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The financial crisis and hedge fund returns

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Abstract The financial crisis has focused the lens of politicians and regulators on hedge funds as a source of systemic and operational risk in asset markets. We examine the extent to which available data can provide useful information regarding the impact of hedge funds on the financial system. Using data from January 1994 through September 2008, we find dramatic changes in the exposures of hedge funds to risk factors, accompanied by a significant and widespread increase in correlation between hedge fund and factor returns. Lastly, the discontinuity at zero in the cross-sectional distribution of hedge fund returns persists throughout the sample.

Keywords Hedge funds · Financial crisis · Systemic risk

JEL Classification G01 · G23

1 Introduction

A natural response to any financial crisis is to identify causes and, when appropriate, affect change in regulation or industry structure to try to prevent subsequent episodes. The current situation, fueled by the housing boom and bust, is no different, and features a wide variety of potential culprits including lax credit standards at mortgage lending institutions, conflicts of interest at rating agencies, and greed displacing risk management at insurance companies, investment banks, and other cornerstones of the financial infrastructure.One group in particular—hedge fund managers—has engendered public outrage in the wake of claims of aggressive short selling and recent high-profile cases of fraud.

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Indeed, the hedge fund industry has long been criticized for questionable behavior and destabilizing trading strategies, leading to the 2006 elimination of the private adviser exemption of the Investment Advisers Act, requiring most US hedge fund managers to register with the SEC as investment advisers. The rule was later vacated by the US Court of Appeals for the District of Columbia Circuit. Following the SEC's failure to investigate Bernard Madoff's investment business, however, Mary Schapiro, the new leader of the agency, has been quoted as strongly supporting a registration requirement for hedge funds.[1] Further, Senators Grassley and Levin introduced in January 2009 the Hedge Fund Transparency Act, which would require hedge funds to disclose the identity of their investors and prime brokers.[2] Given the increased scrutiny of hedge funds, and calls for greater transparency of their assets and impact on markets, it is appropriate to study the extent to which currently available data can be used to gain insight regarding hedge fund trading and reporting behavior.

In this paper, we use one of the commonly available hedge fund databases to examine recent changes in hedge fund trading strategies, as well as changes in the cross-sectional distribution of hedge fund returns. We find that, beginning in June 2007, there is a widespread change in hedge fund risk exposures. This is perhaps no surprise, as one would expect that hedge fund managers, who are typically given the freedom to engage in dynamic, high-frequency trading, would respond quickly to the events unfolding in the latter part of our sample. Interestingly, accompanying the change in hedge fund risk exposures is a dramatic increase in the ability of linear factor models to capture the return behavior of hedge funds. The median adjusted R-squared, using 24-month rolling windows, rises from a low of 15% in November 2003 to 50% at the very end of our sample. This result is consistent with some managers abandoning idiosyncratic strategies in favor of more liquid assets that are captured by traditional risk factors. In addition, the increase in adjusted R-squared reflects the increase in correlation across markets during times of financial distress. Our ability to infer changes in hedge fund strategy, and more importantly the interrelation between these changes and the liquidity and stability of financial markets, is severely limited, however, since these can only be observed with a significant lag when using time series analysis.

The cross-sectional distribution of individual hedge funds is characterized by a discontinuity at zero, which Bollen and Pool (2009) link to purposeful misreporting of returns. The number of small losses is significantly less than the number of small gains, and both are significantly different from the number expected under the null hypothesis of a smooth distribution. The discontinuity persists throughout the sample for individual hedge funds, though it weakens in 2008. In contrast, the discontinuity disappears completely for funds of funds towards the end of our sample, and is never present in the distribution of commodity fund returns. These results suggest that some hedge fund managers continue to avoid reporting losses during the financial crisis.

Taken together, our results indicate that one can use currently available hedge fund return databases to capture interesting and relevant features of hedge fund trading strategies and reporting behavior. To a large extent, however, the feasible analysis

[1] See "Crisis on Wall Street: Schapiro pledges vigilance as SEC Chief" in the 16 January 2009 *Wall Street Journal*, page C3.

[2] See "Legislators seek hedge-fund disclosure" in the 2 February 2009 *Wall Street Journal*, page C2.

is limited to cross-sectional work that can only reveal behavior in the aggregate. For investors and regulators, though, fund-specific results are more important. And for this, it appears necessary to achieve the greater transparency sought by some politicians and regulators.

The rest of this paper is organized as follows. Section 2 describes the data used in the study and presents summary statistics of hedge fund returns. Section 3 explains our analysis of changes in hedge fund trading strategies and reports results. Section 4 examines the cross-sectional distribution of hedge fund returns with an emphasis on the relative frequency of small losses versus small gains. Section 5 concludes.

2 Data

We use the Center for International Securities and Derivatives Markets (CISDM) hedge fund database in our empirical analysis. The sample period is January 1994 through September 2008. The CISDM database includes live and defunct hedge funds, funds of funds, commodity trading advisors, commodity pool operators, and indices. We do not study the indices in this paper, since we are interested in manager-specific changes in fund strategy and risk. Raw data are contained in two files, one containing times series of returns, net asset values, and assets under management, the other containing fund name, style, and other supplemental information. We focus attention on the monthly returns of the funds. We eliminate all consecutive returns of 0.0000 or 0.0001 that occur at the beginning and end of a fund's history, as these may simply indicate missing observations or are otherwise uninformative. We also drop funds with less than 36 remaining monthly observations to ensure sufficient data to estimate changes in risk exposures. After applying these exclusionary criteria, there are 7,811 funds with 618,521 observations.

Table 1 lists the unique self-reported styles for each fund type. Several features stand out. The list is long, with some strategies overlapping, such as the three equity strategies and the three fixed income strategies. Furthermore, only the hedge funds have reported strategies that are detailed enough to provide insight regarding the funds' holdings and trading activity. Figure 1 shows, for each hedge fund strategy, the percentage of funds that are active. Those strategies for which live funds constitute more than 50% of the total are growing. The substantial deviations from 50% indicate that the hedge fund sample is quite dynamic—and motivate the need to allow for changes in strategy over time. Presumably, managers of some active funds will decide to switch from a less successful strategy to one with more promise, rather than shut a fund down and start a new one. These results suggest that an objective, statistical procedure for determining fund strategy is warranted.

