Volume Title: The Risks of Financial Institutions

Volume Author/Editor: Mark Carey and René M. Stulz, editors

Volume Publisher: University of Chicago Press

Volume ISBN: 0-226-09285-2

Volume URL: http://www.nber.org/books/care06-1

Conference Date: October 22-23, 2004

Publication Date: January 2007

Title: Systemic Risk and Hedge Funds

Author: Nicholas Chan, Mila Getmansky, Shane M. Haas, Andrew W. Lo

URL: http://www.nber.org/chapters/c9611

6

Systemic Risk and Hedge Funds

Nicholas Chan, Mila Getmansky, Shane M. Haas, and Andrew W. Lo

6.1 Introduction

The term *systemic risk* is commonly used to describe the possibility of a series of correlated defaults among financial institutions—typically banks—that occurs over a short period of time, often caused by a single major event. A classic example is a banking panic, in which large groups of depositors decide to withdraw their funds simultaneously, creating a run on bank assets that can ultimately lead to multiple bank failures. Banking panics were not uncommon in the United States during the nineteenth and early twentieth centuries, culminating in the 1930–1933 period, with an average of 2,000 bank failures per year during these years, according to Mishkin (1997), and which prompted the Glass-Steagall Act of 1933 and the establishment of the Federal Deposit Insurance Corporation (FDIC) in 1934.

Although today banking panics are virtually nonexistent, thanks to the

The views and opinions expressed in this article are those of the authors only, and do not necessarily represent the views and opinions of AlphaSimplex Group, MIT, the University of Massachusetts, or any of their affiliates and employees. The authors make no representations or warranty, either expressed or implied, as to the accuracy or completeness of the information contained in this article, nor are they recommending that this article serve as the basis for any investment decision—this article is for information purposes only. Research support from AlphaSimplex Group and the MIT Laboratory for Financial Engineering is gratefully acknowledged. We thank Mark Carey, David Modest, René Stulz and participants of the NBER Conference on The Risks of Financial Institutions for helpful comments and discussion. Parts of this paper include ideas and exposition from several previously published papers and books of some of the authors. Where appropriate, we have modified the passages to suit the current context and composition without detailed citations and quotation marks so as preserve continuity. Readers interested in the original sources of those passages should consult Getmansky (2004), Getmansky, Lo, and Makarov (2004), Getmansky, Lo, and Mei (2004), and Lo (2001, 2002).

FDIC and related central banking policies, systemic risk exposures have taken shape in other forms. In particular, the proliferation of hedge funds in recent years has indelibly altered the risk/reward landscape of financial investments. Unregulated and opaque investment partnerships that engage in a variety of active investment strategies,[1] hedge funds have generally yielded double-digit returns historically, but not without commensurate risks, and such risks are currently not widely appreciated or well understood. In particular, we argue that the risk/reward profile for most hedge funds differ in important ways from more traditional investments, and such differences may have potentially significant implications for systemic risk. This was underscored by the aftermath of the default of Russian government debt in August 1998, when Long-term Capital Management (LTCM) and many other fixed-income hedge funds suffered catastrophic losses over the course of a few weeks, creating significant stress on the global financial system and several major financial institutions—that is, creating systemic risk.

In this paper, we consider the impact of hedge funds on systemic risk by examining the unique risk-and-return profiles of hedge funds—at both the individual fund and the aggregate industry level—and proposing some new risk measures for hedge fund investments. Two major themes have emerged from August 1998: the importance of liquidity and leverage, and the capriciousness of correlations between instruments and portfolios that were thought to be uncorrelated. The precise mechanism by which these two sets of issues posed systemic risks in 1998 is now well understood. Because many hedge funds rely on leverage, their positions are often considerably larger than the amount of collateral posted to support those 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 reduces the market value of collateral, credit is withdrawn quickly; 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. The more illiquid the portfolio, the larger the price impact of a forced liquidation, which erodes the fund's risk capital that much more quickly. If many funds face the same "death spiral" at a given point in time—that is, if they become more highly correlated during times of distress, and if those funds are obligors of a small number of major financial institutions—then a market event like August 1998 can cascade quickly into a global financial crisis. This is systemic risk.

1. Although hedge funds have avoided regulatory oversight in the past by catering only to "qualified" investors (investors that meet a certain minimum threshold in terms of net worth and investment experience) and refraining from advertising to the general public, a recent ruling by the U.S. Securities and Exchange Commission (Rule 203[b][3]-2) require most hedge funds to register as investment advisers under the Investment Advisers Act of 1940 by February 1, 2006.

Therefore, the two main themes of this study are illiquidity exposure and time-varying hedge fund correlations, both of which are intimately related to the dynamic nature of hedge fund investment strategies and their risk exposures. In particular, one of the justifications for the unusually rich fees that hedge funds charge is the fact that highly skilled hedge fund managers are engaged in active portfolio management. 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 on 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 investment returns. 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 a sufficient statistic in this case—there is currently no single summary measure of the risks of a *dynamic* investment strategy.[2]

To illustrate the challenges and opportunities in modeling the risk exposures of hedge funds, we provide two concrete examples in this section. In section 6.1.1, we present a hypothetical hedge fund strategy that yields remarkable returns with seemingly little risk, yet a closer examination will reveal quite a different story. And in section 6.1.2, we show that standard correlation coefficients may not be able to capture certain risk exposures that are particularly relevant for hedge fund investments.

These examples provide an introduction to the analysis in sections 6.3–6.7, and serve as motivation for developing new quantitative methods for capturing the impact of hedge funds on systemic risk. In section 6.3, we summarize the empirical properties of aggregate and individual hedge fund data used in this study, the Credit Suisse First Boston (CSFB)/Tremont hedge-fund indexes and the Tremont TASS individual hedge fund database. In section 6.4, we turn to the issue of liquidity—one of the central aspects of systemic risk—and present several measures for gauging illiquidity exposure in hedge funds and other asset classes, which we apply to individual and index data. Since systemic risk is directly related to hedge fund failures, in section 6.5 we investigate attrition rates of hedge funds in the TASS database and present a logit analysis that yields estimates of a fund's probability of liquidation as a function of various fund characteristics, such as return history, assets under management, and recent fund flows. In section 6.6, we present three other approaches to measuring systemic risk in the hedge fund industry: risk models for hedge fund indexes, regression models relating the banking sector to hedge funds, and regime-

2. Accordingly, hedge fund track records are often summarized with multiple statistics; for example, mean, standard deviation, Sharpe ratio, market beta, Sortino ratio, maximum drawdown, worst month.

switching models for hedge fund indexes. These three approaches yield distinct insights regarding the risks posed by the hedge fund industry, and we conclude in section 6.7 by discussing the current industry outlook implied by the analytics and empirical results of this study. Our tentative inferences suggest that the hedge fund industry may be heading into a challenging period of lower expected returns, and that systemic risk has been increasing steadily over the recent past.

Our preliminary findings must be qualified by the acknowledgment that all of our measures of systemic risk are *indirect,* and therefore open to debate and interpretation. The main reason for this less-than-satisfying state of affairs is the fact that hedge funds are currently not required to disclose any information about their risks and returns to the public, so empirical studies of the hedge fund industry are based only on very limited hedge fund data, provided voluntarily to TASS, and which may or may not be representative of the industry as a whole. Even after February 1, 2006, when, according to the U.S. Securities and Exchange Commission's Rule 203(b)(3)-2, all hedge funds must become Registered Investment Advisers, the regular filings of hedge funds will not include critical information such as a fund's degree of leverage, the liquidity of a fund's portfolio, the identities of the fund's major creditors and obligors, and the specific terms under which the fund's investors have committed their capital. Without this kind of information for the majority of funds in the industry, it is virtually impossible to construct direct measures of systemic risk, even by regulatory authorities like the SEC. However, as the hedge fund industry grows, the number and severity of hedge fund failures will undoubtedly increase as well, eventually moving the industry toward greater transparency.

6.1.1 Tail Risk

Consider the eight-year track record of a hypothetical hedge fund, Capital Decimation Partners, LP, first described by Lo (2001) and summarized in table 6.1. This track record was obtained by applying a specific investment strategy, to be revealed subsequently, to actual market prices from January 1992 to December 1999. Before discussing the particular strategy that generated these results, let us consider its overall performance: an average monthly return of 3.7 percent versus 1.4 percent for the Standard and Poor's (S&P) 500 during the same period, 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 six negative monthly returns out of ninety-six versus thirty-six out of ninety-six for the S&P 500. In fact, the monthly performance history, given in Lo (2001, 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 enor-

Table 6.1 **Capital Decimation Partners, L.P.: Performance summary, January 1992 to December 1999**

Statistic	S&P 500	CDP
Monthly mean (%)	1.4	3.7
Monthly standard deviation (%)	3.6	5.8
Minimum month (%)	–8.9	–18.3
Maximum month (%)	14.0	27.0
Annual Sharpe ratio	0.98	1.94
No. of negative months	36/96	6/96
Correlation with S&P 500 (%)	100.0	59.9
Total return (%)	367.1	2,721.3

Note: Summary of simulated performance of a particular dynamic trading strategy using monthly historical market prices from January 1992 to December 1999.

mously successful hedge fund with a track record that would be the envy of most managers. What is its secret?

The investment strategy summarized in table 6.1 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, with strikes approximately 7 percent out of the money. The number of contracts sold each month is determined by the combination of: (1) Chicago Board Options Exchange (CBOE) margin requirements,[3] (2) an assumption that we are required to post 66 percent of the margin as collateral,[4] and (3) $10 million of initial risk capital. For concreteness, table 6.2 reports the positions and profit/loss statement for this strategy for 1992. See Lo (2001) for further details of this strategy.

The track record in table 6.1 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 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 6.2 that the manager of Capital Decimation Partners is providing little or no value added. However, there are many ways of implementing this

3. 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.

4. 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 6.2 **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 (%)
12/20/91	387.04	new	2,300	360	4.625	March 1992	6,069,930		10,000,000	6,024,096	
1/17/92	418.86	mark to market	2,300	360	1.125	March 1992	654,120	805,000	10,805,000	6,509,036	8.1
	418.86	new	1,950	390	3.250	March 1992	5,990,205				
						Total margin:	6,644,325				
2/21/92	411.46	mark to market	2,300	360	0.250	March 1992	2,302,070	690,000			
	411.46	mark to market	1,950	390	1.625	March 1992	7,533,630	316,875	11,811,875	7,115,587	9.3
	411.46	liquidate	1,950	390	1.625	March 1992	0	0	11,811,875	7,115,587	
	411.46	new	1,246	390	1.625	March 1992	4,813,796				
						Total margin:	7,115,866				
3/20/92	411.30	expired	2,300	360	0.000	March 1992	0	373,750			
	411.30	expired	1,246	390	0.000	March 1992	0	202,475			
	411.30	new	2,650	380	2.000	May 1992	7,524,675		12,388,100	7,462,711	4.9
						Total margin:	7,524,675				
4/19/92	416.05	mark to market	2,650	380	0.500	May 1992	6,852,238	397,500			
	416.05	new	340	385	2.438	June 1992	983,280		12,785,600	7,702,169	3.2
						Total margin:	7,835,518				
5/15/92	410.09	expired	2,650	380	0.000	May 1992	0	132,500			
	410.09	mark to market	340	385	1.500	June 1992	1,187,399	31,875			
	410.09	new	2,200	380	1.250	July 1992	6,638,170		12,949,975	7,801,190	1.3
						Total margin:	7,825,569				

6/19/92	403.67	expired	340	385	0.000	June 1992	0	51,000			
	403.67	mark to market	2,200	380	1.125	July 1992	7,866,210	27,500	13,028,475	7,848,479	0.6
						Total margin:	7,866,210				
7/17/92	415.62	expired	2,200	380	0.000	July 1992	0	247,500			
	415.62	new	2,700	385	1.8125	September 1992	8,075,835		13,275,975	7,997,575	1.9
						Total margin:	8,075,835				
8/21/92	414.85	mark to market	2,700	385	1	September 1992	8,471,925	219,375	13,495,350	8,129,729	1.7
						Total margin:	8,471,925				
9/18/92	422.92	expired	2,700	385	0	September 1992	0	270,000	13,765,350	8,292,380	2.0
	422.92	new	2,370	400	5.375	December 1992	8,328,891				
						Total margin:	8,328,891				
10/16/92	411.73	mark to market	2,370	400	7	December 1992	10,197,992	(385,125)			
	411.73	liquidate	2,370	400	7	December 1992	0	0	13,380,225	8,060,377	–2.8
	411.73	new	1,873	400	7	December 1992	8,059,425				
						Total margin:	8,059,425				
11/20/92	426.65	mark to market	1,873	400	0.9375	December 1992	6,819,593	1,135,506	14,515,731	8,744,416	8.5
	426.65	new	529	400	0.9375	December 1992	1,926,089				
						Total margin:	8,745,682				
12/18/92	441.20	expired	1,873	400	0	December 1992	0	175,594	14,691,325	8,850,196	1.2
1992 total return											46.9

Note: Simulated positions and profit/loss statement for 1992 for a trading strategy that consists of shorting out-of-the-money put options on the S&P 500 once a month.

strategy that are not nearly so transparent, even when positions are fully disclosed. For example, Lo (2001) provides a more subtle example—Capital Decimation Partners II—in which short positions in put options are synthetically replicated using a standard "delta-hedging" strategy involving the underlying stock and varying amounts of leverage. Casual inspection of the monthly positions of such a strategy seem to suggest a contrarian trading strategy: when the price declines, the position in the underlying stock is increased, and when the price advances, the position is reduced. However, the net effect is to create the same kind of option-like payoff as Capital Decimation Partners, but for many securities, not just for the S&P 500.[5] Now imagine an investor presented with monthly position reports like table 6.2, but on a portfolio of 200 securities, as well as a corresponding track record that is likely to be even more impressive than that of Capital Decimation Partners, LP. Without additional analysis that explicitly accounts for the dynamic aspects of this trading strategy, 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 and the Capital Asset Pricing Model cannot capture the risks of dynamic trading strategies like Capital Decimation Partners (note the impressive Sharpe ratio in table 6.1). 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 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.

5. A portfolio of options is worth more than an option on the portfolio, hence shorting puts on the individual stocks that constitute the SPX will yield substantially higher premiums than shorting puts on the index.

6.1.2 Phase-Locking Risk

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 (see, for example, the correlations between hedge fund indexes and the S&P 500 in table 6.4). 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 these 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.[6] 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:

$$R_{it} = \alpha_i + \beta_i \Lambda_t + I_t Z_t + \varepsilon_{it}, \tag{1}$$

and assume that Λ_t, I_t, Z_t, and ε_{it} are mutually independently and identically distributed (i.i.d.) with the following moments:

$$\begin{aligned} E(\Lambda_t) &= \mu_\lambda, \ \mathrm{Var}(\Lambda_t) = \sigma^2_\lambda \\ E(Z_t) &= 0, \ \mathrm{Var}(Z_t) = \sigma^2_z \\ E(\varepsilon_{it}) &= 0, \ \mathrm{Var}(\varepsilon_{it}) = \sigma^2_{\varepsilon_i}, \end{aligned} \tag{2}$$

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

$$I_t = \begin{cases} 1 \text{ with probability } p \\ 0 \text{ with probability } 1-p \end{cases} \tag{3}$$

According to equation (1), 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

6. 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.

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 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 $I_t = 1$; that is, 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 $I_t = 0$:

$$\text{(4)} \qquad \text{Corr}(R_{it}, R_{jt} \mid I_t = 0) = \frac{\beta_i\beta_j\sigma_\lambda^2}{\sqrt{\beta_i^2\sigma_\lambda^2 + \sigma_{\varepsilon_i}^2}\sqrt{\beta_j^2\sigma_\lambda^2 + \sigma_{\varepsilon_j}^2}}$$

$$\text{(5)} \qquad \approx 0 \quad \text{for } \beta_i \approx \beta_j \approx 0,$$

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 $I_t = 1$:

$$\text{(6a)} \qquad \text{Corr}(R_{it}, R_{jt} \mid I_t = 1) = \frac{\beta_i\beta_j\sigma_\lambda^2 + \sigma_z^2}{\sqrt{\beta_i^2\sigma_\lambda^2 + \sigma_z^2 + \sigma_{\varepsilon_i}^2}\sqrt{\beta_j^2\sigma_\lambda^2 + \sigma_z^2 + \sigma_{\varepsilon_j}^2}}$$

$$\text{(6b)} \qquad \approx \frac{1}{\sqrt{1 + \sigma_{\varepsilon_i}^2/\sigma_z^2}\sqrt{1 + \sigma_{\varepsilon_j}^2/\sigma_z^2}} \quad \text{for } \beta_i \approx \beta_j \approx 0.$$

If σ_z^2 is large relative to $\sigma_{\varepsilon_i}^2$ and $\sigma_{\varepsilon_j}^2$, that is, 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 (6) 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 equation (1) is the fact that it implies a very small value for the *unconditional* correlation, which is the quantity most readily estimated and most commonly used in risk reports, value-at-risk (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:

$$\text{(7a)} \qquad \text{Corr}(R_{it}, R_{jt}) \equiv \frac{\text{Cov}(R_{it}, R_{jt})}{\sqrt{\text{Var}(R_{it})\text{Var}(R_{jt})}}$$

$$\text{(7b)} \qquad \text{Cov}(R_{it}, R_{jt}) = \beta_i\beta_j\sigma_\lambda^2 + \text{Var}(I_tZ_t) = \beta_i\beta_j\sigma_\lambda^2 + p\sigma_z^2$$

$$\text{(7c)} \qquad \text{Var}(R_{it}) = \beta_i^2\sigma_\lambda^2 + \text{Var}(I_tZ_t) + \sigma_{\varepsilon_i}^2 = \beta_i^2\sigma_\lambda^2 + p\sigma_z^2 + \sigma_{\varepsilon_i}^2.$$

Combining these expressions yields the unconditional correlation coefficient under equation (1).

$$\text{(8a)} \qquad \mathrm{Corr}(R_{it}, R_{jt}) = \frac{\beta_i\beta_j\sigma_\lambda^2 + p\sigma_z^2}{\sqrt{\beta_i^2\sigma_\lambda^2 + p\sigma_z^2 + \sigma_{\varepsilon_i}^2}\,\sqrt{\beta_j^2\sigma_\lambda^2 + p\sigma_z^2 + \sigma_{\varepsilon_j}^2}}$$

$$\text{(8b)} \qquad \approx \frac{p}{\sqrt{p + \sigma_{\varepsilon_i}^2/\sigma_z^2}\,\sqrt{p + \sigma_{\varepsilon_j}^2/\sigma_z^2}} \quad \text{for } \beta_i \approx \beta_j \approx 0$$

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:

$$\mathrm{Corr}(R_{it}, R_{jt}) \approx \frac{p}{\sqrt{p + 0.1}\sqrt{p + 0.1}} = 0.001/.101 = 0.0099$$

or less than 1 percent. As the variance σ_z^2 of the phase-locking component increases, the unconditional correlation (8) 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, 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 eqution (1), it is virtually impossible to detect the existence of a phase-locking component from standard correlation coefficients.

These considerations 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; for example, 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 common factors listed previously 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 considerations in the management of a typical long/short equity hedge fund:

- Investment style (value, growth, and so on)
- 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 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, and so on)
- Inflationary pressures, central bank activity
- Other macroeconomic factors and events

The degree of overlap is astonishingly small, which suggests that the relevant risk exposures of the two types of funds are likely to be different as well. For example, changes in accounting standards are likely to have a significant impact on long/short equity funds because of their reliance on fundamental analysis, but will have little effect on a mortgage-backed securities fund. Similarly, changes in the yield curve may have major implications for fixed-income hedge funds but are less likely to affect a long/short equity fund. While such 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.

The point of the two examples in sections 6.1.1 and 6.1.2 is that hedge fund risks are not adequately captured by traditional measures such as market beta, standard deviation, correlation, and VaR. The two most significant risks facing hedge funds—illiquidity exposure and phase-locking behavior—are also the most relevant for systemic risk; hence we turn to these issues after reviewing the literature in section 6.2.

6.2 Literature Review

The explosive growth in 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*). However, none of this literature has considered the impact of hedge funds on systemic risk.[7] Nevertheless, thanks to the availability of hedge fund returns data from sources such as AltVest, Center for International Securities and Derivatives Markets (CISDM), HedgeFund.net, Hedge Fund Research (HFR), and 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, 2000c), 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, 2001b), Fung and Hsieh (1997a, 1997b), Brown, Goetzmann, and Ibbotson (1999), Agarwal and Naik (2000a, 2000d), 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 uncorrelatedness of hedge fund returns with 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—that is, 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 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 percent 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

7. For example, a literature search among all abstracts in the EconLit database—a comprehensive electronic collection of the economics literature that includes over 750 journals—in which the two phrases "hedge fund" and "systemic risk" are specified yields no records.

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; for example, 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 which 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.[8] 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 (2001a), 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.

8. 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 of mutual fund flows, and Kaplan and Schoar (2004) for private-equity fund flows.

The survival rates of hedge funds have been estimated by Brown, Goetzmann, and Ibbotson (1999), Fung and Hsieh (2000), Liang (2000, 2001), Brown, 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 (2001a) 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 percent for the 1994–1998 sample period using TASS data, and Baquero, Horst, and Verbeek (2004) find a slightly higher rate of 8.6 percent for the 1994–2000 sample period. Baquero, Horst, and Verbeek (2004) also find that surviving funds outperform nonsurviving funds by approximately 2.1 percent 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 TASS database from 1994 to 2004 differ significantly across investment styles, from a low of 5.2 percent per year on average for convertible arbitrage funds to a high of 14.4 percent 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 (2001a) find that the half-life of the TASS hedge funds is exactly thirty months, while Brooks and Kat (2002) estimate that approximately 30 percent of new hedge funds do not make it past thirty-six months due to poor performance; in Amin and Kat's (2003c) study, 40 percent 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 percent, only to increase to 20.3 percent in their second year. Poorly performing younger funds drop out of databases at a faster rate than older funds (see Getmansky 2004, and Jen, Heasman, and Boyatt 2001), presumably because younger funds are more likely to take additional risks to obtain good performance which 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 (LTCM). 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 liquidations. 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,[9] in a study of over 100 liquidated hedge funds 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" (p. 5). The last of these issues is, of course, not related to fraud, but Feffer and Kundro (fig. 2) report that only 6 percent of their sample involved inadequate resources, whereas 41 percent involved misrepresentation of investments, 30 percent involved misappropriation of funds, and 14 percent involved unauthorized trading. These results suggest that operational issues are indeed an important factor in hedge fund liquidations, and deserve considerable attention by investors and managers alike.

Collectively, these studies show that the dynamics of hedge funds are quite different than those of more traditional investments, and the potential impact on systemic risk is apparent.

6.3 The Data

It is clear from section 6.1 that hedge funds exhibit unique and dynamic characteristics that bear further study. Fortunately, the returns of many individual hedge funds are now available through a number of commercial databases such as AltVest, CISDM, HedgeFund.net, HFR, and TASS. For the empirical analysis in this paper, we use two main sources: (1) a set of aggregate hedge fund index returns from CSFB/Tremont, and (2) the TASS database of hedge funds, which consists of monthly returns and accompanying information for 4,781 individual hedge funds (as of August 2004) from February 1977 to August 2004.[10]

The CSFB/Tremont indexes are asset-weighted indexes of funds with a minimum of $10 million of assets under management (AUM), a minimum one-year track record, and current audited financial statements. An aggre-

9. 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.

10. For further information about these data see http://www.hedgeindex.com (CSFB/Tremont indexes) and http://www.tassresearch.com (TASS). We also use data from Altvest, the University of Chicago's Center for Research in Security Prices, and Yahoo!Finance.

gate index is computed from this universe, and ten subindexes based on investment style are also computed using a similar method. Indexes are computed and rebalanced on a monthly frequency and the universe of funds is redefined on a quarterly basis.

The TASS database consists of monthly returns, assets under management, and other fund-specific information for 4,781 individual funds from February 1977 to August 2004. The database is divided into two parts: "Live" and "Graveyard" funds. Hedge funds that are in the Live database are considered to be active as of August 31, 2004.[11] As of August 2004, the combined database of both live and dead hedge funds contained 4,781 funds with at least one monthly return observation. Out of these 4,781 funds, 2,920 funds are in the Live database and 1,861 in the Graveyard database. The earliest data available for a fund in either database is February 1977. TASS started tracking dead funds in 1994; hence it is only since 1994 that TASS transferred funds from the Live database to the Graveyard database. Funds that were dropped from the Live database prior to 1994 are not included in the Graveyard database, which may yield a certain degree of survivorship bias.[12]

The majority of 4,781 funds reported returns net of management and incentive fees on a monthly basis,[13] and we eliminated fifty funds that reported only gross returns, leaving 4,731 funds in the "Combined" database (2,893 in the Live and 1,838 in the Graveyard database). We also eliminated funds that reported returns on a quarterly—not monthly—basis, leaving 4,705 funds in the Combined database (2,884 in the Live and 1,821 in the Graveyard database). Finally, we dropped funds that did not report assets

11. Once a hedge fund decides not to report its performance, is liquidated, is closed to new investment, restructured, or merged with other hedge funds, the fund is transferred into the Graveyard database. A hedge fund can only be listed in the Graveyard database after being listed in the Live database. Because the TASS database fully represents returns and asset information for live and dead funds, the effects of survivorship bias are minimized. However, the database is subject to *backfill bias*—when a fund decides to be included in the database, TASS adds the fund to the Live database and includes all available prior performance of the fund. Hedge funds do not need to meet any specific requirements to be included in the TASS database. Due to reporting delays and time lags in contacting hedge funds, some Graveyard funds can be incorrectly listed in the Live database for a period of time. However, TASS has adopted a policy of transferring funds from the Live to the Graveyard database if they do not report over an eight- to ten-month period.

12. For studies attempting to quantify the degree and impact of survivorship bias, see Baquero, Horst, and Verbeek (2004), Brown, Goetzmann, Ibbotson, and Ross (1992), Brown, Goetzmann, and Ibbotson (1999), Brown, Goetzmann, and Park (1997), Carpenter and Lynch (1999), Fung and Hsieh (1997b, 2000), Horst, Nijman, and Verbeek (2001), Hendricks, Patel, and Zeckhauser (1997), and Schneeweis and Spurgin (1996).

13. TASS defines returns as the change in net asset value during the month (assuming the reinvestment of any distributions on the reinvestment date used by the fund) divided by the net asset value at the beginning of the month, net of management fees, incentive fees, and other fund expenses. Therefore, these reported returns should approximate the returns realized by investors. TASS also converts all foreign-currency denominated returns to U.S.-dollar returns using the appropriate exchange rates.

Table 6.3 **Number of funds in the TASS hedge fund Live, Graveyard, and Combined databases, from February 1977 to August 2004**

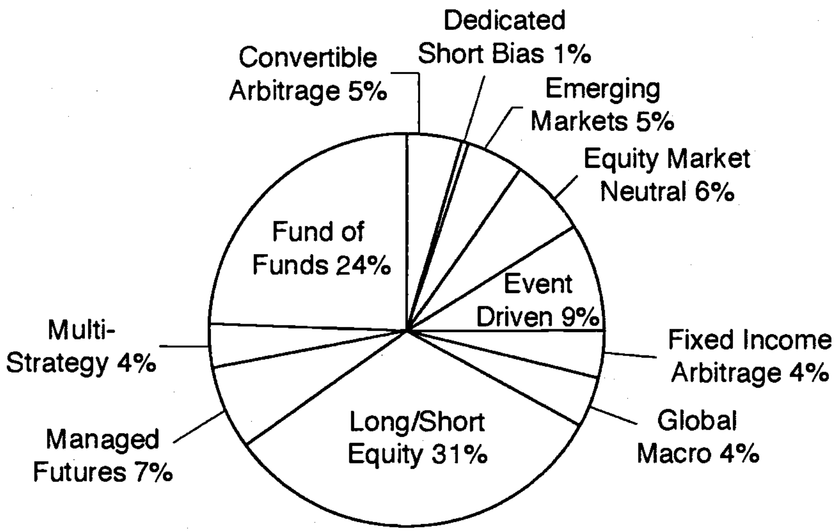
		Number of TASS funds in:		
Category	Definition	Live	Graveyard	Combined
1	Convertible arbitrage	127	49	176
2	Dedicated short bias	14	15	29
3	Emerging markets	130	133	263
4	Equity-market neutral	173	87	260
5	Event driven	250	134	384
6	Fixed-income arbitrage	104	71	175
7	Global macro	118	114	232
8	Long/short equity	883	532	1,415
9	Managed futures	195	316	511
10	Multistrategy	98	41	139
11	Fund of funds	679	273	952
Total		2,771	1,765	4,536

under management, or reported only partial assets under management, leaving a final sample of 4,536 hedge funds in the Combined database, which consists of 2,771 funds in the Live database and 1,765 funds in the Graveyard database. For the empirical analysis in section 6.4, we impose an additional filter in which we require funds to have at least five years of nonmissing returns, leaving 1,226 funds in the Live database and 611 in the Graveyard database, for a combined total of 1,837 funds. This obviously creates additional survivorship bias in the remaining sample of funds, but since the main objective is to estimate measures of illiquidity exposure and not to make inferences about overall performance, this filter may not be as problematic.[14]

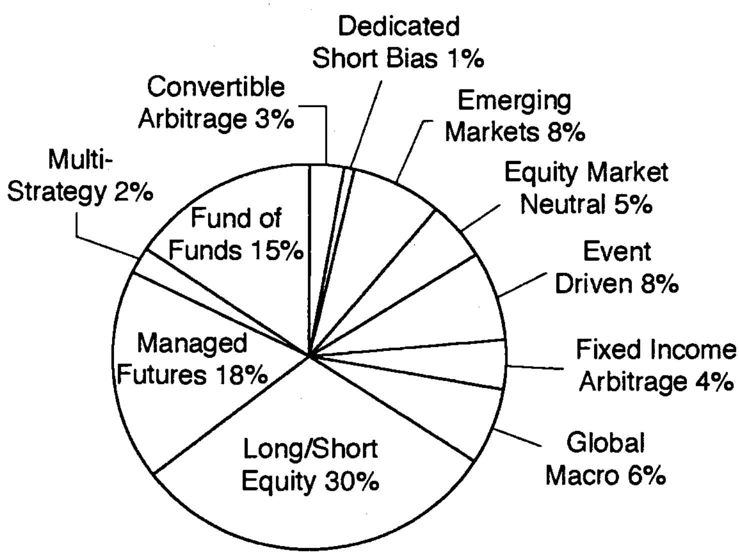
TASS also classifies funds into one of eleven different investment styles, listed in table 6.3 and described in the appendix, of which ten correspond exactly to the CSFB/Tremont subindex definitions.[15] Table 6.3 also reports the number of funds in each category for the Live, Graveyard, and Combined databases; it is apparent from these figures that the representation of investment styles is not evenly distributed, but is concentrated among four categories: Long/Short Equity (1,415), Fund of Funds (952), Managed Futures (511), and Event Driven (384). Together, these four categories account for 71.9 percent of the funds in the Combined database. Figure 6.1 shows that the relative proportions of the Live and Graveyard databases are roughly comparable, with the exception of two categories: Funds of

14. See the references in footnote 12.

15. This is no coincidence—TASS is owned by Tremont Capital Management, which created the CSFB/Tremont indexes in partnership with Credit Suisse First Boston.



