Do Hedge Funds Increase Systemic Risk?

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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 with an average of 2,000 bank failures per year during the 1930–33 period (according to Mishkin 1997) and which in turn prompted the passing of 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 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, 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 differs in important ways from more traditional investments, and such differences may have potentially significant implications for systemic risk. One example is 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 among 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 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. 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. Now 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.

The risk/reward profile for most hedge funds differs in important ways from more traditional investments, and such differences may have potentially significant implications for systemic risk.

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 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.[1]

To begin our discussion, we summarize the empirical properties of aggregate and individual hedge fund data used in this study: the CSFB/Tremont hedge fund indexes and the TASS individual hedge fund database. We then 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, 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 (AUM), and recent fund flows. We then present estimates of statistical regime-switching models for hedge fund indexes that capture certain nonlinearities unique to the hedge fund industry. We conclude 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. To address this growing concern, we put forward a modest proposal to establish a new entity patterned after the U.S. National Transportation Safety Board.

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, in response to the U.S. Securities and Exchange Commission's (SEC's) Rule 203(b)(3)–2 (which was subsequently struck down by the U.S. Court of Appeals in June 2006), many hedge funds became registered investment advisers, the regular filings of those funds did 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, even for regulatory authorities like the SEC, to construct direct measures of systemic risk. 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.

The Data

It is clear from our introduction 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.[2]

The CSFB/Tremont indexes are asset-weighted indexes of funds with a minimum of \$10 million of AUM, a minimum one-year track record, and current audited financial statements. An aggregate 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.

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

Table 1
Number of Funds in the TASS Hedge Fund Databases, February 1977–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

The TASS database consists of monthly returns, AUM, 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.[3] 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 are in the live database and 1,861 in the graveyard database. The earliest data available for a fund in either database are from 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, a circumstance that may yield a certain degree of survivorship bias.[4]

The majority of 4,781 funds reported returns net of management and incentive fees on a monthly basis.[5] We eliminated 50 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 AUM, or reported only partial AUM, leaving a final sample of 4,536 hedge funds in the combined database (2,771 funds in the live database and 1,765 funds in the graveyard database). For the empirical analysis in this paper, 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 filter 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, the filter may not be as problematic. (See the studies cited in footnote 4.)

TASS also classifies funds into one of eleven different investment styles, listed in Table 1 and described in the appendix, of which ten correspond exactly to the CSFB/Tremont subindex definitions.[6] Table 1 also reports the number of funds in each category for the live, graveyard, and combined databases, and these numbers show 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.

CSFB/Tremont indexes. Table 2 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.

Table 2 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 short-sellers 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 short-sellers—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 1. 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,[7] in this case, an additional explanation for the positive trend in

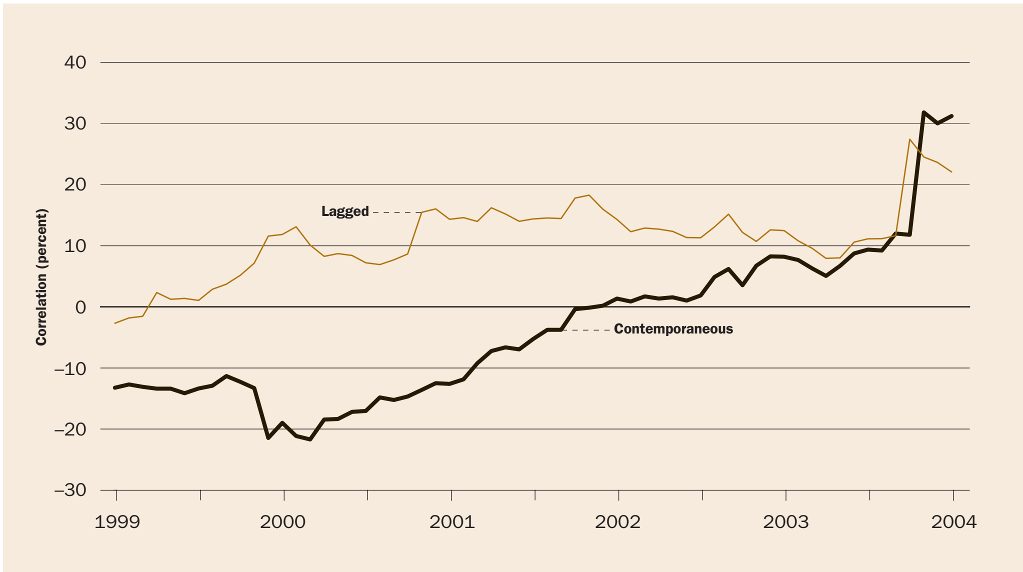
3. Once a hedge fund decides not to report its performance, is liquidated, is closed to new investment, restructured, or merged with other hedge funds, the fund is transferred into the graveyard database. A hedge fund can only be listed in the graveyard database after being listed in the live database. 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. Because of 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.
4. For studies attempting to quantify the degree and impact of survivorship bias, see Baquero, Horst, and Verbeek (2005), Brown et al. (1992), Brown, Goetzmann, and Ibbotson (1999), Brown, Goetzmann, and Park (2001), Carpenter and Lynch (1999), Fung and Hsieh (1997, 2000), Hendricks, Patel, and Zeckhauser (1997), Horst, Nijman, and Verbeek (2001), and Schneeweis, Spurgin, and McCarthy (1996).
5. 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.
6. This correspondence is no coincidence—TASS is owned by Tremont Capital Management (acquired by Lipper in March 2005), which created the CSFB/Tremont indexes in partnership with Credit Suisse First Boston.
7. Under the null hypothesis of no correlation, the approximate standard error of the correlation coefficient is $1/\sqrt{60} = 13\%$.

