Hedge Fund Investing: *A Quantitative Approach to Hedge Fund Manager Selection and De-Selection*

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I. INTRODUCTION

Hedge fund strategies have historically been shown to deliver good risk-adjusted returns and further have proven to enhance the risk/return profile of a generic portfolio of traditional assets. The characteristics of hedge fund returns that suggest they play a beneficial role within a traditional portfolio include high absolute risk-adjusted returns, a measure of downside protection in periods of volatility, and a general lack of correlation with equity and fixed income markets.

Examined at a granular level the hedge fund industry consists of a variety of investment strategies and styles that can be complementary and, when appropriately combined in a multi-strategy hedge fund portfolio, enjoy the benefits of inter-strategy diversification.[1] Further, given that hedge fund strategies tend to move in and out of favor as economic conditions, strategy specific factors, and supply and demand conditions change over time, further enhancement of portfolio returns can be realized from a well-conceived dynamic, tactical rebalancing process.

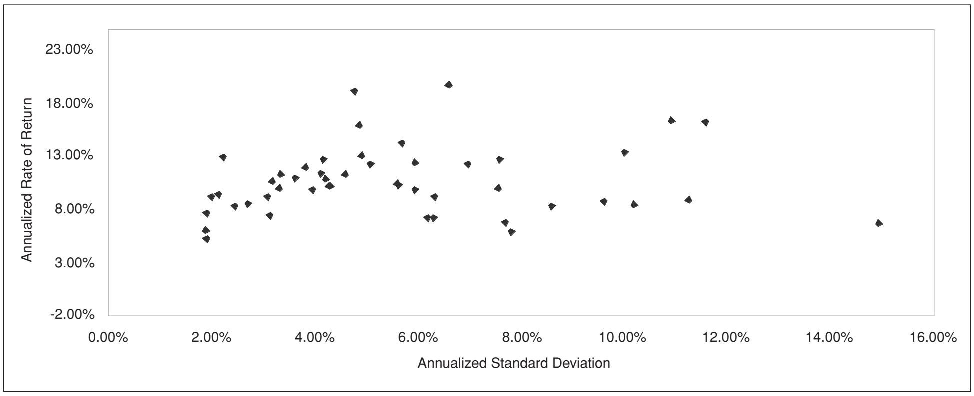
Having identified the appropriate strategy mix, the next step of the portfolio construction process, and the subject of this article, is individual manager research and due diligence to identify those hedge fund managers that are the "best-in-class" and suitable to execute each of the selected strategies. Historically this process has to a large extent been qualitative with quantitative analysis primarily focusing on the elementary analysis of return series.

The scope of this article is to present a number of quantitative tools for different phases of manager selection or de-selection. We recognize as practitioners that there are no substitutes for an understanding of the nuances of investment philosophy, risk control, capital management, timely and accurate information transfer, and ultimately fund level transparency. Our challenge within the context of this article is to utilize commonly available information and derive a number of crucial tests to serve as a primary set of filters for manager analysis. In doing so we address some of the commonly held misconceptions in manager selection and demonstrate the need for an understanding not just of returns and volatility but more importantly the nature of the relevant return distributions. In particular, given the often-complex nature of distribution functions in this space the analyses we propose tend to incorporate measures of the entire distribution function and tend to shy away from the more traditional first or second moment analysis in common use.

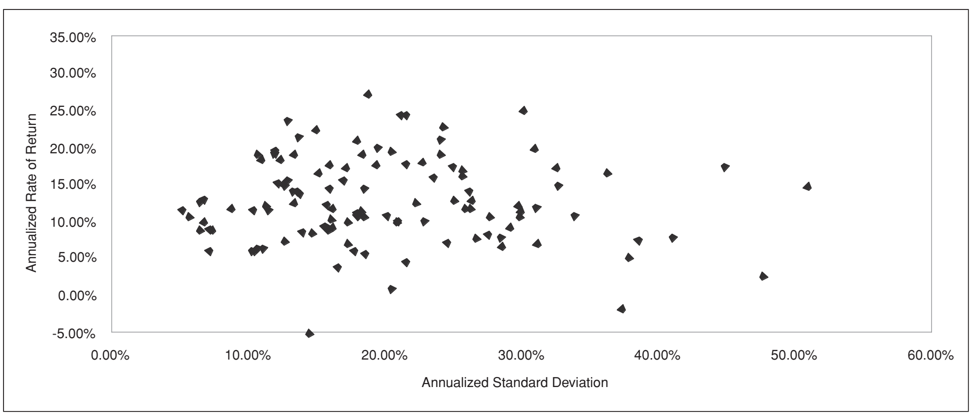
Hedge funds are not a homogeneous asset class. There are a number of distinct strategies with differing risk and return characteristics. Even though there are some common features of individual hedge funds, the heterogeneity of performance as well as investment styles, even within the same strategy, is well known to hedge fund investors. In par-

EXHIBIT 1
Dispersion in Returns, Volatility, and Sharpe Ratio

A – Dispersion in Convertible Arbitrage Managers



B – Dispersion in Equity Long/Short Managers



ticular, Kat [2003] highlights the differences in behavior of the funds using the same type of strategy. Unlike active managers in traditional asset classes, the dispersion of risk and return among hedge fund managers is wide, even among managers pursuing similar strategies. For example Exhibits 1A and 1B demonstrate pictorially the degree of dispersion in risk and return between hedge fund managers in two hedge fund strategies: convertible arbitrage and equity long/short strategies. The degree of dispersion underlies the importance not just of comprehensive hedge fund manager selection, but also the requirement to understand in depth the various relevant structural issues within a strategy accounting for the given dispersion such as degree of leverage, credit or sector concentrations, and individual manager style.[2]

At a more generalized strategy level we demonstrate the degree of heterogeneity among managers within the same strategy for a number of strategies. In particular we analyze monthly returns for 314 hedge funds (52 convertible arbitrage, 15 distressed securities, 23 merger arbitrage, 19 fixed income arbitrage, 43 equity market neutral, 118 equity long/short, and 44 global macro funds) over a six-year period extending from January 1997 to December 2002 and present the results in Exhibit 2. This sample set was chosen by a screening of the HFR database to select all available managers with complete performance history for the most recent six-year period. The six-year time period is selected to balance the need for a sufficiently large sample of managers as well as enough return data to make for statistically significant analysis at the strategy level.

Exhibit 2 shows the mean, standard deviation, skewness, average values for bottom quartile, average values for top quartile and inter-quartile range (the difference between the top and the bottom quartile) for annualized returns and volatility among managers within the same strategy from January 1997 to December 2002. Standard deviation, skewness, and inter-quartile range can all be considered measures of dispersion. All three statistics show varying degrees of dispersion in returns and volatility of the managers within the same strategy. In particular we note that based on standard deviation and inter-quartile range merger arbitrage managers show the least amount of dispersion in return and volatility. Empirically, we believe this is related to the well-defined and therefore restricted nature of merger arbitrage, with dispersion a function of leverage and deal concentration. By comparison equity long/short and global macro managers, with by far the widest and most discretionary mandates, display the largest degree of dispersion in return and volatility.

In summary, the exhibit shows that dispersion exists in performance and risk among hedge fund managers within the same strategy. However, this degree of dispersion varies from one strategy to another. We see a relatively higher degree of dispersion in managers in discretionary-type strategies such as equity long/short and global macro strategies and a relatively lower degree of dispersion in "restricted" mandate strategies such as merger arbitrage or equity market neutral. As a more general observation we note that there exists a high degree of correlation between standard deviation and inter-quartile range. Given that higher volatility is often the result of leverage, we would expect that some of the dispersion in these cases is the result of varying leverage. This argues for a careful selection of managers for peer comparison.

