NBER WORKING PAPER SERIES

SYSTEMIC RISK AND HEDGE FUNDS

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Working Paper 11200
http://www.nber.org/papers/w11200

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2005

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NBER Working Paper No. 11200
March 2005
JEL No. G12

ABSTRACT

Systemic risk is commonly used to describe the possibility of a series of correlated defaults among financial institutions---typically banks---that occur over a short period of time, often caused by a single major event. However, since the collapse of Long Term Capital Management in 1998, it has become clear that hedge funds are also involved in systemic risk exposures. The hedge-fund industry has a symbiotic relationship with the banking sector, and many banks now operate proprietary trading units that are organized much like hedge funds. As a result, the risk exposures of the hedge-fund industry may have a material impact on the banking sector, resulting in new sources of systemic risks. In this paper, we attempt to quantify the potential impact of hedge funds on systemic risk by developing a number of new risk measures for hedge funds and applying them to individual and aggregate hedge-fund returns data. These measures include: illiquidity risk exposure, nonlinear factor models for hedge-fund and banking-sector indexes, logistic regression analysis of hedge-fund liquidation probabilities, and aggregate measures of volatility and distress based on regime-switching models. Our preliminary findings suggest that the hedge-fund industry may be heading into a challenging period of lower expected returns, and that systemic risk is currently on the rise.

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1 Introduction

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

Although today banking panics are virtually non-existent thanks to the FDIC and related central banking policies, systemic risk exposures have taken shape in other forms. With the repeal in 1999 of the Glass-Steagall Act, many banks have now become broad-based financial institutions engaging in the full spectrum of financial services including retail banking, underwriting, investment banking, brokerage services, asset management, venture capital, and proprietary trading. Accordingly, the risk exposures of such institutions have become considerably more complex and interdependent, especially in the face of globalization and the recent wave of consolidations in the banking and financial services sectors.

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

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

leverage to enhance their returns and, consequently, their risks.

In this paper, we attempt to quantify the potential impact of hedge funds on systemic risk by developing a number of new risk measures for hedge-fund investments and applying them to individual and aggregate hedge-fund returns data. We argue that the risk/reward profile for most alternative investments differ in important ways from more traditional investments, and such differences may have potentially important implications for systemic risk, as we experienced during the aftermath of the default of Russian government debt in August 1998 when Long Term Capital Management and many other hedge funds suffered catastrophic losses over the course of a few weeks, creating significant stress on the global financial system and a number of substantial financial institutions. Two major themes emerged from that set of events: the importance of liquidity and leverage, and the capriciousness of correlations among instruments and portfolios that are supposedly uncorrelated. These are the two main themes of this study, and both are intimately related to the dynamic nature of hedge-fund investment strategies and risk exposures.

One of the justifications for the unusually rich fee structures that characterize hedge-fund investments is the fact that hedge funds are active strategies involving highly skilled portfolio managers. Moreover, it is common wisdom that the most talented managers are drawn first to the hedge-fund industry because the absence of regulatory constraints enables them to make the most of their investment acumen. With the freedom to trade as much or as little as they like on any given day, to go long or short any number of securities and with varying degrees of leverage, and to change investment strategies at a moment's notice, hedge-fund managers enjoy enormous flexibility and discretion in pursuing performance. But dynamic investment strategies imply dynamic risk exposures, and while modern financial economics has much to say about the risk of *static* investments—the market beta is sufficient in this case—there is currently no single measure of the risks of a dynamic investment strategy.[2]

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

$$\text{Max}_{\{\omega_i\}} \text{E}[U(W_1)] \tag{1}$$

$$\text{subject to} \quad W_1 = W_0(1 + R_p) \tag{2a}$$

$$R_p \equiv \sum_{i=1}^{n} \omega_i R_i \quad , \quad 1 = \sum_{i=1}^{n} \omega_i \tag{2b}$$

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

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

It is one of the great lessons of modern finance that mean-variance optimization yields benefits through diversification, the ability to lower volatility for a given level of expected return by combining securities that are not perfectly correlated. But what if the securities are hedge funds, and what if their correlations change over time, as hedge funds tend to do (see Section 3.1)?[4] Table 1 shows that for the two-asset case with fixed means of 5% and 30%, respectively, and fixed standard deviations of 20% and 30%, respectively, as the correlation ρ between the two assets varies from −90% to 70%, the optimal portfolio weights—and the properties of the optimal portfolio—change dramatically. For example, with a −30% correlation between the two funds, the optimal portfolio holds 38.6% in the first fund and 61.4% in the second, yielding a Sharpe ratio of 1.01. But if the correlation changes to 10%, the optimal weights change to 5.2% in the first fund and 94.8% in the second, despite the fact that the Sharpe ratio of this new portfolio, 0.92, is virtually identical to the previous portfolio's Sharpe ratio. The mean-variance-efficient frontiers are plotted in Figure 1 for three values of the correlation coefficient between the two funds (−50%, 0%, and 50%), and it is apparent that the optimal portfolio depends heavily on this correlation. For example, as the correlation between the two assets changes from 0% to −50%, the optimal portfolio changes from A to B, which are two very different portfolios. Because of the dynamic nature of hedge-fund strategies, their correlations are particularly unstable through time and over varying market conditions as we shall see in Section 1.2, and swings from −30% to 30% are not unusual.

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

[3] See, for example, Ingersoll (1987).

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

Mean-Variance Optimal Portfolios

For Two-Asset Case

$(\mu_1, \sigma_1) = (5\%, 20\%)$, $(\mu_2, \sigma_2) = (30\%, 30\%)$, $R_f = 2.5\%$

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

Table 1: Mean-variance optimal portfolio weights for the two-asset case with fixed means and variances, and correlations ranging from −90% to 70%.

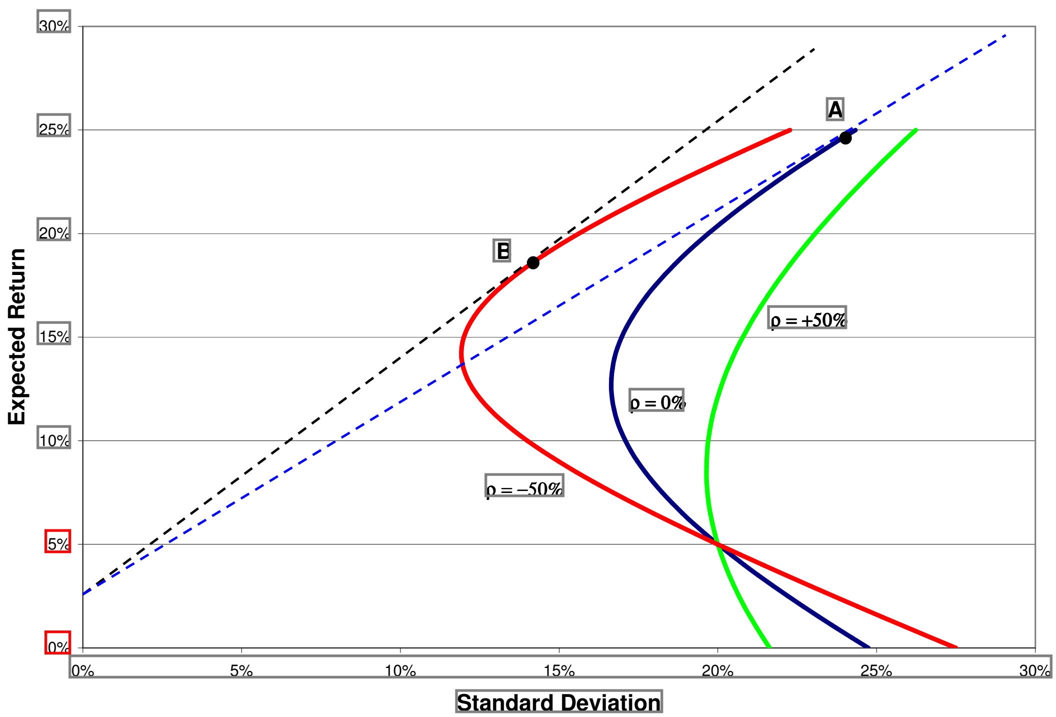


Figure 1: Mean-variance efficient frontiers for the two-asset case with parameters $(\mu_1, \sigma_1) = (5\%, 20\%)$, $(\mu_2, \sigma_2) = (30\%, 30\%)$, and correlation $\rho = -50\%, 0\%, 50\%$.

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

To illustrate the challenges and opportunities in modeling the risk exposures of hedge funds, we provide two concrete examples in this section. In Section 1.1, we present a hypothetical hedge-fund strategy that yields remarkable returns with seemingly little risk, yet a closer examination will reveal quite a different story. And in Section 1.2, we show that correlation analysis may not be able capture certain risk exposures that are particularly relevant for hedge-fund investments.

These examples provide an introduction to the analysis in Sections 3–7, and serve as motivation for developing new quantitative methods for capturing the impact of hedge funds on systemic risk. In Section 3, 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. In Section 4, we turn to the issue of liquidity—one of the central aspects of systemic risk—and present several measures for gauging illiquidity exposure in hedge funds and other asset classes, and apply them to individual and index data. Since systemic risk is directly related to hedge-fund failures, in Section 5 we investigate attrition rates of hedge funds in the TASS database and present a logit analysis that yields estimates of a fund's probability of liquidation as a function of various fund characteristics such as return history, assets under management, and recent fund flows. In Section 6, we present three other approaches to measuring systemic risk in the hedge-fund industry: risk models for hedge-fund indexes, regression models relating the banking sector to hedge funds, and regime-switching models applied to hedge-fund indexes. These three approaches yield distinct insights regarding the risks posed by the hedge-fund industry, and we conclude in Section 7 by discussing the current outlook for the hedge-fund industry based on 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.

1.1 Tail Risk

Consider the 8-year track record of a hypothetical hedge fund, Capital Decimation Partners, LP, summarized in Table 2. This track record was obtained by applying a specific investment strategy, to be revealed below, to actual market prices from January 1992 to December 1999.

Before discussing the particular strategy that generated these results, let us consider its overall performance: an average monthly return of 3.7% versus 1.4% for the S&P 500 during the same period; a total return of 2,721.3% over the 8-year period versus 367.1% for the S&P 500; a Sharpe ratio of 1.94 versus 0.98 for the S&P 500; and only 6 negative monthly returns out of 96 versus 36 out of 96 for the S&P 500. In fact, the monthly performance history—displayed in Table 3—shows that, as with many other hedge funds, the worst months for this fund were August and September of 1998. Yet October and November 1998 were the fund's two best months, and for 1998 as a whole the fund was up 87.3% versus 24.5% for the S&P 500! By all accounts, this is an enormously successful hedge fund with a track record that would be the envy of most managers.[5] What is its secret?

Capital Decimation Partners, L.P.

Performance Summary, January 1992 to December 1999

Statistic	S&P 500	CDP
Monthly Mean	1.4%	3.7%
Monthly Std. Dev.	3.6%	5.8%
Min Month	−8.9%	−18.3%
Max Month	14.0%	27.0%
Annual Sharpe Ratio	0.98	1.94
# Negative Months	36/96	6/96
Correlation with S&P 500	100.0%	59.9%
Total Return	367.1%	2721.3%

Table 2: Summary of simulated performance of a particular dynamic trading strategy using monthly historical market prices from January 1992 to December 1999.

The investment strategy summarized in Tables 2 and 3 consists of shorting out-of-the-money S&P 500 (SPX) put options on each monthly expiration date for maturities less than or equal to three months, and with strikes approximately 7% out of the money. The number of contracts sold each month is determined by the combination of: (1) CBOE margin

[5] In fact, as a mental exercise to check your own risk preferences, take a hard look at the monthly returns in Table 3 and ask yourself whether you would invest in such a fund.

requirements;[6] (2) an assumption that we are required to post 66% of the margin as collateral;[7] and (3) \$10M of initial risk capital. For concreteness, Table 4 reports the positions and profit/loss statement for this strategy for 1992. See Lo (2001) for further details of this strategy.

The track record in Tables 2 and 3 seems much less impressive in light of the simple strategy on which it is based, and few investors would pay hedge-fund-type fees for such a fund. However, given the secrecy surrounding most hedge-fund strategies, and the broad discretion that managers are given by the typical hedge-fund offering memorandum, it is difficult for investors to detect this type of behavior without resorting to more sophisticated risk analytics that can capture *dynamic* risk exposures.

[6] The margin required per contract is assumed to be:

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

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

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

Some might argue that this example illustrates the need for position transparency—after all, it would be apparent from the positions in Table 4 that the manager of Capital Decimation Partners is providing little or no value-added. However, there are many ways of implementing this strategy that are not nearly so transparent, even when positions are fully disclosed. For example, Table 5 reports the weekly positions over a six-month period in one of 500 securities contained in a second hypothetical fund, Capital Decimation Partners II. Casual inspection of the positions of this one security seem to suggest a contrarian trading strategy: when the price declines, the position in XYZ is increased, and when the price advances, the position is reduced. A more careful analysis of the stock and cash positions and the varying degree of leverage in Table 5 reveals that these trades constitute a so-called "delta-hedging" strategy, designed to synthetically replicate a short position in a 2-year European put option on 10,000,000 shares of XYZ with a strike price of $25 (recall that XYZ's initial stock price is $40, hence this is a deep out-of-the-money put).

Shorting deep out-of-the-money puts is a well-known artifice employed by unscrupulous hedge-fund managers to build an impressive track record quickly, and most sophisticated investors are able to avoid such chicanery. However, imagine an investor presented with position reports such as Table 5, but for 500 securities, not just one, as well as a corresponding track record that is likely to be even more impressive than that of Capital Decimation Partners, LP.[8] Without additional analysis that explicitly accounts for the dynamic aspects of the trading strategy described in Table 5, it is difficult for an investor to fully appreciate the risks inherent in such a fund.

In particular, static methods such as traditional mean-variance analysis cannot capture the risks of dynamic trading strategies like Capital Decimation Partners (note the impressive Sharpe ratio in Table 2). In the case of the strategy of shorting out-of-the-money put options on the S&P 500, returns are positive most of the time and losses are infrequent, but when they occur, they are extreme. This is a very specific type of risk signature that is not well-summarized by static measures such as standard deviation. In fact, the estimated standard deviations of such strategies tend to be rather low, hence a naive application of mean-variance analysis such as risk-budgeting—an increasingly popular method used by institutions to make allocations based on risk units—can lead to unusually large allocations to funds like Capital Decimation Partners. The fact that total position transparency does not imply risk transparency is further cause for concern.

This is not to say that the risks of shorting out-of-the-money puts are inappropriate for all

[8] A portfolio of options is worth more than an option on the portfolio, hence shorting 500 puts on the individual stocks that constitute the SPX will yield substantially higher premiums than shorting puts on the index.

Capital Decimation Partners, LP
Positions and Profit/Loss For 1992

	S&P 500		# Puts	Strike	Price	Expiration	Margin Required	Profits	Initial Capital+ Cumulative Profits	Capital Available for Investments	Return
12/20/91	387.04	new	2300	360	4.625	Mar-92	$6,069,930		$10,000,000	$6,024,096	
1/17/92	418.86	mark to market	2300	360	1.125	Mar-92	$654,120	$805,000	$10,805,000	$6,509,036	8.1%
	418.86	new	1950	390	3.250	Mar-92	$5,990,205				
						Total Margin	**$6,644,325**				
2/21/92	411.46	mark to market	2300	360	0.250	Mar-92	$2,302,070	$690,000			
	411.46	mark to market	1950	390	1.625	Mar-92	$7,533,630	$316,875	$11,811,875	$7,115,587	9.3%
	411.46	liquidate	1950	390	1.625	Mar-92	$0	$0	$11,811,875	$7,115,587	
	411.46	new	1246	390	1.625	Mar-92	$4,813,796				
						Total Margin	**$7,115,866**				
3/20/92	411.30	expired	2300	360	0.000	Mar-92	$0	$373,750			
	411.30	expired	1246	390	0.000	Mar-92	$0	$202,475			
	411.30	new	2650	380	2.000	May-92	$7,524,675		$12,388,100	$7,462,711	4.9%
						Total Margin	**$7,524,675**				
4/19/92	416.05	mark to market	2650	380	0.500	May-92	$6,852,238	$397,500			
	416.05	new	340	385	2.438	Jun-92	$983,280		$12,785,600	$7,702,169	3.2%
						Total Margin	**$7,835,518**				
5/15/92	410.09	expired	2650	380	0.000	May-92	$0	$132,500			
	410.09	mark to market	340	385	1.500	Jun-92	$1,187,399	$31,875			
	410.09	new	2200	380	1.250	Jul-92	$6,638,170		$12,949,975	$7,801,190	1.3%
						Total Margin	**$7,825,569**				
6/19/92	403.67	expired	340	385	0.000	Jun-92	$0	$51,000			
	403.67	mark to market	2200	380	1.125	Jul-92	$7,866,210	$27,500	$13,028,475	$7,848,479	0.6%
						Total Margin	**$7,866,210**				
7/17/92	415.62	expired	2200	380	0.000	Jul-92	$0	$247,500			
	415.62	new	2700	385	1.8125	Sep-92	$8,075,835		$13,275,975	$7,997,575	1.9%
						Total Margin	**$8,075,835**				
8/21/92	414.85	mark to market	2700	385	1	Sep-92	$8,471,925	$219,375	$13,495,350	$8,129,729	1.7%
						Total Margin	**$8,471,925**				
9/18/92	422.92	expired	2700	385	0	Sep-92	$0	$270,000	$13,765,350	$8,292,380	2.0%
	422.92	new	2370	400	5.375	Dec-92	$8,328,891				
						Total Margin	**$8,328,891**				
10/16/92	411.73	mark to market	2370	400	7	Dec-92	$10,197,992	($385,125)			
	411.73	liquidate	2370	400	7	Dec-92	$0	$0	$13,380,225	$8,060,377	-2.8%
	411.73	new	1873	400	7	Dec-92	$8,059,425				
						Total Margin	**$8,059,425**				
11/20/92	426.65	mark to market	1873	400	0.9375	Dec-92	$6,819,593	$1,135,506	$14,515,731	$8,744,416	8.5%
	426.65	new	529	400	0.9375	Dec-92	$1,926,089				
						Total Margin	**$8,745,682**				
12/18/92	441.20	expired	1873	400	0	Dec-92	$0	$175,594	$14,691,325	$8,850,196	1.2%
									1992 Total Return:		**46.9%**

Table 4: Simulated positions and profit/loss statement for 1992 for a trading strategy that consists of shorting out-of-the-money put options on the S&P 500 once a month.

investors—indeed, the thriving catastrophe reinsurance industry makes a market in precisely this type of risk, often called "tail risk". However, such insurers do so with full knowledge of the loss profile and probabilities for each type of catastrophe, and they set their capital reserves and risk budgets accordingly. The same should hold true for institutional investors of hedge funds, but the standard tools and lexicon of the industry currently provide only an incomplete characterization of such risks. The need for a new set of dynamic risk analytics specifically targeted for hedge-fund investments is clear.

Capital Decimation Partners II, L.P.

Weekly Positions in XYZ

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

Table 5: Simulated weekly positions in XYZ for a particular trading strategy over a six-month period.

1.2 Phase-Locking Risk

One of the most compelling reasons for investing in hedge funds is the fact that their returns seem relatively uncorrelated with market indexes such as the S&P 500, and modern portfolio theory has convinced even the most hardened skeptic of the benefits of diversification (see, for example, the correlations between hedge-fund indexes and the S&P 500 in Table 7 below). However, the diversification argument for hedge funds must be tempered by the lessons of the summer of 1998 when the default in Russian government debt triggered a global flight to quality that changed many of these correlations overnight from 0 to 1. In the physical and natural sciences, such phenomena are examples of "phase-locking" behavior, situations in which otherwise uncorrelated actions suddenly become synchronized.[9] The fact that market conditions can create phase-locking behavior is certainly not new—market crashes have been with us since the beginning of organized financial markets—but prior to 1998, few hedge-fund investors and managers incorporated this possibility into their investment processes in any systematic fashion.

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

$$R_{it} = \alpha_i + \beta_i \Lambda_t + I_t Z_t + \epsilon_{it} \tag{3}$$

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

$$\begin{aligned} \mathrm{E}[\Lambda_t] &= \mu_\lambda \quad , \quad \mathrm{Var}[\Lambda_t] = \sigma_\lambda^2 \\ \mathrm{E}[Z_t] &= 0 \quad , \quad \mathrm{Var}[Z_t] = \sigma_z^2 \\ \mathrm{E}[\epsilon_{it}] &= 0 \quad , \quad \mathrm{Var}[\epsilon_{it}] = \sigma_{\epsilon_i}^2 \end{aligned} \tag{4}$$

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

$$I_t \equiv \begin{cases} 1 & \text{with probability } p \\ 0 & \text{with probability } 1-p \end{cases} . \tag{5}$$

[9]One of the most striking examples of phase-locking behavior is the automatic synchronization of the flickering of Southeast Asian fireflies. See Strogatz (1994) for a description of this remarkable phenomenon as well as an excellent review of phase-locking behavior in biological systems.

According to (3), expected returns are the sum of three components: the fund's alpha, α_i, a "market" component, Λ_t, to which each fund has its own individual sensitivity, β_i, and a phase-locking component that is identical across all funds at all times, taking only one of two possible values, either 0 (with probability p) or Z_t (with probability $1-p$). If we assume that p is small, say 0.001, then most of the time the expected returns of fund i are determined by $\alpha_i + \beta_i \Lambda_t$, but every once in a while an additional term Z_t appears. If the volatility σ_z of Z_t is much larger than the volatilities of the market factor, Λ_t, and the idiosyncratic risk, ϵ_{it}, then the common factor Z_t will dominate the expected returns of all stocks when $I_t = 1$, i.e., phase-locking behavior.

More formally, consider the *conditional* correlation coefficient of two funds i and j, defined as the ratio of the conditional covariance divided by the square root of the product of the conditional variances, conditioned on $I_t = 0$:

$$\begin{aligned} \text{Corr}[R_{it}, R_{jt} \mid I_t = 0] &= \frac{\beta_i \beta_j \sigma_\lambda^2}{\sqrt{\beta_i^2 \sigma_\lambda^2 + \sigma_{\epsilon_i}^2}\sqrt{\beta_j^2 \sigma_\lambda^2 + \sigma_{\epsilon_j}^2}} && (6) \\ &\approx 0 \quad \text{for } \beta_i \approx \beta_j \approx 0 && (7) \end{aligned}$$

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

$$\begin{aligned} \text{Corr}\left[R_{it}, R_{jt} \mid I_t = 1\right] &= \frac{\beta_i \beta_j \sigma_\lambda^2 + \sigma_z^2}{\sqrt{\beta_i^2 \sigma_\lambda^2 + \sigma_z^2 + \sigma_{\epsilon_i}^2}\sqrt{\beta_j^2 \sigma_\lambda^2 + \sigma_z^2 + \sigma_{\epsilon_j}^2}} && (8a) \\ &\approx \frac{1}{\sqrt{1 + \sigma_{\epsilon_i}^2/\sigma_z^2}\sqrt{1 + \sigma_{\epsilon_j}^2/\sigma_z^2}} \quad \text{for} \quad \beta_i \approx \beta_j \approx 0\,. && (8b) \end{aligned}$$

If σ_z^2 is large relative to $\sigma_{\epsilon_i}^2$ and $\sigma_{\epsilon_j}^2$, i.e., if the variability of the catastrophe component dominates the variability of the residuals of both funds—a plausible condition that follows from the very definition of a catastrophe—then (8) will be approximately equal to 1! When phase-locking occurs, the correlation between two funds i and j—close to 0 during normal times—can become arbitrarily close to 1.