Table 2
Summary Statistics for Monthly CSFB/Tremont Hedge Fund Index Returns and Various Hedge Fund Risk Factors, January 1994–August 2004

	Sample size	Annualized mean	Annualized SD	Corr. with S&P 500	Min.	Med.	Max.	Skew.	Kurt.	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 short-seller	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 annualized)	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 annualized)	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 annualized)	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

Notes: The multistrategy return series begins in April 1994, and the S&P 500 return series ends in December 2003. "LB-*Q*" is the Ljung-Box (1978) *Q*-statistic.

Figure 1
Contemporaneous and Lagged Rolling Sixty-Month Correlation Between CSFB/Tremont Multi-Strategy Index and S&P 500 Returns, January 1999–December 2003



correlation is the enormous inflow of capital into multistrategy funds and fund of funds over the past five years. As AUM increase, it becomes progressively more difficult for fund managers to implement strategies that are truly uncorrelated with broad-based market indexes like the S&P 500. Moreover, Figure 1 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 the next section). This increase in illiquidity exposure is also consistent with large inflows of capital into the hedge fund sector.

Despite their heterogeneity, several indexes do share a common characteristic: negative skewness. Convertible arbitrage, emerging markets, event driven, distressed, event-driven multistrategy, risk arbitrage, fixed-income arbitrage, and multistrategy funds all have skewness coefficients less than zero, in some cases substantially so. This property is an indication of tail risk exposure (see Lo 1999 for an explicit example involving short selling out-of-the-money put options on the S&P 500 index) 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 the 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.[8] 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 the next section.

TASS data. Table 3 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. 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.[9]

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 multistrategy (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 the following section). Alternatively, equities and futures are among the most liquid securities in which hedge funds invest, and not surprisingly, 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 short-seller funds also have a low average first-order autocorrelation, 5.9 percent, which is consistent with the high degree of liquidity that often characterize short-sellers (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 that can be captured to some degree by serial correlation and the time-series model of smoothing discussed in the next section.

Measuring Illiquidity Risk

The different categories of hedge funds in the TASS database suggest that these funds are likely to exhibit a heterogeneous array of risk exposures. However, a common

8. Ljung and Box (1978) propose the following statistic to measure the overall significance of the first k autocorrelation coefficients: $Q = T(T+2)\Sigma_{j=1}^{k}\hat{\rho}_j^2/(T-j)$, 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, chap. 50.13) for further details.
9. 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 short-seller.

Table 3
Means and Standard Deviations of Basic Summary Statistics for Hedge Funds in the TASS Hedge Fund Databases, February 1977–August 2004

Category	Sample size	Annualized mean (%) Mean	Annualized mean (%) SD	Annualized SD (%) Mean	Annualized SD (%) SD	ρ_1 (%) Mean	ρ_1 (%) SD	Annualized Sharpe ratio Mean	Annualized Sharpe ratio SD	Ann. adjusted Sharpe ratio Mean	Ann. adjusted Sharpe ratio SD	Ljung-Box *p*-value (%) Mean	Ljung-Box *p*-value (%) 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 short-seller	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 short-seller	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
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 short-seller	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	1,415	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 *p*-values for the Ljung-Box (1978) *Q*-statistic for each fund use the first eleven autocorrelations of returns.

theme surrounding systemic risk 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 1998. Because many hedge funds rely on leverage, the size of the positions is often considerably larger than the amount of collateral supporting those positions. Leverage expands small profit opportunities into larger ones but also expands small losses into larger losses. And when adverse changes in market prices reduce collateral's market value, credit is withdrawn quickly, and the subsequent forced liquidation of large positions over a short time can lead to widespread financial panic, as occurred after the Russian government defaulted on its debt in August 1998. Along with the many benefits of a truly global financial system is the cost that a financial crisis in one country can have dramatic repercussions in several others—that is, contagion.

While modern financial economics has much to say about the risk of static investments, there is currently no single summary measure of the risks of a dynamic investment strategy.

The basic mechanisms driving liquidity and credit are familiar to most hedge fund managers and investors, and the recent literature has made considerable progress in modeling both credit and illiquidity risk. (See, for example, Bookstaber 1999, 2000 and Kao 2000 and their citations.) 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.

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 kth-order autocorrelation of $\{R_t\}$,[10] 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. (See, for example, Farmer and Lo 1999 and Lo 2004.) In particular, market frictions such as transactions costs, borrowing constraints, costs of gathering and processing information, and institutional restrictions on short sales and other trading practices do exist, and they all contribute to the possibility of serial correlation in asset returns that cannot easily be "arbitraged" away precisely because of the presence of these frictions. From this perspective, the degree of serial correlation in an asset's returns can be viewed as a proxy for the magnitude of the frictions, and illiquidity is one of most common forms of such frictions.

For example, it is well known that the historical returns 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 short sell properties, and other frictions.[11]

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, chap. 3). But in contrast to the studies by Lo and MacKinlay (1988, 1990) 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 below), 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 (1990) 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—for example, emerging-market debt, real estate, restricted securities, control positions in publicly traded companies, asset-backed securities, and other exotic over-the-counter 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

10. The kth-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.

11. 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.

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 performed frequently.[12] Therefore, serial correlation may serve as a proxy for a fund's liquidity exposure.

Although they are separate sources of risk exposures for hedge funds and their investors, liquidity and credit have been inextricably intertwined in the minds of most investors.

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 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 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 above, 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 showing that none of them can account for the magnitudes of serial correlation. 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, etc.—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 8). To illustrate this approach, we estimate these quantities using monthly historical total returns of the ten largest mutual funds (as of February 11, 2001) 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.[13] 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, etc.

