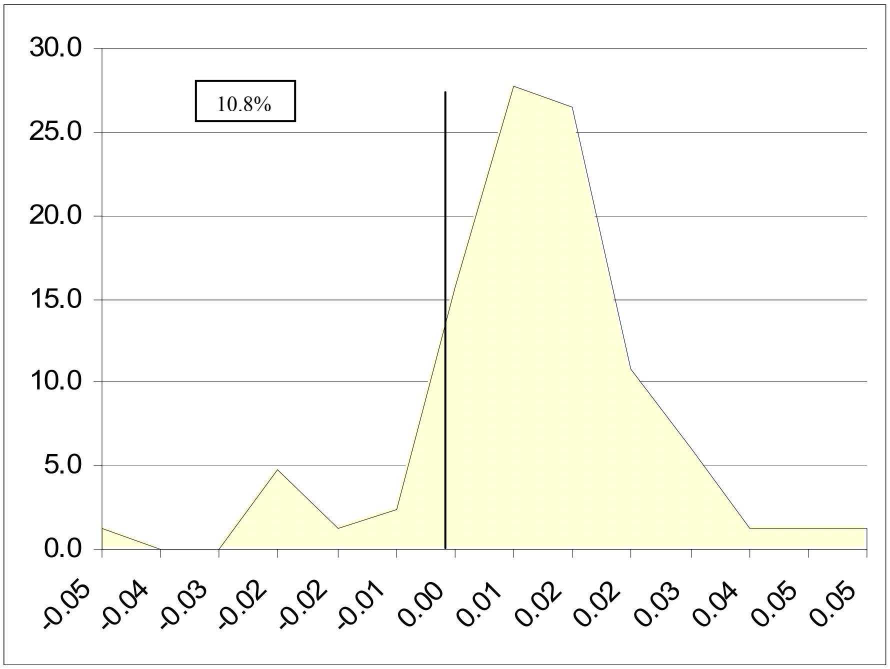
Manager #7 – Event Driven



HFR Event Driven (Mrg #7)



Manager #8 – Convertible Arbitrage



Convertible Arb (Mgr #8)