# Risk Management for Hedge Funds: Introduction and Overview

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*Although risk management has been a well-plowed field in financial modeling for more than two decades, traditional risk management tools such as mean–variance analysis, beta, and Value-at-Risk do not capture many of the risk exposures of hedge-fund investments. In this article, I review several unique aspects of risk management for hedge funds—survivorship bias, dynamic risk analytics, liquidity, and nonlinearities—and provide examples that illustrate their potential importance to hedge-fund managers and investors. I propose a research agenda for developing a new set of risk analytics specifically designed for hedge-fund investments, with the ultimate goal of creating risk transparency without compromising the proprietary nature of hedge-fund investment strategies.*

Despite ongoing concerns regarding the lack of transparency and potential instabilities of hedge-fund investment companies, the hedge-fund industry continues to grow at a rapid pace. Lured by the prospect of double- and triple-digit returns and an unprecedented bull market, investors have committed nearly $500 billion in assets to alternative investments. Even major institutional investors such as the trend-setting California Public Employees Retirement System are starting to take an interest in hedge funds.[1]

However, many institutional investors are not yet convinced that "alternative investments" is a distinct *asset class*, i.e., a collection of investments with a reasonably homogeneous set of characteristics that are stable over time. Unlike equities, fixed-income instruments, and real estate—asset classes each defined by a common set of legal, institutional, and statistical properties—"alternative investments" is a mongrel category that includes private equity, risk arbitrage, commodity futures, convertible bond arbitrage, emerging market equities, statistical arbitrage, foreign currency speculation, and many other strategies, securities, and styles. Therefore, the need for a set of risk management protocols specifically designed for hedge-fund investments has never been more pressing.

Part of the gap between institutional investors and hedge-fund managers is the very different perspectives that these two groups have on the investment process. The typical manager's perspective can be characterized by the following statements:

- The manager is the best judge of the appropriate risk/reward trade-off of the portfolio and should be given broad discretion for making investment decisions.
- Trading strategies are highly proprietary and, therefore, must be jealously guarded lest they be reverse-engineered and copied by others.
- Return is the ultimate and, in most cases, the only objective.
- Risk management is not central to the success of a hedge fund.
- Regulatory constraints and compliance issues are generally a drag on performance; the whole point of a hedge fund is to avoid these issues.
- There is little intellectual property involved in the fund; the general partner *is* the fund.[2]

Contrast these statements with the following views of a typical institutional investor:

- As fiduciaries, institutions need to understand the investment process before committing to it.
- Institutions must fully understand the risk exposures of each manager and, on occasion, may have to circumscribe a manager's strategies to be consistent with the institution's investment objectives.
- Performance is not measured solely by return, but also includes other factors, such as risk, tracking error relative to a benchmark, and peer-group comparisons.
- Risk management and risk transparency are essential.

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- Institutions operate in a highly regulated environment and must comply with a number of federal and state laws governing the rights, responsibilities, and liabilities of pension plan sponsors and other fiduciaries.
- Institutions desire structure, stability, and consistency in a well-defined investment process that is institutionalized and not dependent on any single individual.

While there are, of course, exceptions to these two sets of views, they do represent the essence of the gap between hedge-fund managers and institutional investors. However, despite these differences, hedge-fund managers and institutional investors clearly have much to gain from a better understanding of each other's perspectives, and they do share the common goal of generating superior investment performance for their clients.

In this article, I hope to contribute to the dialogue between hedge-fund managers and institutional investors by providing an overview of several key aspects of risk management for hedge funds, aspects that any institutional investor must grapple with as part of its manager-selection process. While the risk management literature is certainly well-developed,[3] nevertheless, there are at least five aspects of hedge-fund investments that pose unique challenges for existing risk management protocols and analytics: (1) survivorship bias, (2) dynamic risk analytics, (3) nonlinearities, (4) liquidity and credit, and (5) risk preferences. I describe each of these aspects in more detail in this article, and outline an ambitious research agenda for addressing them.

## Why Risk Management?

In contrast to traditional investment vehicles, such as stocks, bonds, and mutual funds, hedge funds have different risk/return objectives. Most hedge-fund investors expect high returns in exchange for the corresponding risks that they are expected to bear. Perhaps because it is taken for granted that hedge funds are riskier, few hedge-fund investors and even fewer hedge-fund managers seem to devote much attention to active risk management. Hedge-fund investors and managers often dismiss risk management as secondary, with "alpha" or return as the main objective. However, if there is one lasting insight that modern finance has given us, it is the inexorable trade-off between risk and expected return; hence, one cannot be considered without reference to the other. Moreover, it is often overlooked that proper risk management can, by itself, be a source of alpha. This is summarized neatly in the old Street wisdom that "one of the best ways to make money is not to lose it."

More formally, consider the case of a manager with a fund that has an annual expected return, $\mathrm{E}[R]$, of 10 percent and an annual volatility, $\mathrm{SD}[R]$, of 75 percent, a rather mediocre fund that few hedge-fund investors would consider seriously. Now suppose that such a manager were to implement a risk management protocol on top of his investment strategy, a protocol that eliminates the possibility of returns lower than –20 percent. His return after implementing this protocol is then $R^*$, where

$$R^* = \mathrm{Max}[R, -20\%]. \tag{1}$$

Under the assumption of lognormally distributed returns, it can be shown that the expected value of $R^*$, $\mathrm{E}[R^*]$, is 20.9 percent—by truncating the left tail of the distribution of $R$ below –20 percent, this manager has doubled the expected value of the strategy! Risk management can be a significant source of alpha. Moreover, the volatility of $R^*$, $\mathrm{SD}[R^*]$, is 66.8 percent, lower than the volatility of $R$; hence, risk management can simultaneously increase alpha and decrease risk. **Table 1** reports $\mathrm{E}[R^*]$ and $\mathrm{SD}[R^*]$ for various values of $\mathrm{E}[R]$, $\mathrm{SD}[R]$, and truncation levels and illustrates the potent and direct impact that risk management can have on performance.

Of course, risk management rarely takes the simple form of a guaranteed floor for returns. Indeed, such "portfolio insurance" is often quite costly, if it can be obtained at all, and is equivalent to the premium of a put option on the value of the portfolio. For example, the Black–Scholes premium for the put option implicit in Equation 1 is equal to 15.4 percent of the value of the portfolio to be insured.[4] But this only highlights the relevance and economic value of risk management. According to the Black–Scholes formula, the ability to manage risks in such a way as to create a floor of –20 percent for annual performance is worth 15.4 percent of assets under management! The more effective a manager's risk management process is, the more it will contribute to alpha.

## Why Not VaR?

Given the impact that risk management can have on performance, a natural reaction might be to adopt a simple risk management program based on Value-at-Risk (VaR), described in J.P. Morgan's *RiskMetrics* system documentation in the following way:

> Value at Risk is an estimate, with a predefined confidence interval, of how much one can lose from holding a position over a set horizon. Potential horizons may be one day for typical trading activities or a month or longer for portfolio management. The methods described in our documentation use historical returns to forecast volatilities and correlations that are then used to estimate the market risk. These statistics can be applied across a set of asset classes covering products used by financial institutions, corporations, and institutional investors. (Morgan Guaranty Trust Company 1995, p. 3)

**Table 1. The Value of Risk Management**

| | E[R] | | | | | | E[R] | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SD[R] | –5% | 0% | 5% | 10% | 15% | 20% | –5% | 0% | 5% | 10% | 15% | 20% |
| | κ = –50% | | | | | | κ = –20% | | | | | |
| 5% | –5.0% | 0.0% | 5.0% | 10.0% | 15.0% | 20.0% | –5.0% | 0.0% | 5.0% | 10.0% | 15.0% | 20.0% |
| | 5.0 | 5.0 | 5.0 | 5.0 | 5.0 | 5.0 | 5.0 | 5.0 | 5.0 | 5.0 | 5.0 | 5.0 |
| 10% | –5.0 | 0.0 | 5.0 | 10.0 | 15.0 | 20.0 | –4.8 | 0.0 | 5.0 | 10.0 | 15.0 | 20.0 |
| | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 9.6 | 9.9 | 10.0 | 10.0 | 10.0 | 10.0 |
| 25% | –5.0 | 0.0 | 5.0 | 10.0 | 15.0 | 20.0 | –1.6 | 2.2 | 6.3 | 10.7 | 15.4 | 20.2 |
| | 24.9 | 25.0 | 25.0 | 25.0 | 25.0 | 25.0 | 21.2 | 22.3 | 23.2 | 23.9 | 24.4 | 24.7 |
| 50% | –3.5 | 1.0 | 5.7 | 10.4 | 15.3 | 20.2 | 5.6 | 8.6 | 11.9 | 15.4 | 19.2 | 23.1 |
| | 48.3 | 48.8 | 49.2 | 49.4 | 49.6 | 49.8 | 41.6 | 42.7 | 43.8 | 44.8 | 45.7 | 46.5 |
| 75% | –0.5 | 3.5 | 7.8 | 12.1 | 16.6 | 21.2 | 12.0 | 14.8 | 17.8 | 20.9 | 24.3 | 27.8 |
| | 71.4 | 72.0 | 72.5 | 73.0 | 73.4 | 73.7 | 64.2 | 65.0 | 65.9 | 66.8 | 67.6 | 68.5 |
| 100% | 2.5 | 6.3 | 10.3 | 14.4 | 18.7 | 23.0 | 17.3 | 20.0 | 22.9 | 25.9 | 29.1 | 32.4 |
| | 95.2 | 95.7 | 96.2 | 96.7 | 97.1 | 97.5 | 88.2 | 88.8 | 89.4 | 90.0 | 90.7 | 91.4 |
| | κ = –40% | | | | | | κ = –10% | | | | | |
| 5% | –5.0 | 0.0 | 5.0 | 10.0 | 15.0 | 20.0 | –4.6 | 0.0 | 5.0 | 10.0 | 15.0 | 20.0 |
| | 5.0 | 5.0 | 5.0 | 5.0 | 5.0 | 5.0 | 4.4 | 4.9 | 5.0 | 5.0 | 5.0 | 5.0 |
| 10% | –5.0 | 0.0 | 5.0 | 10.0 | 15.0 | 20.0 | –3.1 | 0.7 | 5.2 | 10.0 | 15.0 | 20.0 |
| | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 7.8 | 8.9 | 9.6 | 9.9 | 10.0 | 10.0 |
| 25% | –4.7 | 0.1 | 5.1 | 10.0 | 15.0 | 20.0 | 2.2 | 5.1 | 8.5 | 12.3 | 16.4 | 20.8 |
| | 24.5 | 24.8 | 24.9 | 25.0 | 25.0 | 25.0 | 18.3 | 19.8 | 21.1 | 22.2 | 23.1 | 23.8 |
| 50% | –1.5 | 2.6 | 6.8 | 11.3 | 15.9 | 20.6 | 10.7 | 13.2 | 15.9 | 18.9 | 22.2 | 25.7 |
| | 46.6 | 47.3 | 47.9 | 48.5 | 48.9 | 49.2 | 38.7 | 39.9 | 41.0 | 42.2 | 43.3 | 44.4 |
| 75% | 2.8 | 6.4 | 10.2 | 14.2 | 18.3 | 22.6 | 17.7 | 20.2 | 22.7 | 25.5 | 28.4 | 31.5 |
| | 69.3 | 70.0 | 70.7 | 71.3 | 71.9 | 72.4 | 61.5 | 62.3 | 63.2 | 64.1 | 65.0 | 66.0 |
| 100% | 6.7 | 10.2 | 13.8 | 17.5 | 21.4 | 25.4 | 23.5 | 25.9 | 28.5 | 31.2 | 34.0 | 37.0 |
| | 93.0 | 93.6 | 94.2 | 94.7 | 95.3 | 95.8 | 85.7 | 86.2 | 86.8 | 87.5 | 88.2 | 88.9 |
| | κ = –30% | | | | | | κ = –5% | | | | | |
| 5% | –5.0 | 0.0 | 5.0 | 10.0 | 15.0 | 20.0 | –3.0 | 0.4 | 5.0 | 10.0 | 15.0 | 20.0 |
| | 5.0 | 5.0 | 5.0 | 5.0 | 5.0 | 5.0 | 3.0 | 4.4 | 4.9 | 5.0 | 5.0 | 5.0 |
| 10% | –5.0 | 0.0 | 5.0 | 10.0 | 15.0 | 20.0 | –1.0 | 1.9 | 5.7 | 10.2 | 15.0 | 20.0 |
| | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 6.2 | 7.8 | 8.9 | 9.6 | 9.9 | 10.0 |
| 25% | –3.8 | 0.7 | 5.3 | 10.2 | 15.1 | 20.0 | 4.8 | 7.3 | 10.2 | 13.5 | 17.3 | 21.4 |
| | 23.4 | 24.0 | 24.4 | 24.7 | 24.9 | 24.9 | 16.8 | 18.3 | 19.7 | 21.0 | 22.1 | 23.0 |
| 50% | 1.5 | 5.1 | 8.9 | 12.9 | 17.1 | 21.5 | 13.6 | 15.8 | 18.3 | 21.1 | 24.1 | 27.3 |
| | 44.3 | 45.2 | 46.1 | 46.9 | 47.6 | 48.2 | 37.2 | 38.4 | 39.6 | 40.8 | 41.9 | 43.1 |
| 75% | 7.0 | 10.2 | 13.6 | 17.1 | 20.9 | 24.8 | 20.9 | 23.1 | 25.5 | 28.0 | 30.8 | 33.7 |
| | 66.8 | 67.6 | 68.4 | 69.2 | 69.9 | 70.7 | 60.1 | 60.9 | 61.8 | 62.7 | 63.7 | 64.6 |
| 100% | 11.7 | 14.7 | 18.0 | 21.4 | 24.9 | 28.5 | 26.7 | 29.0 | 31.4 | 34.0 | 36.7 | 39.5 |
| | 90.7 | 91.2 | 91.9 | 92.5 | 93.1 | 93.8 | 84.4 | 84.9 | 85.5 | 86.2 | 86.9 | 87.6 |

