



Dynamics of Fund of Hedge Funds: Flow, Size, and Performance

Ibbotson Associates Research Paper
October 2007

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Dynamics of Fund of Hedge Funds: Flow, Size, and Performance

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Abstract

Using a combination of data from the TASS database and the Morningstar Hedge Fund Databases from January 1995 to November 2006, we studied the relationship between performance and fund flow and the relationship between performance and asset size for funds of hedge funds. Our findings confirmed that funds of hedge funds that have better performance experience greater capital inflows. The worst-performing funds experienced net capital outflows and top-performing funds experienced net capital inflows. Using two different measurements, we found a linear relationship between performance and net fund flows. Additionally, as a determinant of capital inflows into funds of hedge funds we found that 18-month Sharpe ratios have higher explanatory power than a) Sharpe ratios measured over other durations and b) average raw returns.

Across the majority of the size spectrum we find a positive correlation between asset size and performance, and a negative correlation between asset size and standard deviation, although the relationship between asset size and performance is flat for larger funds and slightly downward for the largest 5% funds. Therefore, funds with more assets tend to produce higher returns at lower levels of volatility resulting in superior risk-adjusted performance. The smallest 25% of funds of funds underperformed the largest 75% of funds by more than 2% annually at the 95% confidence level from January 1995 to November 2006, and the reason is that a higher portion of funds in this group have failed due to the significantly lower Alpha they delivered.

Introduction

Due to the tremendous growth and popularity of hedge funds, researchers are busy studying all aspects of these relatively new and mysterious investment vehicles that have quickly captured more than \$1 trillion in assets. As money has poured into hedge funds, the range of assets under management (AUM) among hedge funds increased substantially. There are hedge funds with AUM that exceed \$10 billion. This paper sheds light on the effects of the large fund flows and the dramatic increase in the size of funds as it pertains to *funds of hedge funds*. Using a combination of data from the TASS database and the Morningstar Hedge Fund Database from January 1995 to November 2006, we study the relationship between performance and fund flow and the relationship between performance and asset size for funds of hedge funds.

The relationship between capital flow and performance has been mainly characterized as either convex (shaped like a smile indicating that funds with better performance receive more than proportionally higher capital flows) or concave (shaped like a frown indicating that funds with better performance receive higher, but less than proportionally higher capital flows). For mutual funds, the literature demonstrates that the best-performing mutual funds receive significantly higher new capital flows (see for example Sirri and Tufano [1998]). In contrast, the literature is mixed on the performance-flow pattern for hedge funds. Possible reasons may be less transparency and that strong performers may reject new money.

Goetzmann, Ingersoll, and Ross [2003] studied offshore hedge funds and report that money flows out of the top-performing hedge funds. Using a combined data sample based on the HFR, TASS, and ZCM/MAR databases, Agarwal, Daniel and Naik [2004] find that a) hedge funds with good recent performance experience larger money inflows and b) the performance-flow relationship is *convex* (i.e. top performers experience disproportionately higher capital inflows). Using the TASS database, Getmansky [2004] shows a third pattern. He finds that a) better-performing funds are more likely to attract assets than poorly performing funds and b) the performance-flow relationship is *concave*, indicating that the top performers do not grow proportionally as much as the average fund in the market. Using a combined data sample from HFR, TASS, and CISDM, Fung, et al. [2006] breaks the fund of hedge funds universe into two categories, "*Have-Alpha* funds" and "*Beta-Only* funds." They did not observe a convex pattern in either one of the two categories. The mixed conclusions of the literature on the relationship between capital flows and performance, the date ranges of the studies, the data sources, and fund universes are summarized in Table 1.

Table 1: Literature Summary, Performance Impact on Future Capital Flow

Authors	Period Covered	Data Source	Fund Universe	Performance-Flow Relationship
Goetzmann, Ingersoll, and Ross [2003]	Jan1990- Dec1995	Offshore Funds Directory	Hedge Funds	Negative
Agarwal, Daniel and Naik [2004]	Jan 1994- June 2000	HFR, TASS, and ZCM/MAR	Hedge Funds	Convex or Smile
Getmansky [2004]	Jan 1994- Dec 2002	TASS	Hedge Funds	Concave or Frown
Fung, Hsieh, Naik and Ramadorai [2006]	Jan 1995- Dec 2004	HFR, TASS, and CISDM	Funds of Hedge Funds	Not Convex
This Paper, XICI [2007]	Jan 1995- Dec 2006	Morningstar, TASS	Funds of Hedge Funds	Almost Linear

* Papers are listed in the order of publication.

In addition to performance-fund flow relationship, this paper studies the performance-size relationship. Hedges [2003] shows that smaller funds outperform larger funds, while mid-sized funds underperformed both smaller funds and larger funds. Gregoriou and Rouah [2003] find little-to-no correlation between size and performance, although they acknowledge that the data set used in the study suffered from survivorship bias. In contrast, Liang [1999] finds a positive relationship between AUM and performance. Amenc and Martellini [2003] demonstrate that the mean alpha for large funds exceeds the mean alpha for small funds. Getmansky [2004] shows that the asset size-performance relationship varies among different hedge fund categories, most of which are *concave*, which indicates that an optimal asset size can be obtained. Ammann and Moerth [2006] provide evidence that asset size and performance have a concaved relationship for hedge funds. Ibbotson and Chen [2006] report that smaller hedge funds performed substantially worse and list two reasons. First, managers of larger funds are likely to have more skill than average fund managers, and second, larger funds are less distracted by concerns over their financial survival. The conclusions of these studies are summarized in Table 2.

Overall, most of the literature finds a positive or concave relationship between hedge fund asset size and performance, with two exceptions: Hedges [2003] and Gregoriou and Rouah [2003]. Both of these studies used a relatively small sample size of funds; therefore, these exceptions may not be representative of the larger hedge fund industry.

Table 2: Literature Summary, Asset Size Impact on Performance

Authors	Period Covered	Data Source	Fund Universe	Size - Performance Relationship
Liang [1999]	Jan 1992 – Dec 1996	HFR	Hedge Funds	Positive
Gregoriou and Rouah [2003]	Jan 1994 – Dec 1999	204 hedge funds and 72 funds of hedge funds	Hedge Funds & Funds of Hedge Funds	No correlation
Hedges [2003]	Jan 1995-Dec 2001	268 Hedge Funds	Hedge Funds	Small Funds are the Best, Medium ones the Worst
Amenc and Martellini	1996 - 2002	CISDM	Hedge Funds	Positive
Getmansky [2004]	Jan 1994 – Dec 2002	TASS	Hedge Funds & Funds of Hedge Funds	Mostly Concave
Ammann and Moerth	Jan 1994 – April 2005	TASS	Hedge Funds	Concave or Frown
Ibbotson and Chen [2006]	Jan 1995 – April 2006	TASS	Hedge Funds	Positive
This Paper, XICI [2007]	Jan 1995- Dec 2006	Morningstar, TASS	Funds of Hedge Funds	Largely Concave or Frown

* Papers are listed in the order of publication.

Among the different hedge fund categories, the “fund of funds” category is often seen as a desirable investment for its ability to spread manager-specific risk over a greater number of underlying individual funds. Funds of hedge funds offer the opportunity to invest in a diversified hedge fund portfolio typically with a lower minimum investment than individual hedge funds. The growth of funds of hedge funds has been almost exponential and in parallel with their underlying hedge funds.

Within the hedge fund space, the funds-of-funds category has been followed less intensively than the underlying hedge funds. Compared with traditional hedge fund indices, Fung, et al. [2006] suggest that the performance of funds of hedge funds is more indicative of the returns experienced by typical investors. In this paper, using data from January 1995 to November 2006 on the fund of hedge funds category from the TASS and Morningstar databases, we study the empirical relationship between capital flows and performance as well as asset size and performance.

