Performance of Funds of Hedge Funds

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Hedge fund investors have the choice of directly investing in individual hedge funds or the more common approach of investing in funds of hedge funds. A thorough due diligence on individual hedge fund managers is time-consuming and requires expertise of the hedge fund industry. These shortcomings are often bridged by selecting the alternative route of funds of hedge funds.

Funds of hedge funds generally have extensive resources dedicated to the evaluation of hedge funds and provide diversified portfolios of individual managers. Funds of hedge funds generally also accept lower initial investments and therefore are open to a larger investor base.

The 2006 database study of Strategic Financial Solutions counts 6,100 funds of hedge funds compared to 4,150 in 2005, a 47% increase. Assets in funds of hedge funds in 2006 totaled \$700 billion, almost half as much as the \$1.41 trillion directly invested in hedge funds.¹ In 1990 the estimated size of the fund of hedge funds industry was \$1.9 billion, or 5% of the total hedge fund assets.² The strong growth can primarily be explained by the increasing interest of new investor types, from pension funds to retail clients.

Several studies have been conducted about performance measurement in funds of hedge funds. Fung and Hsieh [2000] provide a comprehensive study and find an annual survivorship bias³ of 1.4% for funds of hedge

funds versus 3% for hedge funds, a median incubation period of 484 days for hedge funds versus 343 days for funds of hedge funds, and an instant history bias⁴ of 0.7% per year for funds of hedge funds compared to 1.4% for hedge funds. The study is based on 322 funds of hedge funds and 1,722 hedge funds over a four-year time period from 1994 to 1998.

In a study of 597 funds of hedge funds from 1994 to 2001, Liang [2003] finds a survivorship bias of 0.10% per month or 1.18% per year for funds of hedge funds. The overall fund of hedge funds sample containing both "living" and "dead" funds of hedge funds generates an average monthly return of 0.75% per month compared to 1.16% for hedge funds. The underperformance of funds of hedge funds relative to hedge funds is explained by the double fee structure of funds of hedge funds. The difference in the survivorship bias between hedge funds and funds of hedge funds is only 0.09% per month, while the return difference between the two is 0.41% per month. The higher fee structure of funds of hedge funds can therefore be only partially offset by a lower survivorship bias.

Brown, Goetzmann, and Liang [2004] assess the additional fee load in funds of hedge funds. The study reveals a return of funds of hedge funds of 0.61% per month compared to 0.97% for hedge funds. The analysis is based on the TASS database, with 3,439 hedge funds and 862 funds of hedge funds, from February 1989 to December 2003.

In a recent study, Agarwal and Kale [2007] show that multi-strategy hedge funds outperform funds of hedge funds on a risk-adjusted basis. The outperformance is between 2.6% and 4.8% per year on a net-of-fee basis, suggesting that the double-layered fee structure of funds of hedge funds cannot be the full explanation for the performance differential. In contrast to that Ang, Rhodes-Kropf, and Zhao [2005] argue that on average funds of hedge funds deserve their additional fee load.

Kat and Palaro [2006] show that the majority of funds of hedge funds fail to outperform a passive trading strategy using the S&P 500, T-bond, and Eurodollar futures.

Gregoriou [2003a] investigates the mortality of funds of hedge funds using parametric, semi-parametric, and non-parametric methods over a 12-year period. The findings suggest that the median survival time of funds of hedge funds is 7.5 years, while variables such as assets under management, redemption period, performance fee, leverage, monthly returns, and minimum investment impact mortality expectations.

Kat [2002] discusses opportunities for a portfolio containing a diversified fund of hedge funds to offer skewness protection. Two alternative strategies, buying stock index puts plus leveraging and buying puts on the fund itself, are investigated. Davies, Kat and Lu [2005] discuss fund of hedge funds selection by taking into account investor preferences for return distributions' higher moments in a polynomial optimization model. The results suggest that the introduction of preferences for skewness and kurtosis in the portfolio decision-making process yields portfolios far different from the mean-variance optimal portfolio with much less attractive mean-variance characteristics.

Ineichen [2002a] argues that the value added by fund of hedge funds managers is primarily related to hedge fund selection and monitoring as opposed to portfolio construction. The barriers to entry in hedge fund selection are assumed to be higher than in portfolio construction. Ineichen [2002b] elaborates on the view that funds of hedge funds operate in an inefficient market and therefore have a strong value proposition.

Acito and Fisher [2002] discuss challenges of the fund of hedge funds industry based on their findings in numerous interviews with industry players. Gregoriou [2003b] introduces the technique of data envelopment analysis for the selection of funds of hedge funds.

The objective of this article is to give more insight into the performance evaluation of funds of hedge funds. The study contributes to the existing literature of funds

of hedge funds with a discussion of the impact of fund size on performance. The relationship between fund sizes and returns, standard deviations, Sharpe ratios, and alphas derived from a four-asset-class factor model is investigated. Two different methods are used to analyze the relationship between alphas and fund sizes. The first is based on percentiles of funds as described in Ammann and Moerth [2005]. In a second approach, excess fund returns are directly regressed on the factors without grouping the funds in percentiles. A further contribution is the analysis of the persistence of a relative efficiency measure over different time periods. The relative efficiency measure is derived with the method of data envelopment analysis and is based on a variety of traditional and alternative performance measures.

This article is structured as follows: The data set used in the empirical analysis is described in the next section. The following section discusses the methodology applied. The section after that contains the empirical analysis, and the final section concludes.