Table 4 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. These results are consistent with the notion of serial correlation as a proxy for illiquidity risk because among the various

12. Liang (2003) presents a sobering analysis of the accuracy of hedge fund returns that underscores the challenges of marking a portfolio to market.
13. See www.investorforce.com for further information about the Altvest database.

Table 4
Summary Statistics for Monthly Total Returns of Mutual Funds and Hedge Funds

Fund	Start	Sample Size	$\hat{\mu}$ (%)	$\hat{\sigma}$ (%)	$\hat{\rho}_1$ (%)	$\hat{\rho}_2$ (%)	$\hat{\rho}_3$ (%)	$\hat{\rho}_4$ (%)	$\hat{\rho}_5$ (%)	$\hat{\rho}_6$ (%)	$p(Q_6)$ (%)
Mutual funds											
Vanguard 500 Index	76.10	286	1.30	4.27	–4.0	–6.6	–4.9	–6.4	10.1	–3.6	31.9
Fidelity Magellan	67.01	402	1.73	6.23	12.4	–2.3	–0.4	0.7	7.1	3.1	17.8
Investment Company of America	63.01	450	1.17	4.01	1.8	–3.2	–4.5	–1.6	6.3	–5.6	55.9
Janus	70.03	364	1.52	4.75	10.5	0.0	–3.7	–8.2	2.1	–0.6	30.3
Fidelity Contrafund	67.05	397	1.29	4.97	7.4	–2.5	–6.8	–3.9	2.7	–4.5	42.3
Washington Mutual Investors	63.01	450	1.13	4.09	–0.1	–7.2	–2.6	0.7	11.6	–2.6	16.7
Janus Worldwide	92.01	102	1.81	4.36	11.4	3.4	–3.8	–15.4	–21.4	–10.3	11.0
Fidelity Growth and Income	86.01	174	1.54	4.13	5.1	–1.6	–8.2	–15.6	2.1	–7.3	30.9
American Century Ultra	81.12	223	1.72	7.11	2.3	3.4	1.4	–3.7	–7.9	–6.0	81.0
Growth Fund of America	64.07	431	1.18	5.35	8.5	–2.7	–4.1	–3.2	3.4	0.3	52.5
Hedge funds											
Convertible/option arbitrage	92.05	104	1.63	0.97	42.6	29.0	21.4	2.9	–5.9	–9.7	0.0
Relative value	92.12	97	0.66	0.21	25.9	19.2	–2.1	–16.4	–6.2	1.4	3.3
Mortgage-backed securities	93.01	96	1.33	0.79	42.0	22.1	16.7	22.6	6.6	–2.0	0.0
High-yield debt	94.06	79	1.30	0.87	33.7	21.8	13.1	–0.8	13.8	4.0	1.1
Risk arbitrage A	93.07	90	1.06	0.69	–4.9	–10.8	6.9	–8.5	9.9	3.1	74.1
Long/short equities	89.07	138	1.18	0.83	–20.2	24.6	8.7	11.2	13.5	16.9	0.1
Multistrategy A	95.01	72	1.08	0.75	48.9	23.4	3.4	0.8	–2.3	–12.8	0.1
Risk arbitrage B	94.11	74	0.90	0.77	–4.9	2.5	–8.3	–5.7	0.6	9.8	93.4
Convertible arbitrage A	92.09	100	1.38	1.60	33.8	30.8	7.9	–9.4	3.6	–4.4	0.1
Convertible arbitrage B	94.07	78	0.78	0.62	32.4	9.7	–4.5	6.5	–6.3	–10.6	8.6
Multistrategy B	89.06	139	1.34	1.63	49.0	24.6	10.6	8.9	7.8	7.5	0.0
Fund of funds	94.10	75	1.68	2.29	29.7	21.2	0.9	–0.9	–12.4	3.0	6.8

Notes: Figures reflect various start dates through June 2000 for the mutual fund sample and through December 2000 for the hedge fund sample. "$\hat{\rho}_k$" denotes the kth autocorrelation coefficient, and "$p(Q_6)$" denotes the significance level of the Ljung-Box (1978) Q-statistic, $T(T+2)\Sigma_{k=1}^{6}\hat{\rho}_k^2/T-k$), which is asymptotically χ_6^2 under the null hypothesis of no serial correlation.

Source: AlphaSimplex Group

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.

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 AUM for fund i:

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

$$(2)\ \omega_{it} \equiv \frac{\mathrm{AUM}_{it}}{\sum_{j=1}^{N_t} \mathrm{AUM}_{jt}},$$

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

Figure 2 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.[14] 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 2 also shows considerable swings in ρ_t^* over time, with dynamics that seem to be related to liquidity events. In particular, consider the following 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. Figure 2 shows that over the most recent past, the weighted autocorrelation is on the rise, implying that hedge funds are taking more illiquidity exposure. This is another indirect indicator of a rise in systemic risk in the hedge fund industry.