An insidious feature of (3) is the fact that it implies a very small value for the *unconditional* correlation, which is the quantity most readily estimated and most commonly used in risk reports, Value-at-Risk calculations, and portfolio decisions. To see why, recall that the unconditional correlation coefficient is simply the unconditional covariance divided by the product of the square roots of the unconditional variances:

$$\text{Corr}[R_{it}, R_{jt}] \equiv \frac{\text{Cov}[R_{it}, R_{jt}]}{\sqrt{\text{Var}[R_{it}]\text{Var}[R_{jt}]}} \tag{9a}$$

$$\text{Cov}[R_{it}, R_{jt}] = \beta_i\beta_j\sigma_\lambda^2 + \text{Var}[I_t Z_t] = \beta_i\beta_j\sigma_\lambda^2 + p\sigma_z^2 \tag{9b}$$

$$\text{Var}[R_{it}] = \beta_i^2\sigma_\lambda^2 + \text{Var}[I_t Z_t] + \sigma_{\epsilon_i}^2 = \beta_i^2\sigma_\lambda^2 + p\sigma_z^2 + \sigma_{\epsilon_i}^2 . \tag{9c}$$

Combining these expressions yields the unconditional correlation coefficient under (3):

$$\text{Corr}[R_{it}, R_{jt}] \equiv \frac{\beta_i\beta_j\sigma_\lambda^2 + p\sigma_z^2}{\sqrt{\beta_i^2\sigma_\lambda^2 + p\sigma_z^2 + \sigma_{\epsilon_i}^2}\sqrt{\beta_j^2\sigma_\lambda^2 + p\sigma_z^2 + \sigma_{\epsilon_j}^2}} \tag{10a}$$

$$\approx \frac{p}{\sqrt{p + \sigma_{\epsilon_i}^2/\sigma_z^2}\sqrt{p + \sigma_{\epsilon_j}^2/\sigma_z^2}} \quad \text{for } \beta_i \approx \beta_j \approx 0 \ . \tag{10b}$$

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

$$\text{Corr}[R_{it}, R_{jt}] \approx \frac{p}{\sqrt{p + 0.1}\sqrt{p + 0.1}} = 0.001/.101 = 0.0099$$

or less than 1%. As the variance σ_z^2 of the phase-locking component increases, the unconditional correlation (10) also increases so that eventually, the existence of Z_t will have an impact. However, to achieve an unconditional correlation coefficient of, say, 10%, σ_z^2 would have to be about 100 times larger than σ_ϵ^2. Without the benefit of an explicit risk model such as (3), it is virtually impossible to detect the existence of a phase-locking component from standard correlation coefficients.

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

- Price Factors
- Sectors
- Investment Style
- Volatilities
- Credit
- Liquidity
- Macroeconomic Factors
- Sentiment
- Nonlinear Interactions

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

Finally, although common factors listed above may serve as a useful starting point for developing a quantitative model of hedge-fund risk exposures, it should be emphasized that a certain degree of customization will be required. To see why, consider the following list of key components of a typical long/short equity hedge fund:

- Investment style (value, growth, etc.)
- Fundamental analysis (earnings, analyst forecasts, accounting data)
- Factor exposures (S&P 500, industries, sectors, characteristics)
- Portfolio optimization (mean-variance analysis, market neutrality)
- Stock loan considerations (hard-to-borrow securities, short "squeezes")
- Execution costs (price impact, commissions, borrowing rate, short rebate)
- Benchmarks and tracking error (T-bill rate vs. S&P 500)

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

- Yield-curve models (equilibrium vs. arbitrage models)
- Prepayment models (for mortgage-backed securities)
- Optionality (call, convertible, and put features)
- Credit risk (defaults, rating changes, etc.)
- Inflationary pressures, central bank activity
- Other macroeconomic factors and events

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

2 Literature Review

The explosive growth in the hedge-fund sector over the past several years has generated a rich literature both in academia and among practitioners, including a number of books, newsletters, and trade magazines, several hundred published articles, and an entire journal dedicated solely to this industry (the *Journal of Alternative Investments*). However, none of this literature has considered the impact of hedge funds on systemic risk.[10] Nevertheless, thanks to the availability of hedge-fund returns data from sources such as AltVest, CISDM, HedgeFund.net, HFR, and TASS, a number of empirical studies have highlighted the unique risk/reward profiles of hedge-fund investments. For example, Ackermann, McEnally, and Ravenscraft (1999), Fung and Hsieh (1999, 2000, 2001), Liang (1999, 2000, 2001), Agarwal and Naik (2000b, 2000c), Edwards and Caglayan (2001), Kao (2002), and Amin and Kat (2003a) provide comprehensive empirical studies of historical hedge-fund performance using various hedge-fund databases. Brown, Goetzmann, and Park (2000, 2001a,b), Fung and Hsieh (1997a, 1997b), Brown, Goetzmann, and Ibbotson (1999), Agarwal and Naik (2000a,d), Brown and Goetzmann (2003), and Lochoff (2002) present more detailed performance attribution and "style" analysis for hedge funds.

Several recent empirical studies have challenged the uncorrelatedness of hedge-fund returns with market indexes, arguing that the standard methods of assessing their risks and rewards may be misleading. For example, Asness, Krail and Liew (2001) show that in sev-

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

eral cases where hedge funds purport to be market neutral, i.e., funds with relatively small market betas, including both contemporaneous and lagged market returns as regressors and summing the coefficients yields significantly higher market exposure. Moreover, in deriving statistical estimators for Sharpe ratios of a sample of mutual and hedge funds, Lo (2002) proposes a better method for computing annual Sharpe ratios based on monthly means and standard deviations, yielding point estimates that differ from the naive Sharpe ratio estimator by as much as 70% in his empirical application. Getmansky, Lo, and Makarov (2004) focus directly on the unusual degree of serial correlation in hedge-fund returns, and argue that illiquidity exposure and smoothed returns are the most common sources of such serial correlation. They also propose methods for estimating the degree of return-smoothing and adjusting performance statistics like the Sharpe ratio to account for serial correlation.

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

Fund flows in the hedge-fund industry have been considered by Agarwal, Daniel, and Naik (2004) and Getmansky (2004), with the expected conclusion that funds with higher returns tend to receive higher net inflows and funds with poor performance suffer withdrawals and, eventually, liquidation, much like the case with mutual funds and private equity.[11] Agarwal,

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

Daniel, and Naik (2004), Goetzmann, Ingersoll and Ross (2003), and Getmansky (2004) all find decreasing returns to scale among their samples of hedge funds, implying that an optimal amount of assets under management exists for each fund and mirroring similar findings for the mutual-fund industry by Pérold and Salomon (1991) and the private-equity industry by Kaplan and Schoar (2004). Hedge-fund survival rates have been studied by Brown, Goetzmann and Ibbotson (1999), Fung and Hsieh (2000), Liang (2000, 2001), Bares, Gibson and Gyger (2003), Brown, Goetzmann and Park (2001b), Gregoriou (2002), and Amin and Kat (2003b). Baquero, Horst, and Verbeek (2004) estimate liquidation probabilities of hedge funds and find that they are greatly dependent on past performance.

The survival rates of hedge funds have been estimated by Brown, Goetzmann and Ibbotson (1999), Fung and Hsieh (2000), Liang (2000, 2001), Brown, Goetzmann and Park (2001a,b), Gregoriou (2002), Amin and Kat (2003b), Bares, Gibson and Gyger (2003), and Getmansky, Lo, and Mei (2004). Brown, Goetzmann, and Park (2001b) show that the probability of liquidation increases with increasing risk, and that funds with negative returns for two consecutive years have a higher risk of shutting down. Liang (2000) finds that the annual hedge-fund attrition rate is 8.3% for the 1994–1998 sample period using TASS data, and Baquero, Horst, and Verbeek (2004) find a slightly higher rate of 8.6% for the 1994–2000 sample period. Baquero, Horst, and Verbeek (2004) also find that surviving funds outperform non-surviving funds by approximately 2.1% per year, which is similar to the findings of Fung and Hsieh (2000, 2002b) and Liang (2000), and that investment style, size, and past performance are significant factors in explaining survival rates. Many of these patterns are also documented by Liang (2000), Boyson (2002), and Getmansky, Lo, and Mei (2004). In particular, Getmansky, Lo, and Mei (2004) find that attrition rates in the TASS database from 1994 to 2004 differ significantly across investment styles, from a low of 5.2% per year on average for convertible arbitrage funds to a high of 14.4% per year on average for managed futures funds. They also relate a number of factors to these attrition rates, including past performance, volatility, and investment style, and document differences in illiquidity risk between active and liquidated funds. In analyzing the life cycle of hedge funds, Getmansky (2004) finds that the liquidation probabilities of individual hedge funds depend on fund-specific characteristics such as past returns, asset flows, age, and assets under management as well, as category-specific variables such as competition and favorable positioning within the industry.

Brown, Goetzmann and Park (2001b) find that half-life of the TASS hedge funds is exactly 30 months, while Brooks and Kat (2002) estimate that approximately 30% of new hedge funds do not make it past 36 months due to poor performance, and in Amin and Kat's (2003b) study, 40% of their hedge funds do not make it to the fifth year. Howell

(2001) observed that the probability of hedge funds failing in their first year was 7.4%, only to increase to 20.3% in their second year. Poor-performing younger funds drop out of databases at a faster rate than older funds (see Getmansky, 2004, and Jen, Heasman, and Boyatt, 2001), presumably because younger funds are more likely to take additional risks to obtain good performance which they can use to attract new investors, whereas older funds that have survived already have track records with which to attract and retain capital.

A number of case studies of hedge-fund liquidations have been published recently, no doubt spurred by the most well-known liquidation in the hedge-fund industry to date: Long-Term Capital Management (LTCM). The literature on LTCM is vast, spanning a number of books, journal articles, and news stories; a representative sample includes Greenspan (1998), McDonough (1998), Pérold (1999), the President's Working Group on Financial Markets (1999), and MacKenzie (2003). Ineichen (2001) has compiled a list of selected hedge funds and analyzed the reasons for their liquidations. Kramer (2001) focuses on fraud, providing detailed accounts of six of history's most egregious cases. Although it is virtually impossible to obtain hard data on the frequency of fraud among liquidated hedge funds,[12] in a study of over 100 liquidated hedge funds during the past two decades, Feffer and Kundro (2003) conclude that "half of all failures could be attributed to operational risk alone", of which fraud is one example. In fact, they observe that "The most common operational issues related to hedge fund losses have been misrepresentation of fund investments, misappropriation of investor funds, unauthorized trading, and inadequate resources" (Feffer and Kundro, 2003, p. 5). The last of these issues is, of course, not related to fraud, but Feffer and Kundro (2003, Figure 2) report that only 6% of their sample involved inadequate resources, whereas 41% involved misrepresentation of investments, 30% misappropriation of funds, and 14% unauthorized trading. These results suggest that operational issues are indeed an important factor in hedge-fund liquidations, and deserve considerable attention by investors and managers alike.

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

3 The Data

It is clear from Section 1 that hedge funds exhibit unique and dynamic characteristics that bear further study. Fortunately, the returns of many individual hedge funds are now available through a number of commercial databases such as AltVest, CISDM, HedgeFund.net, HFR,

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

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.[13]

The CSFB/Tremont indexes are asset-weighted indexes of funds with a minimum of $10 million of assets under management ("AUM"), a minimum one-year track record, and current audited financial statements. An aggregate index is computed from this universe, and 10 sub-indexes 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.

Category	Definition	Number of TASS Funds In: 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	Multi-Strategy	98	41	139
11	Fund of Funds	679	273	952
	Total	2,771	1,765	4,536

Table 6: Number of funds in the TASS Hedge Fund Live, Graveyard, and Combined databases, from February 1977 to August 2004.

The TASS database consists of monthly returns, assets under management and other fund-specific information for 4,781 individual funds from February 1977 to August 2004. The database is divided into two parts: "Live" and "Graveyard" funds. Hedge funds that

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

are in the "Live" database are considered to be active as of August 31, 2004.[14] As of August, 2004, the combined database of both live and dead hedge funds contained 4,781 funds with at least one monthly return observation. Out of these 4,781 funds, 2,920 funds are in the Live database and 1,861 in the Graveyard database. The earliest data available for a fund in either database is February 1977. TASS started tracking dead funds in 1994, hence it is only since 1994 that TASS transferred funds from the Live database to the Graveyard database. Funds that were dropped from the Live database prior to 1994 are not included in the Graveyard database, which may yield a certain degree of survivorship bias.[15]

The majority of 4,781 funds reported returns net of management and incentive fees on a monthly basis.[16] and 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 quarterly—not monthly—basis, leaving 4,705 funds in the Combined database (2,884 in the Live and 1,821 in the Graveyard database). Finally, we dropped funds that did not report assets under management, or reported only partial assets under management, leaving a final sample of 4,536 hedge funds in the Combined database which consists of 2,771 funds in the Live database and 1,765 funds in the Graveyard database. For the empirical analysis in Section 4, we impose an additional filter in which we require funds to have at least five years of non-missing returns, leaving 1,226 funds in the Live database and 611 in the Graveyard database for a combined total of 1,837 funds. This obviously creates additional survivorship bias in the remaining sample of funds, but since the main objective is to estimate measures of illiquidity exposure and not

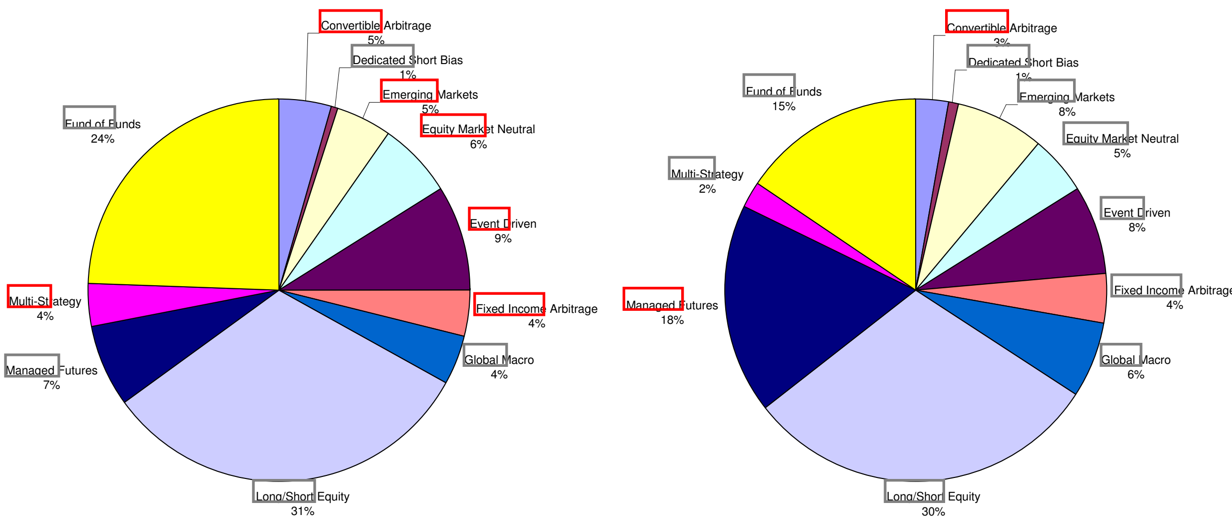
[14] Once a hedge fund decides not to report its performance, is liquidated, is closed to new investment, restructured, or merged with other hedge funds, the fund is transferred into the "Graveyard" database. A hedge fund can only be listed in the "Graveyard" database after being listed in the "Live" database. Because the TASS database fully represents returns and asset information for live and dead funds, the effects of suvivorship bias are minimized. However, the database is subject to *backfill bias*—when a fund decides to be included in the database, TASS adds the fund to the "Live" database and includes all available prior performance of the fund. Hedge funds do not need to meet any specific requirements to be included in the TASS database. Due to reporting delays and time lags in contacting hedge funds, some Graveyard funds can be incorrectly listed in the Live database for a period of time. However, TASS has adopted a policy of transferring funds from the Live to the Graveyard database if they do not report over a 8- to 10-month period.

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

[16] 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.

to make inferences about overall performance, this filter may not be as problematic.[17]

TASS also classifies funds into one of 11 different investment styles, listed in Table 6 and described in the Appendix, of which 10 correspond exactly to the CSFB/Tremont sub-index definitions.[18] Table 6 also reports the number of funds in each category for the Live, Graveyard, and Combined databases, and it is apparent from these figures that the representation of investment styles is not evenly distributed, but is concentrated among four categories: Long/Short Equity (1,415), Fund of Funds (952), Managed Futures (511), and Event Driven (384). Together, these four categories account for 71.9% of the funds in the Combined database. Figure 2 shows that the relative proportions of the Live and Graveyard databases are roughly comparable, with the exception of two categories: Funds of Funds (24% in the Live and 15% in the Graveyard database), and Managed Futures (7% in the Live and 18% in the Graveyard database). This reflects the current trend in the industry towards funds of funds, and the somewhat slower growth of managed futures funds.



(a) Live Funds (b) Graveyard Funds

Figure 2: Breakdown of TASS Live and Graveyard funds by category.

3.1 CSFB/Tremont Indexes

Table 7 reports summary statistics for the monthly returns of the CSFB/Tremont indexes from January 1994 to August 2004. Also included for purposes of comparison are summary statistics for a number of aggregate measures of market conditions which we will use later

[17] See the references in footnote 15.

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

as risk factors for constructing explicit risk models for hedge-fund returns in Section 6, and their definitions are given in Table 30.

Table 7 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% for Dedicated Shortsellers to 13.85% for Global Macro, and the annualized volatility ranges from 3.05% for Equity Market Neutral to 17.28% 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% for Long/Short Equity, and the lowest correlation at −75.6% for Dedicated Shortsellers—as investors have discovered, hedge funds offer greater diversification benefits than many traditional asset classes. However, these correlations can vary over time. For example, consider a rolling 60-month correlation between the CSFB/Tremont Multi-Strategy Index and the S&P 500 from January 1999 to December 2003, plotted in Figure 3. At the start of the sample in January 1999, the correlation is −13.4%, then drops to −21.7% a year later, and increases to 31.0% by December 2003 as the outliers surrounding August 1998 drop out of the 60-month rolling window.

Although changes in rolling correlation estimates are also partly attributable to estimation errors,[19] in this case, an additional explanation for the positive trend in correlation is the enormous inflow of capital into multi-strategy funds and fund-of-funds over the past five years. As assets under management increase, it becomes progressively more difficult for fund managers to implement strategies that are truly uncorrelated with broad-based market indexes like the S&P 500. Moreover, Figure 3 shows that the correlation between the Multi-Strategy Index return and the lagged S&P 500 return has also increased in the past year, indicating an increase in the illiquidity exposure of this investment style (see Getmansky, Lo, and Makarov, 2004 and Section 4 below). This 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 Multi-Strategy, Risk Arbitrage, Fixed-Income Arbitrage, and Fund of Funds all have skewness coefficients less than zero, in some cases substantially so. This property is an indication of tail risk exposure, as in the case of Capital Decimation Partners (see Section 1.1), and is consistent with the nature of the investment strategies employed by funds in those categories. For example, Fixed-Income Arbitrage strategies are known to generate fairly consistent profits, with occasional losses that may be extreme, hence a skewness coefficient of −3.27 is not surprising. A more direct measure of tail risk or "fat tails" is kurtosis—the

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

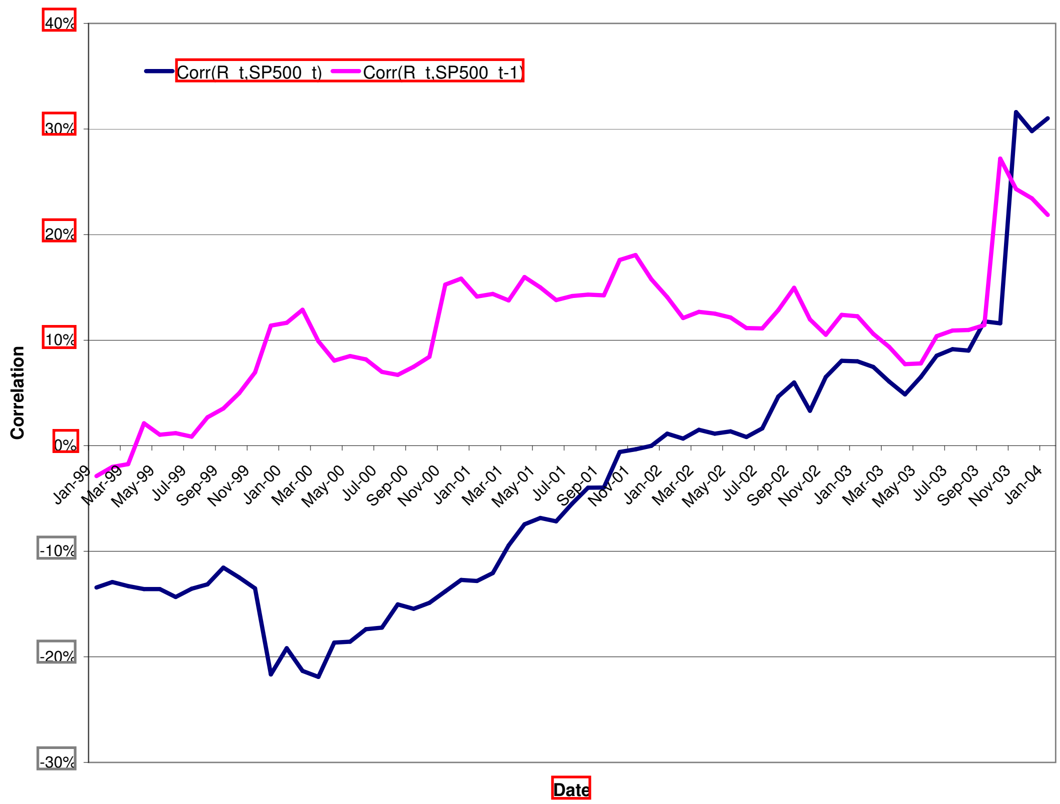


Figure 3: 60-month rolling correlations between CSFB/Tremont Multi-Strategy Index returns and the contemporaneous and lagged return of the S&P 500, from January 1999 to December 2003. Under the null hypothesis of no correlation, the approximate standard error of the correlation coefficient is $1/\sqrt{60} = 13\%$ hence the differences between the beginning-of-sample and end-of-sample correlations are statistically significant at the 1% level.

Variable	Sample Size	Ann. Mean	Ann. 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
Convert Arb	128	9.55	4.72	11.0	-4.68	1.09	3.57	-1.47	3.78	55.8	41.1	14.4	0.0
Dedicated Shortseller	128	-0.69	17.71	-75.6	-8.69	-0.39	22.71	0.90	2.16	9.2	-3.6	0.9	73.1
Emerging Markets	128	8.25	17.28	47.2	-23.03	1.17	16.42	-0.58	4.01	30.5	1.6	-1.4	0.7
Equity Market Neutral	128	10.01	3.05	39.6	-1.15	0.81	3.26	0.25	0.23	29.8	20.2	9.3	0.0
Event Driven	128	10.86	5.87	54.3	-11.77	1.01	3.68	-3.49	23.95	35.0	15.3	4.0	0.0
Distressed	128	12.73	6.79	53.5	-12.45	1.18	4.10	-2.79	17.02	29.3	13.4	2.0	0.3
Event-Driven Multi-Strategy	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 Arb	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 Arb	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
Multi-Strategy	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
SP500	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 ann.)	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 ann.)	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 ann.)	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

Table 7: Summary statistics for monthly CSFB/Tremont hedge-fund index returns and various hedge-fund risk factors, from January 1994 to August 2004 (except for Fund of Funds which begins in April 1994, and SP500 which ends in December 2003).

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.[20] In comparison to the S&P 500, which has a first-order autocorrelation coefficient of -1.0%, the autocorrelations of the hedge-fund indexes are very high, with values of 55.8% for Convertible Arbitrage, 39.2% for Fixed-Income Arbitrage, and 35.0% for Event Driven, all of which are significant at the 1% level according to the corresponding p-values.[21] Serial correlation can be a symptom of illiquidity risk exposure, which is particularly relevant for systemic risk, and we shall focus on this issue in more detail in Section 4.

The correlations among the hedge-fund indexes are given in Table 8, and the entries also display a great deal of heterogeneity, ranging from -71.9% (between Long/Short Equity and Dedicated Shortsellers) and 93.6% (between Event Driven and Distressed). However, these correlations can vary through time as Table 9 illustrates, both because of estimation error and through the dynamic nature of many hedge-fund investment strategies and the changes in fund flows among them. Over the sample period from January 1994 to December 2003, the correlation between the Convertible Arbitrage and Emerging Market Indexes is 31.8%, but during the first half of the sample this correlation is 48.2% and during the second half it is -5.8%. A graph of the 60-month rolling correlation between these two indexes from January 1999 to December 2003 provides a clue as to the source of this nonstationarity: Figure 4

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

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

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

[21] The p-value of a statistic is defined as the smallest level of significance for which the null hypothesis can be rejected based on the statistic's value. For example, a p-value of 73.1% for the Q-statistic of the Dedicated Shortseller index implies that the null hypothesis of no serial correlation can be rejected at the 73.1% significance level—at any smaller level of significance, say 5%, the null hypothesis cannot be rejected. Therefore, smaller p-values indicate stronger evidence against the null hypothesis, and larger p-values indicate stronger evidence in favor of the null. p-values are often reported instead of test statistics because they are easier to interpret (to interpret a test statistic, one must compare it to the critical values of the appropriate distribution; this comparison is performed in computing the p-value). See, for example, Bickel and Doksum (1977, Chapter 5.2.B) for further discussion of p-values and their interpretation.