DATA

This article uses the TASS database, which contains 1,315 funds of hedge funds at June 2005, including funds that ceased reporting to TASS. The data quality is documented in Exhibit 1. For the empirical analysis, four funds of hedge funds with more than 10% missing return data and 479 funds of hedge funds with more than 20% missing asset data are eliminated. The missing asset data of funds is the main restricting criteria in the data cleaning process. Further, 170 funds of hedge funds are eliminated to avoid double counting. The remaining sample of 662 funds of hedge funds is used in the analysis. The study covers the time period from January 1994 to April 2005.

For the data envelopment analysis the sample is reduced to funds with at least a 60-month track record from May 2000 to April 2005, with 167 funds of hedge funds meeting the criteria. A second sample with 55 funds that exhibit at least a 120-month track record over the time period from May 1995 to April 2005 is used to test the persistence of the results.

METHODOLOGY

An asset-class factor model is used to derive alphas and explain excess returns. Eleven asset class factors are therefore defined: MSCI World, NASDAQ Composite

EXHIBIT 1

Fund of Hedge Funds Data Quality in the TASS Database

Missing Returns	in Funds	in %
At least 1 datapoint missing	175	13.31%
More than 1%	146	11.10%
More than 3%	52	3.95%
More than 5%	19	1.44%
More than 10%	4	0.30%
Missing Fund Sizes	in Funds	in %
At least 1 datapoint missing	820	62.36%
More than 1%	810	61.60%
More than 3%	742	56.43%
More than 5%	686	52.17%
More than 10%	583	44.33%
More than 20%	479	36.43%

The exhibit is based on data from the TASS database per June 2005. The total sample contains 1,315 funds of hedge funds. The time period from January 1994 to April 2005 is used for the analysis.

Index, Russell 2000 Index, Wilshire Micro Cap Index, Lehman Aggregate Bond Index, Lehman High Yield Credit Bond Index, JP Morgan Government Bond Index, Goldman Sachs Commodity Index, Crude Oil, London Gold Bullion USD Index, and Chicago Board Options Exchange SPX Volatility Index. Excess funds of hedge funds returns are used in the regression analysis.⁵ The 11 factors are divided into four asset classes and tested for the optimal factor of each asset class. A four-factor model is derived from the optimal combination of factors from all asset classes.⁶ The Newey-West method is used in the calculation of the standard errors in the regression analysis to account for serial correlation and heteroskedasticity.

The impact of fund sizes on fund of hedge funds performance is investigated by breaking the sample into 100 percentiles according to the fund sizes. Annualized returns, annualized standard deviations, and annualized Sharpe ratios for the 100 percentiles are then regressed on the natural logarithm of the average fund sizes. A detailed description of the methodology can be found in Ammann and Moerth [2005].

Alphas are calculated for each individual percentile based on the previously derived four-factor model. The relationship between alphas derived from the 100 factor

models and average fund sizes for the 100 percentiles is then also investigated with a cross-sectional regression.

In a second approach dedicated to the investigation of the relationship between fund sizes and alphas, excess returns are directly regressed on the four factors of the factor model. Individual alphas for the funds of hedge funds are therefore derived without grouping the funds in percentiles. For this analysis the sample of 662 funds of hedge funds is reduced to all funds with at least a 12-month track record in any given time period; 624 funds of hedge funds qualify for the analysis. In a first step, 624 alphas are derived, and in a second step, the resulting alphas are regressed on the logarithms of the average fund sizes.

The key advantage of this panel regression approach is the possibility of using more data points in the analysis. Also, the data series directly represent the individual funds and no regrouping of data series according to asset percentiles is required. The disadvantages are the elimination of funds with insufficient track records and a potential distorting impact of outliers in the regression analysis. A further disadvantage is the loss of the time component with respect to the development of fund sizes over time, since individual fund sizes are averaged over time before they are used in the cross-sectional regressions.

A relatively new and promising technique in the selection of funds of hedge funds is data envelopment analysis.⁷ Data envelopment analysis provides a measure of relative efficiency for funds of hedge funds. The key strength of data envelopment analysis is the ability to take multiple inputs and multiple outputs simultaneously into account. In this article 13 evaluation criteria, four input criteria, and nine output criteria are used simultaneously. The input criteria to be minimized contain standard deviation, drawdown, kurtosis, and modified value at risk. The output criteria to be maximized contain return, skewness, proportion of positive months, omega, Sortino ratio, kappa, upside potential ratio, Calmar ratio, and alpha derived from a four-asset-class factor model.

EMPIRICAL RESULTS

The empirical part of the article contains subsections dedicated to performance analysis, survivorship analysis, asset class factor models, an investigation of the size-performance relationship and a performance evaluation approach based on data envelopment analysis.

Performance Analysis

The average equally weighted return of funds of hedge funds from January 1994 to April 2005 is 6.53% per year compared to 8.42% per year for hedge funds.⁸ The performance difference can be explained primarily by the additional fees charged by funds of hedge funds. A common fee structure for funds of hedge funds is 1% management fee and 10% performance fee. The application of this fee structure to the average hedge fund returns would result in an additional fee load of 1.84% per year for funds of hedge funds.⁹ This number is indeed very close to the actual performance difference of 1.89% per year. The result compares to an average monthly performance of funds of hedge funds of 0.75% per month or 9.4% per year from 1994 to 2001, described in Liang [2003], and 0.61% per month or 7.6% per year, described in Brown, Goetzmann, and Liang [2004]. The difference can be explained by the use of a different data source¹⁰ as well as below-average performance of funds of hedge funds from 2001 to 2005, a time period that is not covered by Liang [2003]. The return difference between hedge funds and funds of hedge funds is 0.41% per month according to Liang [2003] and 0.36% according to Brown, Goetzmann, and Liang [2004], indicating annualized differences of 4.4% per year and more than 5% per year, respectively.

