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Andrew W. Lo: Hedge Funds

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1 Introduction

One of the fastest growing sectors of the financial services industry is the *hedge fund* or *alternative-investments* sector, currently estimated at more than \$1 trillion in assets worldwide. One of the main reasons for such interest is the performance characteristics of hedge funds—often known as “high-octane” investments: Many hedge funds have yielded double-digit returns for their investors and, in many cases, in a fashion that seems uncorrelated with general market swings and with relatively low volatility. Most hedge funds accomplish this by maintaining both long and short positions in securities—hence the term “hedge” fund—which, in principle, gives investors an opportunity to profit from both positive and negative information while at the same time providing some degree of “market neutrality” because of the simultaneous long and short positions. Long the province of foundations, family offices, and high-net-worth investors, alternative investments are now attracting major institutional investors such as large state and corporate pension funds, insurance companies, and university endowments, and efforts are underway to make hedge fund investments available to individual investors through more traditional mutual fund investment vehicles.

However, many institutional investors are not yet convinced that alternative investments comprise 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 categorization 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 portfolio analytics and risk management protocols specifically designed for alternative investments has never been more pressing.

Part of the gap between institutional investors and hedge fund managers is due to differences in investment mandate, regulatory oversight, and business culture between the two groups, yielding very different perspectives on what a good investment process should look like. For example, a typical hedge fund 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 in 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.¹

Contrast these statements with the following characterization 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 the manager's strategies to be consistent with the institution's overall investment objectives and constraints.
- Performance is not measured solely by return but also includes other factors such as risk adjustments, tracking error relative to a benchmark, and peer group comparisons.
- Risk management and risk transparency are essential.
- 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—not dependent on any single individual.

¹ Of course, many experts in intellectual property law would certainly classify trading strategies, algorithms, and their software manifestations as intellectual property which, in some cases, are patentable. However, most hedge fund managers today (and, therefore, most investors) have not elected to protect such intellectual property through patents but 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.

Now, of course, these are rather broad-brush caricatures of the two groups, made extreme for clarity, but they do capture the essence of the existing gulf 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. One of the purposes of this monograph is to help create more common ground between hedge fund managers and investors through new quantitative models and methods for gauging the risks and rewards of alternative investments.

This might seem to be more straightforward a task than it is because of the enormous body of literature on investments and quantitative portfolio management. However, several recent empirical studies have cast some doubt on the applicability of standard methods for assessing the risks and returns of hedge funds, concluding that they can often be quite misleading. For example, Asness, Krail, and Liew (2001) show that in some cases where hedge funds purport to be market neutral (namely, funds with relatively small market betas), including both contemporaneous and lagged market returns as regressors and summing the coefficients yields significantly higher market exposure. Getmansky, Lo, and Makarov (2004) argue that this is due to significant serial correlation in the returns of certain hedge funds, which is likely the result of illiquidity and smoothed returns. Such correlation can yield substantial biases in the variances, betas, Sharpe ratios, and other performance statistics. For example, in deriving statistical estimators for Sharpe ratios of a sample of mutual funds and hedge funds, Lo (2002) shows that the correct method for computing annual Sharpe ratios based on monthly means and standard deviations can yield point estimates that differ from the naive Sharpe ratio estimator by as much as 70%.

These empirical facts suggest that hedge funds and other alternative investments have unique properties, requiring new tools to properly characterize their risks and expected returns. In this monograph, we describe some of these unique properties and propose several new quantitative measures for modeling them.

One of the justifications for the unusually rich fee structures that characterize hedge fund investments is the fact that these funds employ active strategies involving highly skilled portfolio managers. Moreover, it is common wisdom that the most talented managers are first drawn 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 risks of a dynamic investment strategy.²

These challenges have important implications for both managers and investors since both parties seek to manage the risk/reward trade-offs of their investments. Consider, for example, the now-standard approach to constructing an optimal portfolio in the mean-variance sense:

$$\max_{\{\omega_i\}} E[U(W_1)] \quad (1.1)$$

$$\text{subject to } W_1 = W_0(1 + R_p), \quad (1.2a)$$

$$R_p \equiv \sum_{i=1}^n \omega_i R_i, \quad 1 = \sum_{i=1}^n \omega_i, \quad (1.2b)$$

where R_i is the return of security i between this period and the next, W_1 is the individual's next period's wealth (which is determined by the product of $\{R_i\}$ and the portfolio weights $\{\omega_i\}$), and $U(\cdot)$ is the individual's utility function. By assuming that $U(\cdot)$ is quadratic or by assuming that individual security returns R_i are normally distributed random variables, it can be shown that maximizing the individual's expected utility is tantamount to constructing a mean-variance optimal portfolio ω^* .³

It is one of the great lessons of modern finance that mean-variance optimization yields benefits through diversification, the ability to lower volatility for a given level of expected return by combining securities that are not perfectly correlated. But what if the securities are hedge funds, and what if their correlations change over time, as hedge funds tend to do (Section 1.2)?⁴ Table 1.1 shows that for the two-asset case with fixed means of 5% and 30%, respectively, and fixed standard deviations of 20% and 30%, respectively, as the correlation ρ between the two assets varies from -90% to 90% , the optimal portfolio weights—and the properties of the optimal portfolio—change dramatically. For example, with a -30% correlation between the two funds, the optimal portfolio holds 38.6% in the first fund and 61.4% in the second, yielding a Sharpe ratio of 1.01. But if the correlation changes to 10%, the optimal weights change to 5.2% in the first fund and 94.8% in the second, despite the fact that the Sharpe ratio of the new

² For this reason, hedge fund track records are often summarized with multiple statistics, e.g., mean, standard deviation, Sharpe ratio, market beta, Sortino ratio, maximum drawdown, and worst month.

³ See, for example, Ingersoll (1987).

⁴ Several authors have considered mean-variance optimization techniques for determining hedge fund allocations, with varying degrees of success and skepticism. See, in particular, Amenc and Martinelli (2002), Amin and Kat (2003c), Terhaar, Staub, and Singer (2003), and Cremers, Kritzman, and Page (2004).

Table 1.1.
Mean-Variance Optimal Portfolios for the Two-Asset Case*

ρ	$E[R^*]$	$SD[R^*]$	<i>Sharpe</i>	ω_1^*	ω_2^*
-90	15.5	5.5	2.36	58.1	41.9
-80	16.0	8.0	1.70	55.9	44.1
-70	16.7	10.0	1.41	53.4	46.6
-60	17.4	11.9	1.25	50.5	49.5
-50	18.2	13.8	1.14	47.2	52.8
-40	19.2	15.7	1.06	43.3	56.7
-30	20.3	17.7	1.01	38.6	61.4
-20	21.8	19.9	0.97	32.9	67.1
-10	23.5	22.3	0.94	25.9	74.1
0	25.8	25.1	0.93	17.0	83.0
10	28.7	28.6	0.92	5.2	94.8
20	32.7	32.9	0.92	-10.9	110.9
30	38.6	38.8	0.93	-34.4	134.4
40	48.0	47.7	0.95	-71.9	171.9
50	65.3	63.2	0.99	-141.2	241.2
60	108.1	99.6	1.06	-312.2	412.2
70	387.7	329.9	1.17	-1430.8	1530.8
80 [†]	-208.0	-154.0	1.37	952.2	-852.2
90 [†]	-76.8	-42.9	1.85	427.1	-327.1

* Mean-variance optimal portfolio weights for the two-asset case $(\mu_1, \sigma_1) = (5\%, 20\%)$, $(\mu_2, \sigma_2) = (30\%, 30\%)$, and $R_f = 2.5\%$, with fixed means and variances, and correlations ranging from -90% to 90% .