Data

We study the relationship between performance and both capital flow and asset size for funds of hedge funds by combining the TASS and Morningstar hedge fund databases.¹ The time period covered for the study is from January 1995 to November 2006. The data includes defunct or dead funds of hedge funds to mitigate the impact of survivorship bias. Backfill bias is relatively hard to avoid, and it tends to have a larger affect on the performance of smaller funds. Relative to a backfill bias-free data set, Ibbotson and Chen [2006] estimate the backfill bias of an equally weighted portfolio of hedge funds at 4.64% per year and backfill bias of a value-weighted portfolio at only 0.27% per year. The much smaller backfill bias in the value-weighted portfolio indicates that the bigger funds do not suffer significant backfill bias.

We define a “fund of hedge funds” as a single investment vehicle containing two or more hedge funds. These constituent hedge funds are typically single-strategy hedge funds from one or more hedge fund families. Although it is very unusual, a fund of hedge funds may invest money in a fund that is also a fund of hedge funds resulting in three levels of fees and a form of double counting in which a single fund of hedge funds could have double impact on our results. Given the rarity of this and our relatively large sample size the impact of this should be extremely small.

We removed duplicates and erroneous fund data leaving us with 1,839 funds of hedge funds in the TASS database and 2,707 funds of hedge funds in the Morningstar databases for a total sample size of 4,312 funds. The sample includes both live and defunct funds. Somewhat surprisingly, there were only 234 duplicate funds. The 4,312 funds include 1,802 defunct funds and 2,510 live funds. Defunct funds include funds that were liquidated or stopped reporting, and in this study we do not treat them separately.

From the combined database, we estimate that the average annual death rate for funds of hedge funds is about 8%, and the average annual birth rate is about 21% from 1995 to 2006.

For January 1995 the combined databases contained assets under management (AUM) information for 223 funds of hedge funds. By October 2006 this increased nearly eight fold to 1,648. We rank the 223 and 1,648 funds respectively based on reported AUM and identify the corresponding AUM of the funds across the spectrum of percentile ranks. The corresponding size percentile ranks and cumulative weight percentages are listed in Table 3. In Table 3, the zero percentile corresponds to the smallest fund in the sample and 100th percentile corresponds to the largest fund in the sample. Thus, for January 1995 the smallest fund in the sample had assets under management of \$200,000 while the largest fund in the sample had assets under management of \$1.95 billion. Nearly 12 years later, for October 2006, the smallest fund in the sample had assets under management of \$104,000 while the largest fund in the sample had assets under management of approximately \$80.8 billion. The cumulative weight percentage is the ratio between the sum of assets from the corresponding percentile to the 100th percentile and the total assets for all the funds in the corresponding month. For example, for October 2006 the total assets for the 1,648 funds are \$635 billion, and the sum of assets from the 80th

percentile to the 100th percentile sized funds are \$545 billion. The ratio is 85.86%. In other words, the largest 20% of funds account for 85.86% of the total assets for all the funds in October 2006.

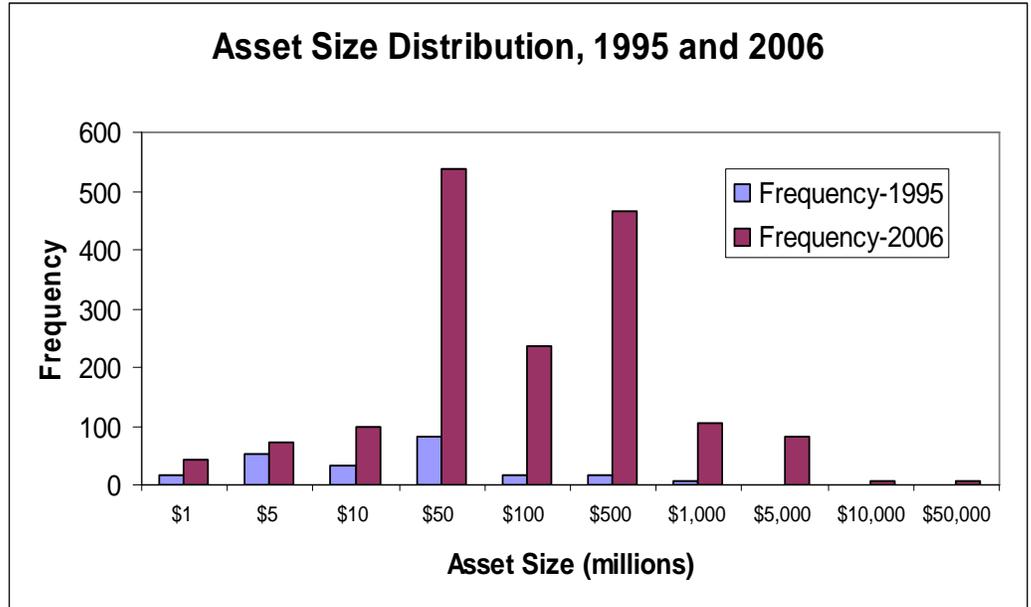
Table 3: Assets Under Management Size Percentiles (asset in millions), and Cumulative Weight Percentages.

Percentile	January-95	Cum. Weight Perc.	October-06	Cum. Weight Perc.
5%	\$0.86	99.97%	\$3.16	99.98%
10%	\$1.51	99.87%	\$7.53	99.91%
15%	\$2.21	99.71%	\$11.89	99.79%
20%	\$3.39	99.45%	\$15.70	99.61%
25%	\$4.45	99.11%	\$20.65	99.37%
30%	\$4.99	98.68%	\$25.81	99.07%
35%	\$7.13	98.14%	\$32.00	98.69%
40%	\$9.01	97.41%	\$40.26	98.23%
45%	\$10.21	96.53%	\$49.25	97.65%
50%	\$14.80	95.33%	\$62.00	96.93%
55%	\$17.20	93.89%	\$80.53	96.00%
60%	\$22.24	92.15%	\$102.84	94.82%
65%	\$27.44	89.82%	\$125.55	93.38%
70%	\$31.68	87.12%	\$159.61	91.53%
75%	\$38.93	83.95%	\$215.16	89.15%
80%	\$46.91	80.09%	\$307.20	85.86%
85%	\$67.07	74.65%	\$409.74	81.29%
90%	\$92.62	67.26%	\$601.25	74.87%
95%	\$225.76	55.25%	\$1,068.00	64.33%
100%	\$1,948.87		\$80,799.63	

Table 3 provides us with one look at the size spectrum of available funds of hedge funds for two different periods highlighting the dramatic increase in assets under management for the range of available funds. Additional insight can be gained by looking at the distribution of funds based on assets under management.

Chart 1 shows the AUM distribution for the available funds of hedge funds for both January 1995 and October 2006. AUM is reported along the horizontal axis where we have included AUM "bins", each of which includes a range ended on the values presented on the horizontal exponential-like scale. The distribution curves from 1995 to 2006 have experienced huge growth on both asset size and number of funds as the 2006 frequency curve expands up and right.

Chart 1. AUM distribution for all the available funds of hedge funds in January 1995 and October 2006



Methodology

For data analysis convenience, we started by forming a matrix dataset for both raw monthly returns and assets under management for all funds of hedge funds. Each matrix dataset has both a cross-sectional and a time-series dimension. Based on the dataset, we can calculate quarterly net capital flow for each of the individual funds as follows:

$$Flow_{i,t} = \frac{A_{i,t} - A_{i,t-1}(1 + r_{i,t})}{A_{i,t-1}} \quad (1)$$

Where $Flow_{i,t}$, $A_{i,t}$, $r_{i,t}$ are the flows into fund i in quarter t as a percentage of last quarter's AUM; the AUM of fund i in quarter t ; and the quarterly net return for fund i in quarter t , respectively.