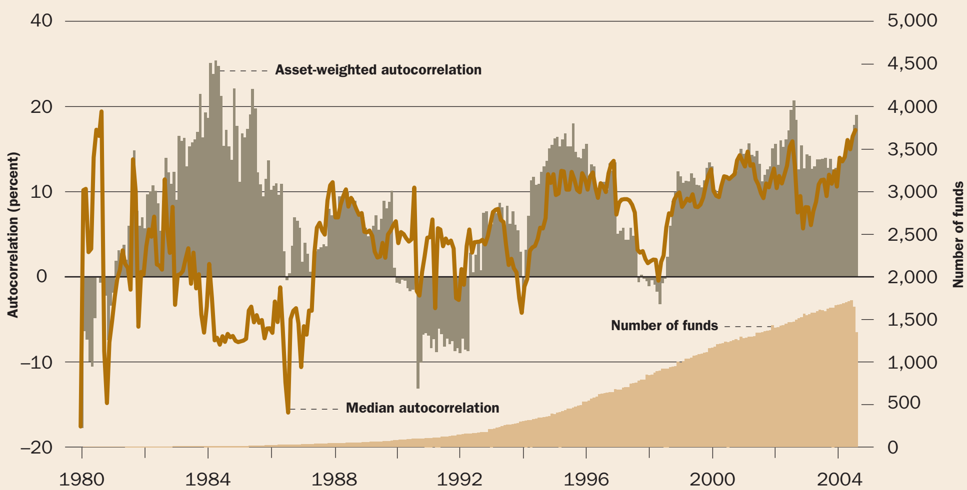
Hedge Fund Liquidations

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 funds 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

14. 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.

Figure 2
Mean and Median Autocorrelations of Hedge Funds in the TASS Combined Database, January 1980–August 2004



Note: Monthly cross-sectional median and weighted-mean first-order autocorrelation coefficients are for individual hedge funds in the TASS combined database with at least thirty-six trailing months of returns.

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.

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 in which 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 a sample of 4,536 TASS 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 earlier, 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.[15] 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 5. The motivation for AGE, ASSETS, and RETURN is well known—older funds, funds with greater assets, and funds with better recent performance are all less likely to be liquidated, so we would expect negative coefficients for these explanatory variables (recall that a larger conditional mean for Z^* implies a higher probability that $Z_{it} = 1$ or

Table 5
Definition of Explanatory Variables in Logit Analysis of Annual Hedge Fund Liquidations in the TASS Database, January 1994–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 $\text{FLOW}_\tau = \text{AUM}_\tau - \text{AUM}_{\tau-1}(1 + R_\tau)$ 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

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). Because AUM is highly persistent—with a correlation of 94.3 percent between its contemporaneous and lagged values—we include only the lagged variable ASSETS_{-1} in our logit analysis, yielding the following specification, which we call model 1:

$$(3)\quad Z_{it} = G(\beta_0 + \beta_1\text{AGE}_{it} + \beta_2\text{ASSETS}_{it-1} + \beta_3\text{RETURN}_{it} + \beta_4\text{RETURN}_{it-1} + \beta_5\text{RETURN}_{it-2} + \beta_6\text{FLOW}_{it} + \beta_7\text{FLOW}_{it-1} + \beta_8\text{FLOW}_{it-2} + \varepsilon_{it}).$$

Table 6 contains maximum-likelihood estimates of equation (3) in the first three columns, with statistically significant parameters in bold. Note that most of the parameter estimates are highly significant. This significance results from 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 result suggests that we may wish to impose a higher

15. Note that a fund cannot "die" more than once, so liquidation occurs exactly once for each fund i in the graveyard database. In particular, the time series observations of funds in this database will always be {0, 0,…, 0, 1}. This fact 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

Maximum Likelihood Estimates of a Logit Model for Annual Hedge Fund Liquidations in the TASS Database, January 1994–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 0 in all prior years.

threshold of statistical significance in this case, so as to provide a better balance between type I and type II errors.[16]

The negative signs of all the coefficients other than the constant term confirm our intuition that age, AUM, 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.[17]

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:

$$(4)\ Z_{it} = \mathrm{G}[\beta_0 + \sum_{k=1}^{10}\zeta_k \mathrm{I}(\text{YEAR}_{k,i,t}) + \sum_{k=1}^{10}\xi_k \mathrm{I}(\text{CAT}_{k,i,t}) + \beta_1\text{AGE}_{it} + \beta_2\text{ASSETS}_{it-1} + \beta_3\text{RETURN}_{it} + \beta_4\text{RETURN}_{it-1} + \beta_5\text{RETURN}_{it-2} + \beta_6\text{FLOW}_{it} + \beta_7\text{FLOW}_{it-1} + \beta_8\text{FLOW}_{it-2} + \varepsilon_{it}].$$

where

$$(5\text{a})\quad \mathrm{I}\left(\text{YEAR}_{k,i,t}\right) \equiv \begin{cases} 1 & \text{if } t = k \\ 0 & \text{otherwise} \end{cases};$$

$$(5\text{b})\quad \mathrm{I}\left(\text{CAT}_{k,i,t}\right) \equiv \begin{cases} 1 & \text{if fund } i \text{ is in category } k \\ 0 & \text{otherwise} \end{cases}.$$

The columns labelled "model 2" in Table 6 contain the maximum-likelihood estimates of (4) 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 LTCM 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. The managed futures category 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 Getmansky, Lo, and Mei 2004 for a more detailed discussion of hedge fund attrition rates). However, the fact that the 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 (see Getmansky, Lo, and Mei 2004). This fact suggests that the conditional probabilities produced by a logit analysis—which control for AUM, fund flows, and performance—yields information not readily available from the unconditional

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

17. This R^2 is the adjusted generalized coefficient of determination proposed by Nagelkerke (1991), which renormalizes 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.

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 (4) 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. The renormalized estimates show that fund flows are an order of magnitude more important in determining the probability of liquidation than AUM, returns, or age, with normalized coefficients of –32.72 and –7.53 for FLOW and FLOW_{-1}, respectively.

Finally, we reestimate the logit model in equation (4) 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. And 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 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 do differ in some ways from those of models 2–4, with significant coefficients for emerging markets, equity market neutral, and multistrategy, as well as for managed futures, suggesting significant differences between the full graveyard sample and the subsample of funds with status code 1.