Correlation Matrix	Hedge Funds	Convert Arb	Dedicated Shortseller	Emerging Markets	Equity Market Neutral	Event Driven	Distressed	Event-Driven Multi-Strategy	Risk Arb	Fixed Income Arb	Global Macro	Long/Short Equity	Managed Futures	Multi-Strategy
Hedge Funds	100.0													
Convert Arb	39.1	100.0												
Dedicated Shortseller	-46.7	-22.3	100.0											
Emerging Markets	65.7	32.0	-56.8	100.0										
Equity Market Neutral	32.0	30.0	-34.6	24.8	100.0									
Event Driven	66.1	59.0	-62.9	66.5	39.3	100.0								
Distressed	56.5	50.7	-62.3	57.7	35.7	93.6	100.0							
Event-Driven Multi-Strategy	69.0	60.1	-54.0	67.1	37.3	93.0	74.9	100.0						
Risk Arb	39.6	41.8	-50.6	44.1	32.1	69.7	58.0	66.6	100.0					
Fixed Income Arb	40.7	53.0	-4.6	27.1	5.7	37.3	28.3	43.3	13.2	100.0				
Global Macro	85.4	27.5	-11.0	41.5	18.6	36.9	29.5	42.7	12.9	41.5	100.0			
Long/Short Equity	77.6	25.0	-71.9	58.9	34.2	65.2	57.0	63.9	51.7	17.0	40.6	100.0		
Managed Futures	12.4	-18.1	21.1	-10.9	15.3	-21.2	-14.6	-24.4	-21.1	-6.7	26.8	-3.6	100.0	
Multi-Strategy	16.0	35.0	-5.8	-3.2	20.6	15.9	10.9	19.7	5.9	27.3	11.3	14.5	-2.4	100.0

Table 8: Correlation matrix for CSFB/Tremont hedge-fund index returns, in percent, based on monthly data from January 1994 to August 2004.

shows a sharp drop in the correlation during the month of September 2003. This is the first month for which the August 1998 data point—the start of the LTCM event—is not included in the 60-month rolling window. Table 10 shows that in August 1998, the returns for the Convertible Arbitrage and Emerging Market Indexes were −4.64% and −23.03, respectively. In fact, 10 out of the 13 style-category indexes yielded negative returns in August 1998, many of which were extreme outliers relative to the entire sample period, hence rolling windows containing this month can yield dramatically different correlations than those without it.

3.2 TASS Data

To develop a sense of the dynamics of the TASS database, in Table 11 we report annual frequency counts of the funds in the database at the start of each year, funds entering during the year, funds exiting during the year, and funds entering and exiting within the year. The table shows that despite the start date of February 1977, the database is relatively sparsely populated until the 1990's, with the largest increase in new funds in 2001 and the largest number of funds exiting the database in the most recent year, 2003. The attrition rates reported in Table 11 are defined as the ratio of funds exiting in a given year to the number of existing funds at the start of the year. TASS began tracking fund exits starting only in 1994 hence attrition rates cannot be computed in prior years. For the unfiltered

Correlation Matrices For Five CSFB/Tremont Hedge-Fund Index Returns

Monthly Data, January 1994 to December 2003

	Dedicated Short	Emerging Mkts	Equity Mkt Neutral	Event Driven	Distressed
	January 1994 to December 2003				
Convert Arb	−23.0	31.8	31.2	58.7	50.8
Dedicated Short		−57.1	−35.3	−63.4	−63.2
Emerging Mkts			22.0	67.8	59.2
Equity Mkt Neutral				37.9	34.9
Event-Driven					93.8
	January 1994 to December 1998				
Convert Arb	−25.2	48.2	32.1	68.4	61.6
Dedicated Short		−52.6	−43.5	−66.2	−69.1
Emerging Mkts			22.1	70.8	65.4
Equity Mkt Neutral				43.4	44.9
Event-Driven					94.9
	January 1999 to December 2003				
Convert Arb	−19.7	−5.8	32.3	41.8	33.5
Dedicated Short		−67.3	−22.9	−63.0	−56.8
Emerging Mkts			22.1	60.6	45.2
Equity Mkt Neutral				20.8	6.4
Event-Driven					91.4

Source: AlphaSimplex Group

Table 9: Correlation matrix for five CSFB/Tremont hedge-fund index returns, in percent, based on monthly data from January 1994 to December 2003.

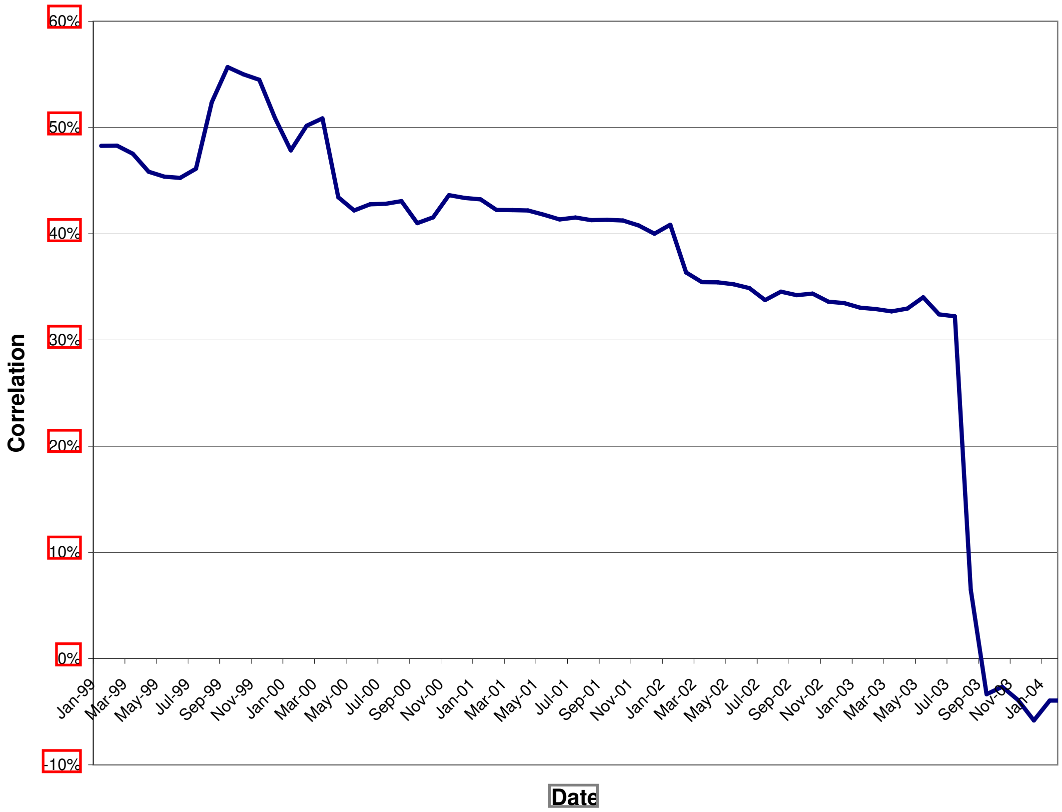


Figure 4: 60-month rolling correlations between CSFB/Tremont Convertible Arbitrage and Emerging Market Index returns, from January 1999 to December 2003. The sharp decline in September 2003 is due to the fact that this is the first month in which the August 1998 observation is dropped from the 60-month rolling window.

CSFB/Tremont Hedge-Fund Index and Market-Index Returns

August to October 2003

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

Source: AlphaSimplex Group

Table 10: Monthly returns of CSFB/Tremont hedge-fund indexes and Ibbotson stock and bond indexes during August, September, and October 1998, in percent. Note: ED = Event Driven.

sample of all funds, the average attrition rate from 1994–1999 is 7.51%, which is very similar to the 8.54% attrition rate obtained by Liang (2001) for the same period.

Table 12 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% and an average standard deviation of 5.51%, but in the Graveyard database, the 49 Convertible Arbitrage funds have an average mean return of 10.02% and a much higher average standard deviation of 8.14%. 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.[22]

Average serial correlations also vary considerably across categories in the Combined database, but six categories stand out: Convertible Arbitrage (31.4%), Fund of Funds (19.6%), Event Driven (18.4%), Emerging Markets (16.5%), Fixed-Income Arbitrage (16.2%), and Multi-Strategy (14.7%). Given the descriptions of these categories provided by TASS (see Appendix A.1) and common wisdom about the nature of the strategies involved—these categories include some of the most illiquid securities traded—serial correlation seems to be a reasonable proxy for illiquidity and smoothed returns (see Lo, 2001; Getmansky, Lo, and Makarov, 2004; and Section 4 below). Alternatively, equities and futures are among the most liquid securities in which hedge funds invest, and not surprising, the average first-order serial correlations for Equity Market Neutral, Long/Short Equity, and Managed Futures are 5.1%, 9.5%, and -0.6%, respectively. Dedicated Shortseller funds also have a low average first-order autocorrelation, 5.9%, which is consistent with the high degree of liquidity that often characterize shortsellers (by definition, the ability to short a security implies a certain degree of liquidity).

These summary statistics suggest that illiquidity and smoothed returns may be important attributes for hedge-fund returns which can be captured to some degree by serial correlation and the time-series model of smoothing in Section 4.

Finally, Table 13 reports the year-end assets under management for funds in each of the 11 TASS categories for the Combined database from 1977 to 2003, and the relative proportions are plotted in Figure 5. Table 13 shows that the total assets in the TASS combined database is approximately $391 billion, which is a significant percentage—though

[22] 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, e.g., Convertible Arbitrage, Equity Market Neutral, and Dedicated Shortseller.

Year	Existing Funds	New Entries	New Exits	Intra-Year Entry and Exit	Total Funds	Attrition Rate (%)
1977	0	4	0	0	4	—
1978	4	2	0	0	6	—
1979	6	2	0	0	8	—
1980	8	4	0	0	12	—
1981	12	3	0	0	15	—
1982	15	6	0	0	21	—
1983	21	9	0	0	30	—
1984	30	15	0	0	45	—
1985	45	9	0	0	54	—
1986	54	23	0	0	77	—
1987	77	29	0	0	106	—
1988	106	35	0	0	141	—
1989	141	45	0	0	186	—
1990	186	107	0	0	293	—
1991	293	94	0	0	387	—
1992	387	155	0	0	542	—
1993	542	247	0	0	789	—
1994	**789**	**252**	**24**	**2**	**1,017**	**3.0%**
1995	**1,017**	**300**	**62**	**1**	**1,255**	**6.1%**
1996	**1,255**	**332**	**122**	**9**	**1,465**	**9.7%**
1997	**1,465**	**357**	**101**	**6**	**1,721**	**6.9%**
1998	**1,721**	**347**	**164**	**9**	**1,904**	**9.5%**
1999	**1,904**	**403**	**186**	**7**	**2,121**	**9.8%**
2000	**2,121**	**391**	**237**	**9**	**2,275**	**11.2%**
2001	**2,275**	**460**	**257**	**6**	**2,478**	**11.3%**
2002	**2,478**	**432**	**249**	**9**	**2,661**	**10.0%**
2003	**2,661**	**325**	**287**	**12**	**2,699**	**10.8%**

Table 11: Annual frequency counts of entries into and exits out of the TASS Hedge Fund Combined Database from February 1977 to August 2004. Note the TASS Graveyard database did not exist prior to 1994, hence attrition rates are only available from 1994 to 2003.

Category	Sample Size	Annualized Mean (%)		Annualized SD (%)		ρ_1 (%)		Annualized Sharpe Ratio		Annualized Adjusted Sharpe Ratio		Ljung-Box p-Value (%)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Live Funds													
Convertible Arbitrage	**127**	9.92	5.89	5.51	4.15	33.6	19.2	2.57	4.20	1.95	2.86	19.5	27.1
Dedicated Shortseller	**14**	0.33	11.11	25.10	10.92	3.5	10.9	-0.11	0.70	0.12	0.46	48.0	25.7
Emerging Markets	**130**	17.74	13.77	21.69	14.42	18.8	13.8	1.36	2.01	1.22	1.40	35.5	31.5
Equity Market Neutral	**173**	6.60	5.89	7.25	5.05	4.4	22.7	1.20	1.18	1.30	1.28	41.6	32.6
Event Driven	**250**	12.52	8.99	8.00	7.15	19.4	20.9	1.98	1.47	1.68	1.47	31.3	34.1
Fixed Income Arbitrage	**104**	9.30	5.61	6.27	5.10	16.4	23.6	3.61	11.71	3.12	7.27	36.6	35.2
Global Macro	**118**	10.51	11.55	13.57	10.41	1.3	17.1	0.86	0.68	0.99	0.79	46.8	30.6
Long/Short Equity	**883**	13.05	10.56	14.98	9.30	11.3	17.9	1.03	1.01	1.01	0.95	38.1	31.8
Managed Futures	**195**	8.59	18.55	19.14	12.52	3.4	13.9	0.48	1.10	0.73	0.63	52.3	30.8
Multi-Strategy	**98**	12.65	17.93	9.31	10.94	18.5	21.3	1.91	2.34	1.46	2.06	31.1	31.7
Fund of Funds	**679**	6.89	5.45	6.14	4.87	22.9	18.5	1.53	1.33	1.48	1.16	33.7	31.6
Graveyard Funds													
Convertible Arbitrage	**49**	10.02	6.61	8.14	6.08	25.5	19.3	1.89	1.43	1.58	1.46	27.9	34.2
Dedicated Shortseller	**15**	1.77	9.41	27.54	18.79	8.1	13.2	0.20	0.44	0.25	0.48	55.4	25.2
Emerging Markets	**133**	2.74	27.74	27.18	18.96	14.3	17.9	0.37	0.91	0.47	1.11	48.5	34.6
Equity Market Neutral	**87**	7.61	26.37	12.35	13.68	6.4	20.4	0.52	1.23	0.60	1.85	46.6	31.5
Event Driven	**134**	9.07	15.04	12.35	12.10	16.6	21.1	1.22	1.38	1.13	1.43	39.3	34.2
Fixed Income Arbitrage	**71**	5.51	12.93	10.78	9.97	15.9	22.0	1.10	1.77	1.03	1.99	46.0	35.7
Global Macro	**114**	3.74	28.83	21.02	18.94	3.2	21.5	0.33	1.05	0.37	0.90	46.2	31.0
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
Multi-Strategy	**41**	5.32	23.46	17.55	20.90	6.1	17.4	1.10	1.55	1.58	2.06	49.4	32.2
Fund of Funds	**273**	4.53	10.07	13.56	10.56	11.3	21.2	0.62	1.26	0.57	1.11	40.9	31.9
Combined Funds													
Convertible Arbitrage	**176**	9.94	6.08	6.24	4.89	31.4	19.5	2.38	3.66	1.85	2.55	21.8	29.3
Dedicated Shortseller	**29**	1.08	10.11	26.36	15.28	5.9	12.2	0.05	0.59	0.19	0.46	52.0	25.2
Emerging Markets	**263**	10.16	23.18	24.48	17.07	16.5	16.2	0.86	1.63	0.84	1.31	42.2	33.7
Equity Market Neutral	**260**	6.94	15.94	8.96	9.21	5.1	21.9	0.97	1.24	1.06	1.53	43.3	32.3
Event Driven	**384**	11.31	11.57	9.52	9.40	18.4	21.0	1.71	1.48	1.49	1.48	34.1	34.3
Fixed Income Arbitrage	**175**	7.76	9.45	8.10	7.76	16.2	22.9	2.59	9.16	2.29	5.86	40.4	35.6
Global Macro	**232**	7.18	22.04	17.21	15.61	2.3	19.3	0.60	0.92	0.70	0.90	46.5	30.8
Long/Short Equity	**1415**	11.79	16.33	18.02	13.25	9.5	18.8	0.82	1.06	0.81	1.07	41.7	31.9
Managed Futures	**511**	6.23	21.59	20.22	17.07	-0.6	17.4	0.34	0.91	0.50	0.88	49.8	30.9
Multi-Strategy	**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

Table 12: Means and standard deviations of basic summary statistics for hedge funds in the TASS Hedge Fund Live, Graveyard, and Combined databases from February 1977 to August 2004. The columns 'p-Value(Q)' contain means and standard deviations of p-values for the Ljung-Box Q-statistic for each fund using the first 11 autocorrelations of returns.

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

Table 13: Assets under management at year-end in millions of U.S. dollars for funds in each of the 11 categories in the TASS Combined Hedge Fund database, from 1977 to 2003.

not nearly exhaustive—of the estimated $1 trillion in the hedge fund industry today.[23] The two dominant categories in the most recent year are Long/Short Equity ($101.5 billion) and Fund of Funds ($76.8 billion), but Figure 5 shows that the relative proportions can change significantly over time (see Getmansky, 2004 for a more detailed analysis of fund flows in the hedge-fund industry).

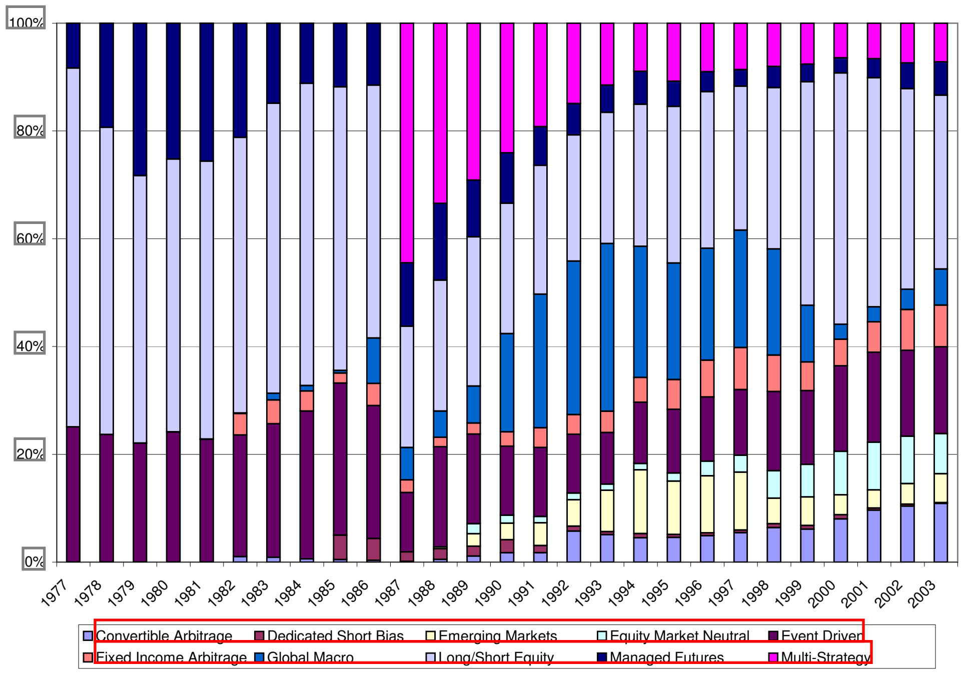


Figure 5: Relative proportions of assets under management at year-end in the 11 categories of the TASS Hedge Fund Combined database, from 1977 to 2003.

4 Measuring Illiquidity Risk

The examples of Section 1 highlight the fact that hedge funds exhibit a heterogeneous array of risk exposures, but a common theme surrounding systemic risk factors is credit and liquidity. Although they are separate sources of risk exposures for hedge funds and their investors—one type of risk can exist without the other—nevertheless, liquidity and credit have been inextricably intertwined in the minds of most investors because of the problems encountered by Long Term Capital Management and many other fixed-income relative-value

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

hedge funds in August and September of 1998. Because many hedge funds rely on leverage, the size of the positions are often considerably larger than the amount of collateral posted to support those positions. Leverage has the effect of a magnifying glass, expanding small profit opportunities into larger ones, but also expanding small losses into larger losses. 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.[24] 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, i.e., contagion.

The basic mechanisms driving liquidity and credit are familiar to most hedge-fund managers and investors, and there has been much progress in the recent literature in modeling both credit and liquidity risk.[25] 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.

4.1 Serial Correlation and Illiquidity

A more immediate method for gauging the liquidity risk exposure of a given hedge fund is to examine the autocorrelation coefficients ρ_k of the fund's monthly returns, where $\rho_k \equiv \mathrm{Cov}[R_t, R_{t-k}]/\mathrm{Var}[R_t]$ is the k-th order autocorrelation of $\{R_t\}$,[26] 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

[24] Note that in the case of Capital Decimation Partners in Section 1.1, the fund's consecutive returns of -18.3% and -16.2% in August and September 1998 would have made it virtually impossible for the fund to continue without a massive injection of capital. In all likelihood, it would have closed down along with many other hedge funds during those fateful months, never to realize the extraordinary returns that it would have earned had it been able to withstand the losses in August and September (see Table 3).

[25] See, for example, Bookstaber (1999, 2000) and Kao (1999), and their citations.

[26] The k-th order autocorrelation of a time series $\{R_t\}$ is defined as the correlation coefficient between R_t and R_{t-k}, which is simply the covariance between R_t and R_{t-k} divided by the square root of the product of the variances of R_t and R_{t-k}. But since the variances of R_t and R_{t-k} are the same under the assumption of stationarity, the denominator of the autocorrelation is simply the variance of R_t.

Properly Anticipated Prices Fluctuate Randomly"—provides a succinct summary for the motivation of the martingale property: In an informationally efficient market, price changes must be unforecastable if they are properly anticipated, i.e., if they fully incorporate the expectations and information of all market participants.

This extreme version of market efficiency is now recognized as an idealization that is unlikely to hold in practice.[27] In particular, market frictions such as transactions costs, borrowing constraints, costs of gathering and processing information, and institutional restrictions on shortsales and other trading practices do exist, and they all contribute to the possibility of serial correlation in asset returns which cannot easily be "arbitraged" away precisely because of the presence of these frictions. From this perspective, the degree of serial correlation in an asset's returns can be viewed as a proxy for the magnitude of the frictions, and illiquidity is one of most common forms of such frictions. For example, it is well known that the historical returns of residential real-estate investments are considerably more highly autocorrelated than, say, the returns of the S&P 500 indexes during the same sample period. Similarly, the returns of S&P 500 futures contracts exhibit less serial correlation than those of the index itself. In both examples, the more liquid instrument exhibits less serial correlation than the less liquid, and the economic rationale is a modified version of Samuelson's (1965) argument—predictability in asset returns will be exploited and eliminated only to the extent allowed by market frictions. Despite the fact that the returns to residential real estate are highly predictable, it is impossible to take full advantage of such predictability because of the high transactions costs associated with real-estate transactions, the inability to shortsell properties, and other frictions.[28]

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

[27] See, for example, Farmer and Lo (2000) and Lo (2004).

[28] 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.

portfolio are actively traded, the manager has little discretion in marking the portfolio; it is "marked to market". The more illiquid the portfolio, the more discretion the manager has in marking its value and smoothing returns, creating serial correlation in the process.[29] The impact of smoothed returns and serial correlation is considered in more detail in Lo (2002) and Getmansky, Lo, and Makarov (2004), and we update their analysis in Section 4.2 using more recent data. However, a simpler method for assessing the overall statistical significance of the autocorrelations is to use the Ljung-Box Q-statistic (see footnote 20).

To illustrate the potential value of autocorrelations and the Q-statistic for measuring liquidity risk, we estimate these quantities with monthly historical total returns of the 10 largest (as of February 11, 2001) mutual funds, from various start dates through June 2000, and 12 hedge funds from various inception dates to December 2000. Monthly total returns for the mutual funds were obtained from the University of Chicago's Center for Research in Securities Prices. The 12 hedge funds were selected from the Altvest database to yield a diverse range of annual Sharpe ratios (from 1 to 5) computed in the standard way ($\sqrt{12}\,\widehat{SR}$, where $\widehat{\mathrm{SR}}$ is the Sharpe ratio estimator applied to monthly returns), with the additional requirement that the funds have a minimum five-year history of returns.[30] The names of the hedge funds have been omitted to maintain their privacy, and we will refer to them only by their stated investment styles, e.g., Relative Value Fund, Risk Arbitrage Fund, etc.