Our approach to identify a fund's strategy involves searching for the subset of factors that best captures time variation in the fund's returns. We collect a set of 14 factors that are used in the existing hedge fund literature to proxy for the trading strategies employed by hedge fund managers. These factors are drawn from three sources. The three Fama-French factors, the excess return of the market and the returns of size and value portfolios, as well as the momentum factor, are from Kenneth French's website. We also include the squared returns of the size, value, and momentum factors to

Table 1 Strategies by fund type

Hedge fund
Capital structure arbitrage
Convertible arbitrage
Distressed securities
Emerging markets
Equity long only
Equity long/short
Equity market neutral
Event driven multi strategy
Fixed income
Fixed income–MBS
Fixed income arbitrage
Global macro
Market timing
Merger arbitrage
Multi strategy
Option arbitrage
Other relative value
Regulation D
Relative value multi strategy
Sector
Short bias
Single strategy
Commodity trading advisor
Discretionary
Systematic
Commodity pool operator
Invest funds in parent company
Multi strategy
Single strategy
Fund of funds
Conservative
Invest funds in parent company
Market neutral
Multi strategy
Opportunistic
Single strategy

Listed are the unique strategies by fund type as self-reported in the September 2008 CISDM hedge fund database

capture non-linearities in exposure generated by derivatives or dynamic trading. Five trend-following factors, which are the returns of portfolios of options on bonds, foreign currencies, commodities, short-term interest rates, and stock indexes, are obtained from David Hsieh's website. The change in the yield of a ten-year Treasury note and

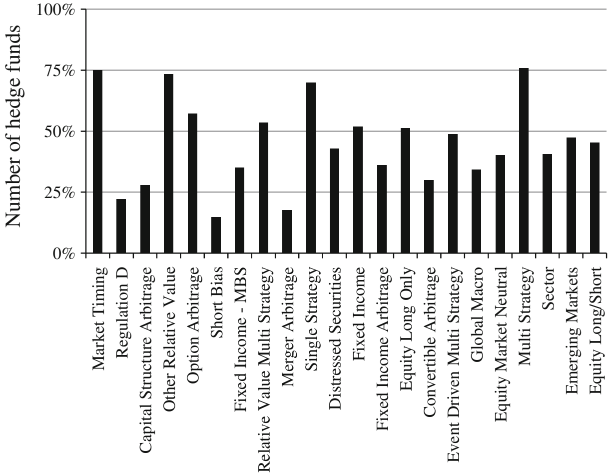

Fig. 1 Percentage of style that is active. Listed for each strategy are the percentage of funds that are active. Data are from the September 2008 CISDM database

the change in the credit spread, defined as the yield on ten-year BAA corporate bonds less the yield of a ten-year Treasury note, are obtained from the US Federal Reserve's website. To estimate the factor model, we also require a risk-free rate, and for this we use the 1 month T-Bill rate from Kenneth French's website.

Table 2 contains summary statistics of the 7,811 CISDM funds in the sample. For each fund type, the table lists the number of funds and equally weighted cross-sectional averages of each fund's average monthly return, standard deviation, Sharpe ratio, skewness, and excess kurtosis. The active hedge funds and funds of funds, listed in Panel A, feature lower average returns than their defunct counterparts in Panel B. Furthermore the active funds of funds have an average Sharpe ratio of 0.1096 compared to 0.2125 for defunct funds. Similarly, active hedge funds and funds of funds have average negative skewness approximately 3 times the magnitude of that of defunct funds. The likely reason for these results is the large number of new active funds with returns affected by the collapse of credit markets in 2007–2008 and the stock market crash of 2008.

To illustrate the impact of the financial crisis on hedge fund returns, Table 3 reports summary statistics for active funds over two sub-periods: January 1994–December 2006 and January 2007–September 2008.[3] The average hedge fund return drops from 1.25% per month in the first period to –0.06% in the second period and the average Sharpe ratios plummet from 0.3913 to 0.0087. Funds of funds feature similar changes. Perhaps surprisingly, commodity fund summary statistics are relatively stable, suggesting that these funds have in aggregate lived up to the promise of "absolute returns." Nonetheless, the dramatic changes in the hedge

[3] Defunct funds are excluded because there are few defunct funds with sufficient observations in the latter period.

Table 2 Summary statistics

Type	No. of funds	μ	σ	SR	$Skew$	$Kurt$
Panel A. Active funds						
HF	1,853	0.85%	3.78%	0.2111	−0.3836	4.5928
FOF	1,687	0.46%	2.11%	0.1096	−1.0998	4.9412
CTA/CPO	498	1.08%	5.52%	0.1421	0.2958	2.3436
Total	4,038					
Panel B. Defunct funds						
HF	1,992	0.96%	4.67%	0.2060	−0.1084	4.3950
FOF	660	0.63%	2.23%	0.2125	−0.3488	3.5972
CTA/CPO	1,121	0.73%	5.77%	0.0592	0.3500	2.6267
Total	3,773					
Panel C. All funds						
HF	3,845	0.91%	4.24%	0.2085	−0.2410	4.4903
FOF	2,347	0.51%	2.14%	0.1386	−0.8886	4.5633
CTA/CPO	1,619	0.84%	5.69%	0.0847	0.3333	2.5396
Total	7,811					

Listed are summary statistics of hedge funds (HF), funds of funds (FOF), commodity trading advisors, and commodity pool operators (CTA/CPO). The summary statistics are the equally-weighted cross-sectional averages of the mean monthly return, μ; the standard deviation of monthly returns, σ; the Sharpe ratio, SR; the skewness, Skew; and the excess kurtosis, Kurt. Data are from January 1994 through September 2008

Table 3 Summary statistics pre and post 2007

Type	No. of funds	μ	σ	SR	$Skew$	$Kurt$
Panel A. Active funds pre–2007						
HF	1,853	1.25%	3.32%	0.3913	0.1677	2.4320
FOF	1,687	0.74%	1.68%	0.3404	−0.3383	1.9444
CTA/CPO	498	1.11%	5.23%	0.1611	0.3943	1.7831
Total	4,038					
Panel B. Active funds post–2007						
HF	1,853	−0.06%	3.99%	0.0087	−0.6325	1.5309
FOF	1,687	−0.14%	2.63%	−0.1291	−0.9745	1.6179
CTA/CPO	498	1.03%	5.53%	0.1167	−0.0143	0.7498
Total	4,038					

Listed are summary statistics of hedge funds (HF), funds of funds (FOF), commodity trading advisors, and commodity pool operators (CTA/CPO). Only active funds, as indicated in the September 2008 CISDM hedge fund database, are included. The summary statistics are the equally-weighted cross-sectional averages of the mean monthly return, μ; the standard deviation of monthly returns, σ; the Sharpe ratio, SR; the skewness, Skew; and the excess kurtosis, Kurt. Panel A includes data from January 1994 through December 2006. Panel B includes data from January 2007 through September 2008

fund and fund of fund summary statistics raise a question: to what extent were fund managers changing styles to mitigate the downturn in traditional asset classes?