*Note*: Each first row gives the new expected return, $R^* \equiv \mathrm{Max}(R, \kappa)$, and each second row gives the new standard deviation of $R^*$ for lognormally distributed returns with various expectations, standard deviations, and truncation points.

While there is no doubt that VaR is a useful generic measure of risk exposure and that its widespread popularity has increased the general level of awareness of risk in the investment community, VaR has a number of limitations that are particularly problematic for hedge-fund investments.

Perhaps the most obvious limitation is the fact that VaR cannot fully capture the spectrum of risks that hedge funds exhibit. To develop a sense for the heterogeneity of risks among various hedge funds, consider the following list of key components of a typical long/short equity hedge fund:

- investment style (value, growth, etc.),
- fundamental analysis (earnings, analyst forecasts, accounting data),
- factor exposures (S&P 500 Index, industries, sectors, characteristics),
- portfolio optimization (mean–variance analysis, market neutrality),
- stock loan considerations (hard-to-borrow securities, "short squeezes"[5]),

- execution costs (price impact, commissions, borrowing rate, short rebate),
- benchmarks and tracking error (T-bill rate versus S&P 500),

and compare them with a similar list for a typical fixed-income hedge fund:

- yield-curve models (equilibrium versus arbitrage models),
- prepayment models (for mortgage-backed securities),
- optionality (call, convertible, and put features),
- credit risk (defaults, rating changes, etc.),
- inflationary pressures, central bank activity,
- other macroeconomic factors and events.

The degree of overlap in these two lists is astonishingly small. While such differences also exist among traditional institutional asset managers, they do not have nearly the latitude that hedge-fund managers have in their investment activities; hence, these differences are not as consequential for traditional managers.

Second, VaR is a purely statistical measure of risk—typically a 95 percent confidence interval or, alternatively, the magnitude of loss corresponding to a 5 percent tail probability—with little or no economic structure underlying its computation. Originally developed by OTC derivatives dealers to evaluate the risk exposure of portfolios of derivative securities, VaR may not be ideally suited to other types of investments, e.g., emerging market debt, risk arbitrage, or convertible bond arbitrage. In particular, as a static snapshot of the marginal distribution of a portfolio's profit and loss, VaR does not capture liquidity risk, event risk, credit risk, factor exposures, or time-varying risks due to dynamic trading strategies that may be systematically keyed to market conditions, e.g., contrarian, short-volatility, and credit-spread strategies.

Third, without additional economic structure, VaR is notoriously difficult to estimate. By definition, "tail events" are events that happen rarely; hence, historical data will contain only a few of these events, generally too small a sample to yield reliable estimates of tail probabilities. For example, suppose we wish to estimate the probability, $p$, of a rare event occurring in any given year. Denote by $I_t$ an indicator function that takes on the value of 1 if the event occurs in year $t$ and 0 otherwise; hence,

$$I_t = \begin{cases} 1 \text{ with probability } p \\ 0 \text{ with probability } 1-p \end{cases}. \tag{2}$$

Now, the usual estimator for $p$ is simply the relative frequency of events in a sample of $T$ observations:

$$\hat{p} = \frac{1}{T}\sum_{t=1}^{T} I_t. \tag{3}$$

This estimator is a binomial random variable; hence, its distribution is known, and we can readily compute its mean and standard error:

$$\mathrm{E}[\hat{p}] = p \tag{4a}$$

$$\mathrm{SD}[\hat{p}] = \sqrt{\frac{p(1-p)}{T}}. \tag{4b}$$

Suppose we wish to obtain a standard error of 1 percent for our estimator $\hat{p}$ (so that we can make the statement that the true $p$ lies in the interval $[\hat{p} - 2\%, \hat{p} + 2\%]$ with 95 percent confidence)—how much data would we need? From Equation 4, we have:

$$0.01 = \sqrt{\frac{p(1-p)}{T}} \Rightarrow T = \frac{p(1-p)}{0.01^2}, \tag{5}$$

and if we assert that the true probability $p$ is 5 percent, Equation 5 yields a value of 475 years of data!

Alternatively, VaR is often computed under the assumption that the distribution is normal; hence, estimates of tail probabilities can be obtained by estimating the mean and variance of the distribution, not just the relative frequency of rare events. But this apparent increase in precision comes at the expense of the parametric assumption of normality, and it is well known that financial data—especially hedge-fund returns—are highly nonnormal; i.e., they are asymmetrically distributed, highly skewed, often multimodal, and with fat tails that imply many more "rare" events than the normal distribution would predict.

Finally, VaR is an unconditional measure of risk, where "unconditional" refers to the fact that VaR calculations are almost always based on the unconditional distribution of a portfolio's profit-and-loss. But for purposes of *active* risk management, conditional measures are more relevant, especially for investment strategies that respond actively to changing market conditions. The fact that a portfolio's VaR for the next week is $10 million may be less informative than a conditional probability statement in which VaR is $100 million if the S&P 500 declines by 5 percent or more and $1 million otherwise. Moreover, implicit in VaR calculations are assumptions regarding the correlations between components of the portfolio, and these correlations are also computed unconditionally. But one of the most important lessons of the summer of 1998 is the fact that correlations are highly dependent on market conditions and that securities which seem uncorrelated during normal times may become extremely highly correlated during market crises (a concrete example is given below in the section "Nonlinearities").

Despite these shortcomings, it is important to keep in mind that VaR does serve a very useful purpose in helping institutional investors think about risk in a more disciplined fashion. Moreover, when applied over longer time spans and with more realistic statistical assumptions, e.g., leptokurtic distributions, time-varying risk factors, and event-dependent correlations (see below), VaR can incorporate some of the considerations described above. Also, proponents of VaR may argue with some justification that VaR was never designed to measure the myriad types of risk that hedge-fund investments exhibit. This is precisely the motivation for this article, and in the remaining sections, I describe in more detail the unique aspects of risk management for hedge funds and the new kinds of tools that are needed to serve this dynamic industry.

## Survivorship Bias

Any quantitative approach to risk management makes use of historical data to some extent. Risk management for hedge funds is no exception, but there is one aspect of hedge-fund data that makes this endeavor particularly challenging: survivorship bias. Few hedge-fund databases maintain histories of funds that have shut down, partly for legal reasons,[6] and partly because the primary users of these databases are investors seeking to evaluate existing managers they can invest in. In the few cases where databases do contain "dead" as well as active funds, studies have concluded that the impact of survivorship bias can be substantial.[7] To see how important survivorship bias can be, consider a collection of $n$ funds with returns $R_1, \ldots, R_n$ and define their excess return per unit of risk as

$$X_j \equiv \frac{R_j - R_f}{\sigma_j}, \tag{6}$$

where $R_f$ is the rate of return on the riskless asset, and $\sigma_j$ is the standard deviation of $R_j$. The $X_j$'s are natural performance statistics that investors might consider in evaluating the funds—observe that the expectation, $E[X_j]$, of these performance statistics is the well-known Sharpe ratio. For simplicity, assume that these performance statistics are independently and identically distributed (i.i.d.) with distribution function $F(X)$.

Suppose that none of these funds possesses any superior performance or alpha, so $E[X_j] = 0$ for all $j$, and consider the "best" fund, defined to be the fund with the best realized performance statistic:

$$X^* \equiv \mathrm{Max}[X_1, X_2, \ldots, X_n]. \tag{7}$$

Now, clearly, this best-performing fund is no better than any of the others—recall that none of the funds has any alpha—but if we attempt to draw inferences from $X^*$ without taking into account the fact that we have selected it from a population of funds solely because of its performance, we will falsely conclude that the manager has substantial skill.