Exhibit 2 illustrates the differences between equally and asset-weighted returns, standard deviations, and Sharpe ratios. Asset-weighted returns of funds of hedge funds are higher than equally weighted returns by an annualized rate of 1.09% from January 1994 to April 2005. The outperformance over the 136-month period is statistically significant at the 5% significance level. The finding suggests that larger funds of hedge funds generate higher returns than smaller funds of hedge funds and is particularly interesting with regard to the opposite relationship for hedge funds described in Ammann and Moerth [2005].

In general, capacity issues observable in the analysis with single hedge funds are not applicable to funds of hedge funds. One possible argument for the outperformance of large funds of hedge funds may be a better access to hedge funds that are closed or only selectively open for investments. Successful hedge fund managers are carefully choosing their investors. Potentially longer industry relationships of large established funds of hedge funds may act in their favor in case of limited capacity. Existing investors are generally benefiting from a preferred treatment over potential new hedge fund investors.

A further argument is a potentially lower fee structure for large funds of hedge funds that primarily target large institutional investors. Larger funds of hedge funds

EXHIBIT 2

Return Comparison Based on a Sample of 662 Funds of Hedge Funds

	Jan 94-Apr 05	Jan 94-Aug 99	Sep 99-Apr 05
Equally weighted returns p.a.	6.53%	6.75%	6.31%
Standard deviation p.a.	5.14%	5.64%	4.64%
Sharpe ratio	0.53	0.33	0.76
Asset weighted returns p.a.	7.62%	8.19%	7.06%
Standard deviation p.a.	5.76%	6.65%	4.75%
Sharpe ratio	0.66	0.50	0.90
Annualized differences in returns	1.09%	1.44%	0.75%
Standard deviation p.a.	1.73%	2.27%	0.90%
T-Statistic	2.13	1.50	1.97

The analysis is conducted over a 136-month time period from January 1994 to April 2005 as well as two sub-periods from January 1994 to August 1999 and from September 1999 to April 2005. The significance of the return differences are tested with T-Statistics. The equally weighted and asset-weighted returns and standard deviations refer to a sample with 662 funds of hedge funds.

also tend to have more resources available for the selection of hedge funds and portfolio construction.

Large funds of hedge funds groups often have a large variety of products and may choose to selectively present only the best-performing products to the public. The self-selection bias of funds of hedge funds affects the fund of hedge funds returns and is difficult to estimate. Funds of hedge funds within large institutions often have their own distribution channels and do not report performance data to database providers to avoid any negative impact on their reputation if they fail to achieve competitive returns. On the other hand smaller funds of hedge funds may be unwilling to report their fund size and therefore drop out of the data sample in the data cleaning process.

The higher returns also go hand in hand with a higher Sharpe ratio for asset-weighted returns, suggesting that the higher standard deviation can only partially explain the increased returns.¹¹

In Exhibit 3, rolling 12-month equally weighted returns are compared with rolling 12-month asset-weighted returns of funds of hedge funds. The performance difference is larger from January 1994 to August 1999. The difference may also be affected by the smaller data sample in the earlier years of the time period, starting with only 81 funds of hedge funds in January 1994. The graphical representation indicates the below-average performance in

more recent years that explains some of the performance differences compared to previous studies.

Survivorship Analysis

The survivorship analysis with funds of hedge funds is illustrated in Exhibits 4 and 5. The survivorship bias derived from equally weighted returns is 1.71% per year and compares to a survivorship bias of 3.54% per year for hedge funds over the same time period. This result is in line with previous findings. Fung and Hsieh [2000] report a survivorship bias of 1.4% per year for funds of hedge funds versus 3% per year for hedge funds, and Liang [2003] reports a survivorship bias of 1.18% per year for funds of hedge funds versus 2.32% per year for hedge funds.

The analysis with funds of hedge funds indicates a significantly higher survivorship bias for equally weighted returns than for asset weighted returns for the entire 136-month period as well as for both sub-periods, January 1994 to August 1999 and September 1999 to April 2005. This result shows that smaller funds that stopped reporting to the database underperformed substantially. Funds with a decreasing asset base may be more reluctant to report data to database providers given the strong growth in the funds of hedge funds industry.

Funds of hedge funds that are facing redemptions are not only suffering from a decreasing asset base, they also

EXHIBIT 3

Equally versus Asset-Weighted Funds of Hedge Funds Returns

Rolling 12-month equally weighted and rolling 12-month asset-weighted returns are calculated over a 136-month time horizon from January 1994 to April 2005; 662 funds of hedge funds from the TASS databases are used for the analysis.

EXHIBIT 4

Survivorship Analysis Based on a Sample of 662 Funds of Hedge Funds

	Jan 94-Feb 05	Sep 99-Feb 05	Jan 94-Aug 99
Equally weighted survivorship bias	1.71%	1.57%	1.84%
Asset weighted survivorship bias	0.32%	0.29%	0.36%
Differences in survivorship bias p.a.	1.39%	1.29%	1.48%
Standard deviation p.a.	0.92%	0.94%	0.91%
T-Statistic	4.99	3.18	3.86

The analysis is conducted over a 136-month time period from January 1994 to April 2005, as well as two sub-periods from January 1994 to August 1999 and from September 1999 to April 2005. The significance of the differences in the survivorship biases are tested with T-Statistics.

have higher costs if they have to pay redemption fees to liquidate positions in underlying hedge funds. Redemption fees, lock-up periods, and redemption gates are covenants used by successful hedge fund managers to assure a stable asset base. Hedge funds with restrictive liquidity provisions are not suitable for funds of hedge funds

with volatile asset bases or funds of hedge funds that promise high liquidity to investors.