3 Factor model dynamics

The standard approach to measure hedge fund risk exposures is to regress fund returns on factors that proxy for different trading strategies.[4] The factors are constructed in an effort to capture the time-varying exposure to underlying assets generated either by holding derivatives or engaging in dynamic trading strategies. In Fung and Hsieh (2001), for example, the payoffs to market timing strategies are mimicked by constructing returns of a hypothetical strategy involving put and call options on underlying assets. Agarwal and Naik (2004) use payoffs of index options with different strike prices to generate a flexible functional form relating a hedge fund's return to that of the market. A growing stream of literature recognizes that constant exposures to these factors are insufficient to model the time variation in exposure to underlying assets, because hedge fund managers can change their style. Fung and Hsieh (2004) analyze the time-series properties of regression residuals in a CUSUM test to identify two breakpoints in aggregate exposure to style factors: September 1998, which they attribute to the LTCM debacle, and March 2000, which they attribute to the end of the internet bubble. These breakpoints are used in Agarwal et al. (2011) and Fung et al. (2008). While these breakpoints are able to reflect industry-wide changes, they cannot accurately capture the time variation of individual hedge fund risk exposures.

We follow the approach of Bollen and Whaley (2009) by searching, for each fund, the optimal changepoint that minimizes the sum of squared errors in a factor model of the fund's returns. All of the coefficients in the factor model are allowed to shift on the changepoint. The methodology can easily be extended to allow for multiple shifts; however, the relatively short data histories of most funds make estimation of multiple shifts intractable.

The first step in the analysis is to determine which of the 14 factors to include in a given fund's factor model.We allow at most three factors in order to limit the number of coefficients to estimate. We try all possible combinations of factors and choose the subset that minimizes the Bayesian Information Criterion in a factor model with no change in coefficients. Table 4 lists average regression statistics for these fixed-parameter regressions. The average adjusted R-squared for hedge funds, as shown in Panel A, is 33%, far below the fit of mutual funds. This result can be caused by idiosyncratic trading strategies that are uncorrelated with the set of factors included in the analysis, as well as time-varying exposures to the strategies that are not accommodated by the fixed-parameter regression. The average hedge fund alpha is 0.39% per month—almost 5% per year—which can be interpreted conservatively as the average return unexplained by the factors. The Table also shows results for subsets of funds formed by the optimal number of factors. The adjusted R-squared increases with the number of factors, from 12% with one factor, to 30% with two factors, and to 44% with three factors. Also, the average alpha decreases from 0.52 to 0.41 to 0.32% as the number of factors increases, consistent with the interpretation that the alpha is the average return unexplained by the factors.

[4] See, for example, Fung and Hsieh (2001); Mitchell and Pulvino (2001) and Agarwal and Naik (2004).

Table 4 Regression statistics

	All	1 Factor	2 Factor	3 Factor
Panel A. HF				
No. of Funds	3,845	860	1,002	1,983
Alpha	0.39%	0.52%	0.41%	0.32%
Adj. R-squared	33.00%	11.73%	29.87%	43.80%
Residual vol.	3.27%	3.42%	3.19%	3.24%
Panel B. FOF				
No. of Funds	2,347	143	291	1,913
Alpha	0.16%	0.26%	0.20%	0.14%
Adj. R-squared	44.87%	14.44%	34.21%	48.77%
Residual vol.	1.51%	2.02%	1.68%	1.44%
Panel C. CTA/CPO				
No. of Funds	1,619	567	493	559
Alpha	0.50%	0.47%	0.45%	0.57%
Adj. R-squared	21.32%	10.81%	22.90%	30.58%
Residual vol.	4.95%	5.45%	4.91%	4.47%

Listed are summary statistics of factor models estimated by OLS. For each fund, the optimal set of factors is selected using the Bayesian Information Criterion with maximum number of factors equal to three. The summary statistics are the number of funds, the average monthly alpha, the average adjusted R-squared, and the average monthly residual volatility. Results are shown for all funds, as well as subsets formed by the number of factors included in the optimal set. Data are from January 1994 through September 2008

Panels B and C show the results for funds of funds and commodity funds, respectively. Funds of funds have lower alphas, higher adjusted R-squareds, and lower residual volatility than hedge funds, whereas commodity funds have higher alphas, lower adjusted R-squareds, and higher residual volatility. Funds of funds reduce idiosyncratic volatility through diversification. In addition, the vast majority of the funds of funds, 1,913 of 2,347 or 82%, have three factors in their factor model, compared to 1,983 of 3,845 or 52% for hedge funds, and 559 of 1,619 or 35% for commodity funds. Most funds of funds appear to diversify across hedge fund styles. The poor fit of commodity funds is consistent with highly dynamic strategies not fully captured by the Fung and Hsieh (1997) trend-following factors, facilitated by the liquidity of the underlying futures contracts.

The second step in the analysis is to allow coefficients of the factor models to shift once at some point in each fund's history. Each possible changepoint is tried, with a minimum of 12 observations required in each period. Thus, for a fund with N observations, the allowed changepoints are observations 13 through $N - 11$. We use the method of Bai and Perron (1998) to assess whether the subsequent reduction in the sum of squared errors is statistically significant.

