Determinants of Funds of Hedge Funds' Performance

By N. Amenc and M. Vaissié

Abstract:

Despite institutional investors' growing interest in funds of hedge funds, little attention has been paid so far to their added value and/or the sources of their added value. This is all the more striking in that funds of funds are far from transparent and are, with their double-fee structure, relatively costly investment vehicles. Our objective in this article is to fill the gap and find out whether funds of funds add value through strategic allocation and active management. To this end, we ran a RBSA on a sample of 97 funds of funds over 1997/2004. 89% of the funds of funds turned out to add value at the strategic allocation level but only 31% at the active management level. Finally, only 20% of funds of funds created value through both strategic allocation and active management. In other words, if picking best performing funds is a challenging task, picking best performing funds of funds appears to be equally difficult.

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Since Markowitz's [1952] seminal work, diversification has been one of the principal tenets of modern portfolio theory (MPT). Indeed, in MPT it is advocated for a rational investor to invest in a wide variety of assets in order to spread risk and in turn maximize long-term risk-adjusted performance. However, investors face budget constraints, and generally restrict their operations to markets or assets they are familiar with. As a consequence, their diversification policy is often sub-optimal. To address this issue, many traditional investors delegate their investments to third parties such as mutual funds. They can thus benefit from the diversification effects available to large investment pools, and from the skill/experience of professional fund managers. Nevertheless, entering into a principal/agent relationship implies not only visible costs (e.g. management fees) but also invisible ones (e.g. agency costs). Since investors and fund managers may, under certain circumstances, have conflicting goals, it is essential for investors to make sure that fund managers are doing what they have been mandated to do. To this end, numerous practitioners and academics have proposed performance attribution models to measure the value added by fund managers through strategic asset allocation and active management (cf. Brinson et al. [1986, 1991], Hensel et al. [1991], Ibbotson and Kaplan [2000], etc.).

Surprisingly, despite the growing interest from institutional investors in hedge fund strategies, little attention has been paid so far to the added value and/or the sources of added value of funds of hedge funds (henceforth FoHF)[1]. This is all the more striking in that FoHF are far from transparent and are, with their double-fee structure, relatively costly investment vehicles. Our objective in this article is to fill this gap and answer the following questions: (i) "Does asset allocation play a central role in FoHF return variability?", (ii) "What is the primary source of added value for FoHF: strategic style allocation or active management?", (iii) "Which factor best explains the cross-sectional dispersion of FoHF performance?".

Applying Traditional Performance Attribution Models to FoHF

Performance measurement and attribution is a recurring topic in both academic and practitioner literature. It is therefore not surprising to find a plethora of models aimed at measuring the contribution of passive management (i.e. strategic asset allocation) and active management (i.e. tactical asset allocation and stock picking) to the total return of mutual funds. These models are typically classified into two categories, namely portfolio-based models (see Daniel et al. [1997]), and return-based models (see Sharpe [1988, 1992]). While the former approach relies on portfolio holdings, the latter is based on the analysis of historical returns. Since information is particularly scarce in the alternative arena, we have opt for the latter approach. In return-based style analysis models, the performance of a fund is decomposed into two distinct components with the help of a constrained regression.

$$R_{FoHF\,t} = \underbrace{\sum_{k=1}^{N} \beta_k R_{I_{k,t}}}_{Strategy\ Benchmark} + \underbrace{(\alpha + \varepsilon_t)}_{Active\ Management} \quad for\, t = 1,...,T \quad with \quad \sum_{k=1}^{N} \beta_k = 1 \quad and \quad \beta_k \geq 0 \quad \forall k. \qquad (1)$$

Where R_{FoHF_t} *is the return of the FoHF at time t,* β_k *is the exposure of the FoHF to style factor k,* $R_{I_{k,t}}$ *is the return of style factor k at time t, α is the intercept term and* ε_t *white noise.*

The first part is due to the investment policy, i.e. the return explained by the fund manager's strategy benchmark (cf. Kuenzi [2003] for further details on strategy benchmarks). The second part corresponds to the return generated through market timing and fund picking. In other words, the first component is explained by beta drivers and the latter by dynamic beta and pure alpha drivers.

It should be noted that the quality of the output of a return-based style analysis strongly relies on the quality of the inputs. As stressed by William Sharpe, indices must be collectively exhaustive and mutually exclusive. They must also be transparent and accountable. As highlighted in Fung and Hsieh [1998] traditional style indices are of little help to capture a significant part of hedge funds' return variability. We should therefore use hedge fund indices. In an attempt to mitigate the impact of performance measurement biases inherent to the alternative arena and address the issue of representativity, we selected the series of indices of hedge fund indices published by Edhec (cf. Amenc et al. [2004] for more details on the construction methodology and a description of their appealing properties).