Performance-Flow Relationship

Before proceeding, we need to highlight some abnormal flows that could potentially distort our regression results. For some periods, a relatively small number of funds experienced excessively large flows. To mitigate the effects of these extreme fund flows, we decided to eliminate those flow points from the sample that we deemed to have suffered extreme flows or abnormal flows. More specifically, we eliminated funds that experienced a quarterly flow in dollars that was more than 10 times greater than the previous quarterly flow. This reduced the number of funds by 32, or 0.11% of the sample size. It is interesting to note that all of the 32 outliers appeared after 2002, and we suspect that institutional investors might be responsible for it since institutional investors poured a lot of money into hedge funds after 2001.

After cleaning the data sample, we run two regression analyses to study the performance-flow relationship.

In the first analysis, we study the relationship between fund flows and average raw returns as well as fund flows and historical Sharpe ratios. We run the following regression to see which performance measurements has relatively higher significance:

$$Flow_{i,t} = a + \sum_{k=6,12,18,24,36} b_k r_{k,i,t} + \sum_{k=6,12,18,24,36} c_k sr_{k,i,t} + \varepsilon_{i,t} \quad (2)$$

where $r_{k,i,t}$ ($k = 6, 12, 18, 24, 36$) are 6-, 12-, 18-, 24-, and 36-monthly average raw returns, respectively, and $sr_{k,i,t}$ ($k = 6, 12, 18, 24, 36$) correspond to 6-, 12-, 18-, 24-, and 36-monthly Sharpe ratios, respectively. We follow the Fama-MacBeth procedure for the multivariate regression as recommended in Sirri and Tufano [1998]. That is, we run the regression quarter by quarter, and calculate the mean of each coefficient and estimate the t-stat on each quarterly

coefficient. As shown later in the results section, the 18-month Sharpe ratio has the highest explanatory power as a performance determinant.

A similar multiple regression is used to determine which factors influence future quarterly flows. The following regression is performed to determine how previous quarterly flow, asset size, management fees, incentives, and past performance affect the future quarterly flow:

$$Flow_{i,t} = a + b_1 Flow_{i,t-1} + b_2 Size_{i,t-1} + b_3 MFee_i + b_4 Incentive_i + \sum_{j=1}^5 c_j QRank_{i,t-1}^j + \varepsilon_{i,t} \quad (3)$$

Where $Flow_{i,t-1}$ is the capital flow into fund i in quarter $t-1$, $Size_{i,t-1}$ is the size measured as the natural logarithm of the AUM for fund i at quarter $t-1$, $MFee_i$ is management fees charged by fund i , $Incentive_i$ is the incentive fees charged by fund i . $QRank_{i,t-1}^j$ is the fractional rank of fund i in quintile j for quarter $t-1$ specified in Sirri and Tofano [1998]. The fractional rank quintiles, $QRank_{i,t-1}^j$, are constructed as follows: first, a fractional rank, $FRank$, is calculated for each fund, from 0 to 1 based on the ascending order of the 18-month Sharpe ratio in quarter $t-1$. For example, if $FRank$ is 0.65, it means that the fund's 18-month Sharpe ratio was higher than 65% of the peer group. The bottom quintile $QRank_{i,t-1}^1$ is defined as $\text{Min}(0.2, FRank)$, the second quintile $QRank_{i,t-1}^2$ is defined as $\text{Min}(0.2, FRank - QRank_{i,t-1}^1)$, the third quintile $QRank_{i,t-1}^3$ is defined as $\text{Min}(0.2, FRank - QRank_{i,t-1}^1 - QRank_{i,t-1}^2)$, and so forth up to the highest quintile. For example, if a fund's fractional rank is 0.65, its $QRank_{i,t-1}^1 = \text{Min}(0.2, 0.65) = 0.2$, $QRank_{i,t-1}^2 = \text{Min}(0.2, 0.65 - 0.2) = 0.2$, $QRank_{i,t-1}^3 = \text{Min}(0.2, 0.65 - 0.2 - 0.2) = 0.2$, $QRank_{i,t-1}^4 = \text{Min}(0.2, 0.65 - 0.2 - 0.2 - 0.2) = 0.05$, and $QRank_{i,t-1}^5 = \text{Min}(0.2, 0.65 - 0.2 - 0.2 - 0.2 - 0.05) = 0$.

The implication for the fractional ranks classification is that for a perfect linear performance-flow relationship, all the coefficients (c_1, \dots, c_5) for $QRank_{i,t-1}^j$ will be identical, for a concave (convex) performance-flow relationship, the coefficients c_4 and c_5 will be lower (higher) than c_1 and c_2 .

Size-Performance Relationship

To determine the impact of size on fund of hedge fund performance we formed 20 portfolios or composites. In each month from January 1995 to November 2006, we sorted all the funds in order of asset size and then assigned them into 20 bins with an equal number of funds in each bin. Similar methods have been used in previous studies, such as Ammann and Moerth [2006].

Portfolio 1 is formed by equally weighting the *smallest* 5% of the funds of hedge funds at each month. For each of the 143 months (from January 1995 to November 2006), the constituents of Portfolio 1 might be different. The average fund return of Portfolio 1 represents the performance of the *smallest* 5% of the funds of hedge funds. The constructed equally-weighted portfolios are also approximately value-weighted because each portfolio contains funds with similar asset size.

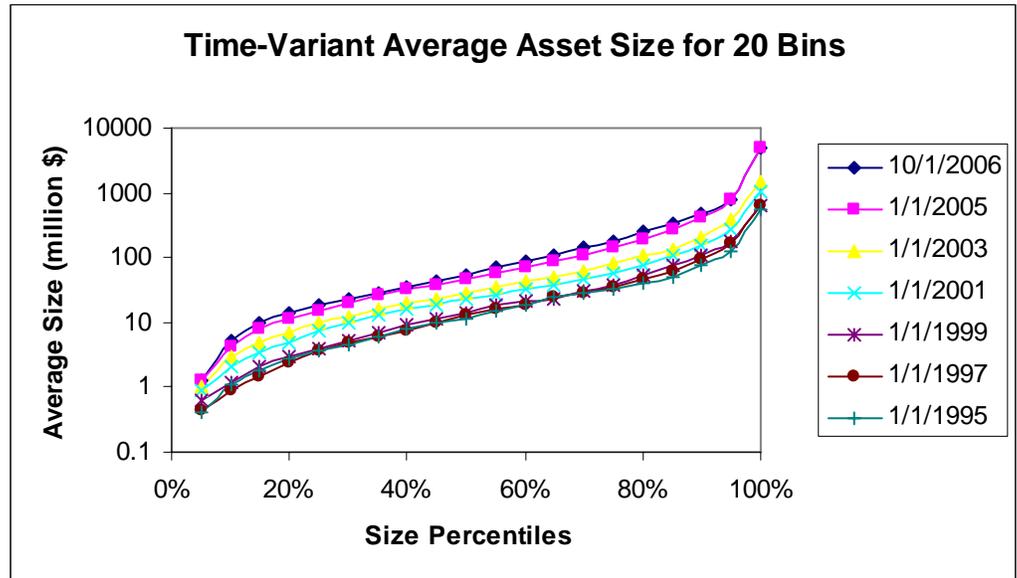
Similarly, Portfolio 20 is formed by equally weighting the *largest* 5% of the funds of hedge funds at each month. For each month, the average fund return of Portfolio 20 represents the performance of the *largest* 5% of the funds of hedge funds. With the twenty portfolios formed in this way, we can calculate 143 monthly returns for each portfolio.