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 $\hat{\beta}$ and specific values for the explanatory variables, which is readily accomplished by observing that

$$\text{(6a)} \quad p_{it} \equiv \text{Prob}\left(Z_{it}=1\right)=\text{Prob}\left(Z_{it}^{*}>0\right)$$

$$\text{(6b)} \qquad =\text{Prob}(\mathbf{X}_{it}'\beta+\varepsilon_{it}>0)=\frac{\exp\left(\mathbf{X}_{it}'\beta\right)}{1+\exp\left(\mathbf{X}_{it}'\beta\right)};$$

$$\text{(6c)} \quad \hat{p}_{it}=\frac{\exp(\mathbf{X}_{it}'\hat{\beta})}{1+\exp(\mathbf{X}_{it}'\hat{\beta})}.$$

Table 7 reports year-by-year summary statistics for the estimated liquidation probabilities $\{\hat{\rho}_{it}\}$ of each fund in our sample, where each $\hat{\rho}_{it}$ is computed using values of the explanatory variables in year t. The left panel of Table 7 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, graveyard funds, and the combined sample.[18]

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 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 includes data only up to August) are 11.24 percent and 7.69 percent, respectively, the highest levels in our entire sample. This result 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—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.[19]

The logit estimates and implied probabilities suggest that a number of factors influence the likelihood of a hedge fund's liquidation, including past performance, AUM, 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.

Regime-Switching Models

Our final hedge fund-based measure of systemic risk is motivated by the phase-locking example of Lo (1999), where the return-generating process exhibits apparent changes in expected returns and volatility that are discrete and sudden—for example, the Mexican peso crisis of 1994–95, the Asian crisis of 1997, and the global flight to quality precipitated by the default of Russian GKO debt in August 1998. 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, that is, the possibility of switching from a normal to a distressed regime.

Denote by R_t the return of a hedge fund index in period t and suppose R_t satisfies the following:

(7a) $R_t = I_t \cdot R_{1t} + (1 - I_t) \cdot R_{2t}$;

(7b) $R_{it} \sim \mathcal{N}\left(u_i, \sigma_i^2\right)$;

18. 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.
19. The TASS reporting delay also affects model 1, suggesting that its estimated liquidation probabilities for 2004 are biased downward as well.

Table 7
Liquidation Probabilities of Logit Models for Annual Hedge Fund Liquidations, January 1994–August 2004

	Model 1										
	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
SD	7.49	9.33	11.15	9.74	9.66	8.61	8.15	9.23	10.15	8.00	10.91
Min	0.01	0.01	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
25%	0.43	0.51	0.52	0.56	0.99	0.79	1.10	1.39	2.05	1.45	2.66
50%	1.16	1.46	1.52	1.59	2.71	2.18	2.80	3.69	5.62	4.49	7.55
75%	4.21	6.03	5.11	4.83	7.20	5.55	6.54	8.39	12.01	10.22	16.31
90%	12.13	16.17	16.85	13.27	16.76	12.80	13.78	16.23	21.61	17.26	26.33
Max	52.49	58.30	72.97	90.06	77.63	87.06	75.83	92.36	79.02	92.44	79.96
Count	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
SD	24.46	22.77	18.86	22.70	21.67	19.24	17.67	20.03	18.22	15.91	14.30
Min	4.91	2.50	1.05	0.25	0.00	0.53	0.22	0.98	0.13	0.02	0.25
10%	6.08	8.39	10.63	9.29	6.86	4.98	2.41	5.94	5.50	2.64	2.26
25%	22.06	16.28	17.47	21.81	12.13	12.84	9.14	12.07	10.58	8.32	6.43
50%	32.82	28.53	27.44	39.78	25.20	24.03	19.81	23.28	21.50	19.18	13.35
75%	48.40	49.79	43.36	56.94	46.21	39.62	34.92	41.01	37.98	32.28	25.26
90%	71.63	58.62	60.08	71.13	61.74	50.75	45.84	58.90	48.81	45.42	34.67
Max	77.37	97.42	79.51	88.70	85.41	84.87	87.89	78.68	94.65	72.29	67.10
Count	10	27	73	62	104	129	176	175	167	158	68
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
SD	9.86	12.10	14.53	14.44	13.59	12.39	11.41	13.01	12.26	9.90	11.10
Min	0.01	0.01	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
25%	0.45	0.55	0.62	0.62	1.10	0.91	1.20	1.62	2.28	1.60	2.72
50%	1.23	1.72	1.84	1.88	3.34	2.63	3.35	4.49	6.31	4.97	7.69
75%	4.89	7.67	8.96	6.25	9.81	7.92	9.03	11.28	13.94	11.74	16.46
90%	14.96	20.53	27.36	22.94	25.11	21.39	20.97	24.21	25.98	21.48	26.97
Max	77.37	97.42	79.51	90.06	85.41	87.06	87.89	92.36	94.65	92.44	79.96
Count	367	510	702	835	1,028	1,212	1,383	1,492	1,647	1,753	1,966

(continued)

$$(7c)\quad I_t = \begin{cases} 1 & \text{with probability } p_{11} \text{ if } I_{t-1} = 1 \\ 1 & \text{with probability } p_{21} \text{ if } I_{t-1} = 0 \\ 0 & \text{with probability } p_{12} \text{ if } I_{t-1} = 1 \\ 0 & \text{with probability } p_{22} \text{ if } I_{t-1} = 0 \end{cases}.$$

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,

Table 7 (continued)
Liquidation Probabilities of Logit Models for Annual Hedge Fund Liquidations, January 1994–August 2004