The presence of dispersion in returns and volatility implies that some degree of the market risk associated with investing in hedge funds is fund specific. This argues that despite strategy factor risk, careful construction of a portfolio of hedge funds still requires an understanding of a fund's idiosyncratic investment and risk features. In particular this idiosyncratic risk has to be addressed via an extensive and well-resourced approach to manager research and selection. This is despite the fact that fund specific risk related to hedge funds can in general be diversified across a number of funds. A variety of easily constructed examples demonstrate that a simplistic increase in the number of managers in a portfolio can often increase the correlation to systematic market risk factors and above a critical total ultimately degrade the diversification benefits. In addition, a large number of managers in a portfolio increases the monitoring and due diligence burden often with no real increase in portfolio added value and is therefore not practical. We believe that a true reduction in fund specific risk can only be achieved through a process of high quality manager selection, due diligence, and ongoing monitoring. This in combination with strong portfolio construction skills, blending strategies with low and stable correlations and factor exposures, dynamically managed can result in a portfolio of hedge funds with consistently high risk-adjusted returns.

The remaining sections of this article are organized as follows. In Section II we address the issue of manager selection by analysis of historical returns and demonstrate in general the lack of persistence in hedge fund manager performance. We however find a general degree of persistence in risk as measured by the volatility of returns. Section III introduces a new algorithm for risk budgeting we believe is particularly useful for hedge fund allocation. Section IV discusses some less conventional quantitative measures for evaluating hedge fund managers, in particular the use of pure persistence measures such as the Hurst exponent. In Section V we discuss the general aspects of a due diligence process and identify a process particularly suited to decision making for this process. Section VI reviews the ongoing monitoring of the hedge fund managers in the portfolio and given the absence of transparency discusses the use of Omega to identify changes in a manager's risk profile and as a key to investor redemptions.

II. PERSISTENCE IN HEDGE FUND PERFORMANCE

More often than not, hedge funds are evaluated based on their historical performance. Good historical performance is almost always followed by a growth in assets under management while poor historical performance is penalized. This suggests that market participants have the belief, conscious or unconscious, that performance is persistent. This is despite numerous studies including Brown and Goetzmann [2003], Kat and Menexe [2003], and Schneeweis et al. [2002], that show that past performance is a very poor guide to future performance.

In this section we replicate the results of these earlier studies albeit with a different sample set and extend both the methodology and the results. In particular we start with the simple monthly returns for the aforementioned 314 hedge funds to initially test for persis-

EXHIBIT 2
Dispersion in Returns, Volatility, and Sharpe Ratio

A — Dispersion in Returns

	Mean	Standard Deviation	Skewness	Bottom Quartile	Top Quartile	Inter-quartile Range
Convertible Arbitrage	10.78%	3.20%	0.86	7.24%	15.03%	7.79%
Distressed Securities	9.26%	3.92%	-0.47	4.11%	14.27%	10.16%
Merger Arbitrage	9.17%	1.55%	0.61	7.29%	11.26%	3.97%
Fixed Income Arbitrage	9.23%	3.62%	1.00	5.77%	15.19%	9.42%
Equity Market Neutral	8.30%	3.63%	0.49	4.39%	13.28%	8.89%
Equity Long/Short	12.89%	5.72%	-0.12	6.03%	20.34%	14.31%
Global Macro	10.77%	6.67%	1.17	4.36%	19.93%	15.57%

B — Dispersion in Volatility

	Mean	Standard Deviation	Skewness	Bottom Quartile	Top Quartile	Inter-quartile Range
Convertible Arbitrage	5.57%	2.98%	1.04	2.46%	9.78%	7.32%
Distressed Securities	10.51%	6.80%	1.21	4.75%	21.88%	17.13%
Merger Arbitrage	5.84%	3.01%	3.11	3.38%	9.40%	6.02%
Fixed Income Arbitrage	7.38%	6.57%	1.89	1.76%	17.35%	15.59%
Equity Market Neutral	8.21%	4.89%	0.96	3.12%	15.35%	12.23%
Equity Long/Short	19.84%	9.23%	0.92	9.90%	32.52%	22.62%
Global Macro	15.41%	7.98%	1.06	7.52%	27.06%	19.54%

tence in hedge fund performance. We divide the six-year period into two sub-periods, the first one extending from January 1997 to December 1999, and the second period extending from January 2000 to December 2002. We calculate average returns, standard deviations, and Sharpe ratios for each fund in two sub-periods. To verify the robustness of our results and to reduce the effects of October 1998 we repeated this analysis for two-year sub-periods. The first sub-period covers January 1999 to December 2000, and the second sub-period covers January 2001 to December 2002.

First, we use non-parametric contingency tables to test the hypothesis of whether or not returns, standard deviations, and Sharpe ratios display any persistence. In order to do this, we calculate the median values for all of the performance variables in each period and categorize each hedge fund as a winner (W) or a loser (L) based on its performance being better or worse than median performance for all the funds in the strategy type. We repeat this analysis for volatility by likewise defining a manager as a loser (winner) if his or her standard deviation is above (below) the median standard deviation of the managers within the same strategy. Similarly, if a manager's Sharpe ratio is greater (less) than the median Sharpe ratio of the managers within the same strategy, the manager is categorized as a winner (loser). The decision of winner or loser is based on a presumed risk-averse investor's utility function that prefers higher return and lower risk.

Persistence exists, if a winner (loser) in the first sub-period as defined above continues to be a winner (loser) in the second sub-period. Formally, we test the hypothesis of persistence by using contingency tables and a cross-product

EXHIBIT 3

Contingency Tables Approach to Test Persistence in Return, Volatility, and Sharpe Ratio Using Three-Year Sub-Periods

A — Persistence in Returns

Strategy	W1W2	W1L2	L1L2	L1W2	CPR	Z SCORE
Convertible Arbitrage	16	10	16	10	2.56	1.65
Distressed Securities	4	5	2	4	0.40	-0.84
Merger Arbitrage	5	7	4	7	0.41	-1.04
Fixed Income Arbitrage	4	5	4	5	0.80	-0.24
Equity Market Neutral	10	12	9	12	0.63	-0.76
Equity Long/Short	20	39	20	39	0.26	-3.43
Global Macro	9	13	9	13	0.48	-1.20

B — Persistence in Volatility

Strategy	W1W2	W1L2	L1L2	L1W2	CPR	Z SCORE
Convertible Arbitrage	19	7	19	7	7.37	3.19
Distressed Securities	7	1	6	1	42.00	2.46
Merger Arbitrage	8	4	7	4	3.50	1.43
Fixed Income Arbitrage	7	3	6	3	4.67	1.56
Equity Market Neutral	18	4	17	4	19.13	3.76
Equity Long/Short	48	11	48	11	19.04	6.23
Global Macro	17	5	17	5	11.56	3.40

C — Persistence in Sharpe Ratio

Strategy	W1W2	W1L2	L1L2	L1W2	CPR	Z SCORE
Convertible Arbitrage	15	11	15	11	1.86	1.10
Distressed Securities	6	2	5	2	7.50	1.72
Merger Arbitrage	3	9	2	9	0.07	-2.53
Fixed Income Arbitrage	5	5	4	5	0.80	-0.24
Equity Market Neutral	9	13	8	13	0.43	-1.37
Equity Long/Short	22	37	22	37	0.35	-2.73
Global Macro	8	14	8	14	0.33	-1.79

ratio (CPR) as in Kat and Menexe (2003). The CPR as defined below captures the ratio of the managers that show persistence to the managers that do not.

$$CPR = \frac{W1W2 * L1L2}{W1L2 * L1W2} \tag{1}$$

where W1 is the winner in the first sub-period, W2 is the winner in the second sub-period, L1 is the loser in the first sub-period, and L2 is the loser in the second sub-period. Therefore if a manager is a winner during both sub-periods, he/she will be labeled as W1W2, etc. Under the null hypothesis of no persistence the CPR so defined equals 1. In other words, when there is no persistence one would expect each of the four categories denoted by W1W2, W1L2, L1L2, and L1W2 to have 25% of the total number of the funds. The significance of CPR is tested by a Z-score, which is the ratio of natural logarithm of the CPR to the standard error

Exhibit 4

Contingency Tables Approach to Test Persistence in Returns, Volatility, and Sharpe Ratio Using Three-Year Sub-Periods