Table 14 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 10 mutual funds have very little serial correlation in returns, with first-order autocorrelations ranging from -3.99% to 12.37%, and with p-values of the corresponding Q-statistics ranging from 10.95% to 80.96%, implying that none of the Q-statistics is significant at the 5% level. The lack of serial correlation in these 10 mutual-fund returns is not surprising. Because of their sheer size, these funds consist primarily of highly liquid securities and, as a result, their managers have very little discretion in marking such portfolios. Moreover, many of the SEC regulations that govern the mutual-fund industry, e.g., detailed prospectuses, daily net asset value calculations, and quarterly filings, were enacted specifically to guard against arbitrary marks, price manipulation, and other unsavory investment practices.

[29] There are, of course, other considerations in interpreting the serial correlation of any portfolio's returns, of which return-smoothing is only one. Others include nonsynchronous trading, time-varying expected returns, and market inefficiencies.

[30] See http://www.investorforce.com for further information about the Altvest database.

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

Of course, there are several other aspects of liquidity that are not captured by serial correlation, and certain types of trading strategies can generate serial correlation even though they invest in highly liquid instruments. In particular, conditioning variables such as investment style, the types of securities traded, and other aspects of the market environment should be taken into account, perhaps through the kind of risk models proposed in Section 6 below. However, as a first cut for measuring and comparing the liquidity exposures of various hedge-fund investments, autocorrelation coefficients and Q-statistics provide a great deal of insight and information in a convenient manner.

4.2 An Econometric Model of Smoothed Returns

There are several potential explanations for serial correlation in financial asset returns—time-varying expected returns, time-varying leverage, and incentive fees with high-water marks, for example—but Getmansky, Lo, and Makarov (2004) conclude that the most plausible explanation in the context of hedge funds is illiquidity and smoothed returns. Although these are two distinct phenomena, it is important to consider illiquidity and smoothed returns in tandem because one facilitates the other—for actively traded securities, both theory and empirical evidence suggest that in the absence of transactions costs and other market frictions, returns are unlikely to be very smooth.

As discussed above, nonsynchronous trading is a plausible source of serial correlation in hedge-fund returns. In contrast to the studies by Lo and MacKinlay (1988, 1990a) 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% to 15% 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 smoothed returns, 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 (1990a) argue that securities would have to go without trading for several days on average to induce serial correlations of 30%, 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, e.g., emerging-market debt, real estate, restricted securities, control positions in publicly traded companies, asset-backed securities, and other exotic OTC derivatives. Therefore, nonsynchronous trading of this magnitude is likely to be an explanation for the serial correlation observed in hedge-fund returns.

But even when prices are synchronously measured—as they are for many funds that mark their portfolios to market at the end of the month to strike a net-asset-value at which investors can buy into or cash out of the fund—there are several other channels by which illiquidity exposure can induce serial correlation in the reported returns of hedge funds. Apart from the nonsynchronous-trading effect, naive methods for determining the fair market value or "marks" for illiquid securities can yield serially correlated returns. For example, one approach to valuing illiquid securities is to extrapolate linearly from the most recent transaction price (which, in the case of emerging-market debt, might be several months ago), which yields a price path that is a straight line, or at best a series of straight lines. Returns computed from such marks will be smoother, exhibiting lower volatility and higher serial correlation than true economic returns, i.e., 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.[31] Therefore, serial correlation may serve as a proxy for a fund's liquidity exposure.

Note that 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

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

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 smoothed returns.

To quantify the impact of all of these possible sources of serial correlation, Getmansky, Lo, and Makarov (2004) propose the following model of hedge-fund returns. Denote by R_t the true economic return of a hedge fund in period t, and let R_t satisfy the following linear single-factor model:

$$R_t \;=\; \mu + \beta\Lambda_t + \epsilon_t \quad , \quad \mathrm{E}[\Lambda_t] = \mathrm{E}[\epsilon_t] = 0 \quad , \quad \epsilon_t \, , \, \Lambda_t \;\sim\; \text{IID} \tag{11a}$$

$$\mathrm{Var}[R_t] \;\equiv\; \sigma^2 \, . \tag{11b}$$

True returns represent the flow of information that would determine the equilibrium value of the fund's securities in a frictionless market. However, true economic returns are not observed. Instead, R_t^o denotes the reported or observed return in period t, and let

$$R_t^o \;=\; \theta_0\, R_t \;+\; \theta_1\, R_{t-1} \;+\; \cdots \;+\; \theta_k\, R_{t-k} \tag{12}$$

$$\theta_j \;\in\; [0,1] \;\;,\;\; j=0,\ldots,k \tag{13}$$

$$1 \;=\; \theta_0 \;+\; \theta_1 \;+\; \cdots \;+\; \theta_k \tag{14}$$

which is a weighted average of the fund's true returns over the most recent $k+1$ periods, including the current period.

This averaging process captures the essence of smoothed returns in several respects. From the perspective of illiquidity-driven smoothing, (12) is consistent with several models in the nonsynchronous trading literature. For example, Cohen, Maier et al. (1986, Chapter 6.1) propose a similar weighted-average model for observed returns.[32] Alternatively, (12) can be viewed as the outcome of marking portfolios to simple linear extrapolations of acquisition prices when market prices are unavailable, or "mark-to-model" returns where the pricing model is slowly varying through time. And of course, (12) also captures the intentional smoothing of performance.

The constraint (14) that the weights sum to 1 implies that the information driving the fund's performance in period t will eventually be fully reflected in observed returns, but this process could take up to $k+1$ periods from the time the information is generated.[33] This is a sensible restriction in the current context of hedge funds for several reasons. Even the most illiquid securities will trade eventually, and when that occurs, all of the cumulative information affecting that security will be fully impounded into its transaction price. Therefore the parameter k should be selected to match the kind of illiquidity of the fund—a fund com-

[32] In particular, their specification for observed returns is:

$$r_{j,t}^o \;=\; \sum_{l=0}^{N} (\gamma_{j,t-l,l}\, r_{j,t-l} + \theta_{j,t-l})$$

where $r_{j,t-l}$ is the true but unobserved return for security j in period $t-l$, the coefficients $\{\gamma_{j,t-l,l}\}$ are assumed to sum to 1, and $\theta_{j,t-l}$ are random variables meant to capture "bid/ask bounce". The authors motivate their specification of nonsynchronous trading in the following way (p. 116): "Alternatively stated, the $\gamma_{j,t,0}, \gamma_{j,t,1}, \ldots, \gamma_{j,t,N}$ comprise a delay distribution that shows how the true return generated in period t impacts on the returns actually observed during t and the next N periods". In other words, the essential feature of nonsynchronous trading is the fact that information generated at date t may not be fully impounded into prices until several periods later.

[33] In Lo and MacKinlay's (1990a) model of nonsynchronous trading, they propose a stochastic non-trading horizon so that observed returns are an infinite-order moving average of past true returns, where the coefficients are stochastic. In that framework, the waiting time for information to become fully impounded into future returns may be arbitrarily long (but with increasingly remote probability).

prised mostly of exchange-traded U.S. equities would require a much lower value of k than a private equity fund. Alternatively, in the case of intentional smoothing of performance, the necessity of periodic external audits of fund performance imposes a finite limit on the extent to which deliberate smoothing can persist.[34]

Under the smoothing mechanism (12), the implications for the statistical properties of observed returns are given by:

Proposition 1 *(Getmansky, Lo, and Makarov, 2004) Under (12)–(14), the statistical properties of observed returns are characterized by:*

$$\mathrm{E}[R_t^o] = \mu \tag{15}$$

$$\mathrm{Var}[R_t^o] = c_\sigma^2 \sigma^2 \leq \sigma^2 \tag{16}$$

$$\mathrm{SR}^o \equiv \frac{\mathrm{E}[R_t^o]}{\sqrt{\mathrm{Var}[R_t^o]}} = c_s \mathrm{SR} \geq \mathrm{SR} \equiv \frac{\mathrm{E}[R_t]}{\sqrt{\mathrm{Var}[R_t]}} \tag{17}$$

$$\beta_m^o \equiv \frac{\mathrm{Cov}[R_t^o, \Lambda_{t-m}]}{\mathrm{Var}[\Lambda_{t-m}]} = \begin{cases} c_{\beta,m}\beta & \text{if } 0 \leq m \leq k \\ 0 & \text{if } m > k \end{cases} \tag{18}$$

$$\mathrm{Cov}[R_t^o, R_{t-m}^o] = \begin{cases} \left(\sum_{j=0}^{k-m} \theta_j \theta_{j+m}\right) \sigma^2 & \text{if } 0 \leq m \leq k \\ 0 & \text{if } m > k \end{cases} \tag{19}$$

$$\mathrm{Corr}[R_t^o, R_{t-m}^o] = \frac{\mathrm{Cov}[R_t^o, R_{t-m}^o]}{\mathrm{Var}[R_t^o]} = \begin{cases} \frac{\sum_{j=0}^{k-m} \theta_j \theta_{j+m}}{\sum_{j=0}^{k} \theta_j^2} & \text{if } 0 \leq m \leq k \\ 0 & \text{if } m > k \end{cases} \tag{20}$$

[34] In fact, if a fund allows investors to invest and withdraw capital only at pre-specified intervals, imposing lock-ups in between, and external audits are conducted at these same pre-specified intervals, then it may be argued that performance smoothing is irrelevant. For example, no investor should be disadvantaged by investing in a fund that offers annual liquidity and engages in annual external audits with which the fund's net-asset-value is determined by a disinterested third party for purposes of redemptions and new investments. However, there are at least two additional concerns that remain—historical track records and estimates of a fund's liquidity exposure are both affected by smoothed returns—and they are important factors in the typical hedge-fund investor's overall investment process. Moreover, given the apparently unscrupulous role that the auditors at Arthur Andersen played in the Enron affair, there is the further concern of whether third-party auditors are truly objective and free of all conflicts of interest.

where:

$$c_\mu \equiv \theta_0 + \theta_1 + \cdots + \theta_k \tag{21}$$

$$c_\sigma^2 \equiv \theta_0^2 + \theta_1^2 + \cdots + \theta_k^2 \tag{22}$$

$$c_s \equiv 1/\sqrt{\theta_0^2 + \cdots + \theta_k^2} \tag{23}$$

$$c_{\beta,m} \equiv \theta_m \ , \quad 0 \le m \le k \tag{24}$$

Proposition 1 shows that smoothed returns of the form (12)–(14) do not affect the expected value of R_t^o but reduce its variance, hence boosting the Sharpe ratio of observed returns by a factor of c_s. From (18), we see that smoothing also affects β_0^o, the contemporaneous market beta of observed returns, biasing it towards 0 or "market neutrality", and induces correlation between current observed returns and lagged market returns up to lag k. This provides a formal interpretation of the empirical analysis of Asness, Krail, and Liew (2001) in which many hedge funds were found to have significant lagged market exposure despite relatively low contemporaneous market betas.

Smoothed returns also exhibit positive serial correlation up to order k according to (20), and the magnitude of the effect is determined by the pattern of weights $\{\theta_j\}$. If, for example, the weights are disproportionately centered on a small number of lags, relatively little serial correlation will be induced. However, if the weights are evenly distributed among many lags, this will result in higher serial correlation. A useful summary statistic for measuring the concentration of weights is

$$\xi \equiv \sum_{j=0}^{k} \theta_j^2 \in [0, 1] \tag{25}$$

which is simply the denominator of (20). This measure is well known in the industrial organization literature as the *Herfindahl index*, a measure of the concentration of firms in a given industry where θ_j represents the market share of firm j. Because $\theta_j \in [0, 1]$, ξ is also confined to the unit interval, and is minimized when all the θ_j's are identical, which implies a value of $1/(k+1)$ for ξ, and is maximized when one coefficient is 1 and the rest are 0, in which case $\xi = 1$. In the context of smoothed returns, a lower value of ξ implies more smoothing, and the upper bound of 1 implies no smoothing, hence we shall refer to ξ as a "smoothing index".

In the special case of equal weights, $\theta_j = 1/(k+1)$ for $j = 0, \ldots, k$, the serial correlation of observed returns takes on a particularly simple form:

$$\mathrm{Corr}[R_t^o, R_{t-m}^o] = 1 - \frac{m}{k+1} , \quad 1 \le m \le k \tag{26}$$

which declines linearly in the lag m. This can yield substantial correlations even when k is small—for example, if $k = 2$ so that smoothing takes place only over a current quarter (i.e. this month and the previous two months), the first-order autocorrelation of monthly observed returns is 66.7%.

4.3 Maximum Likelihood Estimates of Smoothing Profiles

Using the method of maximum-likelihood, Getmansky, Lo, and Makarov (2004) estimate the smoothing model (12)–(14) by estimating an MA(2) process for observed returns assuming normally distributed errors, with the additional constraint that the MA coefficients sum to 1,[35] and we apply the same procedure to our updated and enlarged sample of funds in the TASS Combined Hedge Fund database from February 1977 to August 2004. For purposes of estimating (12), we impose an additional filter on our data, eliminating funds with less than 5 years of non-missing monthly returns. This leaves a sample of 1,840 funds for which we estimate the MA(2) smoothing model. The maximum-likelihood estimation procedure did not converge for three of these funds, indicating some sort of misspecification or data errors, hence we have results for 1,837 funds.[36] Table 15 contains summary statistics for maximum-likelihood estimate of the smoothing parameters $(\theta_0, \theta_1, \theta_2)$ and smoothing index ξ, and Table 16 presents the maximum-likelihood estimates of the smoothing model for the 50 most illiquid funds of the 1,837 funds, as ranked by $\hat{\theta}_0$.

Table 15 shows that three categories seem to exhibit smaller average values of $\hat{\theta}_0$ than the rest—Convertible Arbitrage (0.719), Event Driven (0.786), and Fixed-Income Arbitrage (0.775). Consider, in particular, the Convertible Arbitrage category, which has a mean of 0.719 for $\hat{\theta}_0$. This is, of course, the average across all 79 funds in this category, but if it were the point estimate of a given fund, it would imply that only 71.9% of that fund's true current monthly return would be reported, with the remaining 28.1% distributed over the next two months (recall the constraint that $\hat{\theta}_0 + \hat{\theta}_1 + \hat{\theta}_2 = 1$). The estimates 0.201 and 0.080 for $\hat{\theta}_1$ and $\hat{\theta}_2$ imply that on average, the current reported return also includes 20% of last

[35] However, we do not impose the constraints that $\theta_i \in [0, 1]$ so as to obtain an indication of potential misspecification, i.e., estimates that fall outside the unit interval. See Getmansky, Lo, and Makarov (2004, Section 5.3) for additional specification tests of their smoothing model.

[36] The reference numbers for the funds that did not yield maximum-likelihood estimates are 1018, 1405 and 4201.

Category	Number of Funds	MA(2) Coefficient Estimates								Test Statistic $z(\theta_0)$ for H: $\theta_0 = 1$
		θ_0		θ_1		θ_2		ξ		
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Convertible Arbitrage	79	0.719	0.161	0.201	0.148	0.080	0.101	0.621	0.327	**15.558**
Dedicated Short Bias	16	1.070	0.484	0.045	0.166	-0.115	0.331	1.508	2.254	**-0.579**
Emerging Markets	136	0.836	0.145	0.146	0.098	0.018	0.106	0.762	0.285	**13.179**
Equity Market Neutral	65	0.891	0.203	0.047	0.189	0.062	0.138	0.895	0.396	**4.326**
Event Driven	183	0.786	0.143	0.158	0.105	0.056	0.102	0.687	0.235	**20.307**
Fixed Income Arbitrage	65	0.775	0.169	0.147	0.104	0.078	0.120	0.682	0.272	**10.714**
Global Macro	88	0.999	0.202	0.047	0.161	-0.047	0.147	1.090	0.501	**0.036**
Long/Short Equity	532	0.880	0.179	0.092	0.125	0.028	0.142	0.851	0.398	**15.453**
Managed Futures	230	1.112	0.266	-0.032	0.193	-0.080	0.162	1.379	0.942	**-6.406**
Multi-Strategy	47	0.805	0.157	0.113	0.128	0.082	0.076	0.713	0.270	**8.503**
Fund of Funds	396	0.874	0.638	0.102	0.378	0.024	0.292	1.409	10.917	**3.931**
All	**1837**	**0.890**	**0.357**	**0.092**	**0.223**	**0.017**	**0.188**	**1.014**	**5.096**	

Table 15: Means and standard deviations of maximum-likelihood estimates of MA(2) smoothing process $R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2}$, subject to the normalization $1 = \theta_0 + \theta_1 + \theta_2$, where $\xi \equiv \theta_0^2 + \theta_1^2 + \theta_2^2$, for 1,837 hedge funds in the TASS combined database with at least five years of returns history during the period from February 1977 to August 2004.

month's true return and 8% of the true return two months ago.[37]

To develop a more formal statistical sense of the significance of these average values of $\hat{\theta}_0$, we can compute a z statistic for the null hypothesis that the expected value of $\hat{\theta}_0$ is 1 by dividing the difference between 1 and each mean by its corresponding standard error, which can be approximated by the cross-sectional standard deviation divided by the square root of the number of funds in the average, assuming that the $\hat{\theta}_0$'s are cross-sectionally independently and identically distributed (IID).[38] Under the null hypothesis of no smoothing, the z-statistic is asymptotically standard normal. These z-statistics are reported in the last column of Table 15 and confirm the intuition that the categories with the lowest average $\hat{\theta}_0$'s are significantly different from 1 (recall that the 99% critical value for a standard normal distribution is 2.33). Overall, the summary statistics in Table 15 are broadly consistent with common intuition about the nature of the strategies and securities involved in these fund categories, which contain the most illiquid securities and, therefore, have the most potential for smoothed returns and serial correlation.

Table 16 contains the smoothing parameter estimates for the top 50 funds ranked in order of increasing $\hat{\theta}_0$, which provides a more direct view of illiquidity and smoothed returns. In contrast to the averages of Table 15, the parameter estimates of θ_0 among these 50 funds range from 0.456 to 0.579, implying that only half to two-thirds of the current month's true returns are reflected in observed returns. The asymptotic standard errors are generally quite small, ranging from 0.029 to 0.069, hence the smoothing parameters seem to be estimated reasonably precisely.

The funds in Table 16 fall mainly into five categories: Fund of Funds (15), Convertible Arbitrage (8), Long/Short Equity (8), Fixed-Income Arbitrage (7), and Event Driven (6). Together, these five categories account for 44 of the 50 funds in Table 16. A more complete summary of the distribution of smoothing parameter estimates across the different fund categories is provided in Figure 6, which contains a graph of the smoothing coefficients $\hat{\theta}_0$ by category, where 9 out of the 1,837 funds were omitted because their $\hat{\theta}_0$'s were larger than 2.0 so as to preserve the resolution of the graph.

This figure shows that although there is considerable variation within each category, nevertheless, some clear differences emerge between categories. For example, categories 1, 3, 5, 6, and 10 (Convertible Arbitrage, Emerging Markets, Event Driven, Fixed-Income Arbitrage, and Multi-Strategy, respectively) have clearly discernible concentrations of $\hat{\theta}_0$'s

[37] The averages do not always sum to 1 exactly because of rounding errors.

[38] The IID assumption is almost surely violated in the cross section (after all, the categories are supposed to group funds by certain common characteristics), but the relative rankings of the z-statistics across categories may still contain useful information.

Category	Start	End	T	θ_0	SE(θ_0)	θ_1	SE(θ_1)	θ_2	SE(θ_2)
Equity Market Neutral	199501	200408	116	0.456	0.029	0.324	0.022	0.220	0.026
Equity Market Neutral	199501	200408	116	0.456	0.029	0.330	0.022	0.214	0.026
Event Driven	199501	200011	71	0.468	0.041	0.336	0.029	0.196	0.037
Long/Short Equity	198906	199608	87	0.480	0.040	0.343	0.027	0.177	0.036
Convertible Arbitrage	199409	200408	120	0.485	0.036	0.368	0.022	0.147	0.033
Fixed Income Arbitrage	199501	200106	78	0.495	0.033	0.187	0.034	0.318	0.029
Fixed Income Arbitrage	199312	200005	78	0.506	0.032	0.144	0.035	0.350	0.028
Convertible Arbitrage	199409	200012	76	0.512	0.037	0.172	0.037	0.316	0.032
Convertible Arbitrage	199801	200401	73	0.512	0.046	0.268	0.037	0.220	0.039
Emerging Markets	199808	200408	73	0.513	0.049	0.300	0.035	0.187	0.042
Convertible Arbitrage	199510	200408	107	0.516	0.043	0.336	0.027	0.148	0.038
Event Driven	199901	200408	68	0.518	0.050	0.288	0.038	0.195	0.044
Fund of Funds	199410	200103	78	0.526	0.059	0.442	0.020	0.032	0.056
Long/Short Equity	199510	200408	107	0.528	0.046	0.352	0.027	0.120	0.041
Convertible Arbitrage	199706	200408	87	0.532	0.050	0.321	0.033	0.146	0.044
Fund of Funds	199501	200001	61	0.532	0.066	0.403	0.030	0.065	0.060
Fund of Funds	199907	200408	62	0.534	0.061	0.336	0.038	0.129	0.054
Long/Short Equity	199811	200408	70	0.536	0.055	0.302	0.038	0.162	0.048
Fund of Funds	199601	200401	97	0.537	0.044	0.252	0.035	0.212	0.037
Long/Short Equity	199902	200408	67	0.541	0.058	0.298	0.040	0.161	0.050
Fixed Income Arbitrage	199610	200312	87	0.541	0.046	0.226	0.039	0.232	0.038
Fund of Funds	199704	200401	82	0.542	0.050	0.268	0.038	0.189	0.043
Event Driven	199903	200407	65	0.543	0.063	0.356	0.035	0.101	0.056
Equity Market Neutral	199501	200006	66	0.544	0.056	0.266	0.043	0.190	0.048
Fund of Funds	199903	200408	66	0.544	0.069	0.445	0.022	0.011	0.066
Fixed Income Arbitrage	198207	199810	196	0.545	0.031	0.238	0.026	0.218	0.027
Fund of Funds	199901	200407	67	0.549	0.064	0.354	0.036	0.097	0.056
Fund of Funds	199709	200408	84	0.550	0.048	0.222	0.041	0.229	0.040
Convertible Arbitrage	199903	200408	66	0.551	0.060	0.285	0.042	0.163	0.051
Convertible Arbitrage	199902	200408	67	0.554	0.060	0.288	0.042	0.158	0.051
Long/Short Equity	199711	200408	82	0.554	0.047	0.192	0.043	0.254	0.040
Fund of Funds	199701	200309	81	0.554	0.055	0.295	0.038	0.150	0.047
Fixed Income Arbitrag	199711	200211	61	0.555	0.067	0.336	0.040	0.110	0.058
Long/Short Equity	199802	200408	79	0.555	0.051	0.226	0.042	0.218	0.043
Multi-Strategy	199908	200408	61	0.557	0.060	0.241	0.048	0.201	0.050
Fund of Funds	199801	200408	80	0.558	0.055	0.266	0.040	0.175	0.046
Fund of Funds	199901	200407	67	0.559	0.053	0.185	0.048	0.257	0.044
Fund of Funds	199901	200407	67	0.559	0.062	0.290	0.043	0.151	0.053
Fund of Funds	199906	200408	63	0.559	0.060	0.238	0.048	0.203	0.050
Event Driven	199712	200408	81	0.563	0.064	0.400	0.028	0.038	0.058
Long/Short Equity	199203	200406	148	0.565	0.046	0.359	0.024	0.076	0.041
Event Driven	199112	200408	153	0.567	0.044	0.326	0.027	0.107	0.038
Convertible Arbitrage	198807	199608	98	0.567	0.054	0.307	0.035	0.125	0.046
Fixed Income Arbitrage	199903	200408	66	0.568	0.059	0.224	0.048	0.207	0.049
Fund of Funds	199801	200408	80	0.569	0.058	0.279	0.041	0.152	0.049
Fixed Income Arbitrage	199903	200408	66	0.569	0.060	0.225	0.048	0.207	0.050
Event Driven	199304	199901	70	0.571	0.065	0.312	0.041	0.118	0.056
Long/Short Equity	199610	200408	95	0.575	0.048	0.177	0.043	0.248	0.039
Fund of Funds	199510	200407	106	0.576	0.049	0.238	0.038	0.187	0.041
Multi-Strategy	199410	200408	119	0.579	0.048	0.249	0.036	0.172	0.040

Table 16: First 50 funds of ranked list of 1,837 hedge funds in the TASS Hedge Fund Combined database with at least five years of returns history during the period from February 1977 to August 2004, ranked in increasing order of the estimated smoothing parameter $\hat{\theta}_0$ of the MA(2) smoothing process $R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2}$, subject to the normalization $1 = \theta_0 + \theta_1 + \theta_2$, and estimated via maximum likelihood.

that are lower than 1, and lower than the other categories, suggesting more illiquid funds and more smoothed returns. On the other hand, categories 2, 7, and 9 (Dedicated Shortseller, Global Macro, and Managed Futures, respectively) have concentrations that are at or above 1, suggesting just the opposite—more liquidity and less return-smoothing.