Live Funds



Graveyard Funds

Fig. 6.1 Breakdown of TASS Live and Graveyard funds by category

Funds (24 percent in the Live and 15 percent in the Graveyard database), and Managed Futures (7 percent in the Live and 18 percent in the Graveyard database). This reflects the current trend in the industry toward funds of funds, and the somewhat slower growth of managed futures funds.

6.3.1 CSFB/Tremont Indexes

Table 6.4 reports summary statistics for the monthly returns of the CSFB/Tremont indexes from January 1994 to August 2004. Also included for purposes of comparison are summary statistics for a number of aggregate measures of market conditions, which we will use later as risk factors for constructing explicit risk models for hedge fund returns in section 6.6; their definitions are given in table 6.23.

Table 6.4 shows that there is considerable heterogeneity in the historical risk and return characteristics of the various categories of hedge fund investment styles. For example, the annualized mean return ranges from –0.69 percent for Dedicated Shortsellers to 13.85 percent for Global Macro, and the annualized volatility ranges from 3.05 percent for Equity Market Neutral to 17.28 percent for Emerging Markets. The correlations of the hedge fund indexes with the S&P 500 are generally low, with the largest correlation at 57.2 percent for Long/Short Equity, and the lowest correlation at –75.6 percent for Dedicated Shortsellers—as investors have discovered, hedge funds offer greater diversification benefits than many traditional asset classes. However, these correlations can vary over time. For example, consider a rolling sixty-month correlation between the CSFB/Tremont Multi-Strategy Index and the S&P 500 from January 1999 to December 2003, plotted in figure 6.2. At the start of the sample in January 1999, the correlation is –13.4 percent, then drops to –21.7 percent a year later, and increases to 31.0 percent by December 2003 as the outliers surrounding August 1998 drop out of the sixty-month rolling window.

Although changes in rolling correlation estimates are also partly attributable to estimation errors,[16] in this case an additional explanation for the positive trend in correlation is the enormous inflow of capital into multistrategy funds and fund-of-funds over the past five 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 6.2 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 of this investment style (see Getmansky, Lo, and Makarov 2004, and section 6.4). This is also consistent with large inflows of capital into the hedge fund sector.

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

Table 6.4 **Summary statistics for monthly CSFB/Tremont hedge fund index returns and various hedge fund risk factors from January 1994 to August 2004 (except for Fund of Funds, which begins in April 1994, and S&P 500, which ends in December 2003)**

Variable	Sample size	Annual mean	Annual standard deviation	Correlation with S&P 500	Minimum	Median	Maximum	Skewness	Kurtosis	ρ_1	ρ_2	ρ_3	*p*-value of LB-*Q*
CSFB/Tremont indexes													
Hedge funds	128	10.51	8.25	45.9	–7.55	0.78	8.53	0.12	1.95	12.0	4.0	–0.5	54.8
Convertible arbitrage	128	9.55	4.72	11.0	–4.68	1.09	3.57	–1.47	3.78	55.8	41.1	14.4	0.0
Dedicated shortseller	128	–0.69	17.71	–75.6	–8.69	–0.39	22.71	0.90	2.16	9.2	–3.6	0.9	73.1
Emerging markets	128	8.25	17.28	47.2	–23.03	1.17	16.42	–0.58	4.01	30.5	1.6	–1.4	0.7
Equity-market neutral	128	10.01	3.05	39.6	–1.15	0.81	3.26	0.25	0.23	29.8	20.2	9.3	0.0
Event driven	128	10.86	5.87	54.3	–11.77	1.01	3.68	–3.49	23.95	35.0	15.3	4.0	0.0
Distressed	128	12.73	6.79	53.5	–12.45	1.18	4.10	–2.79	17.02	29.3	13.4	2.0	0.3
Event-driven multistrategy	128	9.87	6.19	46.6	–11.52	0.90	4.66	–2.70	17.63	35.3	16.7	7.8	0.0
Risk arbitrage	128	7.78	4.39	44.7	–6.15	0.62	3.81	–1.27	6.14	27.3	–1.9	–9.7	1.2
Fixed income arbitrage	128	6.69	3.86	–1.3	–6.96	0.77	2.02	–3.27	17.05	39.2	8.2	2.0	0.0
Global macro	128	13.85	11.75	20.9	–11.55	1.19	10.60	0.00	2.26	5.5	4.0	8.8	65.0
Long/short equity	128	11.51	10.72	57.2	–11.43	0.78	13.01	0.26	3.61	16.9	6.0	–4.6	21.3
Managed futures	128	6.48	12.21	–22.6	–9.35	0.18	9.95	0.07	0.49	5.8	–9.6	–0.7	64.5
Multistrategy	125	9.10	4.43	5.6	–4.76	0.83	3.61	–1.30	3.59	–0.9	7.6	18.0	17.2
S&P 500	120	11.90	15.84	100.0	–14.46	1.47	9.78	–0.61	0.30	–1.0	–2.2	7.3	86.4
Banks	128	21.19	13.03	55.8	–18.62	1.96	11.39	–1.16	5.91	26.8	6.5	5.4	1.6
LIBOR	128	–0.14	0.78	3.5	–0.94	–0.01	0.63	–0.61	4.11	50.3	32.9	27.3	0.0
USD	128	–0.52	7.51	7.3	–5.35	–0.11	5.58	0.00	0.08	7.2	–3.2	6.4	71.5
Oil	128	15.17	31.69	–1.6	–22.19	1.38	36.59	0.25	1.17	–8.1	–13.6	16.6	7.3
Gold	128	1.21	12.51	–7.2	–9.31	–0.17	16.85	0.98	3.07	–13.7	–17.4	8.0	6.2
Lehman bond	128	6.64	4.11	0.8	–2.71	0.50	3.50	–0.04	0.05	24.6	–6.3	5.2	3.2
Large minus small cap	128	–1.97	13.77	7.6	–20.82	0.02	12.82	–0.82	5.51	–13.5	4.7	6.1	36.6
Value minus growth	128	0.86	18.62	–48.9	–22.78	0.40	15.85	–0.44	3.01	8.6	10.2	0.4	50.3
Credit spread (not annual)	128	4.35	1.36	–30.6	2.68	3.98	8.23	0.82	–0.30	94.1	87.9	83.2	0.0
Term spread (not annual)	128	1.65	1.16	–11.6	–0.07	1.20	3.85	0.42	–1.25	97.2	94.0	91.3	0.0
VIX (not annual)	128	0.03	3.98	–67.3	–12.90	0.03	19.48	0.72	4.81	–8.2	–17.5	–13.9	5.8

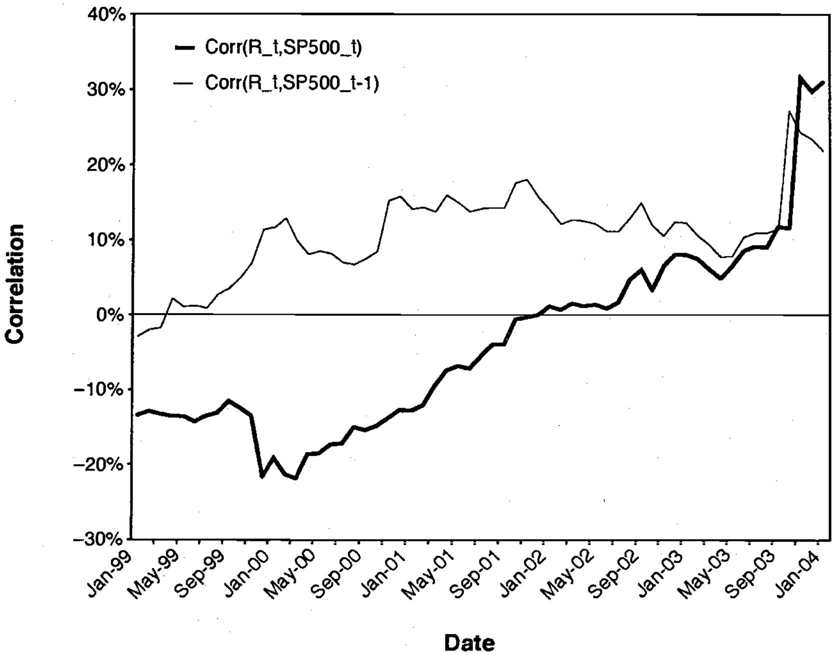


Fig. 6.2 Sixty-month rolling correlations between CSFB/Tremont Multi-Strategy Index returns and the contemporaneous and lagged return of the S&P 500, from January 1999 to December 2003

Notes: Under the null hypothesis of no correlation, the approximate standard error of the correlation coefficient is $1/\sqrt{60} = 13$ percent, hence the differences between the beginning-of-sample and end-of-sample correlations are statistically significant at the 1 percent level.

Despite their heterogeneity, several indexes do share a common characteristic: negative skewness. Convertible Arbitrage, Emerging Markets, Event Driven, Distressed, Event-Driven Multi-Strategy, Risk Arbitrage, Fixed-Income Arbitrage, and Fund of Funds all have skewness coefficients less than zero, in some cases substantially so. This property is an indication of tail risk exposure, as in the case of Capital Decimation Partners (see section 6.1.1), and is consistent with the nature of the investment strategies employed by funds in those categories. For example, Fixed-Income Arbitrage strategies are known to generate fairly consistent profits, with occasional losses that may be extreme; hence a skewness coefficient of –3.27 is not surprising. A more direct measure of tail risk or "fat tails" is kurtosis—the normal distribution has a kurtosis of 3.00, so values greater than this represent fatter tails than normal. Not surprisingly, the two categories with the most negative skewness—Event Driven (–3.49) and Fixed-Income Arbitrage (–3.27)—also have the largest kurtosis, 23.95 and 17.05, respectively.

Several indexes also exhibit a high degree of positive serial correlation, as measured by the first three autocorrelation coefficients ρ_1, ρ_2, and ρ_3, as well as the p-value of the Ljung-Box Q-statistic, which measures the degree of statistical significance of the first three autocorrelations.[17] In comparison to the S&P 500, which has a first-order autocorrelation coefficient of –1.0 percent, the autocorrelations of the hedge fund indexes are very high, with values of 55.8 percent for Convertible Arbitrage, 39.2 percent for Fixed-Income Arbitrage, and 35.0 percent for Event Driven, all of which are significant at the 1 percent level, according to the corresponding p-values. Serial correlation can be a symptom of illiquidity risk exposure, which is particularly relevant for systemic risk, and we shall focus on this issue in more detail in section 6.4.

The correlations between the hedge fund indexes are given in table 6.5, and the entries also display a great deal of heterogeneity, ranging from –71.9 percent (between Long/Short Equity and Dedicated Shortsellers) and 93.6 percent (between Event Driven and Distressed). However, these correlations can vary through time, as table 6.6 illustrates, both because of estimation error and through the dynamic nature of many hedge fund investment strategies and the changes in fund flows among them. Over the sample period from January 1994 to December 2003, the correlation between the Convertible Arbitrage and Emerging Market indexes is 31.8 percent, but during the first half of the sample this correlation is 48.2 percent, and during the second half it is –5.8 percent. A graph of the sixty-month rolling correlation between these two indexes from January 1999 to December 2003 provides a clue as to the source of this nonstationarity: figure 6.3 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 LTCM event—is not included in the sixty-month rolling window. Table 6.7 shows that in August 1998 the returns for the Convertible Arbitrage and Emerging Market Indexes were –4.64 percent and –23.03, respectively. In fact, ten out of the thirteen 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.

17. Ljung and Box (1978) propose the following statistic to measure the overall significance of the first k autocorrelation coefficients:

$$Q = T(T+2)\sum_{j=1}^{k} \hat{\rho}_j^2/(T-j)$$

which is asymptotically χ_k^2 under the null hypothesis of no autocorrelation. By forming the sum of squared autocorrelations, the statistic Q reflects the absolute magnitudes of the $\hat{\rho}_j$s irrespective of their signs; hence funds with large positive or negative autocorrelation coefficients will exhibit large Q-statistics. See Kendall, Stuart, and Ord (1983, chapter 50.13) for further details.

Table 6.5 **Correlation matrix for CSFB/Tremont hedge fund index returns, in percent, based on monthly data from January 1994 to August 2004**

Correlation matrix	Hedge funds	Convertible arbitrage	Dedicated shortseller	Emerging markets	Equity-market neutral	Event driven	Distressed	Event-driven multi-strategy	Risk arbitrage	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy
Hedge funds	100.0													
Convertible arbitrage	39.1	100.0												
Dedicated shortseller	–46.7	–22.3	100.0											
Emerging markets	65.7	32.0	–56.8	100.0										
Equity-market neutral	32.0	30.0	–34.6	24.8	100.0									
Event driven	66.1	59.0	–62.9	66.5	39.3	100.0								
Distressed	56.5	50.7	–62.3	57.7	35.7	93.6	100.0							
Event-driven multistrategy	69.0	60.1	–54.0	67.1	37.3	93.0	74.9	100.0						
Risk arbitrage	39.6	41.8	–50.6	44.1	32.1	69.7	58.0	66.6	100.0					
Fixed income arbitrage	40.7	53.0	–4.6	27.1	5.7	37.3	28.3	43.3	13.2	100.0				
Global macro	85.4	27.5	–11.0	41.5	18.6	36.9	29.5	42.7	12.9	41.5	100.0			
Long/short equity	77.6	25.0	–71.9	58.9	34.2	65.2	57.0	63.9	51.7	17.0	40.6	100.0		
Managed futures	12.4	–18.1	21.1	–10.9	15.3	–21.2	–14.6	–24.4	–21.1	–6.7	26.8	–3.6	100.0	
Multistrategy	16.0	35.0	–5.8	–3.2	20.6	15.9	10.9	19.7	5.9	27.3	11.3	14.5	–2.4	100.0

Table 6.6 Correlation matrices for five CSFB/Tremont hedge fund index returns, in percent, based on monthly data from January 1994 to December 2003

	Dedicated short	Emerging markets	Equity-market neutral	Event driven	Distressed
		January 1994 to December 2003			
Convertible arbitrage	–23.0	31.8	31.2	58.7	50.8
Dedicated short		–57.1	–35.3	–63.4	–63.2
Emerging markets			22.0	67.8	59.2
Equity-market neutral				37.9	34.9
Event-driven					93.8
		January 1994 to December 1998			
Convertible arbitrage	–25.2	48.2	32.1	68.4	61.6
Dedicated short		–52.6	–43.5	–66.2	–69.1
Emerging markets			22.1	70.8	65.4
Equity-market neutral				43.4	44.9
Event-driven					94.9
		January 1999 to December 2003			
Convertible arbitrage	–19.7	–5.8	32.3	41.8	33.5
Dedicated short		–67.3	–22.9	–63.0	–56.8
Emerging markets			22.1	60.6	45.2
Equity-market neutral				20.8	6.4
Event-driven					91.4

Source: AlphaSimplex Group.

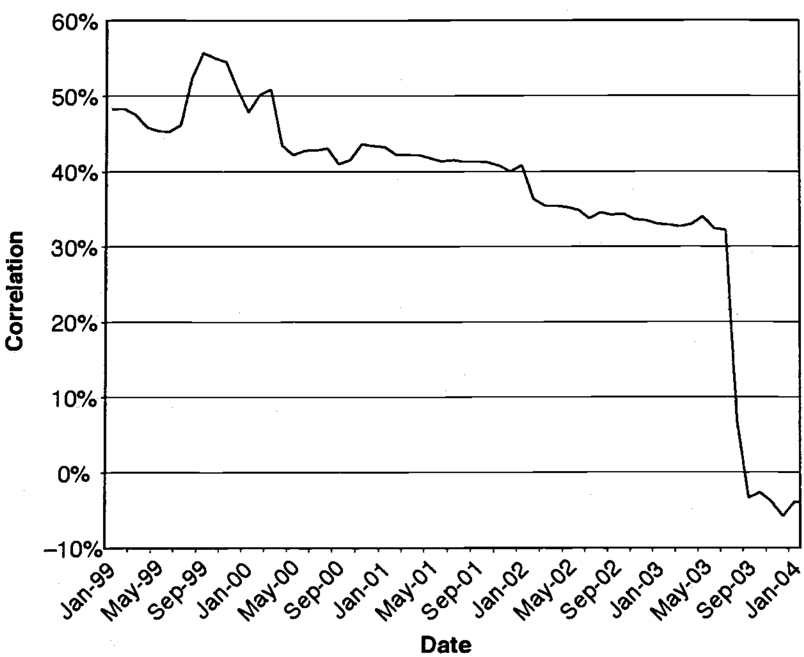


Fig. 6.3 Sixty-month rolling correlations between CSFB/Tremont Convertible Arbitrage and Emerging Market Index returns, from January 1999 to December 2003

Note: 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 sixty-month rolling window.

Table 6.7 **CSFB/Tremont hedge fund index and market-index returns from August to October 2003**

Index	August 1998	September 1998	October 1998
Aggregate index	–7.55	–2.31	–4.57
Convertible arbitrage	–4.64	–3.23	–4.68
Dedicated short	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 multistrategy	–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
Multistrategy	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

Source: AlphaSimplex Group.

Note: Monthly returns of CSFB/Tremont hedge-fund indexes and Ibbotson stock and bond indexes during August, September, and October 1998, in percent.

6.3.2 TASS Data

To develop a sense of the dynamics of the TASS database, in table 6.8 we report annual frequency counts of the funds added to and exiting from the TASS database each year. Not surprisingly, the number of hedge funds in both the Live and Graveyard databases grows over time. Table 6.8 shows that despite the start date of February 1977, the database is relatively sparsely populated until the 1990s, with the largest increase in new funds in 2001 and the largest number of funds exiting the database in the most recent year, 2003. TASS began tracking fund exits starting only in 1994, and for the unfiltered sample of all funds, the average attrition rate from 1994–1999 is 7.51 percent, which is very similar to the 8.54 percent attrition rate obtained by Liang (2001) for the same period. See section 6.5 for a more detailed analysis of hedge fund liquidations.

Table 6.9 contains basic summary statistics for the funds in the TASS Live, Graveyard, and Combined databases. Not surprisingly, there is a great deal of variation in mean returns and volatilities both across and within categories and databases. For example, the 127 Convertible Arbitrage funds in the Live database have an average mean return of 9.92 percent and an average standard deviation of 5.51 percent, but in the Graveyard database,

Table 6.8 **Annual frequency counts of entries into and exits out of the TASS hedge fund database from February 1977 to August 2004**

Year	All funds	Convertible arbitrage	Dedicated short	Emerging markets	Equity-market neutral	Event driven	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy	Fund of funds
Number of funds added to the TASS database each year												
1977	3	0	0	0	0	2	0	0	0	1	0	0
1978	2	0	0	0	0	0	0	0	0	1	0	1
1979	2	0	0	0	0	0	0	1	0	1	0	0
1980	3	0	0	0	0	0	0	0	0	3	0	0
1981	3	0	0	0	0	0	0	0	1	1	0	1
1982	4	0	0	0	0	0	1	0	1	1	0	1
1983	9	0	0	0	0	1	0	1	3	3	0	1
1984	15	0	0	0	0	1	1	0	6	2	0	5
1985	9	0	1	0	0	1	0	1	0	1	0	5
1986	22	0	0	0	0	2	1	2	5	8	0	4
1987	28	0	0	0	0	2	0	2	10	7	1	6
1988	33	4	2	0	0	6	0	1	2	9	1	8
1989	43	1	0	3	3	7	1	2	7	10	0	9
1990	102	4	3	5	1	11	0	7	24	18	2	27
1991	89	2	2	5	1	11	1	11	17	20	1	18
1992	155	8	0	10	4	9	7	10	37	31	2	37
1993	247	7	3	21	3	18	10	12	55	64	10	44
1994	251	13	1	25	7	16	16	11	52	52	5	53
1995	299	12	0	34	10	27	12	19	74	41	7	63
1996	332	14	3	25	10	29	16	16	116	42	14	47
1997	356	10	3	40	14	31	15	19	118	37	13	56
1998	346	14	1	22	29	28	16	20	117	25	8	66

continued

Table 6.8 (continued)

Year	All funds	Convertible arbitrage	Dedicated short	Emerging markets	Equity-market neutral	Event driven	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy	Fund of funds
1999	403	10	4	26	36	29	13	12	159	35	10	69
2000	391	17	2	20	17	38	9	18	186	13	10	61
2001	460	25	1	5	49	34	20	15	156	18	16	121
2002	432	22	1	4	41	40	23	26	137	22	14	102
2003	325	11	1	12	23	21	12	15	83	23	14	110
2004	1	0	0	0	0	0	0	0	0	0	0	1
Number of funds exiting the TASS database each year												
1994	25	0	0	0	1	0	3	3	2	9	4	3
1995	62	0	1	1	0	1	2	5	7	30	2	13
1996	129	7	1	4	0	3	4	17	23	51	1	18
1997	106	3	1	8	0	3	5	7	17	37	3	22
1998	171	5	0	26	4	3	14	9	35	37	6	32
1999	190	3	1	18	15	20	8	16	45	41	2	21
2000	243	3	1	27	13	15	11	33	60	35	3	42
2001	263	5	6	28	9	22	7	9	112	19	1	45
2002	255	6	1	11	16	32	5	9	112	32	5	26
2003	297	10	1	14	32	24	9	9	112	23	18	45
2004	88	10	2	1	5	15	4	1	27	5	0	18

Note: Prior to January 1994, exits were not tracked.

Table 6.9 **Means and standard deviations of basic summary statistics for hedge funds in the TASS Hedge Fund Live, Graveyard, and Combined databases from February 1977 to August 2004**

Category	Sample size	Annualized mean (%)		Annualized SD (%)		ρ_1 (%)		Annualized Sharpe ratio		Annualized adjusted Sharpe ratio		Ljung-Box p-value (%)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Live funds													
Convertible arbitrage	127	9.92	5.89	5.51	4.15	33.6	19.2	2.57	4.20	1.95	2.86	19.5	27.1
Dedicated shortseller	14	0.33	11.11	25.10	10.92	3.5	10.9	–0.11	0.70	0.12	0.46	48.0	25.7
Emerging markets	130	17.74	13.77	21.69	14.42	18.8	13.8	1.36	2.01	1.22	1.40	35.5	31.5
Equity-market neutral	173	6.60	5.89	7.25	5.05	4.4	22.7	1.20	1.18	1.30	1.28	41.6	32.6
Event driven	250	12.52	8.99	8.00	7.15	19.4	20.9	1.98	1.47	1.68	1.47	31.3	34.1
Fixed income arbitrage	104	9.30	5.61	6.27	5.10	16.4	23.6	3.61	11.71	3.12	7.27	36.6	35.2
Global macro	118	10.51	11.55	13.57	10.41	1.3	17.1	0.86	0.68	0.99	0.79	46.8	30.6
Long/short equity	883	13.05	10.56	14.98	9.30	11.3	17.9	1.03	1.01	1.01	0.95	38.1	31.8
Managed futures	195	8.59	18.55	19.14	12.52	3.4	13.9	0.48	1.10	0.73	0.63	52.3	30.8
Multistrategy	98	12.65	17.93	9.31	10.94	18.5	21.3	1.91	2.34	1.46	2.06	31.1	31.7
Fund of funds	679	6.89	5.45	6.14	4.87	22.9	18.5	1.53	1.33	1.48	1.16	33.7	31.6
Graveyard funds													
Convertible arbitrage	49	10.02	6.61	8.14	6.08	25.5	19.3	1.89	1.43	1.58	1.46	27.9	34.2
Dedicated shortseller	15	1.77	9.41	27.54	18.79	8.1	13.2	0.20	0.44	0.25	0.48	55.4	25.2
Emerging markets	133	2.74	27.74	27.18	18.96	14.3	17.9	0.37	0.91	0.47	1.11	48.5	34.6
Equity-market neutral	87	7.61	26.37	12.35	13.68	6.4	20.4	0.52	1.23	0.60	1.85	46.6	31.5
Event driven	134	9.07	15.04	12.35	12.10	16.6	21.1	1.22	1.38	1.13	1.43	39.3	34.2
Fixed income arbitrage	71	5.51	12.93	10.78	9.97	15.9	22.0	1.10	1.77	1.03	1.99	46.0	35.7
Global macro	114	3.74	28.83	21.02	18.94	3.2	21.5	0.33	1.05	0.37	0.90	46.2	31.0

continued

Table 6.9 (continued)

Category	Sample size	Annualized mean (%)		Annualized SD (%)		ρ_1 (%)		Annualized Sharpe ratio		Annualized adjusted Sharpe ratio		Ljung-Box p-value (%)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Long/short equity	532	9.69	22.75	23.08	16.82	6.4	19.8	0.48	1.06	0.48	1.17	47.8	31.3
Managed futures	316	4.78	23.17	20.88	19.35	–2.9	18.7	0.26	0.77	0.37	0.97	48.4	30.9
Multistrategy	41	5.32	23.46	17.55	20.90	6.1	17.4	1.10	1.55	1.58	2.06	49.4	32.2
Fund of funds	273	4.53	10.07	13.56	10.56	11.3	21.2	0.62	1.26	0.57	1.11	40.9	31.9
Combined funds													
Convertible arbitrage	176	9.94	6.08	6.24	4.89	31.4	19.5	2.38	3.66	1.85	2.55	21.8	29.3
Dedicated shortseller	29	1.08	10.11	26.36	15.28	5.9	12.2	0.05	0.59	0.19	0.46	52.0	25.2
Emerging markets	263	10.16	23.18	24.48	17.07	16.5	16.2	0.86	1.63	0.84	1.31	42.2	33.7
Equity-market neutral	260	6.94	15.94	8.96	9.21	5.1	21.9	0.97	1.24	1.06	1.53	43.3	32.3
Event driven	384	11.31	11.57	9.52	9.40	18.4	21.0	1.71	1.48	1.49	1.48	34.1	34.3
Fixed income arbitrage	175	7.76	9.45	8.10	7.76	16.2	22.9	2.59	9.16	2.29	5.86	40.4	35.6
Global macro	232	7.18	22.04	17.21	15.61	2.3	19.3	0.60	0.92	0.70	0.90	46.5	30.8
Long/short equity	1415	11.79	16.33	18.02	13.25	9.5	18.8	0.82	1.06	0.81	1.07	41.7	31.9
Managed futures	511	6.23	21.59	20.22	17.07	–0.6	17.4	0.34	0.91	0.50	0.88	49.8	30.9
Multistrategy	139	10.49	19.92	11.74	15.00	14.7	20.9	1.67	2.16	1.49	2.05	36.7	32.9
Fund of funds	952	6.22	7.17	8.26	7.75	19.6	20.0	1.27	1.37	1.21	1.22	35.8	31.8

Note: The columns "p-value (Q)" contain means and standard deviations of p-values for the Ljung-Box Q-statistic for each fund, using the first eleven autocorrelations of returns. SD = standard deviation.

the forty-nine Convertible Arbitrage funds have an average mean return of 10.02 percent and a much higher average standard deviation of 8.14 percent. Not surprisingly, average volatilities in the Graveyard database are uniformly higher than those in the Live database because the higher-volatility funds are more likely to be eliminated.[18]

Average serial correlations also vary considerably across categories in the Combined database, but six categories stand out: Convertible Arbitrage (31.4 percent), Fund of Funds (19.6 percent), Event Driven (18.4 percent), Emerging Markets (16.5 percent), Fixed-Income Arbitrage (16.2 percent), and Multi-Strategy (14.7 percent). Given the descriptions of these categories provided by TASS (see the appendix) and common wisdom about the nature of the strategies involved—these categories include some of the most illiquid securities traded—serial correlation seems to be a reasonable proxy for illiquidity and smoothed returns (see Lo, 2001; Getmansky, Lo, and Makarov, 2004; and section 6.4). Alternatively, equities and futures are among the most liquid securities in which hedge funds invest, and not surprising, the average first-order serial correlations for Equity Market Neutral, Long/Short Equity, and Managed Futures are 5.1 percent, 9.5 percent, and –0.6 percent, respectively. Dedicated Shortseller funds also have a low average first-order autocorrelation, 5.9 percent, which is consistent with the high degree of liquidity that often characterize shortsellers (by definition, the ability to short a security implies a certain degree of liquidity).

These summary statistics suggest that illiquidity and smoothed returns may be important attributes for hedge fund returns, which can be captured to some degree by serial correlation and the time series model of smoothing in section 6.4.

Finally, table 6.10 reports the year-end assets under management for funds in each of the eleven TASS categories for the Combined database from 1977 to 2003; the relative proportions are plotted in figure 6.4. Table 6.10 shows that the total assets in the TASS combined database is approximately \$391 billion, which is a significant percentage—though not nearly exhaustive—of the estimated \$1 trillion in the hedge fund industry today.[19] The two dominant categories in the most recent year are Long/Short Equity (\$101.5 billion) and Fund of Funds (\$76.8 billion), but figure 6.4 shows that the relative proportions can change significantly over time (see Getmansky 2004 for a more detailed analysis of fund flows in the hedge fund industry).

18. This effect works at both ends of the return distribution—funds that are wildly successful are also more likely to leave the database, since they have less of a need to advertise their performance. That the Graveyard database also contains successful funds is supported by the fact that in some categories, the average mean return in the Graveyard database is the same as or higher than in the Live database—for example, convertible arbitrage, equity market neutral, and dedicated shortseller.

19. Of course, part of the \$391 billion is Graveyard funds, hence the proportion of current hedge fund assets represented by the TASS database is less.