A — Persistence in Returns

Strategy	Slope	t-statistic	R-squared
Convertible Arbitrage	-0.45	-1.07	0.02
Distressed Securities	-0.50	-1.30	0.05
Merger Arbitrage	-0.09	-0.29	-0.04
Fixed Income Arbitrage	0.03	0.10	-0.05
Equity Market Neutral	-0.36	-3.19	0.18
Equity Long/Short	-0.54	-5.90	0.22
Global Macro	-0.12	-0.92	-0.03

B — Persistence in Volatility

Strategy	Slope	t-statistic	R-squared
Convertible Arbitrage	0.93	11.34	0.72
Distressed Securities	2.04	9.05	0.85
Merger Arbitrage	1.20	3.89	0.39
Fixed Income Arbitrage	0.50	2.28	0.19
Equity Market Neutral	0.89	8.82	0.65
Equity Long/Short	0.86	12.69	0.58
Global Macro	0.51	5.76	0.43

C — Persistence in Sharpe Ratio

Strategy	Slope	t-statistic	R-squared
Convertible Arbitrage	1.06	11.06	0.72
Distressed Securities	0.03	0.10	0.01
Merger Arbitrage	0.02	0.17	0.01
Fixed Income Arbitrage	0.15	0.75	0.03
Equity Market Neutral	0.14	2.36	0.11
Equity Long/Short	-0.45	-3.75	0.10
Global Macro	-0.15	-1.02	0.02

of the natural logarithm of CPR and is calculated as follows:

$$\sigma = \sqrt{\left(\frac{1}{W1} + \frac{1}{W2} + \frac{1}{L1} + \frac{1}{L2}\right)} \qquad (2)$$

where σ is the standard error of the natural logarithm of the CPR and the

$$Z - score = \frac{\ln(CPR)}{\sigma} \qquad (3)$$

When the Z-score is greater than 1.96, the null hypothesis of no persistence is rejected at a 5% level of significance. Exhibit 3 presents the contingency tables, CPRs, and Z-scores to test the persistence in returns, standard deviations, and Sharpe ratios of the managers of the seven hedge fund strategies for the three-year sub-periods

E X H I B I T 5

Contingency Tables Approach to Test Persistence in Returns, Volatility, and Sharpe Ratio Using Two-Year Sub-Periods

A — Persistence in Returns

Strategy	W1W2	W1L2	L1L2	L1W2	CPR	Z SCORE
Convertible Arbitrage	14	12	14	12	1.36	0.55
Distressed Securities	4	4	3	4	0.75	-0.28
Merger Arbitrage	7	5	6	5	1.68	0.62
Fixed Income Arbitrage	7	3	6	3	4.67	1.56
Equity Market Neutral	10	12	9	12	0.63	-0.76
Equity Long/Short	21	38	21	38	0.31	-3.08
Global Macro	11	11	11	11	1.00	0.00

B — Persistence in Volatility

Strategy	W1W2	W1L2	L1L2	L1W2	CPR	Z SCORE
Convertible Arbitrage	18	8	18	8	5.06	2.70
Distressed Securities	7	2	5	1	17.50	2.11
Merger Arbitrage	8	4	7	4	3.50	1.43
Fixed Income Arbitrage	8	2	7	2	14.00	2.34
Equity Market Neutral	16	6	15	6	6.67	2.79
Equity Long/Short	44	16	43	15	7.88	4.93
Global Macro	16	6	16	6	7.11	2.90

C — Persistence in Sharpe Ratio

Strategy	W1W2	W1L2	L1L2	L1W2	CPR	Z SCORE
Convertible Arbitrage	13	13	13	13	1.00	0.00
Distressed Securities	4	5	2	4	0.40	0.84
Merger Arbitrage	5	7	4	7	0.41	-1.04
Fixed Income Arbitrage	5	5	4	5	0.80	0.24
Equity Market Neutral	10	12	9	12	0.63	-0.67
Equity Long/Short	30	29	30	29	1.07	0.18
Global Macro	11	11	11	11	1.00	0.00

previously defined. Our results show that none of the strategies display statistically significant persistence in their returns or Sharpe ratios. However, we find much more persistence in standard deviations with the exception of merger and fixed income arbitrage.

In addition to the contingency table tests, we extend this analysis by use of a regression analysis methodology to further test the hypothesis of persistence. In this approach, we regress the parameter values in the second sub-period on the parameter values in the first sub-period. If the coefficient of the slope coefficient is significantly positive we take this as evidence of persistence. Overall, the results of the regression analysis are detailed in Exhibit 4 and support the results of the contingency tables insofar as none of the strategies show significant persistence at the return level. However we do note that in contrast to the CPR analysis convertible arbitrage and equity market neutral strategies show persistence in Sharpe ratios and more interestingly we

EXHIBIT 6

Regression Analysis Approach to Test Persistence in Returns, Volitility, and Sharpe Ratio Using Two-Year Sub-Periods

A — Persistence in Returns

Strategy	Slope	t-statistic	R-squared
Convertible Arbitrage	-0.69	-2.95	0.13
Distressed Securities	-0.11	-0.39	-0.06
Merger Arbitrage	0.32	0.93	-0.01
Fixed Income Arbitrage	-0.71	-4.71	0.50
Equity Market Neutral	-0.34	-4.08	0.27
Equity Long/Short	-0.19	-3.21	0.07
Global Macro	-0.06	-0.49	-0.02

B — Persistence in Volatility

Strategy	Slope	t-statistic	R-squared
Convertible Arbitrage	0.96	12.32	0.75
Distressed Securities	1.14	2.96	0.36
Merger Arbitrage	1.81	5.70	0.59
Fixed Income Arbitrage	0.67	13.36	0.91
Equity Market Neutral	0.64	9.11	0.66
Equity Long/Short	0.41	10.20	0.47
Global Macro	0.23	2.86	0.14

C — Persistence in Sharpe Ratio

Strategy	Slope	t-statistic	R-squared
Convertible Arbitrage	0.58	4.23	0.29
Distressed Securities	0.09	0.42	0.01
Merger Arbitrage	-0.11	-1.26	0.07
Fixed Income Arbitrage	0.04	0.39	0.01
Equity Market Neutral	-0.02	-0.71	0.02
Equity Long/Short	-0.03	-0.27	0.01
Global Macro	-0.01	-0.02	0.01

note the existence of strong persistence in the standard deviations across all strategies. We would note however that the average explanatory power measured by the R-squared for the standard deviation regressions is much higher than the R-squared for return and Sharpe ratio regressions.

For completeness we repeat the CPR and the regression analysis for the two-year sub-periods defined previously. The findings of these analyses are displayed in Exhibits 5 and 6 respectively. Our results are very similar to and strongly support our findings with three-year sub-periods. In summary, we find strong evidence of persistence in risk profiles and no evidence of persistence in returns and Sharpe ratios of hedge fund managers.

A glaring weakness in the analysis above is that little attention is devoted to individual strategy returns. These results in a comparison on an equal basis of both high and low return strategies relative to a median return for all strategies. Equally, none of the macroeconomic factors driving strategy returns over the sample periods are accounted for, creating sample period bias. We address these issues by extending the contingency table analysis by re-defining a winner or a loser in relation to an excess or deficit return over a stylized hedge fund benchmark. Specifically we define the manager as a winner (loser) if his or her return is better (worse) than the respective strategy index return, if s/he is less (more) volatile than the strategy index, or if his or her Sharpe ratio is better (worse) than the Sharpe ratio of the index. The results of this analysis are presented in Appendix A and confirm the previous analysis when the peer group median is used to define a winner or a loser.

In summary, these results imply that the simple use of the performance history of a manager is of very little use in estimating future returns or future risk-adjusted returns; by comparison the historical risk profile as represented by the volatility is in general quite valuable in estimating future volatility. This is of great consequence for both portfolio construction and for manager selection and argues for a risk budgeting approach to either.