To develop further intuition for the smoothing model (12)–(14) and the possible interpretations of the smoothing parameter estimates, we reproduce the analysis in Getmansky, Lo, and Makarov (2004) where they apply the same estimation procedure to the returns of the Ibbotson stock and bond indexes, the Merrill Lynch Convertible Securities Index,[39] the CSFB/Tremont hedge-fund indexes, and two mutual funds: the highly liquid Vanguard 500 Index Fund, and the considerably less liquid American Express Extra Income Fund.[40] Table 17 contains summary statistics, market betas (where the market return is taken to be the S&P 500 total return), contemporaneous and lagged market betas as in Asness, Krail and Liew (2001), and smoothing-coefficient estimates for these index and mutual-fund returns.[41]

Consistent with our interpretation of $\hat{\theta}_0$ as an indicator of liquidity, the returns of the most liquid portfolios in the first panel of Table 17—the Ibbotson Large Company Index, the Vanguard 500 Index Fund (which is virtually identical to the Ibbotson Large Company Index, except for sample period and tracking error), and the Ibbotson Long-Term Government Bond Index—have smoothing parameter estimates near unity: 0.92 for the Ibbotson Large Company Index, 1.12 for the Vanguard 500 Index Fund, and 0.92 for the Ibbotson Long-Term Government Bond Index. The first-order autocorrelation coefficients and lagged market betas also confirm their lack of serial correlation; 9.8% first-order autocorrelation for the Ibbotson Large Company Index , −2.3% for the Vanguard 500 Index Fund, and 6.7% for the

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

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

"The Vanguard 500 Index Fund seeks investment results that correspond with the price and yield performance of the S&P 500 Index. The fund employs a passive management strategy designed to track the performance of the S&P 500 Index, which is dominated by the stocks of large U.S. companies. It attempts to replicate the target index by investing all or substantially all of its assets in the stocks that make up the index."

"AXP Extra Income Fund seeks high current income; capital appreciation is secondary. The fund ordinarily invests in long-term high-yielding, lower-rated corporate bonds. These bonds may be issued by U.S. and foreign companies and governments. The fund may invest in other instruments such as: money market securities, convertible securities, preferred stocks, derivatives (such as futures, options and forward contracts), and common stocks."

[41] Market betas were obtained by regressing returns on a constant and the total return of the S&P 500, and contemporaneous and lagged market betas were obtained by regressing returns on a constant, the contemporaneous total return of the S&P 500, and the first two lags.

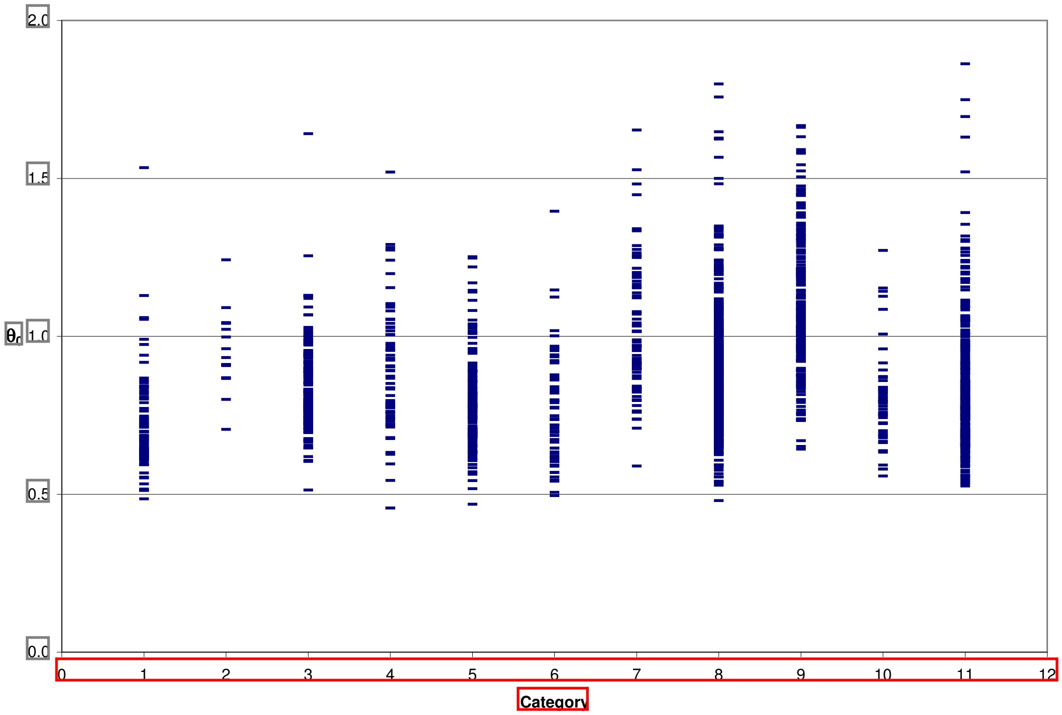


Figure 6: Estimated smoothing coefficients $\hat{\theta}_0$ in the interval [0, 2] for 1,837 funds in the TASS Hedge Fund database with at least five years of returns during the period from February 1977 to August 2004, ordered by categories 1 to 11. Of the 1,837 funds in the sample, only 9 funds yielded $\hat{\theta}_0$'s greater than 2 and have been omitted to preserve the resolution of the graph. Category definitions: 1=Convertible Arbitrage, 2=Dedicated Short Bias, 3=Emerging Markets, 4=Equity Market-Neutral, 5=Event Driven, 6=Fixed-Income Arbitrage, 7=Global Macro, 8=Long/Short Equity, 9=Managed Futures, 10=Multi-Strategy, 11=Fund of Funds.

Ibbotson Long-Term Government Bond Index, and lagged market betas that are statistically indistinguishable from 0. However, the values of $\hat{\theta}_0$ of the less liquid portfolios are less than 1.00: 0.82 for the Ibbotson Small Company Index, 0.84 for the Ibbotson Long-Term Corporate Bond Index, 0.82 for the Merrill Lynch Convertible Securities Index, and 0.67 for the American Express Extra Income Fund, and their first-order serial correlation coefficients are 15.6%, 15.6%, 6.4% and 35.4%, respectively, which, with the exception of the Merrill Lynch Convertible Securities Index, are considerably higher than those of the more liquid portfolios.[42] Also, the lagged market betas are statistically significant at the 5% level for the Ibbotson Small Company Index (a t-statistic for $\hat{\beta}_1$: 5.41), the Ibbotson Long-Term Government Bond Index (t-statistic for $\hat{\beta}_1$: -2.30), the Merrill Lynch Convertible Securities Index (t-statistic for $\hat{\beta}_1$: 3.33), and the AXP Extra Income Fund (t-statistic for $\hat{\beta}_1$: 4.64).

The results for the CSFB Hedge Fund Indexes in the second panel of Table 17 are also consistent with the empirical results in Tables 15 and 16—indexes corresponding to hedge-fund strategies involving less liquid securities tend to have lower $\hat{\theta}_0$'s. For example, the smoothing-parameter estimates $\hat{\theta}_0$ of the Convertible Arbitrage, Emerging Markets, and Fixed-Income Arbitrage Indexes are 0.49, 0.75, and 0.63, respectively, and first-order serial correlation coefficients of 56.6%, 29.4%, and 39.6%, respectively. In contrast, the smoothing-parameter estimates of the more liquid hedge-fund strategies such as Dedicated Short Bias and Managed Futures are 0.99 and 1.04, respectively, with first-order serial correlation coefficients of 7.8% and 3.2%, respectively.

While these findings are generally consistent with the results in Tables 15 and 16, it should be noted that the process of aggregation can change the statistical behavior of any time series. For example, Granger (1980, 1988) observes that the aggregation of a large number of stationary autoregressive processes can yield a time series that exhibits long-term memory, characterized by serial correlation coefficients that decay very slowly (hyperbolically, as opposed to geometrically as in the case of a stationary ARMA process). Therefore, while it is true that the aggregation of a collection of illiquid funds will generally yield an index with smoothed returns,[43] the reverse need not be true—smoothed index returns need not imply that all of the funds comprising the index are illiquid. The latter inference can only be made with the benefit of additional information—essentially identification restrictions—

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

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

about the statistical relations among the funds in the index, i.e., covariances and possibly other higher-order co-moments, or the existence of common factors driving fund returns.

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

Overall, the patterns in Table 17 confirm our interpretation of smoothing coefficients and serial correlation as proxies for liquidity, and suggest that there may be broader applications of this model of smoothed returns to other investment strategies and asset classes.

4.4 An Aggregate Measure of Illiquidity

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

$$\rho^*_t \equiv \sum_{i=1}^{N_t} \omega_{it}\rho_{1t,i} \tag{27}$$

$$\omega_{it} \equiv \frac{\mathrm{AUM}_{it}}{\sum_{j=1}^{N_t} \mathrm{AUM}_{jt}} \tag{28}$$

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

Figure 7 plots these weighted correlations from January 1980 to August 2004 using all funds in the TASS Combined database with at least 36 consecutive trailing months of non-missing returns, along with the number of funds each month (at the bottom, measured by the right vertical axis), and the median correlation in the cross section (in yellow).[44] The

[44] The number of funds in the early years is relatively low, reaching a level of 50 or more only in late 1988, therefore the weighted correlations before then may be somewhat less informative.

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 7 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%; in October 1987 the S&P 500 fell by 21.8%; 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%. 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 36-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.

5 Hedge-Fund Liquidations

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

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, summarized in Table 18. It may seem reasonable to confine our attention to those Graveyard funds categorized as "liquidated" (status code 1) or perhaps to drop those funds that are closed to new investment (status code 4) from our sample. However, because our purpose is to develop a broader perspective on the dynamics of the hedge-fund industry, we argue that using the entire Graveyard database may be more informative. For example, by eliminating Graveyard funds that are closed to new investors, we create a downward bias in the performance statistics of the remaining funds. Because we do not have detailed information about each of these funds, we cannot easily

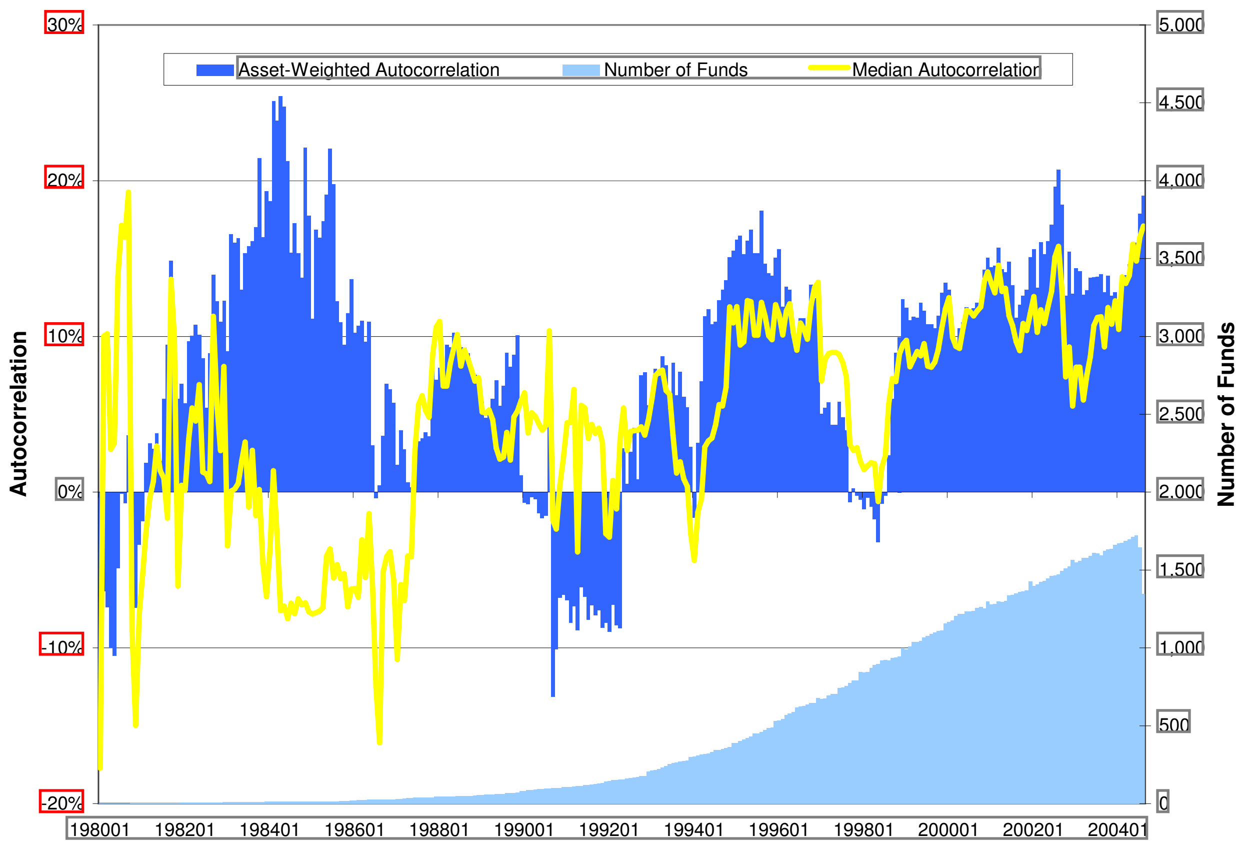


Figure 7: Monthly cross-sectional median and weighted-mean first-order autocorrelation coefficients of individual hedge funds in the TASS Combined hedge-fund database with at least 36 consecutive trailing months of returns, from January 1980 to August 2004.

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.

Status Code	Definition
1	Fund Liquidated
2	Fund No Longer Reporting to TASS
3	TASS Has Been Unable to Contact The Manager for Updated Information
4	Fund Closed to New Investment
5	Fund Has Merged Into Another Entity
7	Fund Dormant
9	Unknown

Table 18: TASS status codes for funds in the Graveyard database.

For concreteness, Table 19 reports frequency counts for Graveyard funds in each status code and style category, as well as assets under management at the time of transfer to the Graveyard.[45] These counts show that 1,571 of the 1,765 Graveyard funds, or 89%, fall into the first three categories, categories that can plausibly be considered liquidations, and within each of these three categories, the relative frequencies across style categories are roughly comparable, with Long/Short Equity being the most numerous and Dedicated Shortseller being the least numerous. Of the remaining 194 funds with status codes 4–9, only status code 4—funds that are closed to new investors—is distinctly different in character from the other status codes. There are only 7 funds in this category, and these funds are all likely to be "success stories", providing some counterbalance to the many liquidations in the Graveyard sample. Of course, this is not to say that 7 out of 1,765 is a reasonable estimate of the success rate in the hedge-fund industry, because we have not included any of the Live funds in this calculation. Nevertheless, these 7 funds in the Graveyard sample do underscore the fact that hedge-fund data are subject to a variety of biases that do not always point in the same direction, and we prefer to leave them in so as to reflect these biases as they occur naturally rather than to create new biases of our own. For the remainder of this article, we

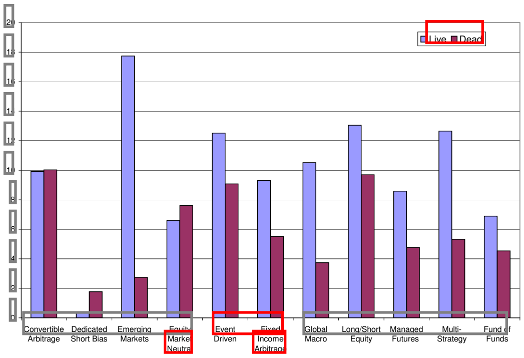
[45] Of the 1,765 funds in the Graveyard database, 4 funds did not have status codes assigned, hence we coded them as 9's ("Unknown"). They are 3882 (Fund of Funds), 34053 (Managed Futures), 34054 (Managed Futures), 34904 (Long/Short Equity).

shall refer to all funds in the TASS Graveyard database as "liquidations" for expositional simplicity.

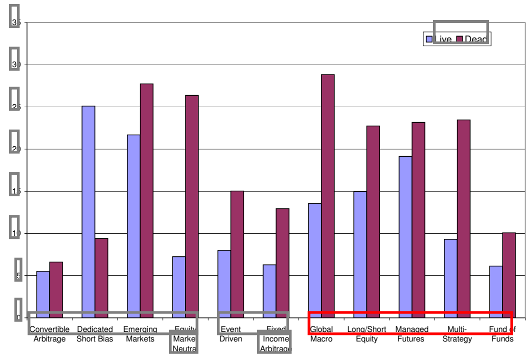
Code	All Funds	Convert Arb	Ded Short	Emrg Mkts	EqMkt Neutral	Event Driven	Fixed Income Arb	Global Macro	L/S Equity	Mged Futures	Mult-Strat	Fund of Funds
Frequency Count												
1	**913**	19	7	78	65	50	29	53	257	190	30	135
2	**511**	21	4	34	12	56	26	29	187	43	7	92
3	**147**	4	1	7	8	17	3	17	54	18	1	17
4	**7**	0	0	0	0	1	2	0	3	0	0	1
5	**56**	2	1	5	0	6	3	6	16	9	1	7
7	**2**	0	0	0	0	1	0	0	1	0	0	0
9	**129**	3	2	9	2	3	8	9	14	56	2	21
Total	**1,765**	49	15	133	87	134	71	114	532	316	41	273
Assets Under Management												
1	**18,754**	1,168	62	1,677	1,656	2,047	1,712	2,615	4,468	975	641	1,732
2	**36,366**	6,420	300	848	992	7,132	2,245	678	10,164	537	882	6,167
3	**4,127**	45	34	729	133	1,398	50	115	931	269	2	423
4	**487**	0	0	0	0	100	31	0	250	0	0	106
5	**3,135**	12	31	143	0	222	419	1,775	473	33	3	24
7	**8**	0	0	0	0	6	0	0	2	0	0	0
9	**3,052**	42	18	222	9	159	152	32	193	1,671	18	538
Total	**65,931**	7,686	445	3,620	2,789	11,063	4,610	5,215	16,482	3,484	1,546	8,991

Table 19: Frequency counts and assets under management (in millions of dollars) of funds in the TASS Graveyard database by category and Graveyard inclusion code. Assets under management are at the time of transfer into the Graveyard database.

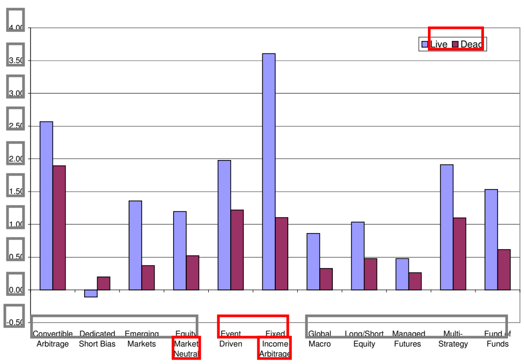
Figure 8 provides a visual comparison of average means, standard deviations, Sharpe ratios, and first-order autocorrelation coefficients ρ_1 in the Live and Graveyard databases (Table 12 contains basic summary statistics for the funds in the TASS Live, Graveyard, and Combined databases). Not surprisingly, 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% and an average standard deviation of 5.51%, but in the Graveyard database, the 49 Convertible Arbitrage funds have an average mean return of 10.02% and a much higher average standard deviation of 8.14%. As expected, average volatilities in the Graveyard database are uniformly higher than those in the Live database because the higher-volatility funds are more likely to be eliminated. This effect operates at both ends of the return distribution—funds that are wildly successful are also more likely to leave the database since they have less motivation to advertise their performance. That the Graveyard database also contains successful funds is supported by the fact that in some categories, the average mean return in the Graveyard database is the same as or higher than in the Live database, e.g., Convertible Arbitrage, Equity Market Neutral, and Dedicated Shortseller.



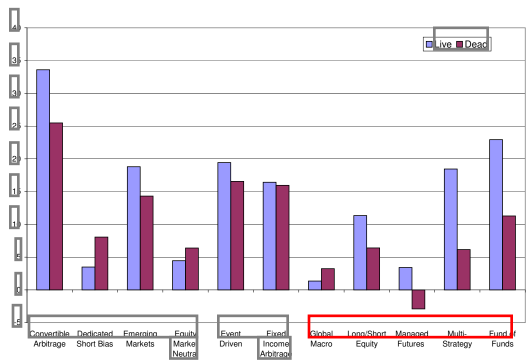
(a) Average Mean Return



(b) Average Standard Deviation



(c) Average Sharpe Ratio



(d) Average Autocorrelation

Figure 8: Comparison of average means, standard deviations, Sharpe ratios, and first-order autocorrelation coefficients for categories of funds in the TASS Live and Graveyard databases from January 1994 to August 2004.

Figure 9 displays the histogram of year-to-date returns at the time of liquidation. The fact that the distribution is skewed to the left is consistent with the conventional wisdom that performance is a major factor in determining the fate of a hedge fund. However, note that there is nontrivial weight in right half of the distribution, suggesting that recent performance is not the only relevant factor.

Finally, Figure 10 provides a summary of two key characteristics of the Graveyard funds: the age distribution of funds at the time of liquidation, and the distribution of their assets under management. The median age of Graveyard funds is 45 months, hence half of all liquidated funds never reached their fourth anniversary. The mode of the distribution is 36 months. The median assets under management for funds in the Graveyard database is \$6.3

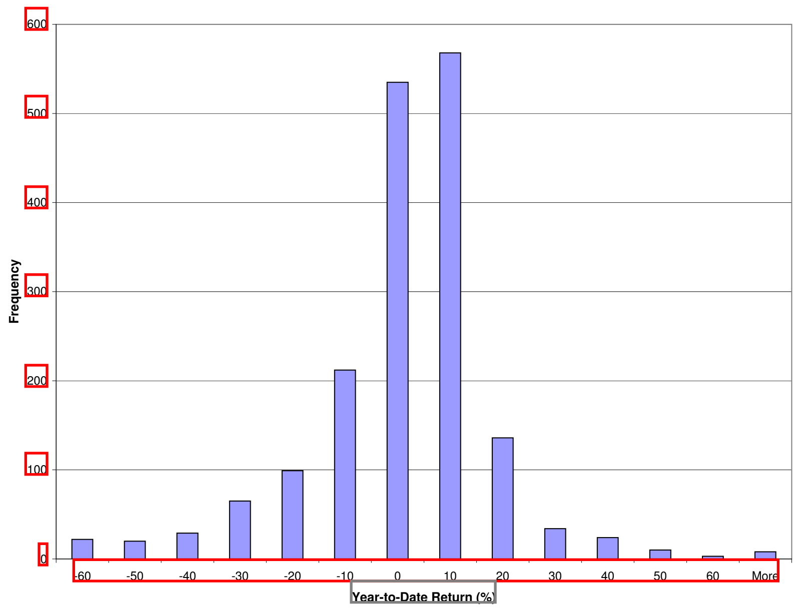


Figure 9: Histogram of year-to-date return at the time of liquidation of hedge funds in the TASS Graveyard database, January 1994 to August 2004.

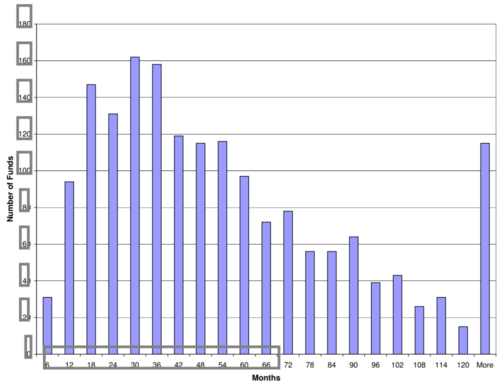
million, not an uncommon size for the typical startup hedge fund.

In Section 5.1, we document the attrition rates of funds in the TASS database, both in the aggregate and for each style category. These attrition rates provide crude baseline measures of the likelihood of liquidation for a given fund. To develop a more precise measure that allows for cross-sectional variability in the likelihood of liquidation—as a function of fund characteristics such as assets under management and recent performance—we estimate a logit model for hedge-fund liquidations in Section 5.2.