Table 5 shows summary statistics of the subset of funds for which the Bai and Perron (1998) test rejects the null hypothesis of constant parameters at the 10% significance level. About half the hedge funds and funds of funds feature significant changes in exposure, but only about one-third of the commodity funds do. For each fund type,

Table 5 Regression statistics for switchers

	Panel A. HF				Panel B. FOF				Panel C. CTA/CPO			
	All	1 Factor	2 Factor	3 Factor	All	1 Factor	2 Factor	3 Factor	All	1 Factor	2 Factor	3 Factor
No. of funds	1,990	392	476	1,122	1,167	63	122	982	597	200	166	231
	No switch allowed				No switch allowed				No switch allowed			
Alpha	0.40%	0.62%	0.44%	0.30%	0.18%	0.22%	0.23%	0.18%	0.51%	0.54%	0.42%	0.53%
Adj. R-squared	33.12%	10.94%	28.51%	42.82%	42.23%	17.13%	31.08%	45.22%	21.31%	10.34%	22.58%	29.90%
Residual vol.	3.36%	3.60%	3.28%	3.32%	1.53%	1.82%	1.64%	1.50%	4.80%	5.14%	4.69%	4.58%
	Switch allowed				Switch allowed				Switch allowed			
Alpha	0.43%	0.63%	0.48%	0.34%	0.19%	0.24%	0.23%	0.19%	0.49%	0.52%	0.47%	0.48%
Adj. R-squared	47.32%	28.20%	43.84%	55.48%	54.44%	30.73%	46.39%	56.96%	34.94%	24.91%	35.31%	43.36%
Residual vol.	2.89%	3.16%	2.83%	2.82%	1.32%	1.62%	1.40%	1.29%	4.26%	4.64%	4.17%	3.99%
	Pre-period				Pre-period				Pre-period			
Alpha	0.92%	1.62%	0.91%	0.68%	0.26%	0.46%	0.30%	0.24%	1.29%	1.82%	1.18%	0.91%
Adj. R-squared	33.43%	13.05%	28.02%	42.85%	36.18%	11.19%	27.87%	38.81%	30.84%	19.47%	33.21%	38.99%
Residual vol.	3.21%	3.85%	3.18%	3.00%	1.34%	1.83%	1.47%	1.29%	4.87%	5.92%	4.48%	4.25%
	Post-period				Post-period				Post-period			
Alpha	−0.06%	−0.21%	0.07%	−0.07%	0.05%	−0.28%	0.15%	0.06%	−0.05%	−0.27%	−0.03%	0.11%
Adj. R-squared	39.78%	14.80%	34.81%	50.62%	53.49%	24.18%	41.26%	56.89%	25.07%	12.20%	25.69%	35.78%
Residual vol.	2.93%	2.89%	2.96%	2.93%	1.41%	1.71%	1.50%	1.37%	4.18%	4.21%	4.27%	4.10%

Listed are summary statistics of factor models estimated by OLS for funds with a significant switch in factor loadings. For each fund, the optimal set of factors is selected using the Bayesian Information Criterion with maximum number of factors equal to three. The optimal changepoint in factor loadings is selected to minimize the sum of squared errors. Significance is assessed at the 90% level using the method of Bai and Perron (1998). The summary statistics are the number of funds, the average monthly alpha, the average adjusted R-squared, and the average monthly residual volatility. Results are shown for all funds, as well as subsets formed by the number of factors included in the optimal set. Results are shown for the regressions with no switch in parameters, with the optimal switch in parameters, and on the pre- and post- switch sub-periods. Data are from January 1994 through September 2008 four sets of summary statistics are listed. The first are from the fixed-parameter regressions, corresponding to the results in Table 4 for the subset of funds with significant changes, i.e.

$$R_t = \alpha + \beta^{\mathrm{T}} F_t + \varepsilon_t, \tag{1}$$

where R_t is the excess return of a fund, β^{T} is the transpose of a vector of factor loadings and the vector F contains observations of the factors. The second are from the factor models with a switch in parameters, i.e.

$$\begin{array}{ll} R_t = \alpha_0 + \beta_0^{\mathrm{T}} F_t + \varepsilon_t & \text{for} \quad t = 1, \ldots, T\pi \\ R_t = \alpha_0 + \alpha_1 + \left(\beta_0^{\mathrm{T}} + \beta_1^{\mathrm{T}}\right) F_t + \varepsilon_t & \text{for} \quad t = T\pi + 1, \ldots, T, \end{array} \tag{2}$$

where the unknown changepoint π satisfies $0 < \pi < 1$ and $T\pi$ is an integer. The third and fourth are fixed-parameter regressions estimated over the two sub-periods defined by a fund's changepoint. We label the two periods the "Pre" and "Post" period, respectively.

The improvement in adjusted R-squared is quite substantial, consistent with the results in Bollen and Whaley (2009). For hedge funds in Panel A, the average adjusted R-squared increases from 33.12 to 47.32%, with the largest increase for the 392 funds with only one factor, for which the adjusted R-squared rises from 10.94 to 28.20%. The Post-period features a tighter fit than the Pre-period, 39.78% versus 33.43%, as well as a dramatically lower alpha, –0.06% versus 0.92%. The reduction in alpha has at least three possible causes. First, as described by Lowenstein (2000), opportunities for abnormal returns are reduced over time by competition from other funds. Second, back-fill bias could result in better performance in the early part of a fund's life, as described in Ackermann et al. (1999). Third, the decrease in alpha could simply reflect a wide-spread reduction in returns towards the end of the 1994–2008 sample period. We explore this last explanation in subsequent analysis. The alphas of funds of funds and commodity funds, in Panels B and C, respectively, show similar reductions. Funds of funds feature a more pronounced increase in adjusted R-squared across the Pre and Post periods, whereas the commodity funds actually show a reduction.

To gain further insight, we plot in Fig. 2a time series of the number of funds undergoing a change in risk exposures along with the growth of a \$1 investment in the market factor invested at the beginning of our sample in January 1994. Note that the first allowable changepoint is January 1995 and the last allowable is October 2007. The number of funds with a switch in parameters has two pronounced peaks. The first occurs on March 2000, corresponding to the peak of the tech bubble, while the second occurs at the end of the sample, with a sharp rising commencing in June 2007. Many market observers point to the collapse of two Bear Stearns hedge funds in June 2007 as the beginning of the financial crisis. Note that this latter episode has five consecutive months with a large number of switches, whereas the March 2000 event appears to last only one month, suggesting that the financial crisis has resulted in a more fundamental and lasting change in hedge fund activity than the tech bubble.