	Model 5										
	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
					Live funds						
Mean	1.06	2.22	4.30	3.43	4.70	4.05	3.80	3.40	4.07	4.45	1.76
SD	3.28	6.01	10.97	8.70	9.51	8.87	7.72	6.76	6.58	6.33	2.70
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10%	0.00	0.01	0.02	0.02	0.06	0.04	0.07	0.07	0.09	0.07	0.03
25%	0.02	0.04	0.09	0.10	0.27	0.23	0.33	0.33	0.44	0.43	0.15
50%	0.07	0.16	0.36	0.45	1.03	0.96	1.18	1.26	1.74	2.04	0.72
75%	0.52	1.25	2.61	2.26	4.03	3.22	3.49	3.63	4.75	6.01	2.31
90%	2.61	5.85	11.24	9.12	14.21	10.09	9.88	8.10	10.52	12.03	4.71
Max	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
					Graveyard funds						
Mean	24.23	23.50	34.07	42.30	36.17	31.46	32.55	22.82	20.68	20.18	4.60
SD	24.12	20.12	25.19	26.95	25.12	21.96	22.47	19.84	18.94	16.27	6.20
Min	1.00	4.92	1.88	1.49	0.00	0.11	0.02	0.51	0.03	0.03	0.04
10%	5.31	5.53	5.25	8.61	4.49	2.12	3.95	2.00	2.61	3.02	0.13
25%	11.79	7.99	11.28	21.29	15.56	12.66	15.91	6.43	5.29	6.42	0.97
50%	18.02	17.66	33.94	37.54	28.92	30.16	27.57	19.11	14.32	14.03	3.16
75%	26.24	32.58	54.36	64.53	60.14	46.31	48.38	33.10	33.19	30.61	5.51
90%	48.95	51.10	68.87	80.97	69.54	64.68	61.91	55.75	46.84	43.06	10.17
Max	64.10	69.64	82.29	93.17	87.67	89.00	90.90	76.34	90.02	67.86	33.31
Count	5	14	41	46	68	64	68	58	76	89	35
					Combined funds						
Mean	1.38	2.82	6.12	5.62	6.85	5.58	5.33	4.22	4.88	5.29	1.81
SD	4.94	7.62	14.21	13.84	13.79	11.85	11.17	8.68	8.44	8.01	2.82
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10%	0.00	0.01	0.02	0.03	0.06	0.05	0.07	0.07	0.09	0.08	0.03
25%	0.02	0.04	0.10	0.11	0.30	0.24	0.35	0.35	0.48	0.49	0.15
50%	0.08	0.19	0.43	0.54	1.24	1.06	1.32	1.42	1.93	2.28	0.73
75%	0.56	1.38	3.58	3.02	5.57	4.27	4.40	4.15	5.36	6.63	2.36
90%	3.06	7.02	19.05	16.84	22.27	17.07	15.37	9.65	12.50	13.79	4.85
Max	64.10	69.64	82.29	93.17	87.67	89.00	90.90	91.82	90.02	81.10	33.31
Count	362	497	670	819	992	1,147	1,275	1,375	1,556	1,684	1,933

Note: The summary statistics use annual observations of the liquidation status of individual hedge funds in the TASS database.

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:

$$\text{(8a)} \quad \text{Prob}(I_{t+k} = 1 | \mathcal{R}_t) = \pi_1 + (p_{11} - p_{21})^k \, [\text{Prob}(I_t = 1 | \mathcal{R}_t) - \pi_1],$$

$$\text{(8b)} \quad \pi_1 \equiv \frac{p_{21}}{p_{12} + p_{21}},$$

where $\text{Prob}(I_t = 1 | \mathcal{R}_t)$ 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

Table 8
Maximum Likelihood Estimates of a Two-State Regime-Switching Model for CSFB/Tremont Hedge Fund Indexes, January 1994–August 2004

					Annualized mean		Annualized SD		
Index	p_{11} (%)	p_{21} (%)	p_{12} (%)	p_{22} (%)	State 1 (%)	State 2 (%)	State 1 (%)	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 short-seller	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

Note: Highlighted rows indicate unreliable maximum likelihood estimates (either nonconvergence or multiple local maxima).

estimation procedure). Using similar recursions of the Markov chain, the conditional expectation of R_{t+k} can be readily derived as

$$\text{(9a)}\quad \mathrm{E}[R_{t+k} | \mathcal{R}_t] = a'_t \mathbf{P}_k \mu;$$