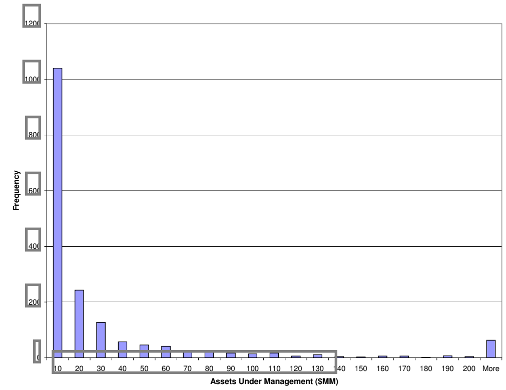
5.1 Attrition Rates

To develop a sense of the dynamics of the TASS database and the birth and death rates of hedge funds over the past decade,[46] in Table 20 we report annual frequency counts of the funds in the database at the start of each year, funds entering the Live database during the year, funds exiting during the year and moving to the Graveyard database, and funds entering and exiting within the year. The panel labelled "All Funds" contains frequency counts for all funds, and the remaining 11 panels contain the same statistics for each category. Also included in Table 20 are attrition rates, defined as the ratio of funds exiting in a given year

[46] Recall that TASS launched their Graveyard database in 1994, hence this is the beginning of our sample for Table 20.



(a) Age Distribution



(b) Assets Under Management

Figure 10: Histograms of age distribution and assets under management at the time of liquidation for funds in the TASS Graveyard database, January 1994 to August 2004.

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

For the unfiltered sample of all funds in the TASS database, and over the sample period from 1994 to 2003, the average attrition rate is 8.8%.[47] This is similar to the 8.5% attrition rate obtained by Liang (2001) for the 1994-to-1999 sample period. The aggregate attrition rate rises in 1998, partly due to LTCM's demise and the dislocation caused by its aftermath. The attrition rate increases to a peak of 11.4% in 2001, mostly due to the Long/Short Equity category—presumably the result of the bursting of the technology bubble.

Although 8.8% is the average attrition rate for the entire TASS database, there is considerable variation in average attrition rates across categories. Averaging the annual attrition

[47] We do not include 2004 in this average because TASS typically waits 8 to 10 months before moving a non-reporting fund from the Live to the Graveyard database. Therefore, the attrition rate is severely downward biased for 2004 since the year is not yet complete, and many non-reporting funds in the Live database have not yet been classified as Graveyard funds. Also, note that there is only 1 new fund in 2004—this figure is grossly downward-biased as well. Hedge funds often go through an "incubation period" where managers trade with limited resources to develop a track record. If successful, the manager will provide the return stream to a database vendor like TASS, and the vendor usually enters the entire track record into the database, providing the fund with an "instant history". According to Fung and Hsieh (2000), the average incubation period—from a fund's inception to its entry into the TASS database—is one year.

rates from 1994–2003 within each category yields the following:

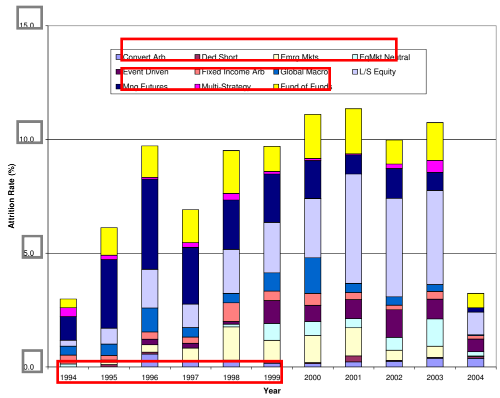
Convertible Arbitrage:	5.2%	Global Macro:	12.6%
Dedicated Shortseller:	8.0%	Long/Short Equity:	7.6%
Emerging Markets:	9.2%	Managed Futures:	14.4%
Equity Market Neutral:	8.0%	Multi-Strategy:	8.2%
Event Driven:	5.4%	Fund of Funds:	6.9%
Fixed Income Arbitrage:	10.6%		

These averages illustrate the different risks involved in each of the 11 investment styles. At 5.2%, Convertible Arbitrage enjoys the lowest average attrition rate, which is not surprising since this category has the second-lowest average return volatility of 5.89% (see Table 12). The highest average attrition rate is 14.4% for Managed Futures, which is also consistent with the 18.55% average volatility of this category, the highest among all 11 categories.

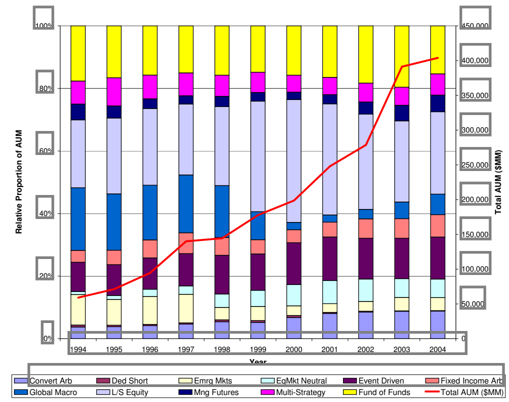
Within each category, the year-to-year attrition rates exhibit different patterns, partly attributable to the relative performance of the categories. For example, Emerging Markets experienced a 16.1% attrition rate in 1998, no doubt because of the turmoil in emerging markets in 1997 and 1998, which is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

To develop a better sense of the relative magnitudes of attrition across categories, Table 21 and Figure 11(a) provide a decomposition by category where the attrition rates in each category are renormalized so that when they are summed across categories in a given year, the result equals the aggregate attrition rate for that year. From these renormalized figures, it is apparent that there is an increase in the proportion of the total attrition rate due to Long/Short Equity funds beginning in 2001. In fact, Table 21 shows that of the total attrition rates of 11.4%, 10.0%, and 10.7% in years 2001–2003, the Long/Short Equity category was responsible for 4.8, 4.3, and 4.1 percentage points of those totals, respectively. Despite the fact that the average attrition rate for the Long/Short Equity category is only 7.6% from

1994 to 2003, the funds in this category are more numerous, hence they contribute more to the aggregate attrition rate. Figure 11(b) provides a measure of the impact of these attrition rates on the industry by plotting the total assets under management of funds in the TASS database along with the relative proportions in each category. Long/Short Equity funds are indeed a significant fraction of the industry, hence the increase in their attrition rates in recent years may be cause for some concern.



(a) Attrition Rates



(b) Assets Under Management

Figure 11: Attrition rates and total assets under management for funds in the TASS Live and Graveyard database from January 1994 to August 2004. Note: the data for 2004 is incomplete, and attrition rates for this year are severely downward biased because of a 8- to 10-month lag in transferring non-reporting funds from the Live to the Graveyard database.

5.2 Logit Analysis of Liquidations

To estimate the influence of various hedge-fund characteristics on the likelihood of liquidation, in this section we report the results of a logit analysis of liquidations in the TASS database. Logit can be viewed as a generalization of the linear regression model to situations where the dependent variable takes on only a finite number of discrete values (see, for example, Maddala, 1983, for details). The logit model is based on a "virtual" regression equation with an unobserved continuous dependent variable Z^* whose conditional mean is a linear function of observed "explanatory" variables $\mathbf{X}$:

$$Z^* \;=\; \mathbf{X}'\boldsymbol{\beta} \;+\; \epsilon \; . \tag{29}$$

Although Z^* is unobserved, it is related to an observable discrete random variable Z, whose realizations are determined by where Z^* lies in its domain or state space. By partitioning the state space into a finite number of distinct regions, Z may be viewed as an indicator function for Z^* over these regions. For example, a binary random variable Z taking on the values 0 (live) and 1 (liquidated) may be modelled as an indicator variable that takes on the

Year	All Funds	Convert Arb	Ded Short	Emrg Mkts	EqMkt Neutral	Event Driven	Fixed Income Arb	Global Macro	L/S Equity	Man Futures	Multi-Strategy	Fund of Funds
Total Attrition Rates and Components by Category (in %)												
1994	3.0	0.0	0.0	0.0	0.1	0.0	0.4	0.4	0.3	1.0	0.4	0.4
1995	6.1	0.0	0.1	0.1	0.0	0.1	0.2	0.5	0.7	3.0	0.2	1.2
1996	9.7	0.6	0.1	0.3	0.0	0.2	0.3	1.1	1.7	4.0	0.1	1.4
1997	6.9	0.2	0.1	0.6	0.0	0.2	0.3	0.4	1.0	2.5	0.2	1.5
1998	9.5	0.3	0.0	1.5	0.1	0.1	0.8	0.4	1.9	2.2	0.3	1.9
1999	9.7	0.2	0.1	1.0	0.7	1.0	0.4	0.8	2.2	2.1	0.1	1.1
2000	11.1	0.1	0.0	1.2	0.6	0.7	0.5	1.6	2.6	1.7	0.1	1.9
2001	11.4	0.2	0.3	1.2	0.4	0.8	0.3	0.4	4.8	0.8	0.0	2.0
2002	10.0	0.2	0.0	0.4	0.6	1.2	0.2	0.4	4.3	1.3	0.2	1.1
2003	10.7	0.4	0.0	0.5	1.2	0.9	0.3	0.3	4.1	0.8	0.5	1.7
2004	3.2	0.4	0.1	0.0	0.2	0.6	0.1	0.0	1.0	0.2	0.0	0.6
Mean	8.8	0.2	0.1	0.7	0.4	0.5	0.4	0.6	2.4	1.9	0.2	1.4
SD	2.7	0.2	0.1	0.5	0.4	0.4	0.2	0.4	1.6	1.0	0.2	0.5
Annual Returns of CSFB/Tremont Hedge Fund Indexes by Category (in %)												
1994	-4.4	-8.1	14.9	12.5	-2.0	0.7	0.3	-5.7	-8.1	11.9	—	—
1995	21.7	16.6	-7.4	-16.9	11.0	18.4	12.5	30.7	23.0	-7.1	11.9	—
1996	22.2	17.9	-5.5	34.5	16.6	23.0	15.9	25.6	17.1	12.0	14.0	—
1997	25.9	14.5	0.4	26.6	14.8	20.0	9.4	37.1	21.5	3.1	18.3	—
1998	-0.4	-4.4	-6.0	-37.7	13.3	-4.9	-8.2	-3.6	17.2	20.7	7.7	—
1999	23.4	16.0	-14.2	44.8	15.3	22.3	12.1	5.8	47.2	-4.7	9.4	—
2000	4.8	25.6	15.8	-5.5	15.0	7.2	6.3	11.7	2.1	4.3	11.2	—
2001	4.4	14.6	-3.6	5.8	9.3	11.5	8.0	18.4	-3.7	1.9	5.5	—
2002	3.0	4.0	18.2	7.4	7.4	0.2	5.7	14.7	-1.6	18.3	6.3	—
2003	15.5	12.9	-32.6	28.7	7.1	20.0	8.0	18.0	17.3	14.2	15.0	—
2004	2.7	0.6	9.1	3.1	4.7	5.7	4.7	4.4	1.5	-7.0	2.8	—
Mean	11.6	11.0	-2.0	10.0	10.8	11.8	7.0	15.3	13.2	7.5	11.0	—
SD	11.3	10.5	15.5	25.2	5.6	10.4	6.8	13.9	16.5	9.4	4.3	—
Total Assets Under Management (in $MM) and Percent Breakdown by Category (in %)												
1994	57,684	3.8	0.7	9.3	1.0	9.5	3.9	20.5	20.7	5.1	7.5	18.0
1995	69,477	3.9	0.5	8.1	1.3	10.0	4.7	18.5	22.9	4.0	9.2	17.0
1996	92,513	4.2	0.4	8.7	2.3	10.1	5.9	17.9	23.4	3.2	7.8	16.1
1997	137,814	4.7	0.4	8.9	2.7	10.4	6.7	18.8	21.9	2.7	7.5	15.3
1998	142,669	5.5	0.6	4.0	4.4	12.5	5.7	16.8	24.4	3.3	6.8	16.0
1999	175,223	5.3	0.6	4.6	5.2	11.7	4.6	9.1	34.5	2.8	6.6	15.1
2000	197,120	5.4	0.5	2.5	5.5	10.6	3.3	1.9	31.1	1.9	4.4	12.7
2001	246,695	8.1	0.3	2.8	7.4	13.9	4.7	2.3	35.3	3.0	5.5	16.6
2002	277,695	8.5	0.3	3.1	7.2	13.0	6.2	3.1	30.2	3.9	6.1	18.4
2003	389,965	8.8	0.1	4.3	6.0	13.0	6.2	5.4	25.7	5.0	5.8	19.7
2004	403,974	8.8	0.2	4.2	5.9	13.5	7.1	6.6	26.3	5.3	6.8	15.3
Mean	178,685	5.8	0.5	5.6	4.3	11.5	5.2	11.4	27.0	3.5	6.7	16.5
SD	103,484	1.9	0.2	2.8	2.4	1.5	1.1	7.8	5.3	1.0	1.4	2.0

Table 21: Decomposition of attribution rates by category for all hedge funds in the TASS Hedge Fund database, from January 1994 to August 2004, and corresponding CSFB/Tremont Hedge-Fund Index returns, and assets under management. Note: attrition rates for 2004 are severely downward-biased because TASS typically waits 8 to 10 months before moving a non-reporting fund from the Live to the Graveyard database; therefore, as of August 2004, many non-reporting funds in the Live database have not yet been moved to the Graveyard. Consequently, the reported means and standard deviations in all three panels are computed over the 1994–2003 period.

value 0 whenever $Z^* \leq 0$ and 1 whenever $Z^* > 0$:

$$Z \equiv \begin{cases} 0 & \text{if } Z^* = \mathbf{X}'\boldsymbol{\beta} + \epsilon \leq 0 \\ 1 & \text{if } Z^* = \mathbf{X}'\boldsymbol{\beta} + \epsilon > 0 \end{cases} . \tag{30}$$

Logit analysis involves imposing a logistic distributional assumption on ϵ (hence the term "logit") and estimating the coefficients $\boldsymbol{\beta}$, and the parameters of the distribution of ϵ, typically by maximum likelihood. Although traditional regression diagnostics such as t-statistics, R^2, and the F-statistic do not apply, approximate counterparts are available by appealing to the asymptotic properties of maximum-likelihood estimators (see, for example, Pregibon, 1981, and Simonoff, 2003).

To estimate the logit model of liquidation, we use the same sample of TASS Live and Graveyard funds as in Section 5.1: 4,536 funds from February 1977 to August 2004, of which 1,765 are in the Graveyard database and 2,771 are in the Live database. As discussed in Sections 3.2 and 5.1, the Graveyard database was initiated only in January 1994, hence this will be the start date of our sample for purposes of estimating the logit model of liquidation. For tractability, we focus on annual observations only, so the dependent variable Z_{it} indicates whether fund i is live or liquidated in year t.[48] Table 22 provides a frequency count of the funds entering and exiting the TASS database in each year. Not surprisingly, the number of hedge funds in both the Live and Graveyard databases grows over time. 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 2 years of history, we are left with 12,895 observations.

Associated with each Z_{it} is a set of explanatory variables listed in Table 23. The motivation for AGE, ASSETS, and RETURN are well-known—older funds, funds with greater assets, and funds with better recent performance are all less likely to be liquidated, hence we would expect negative coefficients for these explanatory variables (recall that a larger conditional mean for Z^* implies a higher probability that $Z_{it} = 1$ or liquidation). The FLOW variable is motivated by the well-known "return-chasing" phenomenon in which investors flock to funds that have had good recent performance, and leave funds that have underper-

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

Year	All Funds	Convert Arb	Ded Short	Emrg Mkts	EqMkt Neutral	Event Driven	Fixed Income Arb	Global Macro	L/S Equity	Man Futures	Multi-Strategy	Fund of Funds
Number of Funds Added to the TASS Database Each Year												
1977	3	0	0	0	0	2	0	0	0	1	0	0
1978	2	0	0	0	0	0	0	0	0	1	0	1
1979	2	0	0	0	0	0	0	1	0	1	0	0
1980	3	0	0	0	0	0	0	0	0	3	0	0
1981	3	0	0	0	0	0	0	0	1	1	0	1
1982	4	0	0	0	0	0	1	0	1	1	0	1
1983	9	0	0	0	0	1	0	1	3	3	0	1
1984	15	0	0	0	0	1	1	0	6	2	0	5
1985	9	0	1	0	0	1	0	1	0	1	0	5
1986	22	0	0	0	0	2	1	2	5	8	0	4
1987	28	0	0	0	0	2	0	2	10	7	1	6
1988	33	4	2	0	0	6	0	1	2	9	1	8
1989	43	1	0	3	3	7	1	2	7	10	0	9
1990	102	4	3	5	1	11	0	7	24	18	2	27
1991	89	2	2	5	1	11	1	11	17	20	1	18
1992	155	8	0	10	4	9	7	10	37	31	2	37
1993	247	7	3	21	3	18	10	12	55	64	10	44
1994	251	13	1	25	7	16	16	11	52	52	5	53
1995	299	12	0	34	10	27	12	19	74	41	7	63
1996	332	14	3	25	10	29	16	16	116	42	14	47
1997	356	10	3	40	14	31	15	19	118	37	13	56
1998	346	14	1	22	29	28	16	20	117	25	8	66
1999	403	10	4	26	36	29	13	12	159	35	10	69
2000	391	17	2	20	17	38	9	18	186	13	10	61
2001	460	25	1	5	49	34	20	15	156	18	16	121
2002	432	22	1	4	41	40	23	26	137	22	14	102
2003	325	11	1	12	23	21	12	15	83	23	14	110
2004	1	0	0	0	0	0	0	0	0	0	0	1
Number of Funds Exiting the TASS Database Each Year												
1994	25	0	0	0	1	0	3	3	2	9	4	3
1995	62	0	1	1	0	1	2	5	7	30	2	13
1996	129	7	1	4	0	3	4	17	23	51	1	18
1997	106	3	1	8	0	3	5	7	17	37	3	22
1998	171	5	0	26	4	3	14	9	35	37	6	32
1999	190	3	1	18	15	20	8	16	45	41	2	21
2000	243	3	1	27	13	15	11	33	60	35	3	42
2001	263	5	6	28	9	22	7	9	112	19	1	45
2002	255	6	1	11	16	32	5	9	112	32	5	26
2003	297	10	1	14	32	24	9	9	112	23	18	45
2004	88	10	2	1	5	15	4	1	27	5	0	18

Table 22: Annual frequency counts of entries into and exits out of the TASS Hedge Fund Database from February 1977 to August 2004. Note that prior to January 1994, exits were not tracked.

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

Table 23: Definition of explanatory variables in logit analysis of hedge-fund liquidations in the TASS database from January 1994 to August 2004.

formed (see, for example, Chevalier and Ellison, 1997; Sirri and Tufano, 1998; and Agarwal, Daniel and Naik, 2004).

Table 24 contains summary statistics for these explanatory variables, as well as for the dependent variable Z_{it}. Note that the sample mean of Z_{it} is 0.09, which may be viewed as an unconditional estimate of the probability of liquidation, and is consistent with the attrition rate of 8.8% reported in Section 5.1.[49] The objective of performing a logit analysis of Z_{it} is, of course, to estimate the *conditional* probability of liquidation, conditional on the explanatory variables in Table 23.

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

Table 24: Summary statistics for dependent and explanatory variables of a logit analysis of hedge-fund liquidations in the TASS database, from 1994 to 2004. Note that the dependent variable Z takes on the value 1 in the year a hedge fund is liquidated, and is 0 in all prior years. The units of measurement for the explanatory variables are: months for AGE, the natural logarithm of millions of dollars for ASSETS, and raw ratios (not percentages) for RETURN and FLOW.

The correlation matrix for Z_{it} and the explanatory variables is given in Table 25. As expected, Z_{it} is negatively correlated with age, assets under management, cumulative return, and fund flows, with correlations ranging from -26.2% for AGE to -5.8% for RETURN_{-2}. Table 25 also shows that assets under management is highly persistent, with a correlation of 94.3% between its contemporaneous and lagged values. To avoid multicollinearity problems, we include only the lagged variable ASSETS_{-1} in our logit analysis, yielding the following

[49] A slight discrepancy should be expected since the selection criterion for the sample of funds in this section is not identical to that of Section 5.1 (e.g., funds in the logit sample must have non-missing observations for the explanatory variables in Table 23).

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

Table 25: Correlation matrix of dependent and explanatory variables of a logit analysis of hedge-fund liquidations in the TASS database, from 1994 to 2004. Note that the dependent variable Z takes on the value 1 in the year a hedge fund is liquidated, and is 0 in all prior years.

final specification which we call Model 1:

$$
\begin{aligned}
Z_{it} \;=\; \mathrm{G}\Big(& \beta_0 \;+\; \beta_1 \mathrm{AGE}_{it} \;+\; \beta_2 \mathrm{ASSETS}_{it-1} \;+ \\
& \beta_3 \mathrm{RETURN}_{it} \;+\; \beta_4 \mathrm{RETURN}_{it-1} \;+\; \beta_5 \mathrm{RETURN}_{it-2} \;+ \\
& \beta_6 \mathrm{FLOW}_{it} \;+\; \beta_7 \mathrm{FLOW}_{it-1} \;+\; \beta_8 \mathrm{FLOW}_{it-2} \;+\; \epsilon_{it} \Big) \;. \qquad (31)
\end{aligned}
$$

Table 26 contains maximum-likelihood estimates of (31) in the first three columns, with statistically significant parameters in bold. Note that most of the parameter estimates are highly significant. This is due to the unusually large sample size, which typically yields statistically significant estimates because of the small standard errors implied by large samples (recall that the standard errors of consistent and asymptotically normal estimators converge to 0 at a rate of $1/\sqrt{n}$ where n is the sample size). This suggests that we may wish to impose a higher threshold of statistical significance in this case, so as to provide a better balance between Type I and Type II errors.[50]

The negative signs of all the coefficients other than the constant term confirm our intuition that age, assets under management, cumulative return, and fund flows all have a negative impact on the probability of liquidation. The fact that RETURN_{-2} is not statistically significant suggests that only the most recent returns are relevant 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%, which implies a reasonable level of explanatory power for

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

this specification.[51]

To address fixed effects associated with the calendar year and hedge-fund style category, in Model 2 we include indicator variables for 10 out of 11 calendar years, and 10 out of 11 hedge-fund categories, yielding the following specification:

$$\begin{aligned} Z_{it} \;=\; \mathrm{G}\Bigg(& \beta_0 \;+\; \sum_{k=1}^{10} \zeta_k \mathrm{I}(\mathrm{YEAR}_{k,i,t}) \;+\; \sum_{k=1}^{10} \xi_k \mathrm{I}(\mathrm{CAT}_{k,i,t}) \;+ \\ & \beta_1 \mathrm{AGE}_{it} \;+\; \beta_2 \mathrm{ASSETS}_{it-1} \;+ \\ & \beta_3 \mathrm{RETURN}_{it} \;+\; \beta_4 \mathrm{RETURN}_{it-1} \;+\; \beta_5 \mathrm{RETURN}_{it-2} \;+ \\ & \beta_6 \mathrm{FLOW}_{it} \;+\; \beta_7 \mathrm{FLOW}_{it-1} \;+\; \beta_8 \mathrm{FLOW}_{it-2} \;+\; \epsilon_{it} \Bigg) \end{aligned} \tag{32}$$

where

$$\mathrm{I}(\mathrm{YEAR}_{k,i,t}) \;\equiv\; \begin{cases} 1 & \text{if } t = k \\ 0 & \text{otherwise} \end{cases} \tag{33a}$$

$$\mathrm{I}(\mathrm{CAT}_{k,i,t}) \;\equiv\; \begin{cases} 1 & \text{if fund } i \text{ is in Category } k \\ 0 & \text{otherwise} \end{cases} . \tag{33b}$$

The columns labelled "Model 2" in Table 26 contain the maximum-likelihood estimates of (32) 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%. 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 10 categories. Managed Futures has a comparable coefficient of 0.49, which is consistent with the higher volatility of such funds and the fact that this

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

category exhibits the highest attrition rate during the 1994–2003 sample period (see Section 5.1), 14.4%. However, the fact that Convertible Arbitrage and Event-Driven categories are the next largest, with coefficients of 0.44 and 0.33, respectively, is somewhat surprising given their unusually low attrition rates of 5.2% and 5.4%, respectively, reported in Section 5.1. This suggests that the conditional probabilities produced by a logit analysis—which control for assets under management, fund flows, and performance—yields information not readily available from the unconditional frequency counts of simple attrition statistics. The remaining category indicators are statistically insignificant at the 5% level.