Table 6.10 **Assets under management at year end in millions of U.S. dollars for funds in each of the eleven categories in the TASS combined hedge fund database from 1977 to 2003**

Year	Convertible arbitrage	Dedicated shortseller	Emerging markets	Equity-market neutral	Event driven	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy	Fund of funds	Total
1977					16.2			42.9	5.4			64.4
1978					22.1			53.2	18.0		32.2	125.5
1979					34.5		0.0	77.6	44.3		46.9	203.4
1980					52.7		0.1	110.6	55.1		76.9	295.4
1981					55.5		0.2	125.6	62.4		80.0	323.7
1982	3.5				76.9	13.5	0.3	174.3	72.2		172.0	512.8
1983	4.1				114.9	20.4	5.8	249.7	68.9		233.0	696.9
1984	3.7				168.7	23.0	6.2	345.0	68.8		245.6	860.9
1985	4.4	44.2			274.0	18.0	4.8	510.8	114.7		386.3	1,357.3
1986	5.2	63.4			387.5	64.9	132.6	737.3	180.7		641.9	2,213.4
1987	5.7	72.6			452.0	96.7	248.5	925.2	484.7	1,830.0	898.2	5,013.6
1988	27.5	108.5	17.9		1,012.1	95.1	265.2	1,324.8	775.4	1,821.6	1,318.7	6,766.9
1989	82.4	133.8	169.3	134.6	1,216.5	152.0	501.6	2,025.5	770.5	2,131.2	1,825.5	9,143.0
1990	188.2	260.4	330.3	156.5	1,383.4	289.0	1,964.9	2,609.8	1,006.6	2,597.8	2,426.2	13,213.2
1991	286.9	221.7	696.4	191.0	2,114.7	605.6	4,096.2	3,952.2	1,183.3	3,175.6	3,480.4	20,004.0
1992	1,450.7	237.0	1,235.4	316.2	2,755.3	928.2	7,197.0	5,925.5	1,466.8	3,778.0	4,941.8	30,231.9
1993	2,334.9	260.2	3,509.6	532.1	4,392.4	1,801.7	14,275.5	11,160.6	2,323.2	5,276.0	10,224.3	56,090.6
1994	2,182.4	388.2	5,739.4	577.2	5,527.6	2,237.5	11,822.6	12,809.7	2,965.4	4,349.9	10,420.2	59,020.2
1995	2,711.1	342.8	5,868.8	888.3	7,025.5	3,279.6	12,835.3	17,257.1	2,768.8	6,404.2	11,816.1	71,197.5
1996	3,913.3	397.4	8,439.8	2,168.7	9,493.3	5,428.4	16,543.2	23,165.7	2,941.0	7,170.1	14,894.0	94,554.9
1997	6,488.7	581.5	12,780.2	3,747.4	14,508.8	9,290.5	25,917.6	31,807.0	3,665.0	10,272.4	21,056.9	140,116.1
1998	7,802.7	868.2	5,743.9	6,212.5	17,875.4	8,195.3	23,960.9	36,432.9	4,778.5	9,761.3	22,778.5	144,410.3
1999	9,228.6	1,061.2	7,991.5	9,165.5	20,722.1	8,052.1	15,928.3	62,817.2	4,949.3	11,520.2	26,373.3	177,809.3
2000	13,365.2	1,312.7	6,178.7	13,507.5	26,569.6	8,245.0	4,654.9	78,059.0	4,734.8	10,745.2	31,378.5	198,751.0
2001	19,982.4	802.8	6,940.1	18,377.9	34,511.9	11,716.3	5,744.1	88,109.3	7,286.4	13,684.2	40,848.5	248,003.9
2002	23,649.4	812.8	8,664.8	20,008.2	36,299.0	17,256.8	8,512.8	84,813.5	10,825.4	16,812.1	51,062.7	278,717.4
2003	34,195.7	503.8	16,874.0	23,408.4	50,631.1	24,350.1	21,002.2	101,461.0	19,449.1	22,602.6	76,792.4	391,270.5

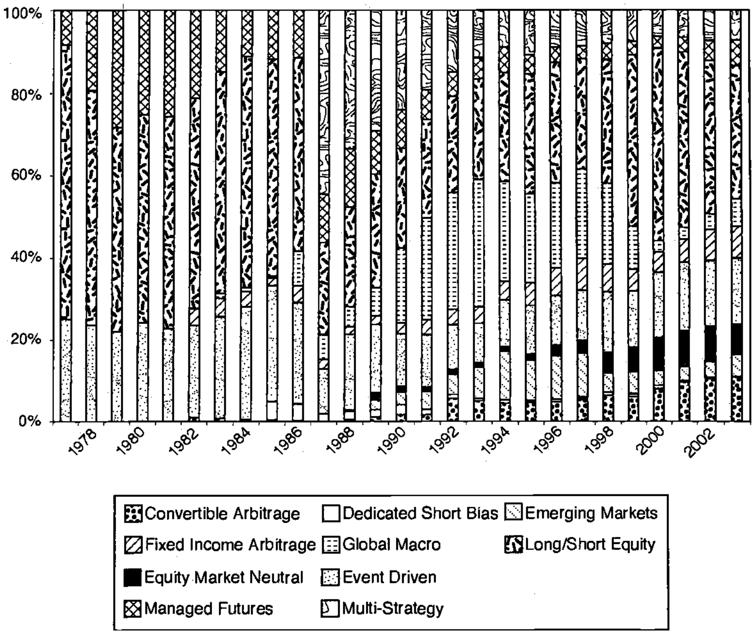


Fig. 6.4 Relative proportions of assets under management at year-end in the eleven categories of the TASS Hedge Fund Combined database, from 1977 to 2003

6.4 Measuring Illiquidity Risk

The examples of section 6.1 highlight the fact that hedge funds exhibit a heterogeneous array of risk exposures, but a common theme surrounding systemic risk factors is credit and liquidity. Although they are separate sources of risk exposures for hedge funds and their investors—one type of risk can exist without the other—nevertheless, liquidity and credit 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 those positions. Leverage has the effect of a magnifying glass, expanding small profit opportunities into larger ones, but also expanding small losses into larger losses. 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.[20] Along with the many benefits

20. Note that in the case of Capital Decimation Partners in section 6.1.1, the fund's consecutive returns of –18.3 percent and –16.2 percent in August and September 1998 would have

of a truly global financial system is the cost that a financial crisis in one country can have dramatic repercussions in several others—that is, contagion.

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 illiquidity risk.[21] 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 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.

6.4.1 Serial Correlation and Illiquidity

A more immediate method for gauging the illiquidity 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),[22] 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 for the motivation of the martingale property: in an informationally efficient market, price changes must be unforecastable if they are properly anticipated—that is, 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.[23] In particular, market frictions such as transactions costs, borrowing constraints, costs of gathering and processing information, and institutional restrictions on shortsales and

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 Lo 2001, table 6.4).

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

22. 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.

23. See, for example, Farmer and Lo (1999) and Lo (2004).

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 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 of residential real estate investments are considerably more highly autocorrelated than, say, the returns of the S&P 500 indexes during the same sample period. Similarly, the returns of S&P 500 futures contracts exhibit less serial correlation than those of the index itself. In both examples, the more liquid instrument exhibits less serial correlation than the less liquid, and 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 shortsell properties, and other frictions.[24]

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). But in contrast to the studies by Lo and MacKinlay (1988, 1990b) and Kadlec and Patterson (1999), in which they conclude that it is difficult to generate serial correlations in weekly U.S. equity portfolio returns much greater than 10 percent to 15 percent through nonsynchronous trading effects alone, Getmansky, Lo, and Makarov (2004) argue that in the context of hedge funds, significantly higher levels of serial correlation can be explained by the combination of illiquidity and performance smoothing (see the following), of which nonsynchronous trading is a special case. To see why, note that the empirical analysis in the nonsynchronous-trading literature is devoted exclusively to exchange-traded equity returns, not hedge fund returns, hence the corresponding conclusions may not be relevant in this context. For example, Lo and MacKinlay (1990b) argue that securities would have to go without trading for several days on average to induce serial correlations of 30 percent, and they dismiss such nontrading intervals as unrealistic for most exchange-traded U.S. equity issues. However, such nontrading intervals are considerably more realistic for the types of securities held by many hedge funds;

24. 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.

for example, emerging-market debt, real estate, restricted securities, control positions in publicly traded companies, asset-backed securities, and other exotic over-the-counter (OTC) derivatives. Therefore, nonsynchronous trading of this magnitude is likely to be an explanation for the serial correlation observed in hedge fund returns.

But even when prices are synchronously measured—as they are for many funds that mark their portfolios to market at the end of the month to strike a net asset value at which investors can buy into or cash out of the fund—there are several other channels by which illiquidity exposure can induce serial correlation in the reported returns of hedge funds. Apart from the nonsynchronous-trading effect, naive methods for determining the fair market value or "marks" for illiquid securities can yield serially correlated returns. For example, one approach to valuing illiquid securities is to extrapolate linearly from the most recent transaction price (which, in the case of emerging-market debt, might be several months ago), which yields a price path that is a straight line, or at best a series of straight lines. Returns computed from such marks will be smoother, exhibiting lower volatility and higher serial correlation than true economic returns; that is, returns computed from mark-to-market prices where the market is sufficiently active to allow all available information to be impounded in the price of the security. Of course, for securities that are more easily traded and with deeper markets, mark-to-market prices are more readily available, extrapolated marks are not necessary, and serial correlation is therefore less of an issue. But for securities that are thinly traded, or not traded at all for extended periods of time, marking them to market is often an expensive and time-consuming procedure that cannot easily be frequently performed.[25] Therefore, serial correlation may serve as a proxy for a fund's liquidity exposure.

Even if a hedge fund manager does not make use of any form of linear extrapolation to mark the securities in his portfolio, he may still be subject to smoothed returns if he obtains marks from broker-dealers that engage in such extrapolation. For example, consider the case of a conscientious hedge fund manager attempting to obtain the most accurate mark for his or her portfolio at month end by getting bid/offer quotes from three independent broker-dealers for every security in his portfolio, and then marking each security at the average of the three quote midpoints. By averaging the quote midpoints, the manager is inadvertently downward-biasing price volatility, and if any of the broker-dealers employ linear extrapolation in formulating their quotes (and many do, through sheer necessity because they have little else to go on for the most illiquid securities), or if they fail to update their quotes because of light volume, serial correlation will also be induced in reported returns.

Finally, a more prosaic channel by which serial correlation may arise in

25. Liang (2003) presents a sobering analysis of the accuracy of hedge fund returns that underscores the challenges of marking a portfolio to market.

the reported returns of hedge funds is through "performance smoothing," the unsavory practice of reporting only part of the gains in months when a fund has positive returns so as to partially offset potential future losses and thereby reduce volatility and improve risk-adjusted performance measures such as the Sharpe ratio. For funds containing liquid securities that can be easily marked to market, performance smoothing is more difficult and, as a result, less of a concern. Indeed, it is only for portfolios of illiquid securities that managers and brokers have any discretion in marking their positions. Such practices are generally prohibited by various securities laws and accounting principles, and great care must be exercised in interpreting smoothed returns as deliberate attempts to manipulate performance statistics. After all, as discussed previously, there are many other sources of serial correlation in the presence of illiquidity, none of which is motivated by deceit. Nevertheless, managers do have certain degrees of freedom in valuing illiquid securities—for example, discretionary accruals for unregistered private placements and venture capital investments—and Chandar and Bricker (2002) conclude that managers of certain closed-end mutual funds do use accounting discretion to manage fund returns around a passive benchmark. Therefore, the possibility of deliberate performance smoothing in the less regulated hedge fund industry must be kept in mind in interpreting any empirical analysis of serial correlation in hedge fund returns.

Getmansky, Lo, and Makarov (2004) address these issues in more detail by first examining other explanations of serial correlation in hedge fund returns that are unrelated to illiquidity and smoothing—in particular, time-varying expected returns, time-varying leverage, and incentive fees with high-water marks—and show that none of them can account for the magnitudes of serial correlation in hedge fund returns. They propose a specific econometric model of smoothed returns that is consistent with both illiquidity exposure and performance smoothing, and they estimate it using the historical returns of individual funds in the TASS hedge fund database. They find that funds with the most significant amount of smoothing tend to be the more illiquid—for example, emerging market debt, fixed income arbitrage, and so forth, and after correcting for the effects of smoothed returns, some of the most successful types of funds tend to have considerably less attractive performance characteristics.

However, for the purpose of developing a more highly aggregated measure to address systemic risk exposure, a simpler approach is to use serial correlation coefficients and the Ljung-Box Q-statistic (see footnote 17). To illustrate this approach, we estimate these quantities using monthly historical total returns of the ten largest (as of February 11, 2001) mutual funds, from various start dates through June 2000, and twelve hedge funds from various inception dates to December 2000. Monthly total returns for the mutual funds were obtained from the University of Chicago's Center for Research in Securities Prices. The twelve 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 $\widehat{SR}$ is the Sharpe ratio estimator applied to monthly returns), with the additional requirement that the funds have a minimum five-year history of returns.[26] 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; for example, Relative Value Fund, Risk Arbitrage Fund.

Table 6.11 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 and hedge funds. The first subpanel shows that the ten 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. The lack of serial correlation in these ten 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—for example, 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 twelve 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 percent to 49.01 percent, with eight out of twelve funds that have Q-statistics with p-values less than 5 percent, and ten out of twelve funds with p-values less than 10 percent. The only two funds with p-values that are 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 illiquidity 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.

To develop further intuition for serial correlation in hedge fund returns, we reproduce a small portion of the analysis in Getmansky, Lo, and Makarov (2004), in which they report the serial correlation coefficients of the returns of the Ibbotson stock and bond indexes, the Merrill Lynch Convertible Securities Index,[27] the CSFB/Tremont hedge-fund indexes, and

26. See http://www.investorforce.com for further information about the Altvest database.

27. This is described by Merrill Lynch as a "market value-weighted index that tracks the daily price only, income and total return performance of corporate convertible securities, including U.S. domestic bonds, Eurobonds, preferred stocks and Liquid Yield Option Notes."

Table 6.11 **Autocorrelations of mutual fund and hedge fund returns: Monthly data, various sample periods**

Fund	Start date	T	$\hat{\mu}$ (%)	$\hat{\sigma}$ (%)	$\hat{\rho}_1$ (%)	$\hat{\rho}_2$ (%)	$\hat{\rho}_3$ (%)	ρ_4 (%)	$\hat{\rho}_5$ (%)	$\hat{\rho}_6$ (%)	p-value of Q_6 (percent)
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
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

Source: AlphaSimplex Group.

Notes: 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 $T(T+2)\sum_{k=1}^{6}\rho_k^2/(T-k)$, which is asymptotically χ^2_6 under the null hypothesis of no serial correlation.

two mutual funds: the highly liquid Vanguard 500 Index Fund and the considerably less liquid American Express Extra Income Fund.[28] Table 6.12 contains the autocorrelations as well as market betas (where the market return is taken to be the S&P 500 total return) and contemporaneous and lagged market betas.[29]

Consistent with our interpretation of serial correlation as an indicator of illiquidity, the returns of the most liquid portfolios in table 6.12—the Ibbotson Large Company Index, the Vanguard 500 Index Fund (which is virtually identical to the Ibbotson Large Company Index, except for sample period and tracking error), and the Ibbotson Long-Term Government Bond Index—have small autocorrelation coefficients: 9.8 percent for the Ibbotson Large Company Index, –2.3 percent for the Vanguard 500 Index Fund, and 6.7 percent for the Ibbotson Long-Term Government Bond Index. The lagged market betas of these indexes are also statistically indistinguishable from 0. However, first-order autocorrelations of the less liquid portfolios are: 15.6 percent for the Ibbotson Small Company Index, 15.6 percent for the Ibbotson Long-Term Corporate Bond Index, 6.4 percent for the Merrill Lynch Convertible Securities Index, and 35.4 percent for the American Express Extra Income Fund, which, with the exception of the Merrill Lynch Convertible Securities Index, are considerably higher than those of the more liquid portfolios.[30] Also, the lagged market betas are statistically significant at the 5 percent level for the Ibbotson Small Company Index (a t-statistic for $\hat{\beta}_1$: 5.41), the Ibbotson Long-Term Government

28. As of January 31, 2003, the net assets of the Vanguard 500 Index Fund (ticker symbol: VFINX) and the AXP Extra Income Fund (ticker symbol: INEAX) are given by http://finance.yahoo.com/ as $59.7 billion and $1.5 billion, respectively, and the descriptions of the two funds are as follows:

> The Vanguard 500 Index Fund seeks investment results that correspond with the price and yield performance of the S&P 500 Index. The fund employs a passive management strategy designed to track the performance of the S&P 500 Index, which is dominated by the stocks of large U.S. companies. It attempts to replicate the target index by investing all or substantially all of its assets in the stocks that make up the index.
>
> AXP Extra Income Fund seeks high current income; capital appreciation is secondary. The fund ordinarily invests in long-term high-yielding, lower-rated corporate bonds. These bonds may be issued by U.S. and foreign companies and governments. The fund may invest in other instruments such as: money market securities, convertible securities, preferred stocks, derivatives (such as futures, options and forward contracts), and common stocks.

29. Market betas were obtained by regressing returns on a constant and the total return of the S&P 500, and contemporaneous and lagged market betas were obtained by regressing returns on a constant, the contemporaneous total return of the S&P 500, and the first two lags. Asness, Krail, and Liew (2001) observe that many hedge funds that claim to be market neutral are, in fact, not neutral with respect to a lagged market factor, and Getmansky, Lo, and Makarov (2004) show that this is consistent with illiquidity exposure and performance smoothing.

30. However, note that the second-order autocorrelation of the Merrill Lynch Convertible Securities Index is 12.0 percent, which is second only to the AXP Extra Income Fund in absolute magnitude, two orders of magnitude larger than the second-order autocorrelation of the Ibbotson bond indexes, and one order of magnitude larger than the Ibbotson stock indexes.

Table 6.12 **Autocorrelations and market betas for various indexes and mutual funds**

								Market model			Contemporaneous and lagged market model						
Series	Period	T	Mean (%)	SD (%)	$\hat{\rho}_1$ (%)	$\hat{\rho}_2$(%)	$\hat{\rho}_3$ (%)	$\hat{\beta}$	SE($\hat{\beta}$)	R^2 (%)	$\hat{\beta}_0$	SE($\hat{\beta}_0$)	$\hat{\beta}_1$	SE($\hat{\beta}_1$)	$\hat{\beta}_2$	SE($\hat{\beta}_2$)	R^2 (%)
Ibbotson Small Company	192601–200112	912	1.35	8.63	15.6	1.7	–10.6	1.27	0.03	66.9	1.25	0.03	0.16	0.03	0.03	0.03	68.0
Ibbotson Long-Term Government Bonds	192601–200112	912	0.46	2.22	6.7	0.3	–8.3	0.07	0.01	2.8	0.07	0.01	–0.03	0.01	–0.02	0.01	3.6
Ibbotson Long-Term Corporate Bonds	192601–200112	912	0.49	1.96	15.6	0.3	–6.0	0.08	0.01	5.2	0.08	0.01	–0.01	0.01	–0.01	0.01	5.3
Ibbotson Large Company	192601–200112	912	1.03	5.57	9.8	–3.2	–10.7	1.00	0.00	100.0	1.00	0.00	0.00	0.00	0.00	0.00	100.0
Merrill Lynch Convertibles Index	199401–200210	168	0.99	3.43	6.4	12.0	5.1	0.59	0.05	48.6	0.60	0.05	0.15	0.05	0.07	0.04	52.2
AXP Extra Income Fund (INEAX)	198401–200112	216	0.67	2.04	35.4	13.1	2.5	0.21	0.03	20.7	0.21	0.03	0.12	0.03	0.04	0.03	28.7
Vanguard 500 Index Trust (VFINX)	197609–200112	304	1.16	4.36	–2.3	–6.8	–3.2	1.00	0.00	100.0	1.00	0.00	0.00	0.00	0.00	0.00	100.0
CSFB/Tremont Indexes																	
Aggregate hedge fund index	199401–200210	106	0.87	2.58	11.2	4.1	–0.4	0.31	0.05	24.9	0.32	0.05	0.06	0.05	0.16	0.05	32.1
Convertible arbitrage	199401–200210	106	0.81	1.40	56.6	42.6	15.6	0.03	0.03	1.1	0.04	0.03	0.09	0.03	0.06	0.03	12.0
Dedicated short bias	199401–200210	106	0.22	5.29	7.8	–6.3	–5.0	–0.94	0.08	58.6	–0.93	0.08	–0.06	0.08	0.08	0.08	59.3
Emerging markets	199401–200210	106	0.54	5.38	29.4	1.2	–2.1	0.62	0.11	24.0	0.63	0.11	0.19	0.11	0.03	0.12	26.2
Equity-market neutral	199401–200210	106	0.89	0.92	29.4	18.1	8.4	0.10	0.02	21.1	0.10	0.02	0.02	0.02	0.00	0.02	22.1
Event driven	199401–200210	106	0.83	1.81	34.8	14.7	3.8	0.23	0.04	30.2	0.23	0.03	0.11	0.03	0.04	0.03	38.2
Fixed income arbitrage	199401–200210	106	0.55	1.18	39.6	10.8	5.4	0.02	0.03	0.7	0.03	0.03	0.05	0.03	0.09	0.03	12.9
Global macro	199401–200210	106	1.17	3.69	5.6	4.6	8.3	0.24	0.09	7.5	0.26	0.09	–0.01	0.09	0.23	0.09	14.1
Long/Short	199401–200210	106	0.98	3.34	15.9	5.9	–4.6	0.48	0.06	36.7	0.49	0.06	0.06	0.06	0.15	0.06	40.7
Managed futures	199401–200210	106	0.55	3.44	3.2	–6.3	0.7	–0.12	0.08	2.5	–0.13	0.08	–0.17	0.08	0.02	0.08	7.8

Notes: Autocorrelations and contemporaneous and lagged market betas for the returns of various indexes and two mutual funds, the Vanguard 500 Index Trust (which tracks the S&P 500 index), and the AXP Extra Income Fund (which focuses on high current income and invests in long-term, high-yielding, lower-rated corporate bonds). Total returns of the S&P 500 index are used for both market models. SD = standard deviation; SE = standard error.

Bond Index (t-statistic for $\hat{\beta}_1$: –2.30), the Merrill Lynch Convertible Securities Index (t-statistic for $\hat{\beta}_1$: 3.33), and the American Express (AXP) Extra Income Fund (t-statistic for $\hat{\beta}_1$: 4.64).

The results for the CSFB Hedge Fund Indexes in the second panel of table 6.12 are also consistent with the empirical results in table 6.11—indexes corresponding to hedge fund strategies involving less liquid securities tend to have higher autocorrelations. For example, the first-order autocorrelations of the Convertible Arbitrage, Emerging Markets, and Fixed-Income Arbitrage Indexes are 56.6 percent, 29.4 percent, and 39.6 percent, respectively. In contrast, the first-order autocorrelations of the more liquid hedge fund strategies such as Dedicated Short Bias and Managed Futures are 7.8 percent and 3.2 percent, respectively.

While these findings are generally consistent with the results for individual hedge funds in Getmansky, Lo, and Makarov (2004), it should be noted that the process of aggregation can change the statistical behavior of any time series. For example, Granger (1980, 1988) observes that the aggregation of a large number of stationary autoregressive processes can yield a time series that exhibits long-term memory, characterized by serial correlation coefficients that decay very slowly (hyperbolically, as opposed to geometrically as in the case of a stationary autoregressive moving average [ARMA] process). Therefore, while it is true that the aggregation of a collection of illiquid funds will generally yield an index with smoothed returns,[31] the reverse need not be true—smoothed index returns need not imply that all of the funds comprising the index are illiquid. The latter inference can only be made with the benefit of additional information—essentially identification restrictions—about the statistical relations among the funds in the index; that is, covariances and possibly other higher-order co-moments, or the existence of common factors driving fund returns.

It is interesting to note that the first lagged market beta, $\hat{\beta}_1$, for the CSFB/Tremont indexes is statistically significant at the 5 percent level in only three cases (Convertible Arbitrage, Event Driven, and Managed Futures), but the second lagged beta, $\hat{\beta}_2$, is significant in five cases (the overall index, Convertible Arbitrage, Fixed Income Arbitrage, Global Macro, and Long/Short). Obviously, the S&P 500 index is likely to be inappropriate for certain styles—for example, Emerging Markets—and these somewhat inconsistent results suggest that using a lagged market-beta adjustment may not completely account for the impact of illiquidity and smoothed returns.

Overall, the patterns in table 6.12 confirm our interpretation of serial correlation as proxies for illiquidity, and suggest that there may be broader

31. It is, of course, possible that the smoothing coefficients of some funds may exactly offset those of other funds so as to reduce the degree of smoothing in an aggregate index. However, such a possibility is extremely remote and pathological if each of the component funds exhibits a high degree of smoothing.

applications of this model of smoothed returns to other investment strategies and asset classes.

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. 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 models proposed in section 6.6. However, for the purpose of developing a measure of systemic risk in the hedge fund industry, autocorrelation coefficients and Q-statistics provide a great deal of insight and information in a convenient manner.

6.4.2 An Aggregate Measure of Illiquidity

Having established the relevance of serial correlation as a proxy for illiquidity, we now turn to the measurement of illiquidity in the context of systemic risk. To that end, let $\rho_{1t,i}$ denote the first-order autocorrelation coefficient in month t for fund i using a rolling window of past returns. Then an aggregate measure of illiquidity ρ_t^* in the hedge fund sector may be obtained by a cross-sectional weighted average of these rolling autocorrelations, where the weights ω_{it} are simply the proportion of assets under management for fund i:

$$\rho_t^* \equiv \sum_{i=1}^{N_t} \omega_{it}\rho_{1t,i} \tag{9}$$

$$\omega_{it} \equiv \frac{\text{AUM}_{it}}{\sum_{j=1}^{N_t} \text{AUM}_{jt}}, \tag{10}$$

where N_t is the number of funds in the sample in month t, and AUM_{jt} is the assets under management for fund j in month t.

Figure 6.5 plots these weighted correlations from January 1980 to August 2004, using all funds in the TASS Combined database with at least thirty-six consecutive trailing months of nonmissing returns, along with the number of funds each month (at the bottom, measured by the right vertical axis), and the median correlation in the cross-section (in gray).[32] The median correlation is quite different from the asset-weighted correlation in the earlier part of the sample, but as the number of funds increases over time, the behavior of the median becomes closer to that of ρ_t^*.

Figure 6.5 also shows considerable swings in ρ_t^* over time, with dynamics that seem to be related to liquidity events. In particular, consider the fol-

32. The number of funds in the early years is relatively low, reaching a level of fifty or more only in late 1988; therefore the weighted correlations before then may be somewhat less informative.

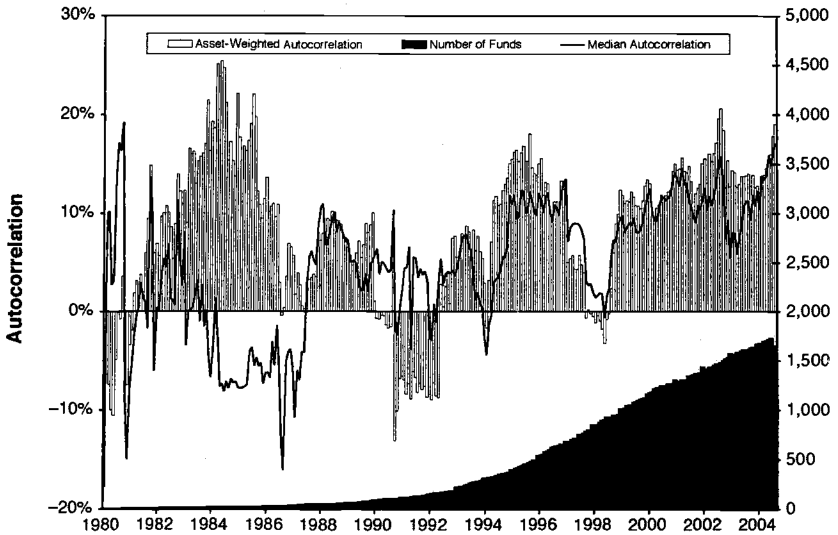


Fig. 6.5 Monthly cross-sectional median and weighted-mean first-order autocorrelation coefficients of individual hedge funds in the TASS Combined hedge-fund database with at least thirty-six consecutive trailing months of returns, from January 1980 to August 2004

lowing events: between November 1980 and July 1982, the S&P 500 dropped 23.8 percent; in October 1987 the S&P 500 fell by 21.8 percent; in 1990, the Japanese "bubble economy" burst; in August 1990, the Persian Gulf War began with Iraq's invasion of Kuwait, ending in January 1991 with Kuwait's liberation by coalition forces; in February 1994, the U.S. Federal Reserve started a tightening cycle that caught many hedge funds by surprise, causing significant dislocation in bond markets worldwide; the end of 1994 witnessed the start of the "Tequila Crisis" in Mexico; in August 1998 Russia defaulted on its government debt; and between August 2000 and September 2002 the S&P 500 fell by 46.3 percent. In each of these cases, the weighted autocorrelation rose in the aftermath, and in most cases abruptly. Of course, the fact that we are using a thirty-six-month rolling window suggests that as outliers drop out of the window, correlations can shift dramatically. However, as a coarse measure of liquidity in the hedge fund sector, the weighted autocorrelation seems to be intuitively appealing and informative.

6.5 Hedge Fund Liquidations

Since the collapse of LTCM in 1998, it has become clear that hedge fund liquidations can be a significant source of systemic risk. In this section, we consider several measures of liquidation probabilities for hedge funds in the TASS database, including a review of hedge fund attrition rates documented in Getmansky, Lo, and Mei (2004) and a logit analysis of hedge fund liquidations in the TASS Graveyard database. By analyzing the factors driving hedge fund liquidations, we may develop a broader understanding of the likely triggers of systemic risk in this sector.

Because of the voluntary nature of inclusion in the TASS database, Graveyard funds do not consist solely of liquidations. TASS gives one of seven distinct reasons for each fund that is assigned to the Graveyard, ranging from "Liquidated" (status code 1) to "Unknown" (status code 9). It may seem reasonable to confine our attention to those Graveyard funds categorized as Liquidated or perhaps to drop those funds that are closed to new investment (status code 4) from our sample. However, because our purpose is to develop a broader perspective on the dynamics of the hedge fund industry, we argue that using the entire Graveyard database may be more informative. For example, by eliminating Graveyard funds that are closed to new investors, we create a downward bias in the performance statistics of the remaining funds. Because we do not have detailed information about each of these funds, we cannot easily determine how any particular selection criterion will affect the statistical properties of the remainder. Therefore, we choose to include the entire set of Graveyard funds in our analysis, but caution readers to keep in mind the composition of this sample when interpreting our empirical results.

For concreteness, table 6.13 reports frequency counts for Graveyard funds in each status code and style category, as well as assets under management at the time of transfer to the Graveyard.[33] These counts show that 1,571 of the 1,765 Graveyard funds, or 89 percent, fall into the first three categories, categories that can plausibly be considered liquidations, and within each of these three categories, the relative frequencies across style categories are roughly comparable, with Long/Short Equity being the most numerous and Dedicated Shortseller being the least numerous. Of the remaining 194 funds with status codes 4–9, only status code 4—funds that are closed to new investors—is distinctly different in character from the other status codes. There are only seven funds in this category, and these funds are all likely to be success stories, providing some counterbalance to the many liquidations in the Graveyard sample. Of course, this is not to say that seven out of 1,765 is a reasonable estimate of the success rate in the hedge fund industry, because we have not included any of the Live funds in this calculation. Nevertheless, these seven funds in the Graveyard sample do underscore the fact that hedge fund data are subject to a variety of biases that do not always point in the same direction, and we prefer to leave

33. Of the 1,765 funds in the Graveyard database, four funds did not have status codes assigned, hence we coded them as 9's ("Unknown"). They are 3882 (Fund of Funds), 34053 (Managed Futures), 34054 (Managed Futures), 34904 (Long/Short Equity).