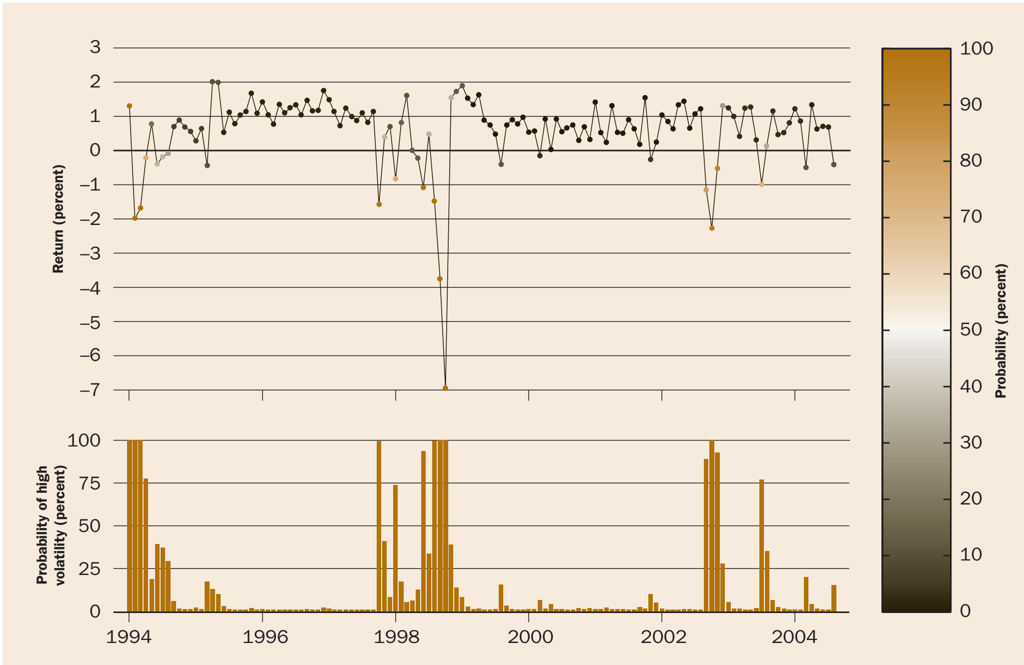
$$\text{(9b)}\quad a_t = [\mathrm{Prob}(I_t = 1 | \mathcal{R}_t)\ \mathrm{Prob}(I_t = 2 | \mathcal{R}_t)]';$$

$$\text{(9c)}\quad \mu \equiv [\mu_1\ \mu_2]'.$$

Table 8 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 8 are shaded—dedicated short-seller 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 rule: For equity market neutral, global macro, and long/short equity, the higher

Figure 3
Monthly Returns and Probabilities of the High-Volatility State for the CSFB/Tremont Fixed-Income Arbitrage Hedge Fund Index, January 1994–August 2004

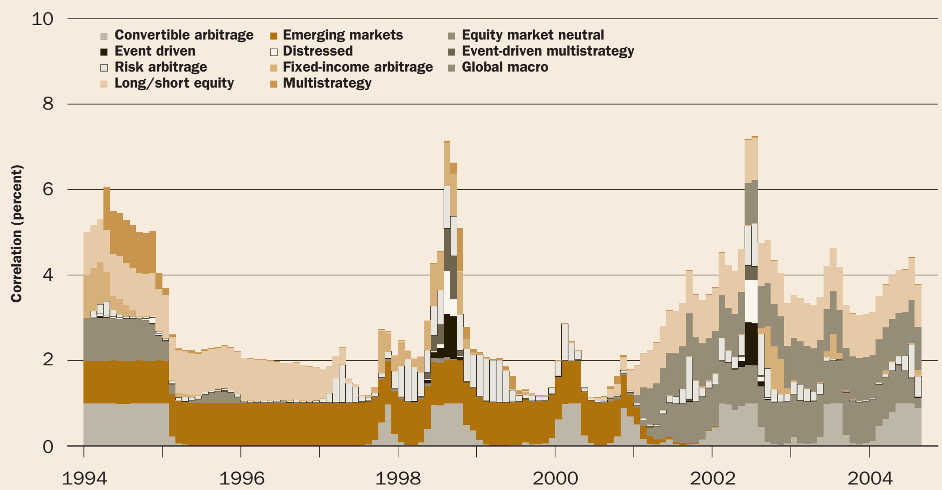


volatility state has higher expected returns. This outcome suggests that for these strategies, volatility may be a necessary ingredient for their expected returns.

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 3 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 low-mean 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. Therefore, the interpretation of the low-mean state for convertible arbitrage may be quite different than the interpretation of the low-mean state 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 4 contains this indicator. The low-mean indicator has local maxima in 1994 and 1998 as expected, but there is a stronger peak around 2002, largely due to equity market neutral, global macro, and long/short equity. This pattern corresponds remarkably well to the common wisdom that, over the past two years, these three strategy classes have underperformed for a variety of

Figure 4
Regime-Switching Probabilities of Low-Mean States for CSFB/Tremont Hedge Fund Indexes, January 1994–August 2004



Note: The figure shows the sum of monthly regime-switching model estimates of the probability of being in the low-mean state for eleven CSFB/Tremont hedge fund indexes.

reasons.[20] The implications of Figure 4 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 increased leverage for funds in these categories as well as fund outflows in the coming months, both of which would place additional stress on the industry, leading to an increase in systemic risk.

The Current Outlook

A definitive assessment of the systemic risks posed by hedge funds requires certain data that are currently unavailable and are unlikely to become available in the near future—for example, counterparty credit exposures, the net degree of leverage of hedge fund managers and investors, the gross amount of structured products involving hedge funds, etc. 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, AUM, fund flows, and age. In particular, our estimates imply that the average liquidation probability for funds in 2004 is over 11 percent—higher than the historical unconditional attri-

tion 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' 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 of lower expected returns. This new regime, 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 we 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. The question is, How?

One possibility, put forward by Getmansky, Lo, and Mei (2004), is to create an independent organization along the lines of the National Transportation Safety Board (NTSB) to sift through the wreckage of all major hedge fund collapses, ultimately producing a publicly available report that documents the specific causes of the collapse, along with recommendations on how to avoid similar disasters in the future. Although there may be common themes in the demise of many hedge funds—too much leverage, too concentrated a portfolio, operational failures, securities fraud, or insufficient AUM—each liquidation has its own unique circumstances and is an opportunity for hedge fund managers and investors to learn and improve.