III. RISK BUDGETING

The previous section demonstrated the persistence of risk as measured by volatility. This feature makes the process of determining hedge fund allocations within a portfolio or strategy group particularly suited to a risk budgeting methodology. Risk budgeting is an asset allocation technique where, unlike more conventional methods that rely on some form of risk-reward optimization, capital is allocated to risk buckets with no consideration of associated returns. Typically most risk budgets allocate capital in a non-formulaic fashion with some form of limit structure that constrains the overall riskiness of the portfolio.

We propose a departure from a subjective methodology and demonstrate below a quantitative algorithm that determines a formulaic allocation to each risk class. The basis for this algorithm is the simple a priori assumption that the risk posed to the portfolio by each risk class should, in the absence of any superior information, be identical.

We assume a total of N risk classes (funds in this case) to be allocated to with the i-th risk class having a volatility of σ_i. The assumption of equal risk to the portfolio from each risk class requires that

$$A_i\sigma_i = A_j\sigma_j \tag{4}$$

where A_i is the capital allocation to manager i and A_j the capital allocation to manager j.

Given the sum of all capital allocated among N risk classes is equal to the total capital A, it follows trivially that

$$\sum_{i=1}^{N} A_i = A \tag{5}$$

Likewise it follows from (5) that A_j, the capital allocated to the j-th, fund can be expressed

$$A_j = A - \sum_{i \neq j}^{N} A_i \tag{6}$$

Simple algebraic manipulation of Equations (4) and (6) then results in

$$A_j = \frac{A}{\left(1 + \sum_{i \neq j}^{N} \sigma_j \big/ \sigma_i\right)} \tag{7}$$

We are therefore able to express the unbiased risk based allocation to each risk class very simply as a function of the volatilities of each of the risk classes that can in theory be allocated to.

We note that the power of this method is such that it applies generally to any definitions of risk bucket or asset class and equally for any definition of the relevant risk variable. This provides for a methodology not just in constructing hedge fund portfolios but also in the wider field of risk budget based asset allocation. Within the hedge fund universe we believe that given the objective nature of the allocations arrived at, this methodology could serve for the purposes of setting benchmark fund weights for peer groups. We note with interest that the recent proliferation of hedge fund indices in fact tends to equal weight allocations with consequences for the overall volatility and risk adjusted returns of the indices under consideration. With broader use of such a methodology, manager selection and capital allocations can be judged relative to objective risk weights and therefore serve as a direct test of manager selection and portfolio construction skill.

We leave to Section IV of this article a demonstration of the utility of a risk budgeting process in the portfolio construction process by creating both risk budgeted and equal weighted test portfolios and examining comparative statistics.

IV. QUANTITATIVE ALPHA GENERATION ESTIMATION

In Section II, we found no evidence of persistence in returns for the managers in the hedge fund strategies covered using a methodology that compares returns to some defined median return as described above. However we note empirically that some managers appear to demonstrate some degree of internal performance persistence. The challenge for quantitative manager selection is to identify these persistent managers. The approach we take is

EXHIBIT 7
Strategy Distribution for Three Hurst Portfolios

Strategy	Low Hurst	Medium Hurst	High Hurst
Equity Long/Short	17%	15%	11%
Convertible Arbitrage	9%	11%	22%
Equity Market Neutral	26%	4%	15%
Fixed Income Arbitrage	13%	8%	21%
Distressed Securities	0%	21%	19%
Global Macro	21%	16%	6%
Merger Arbitrage	13%	24%	5%

Exhibit 8
Equally Weighted Hurst Portfolio Summary Statistics

A — In-Sample Development Period: January 1997 to December 1999

	Low Hurst	Medium Hurst	High Hurst
Number of Managers	105	105	104
Hurst Exponent Range	0.32-0.58	0.59-0.69	0.70-0.98
Rate of Return	17.05%	17.64%	16.86%
Standard Deviation	6.51%	6.82%	6.29%
Sharpe Ratio	2.16	2.15	2.20
Maximum Drawdown	-4.54%	-6.03%	-7.10%
Calmar Ratio	3.76	2.93	2.37
Number of Up Months	29	30	29
Number of Down Months	7	6	7
Maximum Consecutive Gain Length	5	10	10
Maximum Consecutive Loss Length	1	2	5

B — Out-of-Sample Validation Period: January 2000 to December 2002

	Low Hurst	Medium Hurst	High Hurst
Number of Managers	105	105	104
Hurst Exponent Range	0.32-0.58	0.59-0.69	0.70-0.98
Rate of Return	3.47%	6.22%	8.83%
Standard Deviation	5.39%	5.01%	3.69%
Sharpe Ratio	0.09	0.64	1.58
Maximum Drawdown	-4.57%	-3.52%	-2.77%
Calmar Ratio	0.76	1.77	3.19
Number of Up Months	19	26	29
Number of Down Months	17	10	7
Maximum Consecutive Gain Length	4	4	9
Maximum Consecutive Loss Length	4	2	2

to examine the problem of persistence directly, and not define it by some relative return. An approach that makes no assumptions on either the nature of the return distribution or relative value of returns is the Hurst exponent.

The Hurst exponent is a measure of whether a trend (negative or positive) will persist or mean revert to some historical average. The Hurst exponent H makes no assumptions about the frequency distribution of the underlying data and can be formulated as follows:

$$RS_t \cong (ct)^H \tag{8}$$

or

$$\ln RS_t = \ln(c) + H\ln(t) \tag{9}$$

where is RS_t the range of cumulative deviations from the mean divided by the standard deviation. H as defined above is the Hurst exponent and varies between zero and one.

In this derivation a Hurst exponent of 0.5 corresponds to manager performance that is truly random: for example with returns in a given period completely independent of returns in the previous period. An exponent such that $0.5 < H \leq 1$ describes performance

EXHIBIT 9

Risk Budgeted Hurst Portfolio Summary Statistics

A — In-Sample Development Period: January 1997 to December 1999

	Low Hurst	Medium Hurst	High Hurst
Number of Managers	105	105	104
Hurst Exponent Range	0.32-0.58	0.59-0.69	0.70-0.98
Rate of Return	12.70%	10.50%	13.40%
Standard Deviation	3.54%	2.93%	2.17%
Sharpe Ratio	2.74	2.56	4.79
Maximum Drawdown	-2.20%	-2.27%	-1.99%
Calmar Ratio	5.77	4.63	6.73
Number of Up Months	31	35	33
Number of Down Months	5	1	3
Maximum Consecutive Gain Length	9	19	19
Maximum Consecutive Loss Length	1	1	3

B — Out-of-Sample Validation Period: January 2000 to December 2002

	Low Hurst	Medium Hurst	High Hurst
Number of Managers	105	105	104
Hurst Exponent Range	0.32-0.58	0.59-0.69	0.70-0.98
Rate of Return	6.35%	7.57%	8.48%
Standard Deviation	2.56%	2.21%	1.50%
Sharpe Ratio	1.31	2.07	3.65
Maximum Drawdown	-0.84%	-1.53%	-0.57%
Calmar Ratio	7.56	4.95	14.88
Number of Up Months	30	32	35
Number of Down Months	6	4	1
Maximum Consecutive Gain Length	17	20	30
Maximum Consecutive Loss Length	1	2	1

that is persistent. We note that persistence as defined by this criterion relates to persistence of either negative returns or positive returns. Finally, we note that an exponent such that $0 < H \leq 0.5$ describes anti-persistent or mean reverting manager performance. Anti-persistent performance implies that a period of poor performance will generally be followed by a period of good performance and vice versa. Appendix B contains a more detailed derivation of the Hurst exponent.