[†] These correlations imply non-positive-definite covariance matrices for the two assets.

portfolio, 0.92, is virtually identical to the previous portfolio's Sharpe ratio. The mean-variance-efficient frontiers are plotted in Figure 1.1 for various correlations between the two funds, and it is apparent that the optimal portfolio depends heavily on the correlation structure of the underlying assets. Because of the dynamic nature of hedge fund strategies, their correlations are particularly unstable over time and over varying market conditions, as we shall see in Section 1.2, and swings from -30% to 30% are not unusual.

Table 1.1 shows that as the correlation between the two assets increases, the optimal weight for asset 1 eventually becomes negative, which makes intuitive sense from a hedging perspective even if it is unrealistic for hedge fund investments and other assets that cannot be shorted. Note that for correlations of 80% and greater, the optimization approach does not yield a well-defined solution because a mean-variance-efficient tangency portfolio does not exist for the parameter values we hypothesized for the two assets. However, numerical

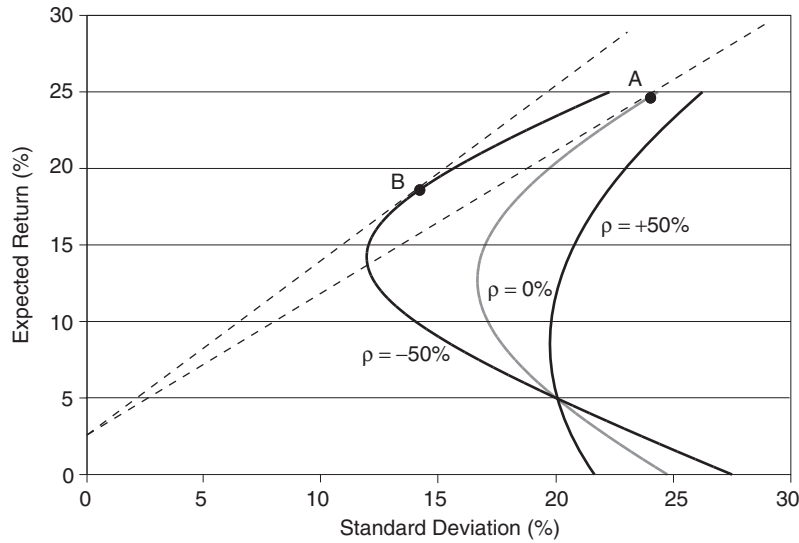


Figure 1.1. Mean-variance efficient frontiers for the two-asset case. Parameters $(\mu_1, \sigma_1) = (5\%, 20\%)$, $(\mu_2, \sigma_2) = (30\%, 30\%)$, and correlation $\rho = -50\%, 0\%, 50\%$.

optimization procedures may still yield a specific portfolio for this case (e.g., a portfolio on the lower branch of the mean-variance parabola) even if it is not optimal. This example underscores the importance of modeling means, standard deviations, and correlations in a consistent manner when accounting for changes in market conditions and statistical regimes; otherwise, degenerate or nonsensical “solutions” may arise.

To illustrate the challenges and opportunities in modeling the risk exposures of hedge funds, we provide three extended examples in this chapter. In Section 1.1, we present a hypothetical hedge fund strategy that yields remarkable returns with seemingly little risk; yet a closer examination reveals a different story. In Section 1.2, we show that correlations and market beta are sometimes incomplete measures of risk exposure for hedge funds, and that such measures can change over time, in some cases quite rapidly and without warning. And in Section 1.3, we describe one of the most prominent empirical features of the returns of many hedge funds—large positive serial correlation—and argue that serial correlation can be a very useful proxy for liquidity risk. These examples will provide an introduction to the more involved quantitative analysis in Chapters 3–8 and serve as motivation for an analytical approach to alternative investments. We conclude by presenting a brief review of the burgeoning hedge fund literature in Section 1.4.

Table 1.2.
Capital Decimation Partners, L. P., Performance Summary (January 1992 to
December 1999)*

	<i>S&P 500</i>	<i>CDP</i>
Monthly mean	1.4%	3.6%
Monthly SD	3.6%	5.8%
Minimum month	-8.9%	-18.3%
Maximum month	14.0%	27.0%
Annual Sharpe ratio	1.39	2.15
No. of negative months	36	6
Correlation to S&P 500	100%	61%
Growth of \$1 since inception	\$4	\$26

* Performance summary of a simulated short-put-option strategy consisting of short-selling out-of-the-money S&P 500 put options with strikes approximately 7% out of the money and with maturities less than or equal to 3 months.

1.1 Tail Risk

Consider the 8-year track record of a hypothetical hedge fund, Capital Decimation Partners, LP. (CDP), summarized in Table 1.2. 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. Before discussing the particular strategy that generated these results, consider its overall performance: an average monthly return of 3.6% versus 1.4% for the S&P 500 during the same period; a total return of 2,560% over the 8-year period versus 367% for the S&P 500; a Sharpe ratio of 2.15 versus 1.39 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 1.3—shows that, as with many other hedge funds, the worst months for this fund were August and September of 1998. Yet October and November of 1998 were the fund's two best months, and for 1998 as a whole the fund was up 87.3% versus 24.5% 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.⁵ What is its secret?

The investment strategy summarized in Tables 1.2 and 1.3 consists of shorting out-of-the-money S&P 500 put options on each monthly expiration date for maturities less than or equal to 3 months and with strikes approximately 7% out of the money. According to Lo (2001), the number of contracts sold each month is determined by the combination of: (1) Chicago Board, Options Exchange

⁵ In fact, as a mental exercise to check your own risk preferences, take a hard look at the monthly returns in Table 1.3 and ask yourself whether you would invest in such a fund.

Table 1.3.
Capital Decimation Partners, L.P., Monthly Performance History (January 1992 to December 1999)*

Month	1992		1993		1994		1995		1996		1997		1998		1999	
	SPX	CDP	SPX	CDP	SPX	CDP	SPX	CDP	SPX	CDP	SPX	CDP	SPX	CDP	SPX	CDP
Jan	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
Feb	-1.8	4.8	-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
Mar	0.0	2.3	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
Apr	1.2	3.4	-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	1.4	-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
Jun	-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
Jul	3.0	2.0	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
Aug	-0.2	1.8	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
Sep	1.9	2.1	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
Oct	-2.6	-3.0	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
Nov	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
Dec	3.4	1.3	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	38.2	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

* Monthly returns of a simulated short-put-option strategy consisting of short-selling out-of-the-money S&P 500 (SPX) put options with strikes approximately 7% out of the money and with maturities less than or equal to 3 months.

(CBOE) margin requirements;⁶ (2) an assumption that the fund is required to post 66% of the margin as collateral;⁷ and (3) \$10 million of initial risk capital. For concreteness, Table 1.4 reports the positions and profit/loss statement for this strategy for 1992.

The essence of this strategy is the provision of insurance. CDP investors receive option premia for each option contract sold short, and as long as the option contracts expire out of the money, no payments are necessary. Therefore, the only time CDP experiences losses is when its put options are in the money, i.e., when the S&P 500 declines by more than 7% during the life of a given option. From this perspective, the handsome returns to CDP investors seem more justifiable—in exchange for providing downside protection, CDP investors are paid a risk premium in the same way that insurance companies receive regular payments for providing earthquake or hurricane insurance.

The track record in Tables 1.2 and 1.3 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 is apparent from the positions in Table 1.1 that the manager of Capital Decimation Partners 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 1.5 reports the weekly positions over a 6-month period in 1 of 500 securities contained in a second hypothetical fund, Capital Decimation Partners II. Casual inspection of the positions of 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 1.5 reveals that these trades constitute a delta-hedging strategy designed to synthetically replicate a short position in a 2-year European put option on 10 million 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).