In the event of an airplane crash, the NTSB assembles a team of engineers and flight-safety experts who are immediately dispatched to the crash site to conduct a thorough investigation, including interviewing witnesses, poring over historical flight logs and maintenance records, and sifting through the wreckage to recover the flight recorder or "black box" and, if necessary, reassembling the aircraft from its parts to determine the ultimate cause of the crash. Once its work is completed, the NTSB publishes a report summarizing the team's investigation, concluding with specific recommendations for avoiding future occurrences of this type of accident. The report is entered into a searchable database that is available to the general public (see www.ntsb.gov/ntsb/query.asp), and this kind of information has been one of the major factors underlying the remarkable safety record of commercial air travel.

For example, it is now current practice to spray airplanes with deicing fluid just prior to takeoff when the temperature is near freezing and it is raining or snowing. This procedure was instituted in the aftermath of USAir Flight 405's crash on March 22, 1992. Flight 405 stalled just after becoming airborne because of ice on its wings,

20. Large fund flows into these strategies and changes in equity markets such as decimalization, the rise of electronic communication networks (ECNs), automated trading, and Regulation FD are often cited as reasons for the decreased profitability of these strategies.

despite the fact that deicing fluid was applied before it left its gate. Apparently, Flight 405's takeoff was delayed because of air traffic, and ice reaccumulated on its wings while it waited for a departure slot on the runway in the freezing rain. The NTSB Aircraft Accident Report AAR-93/02—published February 17, 1993, and available through several Internet sites—contains a sobering summary of the NTSB's findings:

> The National Transportation Safety Board determines that the probable causes of this accident were the failure of the airline industry and the Federal Aviation Administration to provide flightcrews with procedures, requirements, and criteria compatible with departure delays in conditions conducive to airframe icing and the decision by the flightcrew to take off without positive assurance that the airplane's wings were free of ice accumulation after 35 minutes of exposure to precipitation following deicing. The ice contamination on the wings resulted in an aerodynamic stall and loss of control after liftoff. Contributing to the cause of the accident were the inappropriate procedures used by, and inadequate coordination between, the flightcrew that led to a takeoff rotation at a lower than prescribed air speed. (Report AAR-93/02, page vi)

Current deicing procedures have no doubt saved many lives thanks to NTSB Report AAR-93/02, but this particular innovation was paid for by the lives of the twenty-seven individuals who did not survive the crash of Flight 405. Imagine the waste if the NTSB did not investigate this tragedy and produce concrete recommendations to prevent such situations from happening again.

Hedge fund liquidations are, of course, considerably less dire, generally involving no loss of life. However, as more pension funds make allocations to hedge funds, and as the "retailization" of hedge funds continues, losses in the hedge fund industry may have more significant implications for individual investors, in some cases threatening retirement wealth and basic living standards. Moreover, the spillover effects of an industrywide shock to hedge funds should not be underestimated, as the events surrounding LTCM in the fall of 1998 illustrated. For these reasons, a "Capital Markets Safety Board" (CMSB) dedicated to investigating, reporting, and archiving the "accidents" of the hedge fund industry—and the financial services sector more generally—may yield significant social benefits in much the same way that the NTSB has improved transportation safety enormously for all air travelers. By maintaining teams of experienced professionals—forensic accountants, financial engineers from industry and academia, and securities and tax attorneys—who work together on a regular basis to investigate a number of hedge fund liquidations, this investigative body would be able to determine quickly and accurately how each liquidation came about, and the resulting reports would be an invaluable source of ideas for improving financial markets and avoiding future liquidations of a similar nature.

Of course, formal government investigations of major financial events do occur from time to time, as in the April 1999 report of the President's Working Group on Financial Markets. However, this interagency report was put together on an ad hoc basis with committee members that had not worked together previously and regularly on forensic investigations of this kind. With multiple agencies involved, and none in charge of the investigation, the administrative overhead becomes more significant. Although any thorough investigation of the financial services sector is likely to involve the SEC, the Commodity Futures Trading Commission, the U.S. Treasury, and the Federal Reserve—and interagency cooperation should be promoted—there are important operational advantages in tasking a single independent office with the responsibility for coordinating all such investigations and serving as a repository for the expertise in conducting forensic examinations of financial incidents.

The establishment of the CMSB will not be inexpensive. Currently, regulatory agencies like the SEC are understaffed and overburdened, and this condition is likely to worsen as financial markets grow in size and complexity. In addition, the lure of the private sector makes it challenging for government agencies to attract and retain individuals with expertise in these highly employable fields. Individuals trained in forensic accounting, financial engineering, and securities law now command substantial premiums on Wall Street over government pay scales. Although the typical public-sector employee is likely to be motivated more by civic duty than financial gain, it would be unrealistic to build an organization on altruism alone.

Valuable lessons could be garnered from a systematic analysis of financial incidents and the public dissemination of recommendations by seasoned professionals that review multiple cases each year.

However, the cost of an independent CMSB is more than justified by the valuable lessons that would be garnered from a systematic analysis of financial incidents and the public dissemination of recommendations by seasoned professionals that review multiple cases each year. The benefits would accrue not only to the wealthy—which is currently how the hedge fund industry is tilted—but would also flow to retail investors in the form of more stable financial markets, greater liquidity, reduced borrowing and lending costs as a result of decreased systemic risk exposures, and a wider variety of investment choices available to a larger segment of the population because of increased transparency, oversight, and ultimately, financial security. It is unrealistic to expect that market crashes, panics, collapses, and fraud will ever be completely eliminated from our capital markets, but we should avoid compounding our mistakes by failing to learn from them.

Appendix
A Description of TASS Hedge Fund Categories

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 short-seller. 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 or 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 derivative 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 health care 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 advisers, 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.

Multistrategy. 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 multistrategy 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 advisers or hedge funds who will be allocated cash by the trading manager to trade on behalf of the fund.

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