Figure 3 shows a similar plot—the number of switches versus the median adjusted R-squared. Each month, all funds with at least 24 months centered on the given month

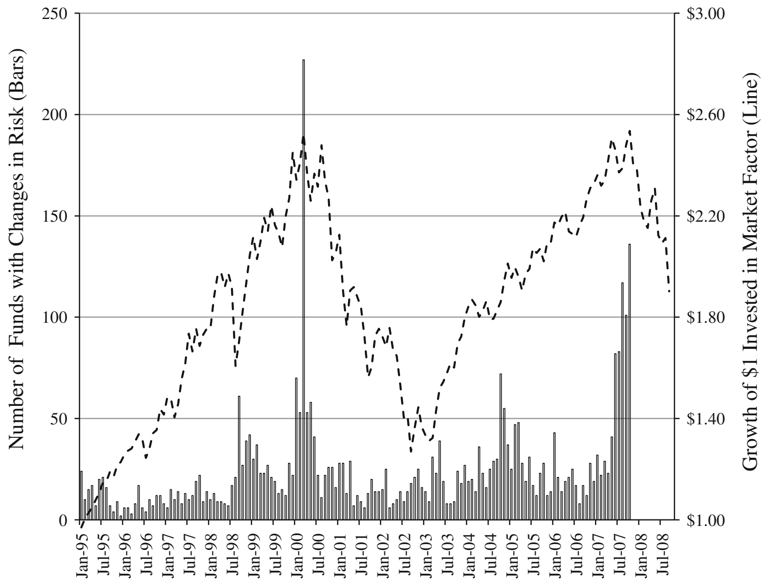

Fig. 2 Changes in fund risk. *Vertical bars* show the number of funds with switch date in a given month. Only those funds with a significant switch in parameters assessed at the 90% significance level using the method of Bai and Perron (1998) are included. The *dashed line* shows the growth in $1 invested in the market factor. Data are from January 1994 through September 2008

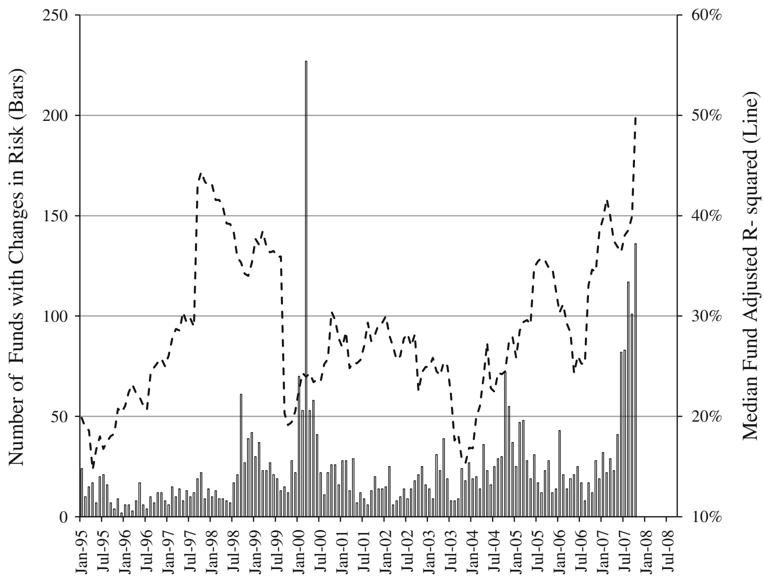

Fig. 3 Median fund adjusted R-squared. *Vertical bars* show the number of funds with switch date in a given month. Only those funds with a significant switch in parameters assessed at the 90% significance level using the method of Bai and Perron (1998) are included. The *dashed line* shows the median adjusted R-squared for all funds using 24 monthly observations centered on a given month. Data are from January 1994 through September 2008

are included. A fixed-coefficient regression using these 24 months is estimated. This rolling window measures the time-varying ability of the factors to explain hedge fund returns. Three pronounced features merit discussion.

First, there is a dramatic rise on September 1997, when the median adjusted R-squared increased from 29 to 43%, and a corresponding drop on September 1999, when it fell from 36 to 20%. These dates define the time period wherein the rolling regressions include August 1998, a month during which the market factor dropped by 16.2%, caused by the Russian financial crisis and the collapse of Long Term Capital Management. Many markets were affected and many hedge funds experienced large losses, hence the correlation between funds and their factors increase with the inclusion of this influential observation.

Second, the median adjusted R-squared reached its lowest level of 15% on November 2003, presumably as funds focused on idiosyncratic trading.

Third, the median adjusted R-squared climbs steadily towards the end of the sample reaching its highest level of 50% on the last possible date. Unlike the earlier rise in median adjusted R-squared, this period is not defined by a single monthly observation driving correlations upwards. Rather, asset markets around the world are experiencing increased correlation in the wake of the financial crisis. Furthermore, investor withdrawals are forcing managers to sell assets and realize losses. This too would increase the correlation between reported returns and the returns of the factors. In addition, it might be the case that managers are shifting exposure to more liquid assets with returns that correspond more closely to those of the factors. More in-depth analysis of these conjectures requires data on hedge fund holdings which are generally unavailable.

4 Discontinuities in return distributions

The results of Sects. 2 and 3 indicate dramatic changes in the data generating processes for hedge fund returns towards the end of our sample period. Average returns fell precipitously, accompanied by an apparent increase in correlation of returns across asset classes, as evidenced by the rise in adjusted R-squareds. Naturally, changes such as these motivate investors to reallocate their own portfolios, as shown by the massive withdrawals from hedge funds in 2008 reported in the financial press.[5] Capital flight is quite costly from a managerial perspective for at least two reasons. First, satisfying investor liquidity demands force managers to sell assets. In a falling market, forced sales are likely to incur large price concessions which are shared by all investors in the fund, including the manager who typically holds a large stake. In addition, investor redemptions can cause managers to close arbitrage positions before realizing a profit, as in Shleifer and Vishny (1997). Second, managerial income falls with a decline in the asset base of a hedge fund, ceteris paribus, since both fixed management fees and variable performance bonuses are proportional to the size of the fund.

Many managers have responded to the flood of withdrawal requests by exercising their option to suspend redemptions during periods of market stress. As discussed in

[5] See, for example, "Another wave of withdrawals expected to hit hedge funds" in the 2 March 2009 *Wall Street Journal* p. C1.

Ang and Bollen (2009), the majority of hedge fund partnership agreements include clauses that describe the manager's right to postpone or limit withdrawals in situations where satisfying them would cause undo harm to other investors, or when computation of fund net asset value is not possible due to a lack of liquidity in underlying assets. The lack of liquidity suggests another potential response of managers to the risk of capital flight: the use of discretion to make a fund's return series as attractive as possible when reporting returns to hedge fund databases.