⁶ The margin required per contract is assumed to be

$$100 \times \{15\% \times (\text{current level of the SPX}) - (\text{put premium}) - (\text{amount out of the money})\}$$

where the amount out of the money is equal to the current level of the SPX minus the strike price of the put.

⁷ This figure varies from broker to broker, and is meant to be a rather conservative estimate that might apply to a \$10 million startup hedge fund with no prior track record.

Table 1.4.
Capital Decimation Partners, L.P., Positions and Profit/Loss for 1992*

	S&P 500		No. of Puts	Strike	Price	Expiration	Margin Required	Profits	Initial Capital + Cumulative Profits	Capital Available for Investments	Return
20 Dec 1991	387.04	New	2,300	360	\$4.625	Mar 92	\$6,069,930				
17 Jan 1992	418.86	Mark to Market	2,300	360	\$1.125	Mar 92	\$654,120	\$805,000	\$10,805,000	\$6,509,036	8.1%
	418.86	New	1,950	390	\$3.250	Mar 92	\$5,990,205				
						Total Margin	\$6,644,325				
21 Feb 1992	411.46	Mark to Market	2,300	360	\$0.250	Mar 92	\$2,302,070	\$201,250			
	411.46	Mark to Market	1,950	390	\$1.625	Mar 92	\$7,533,630	\$316,875	\$11,323,125	\$6,821,160	4.8%
	411.46	Liquidate	1,950	390	\$1.625	Mar 92	\$0	\$0	\$11,323,125	\$6,821,160	
	411.46	New	1,170	390	\$1.625	Mar 92	\$4,520,178				
						Total Margin	\$6,822,248				
20 Mar 1992	411.30	Expired	2,300	360	\$0.000	Mar 92	\$0	\$57,500			
	411.30	Expired	1,246	390	\$0.000	Mar 92	\$0	\$202,475			
	411.30	New	2,650	380	\$2.000	May 92	\$7,524,675		\$11,583,100	\$6,977,771	2.3%
						Total Margin	\$7,524,675				
19 Apr 1992	416.05	Mark to Market	2,650	380	\$0.500	May 92	\$6,852,238	\$397,500			
	416.05	New	340	385	\$2.438	Jun 92	\$983,280		\$11,980,600	\$7,217,229	3.4%
						Total Margin	\$7,835,518				
15 May 1992	410.09	Expired	2,650	380	\$0.000	May 92	\$0	\$132,500			
	410.09	Mark to Market	340	385	\$1.500	Jun 92	\$1,187,399	\$31,875			
	410.09	New	2,200	380	\$1.250	Jul 92	\$6,638,170		\$12,144,975	\$7,316,250	1.4%
						Total Margin	\$7,825,569				

Table 1.5.
Capital Decimation Partners II, L.P., Weekly Positions in XYZ*

<i>Week</i> <i>t</i>	P_t (\$)	<i>Position</i> (no. of shares)	<i>Value</i> (\$)	<i>Financing</i> (\$)
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

* Simulated weekly positions in XYZ for a particular trading strategy over a 6-month period.

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 a position report such as Table 1.5, but for 500 securities, not just 1, as well as a corresponding track record that is likely to be even more impressive than that of Capital Decimation Partners, L.P.⁸ Without additional analysis that explicitly accounts for the dynamic aspects of the trading

⁸ 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 yields substantially higher premiums than shorting puts on the index.

strategy described in Table 1.5, 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 such as those of Capital Decimation Partners (note the impressive Sharpe ratio in Table 1.2). 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 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 Capital Decimation Partners. 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 in 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.

1.2 Nonlinear Risks

One of the most compelling reasons for investing in hedge funds is 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 1.6 reports the correlation matrix for the returns of the Credit Suisse/Tremont (CS/Tremont) hedge fund indexes, where each index represents a particular hedge fund *style* such as currencies, emerging markets, relative value and so on. The last four rows report the correlations of all these hedge fund indexes with the returns of more traditional investments: the S&P 500 and indexes for small-cap equities, long-term government bonds, and long-term corporate bonds. These correlations show that many hedge fund styles have low or, in some cases, negative correlation with broad-based market indexes and also exhibit a great deal of heterogeneity, ranging from -71.9% (between Long/Short Equity and Dedicated Short sellers) to 92.9% (between Event Driven and Distressed).

Table 1.6.
Correlation Matrix for CS/Tremont Hedge Fund Index Returns (January 1994 to July 2007)*

	Hedge Fund Index	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long/Short Equity
Index	100.0								
Hedge Fund Index	100.0	41.1	-48.8	65.2	33.3	67.4	44.2	85.4	79.3
Convertible Arbitrage	41.1	100.0	-25.7	30.1	33.9	56.5	53.7	29.1	28.7
Dedicated Short Bias	-48.8	-25.7	100.0	-54.5	-31.8	-62.6	-9.9	-13.5	-71.9
Emerging Markets	65.2	30.1	-54.5	100.0	22.1	67.2	27.1	41.5	59.7
Equity Market Neutral	33.3	33.9	-31.8	22.1	100.0	35.1	13.1	21.9	34.8
Event Driven	67.4	56.5	-62.6	67.2	35.1	100.0	38.3	37.9	66.7
Fixed Income Arbitrage	44.2	53.7	-9.9	27.1	13.1	38.3	100.0	44.2	21.7
Global Macro	85.4	29.1	-13.5	41.5	21.9	37.9	44.2	100.0	43.0
Long/Short Equity	79.3	28.7	-71.9	59.7	34.8	66.7	21.7	43.0	100.0
Managed Futures	16.1	-11.2	8.6	-6.9	12.4	-11.3	-3.9	24.7	3.4
Multi-Strategy	23.0	39.8	-12.3	2.6	23.1	24.6	30.2	14.3	22.1
Event Driven Multi-Strategy	68.6	56.4	-54.0	66.7	32.0	93.5	40.8	41.9	64.5
Distressed	58.6	49.5	-62.0	58.9	33.4	92.9	32.2	31.4	59.0
Risk Arbitrage	39.8	40.2	-49.8	42.2	30.7	66.0	15.0	13.9	51.3
Large Company Stocks	48.6	14.1	-75.6	48.2	36.5	56.1	3.4	23.5	59.2
Small Company Stocks	57.7	27.6	-78.4	54.9	24.2	65.4	12.4	23.3	76.4
Long-Term Corporate Bonds	18.4	7.6	-0.9	1.4	7.2	5.6	11.9	23.7	10.6
Long-Term Government Bonds	11.7	2.7	10.9	-8.9	4.4	-8.1	8.3	21.4	2.4

Table 1.6.
(continued)

	Managed Futures	Multi- Strategy	Event Driven Multi-Strategy	Distressed	Risk Arbitrage	Large Stocks	Small Stocks	Long-Term Corporate Bonds	Long-Term Government Bonds
Index									
Hedge Fund Index	16.1	23.0	68.6	58.6	39.8	48.6	57.7	18.4	11.7
Convertible Arbitrage	-11.2	39.8	56.4	49.5	40.2	14.1	27.6	7.6	2.7
Dedicated Short Bias	8.6	-12.3	-54.0	-62.0	-49.8	-75.6	-78.4	-0.9	10.9
Emerging Markets	-6.9	2.6	66.7	58.9	42.2	48.2	54.9	1.4	-8.9
Equity Market Neutral	12.4	23.1	32.0	33.4	30.7	36.5	24.2	7.2	4.4
Event Driven	-11.3	24.6	93.5	92.9	66.0	56.1	65.4	5.6	-8.1
Fixed Income Arbitrage	-3.9	30.2	40.8	32.2	15.0	3.4	12.4	11.9	8.3
Global Macro	24.7	14.3	41.9	31.4	13.9	23.5	23.3	23.7	21.4
Long/Short Equity	3.4	22.1	64.5	59.0	51.3	59.2	76.4	10.6	2.4
Managed Futures	100.0	6.8	-12.7	-8.0	-13.7	-13.8	-10.6	18.1	24.0
Multi-Strategy	6.8	100.0	28.7	17.0	12.0	10.2	24.0	2.8	-1.8
Event Driven Multi-Strategy	-12.7	28.7	100.0	74.3	63.0	48.9	62.0	1.6	-9.8
Distressed	-8.0	17.0	74.3	100.0	55.0	54.8	59.9	9.3	-4.7
Risk Arbitrage	-13.7	12.0	63.0	55.0	100.0	44.5	56.7	1.8	-8.9
Large Company Stocks	-13.8	10.2	48.9	54.8	44.5	100.0	61.2	8.0	-5.1
Small Company Stocks	-10.6	24.0	62.0	59.9	56.7	61.2	100.0	-0.1	-14.0
Long-Term Corporate Bonds	18.1	2.8	1.6	9.3	1.8	8.0	-0.1	100.0	94.3
Long-Term Government Bonds	24.0	-1.8	-9.8	-4.7	-8.9	-5.1	-14.0	94.3	100.0