To facilitate comparisons across explanatory variables, we standardize each of the non-indicator explanatory variables by subtracting its mean and dividing by its standard deviation and then re-estimating the parameters of (32) 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 26. The renormalized estimates show that fund flows are an order of magnitude more important in determining the probability of liquidation than assets under management, returns or age, with normalized coefficients of -32.72 and -7.53 for FLOW and FLOW_{-1}, respectively.

Finally, we re-estimate the logit model (32) 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 in Table 18), 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 26 show that the qualitative features of most of the estimates are unchanged, with the funds in Model 5 exhibiting somewhat higher sensitivity to the lagged FLOW variable. However, the category fixed-effects in Model 5 does differ in some ways from those of Models 2–4, with significant coefficients for Emerging Markets, Equity Market Neutral, and Multi-Strategy, as well as for Managed Futures. This suggests that there are significant differences between the full Graveyard sample and the subsample of funds with status code 1, and bears further study.

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

$$p_{it} \equiv \text{Prob}\,(Z_{it}=1) = \text{Prob}\,(Z_{it}^* > 0) \tag{34a}$$

$$= \text{Prob}\,(\mathbf{X}_{it}'\boldsymbol{\beta} + \epsilon_{it} > 0) = \frac{\exp(\mathbf{X}_{it}'\boldsymbol{\beta})}{1+\exp(\mathbf{X}_{it}'\boldsymbol{\beta})} \tag{34b}$$

$$\hat{p}_{it} \equiv \frac{\exp(\mathbf{X}_{it}'\hat{\boldsymbol{\beta}})}{1+\exp(\mathbf{X}_{it}'\hat{\boldsymbol{\beta}})} . \tag{34c}$$

Table 27 reports year-by-year summary statistics for the estimated liquidation probabilities $\{\hat{p}_{it}\}$ of each fund in our sample, where each $\hat{p}_{it}$ is computed using values of the explanatory variables in year t. The left panel of Table 27 contains summary statistics for estimated liquidation probabilities from Model 1, and the right panel contains corresponding figures from Model 5. We have also stratified the estimated liquidation probabilities by their liquidation status—Live funds in the top panel, Graveyard funds in the middle panel, and the Combined sample of funds in the bottom panel.[52]

[52]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.

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, however, is the fact that the mean and median liquidation probabilities for 2004 (which only includes data up to August) are 11.24% and 7.69%, respectively, the highest levels in our entire sample. This may be a symptom of the enormous growth that the hedge-fund industry has enjoyed in recent years, which increases both the number of funds entering and exiting the industry, but may also indicate more challenging market conditions for hedge funds in the coming months. Note that the mean and median liquidation probabilities for Model 5 do not show the same increase in 2004—this is another manifestation of the time lag with which the Graveyard database is updated (recall that Model 5 includes only those funds with status code 1, but a large number of funds that eventually receive this classification have not yet reached their 8- to 10-month limit by August 2004). Therefore, Model 1's estimated liquidation probabilities are likely to be more accurate for the current year. [53]

The logit estimates and implied probabilities suggest that a number of factors influence the likelihood of a hedge fund's liquidation, including past performance, assets under management, fund flows, and age. Given these factors, our estimates imply that the average liquidation probability for funds in 2004 is over 11%, which is higher than the historical unconditional attrition rate of 8.8%.

6 Other Hedge-Fund Measures of Systemic Risk

In addition to measures of liquidity exposure, there are several other hedge-fund related metrics for gauging the degree of systemic risk exposure in the economy. In this section, we propose three alternatives: (1) risk models for hedge funds; (2) regressions of banking sector indexes on hedge-fund and other risk factors; and (3) a regime-switching model for hedge-fund indexes. We describe these alternatives in more detail in Sections 6.1–6.3.

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

6.1 Risk Models for Hedge Funds

As the examples in Section 1 illustrate, hedge-fund returns may exhibit a number of nonlinearities that are not captured by linear methods such as correlation coefficients and linear factor models. An example of a simple nonlinearity is an asymmetric sensitivity to the S&P 500, i.e., different beta coefficients for down-markets versus up-markets. Specifically, consider the following regression:

$$R_{it} \;=\; \alpha_i \;+\; \beta_i^+ \Lambda_t^+ \;+\; \beta_i^- \Lambda_t^- \;+\; \epsilon_{it} \tag{35}$$

where

$$\Lambda_t^+ \;\equiv\; \begin{cases} \Lambda_t & \text{if } \Lambda_t > 0 \\ 0 & \text{otherwise} \end{cases} \;, \quad \Lambda_t^- \;\equiv\; \begin{cases} \Lambda_t & \text{if } \Lambda_t \le 0 \\ 0 & \text{otherwise} \end{cases} \tag{36}$$

and Λ_t is the return on the S&P 500 index. Since $\Lambda_t = \Lambda_t^+ + \Lambda_t^-$, the standard linear model in which fund i's market betas are identical in up and down markets is a special case of the more general specification (35), the case where $\beta_i^+ = \beta_i^-$. However, the estimates reported in Table 28 for the CSFB/Tremont hedge-fund index returns show that beta asymmetries can be quite pronounced for certain hedge-fund styles. For example, the Distressed index has an up-market beta of 0.04—seemingly market neutral—however, its down-market beta is 0.43! For the Managed Futures index, the asymmetries are even more pronounced: the coefficients are of opposite sign, with a beta of 0.05 in up markets and a beta of -0.41 in down markets. These asymmetries are to be expected for certain nonlinear investment strategies, particularly those that have option-like characteristics such as the short-put strategy of Capital Decimation Partners (see Section 1.1). Such nonlinearities can yield even greater diversification benefits than more traditional asset classes—for example, Managed Futures seems to provide S&P 500 downside protection with little exposure on the upside—but investors must first be aware of the specific nonlinearities to take advantage of them.

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

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

Table 28: Regressions of monthly CSFB/Tremont hedge-fund index returns on the S&P 500 index return, and on positive and negative S&P 500 index returns, from January 1994 to August 2004.

However, this is beyond the scope of this study, and we focus our attention instead on the risk characteristics of the indexes.

Correlation Matrix	S&P500	S&P500^2	S&P500^3	Banks	Libor	USD	Oil	Gold	Lehman Bond	Large Minus Small Cap	Value Minus Growth	Credit Spread	Term Spread	VIX	Hedge Funds	Convert Arb	Dedicated Shortseller	Emerging Markets	Equity Market Neutral	Event Driven	Distressed	Event-Driven Multi-Strategy	Risk Arb	Fixed Income Arb	Global Macro	Long/Short Equity	Managed Futures	Multi-Strategy
S&P500	100.0																											
S&P500^2	-12.3	100.0																										
S&P500^3	77.1	-43.3	100.0																									
Banks	55.8	-33.0	59.1	100.0																								
Libor	3.5	-19.4	12.7	-16.9	100.0																							
USD	7.3	-4.6	4.5	-1.2	8.9	100.0																						
Oil	-1.6	-15.1	-1.7	-2.0	14.0	-13.4	100.0																					
Gold	-7.2	-7.8	-2.6	6.1	-12.2	-35.2	20.1	100.0																				
Lehman Bond	0.8	15.2	-8.9	7.5	-42.1	-55.6	7.0	25.7	100.0																			
Large Minus Small Cap	7.6	21.8	-0.6	-27.6	3.8	11.0	-19.7	-24.5	8.1	100.0																		
Value Minus Growth	-48.9	14.4	-30.3	-5.4	-2.1	-4.0	-21.3	-3.9	10.9	32.7	100.0																	
Credit Spread	-30.6	30.1	-19.8	-16.0	-40.2	-13.0	-2.9	16.4	14.3	-7.2	16.5	100.0																
Term Spread	-11.6	-6.1	-0.2	11.5	4.9	-21.5	7.0	20.4	-10.5	-13.7	2.6	38.7	100.0															
VIX	-67.3	26.2	-67.8	-49.6	-8.2	-9.2	-1.5	-3.4	15.3	9.7	38.5	3.1	-6.9	100.0														
CSFB/Tremont Indexes																												
Hedge Funds	45.9	-22.5	38.2	41.6	-0.2	22.0	7.9	8.9	3.6	-29.6	-41.0	-24.4	-8.1	-25.7	100.0													
Convert Arb	11.0	-19.1	29.4	29.8	-9.0	19.6	-4.3	2.1	2.2	-19.6	-6.2	-6.4	-15.2	-0.2	38.4	100.0												
Dedicated Shortseller	-75.6	20.1	-66.4	-52.1	4.0	-4.4	-9.2	-9.8	7.5	34.9	64.5	11.9	-10.5	57.2	-46.5	-21.7	100.0											
Emerging Markets	47.2	-24.6	50.1	43.8	5.6	19.4	0.7	7.7	-17.7	-27.2	-34.2	-9.9	16.2	-36.6	65.7	32.0	-57.0	100.0										
Equity Market Neutral	39.6	3.2	34.5	30.9	-9.4	9.1	4.8	-6.8	7.3	1.4	-12.6	-12.6	-29.2	-17.1	31.8	29.9	-34.9	24.2	100.0									
Event Driven	54.3	-44.8	67.8	65.4	-0.9	14.6	6.9	8.2	-7.6	-32.4	-30.7	-24.8	-3.6	-44.4	66.0	59.2	-63.1	66.6	39.8	100.0								
Distressed	53.5	-43.4	62.8	64.3	-10.7	9.7	5.2	13.5	-0.3	-26.7	-27.8	-21.6	-1.2	-43.9	56.3	50.8	-62.7	57.7	36.2	93.6	100.0							
Event-Driven Multi-Strategy	46.6	-39.7	62.1	56.2	8.4	20.0	7.7	1.2	-14.6	-33.0	-29.9	-23.0	-3.4	-37.6	68.9	60.3	-53.9	67.2	37.6	93.0	74.8	100.0						
Risk Arb	44.7	-32.5	53.4	55.7	7.0	4.9	2.6	7.4	-6.4	-42.0	-22.0	-29.9	-20.5	-42.2	39.0	41.4	-49.1	44.2	31.9	70.1	58.4	66.9	100.0					
Fixed Income Arb	-1.3	-29.2	5.9	18.8	6.9	18.5	9.4	0.9	2.0	-10.3	1.9	-17.6	3.5	16.9	41.2	54.4	-5.3	28.2	7.0	37.4	28.1	43.4	14.1	100.0				
Global Macro	20.9	-10.8	14.4	28.5	-5.7	28.7	-4.0	-2.3	7.4	-8.8	-6.6	-11.2	-4.7	-5.3	85.4	27.1	-10.6	41.6	19.1	36.8	29.3	42.6	12.4	41.8	100.0			
Long/Short Equity	57.2	-20.2	47.2	40.5	-4.3	-2.1	19.5	14.2	7.0	-48.9	-67.1	-22.9	-13.1	-36.2	77.4	24.1	-71.8	58.8	33.9	65.0	56.9	63.6	51.0	17.2	40.3	100.0		
Managed Futures	-22.6	22.4	-32.2	-14.3	-13.0	-19.9	17.5	15.9	35.4	4.6	21.9	17.9	2.0	25.7	10.5	-21.5	24.5	-13.1	13.8	-23.4	-16.1	-26.8	-25.3	-6.9	26.6	-6.4	100.0	
Multi-Strategy	5.6	-4.1	2.2	10.5	0.9	-13.3	5.6	-1.7	12.5	-8.8	-13.5	-18.9	-7.8	9.5	15.0	33.5	-4.4	-3.9	20.1	14.9	10.0	18.8	4.2	27.5	10.8	13.4	-4.1	100.0

Table 29: Correlation matrix for monthly returns of hedge-fund risk factors, from January 1994 to August 2004.

We begin with a comprehensive set of risk factors that will be candidates for each of the risk models, covering stocks, bonds, currencies, commodities, and volatility. These factors are described in Table 30, and their basic statistical properties have been summarized in Table 7. Given the heterogeneity of investment strategies represented by the hedge-fund industry, the variables in Table 30 are likely to be the smallest set of risk factors capable of spanning the risk exposures of most hedge funds.

Table 29 is a joint correlation matrix of the risk factors and the hedge-fund indexes. Note that we have also included squared and cubed S&P 500 returns in the correlation matrix; they will be included as factors to capture nonlinear effects.[54] It is apparent from the lower left block of the correlation matrix that there are indeed nontrivial correlations between the risk factors and the hedge-fund indexes. For example, there is a 67.8% correlation between the Event Driven index and the cubed S&P 500 return, implying skewness effects in this category of strategies. Also, the Long/Short Equity index has correlations of −48.9% and −67.1 with the market-cap and equity-style factors, respectively, which is not surprising given the nature of this category.

Using a combination of statistical methods and empirical judgment, we use these factors to estimate risk models for each of the 14 indexes, and the results are contained in Table 31. The first row reports the sample size, the second contains the adjusted R^2, and the remaining rows contain regression coefficients and, in parentheses, t-statistics. The number of factors selected for each risk model varies from a minimum of 4 for Equity Market Neutral and Managed Futures to a maximum of 13 for Event Driven, not including the constant term. This pattern is plausible because the Event Driven category includes a broad set of strategies, i.e., various types of "events", hence a broader array of risk factors will be needed to capture the variation in this category versus Equity Market Neutral.

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

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

Variable	Definition
S&P500:	Monthly return of the S&P 500 index including dividends
Banks:	Monthly return of equal-weighted portfolio of bank stocks in CRSP (SIC codes 6000–6199 and 6710)
LIBOR:	Monthly first-difference in U.S.-dollar 6-month London interbank offer rate
USD:	Monthly return on U.S. Dollar Spot Index
Oil:	Monthly return on NYMEX crude-oil front-month futures contract
Gold:	Monthly return on gold spot price index
Lehman Bond:	Monthly return on Dow Jones/Lehman Bond Index
Large-Cap Minus Small-Cap:	Monthly return difference between Dow Jones large-cap and small-cap indexes
Value Minus Growth:	Monthly return difference between Dow Jones value and growth indexes
Credit Spread:	Beginning-of-month difference between KDP High Yield Daily Index and U.S. 10-Year yield
Term Spread:	Beginning-of-month 10-year U.S.-dollar swap rate minus 6-month U.S.-dollar LIBOR
VIX:	Monthly first-difference in the VIX implied volatility index

Table 30: Definitions of aggregate measures of market conditions and risk factors.

exploit tail risk in equity markets, do show significant exposure to higher-order S&P 500 terms as expected.

The last column of Table 31 reports the number of times each risk factor is included in a particular risk model, and this provides an indication of systemic risk exposures in the hedge-fund sector. In particular, if we discover a single factor that is included and significant in all hedge-fund risk models, such a factor may be a bellwether for broad dislocation in the industry. But apart from the constant term, there is no such factor. Nevertheless, the first lag of the squared S&P 500 return, and the cubed S&P 500 return appear in 10 out of 14 risk models, implying that time-varying volatility, tail risk, and skewness are major risk factors across many different hedge-fund styles. Close runners-up are the U.S. Dollar index and the market-capitalization factors, appearing in 9 of 14 risk models. Liquidity exposure, as measured by either the lagged S&P 500 return (see Asness, Krail, and Liew, 2001 and Getmansky, Lo, and Makarov, 2004), or the credit spread factor, is significant for some indexes such as Convertible Arbitrage, Event Driven, and Fixed-Income Arbitrage, but apparently does not affect other indexes.

The $\bar{R}^2$'s for these risk models vary, ranging from 16.3% for Fund of Funds to 79.7% for Dedicated Shortsellers. Given the relatively small sample of about 10 years of monthly returns, the overall explanatory power of these risk models is encouraging. Of course, we must recognize that the process of variable selection has inevitably biased upward the $\bar{R}^2$'s, hence these results should be viewed as useful summaries of risk exposures and correlations rather than structural factor models of hedge-fund returns.

6.2 Hedge Funds and the Banking Sector

To the extent that systemic risk involves distress in the banking sector, a more direct method for investigating the impact of hedge funds on systemic risk is to determine the relation between the returns of publicly traded banks and hedge-fund returns. Using monthly total returns data from the University of Chicago's Center for Research in Security Prices database, we construct equal-weighted and value-weighted portfolios of all stocks with SIC codes 6000–6199, and 6710, rebalanced monthly, and use the returns of these portfolios as proxies for the banking sector. Table 32 contains regressions of the equal-weighted bank index return on the S&P 500 and CSFB/Tremont hedge-fund index returns, and Table 33 contains the same regressions for the value-weighted bank index.

The first column of Table 32 is a regression of the equal-weighted bank index on the S&P 500 return and its first two lags. The fact that both contemporaneous and lagged S&P 500 returns are significant suggests that banks are exposed to market risk and also have some illiquidity exposure, much like serially correlated hedge-fund returns in Section 4 and the other the serially correlated asset returns in Table 17.

The next 14 columns contain regressions with both S&P 500 returns and two lags as well as each of the 14 hedge-fund index returns and two lags, respectively. A comparison of these regressions may provide some insight into links between certain hedge-fund styles and the banking industry. These regressions have reasonable explanatory power, with $\bar{R}^2$'s ranging from 31.2% for Managed Futures to 48.4% for Event Driven. Among the 14 indexes, the ones yielding the highest explanatory power are the event-related indexes: Event Driven, Distressed, Event-Driven Multi-Strategy, Risk Arbitrage, with $\bar{R}^2$'s of 48.4%, 47.3%, 42.4%, and 40.8%, respectively. The coefficients for the contemporaneous hedge-fund indexes in each of these four regressions are also numerically comparable, suggesting that these four strategy groups have similar effects on the banking sector. The least significant hedge-fund index for explaining the equal-weighted bank index is Managed Futures, with coefficients that are both statistically insignificant and numerically close to zero. Managed futures strategies are known to be relatively uncorrelated with most other asset classes, and the banking sector is apparently one of these asset classes.

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

Table 33 presents corresponding regression results for the value-weighted bank index, and some intriguing patterns emerge. For the contemporaneous and lagged S&P 500 return regression, the results are somewhat different than those of Table 32—the contemporaneous coefficient is significant but the lagged coefficients are not, implying the presence of market exposure but little liquidity exposure. This is plausible given the fact that the value-weighted index consists mainly of the largest banks and bank holding-companies, whereas the equal-weighted index is tilted more towards smaller banking institutions.

The single-hedge-fund-index regressions in the next 14 columns also differs from those in Table 32 in several respects. The explanatory power is uniformly higher in these regressions

Regressors	Market Model	Hedge Funds	Convert Arb	Dedicated Shortseller	Emerging Markets	Equity Market Neutral	Event Driven	Distressed	Event-Driven Multi-Strategy	Risk Arb	Fixed Income Arb	Global Macro	Long/Short Equity	Managed Futures	Multi-Strategy	Multiple Hedge-Fund Indexes
		Regression of Equal-Weighted Bank Index on S&P 500 and Single Hedge Fund Index:														
Sample Size:	118	118	118	118	118	118	118	118	118	118	118	118	118	118	115	115
R^2	32.8%	35.2%	38.9%	33.0%	35.9%	32.1%	48.4%	47.3%	42.4%	40.8%	36.6%	35.8%	35.7%	31.2%	31.5%	63.7%
Constant	1.30	1.21	0.99	1.41	1.29	0.81	0.70	0.61	0.93	0.70	0.76	0.96	1.43	1.35	1.08	0.38
	(4.22)	(3.61)	(2.82)	(4.38)	(4.24)	(1.64)	(2.21)	(1.88)	(2.92)	(2.00)	(2.14)	(2.85)	(4.50)	(3.92)	(2.50)	(1.20)
SP500	0.47	0.37	0.42	0.34	0.37	0.45	0.22	0.25	0.31	0.34	0.47	0.44	0.39	0.47	0.46	0.24
	(7.42)	(5.19)	(6.76)	(3.40)	(4.89)	(6.32)	(3.06)	(3.56)	(4.32)	(5.14)	(7.58)	(6.83)	(5.02)	(7.15)	(7.14)	(3.21)
SP500{1}	0.13	0.14	0.09	0.11	0.17	0.11	0.05	0.04	0.08	0.04	0.12	0.14	0.19	0.12	0.12	0.10
	(2.05)	(1.92)	(1.41)	(1.08)	(2.28)	(1.52)	(0.67)	(0.57)	(1.13)	(0.54)	(1.84)	(2.15)	(2.46)	(1.83)	(1.88)	(1.56)
SP500{2}	-0.05	-0.08	-0.05	-0.03	-0.09	-0.06	-0.10	-0.12	-0.08	-0.08	-0.11	-0.11	0.01	-0.07	-0.06	
	(-0.86)	(-1.14)	(-0.82)	(-0.28)	(-1.25)	(-0.92)	(-1.48)	(-1.76)	(-1.24)	(-1.20)	(-1.64)	(-1.65)	(0.17)	(-0.98)	(-0.86)	
CSFBHEDGE		0.36														
		(2.61)														
CSFBHEDGE{1}		-0.11														
		(-0.85)														
CSFBHEDGE{2}		-0.03														-1.66
		(-0.24)														(-5.52)
CSFBCONVERT			0.89													
			(3.50)													
CSFBCONVERT{1}			-0.63													-0.39
			(-2.28)													(-1.67)
CSFBCONVERT{2}			0.20													
			(0.79)													
CSFBSHORT				-0.15												-0.10
				(-1.77)												(-1.32)
CSFBSHORT{1}				-0.02												
				(-0.19)												
CSFBSHORT{2}				0.02												-0.15
				(0.25)												(-2.27)
CSFBEMKTS					0.19											
					(2.70)											
CSFBEMKTS{1}					-0.11											
					(-1.39)											
CSFBEMKTS{2}					0.08											
					(1.21)											
CSFBEQMKTNEUT						0.32										
						(0.82)										
CSFBEQMKTNEUT{1}						0.23										
						(0.58)										
CSFBEQMKTNEUT{2}						0.08										
						(0.22)										
CSFBED							1.19									0.91
							(5.85)									(3.83)
CSFBED{1}							-0.24									-0.27
							(-1.12)									(-1.30)
CSFBED{2}							0.13									0.62
							(0.67)									(2.60)
CSFBDST								0.93								
								(5.55)								
CSFBDST{1}								-0.04								
								(-0.20)								
CSFBDST{2}								0.12								
								(0.77)								
CSFBEDM									0.85							
									(4.41)							
CSFBEDM{1}									-0.25							
									(-1.24)							
CSFBEDM{2}									0.14							
									(0.79)							
CSFBRISKARB										1.02						0.74
										(4.11)						(3.05)
CSFBRISKARB{1}										0.11						
										(0.42)						
CSFBRISKARB{2}										0.08						
										(0.33)						
CSFBFIARB											0.68					
											(2.33)					
CSFBFIARB{1}											0.03					0.57
											(0.10)					(2.23)
CSFBFIARB{2}											0.35					
											(1.27)					
CSFBGMACRO												0.22				
												(2.60)				
CSFBGMACRO{1}												0.01				
												(0.08)				
CSFBGMACRO{2}												0.10				0.99
												(1.15)				(5.68)
CSFBLSE													0.19			-0.24
													(1.66)			(-2.18)
CSFBLSE{1}													-0.16			
													(-1.45)			
CSFBLSE{2}													-0.19			
													(-1.75)			
CSFBMF														0.01		
														(0.11)		
CSFBMF{1}														-0.02		
														(-0.20)		
CSFBMF{2}														-0.05		
														(-0.57)		
CSFBMULT															0.27	
															(1.09)	
CSFBMULT{1}															-0.13	
															(-0.57)	
CSFBMULT{2}															0.14	
															(0.62)	

Table 32: Regressions of monthly equal-weighted banking sector returns on the S&P 500 and various CSFB/Tremont hedge-fund index returns, from January 1994 to August 2004.

than in Table 32, and also remarkably consistent across all 14 regressions—the $\overline{R}^2$'s range from 54.6% (Managed Futures) to 58.2% (Risk Arbitrage). However, this does not imply that larger banking institutions have more in common with all hedge-fund investment strategies. In fact, it is the S&P 500 that seems to be providing most of the explanatory power (compare the first column with the next 14 in Table 33), and although some hedge-fund indexes do have significant coefficients, the $\overline{R}^2$'s change very little when hedge-fund indexes are included one at a time. The multiple-hedge-fund-index regression in the last column does yield somewhat higher explanatory power, an $\overline{R}^2$ of 64.2%, but in contrast to the negative coefficients in the equal-weighted bank index regression, in this case most of the coefficients are positive. In particular, Convertible Arbitrage, Dedicated Shortsellers, Risk Arbitrage, and Fixed-Income Arbitrage all have positive coefficients. One possible explanation is that the larger banking institutions are involved in similar investment activities through their proprietary trading desks. Another explanation is that large banks offer related fee-based services to such hedge funds (e.g., credit, prime brokerage, trading, and structured products), and do well when their hedge-fund clients do well.