To illustrate how significant an effect this selection bias can be, **Table 2** reports the mean, standard deviation, and 2.5 percent and 97.5 percent quantiles, $C_{0.025}$ and $C_{0.975}$, of $X^*$ for various values of $n$, under the assumption that the $X_j$'s are standard normal random variables.[8] Even with a sample of only five funds, the Sharpe ratio, $E[X^*]$, of the best-performing fund is 1.16, despite the fact that the true Sharpe ratios of all of the funds are exactly zero! This bias becomes even more pronounced as the number of funds $n$ increases, yielding a Sharpe ratio of 2.04 for the best performing of 30 funds. Moreover, the variation of the performance statistic $X^*$, as measured by its standard deviation, declines as the number of funds $n$ increases, giving the false appearance of more stable performance in larger populations of funds.

**Table 2. Impact of Selection Bias**

| $n$ | $E[X^*]$ | $SD[X^*]$ | $C_{0.025}$ | $C_{0.975}$ |
|---|---|---|---|---|
| 1 | 0.00000 | 1.00000 | –1.960 | 1.960 |
| 5 | 1.16296 | 0.66898 | –0.055 | 2.572 |
| 10 | 1.53875 | 0.58681 | 0.506 | 2.803 |
| 15 | 1.73591 | 0.54867 | 0.779 | 2.932 |
| 20 | 1.86748 | 0.52507 | 0.960 | 3.020 |
| 25 | 1.96531 | 0.50844 | 1.093 | 3.087 |
| 30 | 2.04276 | 0.49582 | 1.197 | 3.140 |

*Note*: Moments and extreme quantiles of the performance statistic of the best-performing fund.

Now of course, if it were truly possible to invest today in the fund that will perform best over the *next* 12 months, this would certainly yield substantial returns with greatly reduced risks. In such circumstances of perfect foresight, the entries in Table 2 would represent genuine performance, not statistical biases. But 20/20 hindsight is not equivalent to perfect foresight. In our example, the best-performing fund of the past year is unlikely to be the best-performing fund the next year, simply because we have assumed that no manager possesses alpha; hence, performance and rank ordering are completely random.

The fact that most existing hedge-fund databases contain only current funds implies that only the survivors are included, i.e., a selection process not unlike Equation 7 has been imposed on the larger set of all hedge funds, both current and defunct. Although this form of survivorship bias may not be as extreme as the example in Table 2 for any given fund, it does affect the entire cross-section of funds, and its impact is compounded over time in the returns of each survivor. The end result can be enormous for the unwary investor seeking to construct an optimal portfolio of hedge funds. Any quantitative approach to hedge-fund investments must address this issue explicitly, and there are several statistical methods ideally suited to this purpose.[9]

## Dynamic Risk Analytics

One of the justifications for the unusually rich fee structures that characterize hedge-fund investments is that hedge funds implement highly active strategies involving highly skilled portfolio managers. Moreover, it is common wisdom that the most talented managers are drawn first to the hedge-fund industry because the absence of regulatory constraints enables them to make the most of their investment acumen. With the freedom to trade as much or as little as they like on any given day, to go long or short any number of securities and with varying degrees of leverage, and to change investment strategies at a moment's notice, hedge-fund managers enjoy enormous flexibility and discretion in pursuing performance. But dynamic investment strategies imply dynamic risk exposures, and while modern financial economics has much to say about the risk of *static* investments—the market beta is sufficient in this case—there is currently no single measure of the risk of a dynamic investment strategy.[10]

To illustrate the difficulties involved in measuring the risk exposures of a dynamic investment strategy, consider the eight-year track record of a hypothetical hedge fund, Capital Decimation Partners, LP (CDP), summarized in **Table 3**. This track record was obtained by applying a specific investment strategy, to be revealed below, to actual market prices from January 1992 to December 1999. But before discussing the particular strategy that generated these results, consider the strategy's overall performance: an average monthly return of 3.7 percent versus 1.4 percent for the S&P 500; a total return of 2,721.3 percent over the eight-year period versus 367.1 percent for the S&P 500; a Sharpe ratio of 1.94 versus 0.98 for the S&P 500; and only 6 negative monthly returns out of 96 versus 36 out of 96 for the S&P 500. In fact, the monthly performance history—displayed in **Table 4**—shows that, as with many other hedge funds, the worst months for this fund were August and September of 1998. Yet, October and November 1998 were the fund's two best months, and for 1998 as a whole, the fund was up 87.3 percent versus 24.5 percent for the S&P 500! By all accounts, this is an enormously successful hedge fund with a track record that would be the envy of most managers.[11] What is its secret?

**Table 3. Capital Decimation Partners, LP, January 1992–December 1999**

| Statistic | CDP | S&P 500 |
|---|---|---|
| Monthly mean (%) | 3.7 | 1.4 |
| Monthly standard deviation (%) | 5.8 | 3.6 |
| Minimum month (%) | –18.3 | –8.9 |
| Maximum month (%) | 27.0 | 14.0 |
| Annual Sharpe ratio | 1.94 | 0.98 |
| Number of negative months (out of total) | 6/96 | 36/96 |
| Correlation with S&P 500 | 59.9 | 100.0 |
| Total return (%) | 2,721.3 | 367.1 |

The investment strategy summarized in Tables 3 and 4 consists of shorting out-of-the-money S&P 500 (SPX) put options on each monthly expiration date for maturities less than or equal to three months, and with strikes approximately 7 percent out of the money. The number of contracts to be sold each month is determined by the combination of: (1) Chicago Board Options Exchange margin requirements,[12] (2) an assumption that 66 percent of the margin is required to be posted as collateral,[13] and (3) $10 million of initial risk capital. For concreteness, **Table 5** reports the positions and profit/loss statement for this strategy for 1992.

The track record in Tables 3 and 4 seems much less impressive in light of the simple strategy on which it is based, and few investors would pay hedge-fund-type fees for such a fund. However, given the secrecy surrounding most hedge-fund strategies and the broad discretion that managers are given by the typical hedge-fund offering memorandum, it is difficult for investors to detect this type of behavior without resorting to more sophisticated risk analytics, analytics that can capture *dynamic* risk exposures.

Some might argue that this example illustrates the need for position transparency—after all, it would be apparent from the positions in Table 5 that the manager of CDP is providing little or no value-added. However, there are many ways of implementing this strategy that are not nearly so transparent, even when positions are fully disclosed. For example, **Table 6** reports the weekly positions over a six-month period in one of 500 securities contained in a second hypothetical fund, Capital Decimation Partners II, LLC. Casual inspection of the positions

**Table 4. Monthly Performance History of Capital Decimation Partners, LP, January 1992–December 1999**
(returns, in percent)

| | 1992 | | 1993 | | 1994 | | 1995 | | 1996 | | 1997 | | 1998 | | 1999 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Month | SPX | CDP | SPX | CDP | SPX | CDP | SPX | CDP | SPX | CDP | SPX | CDP | SPX | CDP | SPX | CDP |
| January | 8.2 | 8.1 | –1.2 | 1.8 | 1.8 | 2.3 | 1.3 | 3.7 | –0.7 | 1.0 | 3.6 | 4.4 | 1.6 | 15.3 | 5.5 | 10.1 |
| February | –1.8 | 9.3 | –0.4 | 1.0 | –1.5 | 0.7 | 3.9 | 0.7 | 5.9 | 1.2 | 3.3 | 6.0 | 7.6 | 11.7 | –0.3 | 16.6 |
| March | 0.0 | 4.9 | 3.7 | 3.6 | 0.7 | 2.2 | 2.7 | 1.9 | –1.0 | 0.6 | –2.2 | 3.0 | 6.3 | 6.7 | 4.8 | 10.0 |
| April | 1.2 | 3.2 | –0.3 | 1.6 | –5.3 | –0.1 | 2.6 | 2.4 | 0.6 | 3.0 | –2.3 | 2.8 | 2.1 | 3.5 | 1.5 | 7.2 |
| May | –1.4 | 1.3 | –0.7 | 1.3 | 2.0 | 5.5 | 2.1 | 1.6 | 3.7 | 4.0 | 8.3 | 5.7 | –1.2 | 5.8 | 0.9 | 7.2 |
| June | –1.6 | 0.6 | –0.5 | 1.7 | 0.8 | 1.5 | 5.0 | 1.8 | –0.3 | 2.0 | 8.3 | 4.9 | –0.7 | 3.9 | 0.9 | 8.6 |
| July | 3.0 | 1.9 | 0.5 | 1.9 | –0.9 | 0.4 | 1.5 | 1.6 | –4.2 | 0.3 | 1.8 | 5.5 | 7.8 | 7.5 | 5.7 | 6.1 |
| August | –0.2 | 1.7 | 2.3 | 1.4 | 2.1 | 2.9 | 1.0 | 1.2 | 4.1 | 3.2 | –1.6 | 2.6 | –8.9 | –18.3 | –5.8 | –3.1 |
| September | 1.9 | 2.0 | 0.6 | 0.8 | 1.6 | 0.8 | 4.3 | 1.3 | 3.3 | 3.4 | 5.5 | 11.5 | –5.7 | –16.2 | –0.1 | 8.3 |
| October | –2.6 | –2.8 | 2.3 | 3.0 | –1.3 | 0.9 | 0.3 | 1.1 | 3.5 | 2.2 | –0.7 | 5.6 | 3.6 | 27.0 | –6.6 | –10.7 |
| November | 3.6 | 8.5 | –1.5 | 0.6 | –0.7 | 2.7 | 2.6 | 1.4 | 3.8 | 3.0 | 2.0 | 4.6 | 10.1 | 22.8 | 14.0 | 14.5 |
| December | 3.4 | 1.2 | 0.8 | 2.9 | –0.6 | 10.0 | 2.7 | 1.5 | 1.5 | 2.0 | –1.7 | 6.7 | 1.3 | 4.3 | –0.1 | 2.4 |
| Year | 14.0 | 46.9 | 5.7 | 23.7 | –1.6 | 33.6 | 34.3 | 22.1 | 21.5 | 28.9 | 26.4 | 84.8 | 24.5 | 87.3 | 20.6 | 105.7 |

*Note*: SPX = S&P 500.