The graphical representation of 12-month rolling survivorship biases emphasizes the dependency of the survivorship bias on the time period. Generally it can be observed that the survivorship bias decreases in the last few years of the time period.

Asset-Class Factor Models

Exhibit 6 illustrates the results of a multiple regression of the returns of the sample of 662 funds of hedge funds on 11 asset-class factors.¹² The 11-factor model explains 56.3% of the excess returns in funds of hedge funds. The factors are ranked by their explanatory power. Equities have the highest explanatory power, similar to the study based on hedge funds data. Small-cap equities represented by the Wilshire micro cap index top the list before the MSCI world. In contrast to the analysis with hedge funds reported in Ammann and Moerth [2005], the analysis with funds of hedge funds reveals the CBOE volatility index as a relevant explanatory factor that is statistically significant at the 10% significance

EXHIBIT 5

12-Month Rolling Survivorship Biases

Rolling 12-month equally weighted and rolling 12-month asset-weighted survivorship biases are calculated over a 136-month time horizon from January 1994 to April 2005; 662 funds of hedge funds from the TASS database are used for the analysis.

EXHIBIT 6

Asset-Class Factor Model with 11 Factors

Independent Variable	Coefficient
ALPHA	-0.001 (0.001)
WILSHIRE MICRO CAP INDEX	0.207 (0.047)***
MSCI WORLD	0.206 (0.058)***
NASDAQ	-0.057 (0.026)**
VIX	0.015 (0.009)*
RUSSELL 2000	-0.081 (0.054)
GSCI	0.038 (0.029)
GOLD INDEX	0.033 (0.025)
JPM GL. GOV. BOND INDEX	0.188 (0.261)
LEHMAN HIGH YIELD INDEX	-0.001 (0.007)
CRUDE OIL	-0.001 (0.021)
LEHMAN BOND INDEX	-0.007 (0.262)
R-squared	0.563
Adjusted R-squared	0.524

*, **, *** indicate significance at the 10%, 5%, and 1% significance levels, respectively.

A multi-asset-class factor model with 11 factors is used to explain excess returns of 662 funds of hedge funds of the TASS database. Standard errors and p-values are calculated for each factor. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the regression analysis.

level. The alpha of funds of hedge funds is not statistically significant.

Due to high correlations of variables used in the multi-factor approach, multicollinearity impacts the p-values. Variables may be relevant despite high p-values and are therefore tested on a stand-alone basis in single-factor models. A multi-factor model with fewer variables is then derived in a systematic approach to account for multicollinearity.

Single-factor models for the 11 factors are illustrated in Exhibit 7. All four single-factor models based

on equities have a statistically significant coefficient at the 1% significance level with R-squares between 25% and 45%. The dominance of equity factors is nevertheless weaker than in the analysis with single hedge funds, where individual factor models based on equities explain more than 55% of excess returns. The single-factor model based on equity volatility also shows a statistically significant factor exposure at the 5% significance level. The factor exposure of the factor model based on the Lehman Aggregate Bond Index is statistically significant at the 10% significance level, a relationship that has not been significant in the analysis based on hedge funds. In the commodity space the single-factor model based on the Goldman Sachs Commodity Index reveals a significant relationship at the 1% significance level. The factor models based on crude oil indicate a significant relationship at the 5% significance level, and the factor model based on gold is still significant at the 10% significance level.

In summary, 9 out of 11 single-factor models have statistically significant coefficients at least at the 10% significance level. The two factor models that fail to exhibit statistically significant relationships are based on the JP Morgan Government Bond Index and the Lehman High Yield Credit Bond Index.

The number of factors in the multifactor models is reduced to account for multicollinearity and to facilitate the interpretation of the results. The objective is to find the best factor combination with one factor from each of the four asset classes: equities, bonds, commodities, and volatility. The R-squares of various four-factor models are illustrated in Exhibit 8. The highest explanatory power with an adjusted R-squared of 47.91% can be found in the four-factor model containing the Wilshire Micro Cap Index, the Lehman Aggregate Bond Index, the Goldman Sachs Commodity Index, and the CBOE Volatility Index. The four-factor model is specified in Exhibit 9. The annualized alpha of funds of hedge funds derived by the four-factor model is not statistically significant.

Impact of Fund Sizes on Performance

The increasing asset base of the hedge fund industry and the strong inflows into funds of hedge funds raise the question of the capacity of the industry. This question is addressed with a detailed analysis of the relationship between funds of hedge funds sizes and returns, standard deviations, Sharpe ratios, and alphas.

EXHIBIT 7

Single-Factor Models for 11 Asset Class Factors

Asset Classes	Factors	Factor Beta	R-Squared	Monthly Alpha
EQUITIES				
	WILSHIRE MICRO CAP IND.	0.147 (0.017)***	0.4410	0.02%
	RUSSELL 2000	0.159 (0.024)***	0.3549	0.11%
	NASDAQ	0.100 (0.022)***	0.2867	0.13%
	MSCI WORLD	0.187 (0.038)***	0.2622	0.10%
BONDS				
	LEHMAN BOND INDEX	0.166 (0.097)*	0.0225	0.23%
	JPM GL. GOV. BOND IND.	0.072 (0.104)	0.0046	0.22%
	LEHMAN HIGH YIELD IND.	0.011 (0.008)	0.0094	0.21%
COMMODITIES				
	GSCI	0.046 (0.017)***	0.0312	0.19%
	CRUDE OIL	0.024 (0.012)**	0.0228	0.19%
	GOLD INDEX	0.062 (0.036)*	0.0228	0.22%
VOLATILITY				
	VIX	-0.023 (0.009)**	0.0778	0.26%

*, **, *** indicate significance at the 10%, 5%, and 1% significance levels, respectively.