* All values are percentages and are based on monthly data. Multi-Strategy index data are for the period from April 1994 to July 2007, while the data for Large Company Stocks, Small Company Stocks, Long-Term Corporate Bonds, and Long-Term Government Bonds are for the period from January 1994 to December 2006.

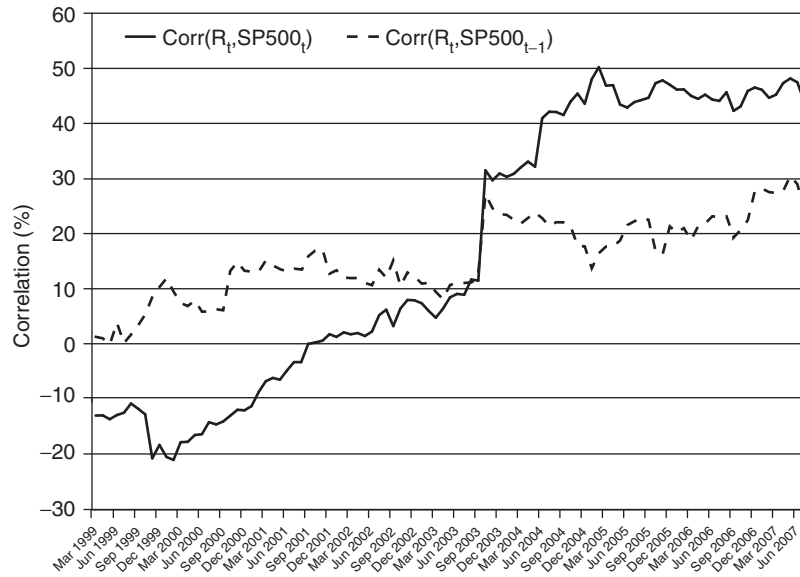


Figure 1.2. Sixty-month rolling correlations between CS/Tremont Multi-Strategy index returns and the contemporaneous and lagged returns of the S&P 500 (March 1999 to July 2007). Under the null hypothesis of no correlation, the approximate standard error of the correlation coefficient is $1/\sqrt{60} = 13\%$; hence the differences between the beginning-of-sample and end-of-sample correlations are statistically significant at the 1% level.

However, correlations can change over time. For example, consider a rolling 60-month correlation between the CS/Tremont Multi-Strategy index and the S&P 500 from March 1999 to July 2007, plotted in Figure 1.2. At the start of the sample in March 1999, the correlation is -13.0% , drops to -17.8% a year later, and increases to 30.3% by January 2004. Although such changes in rolling correlation estimates are partly attributable to estimation errors,⁹ in this case another possible explanation for the positive trend in correlation is the enormous inflow of capital into Multi-strategy funds and Funds of Funds over the past 5 years. As assets under management increase, it becomes progressively more difficult for fund managers to implement strategies that are truly uncorrelated with broad-based market indexes like the S&P 500. Moreover, Figure 1.2 shows that the correlation between the Multi-Strategy index return and the lagged S&P 500 return has also increased in the past year, indicating an increase in the illiquidity exposure

⁹ Under the null hypothesis of no correlation, the approximate standard error of the correlation coefficient is $1/\sqrt{60} = 13\%$.

Table 1.7.
Correlation Matrix for Seven CS/Tremont Hedge Fund Index Returns (April 1994 to July 2007)*

	Hedge Fund Index	Convertible Arbitrage	Emerging Markets	Equity Market Neutral	Distressed	Long/Short Equity	Multi-Strategy
April 1994 to December 1999							
Hedge Fund Index	100.0	52.8	65.5	38.3	58.1	70.9	8.8
Convertible Arbitrage	52.8	100.0	45.7	31.3	62.1	37.9	29.5
Emerging Markets	65.5	45.7	100.0	26.8	60.1	59.2	-11.7
Equity Market Neutral	38.3	31.3	26.8	100.0	48.0	44.9	17.4
Distressed	58.1	62.1	60.1	48.0	100.0	64.3	1.5
Long/Short Equity	70.9	37.9	59.2	44.9	64.3	100.0	4.4
Multi-Strategy	8.8	29.5	-11.7	17.4	1.5	4.4	100.0
January 2000 to July 2007							
Hedge Fund Index	100.0	23.7	74.2	11.8	57.3	97.0	60.5
Convertible Arbitrage	23.7	100.0	3.0	39.2	32.7	16.9	57.7
Emerging Markets	74.2	3.0	100.0	18.9	52.8	72.5	45.4
Equity Market Neutral	11.8	39.2	18.9	100.0	0.8	9.0	36.9
Distressed	57.3	32.7	52.8	0.8	100.0	47.9	53.5
Long/Short Equity	97.0	16.9	72.5	9.0	47.9	100.0	56.1
Multi-Strategy	60.5	57.7	45.4	36.9	53.5	56.1	100.0
Difference Between Two Correlation Matrices							
Hedge Fund Index	0.0	29.0	-8.7	26.5	0.8	-26.1	-51.7
Convertible Arbitrage	29.0	0.0	42.7	-7.9	29.4	21.0	-28.2
Emerging Markets	-8.7	42.7	0.0	7.9	7.2	-13.4	-57.1
Equity Market Neutral	26.5	-7.9	7.9	0.0	47.2	36.0	-19.4
Distressed	0.8	29.4	7.2	47.2	0.0	16.4	-52.0
Long/Short Equity	-26.1	21.0	-13.4	36.0	16.4	0.0	-51.7
Multi-Strategy	-51.7	-28.2	-57.1	-19.4	-52.0	-51.7	0.0

* All values are percentages and are based on monthly data.

of this investment style (Getmansky, Lo, and Makarov, 2004, and Chapter 3). This is also consistent with large inflows of capital into the hedge fund sector.

Correlations between hedge fund style categories can also shift over time, as Table 1.7 illustrates. Over the sample period from April 1994 to July 2007, the correlation between the Convertible Arbitrage and Emerging Market indexes is 30.1%, but Table 1.7 shows that during the first half of the sample (April 1994 to December 1999) this correlation is 45.7% and during the second half (January 2000 to July 2007) it is 3.0%. The third panel in Table 1.7, which reports the difference of the correlation matrices from the two subperiods, suggests that hedge fund–index correlations are not very stable over time.