**Table 5. Positions and Profit/Loss of Capital Decimation Partners, LP, 1992**

| S&P 500 | Contract Status | Number of Puts | Strike | Price | Expiration | Margin Required | Profits | Initial Capital plus Cumulative Profits | Capital Available for Investments | Return |
|---|---|---|---|---|---|---|---|---|---|---|
| *December 20, 1991* | | | | | | | | | | |
| 387.04 | New | 2,300 | 360 | $4.625 | 3/92 | $ 6,069,930 | | $10,000,000 | $6,024,096 | |
| *January 17, 1992* | | | | | | | | | | |
| 418.86 | Mark to market | 2,300 | 360 | $1.125 | 3/92 | $ 654,120 | $ 805,000 | $10,805,000 | $6,509,036 | 8.1% |
| 418.86 | New | 1,950 | 390 | $3.250 | 3/92 | $ 5,990,205 | | | | |
| | | | | | **Total margin** | $ 6,644,325 | | | | |
| *February 21, 1992* | | | | | | | | | | |
| 411.46 | Mark to market | 2,300 | 360 | $0.250 | 3/92 | $ 2,302,070 | $ 690,000 | | | |
| 411.46 | Mark to market | 1,950 | 390 | $1.625 | 3/92 | $ 7,533,630 | $ 316,875 | $11,811,875 | $7,115,587 | 9.3% |
| 411.46 | Liquidate | 1,950 | 390 | $1.625 | 3/92 | $ 0 | $ 0 | $11,811,875 | $7,115,587 | |
| 411.46 | New | 1,246 | 390 | $1.625 | 3/92 | $ 4,813,796 | | | | |
| | | | | | **Total margin** | $ 7,115,866 | | | | |
| *March 20, 1992* | | | | | | | | | | |
| 411.30 | Expired | 2,300 | 360 | $0.000 | 3/92 | $ 0 | $ 373,750 | | | |
| 411.30 | Expired | 1,246 | 390 | $0.000 | 3/92 | $ 0 | $ 202,475 | | | |
| 411.30 | New | 2,650 | 380 | $2.000 | 5/92 | $ 7,524,675 | | $12,388,100 | $7,462,711 | 4.9% |
| | | | | | **Total margin** | $ 7,524,675 | | | | |
| *April 19, 1992* | | | | | | | | | | |
| 416.05 | Mark to market | 2,650 | 380 | $0.500 | 5/92 | $ 6,852,238 | $ 397,500 | | | |
| 416.05 | New | 340 | 385 | $2.438 | 6/92 | $ 983,280 | | $12,785,600 | $7,702,169 | 3.2% |
| | | | | | **Total margin** | $ 7,835,518 | | | | |
| *May 15, 1992* | | | | | | | | | | |
| 410.09 | Expired | 2,650 | 380 | $0.000 | 5/92 | $ 0 | $ 132,500 | | | |
| 410.09 | Mark to market | 340 | 385 | $1.500 | 6/92 | $ 1,187,399 | $ 31,875 | | | |
| 410.09 | New | 2,200 | 380 | $1.250 | 7/92 | $ 6,638,170 | | $12,949,975 | $7,801,190 | 1.3% |
| | | | | | **Total margin** | $ 7,825,569 | | | | |

**Table 5. Positions and Profit/Loss of Capital Decimation Partners, LP, 1992 (continued)**

| S&P 500 | Contract Status | Number of Puts | Strike | Price | Expiration | Margin Required | Profits | Initial Capital plus Cumulative Profits | Capital Available for Investments | Return |
|---|---|---|---|---|---|---|---|---|---|---|
| *June 19, 1992* | | | | | | | | | | |
| 403.67 | Expired | 340 | 385 | $0.000 | 6/92 | $ 0 | $ 51,000 | | | |
| 403.67 | Mark to market | 2,200 | 380 | $1.125 | 7/92 | $ 7,866,210 | $ 27,500 | $13,028,475 | $7,848,479 | 0.6% |
| | | | | | **Total margin** | $ 7,866,210 | | | | |
| *July 17, 1992* | | | | | | | | | | |
| 415.62 | Expired | 2,200 | 380 | $0.000 | 7/92 | $ 0 | $ 247,500 | | | |
| 415.62 | New | 2,700 | 385 | $1.8125 | 9/92 | $ 8,075,835 | | $13,275,975 | $7,997,575 | 1.9% |
| | | | | | **Total margin** | $ 8,075,835 | | | | |
| *August 21, 1992* | | | | | | | | | | |
| 414.85 | Mark to market | 2,700 | 385 | $1 | 9/92 | $ 8,471,925 | $ 219,375 | $13,495,350 | $8,129,729 | 1.7% |
| | | | | | **Total margin** | $ 8,471,925 | | | | |
| *September 18, 1992* | | | | | | | | | | |
| 422.92 | Expired | 2,700 | 385 | $0 | 9/92 | $ 0 | $ 270,000 | $13,765,350 | $8,292,380 | 2.0% |
| 422.92 | New | 2,370 | 400 | $5.375 | 12/92 | $ 8,328,891 | | | | |
| | | | | | **Total margin** | $ 8,328,891 | | | | |
| *October 16, 1992* | | | | | | | | | | |
| 411.73 | Mark to market | 2,370 | 400 | $7 | 12/92 | $10,197,992 | ($ 385,125) | | | |
| 411.73 | Liquidate | 2,370 | 400 | $7 | 12/92 | $ 0 | $ 0 | $13,380,225 | $8,060,377 | –2.8% |
| 411.73 | New | 1,873 | 400 | $7 | 12/92 | $ 8,059,425 | | | | |
| | | | | | **Total margin** | $ 8,059,425 | | | | |
| *November 20, 1992* | | | | | | | | | | |
| 426.65 | Mark to market | 1,873 | 400 | $0.9375 | 12/92 | $ 6,819,593 | $1,135,506 | $14,515,731 | $8,744,416 | 8.5% |
| 426.65 | New | 529 | 400 | $0.9375 | 12/92 | $ 1,926,089 | | | | |
| | | | | | **Total margin** | $ 8,745,682 | | | | |
| *December 18, 1992* | | | | | | | | | | |
| 441.20 | Expired | 1,873 | 400 | $0 | 12/92 | $ 0 | $ 175,594 | $14,691,325 | $8,850,196 | 1.2% |
| **1992 Total return** | | | | | | | | | | **46.9%** |

in this one security seems to suggest a contrarian trading strategy—when the price declines, the position in XYZ is increased, and when the price advances, the position is reduced. A more careful analysis of the stock and cash positions and the varying degree of leverage in Table 6 reveals that these trades constitute a so-called "delta-hedging" strategy, designed to synthetically replicate a short position in a two-year European put option on 10,000,000 shares of XYZ with a strike price of $25 (recall that XYZ's initial stock price was $40; hence, this is a deep-out-of-the-money put).

Shorting deep out-of-the-money puts is a well-known artifice employed by unscrupulous hedge-fund managers to build an impressive track record quickly, and most sophisticated investors are able to avoid such chicanery. However, imagine an investor presented with position reports such as Table 6, but for 500 securities, not just one, as well as a corresponding track record that is likely to be even more impressive than that of CDP.[14] Without additional analysis that explicitly accounts for the dynamic aspects of the trading strategy described in Table 6, it is difficult for an investor to fully appreciate the risks inherent in such a fund.

In particular, static methods such as traditional mean–variance analysis cannot capture the risks of dynamic trading strategies like those of CDP (note the impressive Sharpe ratio in Table 3). In the case of the strategy of shorting out-of-the-money put options on the S&P 500, returns are positive most of the time, and losses are infrequent, but when they occur, they are extreme. This is a very specific type of risk signature that is not well summarized by static measures such as standard deviation. In fact, the estimated standard deviations of such strategies tend to be rather low; hence, a naive application of mean–variance analysis, such as

**Table 6. Weekly Positions in XYZ: Capital Decimation Partners II, LLC**

| Week $t$ | Price ($) | Position (shares) | Value ($) | Financing ($) |
|---|---|---|---|---|
| 0 | 40.000 | 7,057 | 282,281 | –296,974 |
| 1 | 39.875 | 7,240 | 288,712 | –304,585 |
| 2 | 40.250 | 5,850 | 235,456 | –248,918 |
| 3 | 36.500 | 33,013 | 1,204,981 | –1,240,629 |
| 4 | 36.875 | 27,128 | 1,000,356 | –1,024,865 |
| 5 | 36.500 | 31,510 | 1,150,101 | –1,185,809 |
| 6 | 37.000 | 24,320 | 899,841 | –920,981 |
| 7 | 39.875 | 5,843 | 232,970 | –185,111 |
| 8 | 39.875 | 5,621 | 224,153 | –176,479 |
| 9 | 40.125 | 4,762 | 191,062 | –142,159 |
| 10 | 39.500 | 6,280 | 248,065 | –202,280 |
| 11 | 41.250 | 2,441 | 100,711 | –44,138 |
| 12 | 40.625 | 3,230 | 131,205 | –76,202 |
| 13 | 39.875 | 4,572 | 182,300 | –129,796 |
| 14 | 39.375 | 5,690 | 224,035 | –173,947 |
| 15 | 39.625 | 4,774 | 189,170 | –137,834 |
| 16 | 39.750 | 4,267 | 169,609 | –117,814 |
| 17 | 39.250 | 5,333 | 209,312 | –159,768 |
| 18 | 39.500 | 4,447 | 175,657 | –124,940 |
| 19 | 39.750 | 3,692 | 146,777 | –95,073 |
| 20 | 39.750 | 3,510 | 139,526 | –87,917 |
| 21 | 39.875 | 3,106 | 123,832 | –71,872 |
| 22 | 39.625 | 3,392 | 134,408 | –83,296 |
| 23 | 39.875 | 2,783 | 110,986 | –59,109 |
| 24 | 40.000 | 2,445 | 97,782 | –45,617 |
| 25 | 40.125 | 2,140 | 85,870 | –33,445 |

risk-budgeting—an increasingly popular method used by institutions to make allocations based on risk units—can lead to unusually large allocations to funds like CDP. The fact that total position transparency does not imply risk transparency is further cause for concern.

This is not to say that the risks of shorting out-of-the-money puts are inappropriate for all investors. Indeed, the thriving catastrophe reinsurance industry makes a market in precisely this type of risk, often called "tail risk." However, such insurers do so with full knowledge of the loss profile and probabilities for each type of catastrophe, and they set their capital reserves and risk budgets accordingly. The same should hold true for institutional investors of hedge funds, but the standard tools and lexicon of the industry currently provide only an incomplete characterization of such risks. The need for a new set of dynamic risk analytics specifically targeted for hedge fund investments is clear.

## Nonlinearities

One of the most compelling reasons for investing in hedge funds is the fact that their returns seem relatively uncorrelated with market indexes such as the S&P 500, and modern portfolio theory has convinced even the most hardened skeptic of the benefits of diversification. For example, **Table 7** reports the correlation matrix for the returns of hedge fund indexes, where each index represents a particular hedge-fund "style," such as currencies, emerging markets, relative value, etc. The last row reports the correlations of all these hedge-fund indexes with the returns on the S&P 500, and it is apparent that many hedge-fund styles have low or, in some cases, negative correlation with the market.