The number of funds of hedge funds during any given month may or may not be perfectly divisible into 20 portfolios. At each point in time, we attempt to keep the number of funds in each portfolio as close as possible. For example, for January 1995 the database contained 223 funds; thus, 17 of the portfolios contained 11 funds and three of the portfolios contained 12 funds. For October 2006, the database contained 1,648 funds; 12 of the portfolios contained 82 funds and eight of the portfolios contained 83 funds.

The constituents of the 20 portfolios evolve each month due to positive or negative fund flows, fund performance, new funds being added to the data base, and the demise of other funds. We track the performance of the 20 portfolios from January 1995 to November 2006 using monthly *net* (after-fee) return data to study the size-performance relationship.

Chart 2 shows the average assets under management for the 20 portfolios at seven different points in time. The average assets under management associated with each portfolio increases almost exponentially with time (the vertical axis is in log scale), indicating the prosperity of the fund of hedge funds industry. The average size of the largest 5% of funds of hedge funds grows from \$548 million in January 1995 to \$4,921 million in October 2006.

Chart 2. Time-variant average asset size for the 20 portfolios.



Next, we repeat the analysis this time grouping the available funds into four size-based portfolios rather than the more granular 20 size-based portfolios. We analyze the risks associated with each of the four portfolios with an 11-factor model.

Two of the 11 factors are the yield spread of the U.S. 10-year Treasury bond over the three-month T-bill, (excess return of Merrill Lynch 10-15 Yr Treasury); and the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond (*BAA-GOV*). The remaining nine factors are the Russell 1000 Growth, the Russell 1000 Value, the Russell 2000 Growth, the Russell 2000 Value, MSCI EAFE, the MSCI Emerging Market, the FSTE NAREIT-Equity, the Lehman Brothers Corp High Yield, and the DJ-AIG Commodities indices.ⁱⁱ

The regressions of the four portfolios on the 11 factors are performed using stepwise regression. Stepwise regression involves adding and/or deleting variables sequentially depending on the F-value of the regression. A benefit of this procedure is its parsimonious selection of factors, while a drawback is a breakdown in the standard statistical inferences that can be made, although most of the 11 factors have been shown to have out-of-sample explanatory power for hedge funds or funds of hedge funds in other works. For our purposes, the stepwise regression identifies the sensitivities and significance of the sensitivities of the four size-based portfolios to the 11 factors.

Results

Performance Impact on Future Flow

Table 4A shows the regression results for equation (2) explained in the Methodology section designed to measure the relationship between fund flows and average raw returns as well as fund flows and historical Sharpe ratios. There is only one significant independent variable, the 18-month Sharpe ratio. The regression might suffer from multi-collinearity, which occurs when two or more independent variables are highly correlated with each other. Multi-collinearity tends to suppress the t-statistics of correlated variables' coefficients. Thus, the t-stats of the correlated factors are probably understated. .

Table 4A. Regression for Flow on All Sharpe Ratios and All Raw Returns

	coefficient	t-stat
6-Month Sharpe Ratio	0.002	0.70
12-Month Sharpe Ratio	-0.006	-0.74
18-Month Sharpe Ratio	0.044	3.82
24-Month Sharpe Ratio	-0.006	-0.38
36-Month Sharpe Ratio	0.006	0.52
6-Month Raw Return	0.008	1.27
12-Month Raw Return	0.023	1.01
18-Month Raw Return	-0.025	-1.44
24-Month Raw Return	0.034	1.17
36-Month Raw Return	-0.019	-1.11
R-squared	9.57%	

Table 4B shows the results of a series of one-by-one, single-factor regressions of the flow on each of the dependent variables, the various periods of average raw returns, and the Sharpe ratios. The 18-month Sharpe ratio has the highest R^2 at 4.59%. While certainly low, it supports the regression results in Table 4A. All of the R^2 values in Table 4B are much less than the R^2 in Table 4A, indicating that different types or periods of performance measurement variables may have some independent explanatory power. All of past performance measurements result in a highly significant coefficient, indicating a positive relationship between fund flows and past performance.

Table 4B. Regression for Flow on Individual Sharpe ratio and Individual Raw Return

	R-squared	coefficient	t-stat
6-Month Sharpe Ratio	3.29%	0.017	8.90
12-Month Sharpe Ratio	4.11%	0.029	8.96
18-Month Sharpe Ratio	4.59%	0.035	8.96
24-Month Sharpe Ratio	4.35%	0.038	9.11
36-Month Sharpe Ratio	3.79%	0.040	9.04
6-Month Raw Return	2.99%	0.038	6.30
12-Month Raw Return	3.80%	0.058	5.77
18-Month Raw Return	3.50%	0.064	6.16
24-Month Raw Return	3.33%	0.067	6.40
36-Month Raw Return	2.32%	0.060	8.77

Table 5 shows the results for regression equation (3) designed to determine which factors influence future quarterly flows. Consistent with the results of Getmansky [2004], we find that past flows positively affect future flows and past size negatively affect future flows. Among the five quintile coefficients, only the first and second quintiles are significantly different from each other (results are not shown). The others are not significantly different at the 95% confidence level, indicating an approximate linear relationship between past performance and future capital flows.

Table 5. Regression results for future capital flow on previous quarter flow, asset size, management fees, incentive fees, and five fractional performance ranks.

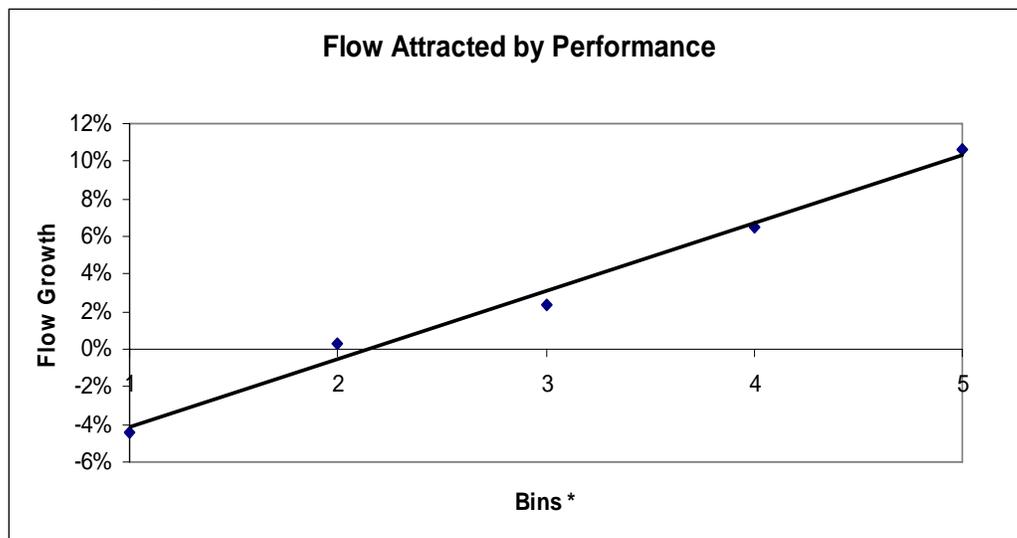
	Coefficient	t-stat
Intercept	0.008	0.230
Previous Flow	0.135	6.451
Asset Size	-0.005	-2.278
Management Fee	-0.002	-0.988
Incentives	-0.001	-1.617
1 st Quintile	0.335	3.732
2 nd Quintile	0.098	2.523
3 rd Quintile	0.146	4.075
4 th Quintile	0.153	3.812
5 th Quintile	0.215	2.929
R-squared	9.83%	
Number of Observations	28174	

* Five fractional performance ranks are defined in the Methodology section

An alternate method to look into the performance-flow relationship is to construct five bins based on the rankings of 18-month Sharpe ratios, and track the absorbed flows for the five bins. The average flows for the five bins from January 1995 to November 2006 are shown in Chart 3. Chart 3 clearly shows an almost linear relationship between performance quintile and future

flow. This is consistent with regression results on the five quintiles shown in Table 4B. The 1st Quintile portfolio containing the 20% of all funds with the worst 18-month Sharpe ratios at each quarter experienced an average net outflow of 4.4%, while the 5th quintile portfolio containing the 20% of all funds with the best 18-month Sharpe ratio enjoyed an average net inflow of 10.7%. Thus, using two different methods, we demonstrate an approximate one-to-one relationship between past performance and future flow.