Table 6.13 **Frequency counts and assets under management (in millions of dollars) of funds in the TASS Graveyard database by Category and Graveyard status code**

Code	All funds	Convertible arbitrage	Dedicated short	Emerging markets	Equity-market neutral	Event driven	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy	Fund of funds
						Frequency count						
1	913	19	7	78	65	50	29	53	257	190	30	135
2	511	21	4	34	12	56	26	29	187	43	7	92
3	147	4	1	7	8	17	3	17	54	18	1	17
4	7	0	0	0	0	1	2	0	3	0	0	1
5	56	2	1	5	0	6	3	6	16	9	1	7
7	2	0	0	0	0	1	0	0	1	0	0	0
9	129	3	2	9	2	3	8	9	14	56	2	21
Total	1,765	49	15	133	87	134	71	114	532	316	41	273
						Assets under management						
1	18,754	1,168	62	1,677	1,656	2,047	1,712	2,615	4,468	975	641	1,732
2	36,366	6,420	300	848	992	7,132	2,245	678	10,164	537	882	6,167
3	4,127	45	34	729	133	1,398	50	115	931	269	2	423
4	487	0	0	0	0	100	31	0	250	0	0	106
5	3,135	12	31	143	0	222	419	1,775	473	33	3	24
7	8	0	0	0	0	6	0	0	2	0	0	0
9	3,052	42	18	222	9	159	152	32	193	1,671	18	538
Total	65,931	7,686	445	3,620	2,789	11,063	4,610	5,215	16,482	3,484	1,546	8,991

Note: Graveyard status code: 1 = fund liquidated; 2 = fund no longer reporting to TASS; 3 = TASS has been unable to contact the manager for updated information; 4 = fund closed to new investment; 5 = fund has merged into another entity; 7 = fund dormant; 9 = unknown assets under management are at the time of transfer into the graveyard database.

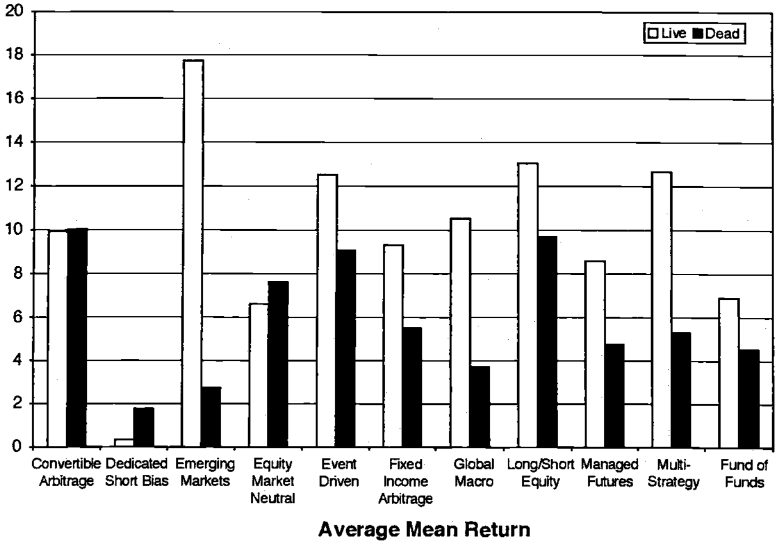
them in so as to reflect these biases as they occur naturally rather than to create new biases of our own. For the remainder of this article, we shall refer to all funds in the TASS Graveyard database as "liquidations" for expositional simplicity.

Figure 6.6 provides a visual comparison of average means, standard deviations, Sharpe ratios, and first-order autocorrelation coefficients ρ_1 in the Live and Graveyard databases (table 6.9 contains basic summary statistics for the funds in the TASS Live, Graveyard, and Combined databases). Not surprisingly, there is a great deal of variation in mean returns and volatilities, both across and within categories and databases. For example, the 127 Convertible Arbitrage funds in the Live database have an average mean return of 9.92 percent and an average standard deviation of 5.51 percent, but in the Graveyard database, the forty-nine Convertible Arbitrage funds have an average mean return of 10.02 percent and a much higher average standard deviation of 8.14 percent. As expected, average volatilities in the Graveyard database are uniformly higher than those in the Live database because the higher-volatility funds are more likely to be eliminated. This effect operates at both ends of the return distribution—funds that are wildly successful are also more likely to leave the database, since they have less motivation to advertise their performance. That the Graveyard database also contains successful funds is supported by the fact that in some categories, the average mean return in the Graveyard database is the same as or higher than in the Live database—for example, Convertible Arbitrage, Equity Market Neutral, and Dedicated Shortseller.

Figure 6.7 displays the histogram of year-to-date returns at the time of liquidation. The fact that the distribution is skewed to the left is consistent with the conventional wisdom that performance is a major factor in determining the fate of a hedge fund. However, note that there is nontrivial weight in the right half of the distribution, suggesting that recent performance is not the only relevant factor.

Finally, figure 6.8 provides a summary of two key characteristics of the Graveyard funds: the age distribution of funds at the time of liquidation, and the distribution of their assets under management. The median age of Graveyard funds is forty-five months, hence half of all liquidated funds never reached their fourth anniversary. The mode of the distribution is 36 months. The median assets under management for funds in the Graveyard database is \$6.3 million, not an uncommon size for the typical startup hedge fund.

In section 6.5.1, we document the attrition rates of funds in the TASS database, both in the aggregate and for each style category. These attrition rates provide crude baseline measures of the likelihood of liquidation for a given fund. To develop a more precise measure that allows for cross-sectional variability in the likelihood of liquidation—as a function of fund characteristics such as assets under management and recent performance—we estimate a logit model for hedge fund liquidations in section 6.5.2.



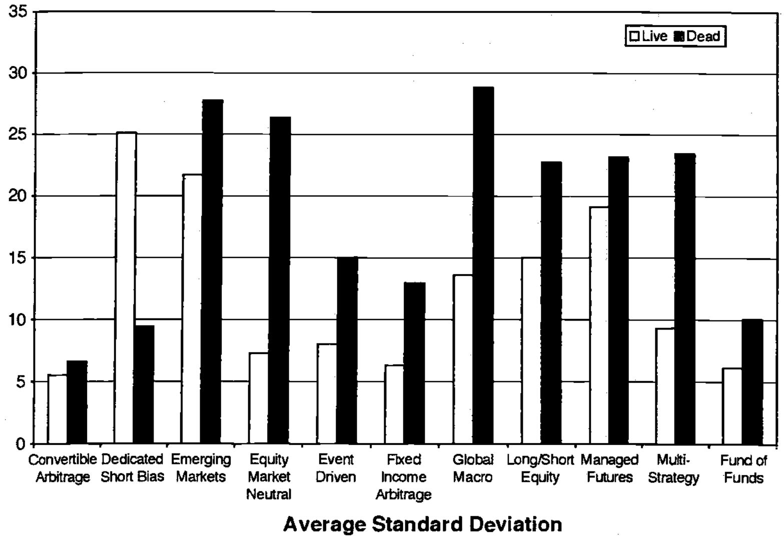


Fig. 6.6 Comparison of average means, standard deviations, Sharpe ratios, and first-order autocorrelation coefficients for categories of funds in the TASS Live and Graveyard databases from January 1994 to August 2004

6.5.1 Attrition Rates

To develop a sense of the dynamics of the TASS database and the birth and death rates of hedge funds over the past decade,[34] in table 6.14 we re-

34. Recall that TASS launched their Graveyard database in 1994, hence this is the beginning of our sample for table 6.14.

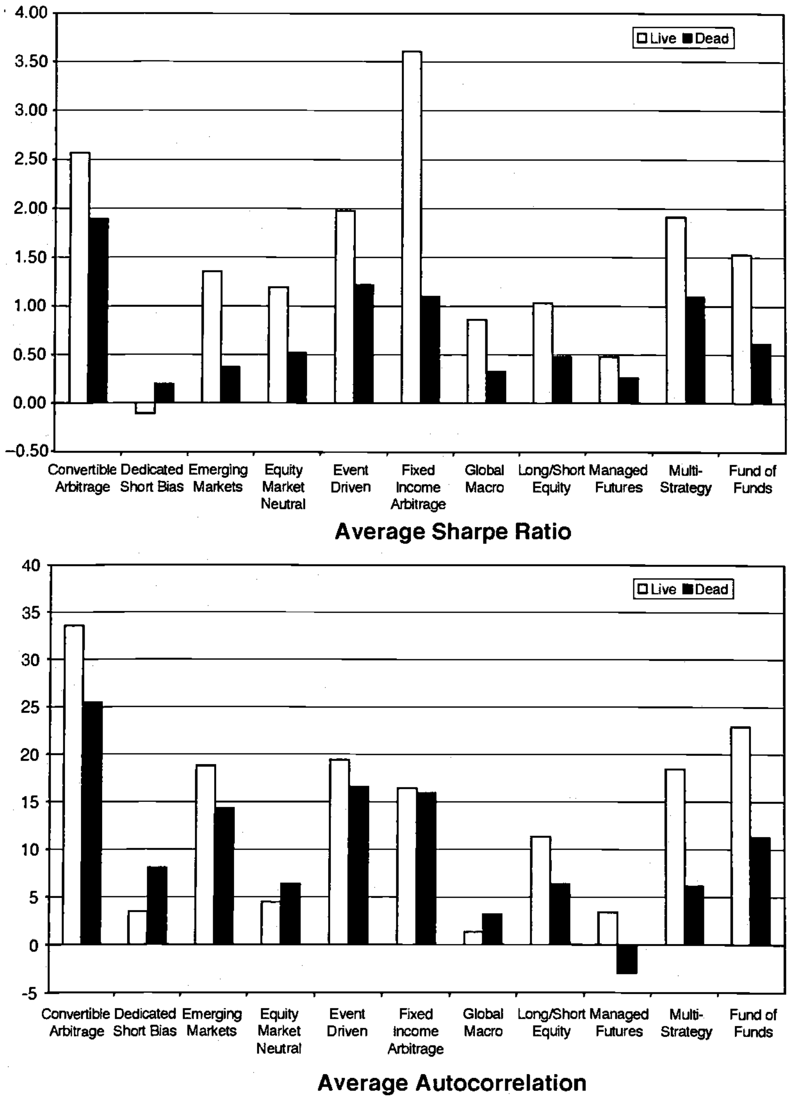


Fig. 6.6 (cont.)

port annual frequency counts of the funds in the database at the start of each year, funds entering the Live database during the year, funds exiting during the year and moving to the Graveyard database, and funds entering and exiting within the year. The panel labelled "All Funds" contains frequency counts for all funds, and the remaining eleven panels contain the same statistics for each category. Also included in table 6.14 are attrition rates, defined as the ratio of funds exiting in a given year to the number of

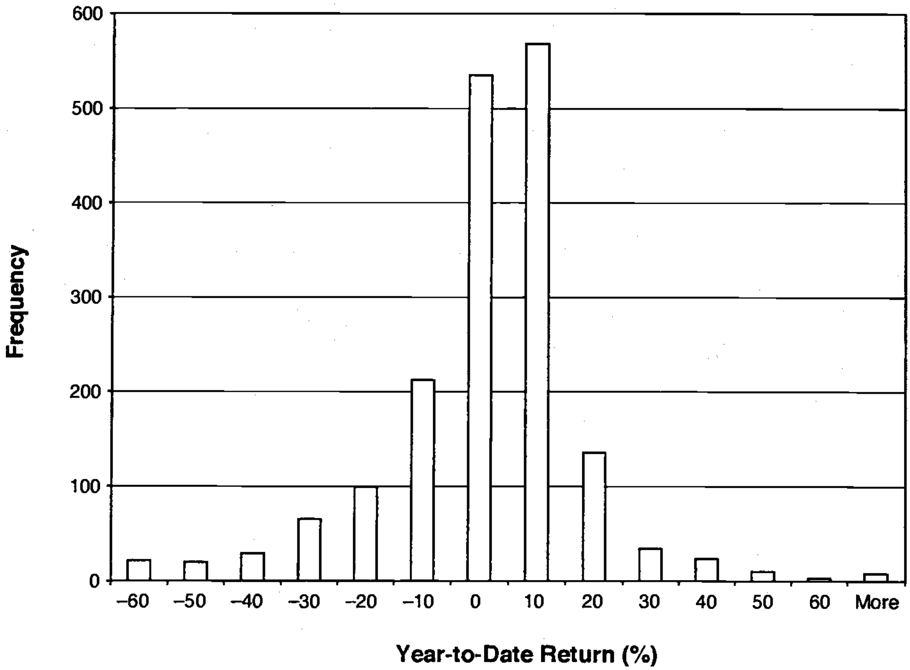


Fig. 6.7 Histogram of year-to-date return at the time of liquidation of hedge funds in the TASS Graveyard database, January 1994 to August 2004

existing funds at the start of the year, and the performance of the category as measured by the annual compound return of the CSFB/Tremont Index for that category.

For the unfiltered sample of all funds in the TASS database, and over the sample period from 1994 to 2003, the average attrition rate is 8.8 percent.[35] This is similar to the 8.5 percent attrition rate obtained by Liang (2001) for the 1994-to-1999 sample period. The aggregate attrition rate rises in 1998, partly due to LTCM's demise and the dislocation caused by its aftermath. The attrition rate increases to a peak of 11.4 percent in 2001, mostly due to

35. We do not include 2004 in this average because TASS typically waits eight to ten months before moving a nonreporting fund from the Live to the Graveyard database. Therefore, the attrition rate is severely downward biased for 2004, since the year is not yet complete, and many nonreporting funds in the Live database have not yet been classified as Graveyard funds (we use the TASS database from February 1997 to August 2004). Also, note that there is only 1 new fund in 2004—this figure is grossly downward biased as well. Hedge funds often go through an "incubation period" where managers trade with limited resources to develop a track record. If successful, the manager will provide the return stream to a database vendor like TASS, and the vendor usually enters the entire track record into the database, providing the fund with an "instant history." According to Fung and Hsieh (2000), the average incubation period—from a fund's inception to its entry into the TASS database—is one year.

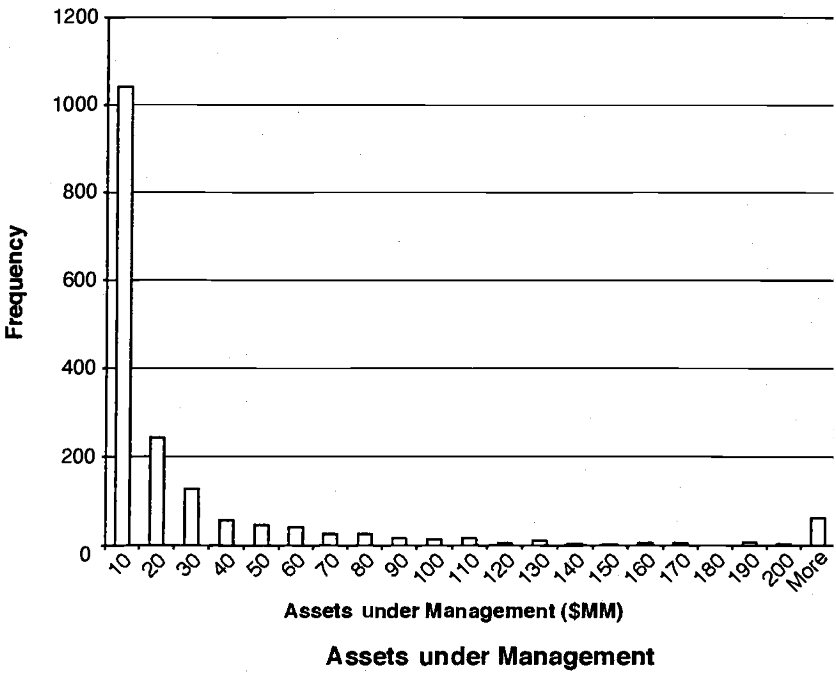


Fig. 6.8 Histograms of age distribution and assets under management at the time of liquidation for funds in the TASS Graveyard database, January 1994 to August 2004

Table 6.14 **Attrition rates for all hedge funds in the TASS hedge fund database, and within each style category, from January 1994 to August 2004**

Year	Existing funds	New entries	New exits	Intra-year entry and exit	Total funds	Attrition rate (%)	Index return (%)	Existing funds	New entries	New exits	Intra-year entry and exit	Total funds	Attrition rate (%)	Index return (%)	Existing funds	New entries	New exits	Intra-year entry and exit	Total funds	Attrition rate (%)	Index return (%)
	All funds							*Equity-markets neutral*							*Long/Short equity*						
1994	769	251	23	2	997	3.0	–4.4	12	7	1	0	18	8.3	–2.0	168	52	2	0	218	1.2	–8.1
1995	997	299	61	1	1,235	6.1	21.7	18	10	0	0	28	0.0	11.0	218	74	7	0	285	3.2	23.0
1996	1,235	332	120	9	1,447	9.7	22.2	28	10	0	0	38	0.0	16.6	285	116	21	2	380	7.4	17.1
1997	1,447	356	100	6	1,703	6.9	25.9	38	14	0	0	52	0.0	14.8	380	118	15	2	483	3.9	21.5
1998	1,703	346	162	9	1,887	9.5	–0.4	52	29	2	2	79	3.8	13.3	483	117	33	2	567	6.8	17.2
1999	1,887	403	183	7	2,107	9.7	23.4	79	36	14	1	101	17.7	15.3	567	159	42	3	684	7.4	47.2
2000	2,107	391	234	9	2,264	11.1	4.8	101	17	13	0	105	12.9	15.0	684	186	55	5	815	8.0	2.1
2001	2,264	460	257	6	2,467	11.4	4.4	105	49	9	0	145	8.6	9.3	815	156	109	3	862	13.4	–3.7
2002	2,467	432	246	9	2,653	10.0	3.0	145	41	14	2	172	9.7	7.4	862	137	107	5	892	12.4	–1.6
2003	2,653	325	285	12	2,693	10.7	15.5	172	23	32	0	163	18.6	7.1	892	83	110	2	865	12.3	17.3
2004	2,693	1	87	1	2,607	3.2	2.7	163	0	5	0	158	3.1	4.7	865	0	27	0	838	3.1	1.5
	Convertible arbitrage							*Event driven*							*Managed futures*						
1994	26	13	0	0	39	0.0	–8.1	71	16	0	0	87	0.0	0.7	181	52	8	1	225	4.4	11.9
1995	39	12	0	0	51	0.0	16.6	87	27	1	0	113	1.1	18.4	225	41	30	0	236	13.3	–7.1
1996	51	14	7	0	58	13.7	17.9	113	29	3	0	139	2.7	23.0	236	42	49	2	229	20.8	12.0
1997	58	10	3	0	65	5.2	14.5	139	31	3	0	167	2.2	20.0	229	37	36	1	230	15.7	3.1
1998	65	14	5	0	74	7.7	–4.4	167	28	2	1	193	1.2	–4.9	230	25	37	0	218	16.1	20.7
1999	74	10	3	0	81	4.1	16.0	193	29	19	1	203	9.8	22.3	218	35	40	1	213	18.3	–4.7
2000	81	17	3	0	95	3.7	25.6	203	38	15	0	226	7.4	7.2	213	13	35	0	191	16.4	4.3
2001	95	25	5	0	115	5.3	14.6	226	34	19	3	241	8.4	11.5	191	18	19	0	190	9.9	1.9
2002	115	22	6	0	131	5.2	4.0	241	40	30	2	251	12.4	0.2	190	22	32	0	180	16.8	18.3
2003	131	11	10	0	132	7.6	12.9	251	21	23	1	249	9.2	20.0	180	23	21	2	182	11.7	14.2
2004	132	0	10	0	122	7.6	0.6	249	0	15	0	234	6.0	5.7	182	0	5	0	177	2.7	–7.0

	Dedicated shortseller							*Fixed income arbitrage*							*Multistrategy*						
1994	11	1	0	0	12	0.0	14.9	22	16	3	0	35	13.6	0.3	17	5	3	1	19	17.6	
1995	12	0	1	0	11	8.3	–7.4	35	12	2	0	45	5.7	12.5	19	7	2	0	24	10.5	11.9
1996	11	3	1	0	13	9.1	–5.5	45	16	4	0	57	8.9	15.9	24	14	1	0	37	4.2	14.0
1997	13	3	1	0	15	7.7	0.4	57	15	4	1	68	7.0	9.4	37	13	3	0	47	8.1	18.3
1998	15	1	0	0	16	0.0	–6.0	68	16	14	0	70	20.6	–8.2	47	8	5	1	50	10.6	7.7
1999	16	4	1	0	19	6.3	–14.2	70	13	8	0	75	11.4	12.1	50	10	2	0	58	4.0	9.4
2000	19	2	1	0	20	5.3	15.8	75	9	11	0	73	14.7	6.3	58	10	2	1	66	3.4	11.2
2001	20	1	6	0	15	30.0	–3.6	73	20	7	0	86	9.6	8.0	66	16	1	0	81	1.5	5.5
2002	15	1	1	0	15	6.7	18.2	86	23	5	0	104	5.8	5.7	81	14	5	0	90	6.2	6.3
2003	15	1	1	0	15	6.7	–32.6	104	12	9	0	107	8.7	8.0	90	14	14	4	90	15.6	15.0
2004	15	0	2	0	13	13.3	9.1	107	0	4	0	103	3.7	4.7	90	0	0	0	90	0.0	2.8
	Emerging markets							*Global macro*							*Fund of funds*						
1994	44	25	0	0	69	0.0	12.5	50	11	3	0	58	6.0	–5.7	167	53	3	0	217	1.8	
1995	69	34	1	0	102	1.4	–16.9	58	19	5	0	72	8.6	30.7	217	63	12	1	268	5.5	
1996	102	25	4	0	123	3.9	34.5	72	16	13	4	75	18.1	25.6	268	47	17	1	298	6.3	
1997	123	40	8	0	155	6.5	26.6	75	19	6	1	88	8.0	37.1	298	56	21	1	333	7.0	
1998	155	22	25	1	152	16.1	–37.7	88	20	7	2	101	8.0	–3.6	333	66	32	0	367	9.6	
1999	152	26	18	0	160	11.8	44.8	101	12	15	1	98	14.9	5.8	367	69	21	0	415	5.7	
2000	160	20	25	2	155	15.6	–5.5	98	18	33	0	83	33.7	11.7	415	61	41	1	435	9.9	
2001	155	5	28	0	132	18.1	5.8	83	15	9	0	89	10.8	18.4	435	121	45	0	511	10.3	
2002	132	4	11	0	125	8.3	7.4	89	26	9	0	106	10.1	14.7	511	102	26	0	587	5.1	
2003	125	12	13	1	124	10.4	28.7	106	15	8	1	113	7.5	18.0	587	110	44	1	653	7.5	
2004	124	0	1	0	123	0.8	3.1	113	0	1	0	112	0.9	4.4	653	1	17	1	637	2.6	

Note: Index returns are annual compound returns of the CSFB/Tremont hedge fund indexes. Attrition rates for 2004 are severely downward-biased because TASS typically waits 8 to 10 months before moving a nonreporting fund from the Live to the Graveyard database; therefore, as of August 2004, many nonreporting funds in the Live database have not yet been moved to the Graveyard.

the Long/Short Equity category—presumably the result of the bursting of the technology bubble.

Although 8.8 percent is the average attrition rate for the entire TASS database, there is considerable variation in average attrition rates across categories. Averaging the annual attrition rates from 1994–2003 within each category yields the following:

Convertible Arbitrage:	5.2%	Global Macro:	12.6%
Dedicated Shortseller:	8.0%	Long/Short Equity:	7.6%
Emerging Markets:	9.2%	Managed Futures:	14.4%
Equity Market Neutral:	8.0%	Multi-Strategy:	8.2%
Event Driven:	5.4%	Fund of Funds:	6.9%
Fixed Income Arbitrage:	10.6%		

These averages illustrate the different risks involved in each of the eleven investment styles. At 5.2 percent, Convertible Arbitrage enjoys the lowest average attrition rate, which is not surprising since this category has the second-lowest average return volatility of 5.89 percent (see table 6.9). The highest average attrition rate is 14.4 percent for Managed Futures, which is also consistent with the 18.55 percent average volatility of this category, the highest among all eleven categories.

Within each category, the year-to-year attrition rates exhibit different patterns, partly attributable to the relative performance of the categories. For example, Emerging Markets experienced a 16.1 percent attrition rate in 1998, no doubt because of the turmoil in emerging markets in 1997 and 1998, which is reflected in the –37.7 percent return in the CSFB/Tremont Emerging Markets Index for 1998. The opposite pattern is also present—during periods of unusually good performance, attrition rates decline, as in the case of Long/Short Equity from 1995 to 2000, when attrition rates were 3.2 percent, 7.4 percent, 3.9 percent, 6.8 percent, 7.4 percent, and 8.0 percent, respectively. Of course, in the three years following the bursting of the technology bubble—2001 to 2003—the attrition rates for Long/Short Equity shot up to 13.4 percent, 12.4 percent, and 12.3 percent, respectively. These patterns are consistent with the basic economic of the hedge fund industry: good performance begets more assets under management, greater business leverage, and staying power; poor performance leads to the Graveyard.

To develop a better sense of the relative magnitudes of attrition across categories, table 6.15 and figure 6.9 (panel A) provide a decomposition by category, where the attrition rates in each category are renormalized so that when they are summed across categories in a given year, the result equals the aggregate attrition rate for that year. From these renormalized figures, it is apparent that there is an increase in the proportion of the total attrition rate due to Long/Short Equity funds beginning in 2001. In fact, table 6.15 shows that of the total attrition rates of 11.4 percent, 10.0 per-

Table 6.15 **Decomposition of attribution rates by category for all hedge funds in the TASS hedge fund database from January 1994 to August 2004, and corresponding CSFB/Tremont hedge fund index returns and assets under management**

Year	All funds	Convertible arbitrage	Dedicated short	Emerging markets	Equity-market neutral	Event driven	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy	Fund of funds
					Total attrition rates and components by category (In percent)							
1994	3.0	0.0	0.0	0.0	0.1	0.0	0.4	0.4	0.3	1.0	0.4	0.4
1995	6.1	0.0	0.1	0.1	0.0	0.1	0.2	0.5	0.7	3.0	0.2	1.2
1996	9.7	0.6	0.1	0.3	0.0	0.2	0.3	1.1	1.7	4.0	0.1	1.4
1997	6.9	0.2	0.1	0.6	0.0	0.2	0.3	0.4	1.0	2.5	0.2	1.5
1998	9.5	0.3	0.0	1.5	0.1	0.1	0.8	0.4	1.9	2.2	0.3	1.9
1999	9.7	0.2	0.1	1.0	0.7	1.0	0.4	0.8	2.2	2.1	0.1	1.1
2000	11.1	0.1	0.0	1.2	0.6	0.7	0.5	1.6	2.6	1.7	0.1	1.9
2001	11.4	0.2	0.3	1.2	0.4	0.8	0.3	0.4	4.8	0.8	0.0	2.0
2002	10.0	0.2	0.0	0.4	0.6	1.2	0.2	0.4	4.3	1.3	0.2	1.1
2003	10.7	0.4	0.0	0.5	1.2	0.9	0.3	0.3	4.1	0.8	0.5	1.7
2004	3.2	0.4	0.1	0.0	0.2	0.6	0.1	0.0	1.0	0.2	0.0	0.6
Mean	8.8	0.2	0.1	0.7	0.4	0.5	0.4	0.6	2.4	1.9	0.2	1.4
Standard deviation	2.7	0.2	0.1	0.5	0.4	0.4	0.2	0.4	1.6	1.0	0.2	0.5
					Annual returns of CSFB/Tremont hedge fund indexes by category (In percent)							
1994	–4.4	–8.1	14.9	12.5	–2.0	0.7	0.3	–5.7	–8.1	11.9		
1995	21.7	16.6	–7.4	–16.9	11.0	18.4	12.5	30.7	23.0	–7.1	11.9	
1996	22.2	17.9	–5.5	34.5	16.6	23.0	15.9	25.6	17.1	12.0	14.0	
1997	25.9	14.5	0.4	26.6	14.8	20.0	9.4	37.1	21.5	3.1	18.3	
1998	–0.4	–4.4	–6.0	–37.7	13.3	–4.9	–8.2	–3.6	17.2	20.7	7.7	
1999	23.4	16.0	–14.2	44.8	15.3	22.3	12.1	5.8	47.2	–4.7	9.4	
2000	4.8	25.6	15.8	–5.5	15.0	7.2	6.3	11.7	2.1	4.3	11.2	
2001	4.4	14.6	–3.6	5.8	9.3	11.5	8.0	18.4	–3.7	1.9	5.5	

continued

Table 6.15 (continued)

Year	All funds	Convertible arbitrage	Dedicated short	Emerging markets	Equity-market neutral	Event driven	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy	Fund of funds
2002	3.0	4.0	18.2	7.4	7.4	0.2	5.7	14.7	–1.6	18.3	6.3	
2003	15.5	12.9	–32.6	28.7	7.1	20.0	8.0	18.0	17.3	14.2	15.0	
2004	2.7	0.6	9.1	3.1	4.7	5.7	4.7	4.4	1.5	–7.0	2.8	
Mean	11.6	11.0	–2.0	10.0	10.8	11.8	7.0	15.3	13.2	7.5	11.0	
Standard deviations	11.3	10.5	15.5	25.2	5.6	10.4	6.8	13.9	16.5	9.4	4.3	
	Total assets under management (ln $MM) and percent breakdown by category (ln percent)											
1994	57,684	3.8	0.7	9.3	1.0	9.5	3.9	20.5	20.7	5.1	7.5	18.0
1995	69,477	3.9	0.5	8.1	1.3	10.0	4.7	18.5	22.9	4.0	9.2	17.0
1996	92,513	4.2	0.4	8.7	2.3	10.1	5.9	17.9	23.4	3.2	7.8	16.1
1997	137,814	4.7	0.4	8.9	2.7	10.4	6.7	18.8	21.9	2.7	7.5	15.3
1998	142,669	5.5	0.6	4.0	4.4	12.5	5.7	16.8	24.4	3.3	6.8	16.0
1999	175,223	5.3	0.6	4.6	5.2	11.7	4.6	9.1	34.5	2.8	6.6	15.1
2000	197,120	5.4	0.5	2.5	5.5	10.6	3.3	1.9	31.1	1.9	4.4	12.7
2001	246,695	8.1	0.3	2.8	7.4	13.9	4.7	2.3	35.3	3.0	5.5	16.6
2002	277,695	8.5	0.3	3.1	7.2	13.0	6.2	3.1	30.2	3.9	6.1	18.4
2003	389,965	8.8	0.1	4.3	6.0	13.0	6.2	5.4	25.7	5.0	5.8	19.7
2004	403,974	8.8	0.2	4.2	5.9	13.5	7.1	6.6	26.3	5.3	6.8	15.3
Mean	178,685	5.8	0.5	5.6	4.3	11.5	5.2	11.4	27.0	3.5	6.7	16.5
Standard deviation	103,484	1.9	0.2	2.8	2.4	1.5	1.1	7.8	5.3	1.0	1.4	2.0

Note: Attrition rates for 2004 are severely downward biased, because TASS typically waits eight to ten months before moving a nonreporting fund from the Live to the Graveyard database; therefore, as of August 2004, many nonreporting funds in the Live database have not yet been moved to the Graveyard. Consequently, the reported means and standard deviations in all three panels are computed over the 1994–2003 period.