However, the diversification argument for hedge funds must be tempered by the lessons of the summer of 1998, when the default in Russian government debt triggered a global flight to quality that changed many of the correlations overnight from 0 to 1. In the physical and natural sciences, such phenomena are examples of "phase-locking" behavior, situations in which otherwise uncorrelated actions suddenly become synchronized.[15] The fact that market conditions can create phase-locking behavior is certainly not new—market crashes have been with us since the beginning of organized financial markets. But prior to 1998, few hedge-fund investors and managers incorporated this possibility into their investment processes in any systematic fashion.

From a financial-engineering perspective, the most reliable way to capture phase-locking effects is to estimate a risk model for returns in which such events are explicitly allowed. For example, suppose returns are generated by the following two-factor model:

$$R_{it} = \alpha_i + \beta_i \Lambda_t + I_t Z_t + \varepsilon_{it}, \tag{8}$$

where

$R_{it}$ = return on fund $i$ at time $t$,

$\alpha_i$ = fund intercept,

$\Lambda_t$ = a "market" component,

$\beta_i$ = fund sensitivity to the market,

$I_t Z_t$ = "phase-locking" component or catastrophic market event,

$\varepsilon_{it}$ = non-systematic (idiosyncratic) risk of fund $i$ at time $t$.

Also, assume that $\Lambda_t$, $I_t$, $Z_t$, and $\varepsilon_{it}$ are mutually i.i.d. with the following moments:

$$\mathrm{E}[\Lambda_t] = \mu_\lambda, \qquad \mathrm{Var}[\Lambda_t] = \sigma_\lambda^2, \tag{9a}$$

$$\mathrm{E}[\varepsilon_{it}] = 0, \qquad \mathrm{Var}[\varepsilon_{it}] = \sigma_{\varepsilon_i}^2, \tag{9b}$$

$$\mathrm{E}[Z_t] = 0, \qquad \mathrm{Var}[Z_t] = \sigma_z^2, \tag{9c}$$

where $\mu_\lambda$ and $\sigma_\lambda^2$ are the mean and variance of the market factor; $\sigma_{\varepsilon_i}^2$ is the residual variance of fund $i$'s return, and $\sigma_z^2$ is the variance of the

## Table 7. Correlation Matrix for Hedge Fund Index Returns: Monthly Data, January 1996–November 1999 (in percent)

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Currencies | 100.0 | | | | | | | | | | | | | | | | | | | | |
| 2. ED—distress | 4.7 | 100.0 | | | | | | | | | | | | | | | | | | | |
| 3. ED—merger arb | –11.1 | 54.4 | 100.0 | | | | | | | | | | | | | | | | | | |
| 4. EM—equity | –21.0 | 42.8 | 47.2 | 100.0 | | | | | | | | | | | | | | | | | |
| 5. EM | –11.1 | 45.6 | 50.2 | 86.3 | 100.0 | | | | | | | | | | | | | | | | |
| 6. EM—fixed income | –5.8 | 28.7 | 34.2 | 43.8 | 76.3 | 100.0 | | | | | | | | | | | | | | | |
| 7. ED | –5.7 | 85.8 | 80.8 | 54.6 | 58.8 | 40.1 | 100.0 | | | | | | | | | | | | | | |
| 8. Fund of funds | 7.9 | 59.2 | 52.4 | 44.3 | 56.8 | 49.8 | 70.8 | 100.0 | | | | | | | | | | | | | |
| 9. Futures trading | 45.3 | 3.0 | –7.7 | –6.1 | 5.5 | 15.3 | 0.5 | 30.1 | 100.0 | | | | | | | | | | | | |
| 10. Growth | –3.7 | 49.1 | 47.6 | 34.2 | 42.7 | 29.2 | 60.5 | 63.2 | 6.9 | 100.0 | | | | | | | | | | | |
| 11. High yield | 8.0 | 54.2 | 16.7 | 25.2 | 33.5 | 35.4 | 48.2 | 35.8 | 7.2 | 12.9 | 100.0 | | | | | | | | | | |
| 12. Macro | 28.5 | 10.9 | 8.7 | 5.5 | 16.9 | 30.1 | 17.1 | 44.1 | 51.5 | 14.5 | 17.1 | 100.0 | | | | | | | | | |
| 13. Opportunistic | 9.7 | 49.3 | 40.5 | 29.0 | 43.8 | 43.4 | 60.3 | 74.7 | 19.4 | 68.0 | 24.4 | 45.0 | 100.0 | | | | | | | | |
| 14. Other | 8.7 | 53.9 | 51.6 | 37.6 | 52.7 | 48.0 | 64.3 | 68.5 | 27.3 | 76.9 | 20.3 | 29.6 | 73.6 | 100.0 | | | | | | | |
| 15. RV | 12.0 | 48.9 | 36.9 | 37.5 | 39.4 | 26.0 | 53.9 | 46.1 | 13.5 | 19.1 | 51.0 | 18.5 | 34.2 | 31.6 | 100.0 | | | | | | |
| 16. RV—convertible | 8.1 | 52.2 | 36.3 | 28.6 | 41.6 | 37.3 | 54.4 | 45.4 | 6.9 | 25.9 | 49.6 | 22.7 | 47.1 | 33.6 | 56.9 | 100.0 | | | | | |
| 17. RV—EQLS | 6.5 | 30.5 | 43.5 | 33.5 | 26.2 | 12.6 | 42.5 | 34.0 | 4.2 | 34.3 | 17.1 | 9.0 | 26.3 | 41.4 | 50.8 | 13.0 | 100.0 | | | | |
| 18. RV—option arb | –0.3 | 7.1 | 1.5 | 14.6 | 10.6 | 3.4 | 8.9 | 3.0 | –2.1 | –20.3 | 12.2 | 6.5 | 4.7 | –14.0 | 47.3 | 2.0 | –4.0 | 100.0 | | | |
| 19. RV—other—stat arb | 10.2 | 19.9 | –0.2 | 17.2 | 12.4 | –2.4 | 13.6 | 19.4 | 0.6 | 22.4 | 8.1 | –12.8 | 10.2 | 14.4 | 30.2 | 8.1 | 7.0 | 5.3 | 100.0 | | |
| 20. Short selling | 15.1 | –48.1 | –53.8 | –35.2 | –43.4 | –30.1 | –61.8 | –49.9 | 8.6 | –85.7 | –12.3 | –4.3 | –59.1 | –67.9 | –9.6 | –28.6 | –29.5 | 21.6 | –11.0 | 100.0 | |
| 21. Value | –10.6 | 65.7 | 59.3 | 47.9 | 62.0 | 43.5 | 78.4 | 69.4 | 8.7 | 74.3 | 26.0 | 15.2 | 67.0 | 77.7 | 36.6 | 45.5 | 34.3 | –4.3 | 20.3 | –73.8 | 100.0 |
| 22. S&P 500 | 11.1 | 40.7 | 46.6 | 28.6 | 43.1 | 35.4 | 51.0 | 54.6 | 19.3 | 78.0 | 18.1 | 20.5 | 60.4 | 71.3 | 23.4 | 28.3 | 41.5 | –16.3 | 7.6 | –70.1 | 63.9 |

*Note*: ED = event driven; arb = arbitrage; EM = emerging market; RV = relative value; EQLS = equity long/short; stat = statistical.

phase-locking component Z. Let the phase-locking event indicator, $I_t$, be defined by

$$I_t = \begin{cases} 1 \text{ with probability } p \\ 0 \text{ with probability } 1-p \end{cases}. \quad (10)$$

According to Equation 8, the expected returns of fund $i$ are the sum of three components: the fund's intercept, $\alpha_i$; a "market" component $\Lambda_t$, to which each fund has its own individual sensitivity $\beta_i$; and a phase-locking component that is identical across all funds at all times, taking only one of two possible values, 0 (with probability $p$) or $Z_t$ (with probability $1 - p$). If we assume that $p$ is small, say 0.001, then most of the time the expected returns of fund $i$ are determined by $\alpha_i + \beta_i\Lambda_t$, but every once in a while, an additional term, $Z_t$, appears. If the volatility $\sigma_z$ of $Z_t$ is much larger than the volatilities of the market factor, $\Lambda_t$, and the idiosyncratic risk, $\varepsilon_{it}$, then the common factor $Z_t$ will dominate the expected returns of all stocks when $I_t = 1$, i.e., phase-locking behavior.

More formally, consider the *conditional* correlation coefficient of two funds $i$ and $j$, defined as the ratio of the conditional covariance divided by the square root of the product of the conditional variances, conditioned on no catastrophes ($I_t = 0$):

$$\operatorname{Corr}[R_{it}, R_{jt} | I_t = 0] = \frac{\beta_i\beta_j\sigma_\lambda^2}{\sqrt{\beta_i^2\sigma_\lambda^2 + \sigma_{\varepsilon_i}^2}\sqrt{\beta_j^2\sigma_\lambda^2 + \sigma_{\varepsilon_j}^2}} \quad (11)$$

$$\approx 0 \text{ for } \beta_i \approx \beta_j \approx 0, \quad (12)$$

where we have assumed that $\beta_i \approx \beta_j \approx 0$ to capture the market-neutral characteristic that many hedge-fund investors desire. Now, consider the conditional correlation, conditioned on the occurrence of a catastrophe ($I_t = 1$):

$$\operatorname{Corr}[R_{it}, R_{jt} | I_t = 1]$$
$$= \frac{\beta_i\beta_j\sigma_\lambda^2 + \sigma_z^2}{\sqrt{\beta_i^2\sigma_\lambda^2 + \sigma_z^2 + \sigma_{\varepsilon_i}^2}\sqrt{\beta_j^2\sigma_\lambda^2 + \sigma_z^2 + \sigma_{\varepsilon_j}^2}} \quad (13)$$

$$\approx \frac{1}{\sqrt{1 + \sigma_{\varepsilon_i}^2/\sigma_z^2}\sqrt{1 + \sigma_{\varepsilon_j}^2/\sigma_z^2}} \text{ for } \beta_i \approx \beta_j \approx 0. \quad (14)$$

If $\sigma_z^2$ is large relative to $\sigma_{\varepsilon_i}^2$ and $\sigma_{\varepsilon_j}^2$, i.e., if the variability of the catastrophe component dominates the variability of the residuals of both funds—a plausible condition that follows from the very definition of a catastrophe—then Equation 14 will be approximately equal to 1! When phase locking occurs, the correlation between the two funds $i$ and $j$—close to 0 during normal times—can become arbitrarily close to 1.