A graph of the 60-month rolling correlation between the Convertible Arbitrage and the Emerging Market indexes from January 1999 to July 2007 provides a clue as to the source of this nonstationarity: Figure 1.3 shows a sharp drop in the correlation during the month of September 2003. This is the first month for which the August 1998 data point—the start of the Long Term Capital Management (LTCM) event—is not included in the 60-month rolling window. During this period, the default in Russian government debt triggered a global “flight to quality” that apparently changed many correlations from zero to one over the course of just a few days, and Table 1.8 shows that in August 1998 the returns for the Convertible Arbitrage and Emerging Market indexes were -4.64% and -23.03 , respectively. In fact, 10 out of the 13 style category indexes yielded negative returns in August 1998, many of which were extreme outliers relative to the entire sample period; hence rolling windows containing this month can yield dramatically different correlations than those without it.

In the physical and natural sciences, sudden changes from low correlation to high correlation are examples of *phase-locking behavior*, situations in which otherwise uncorrelated actions suddenly become synchronized.¹⁰ 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.

One 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:

$$R_{it} = \alpha_i + \beta_i \Lambda_t + I_t Z_t + \epsilon_{it} \quad (1.3)$$

¹⁰ 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.

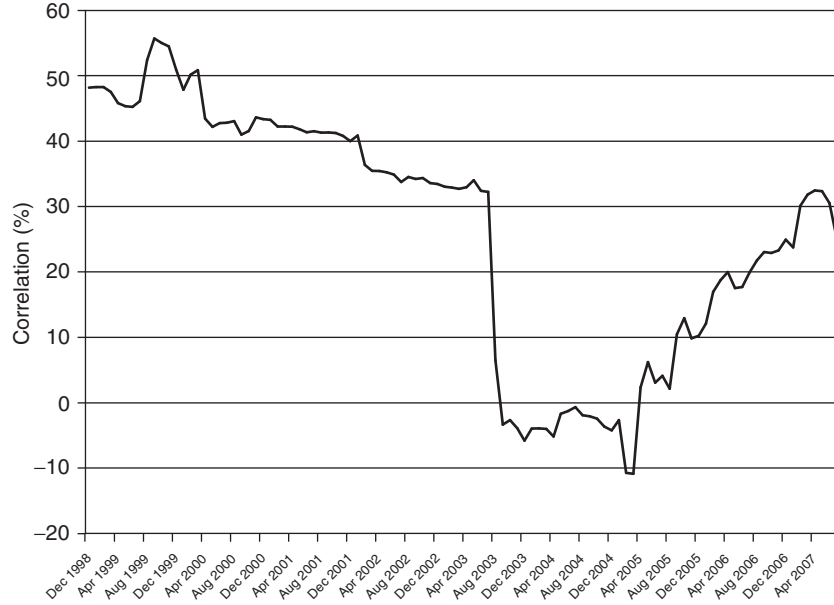


Figure 1.3. Sixty-month rolling correlations between CS/Tremont Convertible Arbitrage and Emerging Market index returns (January 1999 to July 2007). The sharp decline in September 2003 is due to the fact that this is the first month in which the August 1998 observation is dropped from the 60-month rolling window.

Assume that Λ_t , I_t , Z_t , and ϵ_{it} are mutually independently and identically distributed (IID) with the following moments:

$$\begin{aligned} E[\Lambda_t] &= \mu_\lambda, & \text{Var}[\Lambda_t] &= \sigma_\lambda^2, \\ E[Z_t] &= 0, & \text{Var}[Z_t] &= \sigma_z^2, \\ E[\epsilon_{it}] &= 0, & \text{Var}[\epsilon_{it}] &= \sigma_{\epsilon_i}^2, \end{aligned} \quad (1.4)$$

and let the phase-locking event indicator I_t be defined by

$$I_t = \begin{cases} 1 & \text{with probability } p, \\ 0 & \text{with probability } 1 - p. \end{cases} \quad (1.5)$$

According to (1.3), expected returns are the sum of three components: the fund's alpha, α_i a "market" component Λ_t , to which each fund has its own individual sensitivity β_i , and a phase-locking component that is identical across all funds at all times, taking only one of two possible values, either 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

Table 1.8.
CS/Tremont Hedge Fund Index and Market Index Returns (August 1998 to
October 1998)*

	August 1998 (%)	September 1998 (%)	October 1998 (%)
Index			
Aggregate index	-7.55	-2.31	-4.57
Convertible Arbitrage	-4.64	-3.23	-4.68
Dedicated Shortseller	22.71	-4.98	-8.69
Emerging Markets	-23.03	-7.40	1.68
Equity Market Neutral	-0.85	0.95	2.48
Event Driven	-11.77	-2.96	0.66
Distressed	-12.45	-1.43	0.89
Event Driven Multi-Strategy	-11.52	-4.74	0.26
Risk Arbitrage	-6.15	-0.65	2.41
Fixed Income Arbitrage	-1.46	-3.74	-6.96
Global Macro	-4.84	-5.12	-11.55
Long/Short Equity	-11.43	3.47	1.74
Managed Futures	9.95	6.87	1.21
Multi-Strategy	1.15	0.57	-4.76
Ibbotson S&P 500	-14.46	6.41	8.13
Ibbotson Small Cap	-20.10	3.69	3.56
Ibbotson LT Corporate Bonds	0.89	4.13	-1.90
Ibbotson LT Government Bonds	4.65	3.95	-2.18

* Monthly returns of CS/Tremont hedge fund indexes and Ibbotson stock and bond indexes.
Source: AlphaSimplex Group.

once in a while an additional term Z_t appears. If the volatility σ_z of Z_t is much larger than the volatilities of the market factor Λ_t and the idiosyncratic risk ϵ_{it} , then the common factor Z_t will dominate the expected returns of all stocks when $I_t = 1$, i.e., phase-locking behavior occurs.

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 $I_t = 0$:

$$\text{Corr}[R_{it}, R_{jt} | I_t = 0] = \frac{\beta_i \beta_j \sigma_\lambda^2}{\sqrt{\beta_i^2 \sigma_\lambda^2 + \sigma_{\epsilon_i}^2} \sqrt{\beta_j^2 \sigma_\lambda^2 + \sigma_{\epsilon_j}^2}} \quad (1.6)$$

$$\approx 0 \quad \text{for } \beta_i \approx \beta_j \approx 0, \quad (1.7)$$

where we assume $\beta_i \approx \beta_j \approx 0$ to capture the market neutral characteristic that many hedge fund investors desire. Now consider the conditional correlation

conditioned on $I_t = 1$:

$$\text{Corr}[R_{it}, R_{jt} | I_t = 1] = \frac{\beta_i \beta_j \sigma_\lambda^2 + \sigma_z^2}{\sqrt{\beta_i^2 \sigma_\lambda^2 + \sigma_z^2 + \sigma_{\epsilon_i}^2} \sqrt{\beta_j^2 \sigma_\lambda^2 + \sigma_z^2 + \sigma_{\epsilon_j}^2}} \quad (1.8)$$

$$\approx \frac{1}{\sqrt{1 + \sigma_{\epsilon_i}^2 / \sigma_z^2} \sqrt{1 + \sigma_{\epsilon_j}^2 / \sigma_z^2}} \quad \text{for } \beta_i \approx \beta_j \approx 0. \quad (1.9)$$

If σ_z^2 is large relative to $\sigma_{\epsilon_i}^2$ and $\sigma_{\epsilon_j}^2$, 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 (1.9) will be approximately equal to 1! When phase locking occurs, the correlation between two funds i and j —close to 0 during normal times—can become arbitrarily close to 1.