Eleven single-asset-class factor models are used to explain excess returns of 662 funds of hedge funds of the TASS database. Monthly alphas and adjusted R-squares are calculated for each model. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the regression analysis.

In Exhibit 10, deciles of fund sizes are illustrated with the average returns for each decile. The average fund of hedge funds in the sample has a fund size of \$80.7 million, while the average fund size of the funds in the lowest decile is \$1.7 million and the average fund size of the funds in the highest decile is \$490.9 million. This range is lower than the range for individual hedge funds, with an average fund size of \$1.4 million in the lowest decile and \$710.6 million

in the highest decile. The analysis with deciles confirms a positive relationship between fund sizes and returns. The result is supported with an F-test that indicates a significant relationship at the 10% significance level.

The sample is broken into 100 percentiles according to their fund sizes, and cross-sectional regressions are applied. The regression of the average excess returns of the 100 sub-samples on the logarithms of the average fund

EXHIBIT 8

R-Squares of Factor Models Based on Four Asset Classes

Equities	Bonds	Commodities	Volatility	Adjusted R-Squared
WILSHIRE MICRO	LEHMAN BOND	GSCI	VIX	0.4791
MSCI WORLD	LEHMAN BOND	GSCI	VIX	0.3625
NASDAQ	LEHMAN BOND	GSCI	VIX	0.3545
RUSSELL 2000	LEHMAN BOND	GSCI	VIX	0.4295
WILSHIRE MICRO	LEHMAN HY	GSCI	VIX	0.4297
WILSHIRE MICRO	JPM GOV BOND	GSCI	VIX	0.4702
WILSHIRE MICRO	LEHMAN BOND	GOLD	VIX	0.4717
WILSHIRE MICRO	LEHMAN BOND	CRUDE OIL	VIX	0.4734

An asset-class factor model with four factors representing each asset class is used to explain equally weighted excess returns of funds of hedge funds. The initial asset class factors are derived from the highest adjusted R-squares within each asset class from the single-factor models. For each asset class all asset-class factors are tested given the asset-class factors of the other asset classes. Adjusted R-squares are calculated for each model. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the regression analysis; 662 funds of hedge funds of the TASS database are used for the analysis

EXHIBIT 9

Asset-Class Factor Model with Four Factors

Variable	Coefficient
ALPHA	0.000 (0.001)
WILSHIRE MICRO CAP	0.152 (0.018)***
GSCI	0.031 (0.012)
LEHMAN BOND INDEX	0.188 (0.077)*
VIX	0.005 (0.008)
R-squared	0.486
Adjusted R-squared	0.471

*, **, *** indicate significance at the 10%, 5%, and 1% significance levels, respectively.

A multi-asset-class factor model with four factors is used to explain equally weighted excess returns of funds of hedge funds. Standard errors and p-values are calculated for each factor. The time period from January 1994 to April 2005 is used for the regression analysis. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation; 662 funds of hedge funds of the TASS database are used for the analysis.

EXHIBIT 10

Fund of Hedge Fund Sizes and Returns

Percentile	Average Fund Sizes	Average Returns
91st-100th	490,912,281	8.15%
81st-90th	126,356,062	8.00%
71st-80th	68,836,230	8.03%
61st-70th	43,072,780	7.17%
51st-60th	29,350,184	6.50%
41st-50th	19,980,756	6.62%
31st-40th	13,745,540	8.47%
21st-30th	8,627,685	7.07%
11th-20th	4,718,940	5.48%
1st-10th	1,739,117	4.30%
Average	80,733,957	6.98%
F-Statistic	1.9446	P-value 5.54%

The sample of 662 funds of hedge funds is classified in percentiles and deciles according to their fund sizes. The second column illustrates the average fund sizes of each decile. The third column shows the average returns for each decile. An F-test is conducted to find out whether the average returns of the deciles are different from each other. A one tailed F-distribution is used. The time period from July 1994 to April 2005 is used for the analysis.

sizes presented in Exhibit 11 and Panel A of Exhibit 12 shows a positive relationship. In contrast to hedge funds, funds of hedge funds with a larger asset base are outperforming their smaller competitors. The relationship is statistically significant at the 1% significance level.

The relationship between standard deviations and fund sizes is illustrated in Exhibit 13 and Panel B of Exhibit 12. Similar to the analysis with hedge funds conducted by Ammann and Moerth [2005], a negative relationship between standard deviations and fund sizes can be found, suggesting that large funds of hedge funds are taking less risk. The relationship is statistically significant at the 1% significance level.¹³

The relationship between Sharpe ratios and fund sizes is illustrated in Exhibit 14 and Panel C of Exhibit 12. Large funds of hedge funds tend to have higher Sharpe ratios. The relationship is statistically significant at the 1% significance level.

The relationship between alphas derived from the four-factor model illustrated in Exhibit 9, and the fund size is tested with two approaches. The first approach is based on percentiles, and the findings are presented in

Exhibit 15 and Panel D of Exhibit 12. The relationship is positive and statistically significant at the 1% significance level. The relationships with Sharpe ratios and alphas are both in contrast to the findings of the analysis with hedge funds.¹⁴

In a second approach, the relationship between fund sizes and alphas is investigated based on a direct regression of the four factors of the factor model on the excess returns of funds of hedge funds.¹⁵ The results are illustrated in Exhibit 16 and Panel E of Exhibit 12. The analysis confirms a statistically significant relationship between fund sizes and alphas at the 1% significance level. The results are therefore in line with the results of the first approach.