Chart 3. Average Capital Flow Growth vs. Past Performance.



* Bin-1 is constructed with the lowest 20% 18-month Sharpe ratio funds, and Bin-5 is constructed with the highest 20% 18-month Sharpe ratio funds.

Flow Induced Capacity Constraints on Top-Performing Funds

Positive performance and the subsequent inflow of funds may lead to flow induced capacity constraints that are detrimental to future performance. Fung, et al. [2006] show that, across all years, an above-median flow on a *high-Alpha* fund has a 22% probability of being classified as a *high-Alpha* fund in the subsequent non-overlapping classification period. In contrast, a below-median flow on a *high-Alpha* fund has a significantly higher 35% probability of being classified as a *high-Alpha* fund in the subsequent non-overlapping classification period.

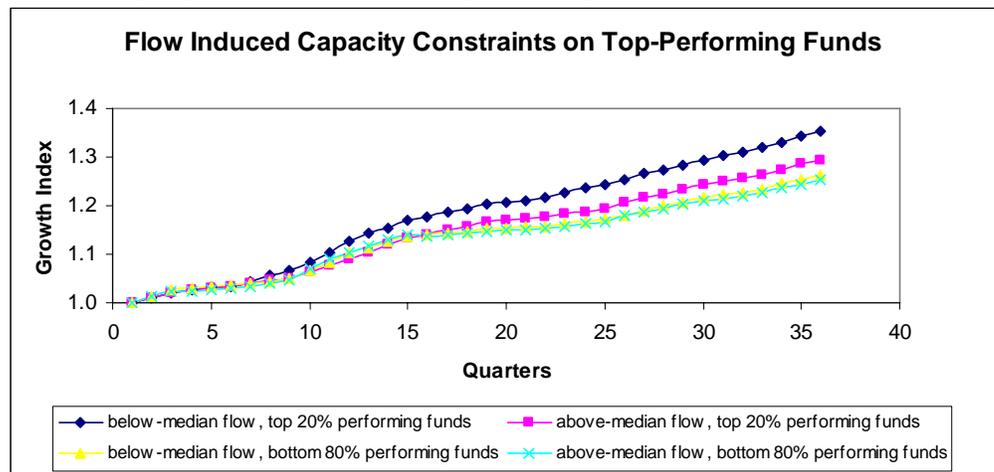
We use a slightly different method to investigate the capacity constraints associated with inflows into top-performing funds (funds with the 20% highest 18-month Sharpe ratios) by constructing two portfolios among the 20% highest 18-month Sharpe ratio funds: a portfolio containing funds with below-median capital inflow and another portfolio containing funds with above-median capital inflows. The performances for the two portfolios are measured at 18-

months *after* the quarter in which the two portfolios were built based on flows. The flow-induced future performance is the average 18-monthly net return of the constituent funds after each quarterly flow. The constituents of these two portfolios are updated in each non-overlapping quarter. In total, we have 47-quarters from 1/1995 to 11/2006. The first 6 quarters are used to detect top-performing funds and the last 6 quarters are used for future performance measurement, which leave us 35 non-overlapping quarters for analysis. We calculate the performance for the 35 non-overlapping quarters, and then build a growth index for these two portfolios for the 35-quarters.

For comparisons, we also constructed two additional portfolios using the remaining 80% of funds in which the funds were split based on capital flows. Chart 4A shows the growth index for the four portfolios. The portfolio containing the top 20% of past performance-winning funds with above-median capital inflows underperformed the top 20% past performance-winning funds with below-median capital inflows at the 95% confidence level, while the remaining 80% of funds with above-median capital inflows are indistinguishable from the other 80% of funds with below-median capital inflows at the 95% confidence level.

Note that the other 80% funds have experienced much less capital inflows than the 20% top-performing funds so that the flow impact might be much less. Arguably the top-performing funds receive the largest fund flows and these large flows in turn seem to hurt future fund performance.

Chart 4A. Capacity Constraints, Flow into Top Performing Funds

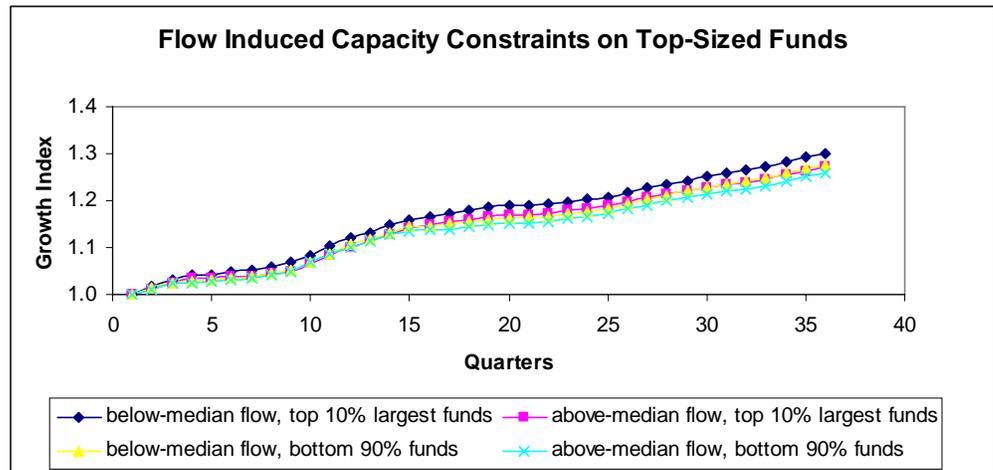


The results shown in Chart 4A are consistent with the findings in Fung, et al. [2006]. This supports Berk and Green [2004], which presents the rational model of active portfolio management in which the capital flows into the better-performing funds lead to the erosion of future performance over time.

Flow Induced Capacity Constraints on Top-Sized Funds

Large funds most likely have been pretty successful and might have attracted above-average capital inflows for an extended period of time. Can higher fund flow drag down the performance of top-sized funds? We perform a similar analysis to the last section (Flow Induced Capacity Constraints on Top-Performing Funds). Chart 4B shows that the largest 10% of funds with above-median capital inflows under-performed the largest 10% of funds with below-median capital inflows at the 95% confidence level, while the remaining 90% of funds with above-median capital inflows are indistinguishable from the other 90% of funds with below-median capital inflows at the 95% confidence level. Therefore, a higher flow into the top-sized funds will hurt their future performance, but it has no significant impact on smaller funds.

Chart 4B. Capacity Constraints, Flow into Top-Sized Funds



To briefly summarize, above-average fund flows seem to adversely affect the future performance of top-performing funds and the largest funds. In contrast, the top-performing and top-sized funds with below average asset flows performed significantly better than those top funds with above average flows.

Size Impact on Performance

Charts 5A, 5B, and 5C show the impact of assets under management on performance for 20 sized-based portfolios as well as the four sized-based portfolios from January 1995 to November 2006. Charts 5A, 5B, and 5C plot average monthly net returns, monthly standard deviations, and Sharpe ratios for the portfolios over the 143 months, respectively.