Prior research has documented several patterns in reported returns that indicate some degree of managerial bias. Getmansky et al. (2004) find that many hedge fund return series feature significant positive autocorrelation, resulting in artificially low volatility and elevated Sharpe ratios. Autocorrelation can be generated by either purposeful smoothing, for example when reported returns are actually moving averages of past and current actual returns, or by conservatively updating valuations of illiquid securities in a fund's portfolio.[6] Asness et al. (2001) and Bollen and Pool (2008) present evidence that the smoothing behavior is asymmetric and stronger in down markets, consistent with a desire to delay reporting losses and fully reporting gains in an effort to limit capital flight on the part of return-sensitive investors.

More recently, Bollen and Pool (2009) document a pronounced discontinuity in hedge fund returns, wherein the fraction of small negatives is significantly lower than the fraction of small positives, and significantly less than expected under the null hypothesis of a smooth distribution. One explanation for this phenomenon is that some managers avoid reporting losses by overstating end-of-month portfolio values. Bollen and Whaley (2009) and Agarwal et al. (2007) show that investors are sensitive to the number of prior reported losses, even after controlling for a fund's average return, hence an unbroken string of gains can help maintain and attract capital.[7] Loss avoidance in this context is analogous to the well-established practice of earnings management in corporations.[8]

In the current financial crisis, managers may feel even more pressure to avoid reporting losses to stem the flood of withdrawal requests. Alternatively, managers may feel that this is an ideal time to fully report losses since investors may be less likely to lay blame on the manager for losses when asset markets crash in unison.To investigate the reporting behavior of fund managers over time, we examine the pooled cross-sectional distribution of returns, and focus on the returns just above and below zero. We include live and defunct funds in the analysis, since Bollen and Pool (2009) find no substantial difference between the distributions of these two subsets.We report results for hedge funds, funds of funds, and commodity funds separately. Hedge fund returns reflect the decisions of individual managers, whereas funds of funds returns are weighted averages of constituent hedge fund returns, and hence may smooth any discontinuity in the return distribution. Commodity funds are less likely to exhibit a

[6] When trade prices are not readily available, managers can rely on broker quotes or model values when computing end-of-month portfolio values and resulting fund returns. See the Financial Accounting Standards Board's FAS 157 for detail.

[7] There are a variety of other explanations for a discontinuity at zero, including managerial skill at avoiding losses, survivorship bias, and asymmetric payoffs of underlying assets.

[8] See, for example, Burgstahler and Dichev (1997) and Dechow et al. (2003).

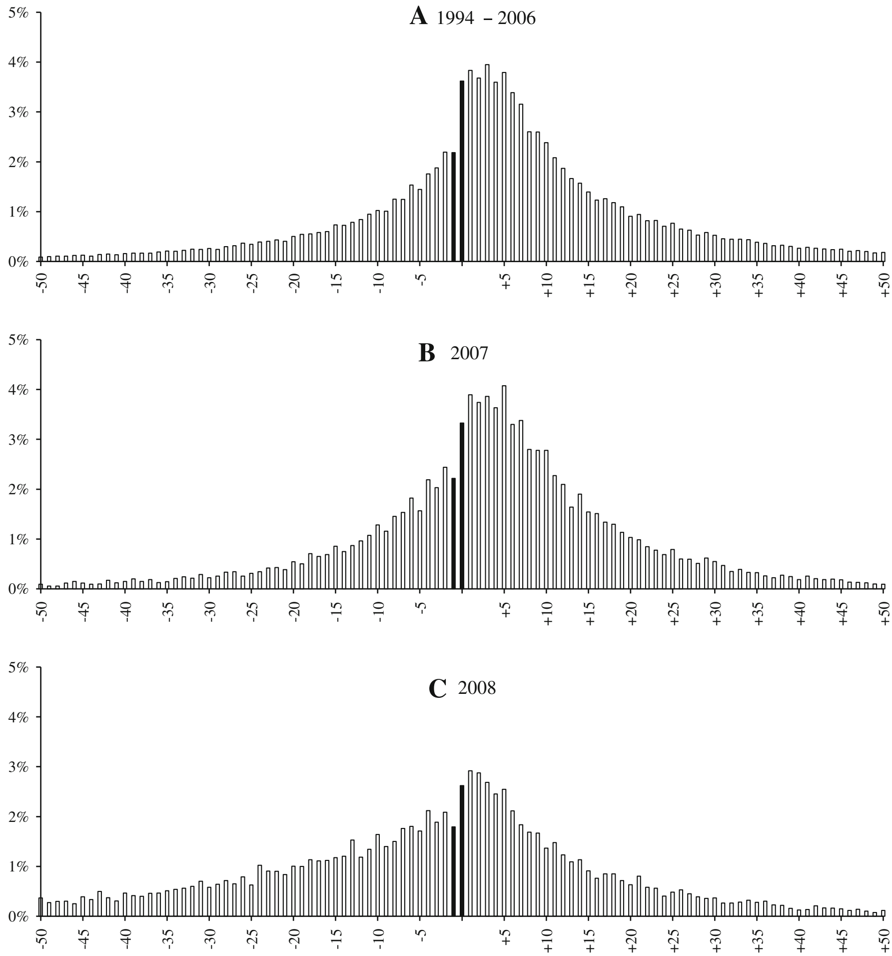

Fig. 4 Pooled hedge fund return distributions. The figuresare histograms of hedge fund monthly returns. Bins are 18 basis points wide with 101 bins displayed, centered on the first bin to the right of zero. *Bold vertical bars* indicate returns bracketing zero, **a** includes observations from 1994–2006 (254,494 observations), **b** includes observations from 2007 (27,107 observations), and **c** includes observations from the first 9 months of 2008 (17,204 observations)

discontinuity, since underlying futures contracts are generally quite liquid and hence little managerial discretion is available. We eliminate returns exactly equal to zero to be conservative, as they might simply reflect managerial conservatism when trade prices are unavailable.