The robustness of the results of the cross-sectional regression analysis is confirmed by repeating the analysis over two sub-periods of 65 months from July 1994 to November 1999 and from December 1999 to April 2005. The relationship between fund sizes and returns, standard deviations, and Sharpe ratios is statistically significant at the 1% significance level in both sub-periods. The relationship between fund sizes and alphas is significant at the

EXHIBIT 11

Fund Sizes Versus Returns of Funds of Hedge Funds

The funds are ranked according to their fund sizes and 100 asset percentiles are built in each month. In the regression analysis the average annualized returns are regressed on the logarithms of the average fund sizes of each of the 100 percentiles. The time period from July 1994 to April 2005 and a sample of 662 funds of hedge funds are used for the analysis.

EXHIBIT 12

Regression Results of Fund Sizes Versus Returns, Standard Deviations, Sharpe Ratios, and Alphas

Dependent Variable	Constant	Log(Fund Sizes)	R-squared	Adjusted R-squared
Panel A: Annualized Returns				
Annualized returns	-0.0340 (0.024)	0.0061 (0.001)***	0.1269	0.1180
Panel B: Annualized Standard Deviations				
Annualized stand. dev.	0.2349 (0.020)***	-0.0085 (0.001)***	0.3348	0.3280
Panel C: Annualized Sharpe Ratios				
Annualized Sharpe ratios	-1.3613 (0.2395)***	0.1032 (0.014)***	0.2479	0.2402
Panel D: Annualized Alphas - Percentile Approach				
Annualized alphas	-0.0882 (0.0182)***	0.0051 (0.001)***	0.0907	0.0814
Panel E: Annualized Alphas - Panel Approach				
Annualized alphas	-0.2760 (0.0542)***	0.0174 (0.003)***	0.1194	0.1180

*, **, *** indicate significance at the 10%, 5%, and 1% significance levels, respectively.

The funds of hedge funds are ranked according to their fund sizes and 100 asset percentiles are built in each month. In the regression analyses the average annualized returns, the annualized standard deviations, the annualized Sharpe ratios, and the annualized alphas of each of the 100 percentiles are regressed on the logarithms of the average fund sizes of the percentiles. The alphas are derived from excess returns and an asset-class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the Lehman Aggregate Bond Index, and the CBOE Volatility Index. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from July 1994 to April 2005 and a sample with 662 funds of hedge funds are used for the analysis.

5% significance level for the first sub-period and the 1% significance level for the second sub-period.

To test the stability of the alphas, four three-factor models are derived by dropping one of the original four factors each time. Using the alphas based on the four three-factor models for the cross-sectional regression analysis, a statistically significant relationship between fund sizes and alphas can be confirmed at the 1% significance level in each of the four cases.

Quadratic regressions with fund sizes and returns, standard deviations, Sharpe ratios, and alphas reveal that the coefficients of the quadratic terms are not statistically significant.

Data Envelopment Analysis

Data envelopment analysis is conducted with the objective to derive a relative efficiency measure for the evaluation of funds of hedge funds. In a comprehensive analysis, 13 evaluation criteria are used simultaneously to benchmark the funds.¹⁶ The analysis is based on a data set of 167 funds of hedge funds over the 60-month time period from May 2000 to April 2005. The data envelopment analysis differentiates between efficient and non-efficient funds. In the analysis with 167 funds, 13 funds are classified as efficient and span the efficient

EXHIBIT 13

Fund Sizes versus Standard Deviations of Funds of Hedge Funds

The funds are ranked according to their fund sizes, and 100 asset percentiles are built in each month. In the regression analysis the average annualized standard deviations are regressed on the logarithms of the average fund sizes of each of the 100 percentiles. The time period from July 1994 to April 2005 and a sample of 662 funds of hedge funds are used for the analysis.

EXHIBIT 14

Fund Sizes versus Sharpe Ratios of Funds of Hedge Funds

The funds are ranked according to their fund sizes, and 100 asset percentiles are built in each month. In the regression analysis the average Sharpe ratios are regressed on the logarithms of the average fund sizes of each of the 100 percentiles. The time period from July 1994 to April 2005 and a sample of 662 funds of hedge funds are used for the analysis.

EXHIBIT 15

Fund Sizes versus Alphas of Funds of Hedge Funds—Part I

The alphas are derived from funds of hedge funds excess returns and a multi-asset-class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the CBOE Volatility Index, and the Lehman Aggregate Bond Index. For the regression analysis the funds are ranked according to their fund sizes and 100 asset percentiles are built in each month. In the regression analysis the alphas derived from the four-factor models for each of the 100 percentiles are regressed on the logarithms of the average fund sizes of each of the 100 percentiles. The time period from July 1994 to April 2005 and a sample with 662 funds of hedge funds are used for the analysis. Each data point represents the average returns and average fund sizes of the funds grouped in a percentile.

EXHIBIT 16

Log of Asset Sizes versus Annualized Alphas—Part II

Alphas are derived from excess returns and an asset-class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the CBOE Volatility Index, and the Lehman Aggregate Bond Index. The time period from July 1994 to April 2005 and a sample of 662 funds of hedge funds are used for the analysis. The excess returns of the funds are directly regressed on the factors without the construction of asset percentiles.

frontier. The remaining 154 funds are non-efficient. The analysis shows that efficient funds exhibit better median characteristics across all 13 evaluation criteria. Median values are illustrated instead of average values to avoid any distorting impact of potential outliers. Minimum and maximum values are shown to indicate the presence of outliers. The results are presented in Exhibit 17.