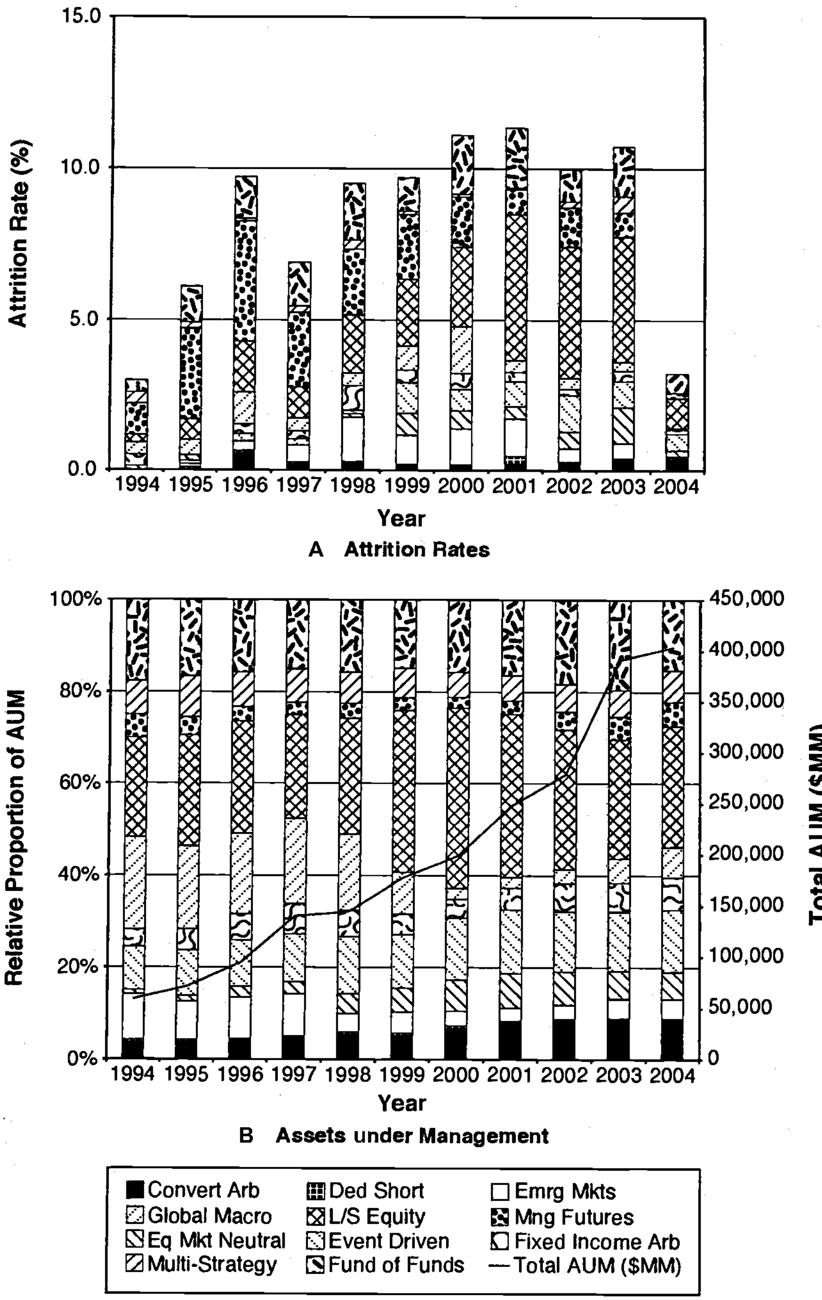


Fig. 6.9 Attrition rates and total assets under management for funds in the TASS Live and Graveyard database from January 1994 to August 2004.

Note: The data for 2004 is incomplete, and attrition rates for this year are severely downward biased because of an eight- to ten-month lag in transferring nonreporting funds from the Live to the Graveyard database.

cent, and 10.7 percent in years 2001–2003, the Long/Short Equity category was responsible for 4.8, 4.3, and 4.1 percentage points of those totals, respectively. Despite the fact that the average attrition rate for the Long/Short Equity category is only 7.6 percent from 1994 to 2003, the funds in this category are more numerous; hence they contribute more to the aggregate attrition rate. Figure 9 (panel B) provides a measure of the impact of these attrition rates on the industry by plotting the total assets under management of funds in the TASS database along with the relative proportions in each category. Long/Short Equity funds are indeed a significant fraction of the industry, hence the increase in their attrition rates in recent years may be cause for some concern.

6.5.2 Logit Analysis of Liquidations

To estimate the influence of various hedge-fund characteristics on the likelihood of liquidation, in this section we report the results of a logit analysis of liquidations in the TASS database. Logit can be viewed as a generalization of the linear regression model to situations where the dependent variable takes on only a finite number of discrete values (see, for example, Maddala 1983 for details).

To estimate the logit model of liquidation, we use the same sample of TASS Live and Graveyard funds as in section 6.5.1: 4,536 funds from February 1977 to August 2004, of which 1,765 are in the Graveyard database and 2,771 are in the Live database. As discussed in sections 6.3.2 and 6.5.1, the Graveyard database was initiated only in January 1994, hence this will be the start date of our sample for purposes of estimating the logit model of liquidation. For tractability, we focus on annual observations only, so the dependent variable Z_{it} indicates whether fund i is live or liquidated in year t.[36] See table 6.8 for a frequency count of the funds entering and exiting the TASS database in each year. Over the sample period from January 1994 to August 2004, we have 23,925 distinct observations for Z_{it}, and after filtering out funds that do not have at least two years of history, we are left with 12,895 observations.

Associated with each Z_{it} is a set of explanatory variables listed in table 6.16. The motivation for AGE, ASSETS, and RETURN are well-known—older funds, funds with greater assets, and funds with better recent performance are all less likely to be liquidated, hence we would expect negative coefficients for these explanatory variables (recall that a larger conditional

36. Note that a fund cannot die more than once, hence liquidation occurs exactly once for each fund i in the Graveyard database. In particular, the time series observations of funds in the Graveyard database will always be (0,0, . . . , 0,1). This suggests that a more appropriate statistical technique for modeling hedge fund liquidations is survival analysis, which we plan to pursue in a future study. However, for purposes of summarizing the impact of certain explanatory variables on the probability of hedge fund liquidations, logit analysis is a reasonable choice.

Table 6.16 Definition of explanatory variables in logit analysis of hedge fund liquidations in the TASS database from January 1994 to August 2004

Variable	Definition
AGE	The current age of the fund (in months).
ASSETS	The natural logarithm of current total assets under management.
ASSETS_{-1}	The natural logarithm of total assets under management as of December 31 of the previous year.
RETURN	Current year-to-date total return.
RETURN_{-1}	Total return last year.
RETURN_{-2}	Total return two years ago.
FLOW	Fund's current year-to-date total dollar inflow divided by previous year's assets under management, where dollar inflow in month τ is defined as $\text{FLOW}_\tau \equiv \text{AUM}_\tau - \text{AUM}_{\tau-1}(1 + R_\tau)$ and AUM_τ is the total assets under management at the beginning of month τ, R_τ is the fund's net return for month τ, and year-to-date total dollar inflow is simply the cumulative sum of monthly inflows since January of the current year.
FLOW_{-1}	Previous year's total dollar inflow divided by assets under management the year before.
FLOW_{-2}	Total dollar inflow two years ago divided by assets under management the year before.

mean for Z^* implies a higher probability that $Z_{it} = 1$ or liquidation). The FLOW variable is motivated by the well-known "return-chasing" phenomenon, in which investors flock to funds that have had good recent performance, and leave funds that have underperformed (see, for example, Chevalier and Ellison 1997; Sirri and Tufano 1998; and Agarwal, Daniel, and Naik 2004).

Table 6.17 contains summary statistics for these explanatory variables as well as for the dependent variable Z_{it}. Note that the sample mean of Z_{it} is 0.09, which may be viewed as an unconditional estimate of the probability of liquidation, and is consistent with the attrition rate of 8.8 percent reported in section 6.5.1.[37] The objective of performing a logit analysis of Z_{it} is, of course, to estimate the *conditional* probability of liquidation, conditional on the explanatory variables in table 6.16.

The correlation matrix for Z_{it} and the explanatory variables are given in table 6.18. As expected, Z_{it} is negatively correlated with age, assets under management, cumulative return, and fund flows, with correlations ranging from –26.2 percent for AGE to –5.8 percent for RETURN_{-2}. Table 6.18 also shows that the assets under management variable is highly persistent, with a correlation of 94.3 percent between its contemporaneous and lagged values. To avoid multicollinearity problems, we include only the lagged

37. A slight discrepancy should be expected, since the selection criterion for the sample of funds in this section is not identical to that of section 6.5.1 (e.g., funds in the logit sample must have nonmissing observations for the explanatory variables in table 6.16).

Table 6.17 **Summary statistics for dependent and explanatory variables of a logit analysis of hedge fund liquidations in the TASS database from 1994 to 2004**

Variable	Mean	SD	Skewness	Kurtosis	Min.	10%	25%	50%	75%	90%	Max.
Z	0.09	0.28	2.88	6.32	0.00	0.00	0.00	0.00	0.00	0.00	1.00
AGE	108.20	48.94	1.02	1.50	27	52	72	101	135	175	331
ASSETS	17.25	1.88	–0.33	0.32	7.67	14.82	16.06	17.34	18.53	19.58	23.01
ASSETS_{-1}	17.20	1.79	–0.29	0.29	8.11	14.87	16.07	17.28	18.42	19.42	23.01
RETURN	0.09	0.24	2.81	30.81	–0.96	–0.12	–0.01	0.06	0.16	0.31	4.55
RETURN_{-1}	0.12	0.26	2.83	28.24	–1.00	–0.11	0.01	0.10	0.20	0.37	4.55
RETURN_{-2}	0.13	0.32	22.37	1,340.37	–0.95	–0.10	0.01	0.10	0.22	0.38	20.85
FLOW	0.84	66.32	112.48	12,724.87	–1.98	–0.39	–0.16	0.00	0.21	0.71	7,505.99
FLOW_{-1}	1.07	67.34	108.00	11,978.17	–3.15	–0.38	–0.15	0.00	0.30	1.01	7,505.99
FLOW_{-2}	0.85	15.82	74.41	5,857.91	–3.15	–0.33	–0.11	0.02	0.46	1.55	1,323.53

Notes: The dependent variable Z takes on the value 1 in the year a hedge fund is liquidated, and is 0 in all prior years. The units of measurement for the explanatory variables are: months for AGE, the natural logarithm of millions of dollars for ASSETS, and raw ratios (not percentages) for RETURN and FLOW.

Table 6.18 **Correlation matrix of dependent and explanatory variables of a logit analysis of hedge fund liquidations in the TASS database from 1994 to 2004**

Variable	Z	AGE	ASSETS	$ASSETS_{-1}$	RETURN	$RETURN_{-1}$	$RETURN_{-2}$	FLOW	$FLOW_{-1}$	$FLOW_{-2}$
Z	100.0	–26.2	–21.4	–17.3	–20.4	–14.6	–5.8	–13.0	–11.6	–6.8
AGE	–26.2	100.0	13.8	13.2	15.9	8.5	5.5	–3.8	–9.7	–21.4
ASSETS	–21.4	13.8	100.0	94.3	15.0	17.8	15.2	27.6	28.9	22.1
$ASSETS_{-1}$	–17.3	13.2	94.3	100.0	1.4	11.1	14.0	2.6	23.8	22.1
RETURN	–20.4	15.9	15.0	1.4	100.0	4.2	8.9	16.3	–0.7	1.0
$RETURN_{-1}$	–14.6	8.5	17.8	11.1	4.2	100.0	3.3	29.2	16.6	–2.9
$RETURN_{-2}$	–5.8	5.5	15.2	14.0	8.9	3.3	100.0	7.4	29.1	17.0
FLOW	–13.0	–3.8	27.6	2.6	16.3	29.2	7.4	100.0	28.7	9.0
$FLOW_{-1}$	–11.6	–9.7	28.9	23.8	–0.7	16.6	29.1	28.7	100.0	28.6
$FLOW_{-2}$	–6.8	–21.4	22.1	22.1	1.0	–2.9	17.0	9.0	28.6	100.0

Note: The dependent variable Z takes on the value 1 in the year a hedge fund is liquidated, and is 0 in all prior years.

variable ASSETS_{-1} in our logit analysis, yielding the following final specification, which we call Model 1:

$$(11)\quad Z_{it} = G(\beta_0 + \beta_1\text{AGE}_{it} + \beta_2\text{ASSETS}_{it-1} + \beta_3\text{RETURN}_{it} + \beta_4\text{RETURN}_{it-1} + \beta_5\text{RETURN}_{it-2} + \beta_6\text{FLOW}_{it} + \beta_7\text{FLOW}_{it-1} + \beta_8\text{FLOW}_{it-2} + \varepsilon_{it}).$$

Table 6.19 contains maximum-likelihood estimates of equation (11) in the first three columns, with statistically significant parameters in bold. Note that most of the parameter estimates are highly significant. This is due to the unusually large sample size, which typically yields statistically significant estimates because of the small standard errors implied by large samples (recall that the standard errors of consistent and asymptotically normal estimators converge to 0 at a rate of $1/\sqrt{n}$ where n is the sample size). This suggests that we may wish to impose a higher threshold of statistical significance in this case, so as to provide a better balance between Type I and Type II errors.[38]

The negative signs of all the coefficients other than the constant term confirm our intuition that age, assets under management, cumulative return, and fund flows all have a negative impact on the probability of liquidation. The fact that RETURN_{-2} is not statistically significant suggests that the most recent returns have the highest degree of relevance for hedge fund liquidations, a possible indication of the short-term, performance-driven nature of the hedge fund industry. The R^2 of this regression is 29.3 percent, which implies a reasonable level of explanatory power for this simple specification.[39]

To address fixed effects associated with the calendar year and hedge fund style category, in Model 2 we include indicator variables for ten out of eleven calendar years, and ten out of eleven hedge fund categories, yielding the following specification:

$$(12)\quad Z_{it} = G\left[\beta_0 + \sum_{k=1}^{10}\zeta_k I(\text{YEAR}_{k,i,t}) + \sum_{k=1}^{10}\xi_k I(\text{CAT}_{k,i,t}) + \beta_1\text{AGE}_{it} + \beta_2\text{ASSETS}_{it-1} + \beta_3\text{RETURN}_{it} + \beta_4\text{RETURN}_{it-1} + \beta_5\text{RETURN}_{it-2} + \beta_6\text{FLOW}_{it} + \beta_7\text{FLOW}_{it-1} + \beta_8\text{FLOW}_{it-2} + \varepsilon_{it}\right]$$

38. See Leamer (1978) for further discussion of this phenomenon, known as "Lindley's Paradox."

39. This R^2 is the adjusted generalized coefficient of determination proposed by Nagelkerke (1991), which renormalizes the Cox and Snell's (1989) R^2 measure by its maximum (which is less than unity) so that it spans the entire unit interval. See Nagelkerke (1991) for further discussion.

Table 6.19 **Maximum likelihood estimates of a logit model for hedge fund liquidations using annual observations of liquidation status from the TASS database from January 1994 to August 2004**

	Model 1			Model 2			Model 3			Model 4			Model 5		
Variable	β	SE(β)	*p*-value (%)	β	SE(β)	*p*-value (%)	β	SE(β)	*p*-value (%)	β	SE(β)	*p*-value (%)	β	SE(β)	*p*-value (%)
Sample size		**12,895**			**12,895**			**12,895**			**12,846**			**12,310**	
R^2 (%)		**29.3**			**34.2**			**34.2**			**34.5**			**35.4**	
Constant	**4.73**	**0.34**	**<.01**	**2.31**	**0.41**	**<.01**	**–5.62**	**0.18**	**<.01**	**–5.67**	**0.18**	**<.01**	**–7.04**	**0.26**	**<.01**
AGE	**–0.03**	**0.00**	**<.01**	**–0.03**	**0.00**	**<.01**	**–1.62**	**0.07**	**<.01**	**–1.66**	**0.07**	**<.01**	**–2.08**	**0.10**	**<.01**
ASSETS_{-1}	**–0.26**	**0.02**	**<.01**	**–0.19**	**0.02**	**<.01**	**–0.34**	**0.04**	**<.01**	**–0.36**	**0.04**	**<.01**	**–0.38**	**0.06**	**<.01**
RETURN	**–2.81**	**0.19**	**<.01**	**–2.86**	**0.20**	**<.01**	**–0.67**	**0.05**	**<.01**	**–0.67**	**0.05**	**<.01**	**–0.61**	**0.06**	**<.01**
RETURN_{-1}	**–1.39**	**0.16**	**<.01**	**–1.40**	**0.17**	**<.01**	**–0.36**	**0.04**	**<.01**	**–0.36**	**0.04**	**<.01**	**–0.44**	**0.06**	**<.01**
RETURN_{-2}	–0.04	0.09	67.5	**–0.38**	**0.14**	**0.7**	**–0.12**	**0.04**	**0.7**	**–0.12**	**0.05**	**1.1**	**–0.17**	**0.07**	**1.3**
FLOW	**–0.63**	**0.08**	**<.01**	**–0.49**	**0.07**	**<.01**	**–32.72**	**4.91**	**<.01**	**–33.27**	**5.04**	**<.01**	**–32.93**	**6.74**	**<.01**
FLOW_{-1}	**–0.13**	**0.04**	**0.0**	**–0.11**	**0.03**	**0.1**	**–7.53**	**2.33**	**0.1**	**–7.60**	**2.37**	**0.1**	**–19.26**	**4.71**	**<.01**
FLOW_{-2}	**–0.09**	**0.02**	**<.01**	**–0.11**	**0.02**	**<.01**	**–1.74**	**0.36**	**<.01**	**–1.64**	**0.36**	**<.01**	**–1.83**	**0.51**	**0.0**
I(1994)				**0.79**	**0.38**	**3.9**	**0.79**	**0.38**	**3.9**	**0.82**	**0.39**	**3.4**	1.01	0.54	5.9
I(1995)				**1.24**	**0.27**	**<.01**	**1.24**	**0.27**	**<.01**	**1.18**	**0.28**	**<.01**	**1.37**	**0.37**	**0.0**
I(1996)				**1.83**	**0.20**	**<.01**	**1.83**	**0.20**	**<.01**	**1.83**	**0.21**	**<.01**	**1.92**	**0.28**	**<.01**
I(1997)				**1.53**	**0.21**	**<.01**	**1.53**	**0.21**	**<.01**	**1.52**	**0.21**	**<.01**	**2.03**	**0.27**	**<.01**
I(1998)				**1.81**	**0.18**	**<.01**	**1.81**	**0.18**	**<.01**	**1.80**	**0.19**	**<.01**	**2.29**	**0.24**	**<.01**
I(1999)				**2.10**	**0.18**	**<.01**	**2.10**	**0.18**	**<.01**	**2.05**	**0.18**	**<.01**	**2.25**	**0.24**	**<.01**
I(2000)				**2.25**	**0.17**	**<.01**	**2.25**	**0.17**	**<.01**	**2.19**	**0.17**	**<.01**	**2.08**	**0.24**	**<.01**
I(2001)				**1.97**	**0.17**	**<.01**	**1.97**	**0.17**	**<.01**	**1.96**	**0.17**	**<.01**	**1.80**	**0.25**	**<.01**
I(2002)				**1.46**	**0.16**	**<.01**	**1.46**	**0.16**	**<.01**	**1.41**	**0.16**	**<.01**	**1.50**	**0.22**	**<.01**
I(2003)				**1.55**	**0.16**	**<.01**	**1.55**	**0.16**	**<.01**	**1.53**	**0.16**	**<.01**	**1.71**	**0.22**	**<.01**
I(ConvertArb)				**0.44**	**0.20**	**2.9**	**0.44**	**0.20**	**2.9**	**0.43**	**0.20**	**3.4**	0.16	0.34	62.5
I(DedShort)				0.05	0.37	88.9	0.05	0.37	88.9	–0.03	0.39	94.3	0.20	0.49	68.0
I(EmrgMkt)				0.25	0.15	10.2	0.25	0.15	10.2	0.24	0.15	11.7	**0.54**	**0.20**	**0.7**
I(EqMktNeut)				0.12	0.20	54.7	0.12	0.20	54.7	0.15	0.20	46.7	**0.53**	**0.25**	**3.4**
I(EventDr)				**0.33**	**0.15**	**3.0**	**0.33**	**0.15**	**3.0**	**0.31**	**0.15**	**4.7**	–0.01	0.24	97.4
I(FixedInc)				**0.50**	**0.19**	**1.1**	**0.50**	**0.19**	**1.1**	**0.45**	**0.20**	**2.3**	0.33	0.30	26.8
I(GlobMac)				0.32	0.18	7.4	0.32	0.18	7.4	0.24	0.18	20.2	0.33	0.25	17.9
I(LongShortEq)				0.18	0.11	10.2	0.18	0.11	10.2	0.15	0.11	16.6	0.14	0.15	36.4
I(MgFut)				**0.49**	**0.12**	**<.01**	**0.49**	**0.12**	**<.01**	**0.49**	**0.13**	**0.0**	**0.71**	**0.16**	**<.01**
I(Multistrat)				0.17	0.25	49.4	0.17	0.25	49.4	0.18	0.25	48.5	**0.85**	**0.29**	**0.3**

Note: The dependent variable Z takes on the value 1 in the year a hedge fund is liquidated, and is zero in all prior years.

where

$$(13a) \qquad I(\text{YEAR}_{k,i,t}) \equiv \begin{cases} 1 \text{ if } t = k \\ 0 \text{ otherwise} \end{cases}$$

$$(13b) \qquad I(\text{CAT}_{k,i,t}) \equiv \begin{cases} 1 \text{ if fund } i \text{ is in Category } k \\ 0 \text{ otherwise} \end{cases}$$

The columns labelled "Model 2" in table 6.19 contain the maximum-likelihood estimates of equation (12) for the same sample of funds as Model 1. The coefficients for AGE, ASSETS, and RETURN exhibit the same qualitative properties as in Model 1, but the fixed-effect variables do provide some additional explanatory power, yielding an R^2 of 34.2 percent. In particular, the coefficients for the 1999 and 2000 indicator variables are higher than those of the other year indicators, a manifestation of the impact of August 1998 and the collapse of LTCM and other fixed-income, relative-value hedge funds. The impact of the LTCM collapse can also be seen from the coefficients of the category indicators—at 0.50, Fixed-Income Relative Value has the largest estimate among all ten categories. Managed Futures has a comparable coefficient of 0.49, which is consistent with the higher volatility of such funds and the fact that this category exhibits the highest attrition rate, 14.4 percent, during the 1994–2003 sample period (see section 6.5.1). However, the fact that Convertible Arbitrage and Event-Driven categories are the next largest, with coefficients of 0.44 and 0.33, respectively, is somewhat surprising given their unusually low attrition rates of 5.2 percent and 5.4 percent, respectively, reported in section 6.5.1. This suggests that the conditional probabilities produced by a logit analysis—which control for assets under management, fund flows, and performance—yields information not readily available from the unconditional frequency counts of simple attrition statistics. The remaining category indicators are statistically insignificant at the 5 percent level.

To facilitate comparisons across explanatory variables, we standardize each of the nonindicator explanatory variables by subtracting its mean and dividing by its standard deviation and then reestimating the parameters of equation (12) via maximum likelihood. This procedure yields estimates that are renormalized to standard deviation units of each explanatory variable, and are contained in the columns labelled "Model 3" of table 6.19. The renormalized estimates show that fund flows are an order of magnitude more important in determining the probability of liquidation than assets under management, returns, or age, with normalized coefficients of –32.72 and –7.53 for FLOW and FLOW_{-1}, respectively.

Finally, we reestimate the logit model (12) for two subsets of funds using standardized explanatory variables. In Model 4, we omit Graveyard funds that have either merged with other funds or are closed to new investments (status codes 4 and 5), yielding a subsample of 12,846 observations. In Model 5, we omit all Graveyard funds except those that have liquidated (status code 1), yielding a subsample of 12,310 observations. The last two sets of columns in table 6.19 show that the qualitative features of most of the estimates are unchanged, with the funds in Model 5 exhibiting somewhat higher sensitivity to the lagged FLOW variable. However, the category fixed-effects in Model 5 does differ in some ways from those of Models 2–4, with significant coefficients for Emerging Markets, Equity Market Neutral, and Multi-Strategy, as well as for Managed Futures. This suggests that there are significant differences between the full Graveyard sample and the subsample of funds with status code 1, and bears further study.

Because of the inherent nonlinearity of the logit model, the coefficients of the explanatory variables cannot be as easily interpreted as in the linear regression model. One way to remedy this situation is to compute the estimated probability of liquidation implied by the parameter estimates $\hat{\boldsymbol{\beta}}$ and specific values for the explanatory variables, which is readily accomplished by observing that:

$$p_{it} \equiv \text{Prob}(Z_{it} = 1) = \text{Prob}(Z^*_{it} > 0) \tag{14a}$$

$$= \text{Prob}(\mathbf{X}'_{it}\boldsymbol{\beta} + \varepsilon_{it} > 0 = \frac{\exp(\mathbf{X}'_{it}\boldsymbol{\beta})}{1 + \exp(\mathbf{X}'_{it}\boldsymbol{\beta})} \tag{14b}$$

$$\hat{p}_{it} = \frac{\exp(\mathbf{X}'_{it}\hat{\boldsymbol{\beta}})}{1 + \exp(\mathbf{X}'_{it}\hat{\boldsymbol{\beta}})}. \tag{14c}$$

Table 6.20 reports year-by-year summary statistics for the estimated liquidation probabilities ($\hat{p}_{it}$) of each fund in our sample, where each $\hat{p}_{it}$ is computed using values of the explanatory variables in year t. The left panel of table 6.20 contains summary statistics for estimated liquidation probabilities from Model 1, and the right panel contains corresponding figures from Model 5. We have also stratified the estimated liquidation probabilities by their liquidation status—Live funds in the top panel, Graveyard funds in the middle panel, and the Combined sample of funds in the bottom panel.[40]

For both Models 1 and 5, the mean and median liquidation probabilities are higher for Graveyard funds than for Live funds, a reassuring sign that the explanatory variables are indeed providing explanatory power for the liquidation process. For Model 1, the Combined sample shows an increase in the mean and median liquidation probabilities in 1998 as expected, and another increase in 2001, presumably due to the bursting of the technology

40. Note that the usage of "Graveyard funds" in this context is somewhat different, involving a time dimension as well as liquidation status. For example, in this context the set of Graveyard funds in 1999 refers to only those funds that liquidated in 1999, and does not include liquidations before or after 1999.

Table 6.20 **Year-by-year summary statistics for the probabilities of liquidation implied by the parameter estimates of two specifications of a logit model for hedge fund liquidations using annual observations of the liquidation status of individual hedge funds in the TASS database from January 1994 to August 2004**

	Model 1											Model 5										
Statistic	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Live funds																						
Mean	4.19	5.47	5.84	5.04	6.32	5.17	5.59	6.84	8.92	7.11	11.04	1.06	2.22	4.30	3.43	4.70	4.05	3.80	3.40	4.07	4.45	1.76
SD	7.49	9.33	11.15	9.74	9.66	8.61	8.15	9.23	10.15	8.00	10.91	3.28	6.01	10.97	8.70	9.51	8.87	7.72	6.76	6.58	6.33	2.70
Min.	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10%	0.13	0.19	0.19	0.18	0.31	0.20	0.35	0.44	0.68	0.41	0.89	0.00	0.01	0.02	0.02	0.06	0.04	0.07	0.07	0.09	0.07	0.03
25%	0.43	0.51	0.52	0.56	0.99	0.79	1.10	1.39	2.05	1.45	2.66	0.02	0.04	0.09	0.10	0.27	0.23	0.33	0.33	0.44	0.43	0.15
50%	1.16	1.46	1.52	1.59	2.71	2.18	2.80	3.69	5.62	4.49	7.55	0.07	0.16	0.36	0.45	1.03	0.96	1.18	1.26	1.74	2.04	0.72
75%	4.21	6.03	5.11	4.83	7.20	5.55	6.54	8.39	12.01	10.22	16.31	0.52	1.25	2.61	2.26	4.03	3.22	3.49	3.63	4.75	6.01	2.31
90%	12.13	16.17	16.85	13.27	16.76	12.80	13.78	16.23	21.61	17.26	26.33	2.61	5.85	11.24	9.12	14.21	10.09	9.88	8.10	10.52	12.03	4.71
Max.	52.49	58.30	72.97	90.06	77.63	87.06	75.83	92.36	79.02	92.44	79.96	35.62	42.56	76.54	86.91	77.72	80.45	75.95	91.82	73.06	81.10	29.28
Count	357	483	629	773	924	1,083	1,207	1,317	1,480	1,595	1,898	357	483	629	773	924	1,083	1,207	1,317	1,480	1,595	1,898
Graveyard funds																						
Mean	36.59	32.85	31.89	39.75	30.64	27.68	22.78	28.17	25.22	21.55	17.01	24.23	23.50	34.07	42.30	36.17	31.46	32.55	22.82	20.68	20.18	4.60
SD	24.46	22.77	18.86	22.70	21.67	19.24	17.67	20.03	18.22	15.91	14.30	24.12	20.12	25.19	26.95	25.12	21.96	22.47	19.84	18.94	16.27	6.20
Min.	4.91	2.50	1.05	0.25	0.00	0.53	0.22	0.98	0.13	0.02	0.25	1.00	4.92	1.88	1.49	0.00	0.11	0.02	0.51	0.03	0.03	0.04
10%	6.08	8.39	10.63	9.29	6.86	4.98	2.41	5.94	5.50	2.64	2.26	5.31	5.53	5.25	8.61	4.49	2.12	3.95	2.00	2.61	3.02	0.13
25%	22.06	16.28	17.47	21.81	12.13	12.84	9.14	12.07	10.58	8.32	6.43	11.79	7.99	11.28	21.29	15.56	12.66	15.91	6.43	5.29	6.42	0.97
50%	32.82	28.53	27.44	39.78	25.20	24.03	19.81	23.28	21.50	19.18	13.35	18.02	17.66	33.94	37.54	28.92	30.16	27.57	19.11	14.32	14.03	3.16
75%	48.40	49.79	43.36	56.94	46.21	39.62	34.92	41.01	37.98	32.28	25.26	26.24	32.58	54.36	64.53	60.14	46.31	48.38	33.10	33.19	30.61	5.51
90%	71.63	58.62	60.08	71.13	61.74	50.75	45.84	58.90	48.81	45.42	34.67	48.95	51.10	68.87	80.97	69.54	64.68	61.91	55.75	46.84	43.06	10.17
Max.	77.37	97.42	79.51	88.70	85.41	84.87	87.89	78.68	94.65	72.29	67.10	64.10	69.64	82.29	93.17	87.67	89.00	90.90	76.34	90.02	67.86	33.31
Count	10	27	73	62	104	129	176	175	167	158	68	5	14	41	46	68	64	68	58	76	89	35
Combined funds																						
Mean	5.07	6.92	8.55	7.61	8.78	7.56	7.77	9.35	10.57	8.42	11.24	1.38	2.82	6.12	5.62	6.85	5.58	5.33	4.22	4.88	5.29	1.81
SD	9.86	12.10	14.53	14.44	13.59	12.39	11.41	13.01	12.26	9.90	11.10	4.94	7.62	14.21	13.84	13.79	11.85	11.17	8.68	8.44	8.01	2.82
Min.	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10%	0.14	0.20	0.22	0.20	0.38	0.22	0.39	0.53	0.77	0.43	0.93	0.00	0.01	0.02	0.03	0.06	0.05	0.07	0.07	0.09	0.08	0.03
25%	0.45	0.55	0.62	0.62	1.10	0.91	1.20	1.62	2.28	1.60	2.72	0.02	0.04	0.10	0.11	0.30	0.24	0.35	0.35	0.48	0.49	0.15
50%	1.23	1.72	1.84	1.88	3.34	2.63	3.35	4.49	6.31	4.97	7.69	0.08	0.19	0.43	0.54	1.24	1.06	1.32	1.42	1.93	2.28	0.73
75%	4.89	7.67	8.96	6.25	9.81	7.92	9.03	11.28	13.94	11.74	16.46	0.56	1.38	3.58	3.02	5.57	4.27	4.40	4.15	5.36	6.63	2.36
90%	14.96	20.53	27.36	22.94	25.11	21.39	20.97	24.21	25.98	21.48	26.97	3.06	7.02	19.05	16.84	22.27	17.07	15.37	9.65	12.50	13.79	4.85
Max.	77.37	97.42	79.51	90.06	85.41	87.06	87.89	92.36	94.65	92.44	79.96	64.10	69.64	82.29	93.17	87.67	89.00	90.90	91.82	90.02	81.10	33.31
Count	367	510	702	835	1,028	1,212	1,383	1,492	1,647	1,753	1,966	362	497	670	819	992	1,147	1,275	1,375	1,556	1,684	1,933

bubble in U.S. equity markets. Most troubling from the perspective of systemic risk, however, is the fact that the mean and median liquidation probabilities for 2004 (which only includes data up to August) are 11.24 percent and 7.69 percent, respectively, the highest levels in our entire sample. This may be a symptom of the enormous growth that the hedge fund industry has enjoyed in recent years, which increases both the number of funds entering and exiting the industry, but may also indicate more challenging market conditions for hedge funds in the coming months. Note that the mean and median liquidation probabilities for Model 5 do not show the same increase in 2004—this is another manifestation of the time lag with which the Graveyard database is updated (recall that Model 5 includes only those funds with status code 1, but a large number of funds that eventually receive this classification have not yet reached their eight- to ten-month limit by August 2004). Therefore, Model 1's estimated liquidation probabilities are likely to be more accurate for the current year.[41]

The logit estimates and implied probabilities suggest that a number of factors influence the likelihood of a hedge fund's liquidation, including past performance, assets under management, fund flows, and age. Given these factors, our estimates imply that the average liquidation probability for funds in 2004 is over 11 percent, which is higher than the historical unconditional attrition rate of 8.8 percent. To the extent that a series of correlated liquidations stresses the capital reserves of financial counterparties, this is yet another indirect measure of an increase in systemic risk from the hedge fund industry.