An insidious feature of Equation 8 is the fact that it implies a very small value for the *unconditional* correlation, which is the quantity most readily estimated and the most commonly used in risk reports, VaR calculations, and portfolio decisions. To see why, recall that the unconditional correlation coefficient is simply the unconditional covariance divided by the product of the square roots of the unconditional variances:

$$\operatorname{Corr}[R_{it}, R_{jt}] \equiv \frac{\operatorname{Cov}[R_{it}, R_{jt}]}{\sqrt{\operatorname{Var}[R_{it}]\operatorname{Var}[R_{jt}]}}, \quad (15)$$

$$\begin{aligned} \operatorname{Cov}[R_{it}, R_{jt}] &= \beta_i\beta_j\sigma_\lambda^2 + \operatorname{Var}[I_t Z_t] \\ &= \beta_i\beta_j\sigma_\lambda^2 + p\sigma_z^2, \end{aligned} \quad (16)$$

$$\begin{aligned} \operatorname{Var}[R_{it}] &= \beta_i^2\sigma_\lambda^2 + \operatorname{Var}[I_t Z_t] + \sigma_{\varepsilon_i}^2 \\ &= \beta_i^2\sigma_\lambda^2 + p\sigma_z^2 + \sigma_{\varepsilon_i}^2 \end{aligned}. \quad (17)$$

Combining these expressions yields the unconditional correlation coefficient under Equation 8:

$$\operatorname{Corr}[R_{it}, R_{jt}]$$
$$= \frac{\beta_i\beta_j\sigma_\lambda^2 + p\sigma_z^2}{\sqrt{\beta_i^2\sigma_\lambda^2 + p\sigma_z^2 + \sigma_{\varepsilon_i}^2}\sqrt{\beta_j^2\sigma_\lambda^2 + p\sigma_z^2 + \sigma_{\varepsilon_j}^2}} \quad (18)$$

$$\approx \frac{p}{\sqrt{p + \sigma_{\varepsilon_i}^2/\sigma_z^2}\sqrt{p + \sigma_{\varepsilon_j}^2/\sigma_z^2}} \text{ for } \beta_i \approx \beta_j \approx 0. \quad (19)$$

If we let $p = 0.001$ and assume that the variability of the phase-locking component is 10 times the variability of residuals $\varepsilon_i$ and $\varepsilon_j$, this implies an unconditional correlation of

$$\begin{aligned} \operatorname{Corr}[R_{it}, R_{jt}] &\approx \frac{p}{\sqrt{p + 0.1}\sqrt{p + 0.1}} \\ &= \frac{0.001}{0.101} = 0.0099, \end{aligned}$$

or less than 1 percent. As the variance, $\sigma_z^2$, of the phase-locking component increases, the unconditional correlation Equation 19 also increases, so that, eventually, the existence of $Z_t$ will have an impact. However, to achieve an unconditional correlation coefficient of, say, 10 percent, $\sigma_z^2$ would have to be about 100 times larger than $\sigma_\varepsilon^2$. Without the benefit of an explicit risk model such as Equation 8, it is virtually impossible to detect the existence of a phase-locking component from standard correlation coefficients.

Hedge-fund returns exhibit other nonlinearities that are not captured by linear measures such as correlation coefficients and linear factor models. An example of a simple nonlinearity is an asymmetric sensitivity to the S&P 500, i.e., different beta coefficients for down markets versus up markets. Specifically, consider the following regression:

$$R_{it} = \alpha_i + \beta_i^+\Lambda_t^+ + \beta_i^-\Lambda_t^- + \varepsilon_{it}, \quad (20)$$

where

$$\Lambda_t^+ = \begin{cases} \Lambda_t \text{ if } \Lambda_t > 0 \\ 0 \text{ otherwise} \end{cases}, \tag{21a}$$

$$\Lambda_t^- = \begin{cases} \Lambda_t \text{ if } \Lambda_t \leq 0 \\ 0 \text{ otherwise} \end{cases}, \tag{21b}$$

and $\Lambda_t$ is the return on the S&P 500. Since $\Lambda_t = \Lambda_t^+ + \Lambda_t^-$, the standard linear model in which fund $i$'s market betas are identical in up and down markets is a special case of the more general specification in Equation 20 (the case where $\beta_i^+ = \beta_i^-$). However, the estimates reported in **Table 8** for the hedge-fund index returns of Table 7 show that beta asymmetries can be quite pronounced for certain hedge-fund styles. For example, the emerging-market equities index ("EM—equity") has an up-market beta of 0.16—seemingly close to market neutral; however, its down-market beta is 1.49! For the relative-value option-arbitrage index ("RV—option arb"), the asymmetries are even more severe—the coefficients are of opposite sign, with a beta of –0.78 in up markets and a beta of 0.33 in down markets. This is not surprising given the highly nonlinear payoff structures of derivative securities; nevertheless, it would be a mistake to classify this set of returns as "market neutral."

These empirical results suggest the need for a more sophisticated analysis of hedge-fund returns, one that accounts for asymmetries in factor exposures, phase-locking behavior, and other nonlinearities that are endemic to high-performance active investment strategies. In particular, nonlinear risk models must be developed for the various types of securities that hedge funds trade, e.g., equities, fixed-income instruments, foreign exchange, commodities, and derivatives, and for each type of security, the risk model should include the following general groups of factors:

- market index returns,
- sectors,
- investment style,
- volatilities,
- credit,
- liquidity,
- macroeconomic indicators.

**Table 8. Nonlinearities in Hedge-Fund Index Returns: Monthly Data, January 1996–November 1999**

| Style Index | $\hat{\alpha}$ | $t(\hat{\alpha})$ | $\hat{\beta}^+$ | $t(\hat{\beta}^+)$ | $\hat{\beta}^-$ | $t(\hat{\beta}^-)$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| Currencies | 0.93 | 1.97 | 0.05 | 0.34 | 0.13 | 0.81 | 0.01 |
| ED—distress | 1.95 | 7.84 | –0.11 | –1.50 | 0.58 | 6.95 | 0.36 |
| ED—merger arb | 1.35 | 7.99 | 0.04 | 0.91 | 0.27 | 4.78 | 0.27 |
| EM—equity | 3.78 | 2.41 | 0.16 | 0.34 | 1.49 | 2.84 | 0.11 |
| EM | 2.64 | 3.20 | 0.21 | 0.88 | 1.18 | 4.27 | 0.23 |
| EM—fixed income | 1.88 | 3.99 | 0.07 | 0.49 | 0.56 | 3.56 | 0.16 |
| ED | 1.61 | 9.35 | –0.01 | –0.26 | 0.43 | 7.37 | 0.41 |
| Fund of funds | 1.07 | 6.89 | 0.08 | 1.84 | 0.27 | 5.13 | 0.33 |
| Futures trading | 0.69 | 1.35 | 0.18 | 1.23 | 0.13 | 0.76 | 0.04 |
| Growth | 1.49 | 3.65 | 0.69 | 5.80 | 0.98 | 7.13 | 0.62 |
| High yield | 1.11 | 8.05 | –0.08 | –1.92 | 0.19 | 4.10 | 0.15 |
| Macro | 0.61 | 1.09 | 0.30 | 1.84 | 0.05 | 0.28 | 0.05 |
| Opportunistic | 1.35 | 3.95 | 0.33 | 3.31 | 0.52 | 4.53 | 0.37 |
| Other | 1.41 | 5.58 | 0.23 | 3.05 | 0.69 | 8.19 | 0.57 |
| RV | 1.36 | 12.22 | –0.04 | –1.27 | 0.15 | 4.02 | 0.15 |
| RV—convertible | 1.25 | 8.44 | –0.01 | –0.31 | 0.18 | 3.55 | 0.14 |
| RV—EQLS | 0.87 | 5.64 | 0.09 | 2.04 | 0.14 | 2.65 | 0.17 |
| RV—option arb | 4.48 | 4.29 | –0.78 | –2.56 | 0.33 | 0.95 | 0.07 |
| RV—other—stat arb | 1.40 | 4.38 | –0.02 | –0.18 | 0.11 | 0.99 | 0.01 |
| Short selling | 0.04 | 0.07 | –0.67 | –3.94 | –1.25 | –6.41 | 0.51 |
| Value | 1.46 | 4.49 | 0.24 | 2.54 | 0.69 | 6.41 | 0.45 |

*Note*: Regression analysis of monthly hedge-fund index returns with positive and negative returns on the S&P 500 used as separate regressors. ED = event driven; arb = arbitrage; EM = emerging market; RV = relative value; EQLS = equity long/short; stat = statistical.

*Source*: AlphaSimplex Group.

## Liquidity and Credit

Although liquidity and credit are separate sources of risk exposures for hedge funds and their investors—one type of risk can exist without the other—nevertheless, they have been inextricably intertwined in the minds of most investors because of the problems encountered by Long-Term Capital Management and many other fixed-income relative-value hedge funds in August and September of 1998. Because many hedge funds rely on leverage, the magnitudes of the positions are often considerably larger than the amount of collateral posted to support them. Leverage has the effect of a magnifying glass, expanding small profit opportunities into larger ones but also expanding small losses into larger losses. And when adverse changes in market prices reduce the market value of collateral, credit is withdrawn quickly and the subsequent forced liquidation of large positions over short periods of time can lead to widespread financial panic, as in the aftermath of the default of Russian government debt in August 1998.[16] Along with the many benefits of a truly global financial system is the cost that a financial crisis in one country can have dramatic repercussions in several others.

The basic mechanisms driving liquidity and credit are familiar to most hedge-fund managers and investors, and there has been much progress in the recent literature in modeling both credit and liquidity risk.[17] However, the complex network of creditor/obligor relationships, revolving credit agreements, and other financial interconnections is largely unmapped. Perhaps some of the newly developed techniques in the mathematical theory of networks will allow us to construct systemic measures for liquidity and credit exposures, and for the robustness of the global financial system to idiosyncratic shocks. The "small world" networks considered by Watts and Strogatz (1998) and Watts (1999) seem to be particularly promising starting points.

A more immediate method for gauging the liquidity-risk exposure of a given hedge fund is to examine the autocorrelation coefficients, $\rho_k$, of the fund's monthly returns, where $\rho_k \equiv \text{Cov}[R_t, R_{t-k}]/\text{Var}[R_t]$ is the $k$th order autocorrelation of $\{R_t\}$,[18] which measures the degree of correlation between the returns of months $t$ and $t - k$. To see why autocorrelations may be useful indicators of liquidity exposure, recall that one of the earliest financial asset pricing models is the martingale model, in which asset returns are serially uncorrelated ($\rho_k = 0$ for all $k \neq 0$). Indeed, the title of Samuelson's (1965) seminal paper—"Proof That Properly Anticipated Prices Fluctuate Randomly"—provides a succinct summary for the motivation of the martingale property: In an informationally efficient market, price changes must be unforecastable if they are properly anticipated, i.e., if they fully incorporate the expectations and information of all market participants.