Similar to the persistence analysis discussed in Section II, we divide the six-year time period into two three-year sub-periods and repeat the methodology of the previous section, only this time using the Hurst component as the determiner of persistence. For the purpose of clarity we define the first sub-period as the in-sample development period and the second sub-period as the out-of-sample validation period. The process is then as follows. First, we calculate the Hurst exponent for 314 managers in our database by using the three-year performance data in the in-sample development period. We then rank the managers based on their Hurst exponent, and create three groups. These groups are the low Hurst (105 managers), the medium Hurst (105 managers), and the high Hurst (104 managers). Exhibit 7 defines the strategy distributions in each of the Hurst groups. In general, none of the groups are strategy specific and all of the strategies are represented

Exhibit 10

Equally Weighted D-Statistic Portfolio Summary Statistics

A — In-Sample Development Period: January 1997 to December 1999

	Low D	Medium D	High D
Number of Managers	35	35	34
D-Statistic Range	0.00-0.22	0.23-0.31	0.32-0.52
Rate of Return	16.88%	19.82%	11.00%
Standard Deviation	3.44%	7.23%	7.67%
Sharpe Ratio	3.45	2.05	0.78
Maximum Drawdown	-1.91%	-7.65%	-12.69%
Calmar Ratio	8.84	2.59	0.87
Number of Up Months	35	28	25
Number of Down Months	1	8	11
Maximum Consecutive Gain Length	19	16	6
Maximum Consecutive Loss Length	1	6	5

B — Out-of-Sample Validation Period: January 2000 to December 2002

	Low D	Medium D	High D
Number of Managers	35	35	34
D-Statistic Range	0.00-0.22	0.23-0.31	0.32-0.52
Rate of Return	9.12%	9.26%	9.03%
Standard Deviation	2.57%	4.34%	4.52%
Sharpe Ratio	2.38	1.44	1.33
Maximum Drawdown	-1.60%	-3.56%	-3.85%
Calmar Ratio	5.70	2.60	2.35
Number of Up Months	32	26	28
Number of Down Months	4	10	8
Maximum Consecutive Gain Length	14	6	9
Maximum Consecutive Loss Length	2	2	2

in all Hurst groups, with the sole exception being that distressed securities does not appear in the low Hurst group. Given this independence at the strategy level we now proceed to construct portfolios around these three groupings by assigning equal weights to each manager. The final part of this analysis is to then construct the returns of these Hurst portfolios in the out-of-sample period or validation, i.e., the three years following the in-sample selection period, and then investigate the returns for evidence of persistence.

We construct three portfolios by giving equal weights to each manager in each group. We also construct three portfolios by assigning weights to each manager using a risk budgeting technique. Exhibit 8 presents summary statistics for equally weighted portfolios during in-sample development and out-of-sample validation periods separately. During the in-sample development period, we do not see any significant distinction in returns, standard deviations, and Sharpe ratios; however, the number of consecutive months with up or down performance—another measure of persistence—increases from low to high Hurst portfolio. When we analyze the results within the out-of-sample validation period, we see that the high Hurst portfolio has the

EXHIBIT 11
Risk Budgeted D-Statistic Portfolio Summary Statistics

A — In-Sample Development Period: January 1997 to December 1999

	Low D	Medium D	High D
Number of Managers	35	35	34
D-Statistic Range	0.00-0.22	0.23-0.31	0.32-0.52
Rate of Return	10.68%	12.34%	6.55%
Standard Deviation	0.82%	4.49%	4.93%
Sharpe Ratio	9.37	2.08	0.72
Maximum Drawdown	-0.17%	-6.76%	-8.87%
Calmar Ratio	62.82	1.83	0.74
Number of Up Months	35	30	25
Number of Down Months	1	6	11
Maximum Consecutive Gain Length	19	17	9
Maximum Consecutive Loss Length	1	5	6

B — Out-of-Sample Validation Period: January 2000 to December 2002

	Low D	Medium D	High D
Number of Managers	35	35	34
D-Statistic Range	0.00-0.22	0.23-0.31	0.32-0.52
Rate of Return	7.62%	10.64%	10.08%
Standard Deviation	1.21%	2.63%	2.80%
Sharpe Ratio	3.82	2.90	2.53
Maximum Drawdown	-0.26%	-1.44%	-1.23%
Calmar Ratio	29.31	7.39	8.20
Number of Up Months	35	31	31
Number of Down Months	1	5	5
Maximum Consecutive Gain Length	30	10	19
Maximum Consecutive Loss Length	1	2	2

highest rate of return with the lowest volatility, and therefore the highest Sharpe ratio. Equally the high Hurst portfolio demonstrates the lowest maximum drawdown, the highest Calmar ratio, the largest number of up months, and the highest number of months with consecutive gains.

Exhibit 9 shows the summary statistics of the three portfolios when risk budgeting is used to determine the allocation to each manager. In the out-of-sample validation period, similar to equally weighted portfolios, moving from the low to high Hurst portfolio the outcome becomes more favorable. Furthermore, risk budgeted portfolios produce significantly lower standard deviations and therefore higher Sharpe ratios than equally weighted portfolios with little loss of performance over the period. We also observe that the risk budgeted portfolios had a higher number of up months, and higher number of months with consecutive gains when compared to equally weighted portfolios.

Our findings in Exhibits 8 and 9 show that during the out-of-sample validation period, portfolios containing persistent managers significantly outperform portfolios with managers having little or no persistence. It would therefore appear conclusive that one should in general prefer managers with relatively higher Hurst exponents who therefore

EXHIBIT 12
Average Fund Characteristics for Dead and Alive Funds

	Dead	Alive
Number of Funds	747	2298
Funds Managed	$21,813,578	$89,743,595
Age (in months)	40	64
High-Water Mark	13%	56%
Lockup Period (in months)	0.8	3.4
Required Redemption Notice (in days)	11	33
Average Return	0.3%	1.02%

show more persistence in their performance. Since performance over a given period is as much a function of capital conservation as it is returns, it is not surprising that a pure measure of persistence should demonstrate such efficacy as a predictor of future portfolio returns.

In the previous paragraph, we noted the out-performance of the high Hurst portfolio relative to the medium and low Hurst portfolios. Therefore, we in general prefer managers with higher Hurst values to lower Hurst values. However, we have not as yet chosen to distinguish positive performance persistence from negative performance persistence. As the next step, we further analyze the high Hurst managers and, given the importance we place on capital conservation, eliminate those with high downside risk. To define this parametrically, we use the D-statistic, which compares the value and frequency of a manager's losing months to his or her winning months. This statistic makes no assumptions about a manager's return distribution and is therefore particularly suitable for this asset class. The D-statistic is defined as follows:

$$D\text{-}statistic = \frac{sum|negativereturns|}{sum|allreturns|} \tag{10}$$

The D-statistic thus defined ranges from 0 to 1, with D = 0 representing a return distribution with no downside risk and D = 1 representing one in which a manager has no positive returns. We therefore are predisposed to managers with low D-statistics.

We now repeat the process as defined above; however, we now also calculate the D-statistic for the 104 high Hurst managers using the three-year performance data for the in-sample development period. We now rank the managers based on their D-statistic and create three groups. In keeping with our nomenclature we call these groups the low D (35 managers), medium D (35 managers), and high D (34 managers). We now construct three portfolios by equally weighting the managers in each group. In addition, we construct three portfolios with a risk budgeting technique.

Exhibit 10 presents summary statistics for three equally weighted portfolios for the in-sample development and the out-of-sample validation periods. The exhibit shows that during both periods the low D portfolio has the significantly lowest standard deviation with the highest Sharpe ratio. The low D portfolio also has the lowest maximum drawdown, the highest Calmar ratio, the highest

EXHIBIT 13
Results of the Logistic Regression

	Coefficient	Standard Error
Intercept	10.27	0.64
Funds Managed	0.51	0.04
Age	0.02	0.002
High-Water Mark	2.55	0.16
Lockup Period	0.06	0.01
Required Redemption Notice	0.04	0.004
Average Return	37.34	6.66

EXHIBIT 14
First- and Second-Year Summary Statistic

	Fund A		Fund B	
	1st year	2nd year	1st year	2nd year
Annualized Return	6.79%	6.48%	18.10	16.35
Standard Deviation	3.80%	4.01%	12.29	11.26
Sharpe Ratio (RFR = 5%)	0.47	0.37	1.06	1.01
Maximum Drawdown	-5.80%	-17.68%	-18.55%	-10.04%
Minimum Monthly Return	-4.71%	-8.77%	-9.73%	-4.71%
Maximum Monthly Return	7.83%	3.23%	9.13%	3.85%

number of up months, and the highest number of months with consecutive gains. The summary statistics of the risk budgeted portfolios are presented in Exhibit 11. The statistics of the risk budgeted portfolios strongly support our findings in equally weighted portfolios and display much lower standard deviations, maximum drawdowns, and higher Sharpe ratios than their equally weighted counterparts.