An insidious feature of (1.3) 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, Value-at-Risk 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:

$$\text{Corr}[R_{it}, R_{jt}] \equiv \frac{\text{Cov}[R_{it}, R_{jt}]}{\sqrt{\text{Var}[R_{it}] \text{Var}[R_{jt}]}} \quad (1.10)$$

$$\text{Cov}[R_{it}, R_{jt}] = \beta_i \beta_j \sigma_\lambda^2 + \text{Var}[I_t Z_t] = \beta_i \beta_j \sigma_\lambda^2 + p \sigma_z^2, \quad (1.11)$$

$$\text{Var}[R_{it}] = \beta_i^2 \sigma_\lambda^2 + \text{Var}[I_t Z_t] + \sigma_{\epsilon_i}^2 = \beta_i^2 \sigma_\lambda^2 + p \sigma_z^2 + \sigma_{\epsilon_i}^2. \quad (1.12)$$

Combining these expressions yields the unconditional correlation coefficient under (1.3):

$$\text{Corr}[R_{it}, R_{jt}] = \frac{\beta_i \beta_j \sigma_\lambda^2 + p \sigma_z^2}{\sqrt{\beta_i^2 \sigma_\lambda^2 + p \sigma_z^2 + \sigma_{\epsilon_i}^2} \sqrt{\beta_j^2 \sigma_\lambda^2 + p \sigma_z^2 + \sigma_{\epsilon_j}^2}} \quad (1.13)$$

$$\approx \frac{p}{\sqrt{p + \sigma_{\epsilon_i}^2 / \sigma_z^2} \sqrt{p + \sigma_{\epsilon_j}^2 / \sigma_z^2}} \quad \text{for } \beta_i \approx \beta_j \approx 0. \quad (1.14)$$

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

correlation of:

$$\text{Corr}[R_{it}, R_{jt}] \approx \frac{p}{\sqrt{p+0.1}\sqrt{p+0.1}} = \frac{0.001}{0.101} = 0.0099,$$

or less than 1%. As the variance σ_z^2 of the phase-locking component increases, the unconditional correlation (1.14) also increases, so that eventually the existence of Z_t will have an impact. However, to achieve an unconditional correlation coefficient of, say, 10%, σ_z^2 would have to be about 100 times larger than σ_ϵ^2 . Without the benefit of an explicit risk model such as (1.3), 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 methods 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:

$$R_{it} = \alpha_i + \beta_i^+ \Lambda_t^+ + \beta_i^- \Lambda_t^- + \epsilon_{it}, \quad (1.15)$$

where

$$\Lambda_t^+ = \begin{cases} \Lambda_t & \text{if } \Lambda_t > 0, \\ 0 & \text{otherwise,} \end{cases} \quad \Lambda_t^- = \begin{cases} \Lambda_t & \text{if } \Lambda_t \leq 0, \\ 0 & \text{otherwise,} \end{cases} \quad (1.16)$$

and Λ_t is the return on the S&P 500 index. 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 (1.15), the case where $\beta_i^+ = \beta_i^-$. However, the estimates reported in Table 1.9 for the hedge fund–index returns in Table 1.6 show that beta asymmetries can be quite pronounced for certain hedge fund styles. For example, the Distressed index has an up-market beta of 0.08—seemingly market neutral—however, its down-market beta is 0.41! For the Managed Futures index, the asymmetries are even more pronounced: The coefficients are of opposite sign, with a beta of 0.14 in up markets and a beta of -0.34 in down markets. These asymmetries are to be expected for certain nonlinear investment strategies, particularly those that have optionlike characteristics such as the short-put strategy of Capital Decimation Partners (Section 1.1). Such nonlinearities can yield even greater diversification benefits than more traditional asset classes—for example, Managed Futures seems to provide S&P 500 downside protection with little exposure on the upside—but investors must first be aware of the specific nonlinearities to take advantage of them.

Table 1.9.
 Regressions of Monthly CS/Tremont Hedge Fund Index Returns on the S&P 500 Index Return and on Positive and Negative S&P 500 Index Returns (January 1994 to July 2007)*

Category	α	$t(\alpha)$	β	$t(\beta)$	Adj. R^2 (%)	R^2 (%)	$p\text{-val}$ (F) (%)	α	$t(\alpha)$	β^+	$t(\beta^+)$	β^-	$t(\beta^-)$	Adj. R^2 (%)	R^2 (%)	$p\text{-val}$ (F) (%)
Hedge Fund	0.66	4.34	0.26	7.12	23.5	23.9	0.0	0.94	3.77	0.18	2.58	0.35	4.87	23.9	24.9	0.0
Convertible Arbitrage	0.68	6.49	0.05	1.90	1.6	2.2	5.9	0.73	4.20	0.03	0.71	0.06	1.27	1.0	2.3	15.9
Dedicated Short Bias	0.79	3.10	-0.90	-14.69	57.0	57.3	0.0	0.50	1.20	-0.82	-7.05	-0.99	-8.24	56.9	57.5	0.0
Emerging Markets	0.39	1.21	0.53	6.86	22.1	22.6	0.0	1.29	2.47	0.26	1.84	0.81	5.41	23.9	24.8	0.0
Equity Market	0.73	11.93	0.07	5.00	12.9	13.4	0.0	0.64	6.29	0.10	3.67	0.04	1.53	13.1	14.2	0.0
Neutral																
Event Driven	0.77	7.29	0.22	8.52	30.6	31.1	0.0	1.26	7.53	0.07	1.56	0.37	7.69	35.7	36.5	0.0
Fixed Income	0.51	5.94	0.01	0.60	-0.4	0.2	54.7	0.72	5.21	-0.05	-1.36	0.08	2.01	1.4	2.6	12.1
Arbitrage																
Global Macro	0.95	4.00	0.18	3.08	5.0	5.6	0.2	1.13	2.87	0.12	1.14	0.23	2.06	4.6	5.7	0.9
Long/Short Equity	0.62	3.35	0.42	9.38	35.0	35.4	0.0	0.82	2.71	0.36	4.24	0.48	5.53	34.8	35.6	0.0
Managed Futures	0.66	2.40	-0.09	-1.39	0.6	1.2	16.6	-0.15	-0.32	0.14	1.17	-0.34	-2.66	3.1	4.2	3.1
Event Driven	0.73	6.04	0.20	6.97	22.7	23.2	0.0	1.20	6.16	0.06	1.21	0.35	6.26	26.4	27.3	0.0
Multi-Strategy																
Distressed	0.87	7.26	0.24	8.35	29.8	30.2	0.0	1.42	7.50	0.08	1.47	0.41	7.60	34.9	35.7	0.0
Risk Arbitrage	0.52	6.07	0.13	6.26	19.1	19.6	0.0	0.71	5.10	0.07	1.85	0.19	4.73	20.1	21.1	0.0
Multi-Strategy	0.77	7.74	0.03	1.44	0.7	1.3	15.3	0.83	5.08	0.02	0.38	0.05	1.13	0.2	1.4	32.5

* Multi-Strategy index is for the period from April 1994 to July 2007.

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, jump risk, nonstationarities, 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:

- Price factors
- Sectors
- Investment style
- Volatilities
- Credit
- Liquidity
- Macroeconomic factors
- Sentiment
- Nonlinear interactions

The last category involves dependencies between the previous groups of factors, some of which are nonlinear in nature. For example, credit factors may become more highly correlated with market factors during economic downturns, and virtually uncorrelated at other times. Often difficult to detect empirically, these types of dependencies are more readily captured through economic intuition and practical experience and should not be overlooked when constructing a risk model.

Finally, although the common factors listed above may serve as a useful starting point for developing a quantitative model of hedge fund risk exposures, it should be emphasized that a certain degree of customization will be required. To see why, 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, industries, sectors, characteristics)
- Portfolio optimization (mean-variance analysis, market neutrality)
- Stock loan considerations (hard-to-borrow securities, short “squeezes”)
- Execution costs (price impact, commissions, borrowing rate, short rebate)
- Benchmarks and tracking error (T-bill rate vs. S&P 500).

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

- Yield-curve models (equilibrium vs. 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 is astonishingly small. While these differences are also present among traditional institutional asset managers, they do not have nearly the latitude that hedge fund managers do in their investment activities, hence the differences are not as consequential for traditional managers. Therefore, the number of unique hedge fund–risk models may have to match the number of hedge fund styles that exist in practice.