This concept of informational efficiency has a wonderfully counterintuitive and seemingly contradictory flavor to it—the more efficient the market, the more random the sequence of price changes generated by such a market must be, and the most efficient market of all is one in which price changes are completely random and unpredictable. This, of course, is not an accident of nature but is the direct outcome of many active participants attempting to profit from their information. Legions of greedy investors aggressively pounce on even the smallest informational advantage at their disposal, and in doing so, they incorporate their information into market prices and quickly eliminate the profit opportunities that gave rise to their actions. If this occurs instantaneously, as it must in an idealized world of "frictionless" markets and costless trading, then prices must always fully reflect all available information and no profits can be garnered from information-based trading (because such profits have already been captured).

This extreme version of market efficiency is now recognized as an idealization that is unlikely to hold in practice.[19] In particular, market frictions—e.g., transactions costs, borrowing constraints, costs of gathering and processing information, and institutional restrictions on short sales and other trading practices—do exist, and they all contribute to the possibility of serial correlation in asset returns, which cannot easily be "arbitraged" away precisely because of these frictions. From this perspective, the degree of serial correlation in an asset's returns can be viewed as a proxy for the magnitude of the frictions, and illiquidity is one of the most common forms of such frictions.

For example, it is well known that the historical returns to residential real-estate investments are considerably more highly autocorrelated than, say, the returns to the S&P 500 indexes during the same sample period. Similarly, the returns of S&P 500 futures exhibit less serial correlation than those of the index itself. In both examples, the more liquid instrument exhibits less serial correlation. The economic rationale is a modified version of Samuelson's (1965) argument: Predictability in asset returns will be exploited and eliminated only to the extent allowed by market frictions. Despite the fact that the returns to residential real estate are highly predictable, it is impossible to take full advantage of such predictability because of the high transactions costs associated with real-estate transactions, the inability to short sell properties, and other frictions.[20]

There is another, more mundane reason for using autocorrelations to proxy for liquidity. For portfolios of illiquid securities, i.e., securities that are not frequently traded and for which there may not be a well-established market price, a hedge-fund manager has considerable discretion in marking the portfolio's value at the end of each month to arrive at the fund's net asset value (NAV). Given the nature of hedge-fund compensation contracts and performance statistics, managers have an incentive to "smooth" their returns by marking their portfolios to less than their actual value in months with large positive returns so as to create a "cushion" for those months with lower returns. Such return-smoothing behavior yields a more consistent set of returns over time with lower volatility and, therefore, a higher Sharpe ratio, but it also produces serial correlation as a side effect. Of course, if the securities in the manager's portfolio are actively traded, the manager has little discretion in marking the portfolio; it is "marked to market." The more illiquid the portfolio, the more discretion the manager has in marking its value and smoothing returns, creating serial correlation in the process.[21]

To obtain a summary measure of the overall statistical significance of the autocorrelations, Ljung and Box (1978) proposed the following statistic:

$$Q = \frac{T(T+2)}{(T-k)} \sum_{k=1}^{p} \hat{\rho}_k^2, \tag{22}$$

which has an approximate chi-squared distribution with $p$ degrees of freedom in large samples and under the null hypothesis of no autocorrelation.[22] By forming the sum of squared autocorrelations, the statistic $Q$ reflects the absolute magnitudes of the $\hat{\rho}_k$'s irrespective of their signs; hence, funds with large positive or negative autocorrelation coefficients will exhibit large $Q$-statistics.

To illustrate the potential value of autocorrelations and the $Q$-statistic for measuring liquidity risk, I estimated these statistics for a sample of 10 mutual funds and 12 hedge funds using monthly historical returns.[23] **Table 9** reports the means, standard deviations, autocorrelations $\hat{\rho}_1$ to $\hat{\rho}_6$, and $p$-values of the $Q$-statistic using the first six autocorrelations for the sample of mutual and hedge funds. Panel A shows that the 10 mutual funds have very little serial correlation in returns, with first-order autocorrelations ranging from –3.99 percent to 12.37 percent, and with $p$-values of the corresponding $Q$-statistics ranging from 10.95 percent to 80.96 percent, implying that none of the $Q$-statistics is significant at the 5 percent level.[24] The lack of serial correlation in these 10 mutual-fund returns is not surprising. Because of their sheer size, these funds consist primarily of highly liquid securities, and, as a result, their managers have very little discretion in marking such portfolios. Moreover, many of the SEC regulations that govern the mutual fund industry, e.g., detailed prospectuses, daily NAV calculations, and quarterly filings, were enacted specifically to guard against arbitrary marking, price manipulation, and other unsavory investment practices.

In sharp contrast to the mutual-fund sample, the hedge-fund sample displays substantial serial correlation, with first-order autocorrelation coefficients that range from –20.17 percent to 49.01 percent, with 8 out of 12 funds that have $Q$-statistics with $p$-values less than 5 percent, and with 10 out of 12 funds with $p$-values less than 10 percent. The only two funds with $p$-values not significant at the 5 percent or 10 percent levels are the "Risk arbitrage A" and "Risk arbitrage B" funds, which have $p$-values of 74.10 percent and 93.42 percent, respectively. This is consistent with the notion of serial correlation as a proxy for liquidity risk because, among the various types of funds in this sample, risk arbitrage is likely to be one of the most liquid, since, by definition, such funds invest in securities that are exchange-traded and where trading volume is typically heavier than usual because of the impending merger events on which risk arbitrage is based.

Of course, there are several other aspects of liquidity that are not captured by serial correlation, and certain types of trading strategies can generate serial correlation even though they invest in highly liquid instruments.[25] In particular, conditioning variables such as investment style, the types of securities traded, and other aspects of the market environment should be taken into account, perhaps through the kind of risk model proposed in the previous section. However, as a first cut for measuring and comparing the liquidity exposures of various hedge-fund investments, autocorrelation coefficients and $Q$-statistics provide a great deal of insight and information in a convenient manner.

## Other Considerations

There are at least two other aspects of risk management for hedge funds that deserve further consideration: risk preferences and operational risks.

Risk preferences play a major role in the risk management of hedge funds from both the manager's and the investor's perspectives. Hedge fund managers are typically compensated with both fixed and incentive fees, and this nonlinear payoff scheme can induce excessive risk-taking behavior if it is not properly managed. Imposing hurdle rates, high-water marks, and other nonlinearities on the manager's compensation creates additional complexities that may have a material impact on the manager's investment decisions, particularly in

**Table 9. Autocorrelations of Mutual-Fund and Hedge-Fund Returns: Monthly Data, Various Sample Periods**

| Fund | Start Date | $T$ | $\hat{\mu}$ | $\hat{\sigma}$ | $\hat{\rho}_1$ | $\hat{\rho}_2$ | $\hat{\rho}_3$ | $\hat{\rho}_4$ | $\hat{\rho}_5$ | $\hat{\rho}_6$ | $p$-Value of $Q_6$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *A. Mutual funds* | | | | | | | | | | | |
| Vanguard 500 Index | 76.10 | 286 | 1.30% | 4.27% | –3.99% | –6.60% | –4.94% | –6.38% | 10.14% | –3.63% | 31.85% |
| Fidelity Magellan | 67.01 | 402 | 1.73 | 6.23 | 12.37 | –2.31 | –0.35 | 0.65 | 7.13 | 3.14 | 17.81 |
| Investment Company of America | 63.01 | 450 | 1.17 | 4.01 | 1.84 | –3.23 | –4.48 | –1.61 | 6.25 | –5.60 | 55.88 |
| Janus | 70.03 | 364 | 1.52 | 4.75 | 10.49 | –0.04 | –3.74 | –8.16 | 2.12 | –0.60 | 30.32 |
| Fidelity Contrafund | 67.05 | 397 | 1.29 | 4.97 | 7.37 | –2.46 | –6.81 | –3.88 | 2.73 | –4.47 | 42.32 |
| Washington Mutual Investors | 63.01 | 450 | 1.13 | 4.09 | –0.10 | –7.22 | –2.64 | 0.65 | 11.55 | –2.61 | 16.73 |
| Janus Worldwide | 92.01 | 102 | 1.81 | 4.36 | 11.37 | 3.43 | –3.82 | –15.42 | –21.36 | –10.33 | 10.95 |
| Fidelity Growth and Income | 86.01 | 174 | 1.54 | 4.13 | 5.09 | –1.60 | –8.20 | –15.58 | 2.10 | –7.29 | 30.91 |
| American Century Ultra | 81.12 | 223 | 1.72 | 7.11 | 2.32 | 3.35 | 1.36 | –3.65 | –7.92 | –5.98 | 80.96 |
| Growth Fund of America | 64.07 | 431 | 1.18 | 5.35 | 8.52 | –2.65 | –4.11 | –3.17 | 3.43 | 0.34 | 52.45 |
| *B. Hedge funds* | | | | | | | | | | | |
| Convertible/option arbitrage | 92.05 | 104 | 1.63 | 0.97 | 42.59 | 28.97 | 21.35 | 2.91 | –5.89 | –9.72 | 0.00 |
| Relative value | 92.12 | 97 | 0.66 | 0.21 | 25.90 | 19.23 | –2.13 | –16.39 | –6.24 | 1.36 | 3.32 |
| Mortgage-backed securities | 93.01 | 96 | 1.33 | 0.79 | 42.04 | 22.11 | 16.73 | 22.58 | 6.58 | –1.96 | 0.00 |
| High-yield debt | 94.06 | 79 | 1.30 | 0.87 | 33.73 | 21.84 | 13.13 | –0.84 | 13.84 | 4.00 | 1.11 |
| Risk arbitrage A | 93.07 | 90 | 1.06 | 0.69 | –4.85 | –10.80 | 6.92 | –8.52 | 9.92 | 3.06 | 74.10 |
| Long/short equities | 89.07 | 138 | 1.18 | 0.83 | –20.17 | 24.62 | 8.74 | 11.23 | 13.53 | 16.94 | 0.05 |
| Multistrategy A | 95.01 | 72 | 1.08 | 0.75 | 48.88 | 23.38 | 3.35 | 0.79 | –2.31 | –12.82 | 0.06 |
| Risk arbitrage B | 94.11 | 74 | 0.90 | 0.77 | –4.87 | 2.45 | –8.29 | –5.70 | 0.60 | 9.81 | 93.42 |
| Convertible arbitrage A | 92.09 | 100 | 1.38 | 1.60 | 33.75 | 30.76 | 7.88 | –9.40 | 3.64 | –4.36 | 0.06 |
| Convertible arbitrage B | 94.07 | 78 | 0.78 | 0.62 | 32.36 | 9.73 | –4.46 | 6.50 | –6.33 | –10.55 | 8.56 |
| Multistrategy B | 89.06 | 139 | 1.34 | 1.63 | 49.01 | 24.60 | 10.60 | 8.85 | 7.81 | 7.45 | 0.00 |
| Fund of funds | 94.10 | 75 | 1.68 | 2.29 | 29.67 | 21.15 | 0.89 | –0.90 | –12.38 | 3.01 | 6.75 |

*Note*: The term $\hat{\rho}_k$ denotes $k$th autocorrelation coefficient; the column heading "$p$-Value of $Q_6$" denotes the significance level of the Ljung–Box (1978) $Q$-statistic.