It is worth mentioning that in the initial Hurst analysis presented, the out-of-sample results of the high Hurst portfolio outperformed both the medium and low Hurst portfolios despite no initial filtering of negative (but persistent) performance from the initial portfolio in the in-sample validation. This says much for consistency of returns in a portfolio (good and bad in this case) being a primary determinant of relatively positive returns when compared with portfolios with average lower persistence.

These results indicate that a pure, non-relative, measure of persistence such as the Hurst exponent, in combination with a downside risk measure such as the D-statistic to filter negative persistence, is a very powerful tool for developing portfolios with consistently good performance and generally lower volatility and downside risk. In our opinion the ability to identify a sample of 35 managers with a "future" return of 9.12% and a volatility of 2.57% (on an equally weighted basis) from a pool of 314 managers with an average return of 6.16% and a volatility of 4.52% over the same period is significant.

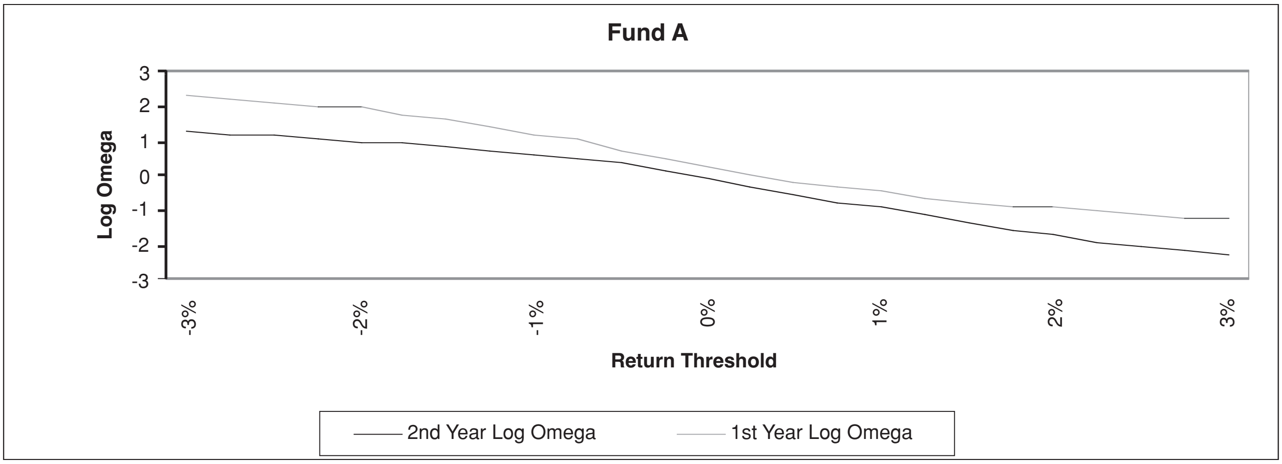
V. DUE DILIGENCE

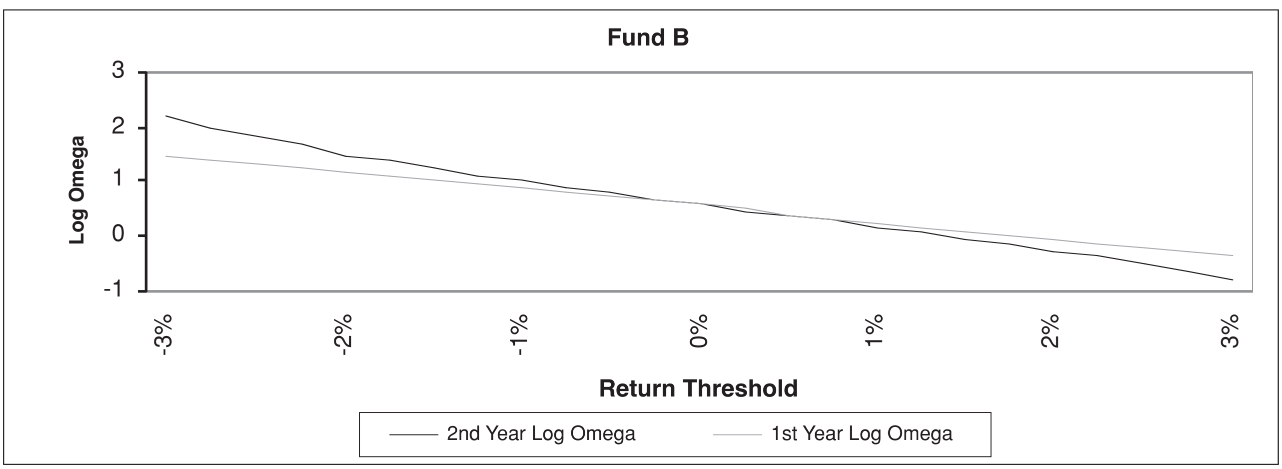
Given the unregulated nature of the hedge fund space, a primary risk in manager selection is the issue of operational risk. Operational risk comprises in part default risk, legal risk, accounting and valuation risk, model risk, key personnel risk, and fraud risk. We define due diligence as the process by which this risk is evaluated both qualitatively and quantitatively. From a portfolio construction process this risk can be lowered by broad diversification; however, within the scope of this article we outline a number of quantitative analysis applied to commonly available information to delineate some of the factor risk at the individual fund level.

At a general level the qualitative aspects of the due diligence process may include, but are not limited to, a thorough understanding of a manager's trading style, decision making process, escalation process, risk management techniques, technology, skills and background of key personnel, level of leverage, transparency, liquidity, marking methods, and use of derivatives. From a quantitative perspective, a manager's return should be analyzed and compared to his or her benchmark and peers. In addition, conventional performance analysis should include: annualized returns, the standard deviation, the downside deviation, Sharpe, Sortino, and Calmar ratios, maximum drawdowns, and the number of down and up months. Equally a manager's alpha, beta, and correlation should be measured in a benchmark or peer analysis. Peer analysis should group peers in deciles based on a careful understanding of the strategy type and an understanding of the risk and return variables and the manager's decile determined to make a best-in-class comparison. A final and important part of this process is a factor analysis of the fund's returns with respect to common market variables to allow for a better understanding of the sources of performance.

However, an important part of the due diligence process is to determine the viability of the fund as an enterprise regardless of performance history. To help in our due diligence process and develop a set of manager pre-screening

EXHIBIT 15
First- and Second-Year Log Omega Curves





rules, we compare some of the characteristics of liquidated funds to those of active funds. Our source for this data is the Tremont (TASS) database sponsored by CSFB has the "graveyard" database, which contains only dead (closed) funds. There are a number of reasons that TASS might include a fund in the graveyard database including funds that no longer report, funds merged into other entities, or funds that were liquidated. In this analysis, we only study those dead funds that are classified as liquidated funds, which make up about 50% of the graveyard database. We extract the performance and characteristics data of the liquidated funds from the graveyard database and merge it with the surviving funds database. Merging these two databases allows us to compare the fund characteristics of the surviving and dead funds and helps us understand some of the factors that might contribute to a fund having to liquidate. Our final database included 747 dead and 2,298 active funds as of December 2002.

We compared the average total funds managed, their age, whether or not there is a high-water mark, lockup period, redemption period, and average returns since the inception of the fund for both dead and surviving funds. We noticed with no great surprise that the average assets managed, age, percent of the funds applying a high-water mark, lockup period, required redemption period, and average returns were significantly higher for the surviving funds than for the dead funds. These results are presented in Exhibit 12 and are very similar to findings of Gregoriou [2003] and Liang [2000].