1.3 Illiquidity and Serial Correlation

In addition to the dynamic and nonlinear risk exposures described in Sections 1.1 and 1.2, many hedge funds exhibit a third characteristic that differentiates them from more traditional investments: credit and liquidity risk. 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—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 size of the positions are often considerably larger than the amount of collateral posted to support these positions. 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 1998.¹¹ Along with the many benefits of an integrated global financial system is the associated cost that a financial crisis in one country can be more easily transmitted to 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.¹² However, the complex network of creditor/obligor relationships, revolving credit agreements, and other

¹¹ Note that in the case of Capital Decimation Partners in Section 1.1, the fund's consecutive returns of -18.3% and -16.2% 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 (Table 1.3).

¹² See, for example, Bookstaber (1999, 2000) and Kao (1999), and their citations.

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 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 ρ_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 $\{R_t\}$,¹³ which measures the degree of correlation between month t ’s return and month $t+k$ ’s return. 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 of 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 extreme version of market efficiency is now recognized as an idealization that is unlikely to hold in practice.¹⁴ In particular, market frictions such as transaction 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 that cannot easily be “arbitraged” away precisely because of the presence 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 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 S&P 500 indexes during the same sample period. Similarly, the returns to the 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, and the economic rationale is a modified version of Samuelson’s (1965) argument—predictability in asset returns is 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

¹³ 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 the assumption of stationarity, the denominator of the autocorrelation is simply the variance of R_t .

¹⁴ See, for example, Farmer and Lo (2000), Lo (2004), and the discussion in Section 9.3.

transaction costs associated with real estate transactions, the inability to short-sell properties, and other frictions.¹⁵

A closely related phenomenon that buttresses this interpretation of serial correlation in hedge fund returns is the “nonsynchronous trading” effect, in which the autocorrelation is induced in a security’s returns because those returns are computed with closing prices that are not necessarily established at the same time each day (see, for example, Campbell, Lo, and MacKinlay, 1997, Chapter 3). In contrast to earlier studies of nonsynchronous trading in exchange-traded equity markets—which were unable to generate empirical levels of serial correlation purely from non-trading (e.g., Lo and MacKinlay, 1988, 1990a, and Kadlec and Patterson, 1999)—Getmansky, Lo, and Makarov (2004) show that for hedge funds, significantly higher levels of serial correlation can be explained by the combination of illiquidity and “performance smoothing,” of which nonsynchronous trading is a special case. However, even when prices are synchronously measured (as they are for most hedge funds, since portfolios are “marked to market” at month end), there are several other channels by which illiquidity exposure can induce serial correlation in the reported returns of hedge funds, including naïve methods for valuing illiquid securities like linear extrapolation or “matrix pricing” heuristics, as well as deliberate “performance smoothing.” We explore these possibilities in more depth in Chapter 3.

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

$$Q = T(T + 2) \sum_{k=1}^p \hat{\rho}_k^2 / (T - k), \quad (1.17)$$

which is asymptotically χ_p^2 under the null hypothesis of no autocorrelation.¹⁶ 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 exhibit large Q -statistics.

To illustrate the potential value of autocorrelations and the Q -statistic for measuring liquidity risk, we estimate these quantities with monthly historical total returns of the 10 largest (as of February 11, 2001) mutual funds from various start dates through June 2000, and 12 hedge funds from various inception dates to January 2001. Monthly total returns for the mutual funds were obtained from the University of Chicago’s Center for Research in Securities Prices. The 12 hedge funds were selected from the Altvest database to yield a diverse range of annual Sharpe ratios (from 1 to 5) computed in the standard way ($\sqrt{12} \widehat{SR}$, where

¹⁵ 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.

¹⁶ See Kendall, Stuart, and Ord (1983, Section 50.13) for details.

\widehat{SR} is the Sharpe ratio estimator applied to monthly returns), with the additional requirement that the funds have a minimum 5-year history of returns. The names of the hedge funds have been omitted to maintain their privacy, and we will refer to them only by their stated investment styles, e.g., Relative Value, Risk Arbitrage.

Table 1.10 reports the means, standard deviations, $\hat{\rho}_1$ to $\hat{\rho}_6$, and the p -values of the Q -statistic using the first six autocorrelations for the sample of mutual funds and hedge funds. The first subpanel shows that the 10 mutual funds have very little serial correlation in returns, with first-order autocorrelations ranging from -3.99% to 12.37% and with p -values of the corresponding Q -statistics ranging from 10.95% to 80.96% , implying that none of the Q -statistics is significant at the 5% level.¹⁷ 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, there is little discretion in valuing such portfolios. Moreover, many of the SEC regulations that govern the mutual fund industry (e.g., detailed prospectuses, daily net asset value calculations, and quarterly filings) were enacted specifically to guard against arbitrary marks, price manipulation, and other unsavory investment practices.

The results for the 12 hedge funds are considerably different. 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% to 49.01% , with 8 out of 12 funds that have Q -statistics with p -values less than 5%, and with 10 out of 12 funds with p -values less than 10%. The only two funds with p -values that are not significant at the 5% or 10% level are the Risk Arbitrage A and Risk Arbitrage B funds, which have p -values of 74.10% and 93.42% , 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 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

¹⁷ 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% for the Q -statistic of Washington Mutual Investors implies that the null hypothesis of no serial correlation can be rejected only at the 16.73% significance level—at any smaller level of significance, say 5%, 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 hypothesis. 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, Section 5.2.B) for further discussion of p -values and their interpretation.

Table 1.10.
Autocorrelations of Mutual Fund and Hedge Fund Returns*

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

* Means, standard deviations, and autocorrelation coefficients for monthly total returns of mutual funds and hedge funds from various start dates through June 2000 for the mutual fund sample and various start dates through December 2000 for the hedge fund sample. " $\hat{\rho}_k$ " denotes the *k*th autocorrelation coefficient, and "*p*-value of Q_6 " denotes the significance level of the Ljung-Box (1978) Q -statistic $T(T+2) \sum_{k=1}^6 \hat{\rho}_k^2 / (T-k)$, which is asymptotically χ_6^2 under the null hypothesis of no serial correlation. Data is monthly with various sample periods.

Source: AlphaSimplex Group.

correlation even though they invest in highly liquid instruments. 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 Section 1.2. 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. A more detailed analysis of serial correlation in hedge fund returns is presented by Getmansky, Lo, and Makarov (2004) and summarized in Chapter 3.

1.4 Literature Review

The explosive growth of the hedge fund sector over the past several years has generated a rich literature both in academia and among practitioners, including a number of books, newsletters, and trade magazines; several hundred published articles and an entire journal dedicated solely to this industry (the *Journal of Alternative Investments*). Thanks to the availability of hedge fund–returns data from sources such as Altvest, CISDM, HedgeFund.net, HFR, and Lipper TASS, a number of empirical studies have highlighted the unique risk/reward profiles of hedge fund investments. For example, Ackermann, McEnally, and Ravenscraft (1999), Fung and Hsieh (1999, 2000, 2001), Liang (1999, 2000, 2001), Agarwal and Naik (2000b,c), Edwards and Caglayan (2001), Kao (2002), and Amin and Kat (2003a) provide comprehensive empirical studies of historical hedge fund performance using various hedge fund databases. Brown, Goetzmann, and Park (2000, 2001a,b), Fung and Hsieh (1997a,b), Brown, Goetzmann, and Ibbotson (1999), Agarwal and Naik (2000a,d), Brown and Goetzmann (2003), and Lochoff (2002) present more detailed performance attribution and style analysis for hedge funds.