6.6 Other Hedge Fund Measures of Systemic Risk

In addition to measures of liquidity exposure, there are several other hedge fund related metrics for gauging the degree of systemic risk exposure in the economy. In this section, we propose three alternatives: (1) risk models for hedge funds; (2) regressions of banking sector indexes on hedge fund and other risk factors; and (3) a regime-switching model for hedge fund indexes. We describe these alternatives in more detail in sections 6.6.1–6.6.3.

6.6.1 Risk Models for Hedge Funds

As the examples in section 6.1 illustrate, hedge fund returns may exhibit a number of 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; that is, different beta coefficients for down-markets versus up-markets. Specifically, consider the following regression:

41. The TASS reporting delay affects Model 1 as well, suggesting that its estimated liquidation probabilities for 2004 are biased downward as well.

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

where

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

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 (15), the case where $\beta_i^+ = \beta_i^-$. However, the estimates reported in table 6.21 for the CSFB/Tremont hedge fund index returns show that beta asymmetries can be quite pronounced for certain hedge fund styles. For example, the Distressed index has an up-market beta of 0.04—seemingly market neutral—however, its down-market beta is 0.43! For the Managed Futures index, the asymmetries are even more pronounced: the coefficients are of opposite sign, with a beta of 0.05 in up markets and a beta of –0.41 in down markets. These asymmetries are to be expected for certain nonlinear investment strategies, particularly those that have option-like characteristics such as the short-put strategy of Capital Decimation Partners (see section 6.1.1). 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.

In this section, we estimate risk models for each of the CSFB/Tremont hedge fund indexes as a "proof-of-concept" for developing more sophisticated risk analytics for hedge funds. With better risk models in hand, the systemic risk posed by hedge funds will be that much clearer. Of course, a more ambitious approach is to estimate risk models for each hedge fund and then aggregate risks accordingly, and for nonlinear risk models, a disaggregated approach may well yield additional insights not apparent from index-based risk models. However, this is beyond the scope of this study, and we focus our attention instead on the risk characteristics of the indexes.

We begin with a comprehensive set of risk factors that will be candidates for each of the risk models, covering stocks, bonds, currencies, commodities, and volatility. These factors are described in table 6.22, and their basic statistical properties have been summarized in table 6.4. Given the heterogeneity of investment strategies represented by the hedge-fund industry, the variables in table 6.22 are likely to be the smallest set of risk factors capable of spanning the risk exposures of most hedge funds.

Table 6.23 is a joint correlation matrix of the risk factors and the hedge fund indexes. Note that we have also included squared and cubed S&P 500

Table 6.21 **Regressions of monthly CSFB/Tremont hedge fund index returns on the S&P 500 index return, and on positive and negative S&P 500 index returns, from January 1994 to August 2004**

Category	α	$t(\alpha)$	β	$t(\beta)$	R^2 (%)	p-value (%)	α	$t(\alpha)$	β^+	$t(\beta^+)$	β^-	$t(\beta^-)$	R^2 (%)	p-value (%)
Hedge funds	0.74	3.60	0.24	5.48	21.0	0.0	1.14	3.22	0.14	1.58	0.34	3.95	22.4	0.0
Convertible arbitrage	0.83	6.31	0.03	1.17	1.2	23.8	1.00	4.37	–0.01	–0.18	0.08	1.36	1.9	33.2
Dedicated shortseller	0.70	2.12	–0.86	–12.26	57.2	0.0	0.23	0.41	–0.74	–5.33	–0.98	–7.01	57.6	0.0
Emerging markets	0.13	0.31	0.52	5.68	22.3	0.0	1.06	1.43	0.28	1.57	0.76	4.18	23.9	0.0
Equity-market neutral	0.80	10.23	0.08	4.57	15.6	0.0	0.67	4.95	0.11	3.34	0.04	1.26	16.7	0.0
Event driven	0.71	5.06	0.20	6.86	29.5	0.0	1.35	5.84	0.04	0.68	0.37	6.54	36.1	0.0
Distressed	0.84	5.16	0.23	6.72	28.6	0.0	1.58	5.86	0.04	0.65	0.43	6.42	35.2	0.0
Event driven multistrategy	0.64	4.09	0.19	5.59	21.7	0.0	1.25	4.76	0.03	0.46	0.34	5.34	27.0	0.0
Risk arbitrage	0.55	4.96	0.13	5.30	20.0	0.0	0.87	4.56	0.04	0.96	0.21	4.46	22.9	0.0
Fixed income arbitrage	0.59	5.57	0.00	–0.13	0.0	89.3	0.95	5.26	–0.10	–2.15	0.09	2.02	5.0	5.4
Global macro	1.14	3.53	0.16	2.27	4.4	2.4	1.48	2.64	0.07	0.50	0.25	1.78	4.8	5.9
Long/Short equity	0.67	2.66	0.39	7.40	32.7	0.0	0.92	2.12	0.33	3.11	0.46	4.32	33.0	0.0
Managed futures	0.80	2.40	–0.17	–2.47	5.1	1.4	–0.09	–0.15	0.05	0.38	–0.41	–2.90	8.1	0.8
Multistrategy	0.77	6.11	0.02	0.60	0.3	54.7	0.86	3.91	–0.01	–0.11	0.04	0.71	0.5	74.2

Table 6.22 **Correlation matrix for monthly returns of hedge fund risk factors from January 1994 to August 2004**

Correlation matrix	S&P 500	S&P 500^2	S&P 500^3	Banks	Libor	USD	Oil	Gold	Lehman bond	Large minus small cap	Value minus growth	Credit spread	Term spread	VIX
S&P 500	100.0													
S&P 500^2	–12.3	100.0												
S&P 500^3	77.1	–43.3	100.0											
Banks	55.8	–33.0	59.1	100.0										
LIBOR	3.5	–19.4	12.7	–16.9	100.0									
USD	7.3	–4.6	4.5	–1.2	8.9	100.0								
Oil	–1.6	–15.1	–1.7	–2.0	14.0	–13.4	100.0							
Gold	–7.2	–7.8	–2.6	6.1	–12.2	–35.2	20.1	100.0						
Lehman Bond	0.8	15.2	–8.9	7.5	–42.1	–55.6	7.0	25.7	100.0					
Large minus small cap	7.6	21.8	–0.6	–27.6	3.8	11.0	–19.7	–24.5	8.1	100.0				
Value minus growth	–48.9	14.4	–30.3	–5.4	–2.1	–4.0	–21.3	–3.9	10.9	32.7	100.0			
Credit spread	–30.6	30.1	–19.8	–16.0	–40.2	–13.0	–2.9	16.4	14.3	–7.2	16.5	100.0		
Term spread	–11.6	–6.1	–0.2	11.5	4.9	–21.5	7.0	20.4	–10.5	–13.7	2.6	38.7	100.0	
VIX	–67.3	26.2	–67.8	–49.6	–8.2	–9.2	–1.5	–3.4	15.3	9.7	38.5	3.1	–6.9	100.0
CSFB/Tremont indexes														
Hedge funds	45.9	–22.5	38.2	41.6	–0.2	22.0	7.9	8.9	3.6	–29.6	–41.0	–24.4	–8.1	–25.7
Convertible arbitrage	11.0	–19.1	29.4	29.8	–9.0	19.6	–4.3	2.1	2.2	–19.6	–6.2	–6.4	–15.2	–0.2
Dedicated shortseller	–75.6	20.1	–66.4	–52.1	4.0	–4.4	–9.2	–9.8	7.5	34.9	64.5	11.9	–10.5	57.2
Emerging markets	47.2	–24.6	50.1	43.8	5.6	19.4	0.7	7.7	–17.7	–27.2	–34.2	–9.9	16.2	–36.6
Equity-market neutral	39.6	3.2	34.5	30.9	–9.4	9.1	4.8	–6.8	7.3	1.4	–12.6	–12.6	–29.2	–17.1
Event driven	54.3	–44.8	67.8	65.4	–0.9	14.6	6.9	8.2	–7.6	–32.4	–30.7	–24.8	–3.6	–44.4
Distressed	53.5	–43.4	62.8	64.3	–10.7	9.7	5.2	13.5	–0.3	–26.7	–27.8	–21.6	–1.2	–43.9
Event driven multistrategy	46.6	–39.7	62.1	56.2	8.4	20.0	7.7	1.2	–14.6	–33.0	–29.9	–23.0	–3.4	–37.6
Risk arbitrage	44.7	–32.5	53.4	55.7	7.0	4.9	2.6	7.4	–6.4	–42.0	–22.0	–29.9	–20.5	–42.2
Fixed income arbitrage	–1.3	–29.2	5.9	18.8	6.9	18.5	9.4	0.9	2.0	–10.3	1.9	–17.6	3.5	16.9
Global macro	20.9	–10.8	14.4	28.5	–5.7	28.7	–4.0	–2.3	7.4	–8.8	–6.6	–11.2	–4.7	–5.3
Long/Short equity	57.2	–20.2	47.2	40.5	–4.3	–2.1	19.5	14.2	7.0	–48.9	–67.1	–22.9	–13.1	–36.2
Managed futures	–22.6	22.4	–32.2	–14.3	–13.0	–19.9	17.5	15.9	35.4	4.6	21.9	17.9	2.0	25.7
Multistrategy	5.6	–4.1	2.2	10.5	0.9	–13.3	5.6	–1.7	12.5	–8.8	–13.5	–18.9	–7.8	9.5

returns in the correlation matrix; they will be included as factors to capture nonlinear effects.[42] It is apparent from the lower left block of the correlation matrix that there are indeed nontrivial correlations between the risk factors and the hedge fund indexes. For example, there is a 67.8 percent correlation between the Event Driven index and the cubed S&P 500 return, implying skewness effects in this category of strategies. Also, the Long/Short Equity index has correlations of –48.9 percent and –67.1 with the

42. We have divided the squared and cubed S&P 500 return series by 10 and 100, respectively, so as to yield regression coefficients of comparable magnitudes to the other coefficients.

Hedge funds	Convertible arbitrage	Dedicated shortseller	Emerging markets	Equity-market neutral	Event driven	Distressed	Event driven multi-strategy	Risk arbitrage	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy
100.0													
38.4	100.0												
–46.5	–21.7	100.0											
65.7	32.0	–57.0	100.0										
31.8	29.9	–34.9	24.2	100.0									
66.0	59.2	–63.1	66.6	39.8	100.0								
56.3	50.8	–62.7	57.7	36.2	93.6	100.0							
68.9	60.3	–53.9	67.2	37.6	93.0	74.8	100.0						
39.0	41.4	–49.1	44.2	31.9	70.1	58.4	66.9	100.0					
41.2	54.4	–5.3	28.2	7.0	37.4	28.1	43.4	14.1	100.0				
85.4	27.1	–10.6	41.6	19.1	36.8	29.3	42.6	12.4	41.8	100.0			
77.4	24.1	–71.8	58.8	33.9	65.0	56.9	63.6	51.0	17.2	40.3	100.0		
10.5	–21.5	24.5	–13.1	13.8	–23.4	–16.1	–26.8	–25.3	–6.9	26.6	–6.4	100.0	
15.0	33.5	–4.4	–3.9	20.1	14.9	10.0	18.8	4.2	27.5	10.8	13.4	–4.1	100.0

market-cap and equity-style factors, respectively, which is not surprising given the nature of this category.

Using a combination of statistical methods and empirical judgment, we use these factors to estimate risk models for each of the fourteen indexes, and the results are contained in table 6.24. The first row reports the sample size, the second contains the adjusted R^2, and the remaining rows contain regression coefficients and, in parentheses, t-statistics. The number of factors selected for each risk model varies from a minimum of four for Equity Market Neutral and Managed Futures to a maximum of thirteen for Event Driven, not including the constant term. This pattern is plausible because

Table 6.23 Definitions of aggregate measures of market conditions and risk factors

Variable	Definition
S&P 500	Monthly return of the S&P 500 index, including dividends
Banks	Monthly return of equal-weighted portfolio of bank stocks in CRSP (SIC codes 6000–6199 and 6710)
LIBOR	Monthly first-difference in U.S. dollar 6-month London interbank offer rate
USD	Monthly return on U.S. Dollar Spot Index
Oil	Monthly return on NYMEX crude oil front-month futures contract
Gold	Monthly return on gold spot price index
Lehman bond	Monthly return on Dow Jones/Lehman Bond Index
Large-cap minus small-cap	Monthly return difference between Dow Jones large-cap and small-cap indexes
Value minus growth	Monthly return difference between Dow Jones value and growth indexes
Credit spread	Beginning-of-month difference between KDP High Yield Daily Index and U.S. 10-year yield
Term spread	Beginning-of-month 10-year U.S. dollar swap rate minus 6-month U.S. dollar LIBOR
VIX	Monthly first-difference in the VIX implied volatility index

the Event Driven category includes a broad set of strategies; that is, various types of "events," hence a broader array of risk factors will be needed to capture the variation in this category versus Equity Market Neutral.

The statistical significance of squared and cubed S&P 500 returns highlights the presence of nonlinearities in a number of indexes as well as in the overall hedge fund index. Together with the S&P 500 return, these higher-order terms comprise a simple polynomial approximation to a nonlinear functional relation between certain hedge fund returns and the market. The squared term may be viewed as a proxy for volatility dependence, and the cubed term as a proxy for skewness dependence. These are, of course, very crude approximations for such phenomena, because the underlying strategies may not involve market exposure—a fixed-income arbitrage fund may well have nonlinear risk exposures but the nonlinearities are more likely to involve interest rate variables than equity market indexes. However, strategies such as Equity Market Neutral, Risk Arbitrage, and Long/Short Equity, which purposefully exploit tail risk in equity markets, do show significant exposure to higher-order S&P 500 terms as expected.

The last column of table 6.24 reports the number of times each risk factor is included in a particular risk model, and this provides an indication of systemic risk exposures in the hedge fund sector. In particular, if we discover a single factor that is included and significant in all hedge fund risk models, such a factor may be a bellwether for broad dislocation in the industry. But apart from the constant term, there is no such factor. Nevertheless, the first lag of the squared S&P 500 return and the cubed S&P 500

Table 6.24 **Risk models for monthly CSFB/Tremont hedge fund index returns from January 1994 to August 2004**

Regressor	Hedge funds	Convertible arbitrage	Dedicated shortseller	Emerging markets	Equity-market neutral	Event driven	Distressed	Event driven multistrategy	Risk arbitrage	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy	Factor selection count
Sample size	118	118	118	118	118	118	118	118	118	118	118	118	118	117	
R^2 (%)	54.5	45.1	79.7	44.1	25.5	75.1	65.0	66.4	58.0	54.3	34.3	73.2	21.4	16.3	
Constant	0.30	0.08	1.90	–0.58	0.98	0.29	0.94	0.75	1.14	0.06	0.31	1.09	0.19	0.58	14
	(1.22)	(0.22)	(4.25)	(–0.81)	(7.00)	(0.84)	(4.65)	(4.93)	(7.34)	(0.20)	(0.78)	(3.35)	(0.59)	(3.97)	
SP500	0.23		–0.63	0.44			0.13					0.28			5
	(5.81)		(–7.11)	(3.29)			(3.17)					(4.29)			
SP500(Lag 1)						0.06	0.06			–0.05					3
						(2.39)	(1.82)			(–1.80)					
S&P500^2					0.07		–0.10			–0.06					3
					(2.49)		(–2.03)			(–2.08)					
SP500^2(Lag 1)	–0.12		–0.14	–0.30		–0.12	–0.09	–0.10	–0.06		–0.16	–0.09		0.09	10
	(–2.12)		(–1.60)	(–2.44)		(–3.70)	(–2.09)	(–2.68)	(–1.89)		(–1.76)	(–1.74)		(2.07)	
SP500^3		0.21	–0.24	0.44	0.07	0.26	0.21	0.32	0.15			0.15	–0.26		10
		(5.92)	(–2.49)	(2.82)	(2.80)	(8.22)	(3.63)	(12.00)	(5.57)			(2.10)	(–3.15)		
SP500^3(Lag 1)		0.15	–0.15					0.08	0.05	0.19			–0.17	0.08	7
		(5.21)	(–2.27)					(2.31)	(2.32)	(5.82)			(–2.09)	(2.36)	
SP500^3(Lag 2)	0.09	0.13								0.12	0.15			0.14	5
	(1.74)	(4.34)								(4.79)	(1.75)			(4.39)	
Banks					0.06	0.10			0.07	0.10	0.24				5
					(2.47)	(2.94)			(2.65)	(3.76)	(3.43)				
Banks(Lag 1)	0.08					0.07	0.08	0.07		–0.06					5
	(1.85)					(2.16)	(1.80)	(2.19)		(–2.14)					
Banks(Lag 2)	0.09					0.05	0.07			0.05	0.18	0.10			6
	(1.71)					(1.98)	(2.05)			(1.78)	(2.04)	(2.33)			

continued

Table 6.24 (continued)

Regressor	Hedge funds	Convertible arbitrage	Dedicated shortseller	Emerging markets	Equity-market neutral	Event driven	Distressed	Event driven multistrategy	Risk arbitrage	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy	Factor selection count
USD	0.42	0.13		0.65		0.15	0.11	0.21		0.11	0.68			–0.15	9
	(4.86)	(2.21)		(3.74)		(3.00)	(2.06)	(3.95)		(2.97)	(4.85)			(–2.78)	
Gold	0.08			0.17		0.05	0.08							–0.05	5
	(1.62)			(1.50)		(2.14)	(2.33)							(–1.39)	
Lehman Bond	0.59	0.18				0.13		0.22		0.24	0.98	0.38	0.79		8
	(3.77)	(1.56)				(1.32)		(2.16)		(3.17)	(3.69)	(2.82)	(3.08)		
Large minus small cap	–0.19	–0.07	0.34	–0.40		–0.10	–0.11	–0.17	–0.13			–0.36			9
	(–4.30)	(–2.98)	(5.55)	(–4.35)		(–3.98)	(–3.89)	(–6.69)	(–6.24)			(–8.38)			
Value minus growth	–0.08		0.23			–0.04				–0.03	–0.08	–0.21	0.08	–0.05	8
	(–2.09)		(4.59)			(–2.29)				(–2.10)	(–1.71)	(–5.76)	(1.47)	(–2.35)	
LIBOR		–1.09	2.26				–2.02								3
		(–1.93)	(2.16)				(–3.55)								
Credit spread		0.20				0.14				0.09					3
		(2.26)				(1.68)				(1.42)					
Term spread		–0.20	–0.65	0.89	–0.24	–0.20			–0.31			–0.38			7
		(–1.99)	(–3.26)	(2.66)	(–3.86)	(–2.14)			(–4.51)			(–2.69)			
VIX		0.08		0.22						0.07		0.12			4
		(2.37)		(1.69)						(2.80)		(2.11)			
No. of factors selected	10	10	8	8	4	13	11	7	6	12	7	9	4	6	

return appear in ten out of fourteen risk models, implying that time-varying volatility, tail risk, and skewness are major risk factors across many different hedge fund styles. Close runners-up are the U.S. dollar index and the market-capitalization factors, appearing in nine of fourteen risk models. Liquidity exposure, as measured by either the lagged S&P 500 return (see Asness, Krail, and Liew 2001, and Getmansky, Lo, and Makarov 2004), or the credit spread factor, is significant for some indexes, such as Convertible Arbitrage, Event Driven, and Fixed-Income Arbitrage, but apparently does not affect other indexes.

The $\bar{R}^2$'s for these risk models vary, ranging from 16.3 percent for Fund of Funds to 79.7 percent for Dedicated Shortsellers. Given the relatively small sample of about ten years of monthly returns, the overall explanatory power of these risk models is encouraging. Of course, we must recognize that the process of variable selection has inevitably biased upward the $\bar{R}^2$s, hence these results should be viewed as useful summaries of risk exposures and correlations rather than structural factor models of hedge fund returns.

6.6.2 Hedge Funds and the Banking Sector

With the repeal in 1999 of the Glass-Steagall Act, many banks have now become broad-based financial institutions engaging in the full spectrum of financial services, including retail banking, underwriting, investment banking, brokerage services, asset management, venture capital, and proprietary trading. Accordingly, the risk exposures of such institutions have become considerably more complex and interdependent, especially in the face of globalization and the recent wave of consolidations in the banking and financial services sectors.

In particular, innovations in the banking industry have coincided with the rapid growth of hedge funds. Currently estimated at over $1 trillion in size, the hedge fund industry has a symbiotic relationship with the banking sector, providing an attractive outlet for bank capital, investment management services for banking clients, and fees for brokerage services, credit, and other banking functions. Moreover, many banks now operate proprietary trading units that are organized much like hedge funds. As a result, the risk exposures of the hedge fund industry may have a material impact on the banking sector, resulting in new sources of systemic risks. And although many hedge funds engage in *hedged* strategies—where market swings are partially or completely offset through strategically balanced long and short positions in various securities—such funds often have other risk exposures such as volatility risk, credit risk, and illiquidity risk. Moreover, a number of hedge funds and proprietary trading units are not hedged at all, and also use leverage to enhance their returns and, consequently, their risks.

To the extent that systemic risk also involves distress in the banking sector, we must examine the relation between the returns of publicly traded banks and hedge fund index returns. Using monthly total returns data from the University of Chicago's Center for Research in Security Prices database, we construct value-weighted portfolios of all stocks with SIC codes 6000–6199, and 6710, rebalanced monthly, and use the returns of these portfolios as proxies for the banking sector. Table 6.25 contains regressions of the equal-weighted bank index return on the S&P 500 and CSFB/Tremont hedge fund index returns, and table 6.26 contains the same regressions for the value-weighted bank index.

The interpretation of these regressions requires some further discussion because correlations between the return of bank stocks and hedge fund indexes do not necessarily imply any causal relations. For example, illiquidity in a bank stock need not be directly linked to illiquidity in the bank's underlying portfolio—for example, the equity of a small regional bank may be thinly traded—but this need not imply that the bank is engaged in illiquid hedge fund strategies. Nevertheless, if a bank does engage in such strategies—which is becoming more common as banks struggle to deal with increased competition and dwindling margins—then the regressions in table 6.25 and 6.26 should pick up significant factor exposures to certain hedge fund indexes.

The first column of table 6.25 is a regression of the equal-weighted bank index on the S&P 500 return and its first two lags. The fact that both contemporaneous and lagged S&P 500 returns are significant suggests that banks are exposed to market risk and also have some illiquidity exposure, much like serially correlated hedge fund returns in section 6.4 and the serially correlated asset returns in table 6.12.

The next fourteen columns contain regressions with both S&P 500 returns and two lags as well as each of the fourteen hedge fund index returns and two lags, respectively. A comparison of these regressions may provide some insight into links between certain hedge fund styles and the banking industry. These regressions have reasonable explanatory power, with $\bar{R}^2$s ranging from 54.6 percent for Managed Futures to 58.2 percent for Risk Arbitrage and Long/Short Equity. Among the fourteen indexes, the ones yielding the highest explanatory power are the event-related indexes: Event Driven, Distressed, Event-Driven Multi-Strategy, and Risk Arbitrage, with $\bar{R}^2$s of 48.4 percent, 47.3 percent, 42.4 percent, and 40.8 percent, respectively. The coefficients for the contemporaneous hedge fund indexes in each of these four regressions are also numerically comparable, suggesting that these four strategy groups have similar effects on the banking sector. The least significant hedge fund index for explaining the equal-weighted bank index is Managed Futures, with coefficients that are both statistically insignificant and numerically close to zero. Managed futures strategies are known to be relatively uncorrelated with most other asset classes, and the banking sector is apparently one of these asset classes.