In summary, the banking industry has clear ties to the hedge-fund industry, hence dislocations in one is very likely to create repercussions for the other.

6.3 Regime-Switching Models

Our final hedge-fund-based measure of systemic risk is motivated by the phase-locking example of Section 1.2 where the return-generating process exhibits apparent changes in expected returns and volatility that are discrete and sudden. The Mexican peso crisis of 1994–1995, the Asian crisis of 1997, and the global flight to quality precipitated by the default of Russian GKO debt in August 1998 are all examples of such regime shifts. Linear models are generally incapable of capturing such discrete shifts, hence more sophisticated methods are required. In particular, we propose to model such shifts by a "regime-switching" process in which two states of the world are hypothesized, and the data are allowed to determine the parameters of these states and the likelihood of transitioning from one to the other. Regime-switching models have been used in a number of contexts, ranging from with 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, i.e., 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

Regressors	Market Model	Regression of Value-Weighted Bank Index on S&P 500 and Single Hedge Fund Index														Multiple Hedge-Fund Indexes
		Hedge Funds	Convert Arb	Dedicated Shortseller	Emerging Markets	Equity Market Neutral	Event Driven	Distressed	Event-Driven Multi-Strategy	Risk Arb	Fixed Income Arb	Global Macro	Long/Short Equity	Managed Futures	Multi-Strategy	
Sample Size:	118	118	118	118	118	118	118	118	118	118	118	118	118	118	115	115
R^2	55.7%	55.8%	55.6%	57.1%	54.9%	55.0%	56.1%	55.6%	55.5%	58.2%	54.7%	55.1%	58.2%	54.6%	55.5%	64.2%
Constant	0.73	1.02	0.60	0.57	0.76	0.30	0.69	0.67	0.72	0.48	0.71	0.80	1.04	0.75	0.65	0.47
	(2.05)	(2.60)	(1.41)	(1.54)	(2.11)	(0.53)	(1.67)	(1.59)	(1.82)	(1.15)	(1.66)	(2.00)	(2.65)	(1.90)	(1.31)	(1.00)
SP500	0.89	0.91	0.87	1.10	0.89	0.87	0.81	0.83	0.84	0.81	0.90	0.87	0.99	0.90	0.90	1.09
	(12.24)	(10.76)	(11.53)	(9.84)	(9.98)	(10.65)	(8.68)	(9.17)	(9.46)	(10.19)	(11.95)	(11.20)	(11.21)	(11.76)	(12.09)	(10.27)
SP500{1}	0.02	0.04	0.01	-0.03	0.02	0.02	-0.06	-0.03	-0.04	-0.08	0.01	0.03	0.05	0.02	0.03	-0.02
	(0.31)	(0.47)	(0.08)	(-0.23)	(0.19)	(0.22)	(-0.60)	(-0.34)	(-0.40)	(-0.93)	(0.15)	(0.43)	(0.53)	(0.25)	(0.46)	(-0.34)
SP500{2}	-0.02	0.06	-0.01	0.01	0.02	-0.04	0.02	0.01	0.01	0.00	-0.03	-0.02	0.12	-0.03	0.00	
	(-0.25)	(0.70)	(-0.17)	(0.12)	(0.26)	(-0.45)	(0.28)	(0.16)	(0.10)	(-0.05)	(-0.36)	(-0.32)	(1.40)	(-0.38)	(-0.00)	
CSFBHEDGE		-0.12														
		(-0.72)														
CSFBHEDGE{1}		-0.07														
		(-0.47)														
CSFBHEDGE{2}		-0.24														
		(-1.53)														
CSFBCONVERT			0.45													0.83
			(1.46)													(2.51)
CSFBCONVERT{1}			-0.38													-0.59
			(-1.14)													(-1.79)
CSFBCONVERT{2}			0.12													
			(0.40)													
CSFBSHORT				0.24												0.28
				(2.47)												(2.53)
CSFBSHORT{1}				-0.07												
				(-0.73)												
CSFBSHORT{2}				0.06												-0.14
				(0.60)												(-1.58)
CSFBEMKTS					-0.01											
					(-0.11)											
CSFBEMKTS{1}					-0.01											
					(-0.07)											
CSFBEMKTS{2}					-0.07											
					(-0.89)											
CSFBEQMKTNEUT						0.33										
						(0.74)										
CSFBEQMKTNEUT{1}						-0.01										
						(-0.02)										
CSFBEQMKTNEUT{2}						0.23										
						(0.52)										
CSFBED							0.40									
							(1.51)									
CSFBED{1}							0.11									
							(0.41)									
CSFBED{2}							-0.34									
							(-1.30)									
CSFBDST								0.29								
								(1.32)								
CSFBDST{1}								0.07								
								(0.32)								
CSFBDST{2}								-0.22								
								(-1.05)								
CSFBEDM									0.29							
									(1.19)							
CSFBEDM{1}									0.08							
									(0.32)							
CSFBEDM{2}									-0.25							
									(-1.09)							
CSFBRISKARB										0.53						0.86
										(1.79)						(2.69)
CSFBRISKARB{1}										0.53						
										(1.76)						
CSFBRISKARB{2}										-0.48						
										(-1.67)						
CSFBFIARB											0.06					
											(0.17)					
CSFBFIARB{1}											0.19					0.46
											(0.52)					(1.32)
CSFBFIARB{2}											-0.18					
											(-0.55)					
CSFBGMACRO												0.09				
												(0.83)				
CSFBGMACRO{1}												-0.08				
												(-0.81)				
CSFBGMACRO{2}												-0.05				
												(-0.50)				
CSFBLSE													-0.28			-0.23
													(-2.13)			(-1.56)
CSFBLSE{1}													0.00			
													(-0.01)			
CSFBLSE{2}													-0.28			-0.34
													(-2.17)			(-2.38)
CSFBMF														0.03		
														(0.32)		
CSFBMF{1}														-0.03		
														(-0.28)		
CSFBMF{2}														-0.04		
														(-0.37)		
CSFBMULT															-0.33	-0.49
															(-1.18)	(-1.73)
CSFBMULT{1}															0.00	
															(0.00)	
CSFBMULT{2}															0.35	
															(1.33)	

Table 33: Regressions of monthly value-weighted banking sector returns on the S&P 500 and various CSFB/Tremont hedge-fund index returns, from January 1994 to August 2004.

following:

$$
\begin{aligned}
R_t &= I_t \cdot R_{1t} + (1-I_t)\cdot R_{2t} && \text{(37a)}\\
R_{it} &\sim \mathcal{N}\left(\mu_i, \sigma_i^2\right) && \text{(37b)}\\
I_t &\equiv \begin{cases} 1 & \text{with probability } p_{11} \text{ if } I_{t-1}=1 \\ 1 & \text{with probability } p_{21} \text{ if } I_{t-1}=0 \\ 0 & \text{with probability } p_{12} \text{ if } I_{t-1}=1 \\ 0 & \text{with probability } p_{22} \text{ if } I_{t-1}=0 \end{cases} . && \text{(37c)}
\end{aligned}
$$

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

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

$$
\begin{aligned}
\text{Prob}\,(I_{t+k}=1|\mathcal{R}_t) &= \pi_1 + (p_{11}-p_{21})^k \left[\text{Prob}\,(I_t=1|\mathcal{R}_t) - \pi_1\right] && \text{(38a)}\\
\pi_1 &\equiv \frac{p_{21}}{p_{12}+p_{21}} && \text{(38b)}
\end{aligned}
$$

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 estimation procedure). Using similar recursions of the Markov chain, the conditional expectation of

R_{t+k} can be readily derived as:

$$\mathrm{E}[R_{t+k}|\mathcal{R}_t] = \mathbf{a}_t'\mathbf{P}^k\boldsymbol{\mu} \tag{39a}$$

$$\mathbf{a}_t \equiv \left[\ \mathrm{Prob}\,(I_t = 1|\mathcal{R}_t) \quad \mathrm{Prob}\,(I_t = 2|\mathcal{R}_t)\ \right]' \tag{39b}$$

$$\boldsymbol{\mu} \equiv [\ \mu_1 \quad \mu_2\ ]' \tag{39c}$$

Index	p_{11}	p_{21}	p_{12}	p_{22}	Annualized Mean		Annualized SD		Log(L)
					State 1	State 2	State 1	State 2	
Hedge Funds	100.0%	1.2%	0.0%	98.8%	6.8%	12.4%	2.9%	9.9%	323.6
Convertible Arbitrage	89.9%	17.9%	10.1%	82.1%	16.1%	-1.6%	1.9%	6.1%	404.0
Dedicated Shortseller	23.5%	12.6%	76.5%	87.4%	-76.2%	11.7%	2.3%	16.5%	208.5
Emerging Markets	100.0%	1.2%	0.0%	98.8%	11.5%	6.6%	8.2%	20.3%	218.0
Equity Mkt 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
ED Multi-Strategy	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 Arb	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
Multi-Strategy	98.2%	25.0%	1.8%	75.0%	10.8%	-7.6%	3.2%	9.2%	387.9

Table 34: Maximum likelihood parameter estimates of a two-state regime-switching model for CSFB/Tremont hedge-fund indexes from January 1994 to August 2004.

Table 34 reports the maximum-likelihood estimates of the means and standard deviations in each of two states for the 14 CSFB/Tremont hedge-fund indexes, as well as the transition probabilities for the two states. Note that two rows in Table 34 are shaded—Dedicated Shortselling and Managed Futures—because the maximum-likelihood estimation procedure did not converge properly for these two categories, implying that the regime-switching process may not be a good model of their returns. The remaining 12 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% with a volatility of 1.9%, but in state 2, the expected return is -1.6% with a volatility of 6.1%. 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 volatility state has higher expected returns. This suggests that for these strategies, volatility may be a necessary ingredient for their expected returns.

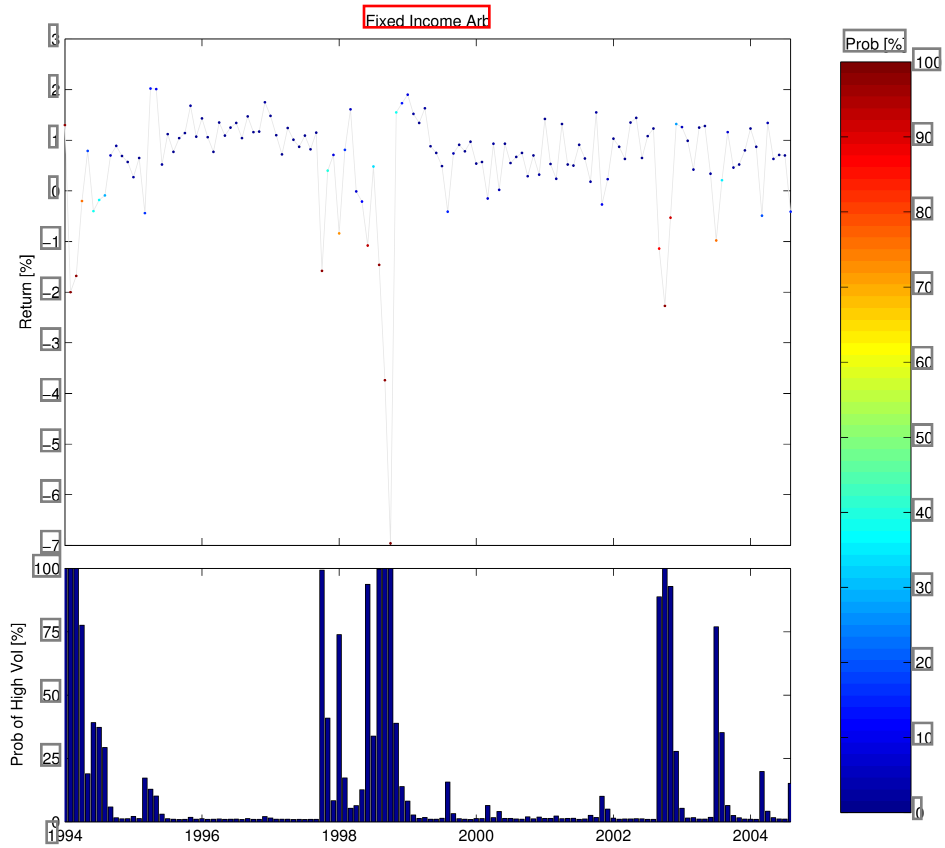


Figure 12: Monthly returns and regime-switching model estimates of the probability of being in the high-volatility state for CSFB/Tremont Fixed-Income Arbitrage hedge-fund index, from January 1994 to August 2004.

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 12 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% in August and several months thereafter. However, this is not an isolated event, but occurs on several occasions both before and after August 1998.

To develop an aggregate measure of systemic risk based on this regime-switching model, we propose summing the state-2 probabilities across all hedge-fund indexes every month to yield a time series that captures the likelihood of being in high-volatility periods. Of course, the summed probabilities—even if renormalized to lie in the unit interval—cannot be interpreted formally as a probability because the regime-switching process was specified individually for each index, not jointly across all indexes. Therefore, the interpretation of "state 2" for Convertible Arbitrage may be quite different than the interpretation of "state 2" for Equity Market Neutral. Nevertheless, as an aggregate measure of the state of the hedge-fund industry, the summed probabilities may contain useful information about systemic risk exposures.

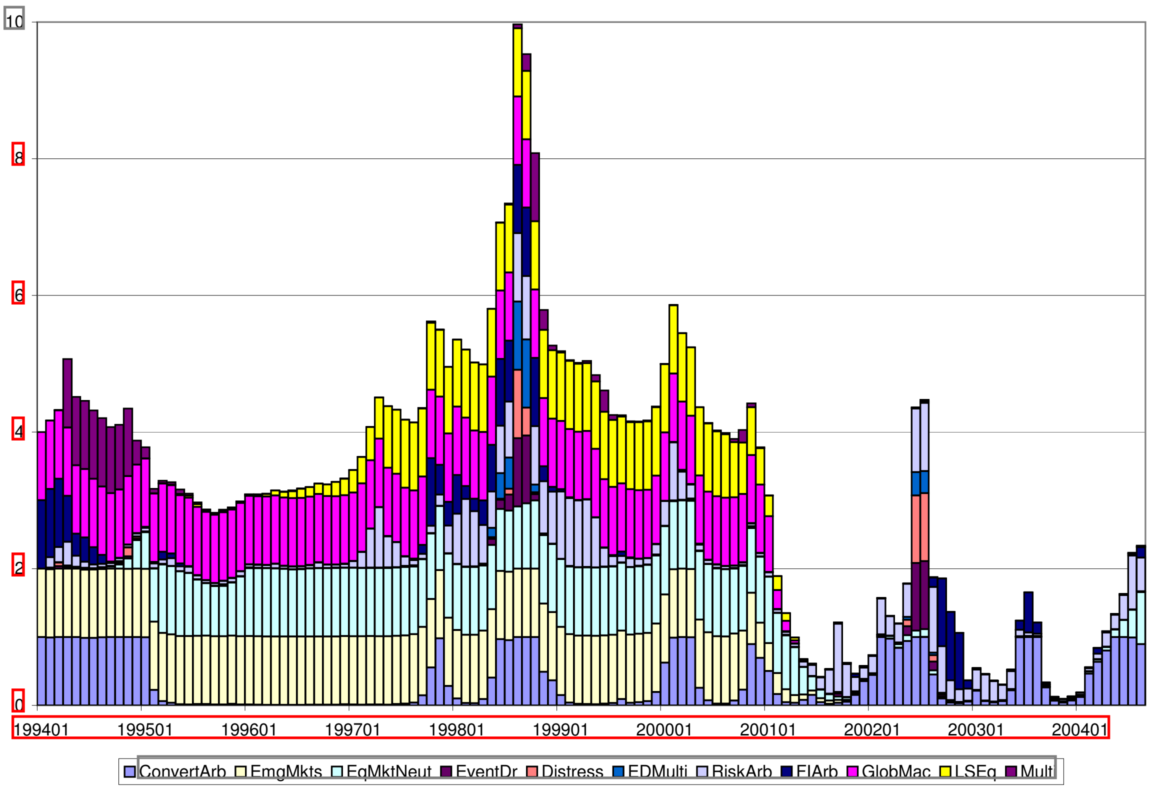


Figure 13: Aggregate hedge-fund risk indicator: sum of monthly regime-switching model estimates of the probability of being in the high-volatility state (p_2) for 11 CSFB/Tremont hedge-fund indexes (Convertible Arbitrage; Emerging Markets; Equity Market Neutral; Event Driven; Distressed; Even-Driven Multi-Strategy; Risk Arbitrage; Fixed-Income Arbitrage; Global Macro; Long/Short Equity; and Multi-Strategy), from January 1994 to August 2004.

Figure 13 plots the monthly summed probabilities from January 1994 to August 2004, and we see that peak occurs around August 1998, with local maxima around the middle of 1994 and the middle of 2002, which corresponds roughly to our intuition of high-volatility periods for the hedge-fund industry.

Alternatively, we can construct a similar aggregate measure by summing the probabilities of being in a low-mean state, which involves summing the state-2 probabilities for those indexes where high volatility is paired with low mean with the state-1 probabilities for those indexes where low volatility is paired with low mean. Figure 14 contains this indicator, which differs significantly from Figure 13. The low-mean indicator also has local maxima in 1994 and 1998 as expected, but now there is a stronger peak around 2002, largely due to Equity Market Neutral, Global Macro, and Long/Short Equity. This corresponds remarkably well to the common wisdom that over the past two years, these three strategy classes have underperformed for a variety of reasons.[55] Therefore, this measure may capture more of the spirit of systemic risk than the high-volatility indicator in Figure 13.

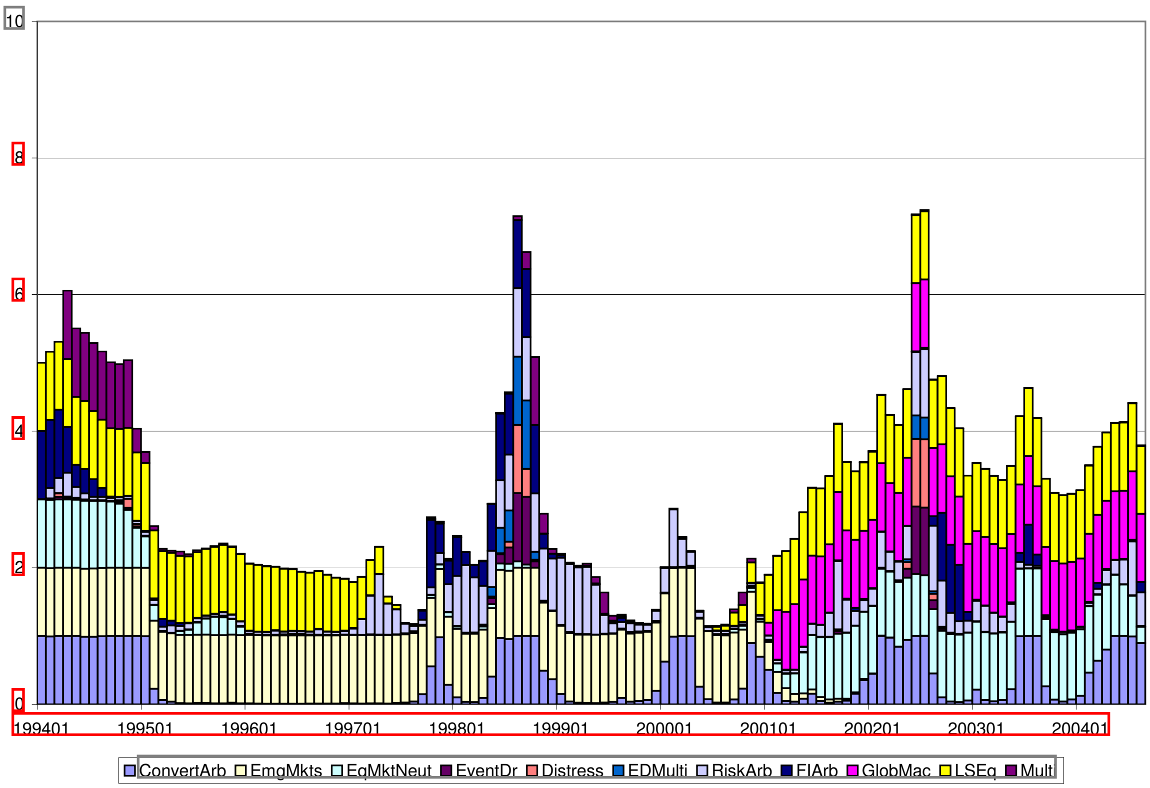


Figure 14: Aggregate hedge-fund risk indicator: sum of monthly regime-switching model estimates of the probability of being in the low-mean state for 11 CSFB/Tremont hedge-fund indexes (Convertible Arbitrage; Emerging Markets; Equity Market Neutral; Event Driven; Distressed; Even-Driven Multi-Strategy; Risk Arbitrage; Fixed-Income Arbitrage; Global Macro; Long/Short Equity; and Multi-Strategy), from January 1994 to August 2004 .

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

7 The Current Outlook

A conclusive assessment of the systemic risks posed by hedge funds requires certain data that is currently unavailable, and is unlikely to become available in the near future, i.e., 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, increased illiquidity as measured by the weighted autocorrelation ρ_t^*, and increased mean and median liquidation probabilities for hedge funds in 2004.

2. 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.

3. 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.

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

We hasten to qualify our tentative conclusions by emphasizing the speculative nature of these inferences, and hope that our analysis spurs additional research and data collection to refine both the analytics and the empirical measurement of systemic risk in the hedge-fund industry.

A Appendix

This appendix contains the TASS category definitions in Section A.1 and some of the more technical aspects of the integrated hedge-fund investment process in Section A.2.

A.1 TASS Category Definitions

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 11 possible categories:

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

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

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

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

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

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

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

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

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

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

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

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

A.2 Constrained Optimization

To solve the following optimization problem:

$$\text{Min}_{\{\boldsymbol{\omega}\}} \ \tfrac{1}{2}\boldsymbol{\omega}'\boldsymbol{\Sigma}\,\boldsymbol{\omega} \tag{A.1}$$

$$\text{subject to} \quad \boldsymbol{\omega}'\boldsymbol{\mu} \ \geq \ \mu_o \tag{A.2}$$

$$\boldsymbol{\omega}'\boldsymbol{\iota} \ = \ 1 \tag{A.3}$$

we define the Lagrangian:

$$\mathcal{L} \ = \ \tfrac{1}{2}\boldsymbol{\omega}'\boldsymbol{\Sigma}\,\boldsymbol{\omega} \ + \ \lambda(\mu_o - \boldsymbol{\omega}'\boldsymbol{\mu}) \ + \ \xi(1 - \boldsymbol{\omega}'\boldsymbol{\iota}) \tag{A.4}$$

which yields the following first-order conditions:

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\omega}} = 0 = \boldsymbol{\Sigma}\boldsymbol{\omega} - \lambda\boldsymbol{\mu} - \xi\boldsymbol{\iota} \tag{A.5}$$

$$\frac{\partial \mathcal{L}}{\partial \gamma} = 0 = \mu_o - \boldsymbol{\omega}'\boldsymbol{\mu} \tag{A.6}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = 0 = 1 - \boldsymbol{\omega}'\boldsymbol{\iota}\ . \tag{A.7}$$

Solving (A.5) for $\boldsymbol{\omega}$ yields the minimum-variance portfolio as a function of the two Lagrange multipliers:

$$\boldsymbol{\omega}^* = \lambda\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} + \xi\boldsymbol{\Sigma}^{-1}\boldsymbol{\iota} \tag{A.8}$$

and applying (A.6) and (A.7) to (A.8) allows us to solve for the Lagrange multipliers explicitly as:

$$\lambda \equiv \frac{\mu_o A - B}{D} \quad , \quad \xi = -\frac{\mu_o B - C}{D} \tag{A.9}$$

where

$$A \equiv \boldsymbol{\iota}'\boldsymbol{\Sigma}^{-1}\boldsymbol{\iota} > 0 \tag{A.10a}$$

$$B \equiv \boldsymbol{\iota}'\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} \tag{A.10b}$$

$$C \equiv \boldsymbol{\mu}'\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} > 0 \tag{A.10c}$$

$$D \equiv AC - B^2 > 0\ . \tag{A.10d}$$

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