To investigate the persistence of the results, a further analysis is conducted over a 120-month time period with a smaller data set of 55 funds of hedge funds. The data envelopment approach classifies 9 funds as efficient and 46 funds as non-efficient. The results are illustrated in Exhibit 18. The median values of the efficient funds are again better than the median values of the non-efficient funds across all 13 evaluation criteria.

The persistence of the results in the data envelopment analysis is further investigated by separating the

120-month time period into two sub-periods of 60 months each, also referred to as in-sample and out-of-sample periods. In a first step the funds are classified as efficient and non-efficient in the in-sample period. Eleven funds are classified as efficient and 44 funds are classified as non-efficient. In a second step the fund characteristics in the out-of-sample period are compared between efficient and non-efficient funds. The results are presented in Exhibit 19. The median efficiency score of efficient funds is 0.874 in the out-of-sample period, higher than the median efficiency score of 0.634 for non-efficient funds. In the out-of-sample period efficient funds have better median values than non-efficient funds in 9 out of 13 evaluation criteria. Efficient funds are outperforming with regard to return, skewness, proportion of positive months, alpha, omega, Sortino ratio, kappa, and Calmar ratio, and they exhibit a lower excess kurtosis. The outperformance comes at the expense of a lower upside potential ratio and

EXHIBIT 17

Data Envelopment Analysis over a 60-Month Time Period

	Median			Minimum	Maximum
	Funds	Efficient Funds	Non-efficient Funds		
<i>Output variables for DEA</i>					
Returns p.a.	5.58%	7.59%	5.49%	-4.87%	18.78%
Skewness	-0.09	0.20	-0.09	-5.34	2.23
Proportion of pos. returns	68.33%	81.67%	66.67%	43.33%	96.67%
Alpha p.m.	0.30%	0.62%	0.30%	-0.88%	1.51%
Omega	2.55	8.28	2.41	0.18	30.40
Sortino ratio	1.78	6.86	1.76	-1.02	24.87
Kappa (3rd order)	0.33	1.22	0.32	-0.18	4.18
Upside potential ratio	0.60	1.28	0.59	0.20	3.83
Calmar ratio	1.15	7.85	1.10	-0.12	46.60
<i>Input variables for DEA</i>					
Standard deviation	4.19%	2.86%	4.26%	1.54%	37.54%
Maximum drawdown	4.48%	1.35%	4.90%	0.16%	50.34%
Excess kurtosis	0.60	0.34	0.62	-0.87	36.42
Modified VaR	2.80%	2.16%	2.89%	1.28%	22.40%

The analysis is conducted with 167 funds of hedge funds over the time period from May 2000 to April 2005. Thirteen funds are classified as efficient and 154 funds are classified as non-efficient. Alphas are derived from excess returns and an asset-class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Microcap Index, the Lehman Aggregate Bond Index, and the CBOE Volatility Index. A modified value-at-risk measure based on a Cornish-Fisher expansion is used to take skewness and excess kurtosis into account. A 95% confidence interval is used for the modified value-at-risk measure.

EXHIBIT 18

Data Envelopment Analysis Over a 120-Month Time Period

	Median				
	All Funds	Efficient Funds	Non-efficient Funds	Minimum	Maximum
<i>Output variables for DEA</i>					
Returns p.a.	8.99%	11.07%	8.96%	-1.08%	19.20%
Skewness	-0.21	0.59	-0.33	-7.25	1.57
Proportion of pos. returns	66.67%	79.17%	65.00%	47.50%	93.33%
Alpha p.m.	0.49%	0.66%	0.48%	-0.36%	1.56%
Omega	1.72	4.01	1.66	0.76	7.72
Sortino ratio	1.09	3.29	0.95	-0.22	6.35
Kappa (3rd order)	0.20	0.44	0.16	-0.03	1.12
Upside potential ratio	0.75	1.09	0.67	0.20	2.17
Calmar ratio	0.67	2.76	0.60	-0.02	5.51
<i>Input variables for DEA</i>					
Standard deviation	8.30%	4.20%	8.64%	2.32%	40.17%
Maximum drawdown	13.02%	4.69%	15.46%	1.73%	81.92%
Excess kurtosis	3.35	1.81	3.35	-0.59	68.42
Modified VaR	5.73%	3.90%	6.33%	1.77%	36.51%

The analysis is conducted with 55 funds of hedge funds over the time period from May 1995 to April 2005. Nine funds are classified as efficient and 46 funds are classified as non-efficient. Alphas are derived from excess returns and an asset-class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the Lehman Aggregate Bond Index, and the CBOE Volatility Index. A modified value-at-risk measure based on a Cornish-Fisher expansion is used. A 95% confidence interval is used for the modified value-at-risk measure.

a higher standard deviation, maximum drawdown, and modified value-at-risk.

Finally, the persistence of relative efficiencies over time is tested with a Spearman rank correlation test applied to relative efficiency scores in the in-sample and out-of-sample time period. The rank correlation is 0.26 for the sample with 55 funds of hedge funds, but is not statistically significant. The lack of statistical significance may be due to the small sample size of only 55 funds of hedge funds.

CONCLUSION

This article investigates the performance of funds of hedge funds. It reveals new findings on the relationship between fund sizes and performance. A further analysis investigates the persistence of a relative efficiency measure based on data envelopment analysis with mixed results.

The analysis reports a performance difference between funds of hedge funds and hedge funds that is in line with the additional fee load charged by funds of hedge funds. The survivorship bias for funds of hedge funds is found to be lower than for hedge funds. A survivorship analysis indicated a substantially lower survivorship bias for larger funds of hedge funds as opposed to smaller funds of hedge funds.