Table 6.25 **Regressions of monthly equal-weighted banking sector returns on the S&P 500 and various CSFB/Tremont hedge fund index returns from January 1994 to August 2004**

		Regression of equal-weighted bank index on S&P 500 and single hedge fund index														
Regressors	Market model	Hedge funds	Convertible arbitrage	Dedicated shortseller	Emerging markets	Equity-market neutral	Event driven	Distressed	Event driven multi-strategy	Risk arbitrage	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy	Multiple hedge fund indexes
Sample size	118	118	118	118	118	118	118	118	118	118	118	118	118	118	115	115
R^2 (%)	32.8	35.2	38.9	33.0	35.9	32.1	48.4	47.3	42.4	40.8	36.6	35.8	35.7	31.2	31.5	63.7
Constant	1.30	1.21	0.99	1.41	1.29	0.81	0.70	0.61	0.93	0.70	0.76	0.96	1.43	1.35	1.08	0.38
	(4.22)	(3.61)	(2.82)	(4.38)	(4.24)	(1.64)	(2.21)	(1.88)	(2.92)	(2.00)	(2.14)	(2.85)	(4.50)	(3.92)	(2.50)	(1.20)
SP500	0.47	0.37	0.42	0.34	0.37	0.45	0.22	0.25	0.31	0.34	0.47	0.44	0.39	0.47	0.46	0.24
	(7.42)	(5.19)	(6.76)	(3.40)	(4.89)	(6.32)	(3.06)	(3.56)	(4.32)	(5.14)	(7.58)	(6.83)	(5.02)	(7.15)	(7.14)	(3.21)
SP500(1)	0.13	0.14	0.09	0.11	0.17	0.11	0.05	0.04	0.08	0.04	0.12	0.14	0.19	0.12	0.12	0.10
	(2.05)	(1.92)	(1.41)	(1.08)	(2.28)	(1.52)	(0.67)	(0.57)	(1.13)	(0.54)	(1.84)	(2.15)	(2.46)	(1.83)	(1.88)	(1.56)
SP500(2)	–0.05	–0.08	–0.05	–0.03	–0.09	–0.06	–0.10	–0.12	–0.08	–0.08	–0.11	–0.11	0.01	–0.07	–0.06	
	(–0.86)	(–1.14)	(–0.82)	(–0.28)	(–1.25)	(–0.92)	(–1.48)	(–1.76)	(–1.24)	(–1.20)	(–1.64)	(–1.65)	(0.17)	(–0.98)	(–0.86)	
CSFBHEDGE		0.36														
		(2.61)														
CSFBHEDGE(1)		–0.11														
		(–0.85)														
CSFBHEDGE(2)		–0.03														–1.66
		(–0.24)														(–5.52)
CSFBCONVERT			0.89													
			(3.50)													
CSFBCONVERT(1)			–0.63													–0.39
			(–2.28)													(–1.67)
CSFBCONVERT(2)			0.20													
			(0.79)													
CSFBSHORT				–0.15												–0.10
				(–1.77)												(–1.32)
CSFBSHORT(1)				–0.02												
				(–0.19)												

continued

Table 6.25 (continued)

Regressors	Market model	Hedge funds	Convertible arbitrage	Dedicated shortseller	Emerging markets	Equity-market neutral	Event driven	Distressed	Event driven multi-strategy	Risk arbitrage	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy	Multiple hedge fund indexes
	Regression of equal-weighted bank index on S&P 500 and single hedge fund index															
CSFBSHORT(2)				0.02												–0.15
				(0.25)												(–2.27)
CSFBEMKTS					0.19											
					(2.70)											
CSFBEMKTS(1)					–0.11											
					(–1.39)											
CSFBEMKTS(2)					0.08											
					(1.21)											
CSFBEQMKTNEUT						0.32										
						(0.82)										
CSFBEQMKTNEUT(1)						0.23										
						(0.58)										
CSFBEQMKTNEUT(2)						0.08										
						(0.22)										
CSFBED							1.19									0.91
							(5.85)									(3.83)
CSFBED(1)							–0.24									–0.27
							(–1.12)									(–1.30)
CSFBED(2)							0.13									0.62
							(0.67)									(2.60)
CSFBDST								0.93								
								(5.55)								
CSFBDST(1)								–0.04								
								(–0.26)								
CSFBDST(2)								0.12								
								(0.77)								
CSFBEDM									0.85							
									(4.41)							
CSFBEDM(1)									–0.25							
									(–1.24)							

CSFBEDM(2)	0.14							
	(0.79)							
CSFBRISKARB		1.02						0.74
		(4.11)						(3.05)
CSFBRISKARB(1)		0.11						
		(0.42)						
CSFBRISKARB(2)		0.08						
		(0.33)						
CSFBFIARB			0.68					
			(2.33)					
CSFBFIARB(1)			0.03					0.57
			(0.10)					(2.23)
CSFBFIARB(2)			0.35					
			(1.27)					
CSFBGMACRO				0.22				
				(2.60)				
CSFBGMACRO(1)				0.01				
				(0.08)				
CSFBGMACRO(2)				0.10				0.99
				(1.15)				(5.68)
CSFBLSE					0.19			–0.24
					(1.66)			(–2.18)
CSFBLSE(1)					–0.16			
					(–1.45)			
CSFBLSE(2)					–0.19			
					(–1.75)			
CSFBMF						0.01		
						(0.11)		
CSFBMF(1)						–0.02		
						(–0.20)		
CSFBMF(2)						–0.05		
						(–0.57)		
CSFBMULT							0.27	
							(1.09)	
CSFBMULT(1)							–0.13	
							(–0.57)	
CSFBMULT(2)							0.14	
							(0.62)	

Table 6.26 **Regressions of monthly value-weighted banking sector returns on the S&P 500 and various CSFB/Tremont hedge fund index returns from January 1994 to August 2004**

		Regression of value-weighted bank index on S&P 500 and single hedge fund index														
Regressors	Market model	Hedge funds	Convertible arbitrage	Dedicated shortseller	Emerging markets	Equity-market neutral	Event driven	Distressed	Event driven multi-strategy	Risk arbitrage	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy	Multiple hedge fund indexes
Sample size	118	118	118	118	118	118	118	118	118	118	118	118	118	118	115	115
R^2 (%)	55.7	55.8	55.6	57.1	54.9	55.0	56.1	55.6	55.5	58.2	54.7	55.1	58.2	54.6	55.5	64.2
Constant	0.73	1.02	0.60	0.57	0.76	0.30	0.69	0.67	0.72	0.48	0.71	0.80	1.04	0.75	0.65	0.47
	(2.05)	(2.60)	(1.41)	(1.54)	(2.11)	(0.53)	(1.67)	(1.59)	(1.82)	(1.15)	(1.66)	(2.00)	(2.85)	(1.90)	(1.31)	(1.00)
SP500	0.89	0.91	0.87	1.10	0.89	0.87	0.81	0.83	0.84	0.81	0.90	0.87	0.99	0.90	0.90	1.09
	(12.24)	(10.76)	(11.53)	(9.84)	(9.98)	(10.65)	(8.68)	(9.17)	(9.46)	(10.19)	(11.95)	(11.20)	(11.21)	(11.76)	(12.09)	(10.27)
SP500(1)	0.02	0.04	0.01	–0.03	0.02	0.02	–0.06	–0.03	–0.04	–0.08	0.01	0.03	0.05	0.02	0.03	–0.02
	(0.31)	(0.47)	(0.08)	(–0.23)	(0.19)	(0.22)	(–0.60)	(–0.34)	(–0.40)	(–0.93)	(0.15)	(0.43)	(0.53)	(0.25)	(0.46)	(–0.34)
SP500(2)	–0.02	0.06	–0.01	0.01	0.02	–0.04	0.02	0.01	0.01	0.00	–0.03	–0.02	0.12	–0.03	0.00	
	(–0.25)	(0.70)	(–0.17)	(0.12)	(0.26)	(–0.45)	(0.28)	(0.16)	(0.10)	(–0.05)	(–0.36)	(–0.32)	(1.40)	(–0.38)	(–0.00)	
CSFBHEDGE		–0.12														
		(–0.72)														
CSFBHEDGE(1)		–0.07														
		(–0.47)														
CSFBHEDGE(2)		–0.24														
		(–1.53)														
CSFBCONVERT			0.45													0.83
			(1.46)													(2.51)
CSFBCONVERT(1)			–0.38													–0.59
			(–1.14)													(–1.79)
CSFBCONVERT(2)			0.12													
			(0.40)													
CSFBSHORT				0.24												0.28
				(2.47)												(2.53)
CSFBSHORT(1)				–0.07												
				(–0.73)												
CSFBSHORT(2)				0.06												–0.14
				(0.60)												(–1.58)

CSFBEMKTS	–0.01							
	(–0.11)							
CSFBEMKTS(1)	–0.01							
	(–0.07)							
CSFBEMKTS(2)	–0.07							
	(–0.89)							
CSFBEQMKTNEUT		0.33						
		(0.74)						
CSFBEQMKTNEUT(1)		–0.01						
		(–0.02)						
CSFBEQMKTNEUT(2)		0.23						
		(0.52)						
CSFBED			0.40					
			(1.51)					
CSFBED(1)			0.11					
			(0.41)					
CSFBED(2)			–0.34					
			(–1.36)					
CSFBDST				0.29				
				(1.32)				
CSFBDST(1)				0.07				
				(0.32)				
CSFBDST(2)				–0.22				
				(–1.05)				
CSFBEDM					0.29			
					(1.19)			
CSFBEDM(1)					0.08			
					(0.32)			
CSFBEDM(2)					–0.25			
					(–1.09)			
CSFBRISKARB						0.53		0.86
						(1.79)		(2.69)
CSFBRISKARB(1)						0.53		
						(1.76)		
CSFBRISKARB(2)						–0.48		
						(–1.67)		
CSFBFIARB							0.06	
							(0.17)	

continued

Table 6.26 (continued)

Regressors	Regression of value-weighted bank index on S&P 500 and single hedge fund index															Multiple hedge fund indexes
	Market model	Hedge funds	Convertible arbitrage	Dedicated shortseller	Emerging markets	Equity-market neutral	Event driven	Distressed	Event driven multi-strategy	Risk arbitrage	Fixed income arbitrage	Global macro	Long/Short equity	Managed futures	Multi-strategy	
CSFBFIARB(1)											0.19					0.46
											(0.52)					(1.32)
CSFBFIARB(2)											–0.18					
											(–0.55)					
CSFBGMACRO												0.09				
												(0.83)				
CSFBGMACRO(1)												–0.08				
												(–0.81)				
CSFBGMACRO(2)												–0.05				
												(–0.50)				
CSFBLSE													–0.28			–0.23
													(–2.13)			(–1.56)
CSFBLSE(1)													0.00			
													(–0.01)			
CSFBLSE(2)													–0.28			–0.34
													(–2.17)			(–2.38)
CSFBMF														0.03		
														(0.32)		
CSFBMF(1)														–0.03		
														(–0.28)		
CSFBMF(2)														–0.04		
														(–0.37)		
CSFBMULT															–0.33	–0.49
															(–1.18)	(–1.73)
CSFBMULT(1)															0.00	
															(0.00)	
CSFBMULT(2)															0.35	
															(1.33)	

The last column reports a final regression that includes multiple hedge fund indexes as well as the S&P 500 return and its two lags. The hedge fund indexes were selected using a combination of statistical techniques and empirical judgment, and the $\bar{R}^2$ of 63.7 percent shows a significant increase in explanatory power with the additional hedge fund indexes. As before, this $\bar{R}^2$ is likely to be upward biased because of the variable-selection process. Unlike the single hedge fund index regressions where the coefficients on the contemporaneous hedge fund indexes were positive except for Dedicated Shortsellers (which is not surprising given that banks have positive market exposure), in this case several hedge fund indexes have negative exposures: the aggregate Hedge Fund, Convertible Arbitrage, Dedicated Shortsellers, and Long/Short Equity. However, the equal-weighted bank index has positive exposure to Event Driven, Risk Arbitrage, Fixed-Income Arbitrage, and Global Macro indexes.

Table 6.26 presents corresponding regression results for the value-weighted bank index, and some intriguing patterns emerge. For the contemporaneous and lagged S&P 500 return regression, the results are somewhat different than those of table 6.25—the contemporaneous coefficient is significant but the lagged coefficients are not, implying the presence of market exposure but little liquidity exposure. This is plausible given the fact that the value-weighted index consists mainly of the largest banks and bank holding-companies, whereas the equal-weighted index is tilted more toward smaller banking institutions.

The single hedge fund index regressions in the next fourteen columns also differ from those in table 6.25 in several respects. The explanatory power is uniformly higher in these regressions than in table 6.25, and also remarkably consistent across all fourteen regressions—the $\bar{R}^2$s range from 54.6 percent (Managed Futures) to 58.2 percent (Risk Arbitrage). However, this does not imply that larger banking institutions have more in common with all hedge fund investment strategies. In fact, it is the S&P 500 that seems to be providing most of the explanatory power (compare the first column with the next fourteen in table 6.26), and although some hedge fund indexes do have significant coefficients, the $\bar{R}^2$s change very little when hedge fund indexes are included one at a time. The multiple hedge fund index regression in the last column does yield somewhat higher explanatory power, an $\bar{R}^2$ of 64.2 percent, but in contrast to the negative coefficients in the equal-weighted bank index regression, in this case most of the coefficients are positive. In particular, Convertible Arbitrage, Dedicated Shortsellers, Risk Arbitrage, and Fixed-Income Arbitrage all have positive coefficients. One possible explanation is that the larger banking institutions are involved in similar investment activities through their proprietary trading desks. Another explanation is that large banks offer related fee-based services to such hedge funds (e.g., credit, prime brokerage, trading, structured products), and do well when their hedge fund clients do well.

In summary, it is apparent from the regressions in table 6.25 and 6.26 that the banking sector has significant exposure to certain hedge fund indexes, implying the presence of some common factors between hedge funds and banks, and raises the possibility that dislocation among the former can affect the latter. This provides yet another channel by which the hedge fund industry generates systemic risk exposures.

6.6.3 Regime-Switching Models

Our final hedge fund-based measure of systemic risk is motivated by the phase-locking example of section 6.1.2 where the return-generating process exhibits apparent changes in expected returns and volatility that are discrete and sudden. The Mexican peso crisis of 1994–1995, the Asian crisis of 1997, and the global flight to quality precipitated by the default of Russian GKO debt in August 1998 are all examples of such regime shifts. Linear models are generally incapable of capturing such discrete shifts, hence more sophisticated methods are required. In particular, we propose to model such shifts by a regime-switching process in which two states of the world are hypothesized, and the data are allowed to determine the parameters of these states and the likelihood of transitioning from one to the other. Regime-switching models have been used in a number of contexts, ranging from Hamilton's (1989) model of the business cycle to Ang and Bekaert's (2004) regime-switching asset allocation model, and we propose to apply it to the CSFB/Tremont indexes to obtain another measure of systemic risk—the possibility of switching from a normal to a distressed regime.

The return of a hedge fund index, R_t is normally distributed with mean (μ_i) and variance (σ_i^2). Denote by R_t the return of a hedge fund index in period t and suppose R_t satisfies the following:

$$R_t = I_t \cdot R_{1t} + (1 - I_t) \cdot R_{2t} \tag{17a}$$

$$R_{it} \sim \mathcal{N}(\mu_i, \sigma_i^2) \tag{17b}$$

$$I_t = \begin{cases} 1 & \text{with probability } p_{11} \text{ if } I_{t-1} = 1 \\ 1 & \text{with probability } p_{21} \text{ if } I_{t-1} = 0 \\ 0 & \text{with probability } p_{12} \text{ if } I_{t-1} = 1 \\ 0 & \text{with probability } p_{22} \text{ if } I_{t-1} = 0 \end{cases} \tag{17c}$$

This is the simplest specification for a two-state regime-switching process where I_t is an indicator that determines whether R_t is in state 1 or state 2, and R_{it} is the return in state i. Each state has its own mean and variance, and the regime-switching process I_t has two probabilities; hence there are a total of six parameters to be estimated. Despite the fact that the state I_t is unobservable, it can be estimated statistically (see, for example, Hamilton 1989, 1990) along with the parameters via maximum likelihood.

This specification is similar to the well-known "mixture of distributions" model. However, unlike standard mixture models, the regime-switching model is not independently distributed over time unless $p_{11} = p_{21}$. Once estimated, forecasts of changes in regime can be readily obtained, as well as forecasts of R_t itself. In particular, because the k-step transition matrix of a Markov chain is simply given by $\mathbf{P}^k$, the conditional probability of the regime I_{t+k} given date-t data $\mathcal{R}_t \equiv (R_t, R_{t-1}, \ldots, R_1)$ takes on a particularly simple form:

$$\text{(18a)}\quad \text{Prob}(I_{t+k} = 1 \mid \mathcal{R}_t) = \pi_1 + (p_{11} - p_{21})^k[\text{Prob}(I_t = 1 \mid \mathcal{R}_t) - \pi_1]$$

$$\text{(18b)}\quad \pi_1 \equiv \frac{p_{21}}{p_{12} + p_{21}},$$

where $\text{Prob}(I_t = 1 \mid \mathcal{R}_t)$ is the probability that the date-t regime is 1 given the historical data up to and including date t (this is a by-product of the maximum-likelihood estimation procedure). Using similar recursions of the Markov chain, the conditional expectation of R_{t+k} can be readily derived as:

$$\text{(19a)}\quad E(R_{t+k} \mid \mathcal{R}_t) = \mathbf{a}_t'\mathbf{P}^k\boldsymbol{\mu}$$

$$\text{(19b)}\quad \mathbf{a}_t = [\text{Prob}(I_t = 1 \mid \mathcal{R}_t)\text{Prob}(I_t = 2 \mid \mathcal{R}_t)]'$$

$$\text{(19c)}\quad \boldsymbol{\mu} \equiv (\mu_1\ \mu_2)'$$

Table 6.27 reports the maximum-likelihood estimates of the means and standard deviations in each of two states for the fourteen CSFB/Tremont hedge fund indexes, as well as the transition probabilities for the two states. Note that two rows in table 6.27 are in boldface—Dedicated Shortselling and Managed Futures—because the maximum-likelihood estimation procedure did not converge properly for these two categories, implying that the regime-switching process may not be a good model of their returns. The remaining twelve series yielded well-defined parameter estimates, and by convention, we denote by state 1 the lower-volatility state.

Consider the second row, corresponding to the Convertible Arbitrage index. The parameter estimates indicate that in state 1, this index has an expected return of 16.1 percent with a volatility of 1.9 percent, but in state 2, the expected return is –1.6 percent with a volatility of 6.1 percent. The latter state is clearly a crisis state for convertible arbitrage, while the former is a more normal state. The other hedge fund indexes have similar parameter estimates—the low-volatility state is typically paired with higher means, and the high-volatility state is paired with lower means. While such pairings may seem natural for hedge funds, there are three exceptions to this

Table 6.27 **Maximum likelihood parameter estimates of a two-state regime-switching model for CSFB/Tremont hedge fund indexes from January 1994 to August 2004**

Index	p_{11} (%)	p_{21} (%)	p_{12} (%)	p_{22} (%)	Annualized mean (%) State 1	Annualized mean (%) State 2	Annualized standard deviation (%) State 1	Annualized standard deviation (%) State 2	Log(L)
Hedge funds	100.0	1.2	0.0	98.8	6.8	12.4	2.9	9.9	323.6
Convertible arbitrage	89.9	17.9	10.1	82.1	16.1	–1.6	1.9	6.1	404.0
Dedicated shortseller	**23.5**	**12.6**	**76.5**	**87.4**	**–76.2**	**11.7**	**2.3**	**16.5**	**208.5**
Emerging markets	100.0	1.2	0.0	98.8	11.5	6.6	8.2	20.3	218.0
Equity market-neutral	95.0	2.4	5.0	97.6	4.4	13.8	2.1	3.1	435.1
Event driven	98.0	45.0	2.0	55.0	13.3	–47.0	3.8	14.0	377.0
Distressed	97.9	58.0	2.1	42.0	15.2	–57.5	4.8	15.6	349.4
Event driven multistrategy	98.7	38.4	1.3	61.6	12.0	–55.2	4.5	15.0	363.6
Risk arbitrage	89.4	25.6	10.6	74.4	9.6	3.1	2.7	6.9	391.8
Fixed income arbitrage	95.6	29.8	4.4	70.2	10.0	–12.2	1.9	6.6	442.3
Global macro	100.0	1.2	0.0	98.8	13.6	14.0	3.2	14.2	286.3
Long/Short equity	98.5	2.5	1.5	97.5	6.1	21.1	6.3	15.3	285.0
Managed futures	**32.0**	**22.2**	**68.0**	**77.8**	**–6.0**	**10.7**	**3.8**	**13.7**	**252.1**
Multistrategy	98.2	25.0	1.8	75.0	10.8	–7.6	3.2	9.2	387.9

rule; for equity market neutral, global macro, and long/short equity, the higher-volatility state has higher expected returns. This suggests that for these strategies, volatility may be a necessary ingredient for their expected returns.

From these parameter estimates, it is possible to estimate the probability of being in state 1 or 2 at each point in time for each hedge fund index. For example, in figure 6.10 we plot the estimated probabilities of being in state 2, the high-volatility state, for the Fixed-Income Arbitrage index for each month from January 1994 to August 2004. We see that this probability begins to increase in the months leading up to August 1998, and hits 100 percent in August and several months thereafter. However, this is not an isolated event, but occurs on several occasions both before and after August 1998.

To develop an aggregate measure of systemic risk based on this regime-switching model, we propose summing the state-2 probabilities across all hedge fund indexes every month to yield a time series that captures the likelihood of being in high-volatility periods. Of course, the summed probabilities—even if renormalized to lie in the unit interval—cannot be interpreted formally as a probability, because the regime-switching process was specified individually for each index, not jointly across all indexes. There-

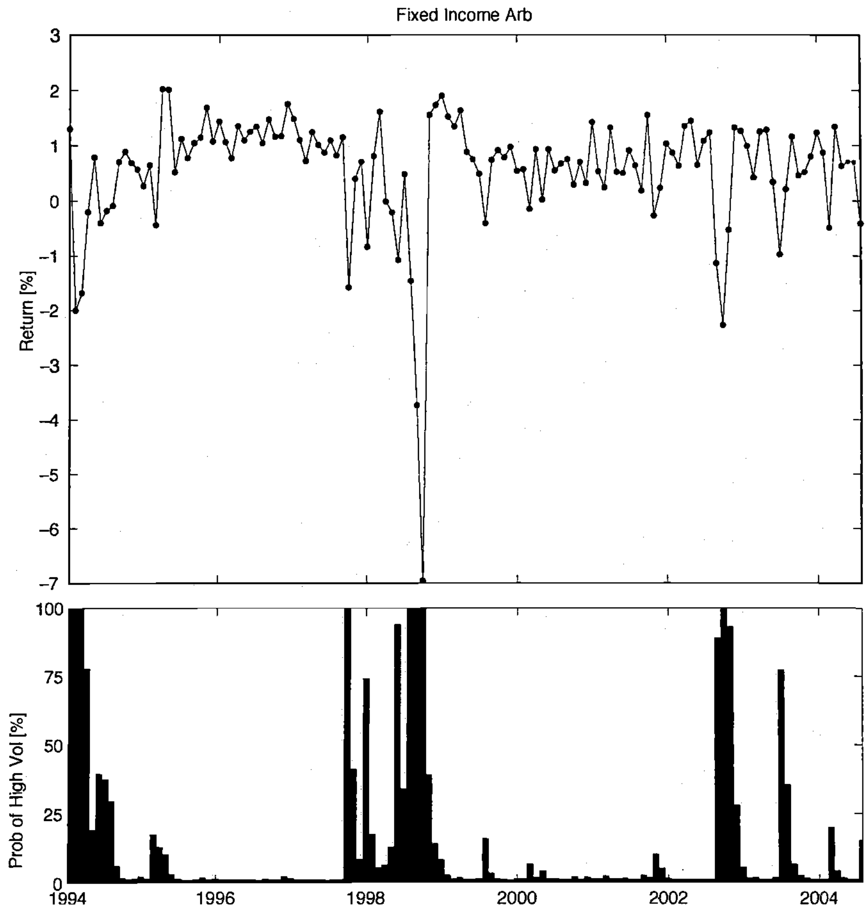


Fig. 6.10 Monthly returns and regime-switching model estimates of the probability of being in the high-volatility state for CSFB/Tremont Fixed-Income Arbitrage hedge-fund index, from January 1994 to August 2004

fore, the interpretation of "state 2" for convertible arbitrage may be quite different than the interpretation of "state 2" for equity market neutral. Nevertheless, as an aggregate measure of the state of the hedge fund industry, the summed probabilities may contain useful information about systemic risk exposures.

Figure 6.11 plots the monthly summed probabilities from January 1994 to August 2004, and we see that peak occurs around August 1998, with local maxima around the middle of 1994 and the middle of 2002, which corresponds roughly to our intuition of high-volatility periods for the hedge fund industry.

Alternatively, we can construct a similar aggregate measure by summing the probabilities of being in a low-mean state, which involves summing the

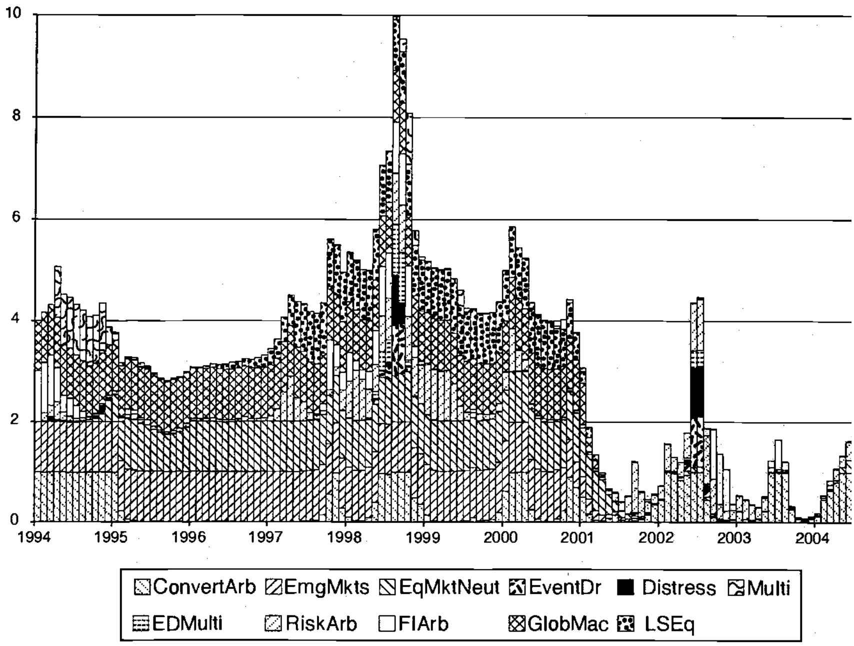


Fig. 6.11 Aggregate hedge-fund risk indicator: Sum of monthly regime-switching model estimates of the probability of being in the high-volatility state (p_2) for eleven CSFB/Tremont hedge-fund indexes from January 1994 to Autust 2004

Notes: Convertible Arbitrage; Emerging Markets; Equity Market Neutral; Event Driven; Distressed; Even-Driven Multi-Strategy; Risk Arbitrage; Fixed-Income Arbitrage; Global Macro; Long/Short Equity; and Multi-Strategy.

state-2 probabilities for those indexes where high volatility is paired with low mean with the state-1 probabilities for those indexes where low volatility is paired with low mean. Figure 6.12 contains this indicator, which differs significantly from figure 6.11. The low-mean indicator also has local maxima in 1994 and 1998 as expected, but now there is a stronger peak around 2002, largely due to equity market neutral, global macro, and long/short equity. This corresponds remarkably well to the common wisdom that over the past two years these three strategy classes have underperformed for a variety of reasons.[43] Therefore, this measure may capture more of the spirit of systemic risk than the high-volatility indicator in figure 6.11. The implications of figure 6.12 for systemic risk are clear: the probabilities of being in low-mean regimes have increased for a number of hedge fund indexes, which may foreshadow fund outflows in the coming

43. Large fund flows into these strategies and changes in equity markets such as decimalization, the rise of ECN's, automated trading, and Regulation FD are often cited as reasons for the decreased profitability of these strategies.

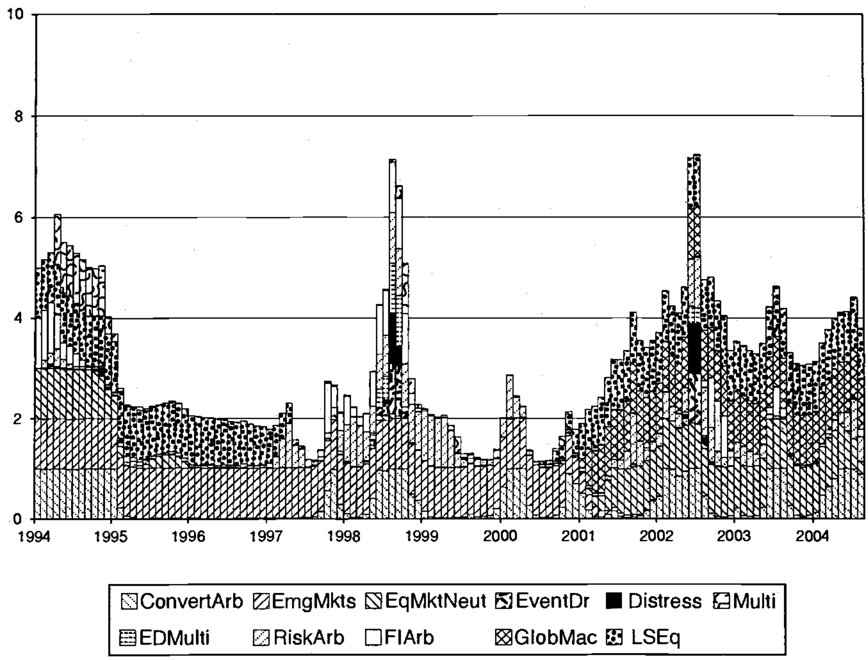


Fig. 6.12 Aggregate hedge-fund risk indicator: sum of monthly regime-switching model estimates of the probability of being in the low-mean state for eleven CSFB/ Tremont hedge-fund indexes, from January 1994 to August 2004

Note: See fig. 6.11.

months. To the extent that investors are disappointed with hedge fund returns, they may reallocate capital quickly, which places additional stress on the industry that can lead to further dislocation and instability.

6.7 The Current Outlook

A definitive assessment of the systemic risks posed by hedge funds requires certain data that is currently unavailable, and is unlikely to become available in the near future—that is, counter-party credit exposures, the net degree of leverage of hedge fund managers and investors, the gross amount of structured products involving hedge funds, and so forth. Therefore, we cannot determine the magnitude of current systemic risk exposures with any degree of accuracy. However, based on the analytics developed in this study, there are a few tentative inferences that we can draw.

1. The hedge fund industry has grown tremendously over the last few years, fueled by the demand for higher returns in the face of stock market declines and mounting pension-fund liabilities. These massive fund inflows

have had a material impact on hedge fund returns and risks in recent years, as evidenced by changes in correlations, reduced performance, and increased illiquidity as measured by the weighted autocorrelation ρ_t^*.

2. Mean and median liquidation probabilities for hedge funds have increased in 2004, based on logit estimates that link several factors to the liquidation probability of a given hedge fund, including past performance, assets under management, fund flows, and age. In particular, our estimates imply that the average liquidation probability for funds in 2004 is over 11 percent, which is higher than the historical unconditional attrition rate of 8.8 percent. A higher attrition rate is not surprising for a rapidly growing industry, but it may foreshadow potential instabilities that can be triggered by seemingly innocuous market events.

3. The banking sector is exposed to hedge fund risks, especially smaller institutions, but the largest banks are also exposed through proprietary trading activities, credit arrangements and structured products, and prime brokerage services.

4. The risks facing hedge funds are nonlinear and more complex than those facing traditional asset classes. Because of the dynamic nature of hedge fund investment strategies, and the impact of fund flows on leverage and performance, hedge fund risk models require more sophisticated analytics, and more sophisticated users.

5. The sum of our regime-switching models' high-volatility or low-mean state probabilities is one proxy for the aggregate level of distress in the hedge fund sector. Recent measurements suggest that we may be entering a challenging period. This, coupled with the recent uptrend in the weighted autocorrelation ρ_t^*, and the increased mean and median liquidation probabilities for hedge funds in 2004 from our logit model, implies that systemic risk is increasing.

We hasten to qualify our tentative conclusions by emphasizing the speculative nature of these inferences, and hope that our analysis spurs additional research and data collection to refine both the analytics and the empirical measurement of systemic risk in the hedge-fund industry. As with all risk management challenges, we should hope for the best, and prepare for the worst.

Appendix

The following is a list of category descriptions, taken directly from TASS documentation, that define the criteria used by TASS in assigning funds in their database to one of eleven possible categories:

Convertible Arbitrage This strategy is identified by hedge investing in the convertible securities of a company. A typical investment is to be long the convertible bond and short the common stock of the same company. Positions are designed to generate profits from the fixed income security as well as the short sale of stock, while protecting principal from market moves.

Dedicated Shortseller Dedicated short sellers were once a robust category of hedge funds before the long bull market rendered the strategy difficult to implement. A new category, short biased, has emerged. The strategy is to maintain net short as opposed to pure short exposure. Short-biased managers take short positions in mostly equities and derivatives. The short bias of a manager's portfolio must be constantly greater than zero to be classified in this category.

Emerging Markets This strategy involves equity or fixed income investing in emerging markets around the world. Because many emerging markets do not allow short selling, nor offer viable futures or other derivative products with which to hedge, emerging market investing often employs a long-only strategy.

Equity Market Neutral This investment strategy is designed to exploit equity market inefficiencies and usually involves being simultaneously long and short matched equity portfolios of the same size within a country. Market neutral portfolios are designed to be either beta or currency neutral, or both. Well-designed portfolios typically control for industry, sector, market capitalization, and other exposures. Leverage is often applied to enhance returns.

Event Driven This strategy is defined as "special situations" investing designed to capture price movement generated by a significant pending corporate event such as a merger, corporate restructuring, liquidation, bankruptcy, or reorganization. There are three popular subcategories in event-driven strategies: risk (merger) arbitrage, distressed/high yield securities, and Regulation D.

Fixed-Income Arbitrage The fixed-income arbitrageur aims to profit from price anomalies between related interest rate securities. Most managers trade globally with a goal of generating steady returns with low volatility. This category includes interest rate swap arbitrage, U.S. and non-U.S. government bond arbitrage, forward yield curve arbitrage, and mortgage-backed securities arbitrage. The mortgage-backed market is primarily U.S.-based, over-the-counter and particularly complex.

Global Macro Global macro managers carry long and short positions in any of the world's major capital or derivative markets. These positions reflect their views on overall market direction as influenced by major economic trends and/or events. The portfolios of these funds can include stocks, bonds, currencies, and commodities in the form of cash or derivatives instruments. Most funds invest globally in both developed and emerging markets.