Figure 4 shows the results for hedge funds. Figure 4a shows the distribution of returns from 1994 through 2006. The bin size is 18 basis points, established using the technique of Silverman (1986):

$$\text{bin size} = \alpha \times 1.364 \min(\sigma, Q/1.340)\, N^{-\frac{1}{5}}\ , \tag{3}$$

Table 6 Return discontinuities

	1994–2006	2007	2008
HF			
Neg.	−14.51	−4.35	−3.17
Pos.	11.62	1.73	1.30
FOF			
Neg.	−3.26	−0.89	0.65
Pos.	7.56	1.94	0.88
CTA/CPO			
Neg.	−3.58	1.01	−0.03
Pos.	13.28	2.08	1.52

Listed are t-statistics measuring the percentage of return observations in two bins bracketing zero against the null established by a kernel density estimate. "Negative" and "Positive" correspond to the bins to the left and right of zero, respectively. The width of the bins are 18 bp, 11 bp, and 34 bp, for hedge funds (HF), funds of funds (FOF), and commodity funds (CTA/CPO), as selected using their 1994–2006 empirical distributions and the approach of Silverman (1986)

where σ is the empirical distribution's standard deviation, Q is its interquartile range, N is the number of observations, and α is a scalar that depends on the type of underlying distribution assumed. To proceed, we set $\alpha = 0.776$, corresponding to a normal distribution.[9] The two bold vertical bars indicate the bins bracketing zero. A discontinuity is clear. Table 6 reports t-statistics that measure the difference between the empirical frequency of returns in each bin and the frequency established by the null hypothesis of a smooth distribution. We follow Bollen and Pool (2009) and construct the smooth distribution by a kernel density estimate of the empirical distribution. For hedge funds in the 1994 through 2006 period, the bin to the left of zero, labeled the Negative bin, has a t-statistic of -14.51, whereas the bin to the right of zero, labeled the Positive bin, has a t-statistic of 11.62, both highly significant. Figure 4b shows the results for returns in 2007. The histogram is somewhat more jagged, indicating that the bin size may be slightly too narrow. We choose to maintain an 18 basis point bin size so we can directly compare the distributions across the time periods. The discontinuity is still present in 2007: the Negative bin is significantly lower than expected, with a t-statistic of -4.35 as reported in Table 6. The Positive bin is no longer larger than expected, though, indicating that the distribution is becoming somewhat smoother. Figure 4c shows the results for 2008. Again the discontinuity is present, though weaker than before. The Negative bin has a t-statistic of -3.17 and the Positive bin has a t-statistic of 1.30. Perhaps more striking in Fig. 4c is the dramatic increase in the thickness of the left tail, illustrating the losses reported in Table 3. These results indicate that some managers are continuing to avoid reporting losses during the financial crisis, though to a large extent reported returns appear to accurately reflect the widespread experience of losses.

[9] Devroye (1997) shows through simulation that the definition in (3) is robust to alternative distributional assumptions.

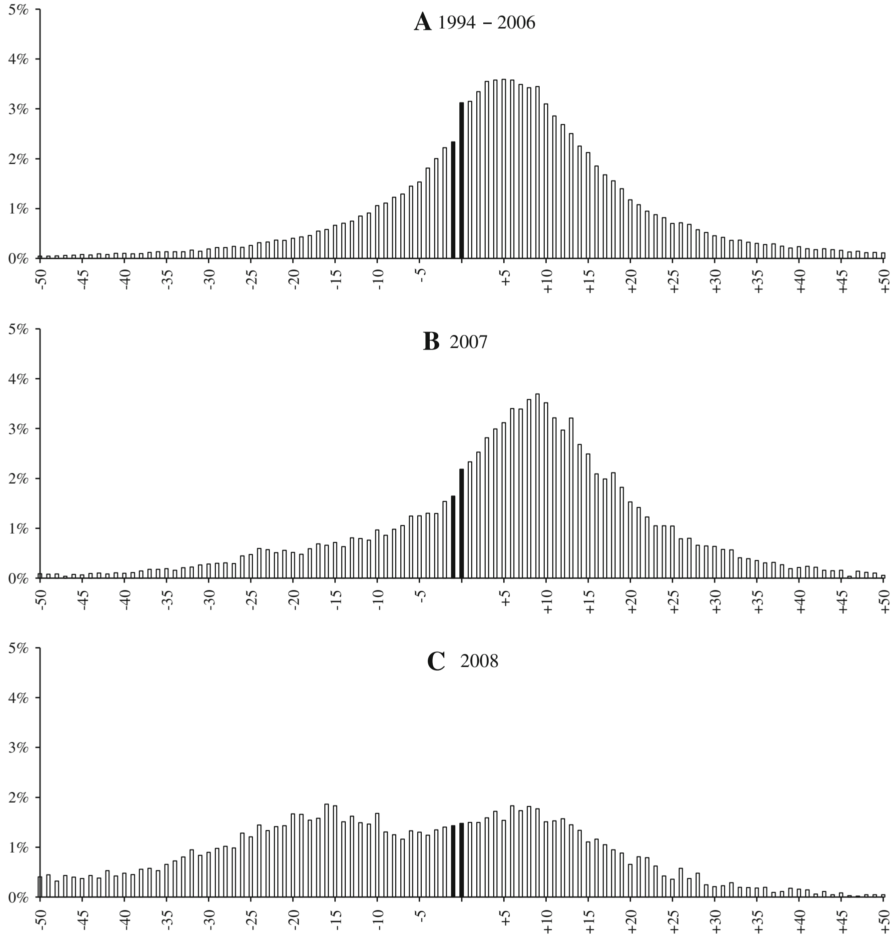

Fig. 5 Pooled fund of funds return distributions. The figuresare histograms of fund of fund monthly returns. Bins are 11 basis points wide with 101 bins displayed, centered on the first bin to the right of zero. *Bold vertical bars* indicate returns bracketing zero, **a** includes observations from 1994–2006 (145,023 observations), **b** includes observations from 2007 (22,854 observations), and **c** includes observations from the first 9 months of 2008 (15,295 observations)

Figure 5 shows corresponding results for the fund of funds return distributions over the same time periods. The optimal bin size for funds of funds is 11 basis points as determined by the 1994 through 2006 period. In the 1994 through 2006 period, displayed in Fig. 5a, funds of funds also feature a discontinuity at zero, and the t-statistics in Table 6 indicates it is statistically significant at any normal level. The discontinuity in hedge fund returns suggests that in this time period, loss avoidance was a common enough reporting behavior that it is present in portfolios of hedge funds, in addition to the individual funds themselves. In Fig. 5b, the discontinuity has all but disappeared, and in fact the Negative bin has a t-statistic of –0.89. The Positive bin, however, has a t-statistic of 1.94, marginally significant. Figure 4c shows that there is no trace of a