Chart 5A. Average Monthly Return and Fund Size

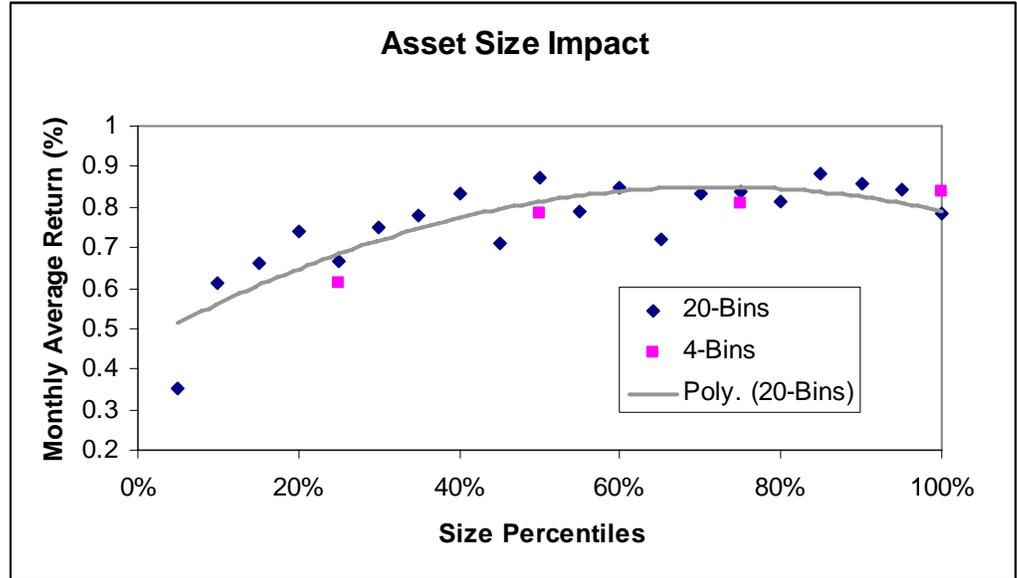


Chart 5A illustrates the relationship between fund size and average monthly return. We have attempted to fit a curve to the data points. Using a polynomial curve with an order of smoothing function of two, we get a best-fit curve that is concave in shape. The fitted curve peaks around the 75th percentile corresponding to Portfolio 15. According to the polynomial curve, the average monthly return increases with assets under management to this point and then decreases with assets under management. If one ignores the performance of the smallest three portfolios (Portfolios 1, 2, and 3), the relationship between assets under management and average monthly return is weakened considerably.

Chart 5B. Average Monthly Standard Deviation and Fund Size

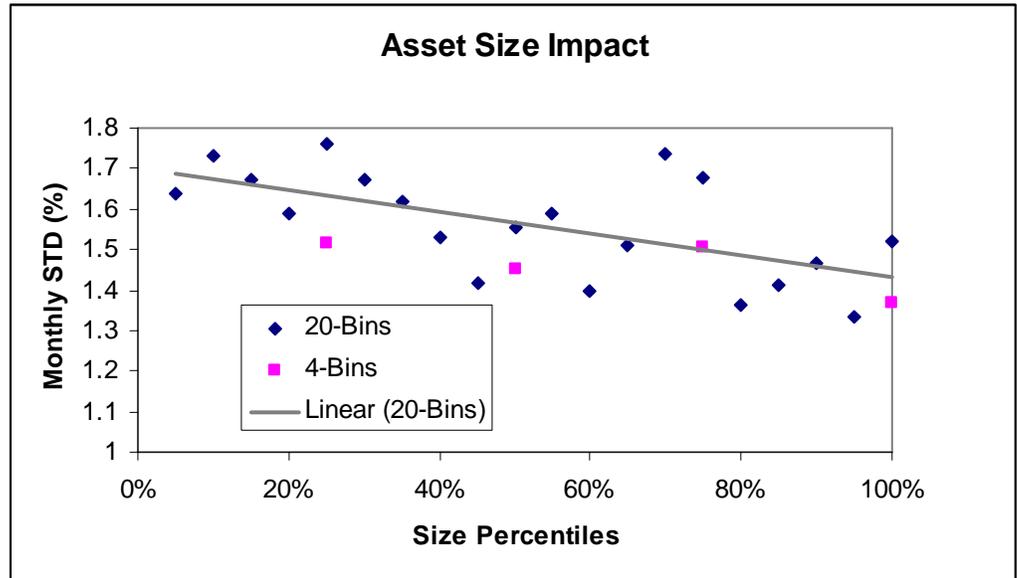


Chart 5B illustrates the relationship between fund size and average monthly standard deviation. The monthly standard deviations in Chart 5B are measured for the portfolios over 143 months. The standard deviation vs. asset-size relationship is negative. One could argue that this is an intuitive result as large funds have less variance than small funds, possibly due to better diversification. In this case the data is fit using a standard linear regression line.

Chart 5C. Average Sharpe Ratio and Fund Size

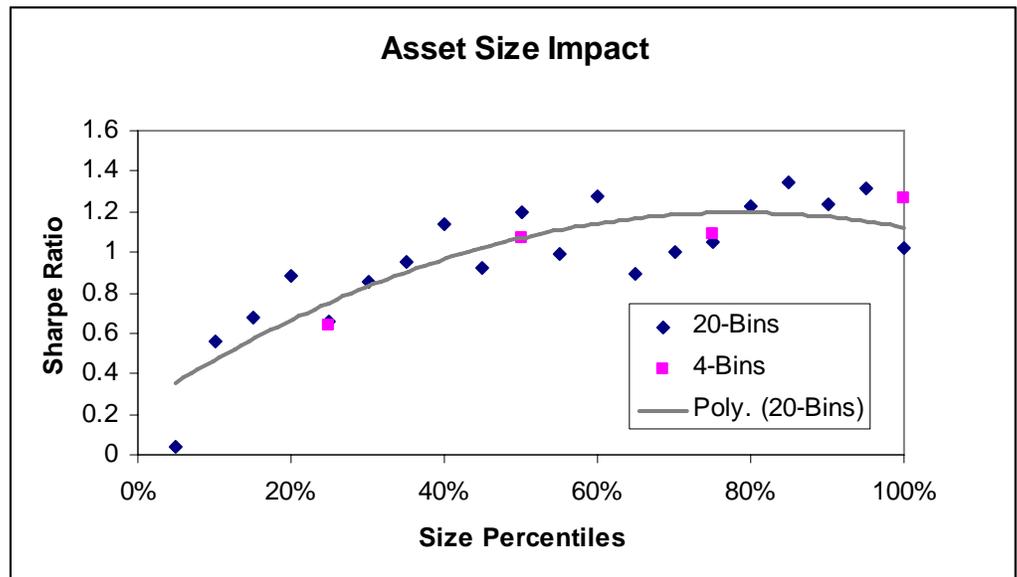


Chart 5C illustrates the relationship between fund size and risk-adjusted performance as measured by the Sharpe ratios of the 20 portfolios. As in Chart 5A, we fit the data using a polynomial curve. Based on this fitted curve, the smallest 50% of funds of hedge funds underperformed the largest 50% of funds of hedge funds. Portfolios 17 and 19 have the highest Sharpe ratios.

The pink square points Charts 5A, 5B, and 5C illustrate the results of organizing the funds of hedge funds universe into four portfolios (Portfolio Q1 (smallest), Q2, Q3, and Q4 (largest)). This increases the number of funds in each of the portfolios, which decreases the potential influence of extreme events in individual funds. It is clear that the smallest 25% of funds of hedge funds underperformed the larger funds of hedge funds. At the 95% confidence level, we determined that the performance of Portfolio Q1, representing the smallest 25% of funds of hedge funds, underperformed Portfolios Q2, Q3, and Q4. Table 6 presents the results.

Table 6: Statistical Inference for the four bins ranked in size (Q1 is smallest, Q4 is largest). Value-added is annualized.