Long/Short Equity This directional strategy involves equity-oriented investing on both the long and short sides of the market. The objective is not to be market neutral. Managers have the ability to shift from value to growth, from small to medium to large capitalization stocks, and from a net long position to a net short position. Managers may use futures and options to hedge. The focus may be regional, such as long/short U.S. or European equity, or sector specific, such as long and short technology or healthcare stocks. Long/short equity funds tend to build and hold portfolios that are substantially more concentrated than those of traditional stock funds.

Managed Futures This strategy invests in listed financial and commodity futures markets and currency markets around the world. The managers are usually referred to as Commodity Trading Advisors, or CTAs. Trading disciplines are generally systematic or discretionary. Systematic traders tend to use price and market-specific information (often technical) to make trading decisions, while discretionary managers use a judgmental approach.

Multi-Strategy The funds in this category are characterized by their ability to dynamically allocate capital among strategies falling within several traditional hedge fund disciplines. The use of many strategies, and the ability to reallocate capital between them in response to market opportunities, means that such funds are not easily assigned to any traditional category.

The Multi-Strategy category also includes funds employing unique strategies that do not fall under any of the other descriptions.

Fund of Funds A "Multi-Manager" fund will employ the services of two or more trading advisors or Hedge Funds who will be allocated cash by the trading manager to trade on behalf of the fund.

References

Ackermann, C., R. McEnally, and D. Ravenscraft. 1999. The performance of hedge funds: Risk, return, and incentives. *Journal of Finance* 54:833–74.

Agarwal, A., N. Daniel, and N. Naik. 2004. Flows, performance and managerial incentives in hedge funds. Working Paper, Georgia State University, J. Mack Robinson College of Business.

Agarwal, V., and N. Naik. 2000a. Generalized style analysis of hedge funds. *Journal of Asset Management* 1:93–109.

Agarwal, V., and N. Naik. 2000b. Multi-period performance persistence analysis of hedge funds source. *Journal of Financial and Quantitative Analysis* 35:327–42.

Agarwal, V., and N. Naik. 2000c. On taking the 'alternative' route: The risks, rewards, and performance persistence of hedge funds. *Journal of Alternative Investments* 2:6–23.

Agarwal, V., and N. Naik. 2000d. Performance evaluation of hedge funds with buy-and-hold and option-based strategies. Hedge Fund Centre Working Paper no. HF-003, London Business School.

Amin, G., and H. Kat. 2003a. Hedge fund performance 1990–2000: DO the money machines really add value? *Journal of Financial and Quantitative Analysis* 38: 251–74.

Amin, G., and H. Kat. 2003b. Stocks, bonds, and hedge funds. *Journal of Portfolio Management* 29:113–19.

Amin, G., and H. Kat. 2003c. Welcome to the dark side: Hedge fund attrition and survivorship bias over the period 1994–2001. *Journal of Alternative Investments* 6:57–73.

Ang, A., and G. Bekaert. 2004. How regimes affect asset allocation. *Financial Analysts Journal* 60:86–99.

Asness, C., R. Krail, and J. Liew. 2001. Do hedge funds hedge? *The Journal of Portfolio Management* 28:6–19.

Baquero, G., J. Horst, and M. Verbeek. 2004. Forthcoming. Survival, look-ahead bias and the performance of hedge funds. *Journal of Financial and Quantitative Analysis.*

Bares, P., R. Gibson, and S. Gyger. 2003. Style consistency and survival probability in the hedge funds industry. Unpublished working paper, University of Zurich, Swiss Banking Institute.

Berk, J., and R. Green. 2004. Mutual fund flows and performance in rational markets. *Journal of Political Economy* 112:1269–95.

Bookstaber, R. 1999. A framework for understanding market crisis. In *Risk management: Principles and practices,* 7–19. Charlottesville, VA: Association for Investment Management and Research.

Bookstaber, R. 2000. Understanding and monitoring the liquidity crisis cycle. *Financial Analysts Journal* 17–22.

Boyson, N. 2002. How are hedge fund manager characteristics related to performance, volatility and survival? Unpublished working paper, Ohio State University, Fisher College of Business.

Brooks, C., and H. Kat. 2002. The statistical properties of hedge fund index returns and their implications for investors. *Journal of Alternative Investments* 5:25–44.

Brown, S., and W. Goetzmann. 2003. Hedge funds with style. *Journal of Portfolio Management* 29:101–12.

Brown, S., W. Goetzmann, and R. Ibbotson. 1999. Offshore hedge funds: Survival and performance 1989–1995. *Journal of Business* 72:91–118.

Brown, S., W. Goetzmann, R. Ibbotson, and S. Ross. 1992. Survivorship bias in performance studies. *Review of Financial Studies* 5:553–80.

Brown, S., W. Goetzmann, and J. Park. 2000. Hedge funds and the Asian currency crisis. *Journal of Portfolio Management* 26:95–101.

Brown, S., W. Goetzmann, and J. Park. 2001a. Careers and survival: Competition and risks in the hedge fund and CTA Industry. *Journal of Finance* 56:1869–86.

Brown, S., W. Goetzmann, and J. Park. 2001b. Conditions for survival: Changing risk and the performance of hedge fund managers and CTAs. Yale School of Management Working Paper no. F-59.

Campbell, J., A. Lo, and C. MacKinlay. 1997. *The econometrics of financial markets.* Princeton, NJ: Princeton University Press.

Carpenter, J., and A. Lynch. 1999. Survivorship bias and attrition effects in measures of performance persistence. *Journal of Financial Economics* 54:337–74.

Chandar, N., and R. Bricker. 2002. Incentives, discretion, and asset valuation in closed-end mutual funds. *Journal of Accounting Research* 40:1037–70.

Chevalier, J., and G. Ellison. 1997. Risk taking by mutual funds as a response to incentives. *Journal of Political Economy* 105:1167–1200.

Cox, D., and E. Snell. 1989. *The analysis of binary data,* 2nd ed. London: Chapman and Hall.

Edwards, F., and M. Caglayan. 2001. Hedge fund and commodity fund investments in bull and bear markets. *The Journal of Portfolio Management* 27:97–108.

Farmer, D., and A. Lo. 1999. Frontiers of finance: Evolution and efficient markets. *Proceedings of the National Academy of Sciences* 96:9991–2.

Feffer, S., and C. Kundro. 2003. Understanding and mitigating operational risk in hedge fund investments. Unpublished working paper, The Capital Markets Company Ltd.

Fung, W., and D. Hsieh. 1997a. Empirical characteristics of dynamic trading strategies: The case of hedge funds. *Review of Financial Studies* 10:275–302.

———. 1997b. Investment style and survivorship bias in the returns of CTAs: The information content of track records. *Journal of Portfolio Management* 24:30–41.

———. 1999. A primer on hedge funds. *Journal of Empirical Finance* 6:309–31.

———. 2000. Performance characteristics of hedge funds and commodity funds: Natural versus spurious biases. *Journal of Financial and Quantitative Analysis* 35:291–307.

———. 2001. The risk in hedge fund strategies: Theory and evidence from trend followers. *Review of Financial Studies* 14:313–41.

———. 2002a. Asset-based style factors for hedge funds. *Financial Analysts Journal* 58:16–27.

———. 2002b. Benchmarks of hedge fund performance: Information content and measurement biases. *Journal of Alternative Investments* 58:22–34.

Getmansky, M. 2004. The life cycle of hedge funds: Fund flows, size and performance. Unpublished working paper. Cambridge, MA: MIT Laboratory for Financial Engineering.

Getmansky, M., A. Lo, and I. Makarov. 2004. An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics* 74 (3): 529–610.

Getmansky, M., A. Lo, and S. Mei. 2004. Sifting through the wreckage: Lessons from recent hedge-fund liquidations. *Journal of Investment Management* 2:6–38.

Goetzmann, W., J. Ingersoll, and S. Ross. 2003. High water marks and hedge fund management contracts. *Journal of Finance* 58:1685–1718.

Goetzmann, W., and N. Peles. 1997. Cognitive dissonance and mutual fund investors. *Journal of Financial Research* 20:145–58.

Greenspan, A. 1998. Statement before the committee on banking and financial services, U.S. House of Representatives. *Federal Reserve Bulletin* 84:1046–50.

Gregoriou, G. 2002. Hedge fund survival lifetimes. *Journal of Asset Management* 3:237–52.

Granger, C. 1980. Long memory relations and the aggregation of dynamic models. *Journal of Econometrics* 14:227–38.

———. 1988. Aggregation of time series variables—A survey. Federal Reserve Bank of Minneapolis Institute for Empirical Macroeconomics, Discussion Paper 1.

Gruber, M. 1996. Another puzzle: The growth in actively managed mutual funds. *The Journal of Finance* 51:783–810.

Hamilton, J. 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica* 57:357–84.

———. 1990. Analysis of time series subject to changes in regime. *Journal of Econometrics* 45:39–70.

Hendricks, D., J. Patel, and R. Zeckhauser. 1997. The J-shape of performance persistence given survivorship bias. *Review of Economics and Statistics* 79:161–70.

Horst, J., T. Nijman, and M. Verbeek. 2001. Eliminating look-ahead bias in evaluating persistence in mutual fund performance. *Journal of Empirical Finance* 8:345–73.

Howell, M. J. 2001. Fund age and performance. *Journal of Alternative Investments* 4:57–60.
Ineichen, A. 2001. The myth of hedge funds: Are hedge funds the fireflies ahead of the storm? *Journal of Global Financial Markets* 2:34–46.
Ippolito, R. 1992. Consumer reaction to measures of poor quality: Evidence from the mutual fund industry. *Journal of Law and Economics* 35:45–70.
Jen, P., C. Heasman, and K. Boyatt. 2001. Alternative asset strategies: Early performance in hedge fund managers. Internal document, Lazard Asset Management, London.
Kadlec, G., and D. Patterson. 1999. A transactions data analysis of nonsynchronous trading. *Review of Financial Studies* 12:609–30.
Kao, D. L. 2000. Estimating and pricing credit risk: An overview. *Financial Analysts Journal* 56 (4): 50–66.
Kao, D. L. 2002. Battle for alphas: Hedge funds versus long-only portfolios. *Financial Analysts Journal* 58:16–36.
Kaplan, S., and A. Schoar. 2004. Forthcoming. Private equity performance: Returns, persistence and capital flows. *Journal of Finance.*
Kendall, M., A. D. Stuart, and J. K. Ord. 1983. *The advanced theory of statistics, Vol. 3* (4th ed.). London: Griffin.
Kramer, D. 2001. Hedge fund disasters: Avoiding the next catastrophe. *Journal of Investment Management* 2 (4): 6–38.
Leamer, E. 1978. *Specification searches.* New York: Wiley.
Liang, B. 1999. On the performance of hedge funds. *Financial Analysts Journal* 55:72–85.
———. 2000. Hedge funds: The living and the dead. *Journal of Financial and Quantitative Analysis* 35:309–26.
———. 2001. Hedge fund performance: 1990–1999. *Financial Analysts Journal* 57: 11–18.
———. 2003. The accuracy of hedge fund returns. *Journal of Portfolio Management* 29:111–22.
Lo, A. 2001. Risk management for hedge funds: Introduction and overview. *Financial Analysts Journal* 57:16–33.
———. 2002. The statistics of Sharpe ratios. *Financial Analysts Journal* 58:36–50.
———. 2004. The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *Journal of Portfolio Management* 30:15–29.
Lo, A., and C. MacKinlay. 1988. Stock market prices do not follow random walks: Evidence from a simple specification test. *Review of Financial Studies* 1:41–66.
———. 1990. Data snooping biases in tests of financial asset pricing models. *Review of Financial Studies* 3:431–68.
Lochoff, R. 2002. Hedge funds and hope. *The Journal of Portfolio Management* 28:92–99.
Ljung, G., and G. Box. 1978. On a measure of lack of fit in time series models. *Biometrika* 67:297–303.
MacKenzie, P. 2003. Long-Term Capital Management and the sociology of arbitrage. *Economy and Society* 32:349–80.
Maddala, G. 1983. *Limited-dependent and qualitative variables in econometrics.* Cambridge: Cambridge University Press.
McDonough, W. 1998. Statement before the committee on banking and financial services, U.S. House of Representatives. *Federal Reserve Bulletin* 84:1050–54.
Mishkin, F. 1996/1997. Financial crises. *NBER Reporter,* 10–12.
Nagelkerke, N. 1991. A note on a general definition of the coefficient of determination. *Biometrika* 78:691–2.

Pérold, A. 1999. Long-Term Capital Management, LP. (A–D) Harvard Business School case study. Boston: Harvard Business School Press.
Pérold, A., and R. Salomon. 1991. The right amount of assets under management. *Financial Analysts Journal* (May–June): 31–39.
President's Working Group on Financial Markets. 1999. *Hedge funds, leverage, and the lessons of Long-Term Capital Management.*
Samuelson, P. 1965. Proof that properly anticipated prices fluctuate randomly. *Industrial Management Review* 6:41–49.
Schneeweis, T., and R. Spurgin. 1996. Survivor bias in commodity trading advisor performance. *Journal of Futures Markets* 16:757–72.
Sirri, E., and P. Tufano. 1998. Costly search and mutual fund flows. *The Journal of Finance* 53:1589–1622.
Strogatz, S. H. 1994. *Nonlinear dynamics and chaos: With applications to physics, biology, chemistry, and engineering.* Reading, MA: Perseus.
Watts, D. 1999. *Small worlds: The dynamics of networks between order and randomness.* Princeton, NJ: Princeton University Press.
Watts, D., and S. Strogatz. 1998. Collective dynamics of 'small-world' networks. *Nature* 393:440–42.
Zheng, L. 1999. Is money smart?—A study of mutual fund investors' fund selection ability. *Journal of Finance* 54:901–33.

Comment David M. Modest

This is an ambitious research effort focused on the risks of hedge funds—both the risks that hedge funds face and the potential risks that hedge funds pose to the global financial system. It makes a significant and important contribution to the nascent and burgeoning research in this area. With over $1 trillion currently invested in over 8,000 hedge funds, and projections of that sum rising to over $2 trillion in the next decade, hedge funds have become an increasingly important part of the financial sector. They account for a substantial and rising share of trading volume on most major stock exchanges, account for a sizable and growing fraction of revenue and profit for global investment and commercial banks, are major risk intermediaries for a full range of publicly traded and private securities, and are a major source of brain drain for competitors ranging from banks to insurance companies to mutual funds to universities.

Two of the most important functions of capital markets are: (a) the pooling of capital that facilitates the undertaking of large-scale projects, and (b) the concomitant diversification of risk. The last fifty years have witnessed a dramatic increase in the scope and breadth of vehicles to transfer and share risk, including: stock and bond mutual funds, index funds, exchange-traded funds, futures, options, asset-backed securities (ABS), ABS tranches, catastrophe (CAT) bonds, credit derivatives, and hedge funds.

Alfred Winslow Jones is credited with launching the first hedge fund in the late 1940s—a long/short equity fund whose goal was to generate consistent returns regardless of the overall direction of the stock market. Jones received notoriety in an article Carol Loomis wrote for *Fortune* in April 1966 entitled: "The Jones Nobody Keeps Up With," in which she describes Jones as outperforming the best mutual fund by 44 percent over a five-year period and 87 percent over a ten-year period. That article helped spurn a boom in hedge funds that has led to an ever-widening scope of investing activities over the last forty years.

As figure 6.4 of the paper illustrates, most of the investment focus of the early hedge funds was concentrated on long/short equity, global macro, and event-driven strategies. Over time, that focus has branched out to include fixed income, convertible bond, and statistical equity arbitrage; long/short credit; distressed debt investing; long/short emerging market equity and debt; mezzanine lending; ABS strategies; pass-through and structured mortgage product-based investments; CDO structured trades, private investment in public equities (PIPES); and other private equity-type strategies typified by ESL's purchase of Kmart and subsequent takeover of Sears. Over time, hedge funds have thus taken a bigger part in bearing the less liquid financial risks of the economy. On the surface, the increased diversification of risks—across hedge funds and other investors—should make the financial markets more stable and less susceptible to cataclysmic shocks and systemic risks. The use of leverage by hedge funds, however, raises the specter of financial market contagion and leaves open the question of whether markets are more robust than in the past or whether increased hedge fund participation has elevated the potential for financial market calamity.

The strength of the paper is the breadth of focus on potential pitfalls and solutions to measuring hedge fund risks. As the paper argues, the risks of many hedge fund strategies are difficult, if not impossible, to detect empirically without an economic understanding of the structure of the trades and of the markets involved—especially given the rapid innovation of financial products and the rapid growth in their investment scope. The hypothetical strategy of Capital Decimation Partners L.P. (i.e., writing out of the money puts) displays the difficulty of capturing low frequency/high intensity tail risk using traditional mean-variance risk measures. And the phase-locking risk model of section 6.1.2 shows the difficulty of measuring correlations during crisis periods (i.e., systemic shocks) using unconditional moments. As mentioned at the outset of this paragraph, the strongest part of the paper is the development of new and better risk measures to measure the dynamic nature of hedge fund risks as illustrated in these two examples. The weakest part of the paper is the causal link between these risks and their impact on the global financial system.

The paper makes use of two main datasets: The CSFB/Tremont hedge fund strategy and aggregate hedge fund indices, and the TASS database for individual hedge fund returns. One of the most important and pervasive features of both the index and individual fund data is the persistent serial correlation of hedge fund returns—far in excess of the serial correlation apparent in the returns of traditional assets such as the returns on major equity benchmarks. The CSFB/Tremont convertible bond (CB) arbitrage index, for instance, has autocorrelation coefficients of 0.558, 0.411, and 0.144 at lags 1, 2, and 3—using monthly data over the January 1994–August 2004 period. Table 6.12 shows the mean first-order autocorrelation coefficient of individual convertible bond arbitrage funds ("combined" databases) was 0.314 over the February 1977–August 2004 period. It is of interest that the first order autocorrelation coefficient of 0.558 for the CB hedge fund index and 0.314 average for individual CB funds far exceeds the AR1 coefficient of 0.064 given in table 6.17 for the Merrill Lynch convertible index. The paper convincingly documents that the serial correlation is more prevalent in some strategies than others (e.g., 0.558 in convertible arbitrage and 0.058 in managed futures), that some pairs of strategies have very high cross-correlations (e.g., event and distressed have a correlation of 0.936 in table 6.8), that the correlations have very significant time variation (e.g., fig. 6.4), and that some strategies have significant correlations with lagged S&P 500 returns (e.g., fig. 6.3).

The authors note that "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." Although the authors note that there are many possible explanations for the serial correlation, they cite Getmansky, Lo, and Makarov (2004) as concluding that illiquidity and smoothed returns are "the most plausible explanation" for hedge funds. The authors distinguish between four distinct sources of serial correlation: (1) nonsynchronous trading, (2) linear extrapolation of past transaction prices for illiquid securities in determining marks, (3) use of dealer-average and potentially linearly extrapolated prices in marking positions, and (4) performance smoothing. A fifth source, and perhaps the most likely, is the pushing of marks in relatively illiquid securities—especially by larger funds and the collective effort of smaller hedge funds that often tend to be on the same side of trades. What is perhaps most striking about the results (and the underlying markets) is how many markets are plagued by evidence of illiquidity. A potentially rich vein for future research would be to try to link the serial correlation pattern of hedge fund returns (e.g., CB hedge funds) to the serial correlation pattern of the underlying instruments that they hold. In this paper, that link is asserted rather than investigated. It would also be interesting to try to link the serial correlation pattern of hedge fund returns to the serial correlation of flows into and out of different strategy groups.

Sections 6.4.2 and 6.4.3 of the paper formalize the econometric modeling of returns and presents the model introduced in Getmansky, Lo, and Makarov (2004). In this model, "true" hedge fund returns are described by a single factor linear model, and observed returns depend on a distributed lag of past true returns—with the restriction that the moving average (MA) coefficients lie between zero and one, and that the sum of the MA coefficients equals one. The authors argue that "(t)his is a sensible restriction" in that "Even the most illiquid securities will trade eventually, and when that occurs, all of the cumulative information affecting that security will be fully impounded into its transaction price." Although the restriction is sensible and the model is elegant, the problem with illiquid securities is that even when the assets trade, the price may not be one that would actually clear markets and hence may not "fully impound" all of the relevant information. Trade may occur (typically in very small size) when two "noise traders" meet, and the executed price may not reflect the price at which more informed traders would trade. Illiquid markets are typically characterized by very thin trading—often at dubious prices—but not necessarily by no trading. Informed traders often have an incentive not to trade—so as to leave prices and marks little changed. In illiquid markets, hedge funds often trade off the benefit of unloading relatively illiquid positions against the price impact it will have on the remaining positions on the book.

Section 6.5 of the paper contains a very interesting analysis of hedge fund liquidations—making use of TASS's Graveyard database. Table 6.19 contains a fascinating breakdown of the reasons funds reached the Graveyard. Of the 1,765 funds in the Graveyard database, the most common reason funds reached the Graveyard is because they were liquidated (913 funds). In principle the Graveyard database also includes funds that still exist, but are closed to new investment. The small number associated with this tag (7), however, strains credulity and raises the question of how closed funds are handled.

The authors present a very thorough analysis of the full range of reasons funds reached the Graveyard, the age distribution and assets under management (AUM) of Graveyard funds, attrition rates by year and by strategy as well as a thorough comparison of the risk and return differences between Graveyard and Live funds. For the strategies of convertible bond arbitrage, equity market neutral, and dedicated short sellers, the average return for Graveyard funds actually exceeds that for Live funds. It would be interesting to know whether this result also holds in excess return space—where the return of the fund is looked at relative to the return on the strategy index (for the sample period over which the fund data exists). As the strategies themselves show significant year-to-year return variation, this may explain part of the result. The median age for Graveyard funds is forty-five months and the median AUM of Graveyard funds is $6.3 million. At a 1.5 percent management fee, the management fee income for this size fund is only on the order of $100,000 (ignoring any incentive fees) and hence it is relatively uneconomic to keep a business of this size going for very long.

Section 6.5.1 of the paper analyzes the attrition rates of the aggregate hedge fund universe and the attrition rates broken down by strategy. The authors find substantial variation in attrition rates across strategies—with convertible bond arbitrage having the lowest attrition rate of 5.2 percent and managed futures having an attrition rate of 14.4 percent. The authors attribute this partly to risk, since convertible bond arbitrage has the second lowest volatility over the sample period and managed futures has the highest volatility. Returns may also be part of the story, however, as convertible bond arbitrage has the second highest Sharpe ratio over the period and managed futures has one of the lowest Sharpe ratios. Evidence suggests that many investors chase returns, so it would not be surprising to funds leaving underperforming hedge fund strategies (resulting in a certain amount of liquidations) and funds flowing into outperforming strategies.

The logit analysis of liquidations (section 6.5.2) is one of the more interesting and new parts of the paper. The authors examine the role of fund age, assets under management, returns, and fund flows in predicting the probability of liquidations. Fixed-effects models are also used to look for differences by year and by strategy (table 6.26). Not too surprisingly, age, assets, cumulative return, and inflows all lower the probability of fund liquidations. In future research, it would be interesting to see whether raw returns or excess returns (relative to an appropriate benchmark) have more explanatory power. Consider, for instance, an individual convertible bond hedge fund which returned 15 percent in 2000. This fund likely returned more than the average hedge fund in 2000, but perhaps underperformed the typical CB hedge fund by upward of 10 percent. It is of interest to know whether this fund was likely to be the recipient of inflows in 2001 for having outperformed the average fund, or be subject to withdrawals since it underperformed its peers. The results for Model 1, presented in table 6.27, show a substantial increase, relative to prior years, in the mean probabilities of liquidation. This is most likely a result of the explosion of new funds (which tend to have smaller AUM and obviously lower age) and the falling level of returns in the hedge fund industry. It would seem to be an open question whether this presages more systemic risk in the global financial system.

The serial correlation patterns of hedge fund returns and the dynamic and wide-ranging investment menu of hedge funds suggest the need in constructing hedge fund risk models for: (1) Scholes-Williams type estimation techniques that adjust for asynchronous prices, (2) estimation techniques consistent with time-varying parameters, and (3) a wide range of risk factors. The authors undertake this endeavor in section 6.6 by illustrating the importance of: (1) allowing different up-market and down-market betas (table 6.28)—especially for certain strategies, such as event-driven arbitrage, (2) incorporating Scholes-Williams types adjustment in estimating market exposures (table 6.31), higher-order moments (table 6.31) which, in part, capture time-varying coefficients, and (3) a wide range of prespecified factors, including the returns on gold, the Lehman bond index, large minus small capitalization stocks, value minus growth stocks, exchange rates, interest rates, credit spreads, term spreads, the volatility index (VIX), and the contemporaneous and lagged returns on a portfolio of bank stocks. As the authors note, "these results should be viewed as useful summaries of risk exposures and correlations rather than structural factor models of hedge fund returns"—as they reflect one sample period (January 1994–August 2004) and no attempt is made to examine the structural stability of the parameters.

In section 6.6, the authors also examine the statistical relationship between hedge funds and the banking sector. The analysis begins with regressions of bank indexes (equally weighted in table 6.32 and value-weighted in table 6.33) on contemporaneous and lagged S&P 500 returns and contemporaneous hedge fund strategy returns. The authors note: "The fact that both contemporaneous and lagged S&P 500 returns are significant suggests that banks are exposed to market risk and also have some illiquidity exposure, much like serially correlated hedge fund returns." This analogy, however, is not entirely appropriate. While the serial correlation properties of hedge fund returns (which reflect the sum of the net asset values of the underlying investments) are an indication of the illiquidity of the underlying assets, the autocorrelation apparent in the bank return data reflects the illiquidity in the bank stocks themselves and says nothing about the illiquidity of the underlying investments or exposures.

Tables 6.25 and 6.26 present data indicating significant contemporaneous and lagged correlations between portfolios of bank stocks and a variety of hedge fund strategies. The coefficient estimates appear relatively unstable—with the signs varying depending on whether the variables are included in univariate or multivariate form and whether the dependent variable is an equally weighted or value-weighted bank return index. While the regressions suggest there are important common factors affecting both banks and hedge funds, the structural link is unclear; the results would seem to offer little causal evidence on the impact that banks have on hedge fund returns or vice versa.

Finally, section 6.6.3 undertakes to implement a two-state regime-switching model to capture hedge fund risk, and is motivated by the phase-locking example given earlier in the paper. The model is estimated for fourteen CSFB/Tremont hedge fund indexes and, in general, the results show that "the low-volatility state is typically paired with higher means, and the high-volatility state is paired with lower means." The authors then aggregate (with a number of caveats) the probabilities of being in the high-volatility state (fig. 6.11) and low mean state (figure 6.12) in an attempt to shed some light on the current state of the hedge fund industry and how it compares to the past. The two figures tell a somewhat different story. Figure 6.11 suggests that, relative to the period since 1994, the probability of being in a high-volatility state is relatively low—although higher than in January 2004. On the other hand, figure 6.12 suggests that the probability of being in a low mean state is relatively high—based on estimated probabilities since 1994.

This seems to reflect that ultra-low volatility that has been apparent in most markets over the past few years—in part generated by the extremely low level of interest rates and the abundance of risk capital. Economic logic, based on the current pricing levels in most markets, where very little premium is being received ex ante for bearing risk, would seem to suggest that in fact the size of crisis shock could be quite large—although this doesn't speak to the probability of a crisis.

One of the most intriguing graphs is figure 6.7, which depicts a time series of the asset-weighted and median first-order autocorrelation coefficients of individual hedge funds. The authors use this graph to conclude in section 6.7:

(1) "These massive fund inflows have had a material impact on hedge fund returns and risks in recent years, as evidenced by . . . increased illiquidity as measured by the weighted autocorrelations" and

(2) "This, coupled with the recent uptrend in the weighted autocorrelation ρ_t^*, and increased mean and median liquidation probabilities for hedge funds in 2004 from our logit model implies, that systemic risk is increasing."

This line of reasoning seems to be the weakest in the paper. Systemic and contagion risk largely arise when there is mismatch between the maturity structure of the assets and the maturity structure of the liabilities. There is no doubt that on an aggregate basis hedge fund strategies have increasingly involved less liquid securities (e.g., high yield and distressed debt, private placements, control positions, thinly traded asset-backed securities, structured product tranches), but the authors fail to make the case that this increases systemic risk. This would require proving that these assets have moved from more stable hands to less stable hands. To the extent these investments are being made by firms like ESL and Eton Park—hedge funds with long lock-ups and proven investing and risk management skill—the move into less liquid securities may be prudent and risk-reducing for the financial system. The implicit assumption of the authors is that hedge fund investors are per se more fickle and that the growth of hedge funds inherently makes the system less stable—but the analyses shed little light on this implicit assertion.

In discussing systemic risk, it is also worth noting that most hedge funds have nowhere near the balance sheet leverage that fixed-income arbitrage funds typically have, which is on the order of 10:1–20:1. Long/short equity and event-driven funds, as illustrated in figures 6.2 and 6.5, account for close to 50 percent of the funds and assets under management, and usually have gross exposures (long plus short positions) on the order of 150 percent and net exposures that are less than 50 percent. Hence a repeat of October 19, 1987, would likely lead to a maximum loss of 12.5 percent for most of these funds—probably not a serious enough loss to generate hysteria and market contagion. A slow bleed, due to high fees and low alpha-generating ability, is much more likely to befall these funds than a cataclysmic crisis.

In sum, this is an interesting paper that covers a wide and disparate set of issues related to modeling hedge fund risk. The authors are very convincing in arguing for and implementing new models that more accurately capture the risk of hedge fund investments. Hedge funds' assets under management have grown significantly over the past few years, and the dearth of return possibilities in traditional hunting grounds had led many funds to seek opportunities in less liquid areas. It is unclear, however, whether this poses more systemic risk to the global financial system—a question left for future research.

Discussion Summary

Gary Gorton opened the general discussion, suggesting that the hedge-fund index data used by Chan et al. may be problematic because the details of index construction may amount to a choice of trading strategy that does not match the strategies the funds follow.

Much of the general discussion focused on the intuition and utility of the portion of the paper that uses serial correlation in hedge fund returns as an indicator of systemic liquidity risk. *Darrell Duffie* suggested that serial correlation may be different for positive and negative returns, and also may differ in high- and low-volatility environments even if the high-volatility periods are not characterized by the phase-locking that characterizes crises. *Philipp Hartmann* noted that some returns of some hedge funds appear to be negatively correlated with bank returns whereas others are positively correlated, so perhaps the hedge fund sector as a whole would not add to systemic risk. *Andrew Lo* responded that exposure to a given set of prices may be limited to a subset of fund styles, and that liquidity problems could affect funds with a wide range of styles.

Peter Garber suggested a different mechanism by which the growth of hedge funds may affect systemic risk. In previous decades, large dealer banks tended to be the main providers of liquidity in many markets, directly or indirectly, and they were able to collect rents from such liquidity provision. Hedge fund activity has been eroding such rents and thus liquidity from banks is less available in at least some markets. In a crisis, if hedge funds withdraw as liquidity providers, banks may no longer be prepared to step in.