We also used a logistic regression model to determine

EXHIBIT 16
Last Twelve Monthly Returns of Liquidated Funds

A — Funds That Give Early Sign of Liquidation

Months Before Liquidation	1	2	3	4	5	6	7	8	9	10	11	12
Fund A	-20.40	-5.70	0.20	-24.60	-20.00	-7.60	14.30	-4.70	20.00	-21.60	-22.80	-25.40
Fund B	-0.71	0.37	0.32	0.10	0.25	0.49	-0.32	-0.31	-1.02	-1.63	-7.85	-26.50
Fund C	-4.17	1.46	1.34	0.44	0.69	1.53	1.36	1.45	26.92	-24.84	-8.82	-16.68
Fund D	-25.23	-27.77	-21.05	-1.86	-12.77	15.09	-20.07	26.17	5.61	-24.05	13.14	-38.09
Fund E	1.71	-22.45	-21.44	-5.96	-25.02	-6.27	-7.90	66.02	-17.82	-37.97	-13.94	5.00

B — Funds That Give Late Sign of Liquidation

Months Before Liquidation	1	2	3	4	5	6	7	8	9	10	11	12
Fund F	-20.33	-4.98	4.00	-4.72	-0.42	0.92	-0.24	3.56	0.20	0.10	-2.56	-1.16
Fund G	-20.34	-4.94	4.01	-4.77	-0.38	0.89	-0.27	3.55	0.20	0.11	-2.57	-1.13
Fund H	-28.64	1.09	1.09	2.22	2.05	1.73	1.31	-0.60	1.54	-1.59	-1.12	0.86
Fund I	-13.19	-78.41	-13.94	28.25	-11.78	66.90	31.30	10.54	13.10	15.97	54.78	-3.23
Fund J	-44.28	-84.27	13.33	-13.14	9.32	-7.14	0.46	-5.96	-11.15	11.33	-5.16	-3.83

C — Funds That Do Not Give Any Sign of Liquidation

Months Before Liquidation	1	2	3	4	5	6	7	8	9	10	11	12
Fund K	-4.14	1.59	1.37	1.39	1.66	0.75	2.83	1.48	0.09	0.35	0.53	1.70
Fund L	1.99	-1.03	-0.67	0.75	-4.04	5.06	-2.77	4.64	1.19	6.13	0.33	-2.06
Fund M	0.38	1.23	2.67	-1.02	-0.88	-1.11	1.89	1.44	1.35	-0.53	0.78	1.85
Fund N	1.68	0.47	0.76	1.73	-0.34	-0.35	-0.47	1.21	0.94	0.95	-0.03	0.62
Fund O	-0.83	0.02	1.70	0.10	1.35	1.56	0.92	-0.59	-0.30	-0.21	2.53	-1.26

the fund characteristics that were significantly different for dead and alive funds. Logit models are appropriate to use when trying to model a dependent variable that can take binary values (e.g., 0 or 1, good or bad, dead or alive). The general form of the model is:

$$P_i = E(Y = 1|X_i) = F(X_i\beta) = \frac{1}{1 + e^{-(X_i\beta)}} \quad (11)$$

where P_i is the predicted probability and ranges between 0 and 1 and nonlinearly related to $X_i\beta$. $F()$ is the cumulative density function (CDF) of the logistic distribution.

The logit model is particularly suited for our purposes given the need to predict the probability, given a fund's characteristics, of the fund's viability, which is binary in nature. Our results are listed in Exhibit 13 and show that young funds with poor performance, minimal assets under management, a short lockup period, a short redemption notice period, and no high-water mark are most likely to liquidate. In a forthcoming article, De Souza and Smirnov [2003] link a number of these variables in a barrier model to describe the path dependent approach to failure that we define as a critical liquidation cycle.

The due diligence process, performed well, is both time and capital intensive. We believe, based on these results, that some initial screening rules can be developed to help eliminate the managers that do not meet the investment mandate, prior to initiating the due diligence process. These rules should include some concept of minimum assets under management and a sense of appropriate redemption and other liquidity features relative to the volatility of the assets and liabilities of the fund under consideration.

VI. ONGOING MONITORING

Once a hedge fund manager passes the due diligence process and is included in the portfolio, systematic ongoing monitoring is crucial to ensure that the manager will not pose any significant risk to the portfolio. Crucial to the process is the receipt of timely and accurate information. Risk analysis at a general level should include monitoring variables such as value-at-risk, conditional value-at-risk, and performing stress tests at both fund and aggregate levels. At a more specialized level, idiosyncratic risk such as optionality, liquidity, and spread blowout risk should be tailored to the individual strategy.

However, in keeping with the scope of this article we describe a measure called "Omega" that was recently developed by Keating and Shadwick [2002]. In addition, Murphy [2002] suggests that widely used statistical measures of investment risk have significant limitations and introduces Omega to capture higher levels of information. Omega is applied to the performance history and monitors the ongoing profile of a fund's risk over time at a level that takes into account the distribution of returns unlike "average" value measures such as volatility. We further find this measure to be particularly sensitive to the investor utility function and therefore effective in determining redemption risk.

Omega can be calculated as follows:

$$\Omega(L) = \frac{\int_L^b (1 - F(r))dr}{\int_a^L F(r)dr} \tag{12}$$

where L is the required return threshold, a and b are the return intervals, and F(r) is the cumulative distribution of returns below threshold L.

Omega involves partitioning returns into loss and gain above and below a required return threshold and then considering the probability-weighted ratio of returns above and below partitioning. It therefore employs all the information contained within the return series.

In the discrete case, with equal frequency, we can write:

$$\Omega(L) = \frac{\sum_a^b Max(0, R^+)}{\sum_a^b Max(0, \left|R^-\right|)} \tag{13}$$

where R positive (negative) is the return above (below) a threshold L.

In this convention, therefore, high Omegas are to be preferred to low Omegas at equal points of the threshold. It is important to note that in keeping with the philosophy of this article the Omega function is equivalent to the return distribution itself, rather than being an approximation of it. Unlike moment information, it does not lose any information and is therefore as statistically significant as the return series itself. No assumptions about distribution function, risk preferences, and utility function are necessary. By definition, since it contains all higher moments, it is particularly well suited for the performance measurement of hedge funds in a very elegant fashion.

To capture the full utility of the Omega function that displays the above, we conduct the following exercise. We divide the two-year performance data for two managers into two one-year sub-periods and calculate Omega and the logarithm of Omega for a return threshold range of negative 3% to positive 3%. The slope of the log Omega curve then reveals the rate of change of the partitioned cumulative returns as a function of threshold return which not only is a measure of risk but also an issue of investor sensitivity to the probability of the frequency and magnitude of monthly drawdowns. The Omega function conveniently summarizes the return distribution function such that for negative threshold returns the more negative the slope the lower the risk. However, for positive threshold returns, a flatter curve indicates a higher probability of outperformance.

Exhibit 14 shows the first-year and second-year summary statistics of two randomly selected hedge fund managers. Based on maximum drawdown, the risk profile of fund A deteriorated significantly, while its maximum drawdown increased from –5.80% in the first year to –17.68% in the second year. However, fund B's risk profile improved during the second year while its maximum drawdown decreased from –18.55% in the first year to –10.04% in the second year.

Log Omega curves in Exhibit 15 capture the changes in the risk profiles of funds A and B over time and conveniently provide information about risk that is similar to that contained in Exhibit 14. During the second year, the log Omega curve of fund A became flatter on the downside and steeper on the upside, indicating that fund A became more aggressive and therefore increased downside risk and deterioration in performance. However, the log Omega curve of fund B became steeper during the second year, indicating that fund B became less aggressive and showed improvement in the risk profile. The less aggressive nature of fund B also impacted its performance which deteriorated during the second year; this can be observed by a steeper log Omega curve on the upside.