Asset-class factor models applied to excess returns indicate that funds of hedge funds fail to generate significant alphas. This result is in contrast to findings for hedge funds and confirms the negative impact of the additional fee load of funds of hedge funds. Of the return variance of excess returns, 56.3% can be explained by an 11-factor model, where equities are revealed as the predominant explanatory factor for funds of hedge funds.

The relationship between performance and fund sizes is analyzed by regressing returns, standard deviations, Sharpe ratios, and alphas derived from a four-factor model on the

EXHIBIT 19

Characteristics of Funds of Hedge Funds In- and Out-of-Sample

	Efficient Funds (defined in the in-sample period)		Non-efficient Funds (defined in the in-sample period)	
	In-sample	Out-of-sample	In-sample	Out-of-sample
Median efficiency scores	1.000	0.874	0.428	0.634
<i>Output variables for DEA</i>				
Returns p.a.	15.81%	5.12%	12.17%	4.97%
Skewness	0.56	0.00	-0.59	-0.24
Proportion of pos. returns	73.33%	65.00%	70.00%	64.17%
Alpha p.m.	0.95%	0.36%	0.76%	0.21%
Omega	3.38	1.67	2.09	1.28
Sortino ratio	3.57	1.01	1.52	0.46
Kappa (3rd order)	0.53	0.15	0.26	0.09
Upside potential ratio	1.34	0.58	0.74	0.73
Calmar ratio	2.47	1.01	1.02	0.78
<i>Input variables for DEA</i>				
Standard deviation	8.13%	5.82%	10.63%	5.05%
Maximum drawdown	4.17%	7.09%	12.20%	6.05%
Excess kurtosis	1.27	0.16	2.22	0.68
Modified VaR	5.46%	3.91%	8.07%	3.42%

The analysis is conducted with 55 funds of hedge funds over the time period from May 1995 to April 2005. Alphas are derived from excess returns and an asset-class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the Lehman Aggregate Bond Index and the CBOE Volatility Index. A modified value-at-risk measure based on a Cornish-Fisher expansion is used. A 95% confidence interval is used for the modified value-at-risk measure.

logarithms of fund sizes. In contrast to hedge funds, funds of hedge funds with a larger asset base are outperforming their smaller competitors. The standard deviations for larger funds of hedge funds are smaller while the Sharpe ratios and the alphas are higher. All relationships are statistically significant at the 1% significance level. Investors in larger funds of hedge funds may benefit from a better performance and a higher survival probability of large funds.

A comprehensive relative efficiency measure is introduced based on 13 traditional and alternative performance and risk measures. The evaluation criteria are return, skewness, proportion of positive months, omega, Sortino ratio, kappa, upside potential ratio, Calmar ratio, alpha, standard deviation, maximum drawdown, kurtosis, and modified value-at-risk. The data envelopment analysis differentiates between efficient funds that span an efficient frontier

according to the 13 evaluation criteria and non-efficient funds. Interestingly, funds that are classified as efficient in the in-sample period also exhibit superior performance and risk characteristics in the out-of-sample period. However, using a rank correlation test, we do not find any evidence for statistically significant performance persistence.

ENDNOTES

¹The annual hedge fund database study of Strategic Financial Solutions examines the hedge fund listings from 12 of the major hedge fund databases. The numbers are adjusted for duplicate records.

²According to Standard & Poor's, "Overall Growth Continues in the Fund of Hedge Funds Industry" (September 2006).

³The survivorship bias is defined by the return difference between surviving funds and all funds in a data sample. For the

calculation, two samples are built. In the first sample, both "living" funds that are still reporting returns on a regular basis and "dead" funds that stopped reporting their returns to the data provider are included. The second sample consists of funds that are still reporting at the end of the data period. The difference in the returns between the two samples is referred to as the survivorship bias.

⁴Instant history bias occurs if database vendors are backfilling the performance of hedge funds when they add new funds to their database. Since only hedge funds with a good initial track record are willing to start reporting their performance to databases, the backfilled track records are biased and are therefore not representative for the industry.

⁵The 90-day T-Bill rate is deducted from the funds of hedge funds returns to derive the excess returns.

⁶The methodology used to derive the factor models is extensively discussed in Ammann and Moerth [2005].

⁷A detailed description of the methodology is given in Nguyen-Thi-Thao [2006] and Eling [2006].

⁸According to Ammann and Moerth [2005].

⁹The calculation for the additional fee load of 1.84% per year is based on the assumption of a 10% performance fee applied to the average hedge fund performance of 8.42%, resulting in fee component of 0.842% in addition to the average 1% management fee. This calculation is an approximation with inherent biases caused by negative performance of fund of hedge funds that reduce the average performance, leading to a lower performance fee estimate than the actual performance fee impact.

¹⁰Liang [2003] is based on the database of Zurich Capital Markets and uses 597 funds of hedge funds.

¹¹The standard deviation and Sharpe ratios presented are calculated based on equally weighted and asset weighted returns of the total sample over the entire time period and therefore differ from the average of all standard deviations and Sharpe ratios of the funds of hedge funds in the sample.

¹²The methodology is explained in the methodology section.

¹³The standard deviations refer to percentiles and therefore portfolios of hedge funds, rather than individual hedge funds. The volatility of portfolios of hedge funds is generally lower than the volatility of individual hedge funds due to diversification benefits.

¹⁴A discussion of the results with hedge funds is given in Ammann and Moerth [2005].

¹⁵The advantages and disadvantages of this approach are discussed in the methodology section.

¹⁶Gregoriou [2003b] uses the first three partial moments of the upper (lower) side of return distributions as input (output) criteria in a data envelopment approach applied to funds of hedge funds.

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