Several recent empirical studies have challenged the lack of correlation between hedge fund returns and market indexes, arguing that the standard methods of assessing their risks and rewards may be misleading. For example, Asness, Krail, and Liew (2001) show that in several cases where hedge funds purport to be market neutral (i.e., funds with relatively small market betas), including both contemporaneous and lagged market returns as regressors and summing the coefficients yields significantly higher market exposure. Moreover, in deriving statistical estimators for Sharpe ratios of a sample of mutual funds and hedge funds, Lo (2002) proposes a better method for computing annual Sharpe ratios based on monthly means and standard deviations, yielding point estimates that differ from the naive Sharpe ratio estimator by as much as 70% in his empirical application. Getmansky, Lo, and Makarov (2004) focus directly on the unusual degree of serial correlation in hedge fund returns and argue that illiquidity exposure and smoothed returns are the most common sources of such serial correlation. They also propose

methods for estimating the degree of return smoothing and adjusting performance statistics like the Sharpe ratio to account for serial correlation.

The persistence of hedge fund performance over various time intervals has also been studied by several authors. Such persistence may be indirectly linked to serial correlation; e.g., persistence in performance usually implies positively autocorrelated returns. Agarwal and Naik (2000c) examine the persistence of hedge fund performance over quarterly, half-yearly, and yearly intervals by examining the series of wins and losses for two, three, and more consecutive time periods. Using net-of-fee returns, they find that persistence is highest at the quarterly horizon and decreases when moving to the yearly horizon. The authors also find that performance persistence, whenever present, is unrelated to the type of hedge fund strategy. Brown, Goetzmann, Ibbotson, and Ross (1992), Ackermann, McEnally, and Ravenscraft (1999), and Baquero, Horst, and Verbeek (2004) show that survivorship bias—the fact that most hedge fund databases do not contain funds that were unsuccessful and went out of business—can affect the first and second moments and cross-moments of returns and generate spurious persistence in performance when there is dispersion of risk among the population of managers. However, using annual returns of both defunct and currently operating offshore hedge funds between 1989 and 1995, Brown, Goetzmann, and Ibbotson (1999) find virtually no evidence of performance persistence in raw returns or risk-adjusted returns, even after breaking funds down according to their returns-based style classifications.

Fund flows in the hedge fund industry have been considered by Agarwal, Daniel, and Naik (2004) and Getmansky (2004), with the expected conclusion that funds with higher returns tend to receive higher net inflows and funds with poor performance suffer withdrawals and eventually liquidation, much like the case with mutual funds and private equity.¹⁸ Agarwal, Daniel, and Naik (2004), Goetzmann, Ingersoll, and Ross (2003), and Getmansky (2004) all find decreasing returns to scale among their samples of hedge funds, implying that an optimal amount of assets under management exists for each fund and mirroring similar findings for the mutual fund industry by Pérold and Salomon (1991) and the private equity industry by Kaplan and Schoar (2004). Hedge fund survival rates have been studied by Brown, Goetzmann, and Ibbotson (1999), Fung and Hsieh (2000), Liang (2000, 2001), Bares, Gibson, and Gyger (2003), Brown, Goetzmann, and Park (2001b), Gregoriou (2002), and Amin and Kat (2003b). Baquero, Horst, and Verbeek (2004) estimate liquidation probabilities of hedge funds and find that they are greatly dependent on past performance.

The survival rates of hedge funds have been estimated by Brown, Goetzmann, and Ibbotson (1999), Fung and Hsieh (2000), Liang (2000, 2001), Brown,

¹⁸ See, for example, Ippolito (1992), Chevalier and Ellison (1997), Goetzmann and Peles (1997), Gruber (1996), Sirri and Tufano (1998), Zheng (1999), and Berk and Green (2004) for studies on mutual fund flows, and Kaplan and Schoar (2004) for private-equity fund flows.

Goetzmann, and Park (2001a,b), Gregoriou (2002), Amin and Kat (2003b), Bares, Gibson, and Gyger (2003), and Getmansky, Lo, and Mei (2004). Brown, Goetzmann, and Park (2001b) show that the probability of liquidation increases with increasing risk and that funds with negative returns for two consecutive years have a higher risk of shutting down. Liang (2000) finds that the annual hedge fund attrition rate is 8.3% for the 1994–1998 sample period using Lipper TASS data, and Baquero, Horst, and Verbeek (2004) find a slightly higher rate of 8.6% for the 1994–2000 sample period. Baquero, Horst, and Verbeek (2004) also find that surviving funds outperform nonsurviving funds by approximately 2.1% per year, which is similar to the findings of Fung and Hsieh (2000, 2002b) and Liang (2000), and that investment style, size, and past performance are significant factors in explaining survival rates. Many of these patterns are also documented by Liang (2000), Boyson (2002), and Getmansky, Lo, and Mei (2004). In particular, Getmansky, Lo, and Mei (2004) find that attrition rates in the Lipper TASS database from 1994 to 2004 differ significantly across investment styles, from a low of 5.2% per year on average for convertible arbitrage funds to a high of 14.4% per year on average for managed futures funds. They also relate a number of factors to these attrition rates, including past performance, volatility, and investment style, and document differences in illiquidity risk between active and liquidated funds. In analyzing the life cycle of hedge funds, Getmansky (2004) finds that the liquidation probabilities of individual hedge funds depend on fund-specific characteristics such as past returns, asset flows, age, and assets under management, as well as category-specific variables such as competition and favorable positioning within the industry.

Brown, Goetzmann, and Park (2001b) find that the half-life of Lipper TASS hedge funds is exactly 30 months, while Brooks and Kat (2002) estimate that approximately 30% of new hedge funds do not make it past 36 months because of poor performance. In Amin and Kat's (2003b) study, 40% of their hedge funds do not make it to the fifth year. Howell (2001) observed that the probability of hedge funds failing in their first year was 7.4%, only to increase to 20.3% in their second year. Poor-performing younger funds drop out of databases at a faster rate than older funds (Getmansky, 2004; Jen, Heasman, and Boyatt, 2001), presumably because younger funds are more likely to take additional risks to obtain a good performance that they can use to attract new investors, whereas older funds that have survived already have track records with which to attract and retain capital.

A number of case studies of hedge fund liquidations have been published recently, no doubt spurred by the most well-known liquidation in the hedge fund industry to date: Long Term Capital Management. The literature on LTCM is vast, spanning a number of books, journal articles, and news stories; a representative sample includes Greenspan (1998), McDonough (1998), Pérold (1999), the President's Working Group on Financial Markets (1999), and MacKenzie (2003). Ineichen (2001) has compiled a list of selected hedge funds and analyzed the reasons for their liquidation. Kramer (2001) focuses on fraud, providing

detailed accounts of six of history's most egregious cases. Although it is virtually impossible to obtain hard data on the frequency of fraud among liquidated hedge funds,¹⁹ in a study of more than 100 hedge funds liquidated during the past two decades, Feffer and Kundro (2003) conclude that "half of all failures could be attributed to operational risk alone," of which fraud is one example. In fact, they observe that, "The most common operational issues related to hedge fund losses have been misrepresentation of fund investments, misappropriation of investor funds, unauthorized trading, and inadequate resources" (Feffer and Kundro, 2003, p. 5). The last of these issues is, of course, not related to fraud, but Feffer and Kundro (2003, Figure 2) report that only 6% of their sample involved inadequate resources, whereas 41% involved misrepresentation of investments, 30% misappropriation of funds, and 14% unauthorized trading. These results suggest that operational issues are indeed an important factor in hedge fund liquidations and deserve considerable attention from investors and managers alike.

Collectively, these studies show that the dynamics of hedge funds are quite different from those of more traditional investments, and the remaining chapters provide more detailed support for this claim.

¹⁹ The lack of transparency and the unregulated status of most hedge funds are significant barriers to any systematic data collection effort, hence it is difficult to draw inferences about industry norms.