*Source*: AlphaSimplex Group.

extreme circumstances, such as after large losses. Moreover, given the large swings that often characterize hedge-fund performance, the financial and psychological pressures faced by managers each day are not trivial and do take their toll.

At the same time, the risk preferences of investors are equally relevant for risk management for hedge funds since the behavior of investors greatly influences the behavior of managers. If the stereotype that hedge-fund investors are "hot money" is true, this will affect the types of risks that hedge-fund managers can bear. Imposing "lock-up" periods and redemption fees are typical methods of dealing with skittish investors, but these can sometimes exacerbate the all-too-human tendency to panic in the face of crisis.

Any complete risk management protocol must take into account the risk preferences of both investors and managers in determining the appropriate risk exposures of a hedge fund. Given the magnitudes and many variations of risk that affect the typical hedge fund, it is even more important to integrate the "Three P's of Total Risk Management"—prices, probabilities, and preferences—in this context.[26]

The importance of risk preferences underscores the human element in hedge funds, which is part of a broader set of issues often categorized as "operational risks." These include organizational aspects such as the reliability of back-office operations, legal infrastructure, accounting and trade reconciliation, personnel issues, and the day-to-day management of the business. Many of these aspects are not subject to quantitative analysis, but they are bona fide risks that cannot be ignored and, in some cases, can quickly overshadow market risks in determining fund performance.

## Conclusion

Despite the rapid growth in hedge-fund assets over the past decade, the industry is poised for even more growth as individual and institutional investors become more attuned to its risks and rewards. However, an important catalyst in this next phase of growth will be risk transparency and more sophisticated risk management protocols for addressing the issues raised in this article.

A better understanding of the risks that hedge-fund investments pose for institutional investors is not just an unavoidable aspect of fiduciary responsibility, but also represents significant business opportunities in this growing industry.[27] For example, by the very nature of their assets and liabilities, pension funds may be in a natural position to provide the kind of liquidity that many hedge funds seek. By doing so, they are able to garner more attractive returns for their plan participants, using hedge funds as the vehicle. However, hedge-fund managers must develop a deeper appreciation for the types of risks that are consistent with the investment mandates of institutional investors. Asset/liability management for pension funds may be a somewhat arcane discipline, but it involves issues and insights that are remarkably similar to those of a typical hedge fund. For example, a plan sponsor must select and constantly manage the fund's asset mix to minimize the risk of defaulting on the plan's liabilities, but completely eliminating such risks is typically too costly; i.e., the funding cost for a completely "immunized" portfolio of liabilities is too high. By maintaining a certain "surplus" of assets to liabilities, plan sponsors can control this risk. The questions they face are how large the surplus should be and what an acceptable level of default risk is over horizons of 1 year, 5 years, and 20 years. These considerations are intimately tied to the dynamic risk exposures of the pension fund's investments, and at least in some cases, hedge funds may provide the best fit for an institutional investor's optimal risk profile.

For this reason, there is likely to be a double coincidence of desires on the part of managers and investors with respect to risk transparency. Managers are unwilling to provide position transparency, and investors usually do not have the time or resources to interpret positions (see, for example, the strategy outlined in Table 6). Instead, both managers and investors seek risk transparency, a handful of risk analytics that could provide investors with a meaningful snapshot of a hedge fund's risk exposures without compromising the proprietary information contained in the manager's positions. Developing such a set of risk analytics is the next challenge in the evolution of the hedge-fund industry. Although this will undoubtedly create more complexities for investors and managers alike, this is the price to be paid for access to a richer and potentially more rewarding set of investment alternatives. In explaining his philosophy of scientific inquiry, Albert Einstein once commented, "Everything should be made as simple as possible, but not simpler." The same can be said for the risk management of hedge funds.

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## Notes

1. In particular, CalPERS allocated up to $1.5 billion to alternative investments in 1999 according to Chernoff (2000).
2. Of course, many experts in intellectual property law would certainly classify trading strategies, algorithms, and their software manifestations as intellectual property that, in some cases, is patentable. However, most hedge-fund managers today (and, therefore, most investors) have elected not to protect such intellectual property through patents. They have chosen instead to keep them as "trade secrets," purposely limiting access to these ideas even within their own organizations. As a result, the departure of key personnel from a hedge fund often causes the demise of the fund.
3. See, for example, Smithson, Smith, and Wilford (1995), Jorion and Khoury (1996), Head and Horn (1997), Harrington and Niehaus (1999), Saunders (1999), and Shimpi (1999).
4. This assumes a one-year term for the put, with a strike that is 20 percent out of the money, an annual volatility of 75 percent, and a risk-free rate of 5 percent.

5. A short squeeze occurs when a heavily shortsold security's price increases suddenly, creating large losses for shortsellers and causing additional price increases as shortsellers attempt to close out their short positions by buying the security.
6. Unlike publicly traded securities with exchange-determined prices that become part of the public record once they are established and recorded, hedge funds are under no obligation to allow their performance data to be included in databases and have no incentives to do so once their funds shut down.
7. See, for example, the TASS Management databases of hedge funds and commodity trading advisors (CTAs) and the studies by Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), Brown, Goetzmann, and Park (2001), Elton, Gruber, and Blake (1996), Fung and Hsieh (1997), and Schneeweis and Spurgin (1996).
8. These values can be readily computed from the cumulative probability distribution of $X^*$, which is well known to be $\Pr(X^* < x) = F^n(x)$; hence, $E[X^*] = \int x dF(x)$, $\mathrm{Var}[X^*] = \int x^2 dF(x) - E[X^*]^2$, and $\delta = F^n(C_\delta) \Rightarrow C_\delta = F^{-1}(\delta^{1/n})$, where $\delta = 0.025, 0.975$.
9. See, for example, Brown, Goetzmann, Ibbotson, and Ross (1992), Lo (1994), and Lo and MacKinlay (1990).
10. For this reason, hedge-fund track records are often summarized by multiple statistics, e.g., Sharpe ratio, Sortino ratio, maximum drawdown, worst month.
11. As a mental exercise to check your own risk preferences, take a hard look at the monthly returns in Table 4 and ask yourself whether you would invest in such a fund.
12. The margin required per contract is assumed to be 100 × {15 percent × (current level of the SPX) – (put premium) – (amount out of the money)}, where the amount out of the money is equal to the current level of the SPX minus the strike price of the put.
13. This figure varies from broker to broker and is meant to be a rather conservative estimate that might apply to a $10 million start-up hedge fund with no prior track record.
14. A portfolio of options is worth more than an option on the portfolio; hence, shorting 500 puts on the individual stocks that constitute the SPX will yield substantially higher premiums than shorting puts on the index.
15. One of the most striking examples of phase-locking behavior is the automatic synchronization of the flickering of Southeast Asian fireflies. See Strogatz (1994) for a description of this remarkable phenomenon, as well as an excellent review of phase-locking behavior in biological systems.
16. Note that in the case of CDP, the fund's consecutive returns of –18.3 percent and –16.2 percent in August and September 1998 would have made it virtually impossible for the fund to continue without a massive injection of capital. In all likelihood, it would have closed down, along with many other hedge funds during those fateful months, never to realize the extraordinary returns that it would have earned had it been able to withstand the losses in August and September (see Table 4).
17. See, for example, Bookstaber (1999, 2000), Kao (2000), and their citations.
18. The $k$th order autocorrelation of a time series $\{R_t\}$ is defined as the correlation coefficient between $R_t$ and $R_{t-k}$, which is simply the covariance between $R_t$ and $R_{t-k}$ divided by the square root of the product of the variances of $R_t$ and $R_{t-k}$. But since the variances of $R_t$ and $R_{t-k}$ are the same under our assumption of stationarity, the denominator of the autocorrelation is simply the variance of $R_t$.
19. See, for example, Farmer and Lo (1999).
20. These frictions have led to the creation of real-estate investment trusts (REITs), and the returns to these securities—which are considerably more liquid than the underlying assets on which they are based—exhibit much less serial correlation.
21. There are, of course, other considerations in interpreting the serial correlation of any portfolio's returns, of which return smoothing is only one. Others include nonsynchronous trading, time-varying expected returns, and market inefficiencies. See Getmansky, Lo, and Makarov (2001) for a more detailed analysis of serial correlation in hedge-fund returns and Lo (forthcoming 2002) for adjustments to the Sharpe ratio to correct for serial correlation.
22. See Kendall, Stuart, and Ord (1983, Chapter 50.13) for details.
23. The 10 mutual funds selected were the 10 largest U.S. mutual funds as of February 11, 2001, and monthly total returns from various start dates through June 2000 were obtained from the University of Chicago's Center for Research in Security Prices. Monthly returns for the 12 hedge funds from various start dates to January 2001 were obtained from the Altvest database. The 12 funds were chosen to yield a diverse range of annual Sharpe ratios (from 1 to 5) computed in the standard way ($\sqrt{12}$SR, where SR is the Sharpe ratio of monthly returns), with the additional requirement that the funds have a minimum five-year history of returns. The names of the hedge funds have been omitted to maintain their privacy, and they are referenced only by their stated investment styles, e.g., relative value fund, risk arbitrage fund, etc.
24. The $p$-value of a statistic is defined as the smallest level of significance for which the null hypothesis can be rejected based on the statistic's value. For example, a $p$-value of 16.73 percent for the $Q$-statistic of Washington Mutual Investors implies that the null hypothesis of no serial correlation can only be rejected at the 16.73 percent significance level—at any smaller level of significance, say 5 percent, the null hypothesis cannot be rejected. Therefore, smaller $p$-values indicate stronger evidence against the null hypothesis, and larger $p$-values indicate stronger evidence in favor of the null. $p$-values are often reported instead of test statistics because they are easier to interpret (to interpret a test statistic, one must compare it to the critical values of the appropriate distribution; this comparison is performed in computing the $p$-value). See, for example, Bickel and Doksum (1977, Chapter 5.2.B) for further discussion of $p$-values and their interpretation.
25. These subtleties are considered in more detail in Getmansky, Lo, and Makarov (2001).
26. See Lo (1999) for further details.
27. I am especially indebted to Leo de Bever for pointing out many of the issues raised in this paragraph.

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