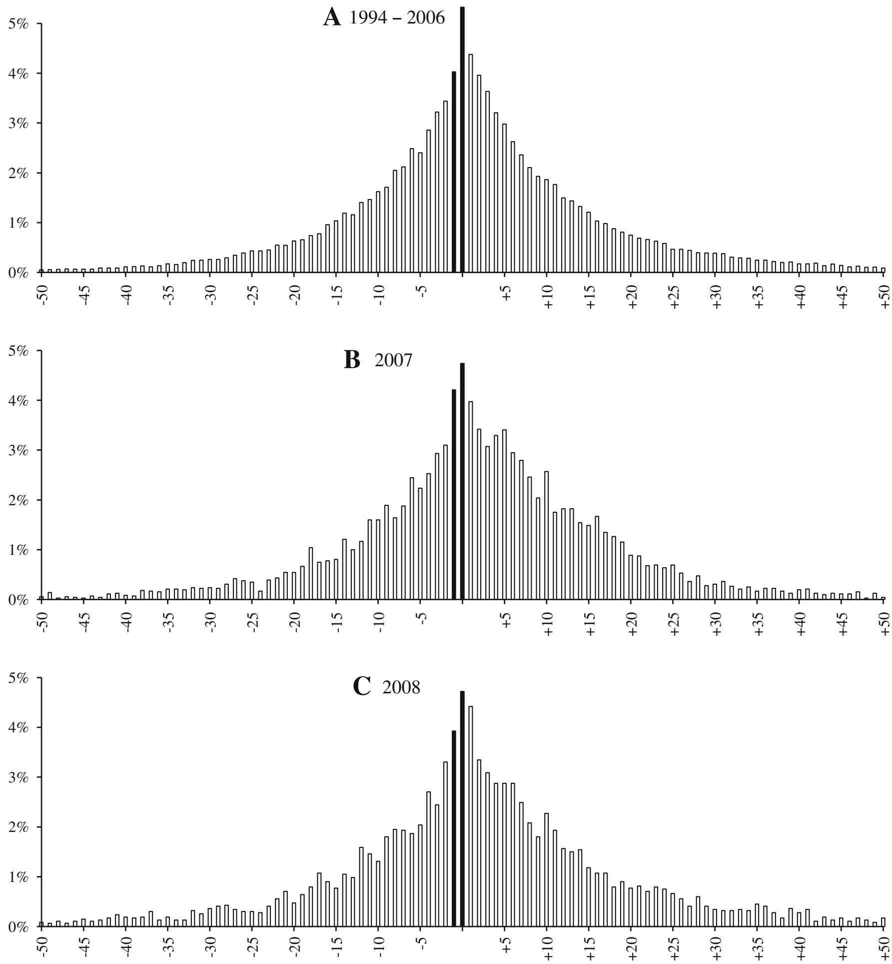

Fig. 6 Pooled CTA/CPO return distributions. The figuresare histograms of commodity fund monthly returns. Bins are 34 basis points wide with 101 bins displayed, centered on the first bin to the right of zero. *Bold vertical bars* indicate returns bracketing zero, **a** includes observations from 1994–2006 (123,290 observations), **b** includes observations from 2007 (7,196 observations), and **c** includes observations from the first 9 months of 2008 (4,659 observations)

discontinuity in hedge fund returns in 2008. The difference between Figs. 4c and 5c have several explanations. Funds of funds managers, as part of their selection decision, have the ability to maintain liquidity for their investors by ensuring that at least some of the underlying hedge funds can supply it. Thus, funds of funds will reflect realized losses that underlying hedge funds are incurring by satisfying investor withdrawals. In addition, the simple act of diversifying across hedge funds will ameliorate the discontinuity so long as only a subset of hedge fund managers is distorting returns.

Another difference between Figs. 4c and 5c is that the hedge fund distribution is bimodal, with one peak between five and ten bins to the right of zero and another about 15 bins to the left of zero. There are several explanations for this phenomenon. First, the hedge funds in our sample are invested in a subset of hedge funds which have a different correlation structure than a randomly selected portfolio. This could result in a thicker left tail than the unconditional distribution of individual hedge funds in Fig. 4b. Second, fund of funds managers may limit their investments to funds that are willing to provide more transparency, and hence are more likely to fully report losses than other funds. These two hypotheses have vastly different implications for investors and regulators; to distinguish between the two would require information regarding positions of hedge funds and funds of funds, which are generally unavailable.

Figure 6 shows that commodity funds as a group feature a fundamentally different distribution than hedge funds and funds of funds. The distribution maintains its general shape over all three subperiods, unlike the other two fund types. Furthermore, to the extent that the discontinuity at zero is present, it is qualitatively different, with the discontinuity driven by the peak in the Positive bin as opposed to a dearth of observations in the Negative bin. These results are consistent with those in Bollen and Pool (2009) and suggest that the liquidity of commodity funds' holdings of futures contracts limit the discretion with which managers can affect reported returns.

5 Conclusion

Calls for additional transparency and regulatory oversight of the hedge fund industry have become more intense in the wake of the financial crisis. Position-level data would allow institutional investors and regulators to more accurately assess the impact of hedge funds on financial markets and to measure the risk exposures of individual funds. Opponents of additional regulation argue that markets would suffer from the chilling effect new disclosure requirements would have on hedge funds' supply of liquidity in otherwise illiquid markets and contribution to price discovery.

The goal of this paper is to determine the extent to which commonly available hedge fund data already provides information necessary for investors and regulators to understand the risks of funds and their impact on markets.

Using monthly return data from January 1994 through September 2008, we document a dramatic change in hedge fund risk exposures towards the end of our sample, and increased correlation between hedge fund returns and the returns of liquid style factors. While important, these results illustrate the limitations of time series analysis: we can observe changes in risk exposures and correlation only with a substantial lag. In addition, the cross-sectional distribution of hedge returns maintains a discontinuity at zero throughout our sample, whereas the distribution of fund of funds returns loses the discontinuity in the first 9 months of 2008. The fund of funds return distribution also features bi-modality and a thicker left tail than the hedge fund distribution, indicating that the funds in which funds of funds invest are more likely to fully report losses during the financial crisis. More granular inference, and any inference regarding the reporting behavior of individual funds, requires richer data.

Taken together, our results suggest that additional transparency of hedge funds is necessary for institutional investors and financial regulators to assess the systemic and operational risks posed by individual funds.

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