	Portfolio Q2 relative to Portfolio Q1	Portfolio Q3 relative to Portfolio Q1	Portfolio Q4 relative to Portfolio Q1	Portfolio Q3 relative to Portfolio Q2	Portfolio Q4 relative to Portfolio Q2	Portfolio Q4 relative to Portfolio Q3
value-added	2.05%	2.33%	2.68%	0.28%	0.63%	0.35%
t-Stat	3.74	3.99	3.85	0.63	1.35	0.93

Portfolios Q2, Q3, and Q4 outperformed Portfolio Q1 by more than 2% annually, while the performance of Portfolios Q2, Q3, and Q4 were indistinguishable in a statistically significant manner at a reasonable confidence level. The smallest 25% of funds correspond to an asset size smaller than \$4.5 million in January 1995, and smaller than \$21 million in October 2006 as shown in Table 2.

Is it possible that smaller funds that constitute portfolio Q1 have a higher cost structure (management fees and incentives) than portfolios Q2, Q3, and Q4 so that the net return for Q1 is lower? As displayed in Table 7, the average annual management fee in portfolio Q1 is indeed slightly higher than the rest, but the differences are not large enough to explain a more than 2% underperformance because the biggest management fee difference is only 0.13% ($1.5\% - 1.37\% = 0.13\%$) for Q1 and Q4. The average incentive for Q1 is also slightly higher than the other portfolios, but the differences are again trivial. Thus the underperformance of smaller funds reported *maybe* either attributed to a systematic difference in investment skill among managers of different size portfolios, or unlucky risk exposures (invested assets into underperformed asset classes). We investigate this further below.

Table 7. Fees and Incentives of Size-Based Composites

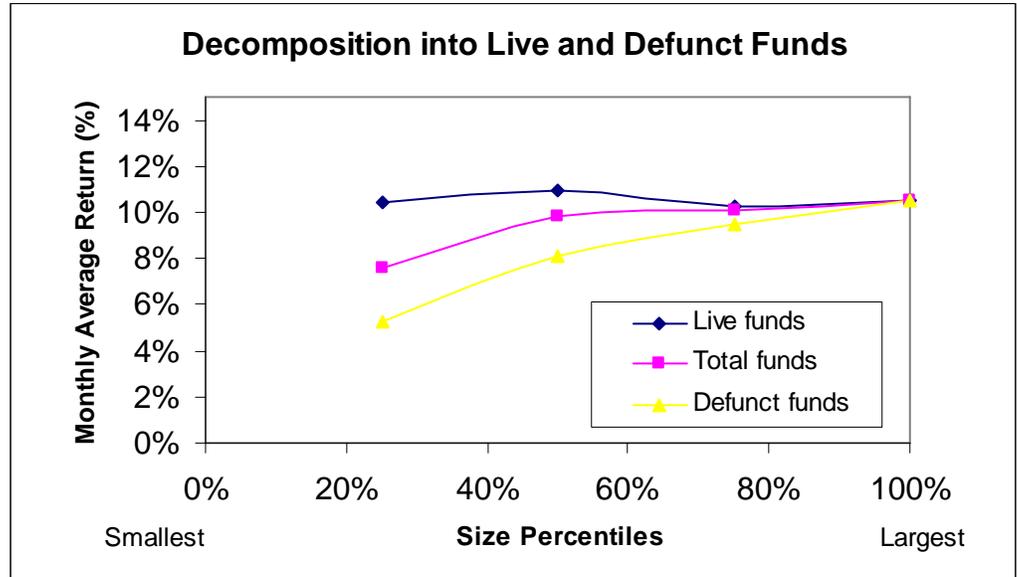
	Portfolio Q1 (smallest)	Portfolio Q2	Portfolio Q3	Portfolio Q4 (largest)
Annual Management Fee	1.50%	1.47%	1.45%	1.37%
Incentive	10.39%	9.38%	8.44%	9.91%

In order to shed more light on the smallest 25% of funds represented by portfolio Q1, in each month, we decompose the funds into live funds and defunct funds. Based on this decomposition we track the number of funds in each segment and calculate the average monthly returns. We repeat the procedures for portfolio Q2, Q3, and Q4 over the 143 months from January 1995 to December 2006. The results are shown in Charts 6A and 6B, respectively.

In Charts 6A and 6B, it is interesting to note that the live funds performed almost equally well for all 4 portfolios. Recall that Gregoriou and Rouah [2002] use only live funds, and report no correlation between size and performance, which is consistent with our results for live funds only. Therefore, if the sample is suffering from survivorship bias, the performance-size relationship can be misrepresented.

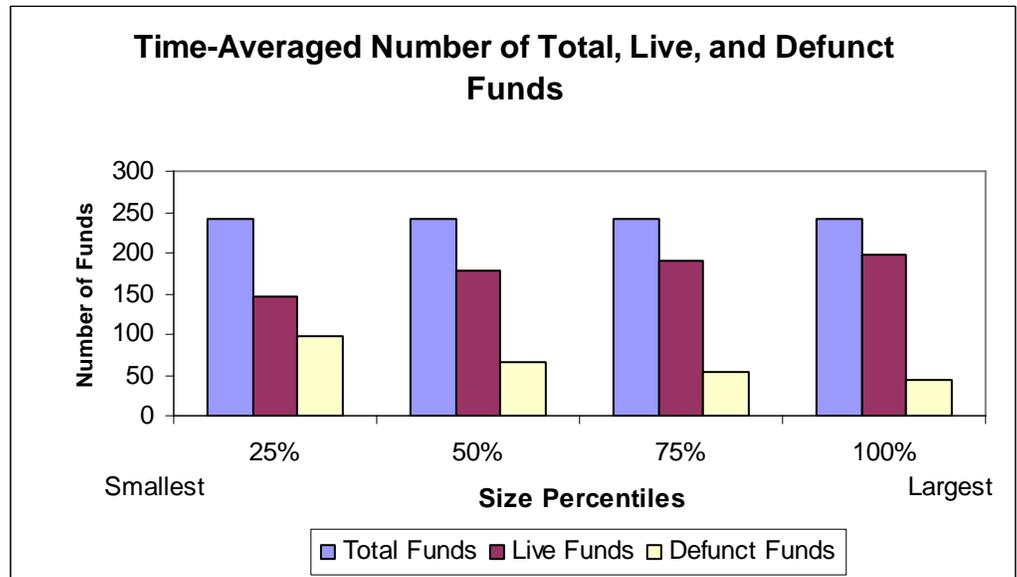
The picture for the defunct funds is quite different. The time-averaged population percentage for defunct funds in portfolio Q1 is the highest at 40%, compared to 18% for portfolio Q4. Among the four defunct fund portfolios, the Q1 group had the worst average annual return of 7.6%, while the Q4 group had the best average annual return of 10.51%. The underperformance of the defunct funds in Q1 exclusively contributed to the underperformance of portfolio Q1.

Chart 6A. Annual Average Return for All Funds, Live Funds Only, and Defunct Funds Only in Portfolios Q1, Q2, Q3, and Q4.



* A size percentile of 25% corresponds to portfolio Q1, and so on.

Chart 6B. Time-Averaged Number of Total, Live, and Defunct Funds in Portfolios Q1, Q2, Q3, and Q4.



* A size percentile of 25% (50%) corresponds to portfolio Q1 (Q2), and so on.

Next, we investigate the performance of the four size-based portfolios with the multi-factor (11-factor) model described in the methodology section. The regression results for total funds

are presented in Table 8. The adjusted-R² for portfolios Q1, Q2, Q3, and Q4 are reasonably robust at 51.44%, 55.88%, 54.08%, and 47.34%, respectively. The factor exposures are used to calculate the beta returns, and the intercepts are simply Alphas. The same regression was repeated for both the live-fund and defunct-fund groups (the results were not shown for possible distractions).

Table 8. Stepwise Regression Results for Average Monthly Returns of All Funds in Portfolios Q1, Q2, Q3, and Q4.