Our findings presented in Exhibits 14 and 15 indicate that the Omega measure reveals all the information contained within return series, and is very useful in identifying changes in a manager's risk profile and performance. This would be an especially helpful tool for the ongoing monitoring process, since the purpose of that process is to capture any changes in a manager's risk profile and performance attributes.

Finally, we present as a matter of completeness, the last 12 monthly returns of various liquidated funds extracted from the graveyard database. We divided the funds into three separate categories based on whether or not we believe the performance history gave noticeable early signs of liquidation. We categorize these funds loosely as: funds that gave early signs of liquidation, funds that gave late signs of liquidation, and funds that gave no sign of liquidation. We present monthly returns for five funds in each group in sections A to C of Exhibit 16 respectively.

These returns indicate that without transparency it is not always possible to identify funds that are in distress and could eventually liquidate by simply examining monthly returns. These findings imply that besides receiving monthly performance data, it is critical to have transparency as to the manager's portfolio and communications on a regular basis to identify distress. In particular, in keeping with the results of the logit analysis presented in the last section that identified a variety of factors relevant to the stability of client capital such as poor performance, short lockup periods, and short redemption notice as criteria pertinent to liquidation, we would also add issues connected with the stability of credit lines as per analysis in De Souza and Smirnov [2003].

VII. CONCLUSION

In this article we introduce various quantitative tools and argue that manager selection, due diligence, and ongoing monitoring processes for funds of funds should be based on a belief that quantitative analysis is at least as important as qualitative analysis. In particular, given the concerns regarding capital conservation in this space we believe that analyses that incorporate the complete return distribution function are generally superior to those that do not.

We started this article by first demonstrating the dispersion in hedge fund returns and followed this by testing the hypothesis that performance persistence does not exist. Our parametric and non-parametric test results in Section II strongly support this hypothesis for two- and three-year periods. We demonstrate convincingly that risk does persist and postulate that risk budgeting is therefore a natural approach to allocating capital between managers. We also demonstrate that by comparison to an equal-weighted portfolio, risk budgeting will in general provide better risk-adjusted returns. For the purposes of manager selection we note the use of the Hurst component filtered for positive persistence. We find that when managers are ranked by Hurst exponents and combined into high, medium, and low Hurst portfolios, high Hurst portfolios significantly outperform low and medium Hurst portfolios during out-of-sample testing.

We also argue for the use of logit-type modeling to determine the factors that point to fund viability and extract several factors from a database of liquidated funds. Finally we note the use of the Omega function to address the fund state that returns, standard deviation, downside deviation, Sharpe, Sortino, and Calmar ratios, maximum drawdowns, Omega, and number of down and up months should be analyzed, and benchmark and peer group analysis should be employed as a part of the due diligence and ongoing monitoring process. We believe that funds of funds that have a well-defined and disciplined manager selection, due diligence, and ongoing monitoring process should outperform their peers and benchmarks.

APPENDIX A

EXHIBIT A1

Contingency Tables Approach to Test Persistence in Returns, Volatility, and Sharpe Ratio Using Three-Year Sub-Periods

A — Persistence in Returns

Strategy	W1W2	W1L2	L1L2	L1W2	CPR	Z SCORE
Convertible Arbitrage	10	11	18	13	1.26	0.40
Distressed Securities	6	5	2	2	1.20	0.16
Merger Arbitrage	1	6	6	10	0.10	-1.92
Fixed Income Arbitrage	10	6	1	2	0.83	-0.14
Equity Market Neutral	9	13	12	9	0.92	-0.13
Equity Long/Short	20	35	15	48	0.18	-4.23
Global Macro	6	11	6	21	0.16	-2.71

B — Persistence in Volatility

Strategy	W1W2	W1L2	L1L2	L1W2	CPR	Z SCORE
Convertible Arbitrage	11	8	32	1	44.00	3.39
Distressed Securities	4	2	8	1	16.00	2.02
Merger Arbitrage	7	5	10	1	14.00	2.20
Fixed Income Arbitrage	6	4	8	1	12.00	2.00
Equity Market Neutral	7	1	34	1	2.38	3.71
Equity Long/Short	11	5	90	12	16.50	4.52
Global Macro	2	5	36	1	14.40	2.03

C — Persistence in Sharpe Ratio

Strategy	W1W2	W1L2	L1L2	L1W2	CPR	Z SCORE
Convertible Arbitrage	6	11	33	2	9.00	2.48
Distressed Securities	4	6	3	2	1.00	0.00
Merger Arbitrage	3	7	7	6	0.50	-0.78
Fixed Income Arbitrage	11	6	1	1	1.83	0.40
Equity Market Neutral	6	7	22	8	2.36	1.24
Equity Long/Short	3	2	41	72	0.85	-0.17
Global Macro	7	1	1	35	0.20	-1.09

EXHIBIT A2

Contingency Tables Approach to Test Persistence in Returns, Volatility, and Sharpe Ratio Using Two-Year Sub-Periods

A — Persistence in Returns

Strategy	W1W2	W1L2	L1L2	L1W2	CPR	Z SCORE
Convertible Arbitrage	5	10	21	16	0.66	-0.66
Distressed Securities	4	2	6	3	4.00	1.24
Merger Arbitrage	5	6	7	5	1.17	0.18
Fixed Income Arbitrage	9	1	5	4	11.25	1.94
Equity Market Neutral	8	11	11	13	0.62	-0.78
Equity Long/Short	22	35	15	46	0.20	-3.93
Global Macro	9	8	16	11	1.64	0.79

B — Persistence in Volatility

Strategy	W1W2	W1L2	L1L2	L1W2	CPR	Z SCORE
Convertible Arbitrage	9	3	38	2	57.00	4.10
Distressed Securities	2	4	8	1	4.00	1.01
Merger Arbitrage	1	1	17	4	4.25	0.95
Fixed Income Arbitrage	4	1	10	4	10.00	1.82
Equity Market Neutral	4	3	33	3	14.67	2.76
Equity Long/Short	13	15	83	7	10.28	4.26
Global Macro	3	8	32	1	12.00	2.04

C — Persistence in Sharpe Ratio

Strategy	W1W2	W1L2	L1L2	L1W2	CPR	Z SCORE
Convertible Arbitrage	5	10	31	6	2.58	1.34
Distressed Securities	2	4	7	2	1.75	0.47
Merger Arbitrage	1	1	9	12	0.75	-0.19
Fixed Income Arbitrage	7	1	6	5	8.40	1.73
Equity Market Neutral	7	7	15	14	1.07	0.11
Equity Long/Short	23	11	29	55	1.10	0.23
Global Macro	3	10	23	8	0.86	-0.19

APPENDIX B

Calculating the Hurst Exponent

Let r_t be the time series of monthly returns for T months, μ the average, and σ the standard deviation.

$$\mu = \frac{1}{T}\sum_{t=1}^{T} r_t$$

$$\sigma = \left\{\frac{1}{T}\sum_{t=1}^{T}\left(r_t - \bar{r}\right)^2\right\}^{0.5}$$

Then calculate monthly deviations from average return for each month

$$x_t = (r_t - \mu) \text{ where } 1 \leq t \leq T$$

For each t calculate cumulative monthly deviations

$$x(\tau, t) = \sum_{\tau} x_t \text{ where } 1 \leq \tau \leq t$$

and range R:

$$R_t = \max(x(\tau, t)) - \min(x(\tau, t))$$

Rescaled range is defined as:

$$RS_t = \frac{R_t}{\sigma}$$

and

$$RS_t \cong (ct)^H$$

where H is the Hurst exponent and c is a constant. Linear regression is performed on $\ln(RS_t)$ and $\ln(t)$. The gradient of the regression line is an estimate for the Hurst exponent.

ENDNOTES

The views expressed herein are solely those of the authors and do not necessarily reflect the views of Citigroup Alternative Investments and its affiliates.

[1]For example, see Jimmy Liew [2003] and De Souza and Gokcan.

[2]We observe various degrees of dispersion in returns and volatility of other strategies; these results are not presented for the sake of brevity.

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