Total Funds	Q1	Q2	Q3	Q4
Alpha	0.4 (4.22)	0.57 (6.58)	0.62 (6.87)	0.66 (7.34)
Excess ML 10-15 Yr Treasury TR	0.12 (2.35)	0.12 (2.63)	0.13 (2.62)	0.11 (2.25)
BAA - GOV	0 (0.62)	0 (0.64)	0 (-0.08)	0 (0.63)
Russell 1000 Growth TR	0 (-1.52)	0 (-1.33)	0 (-1.63)	0 (-0.87)
Russell 1000 Value TR	0 (-1.31)	0 (-0.85)	0 (-0.94)	0 (-0.15)
Russell 2000 Growth TR	0.08 (4.29)	0.09 (5.38)	0.09 (5.26)	0.08 (4.91)
Russell 2000 Value TR	0 (-0.93)	0 (-0.22)	0 (-0.49)	0 (-0.02)
MSCI EAFE TR	0 (0.42)	0 (0.3)	0 (-0.27)	0 (0.08)
FTSE NAREIT-Equity TR	0 (-0.53)	0 (0.06)	0 (-0.56)	0 (-0.4)
MSCI Emerging Mkts TR	0.09 (4.85)	0.08 (4.52)	0.09 (5.02)	0.06 (3.54)
DJ-AIG Commodity TR	0.05 (1.83)	0.05 (2.28)	0 (1.58)	0.04 (1.69)
LB HighYield TR	0 (0.22)	0 (0.25)	0 (-0.25)	0 (0.4)
Adjusted R-squared	51.44%	55.85%	54.08%	47.34%

* Portfolios Q1, Q2, Q3, and Q4 are defined in text. The period covered is from January 1995 to November 2006.

Table 9 summarizes total average annual return, Alpha return, and Beta return for the four size-based portfolios as well as the live and defunct segments. Alpha returns are from the intercepts of regressions, and Beta returns are calculated from the multiplication of a vector of factor exposures by a vector of factor returns. The Beta returns for all categories are very close to each other, about 2%, however, the Alpha returns have a wide range. The Alpha of the defunct funds segment of Q1 is 3.35%, the lowest in the defunct segment.

Table 9. Total Average Annual Return, Annual Alpha Return, and Annual Beta Return for All Funds, Live Funds, and Defunct Funds in Portfolios Q1, Q2, Q3, and Q4.

Total Funds	Q1	Q2	Q3	Q4
Total Annual Return	7.60%	9.82%	10.13%	10.51%
Alpha Return	4.93%	7.08%	7.75%	8.20%
Beta Return	2.52%	2.58%	2.22%	2.21%
Residual	0.15%	0.16%	0.15%	0.10%
Live Funds	Q1	Q2	Q3	Q4
Total Annual Return	10.46%	10.97%	10.23%	10.54%
Alpha Return	8.20%	8.57%	8.41%	8.27%
Beta Return	2.15%	2.27%	1.70%	2.16%
Residual	0.11%	0.13%	0.12%	0.10%
Defunct Funds	Q1	Q2	Q3	Q4
Total Annual Return	5.25%	8.13%	9.49%	10.49%
Alpha Return	3.35%	5.70%	7.25%	8.49%
Beta Return	1.72%	2.30%	2.01%	1.88%
Residual	0.17%	0.12%	0.23%	0.12%

* Portfolios Q1, Q2, Q3, and Q4 are defined in text. The period covered is from January 1995 to November 2006.

Table 9 explains why the portfolio Q1 underperformed portfolios Q2, Q3, and Q4. The underperformance is not because of risk exposures or significantly higher management fees, but the low Alpha that the defunct funds in portfolio Q1 delivered.

Size-Capacity Constraints

Getmansky [2004] and Ammann and Moerth [2006] report that size capacity constraints exist in hedge funds. We study this issue by calculating the relative performance between portfolio 20 and portfolios 17, 18, or 19 pictured in Chart 5, which is shown in Table 10A. It appears that portfolio 17 beats portfolio 20 at the 95% confidence level, while portfolio 18 outperformed portfolio 20 marginally, providing evidence for size-capacity constraints. In contrast, portfolio 19 is not statistically different from portfolios 16, 17, and 18 as shown in Table 10A.

Table 10A. Relative performance between size portfolios 17 or 18 or 19 and 20, and between portfolio 16 or 17 or 18 and 19.

	Portfolio 17 relative to Portfolio 20	Portfolio 18 relative to Portfolio 20	Portfolio 19 relative to Portfolio 20	Portfolio 16 relative to Portfolio 19	Portfolio 17 relative to Portfolio 19	Portfolio 18 relative to Portfolio 19
value-added	1.18%	0.87%	0.70%	-0.32%	0.47%	0.17%
t-stat	2.10	1.51	1.16	-0.56	0.87	0.34

* Portfolios 16, 17, 18, 19, and 20 are shown in Chart 5A. Portfolio 20 contained the largest 5% funds of hedge funds.

How have the largest-sized funds of hedge funds performed in the last two years (2004—2006)? We run the regression for all the live funds of hedge funds with asset size larger than \$1 billion, and the results are shown in Table 10B. The dependent variable is the average monthly return for the two years from 11/2004 to 11/2006, and the independent variable is the natural logarithm of the asset size. Indeed, a statistically significant negative relationship is observed, indicating size-capacity constraints.

Table 10B. Performance Regression on Size for Giant Funds of Hedge Funds

	Coefficient	t-stat
Intercept	2.80	4.58
ln(Asset Size)	-0.10	-3.60
R ²	16.87%	
Number of Observations	66	

* The period covered is from November 2004 to November 2006. There are 66 funds that have a size greater than \$1 billion.

Robustness Check

Finally, we performed all the same analyses presented above in both the TASS and Morningstar Hedge Fund Databases, separately, and we observed qualitatively similar results for all the relationships between performance and both capital flow and asset size for each database. Due to space constraints, these results are not reported. However, the qualitatively similar findings suggest that our results are universal to the larger funds of hedge funds universe and are not data-source dependent.

Conclusions

Our empirical findings about funds of hedge funds improve our understanding of the determinants of capital flows, and relationship between performance and both flow and asset size:

- Past strong performance is attractive to investors, and weak performance is unattractive. Evidence shows that investors prefer 18-month Sharpe ratios to other lengths of Sharpe ratios or raw returns as a determinant of capital inflow.
- The size-performance relationship is positive and concave, and smaller funds have a higher probability of earning significantly lower Alpha, which in turn increases the likelihood of being liquidated. We show that the underperformance of the smallest 25% of funds is not due to risk exposures or significantly higher management fees, but because there is a higher portion of failed funds in this group, and these failed funds delivered much lower average Alpha than the other 75% funds.
- Above average asset flows into top-performing and top-sized funds seem lead to capacity constraints, which hurt future performance. In contrast, the top-performing and top-sized funds with below average asset flows performed significantly better than those top funds with above average flows.

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Notes

ⁱ The TASS hedge fund database is a well-known database distributed by Lipper. Morningstar's hedge fund database is a global institutional research platform that provides integrated data, screening, and analytics on approximately 8,000 active, single-strategy and multi-strategy hedge funds, funds of hedge funds, and commodity trading advisors (CTAs).

ⁱⁱ All of the following 11-factor data are downloaded from Morningstar EnCorr Analyzer software: the yield spread of the U.S. 10-year Treasury bond over the three-month T-bill (Excess Return of ML 10-15 Yr Treasury), the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond (BAA-GOV), Russell 1000 Growth, Russell 1000 Value, Russell 2000 Growth, Russell 2000 Value, MSCI EAFE, MSCI Emerging Market, FSTE NAREIT-Equity, Lehman Brothers Corp High Yield, and DJ-AIG Commodities.