It is worth highlighting that a major weakness of the return-based style analysis is to ignore the degree of significance of the exposures to style indices, which in turn may have significant consequences on the results of the performance attribution process. To circumvent this issue, and reduce statistical noise, we suggest following the procedure introduced in Lobosco and DiBartolomeo [1997] to compute confidence intervals for style weights i.e.:

$$Parameter\ S\tan dard\ deviation = \frac{\sigma_a}{\sigma_{B_i} \times \sqrt{n-k-1}} \qquad (2)$$

Where $\begin{cases} i = \text{index corresponding to the style weight being estimated} \\ \sigma_a = \text{standard error of the style analysis} \\ \sigma_{B_i} = \text{"unexplained Sharpe style index volatility" for index } i \\ n = \text{number of returns used in the style analysis} \\ k = \text{number of market indexes with non-zero style weights} \end{cases}$

This will allow us to select those style factors showing significant factor loadings at a 95% confidence level[2]. As evidenced in Otten and Bams [2000], cases of misclassification might be reduced by 50% when the significance of factor loadings is taken into account. As a result, we expect the resulting models to be more accurate and robust, and in turn better suited for performance measurement purposes.

How much of the variability of returns across time is explained by the Strategy Benchmark?

It has been widely argued that asset allocation accounts for a substantial part of the variability of mutual fund returns (see Brinson et al. [1986, 1991], Hensel et al. [1991], Ibbotson and Kaplan [2000], etc.). This can easily be explained by the fact that they usually follow buy-and-hold strategies. Since FoHF implement style rotation strategies and perform fund picking, we have good reason to believe that the impact of investment policy on FoHF return variability will be significantly lower.

To test this hypothesis, we extracted from the Alternative Asset Center (AAC) database 103 FoHF with continuous track record from January 1997 through December 2004. To avoid any double-counting, we eliminated three funds presenting similar names and a correlation higher than 0.98 with another fund. We further eliminated three funds for which none of the style indices showed a significant factor loading. We therefore ended up with a sample of 97 FoHF with 96 observations of monthly returns. We then constructed a strategy benchmark for each FoHF in our sample, using a return-based style analysis[3]. In an attempt to account for survivorship and instant history biases, we adjusted the different style indices used in the return-based style analysis, as explained in Appendix II. Finally, it should be noted that our sample is subject to survivorship bias. Since AAC is fairly representative of the FoHF universe, we assumed that the performance of the FoHF in our sample was overstated on average by 0.80% p.a., which is consistent with the estimation in Malkiel and Saha [2004] for the FoHF universe.

We then regressed the historical returns of the FoHF onto their respective strategy benchmark. The coefficients of determination of these regressions are presented in the table below.

Exhibit 1: Range of Time Series Regression R^2 Values

As expected, the impact of the investment policy on the variability of FoHF returns is significantly lower than for mutual funds. On average, the strategy benchmark only explains 56.17% of FoHF return variability as opposed to 81.40% for mutual funds. Nevertheless, despite a common perception, it appears that investment policy is still the principal determinant of FoHF return variability.

What is the value added by FoHF at the strategic allocation level and through active management?

The results found in the previous section indicate that FoHF are not that different from mutual funds. We can therefore wonder whether - as is the case for mutual funds - strategy benchmarks account for a significant part of FoHFs' level of return. Again, since FoHF implement style rotation strategies and claim to have particular skill in selecting the best-performing hedge funds, we expect that investment policy will only account for a modest level of FoHFs' total returns. To investigate this issue, we simply divided the average return of strategy benchmarks by the average return of FoHF. The results are presented in the following table.

Exhibit 2: Percentage Range of Total Return Level Explained by Policy Return

Surprisingly, like for mutual funds, FoHF's strategy benchmarks account for more than 100% of total returns. As a matter of fact, while strategy benchmarks account on average for 129.06% of FoHF's total return, they account for 104.00% of mutual funds' total return. This seriously challenges the rationale behind investing in active funds since it seems that the more active the funds are, the more value they destroy. We can also observe that the dispersion of the results is much more significant for FoHF than for mutual funds, with the bottom and top percentile FoHF showing respectively lower and higher percentages than mutual funds.

In an attempt to better understand FoHF performance, we subsequently fine-tuned our analysis and measured the value they added at the strategic style allocation and active management levels. We estimated the value added at the strategic asset allocation level as the difference between the return of FoHF strategy benchmarks and an equally-weighted portfolio made up of the style indices used to construct the strategy benchmarks[4]. Similarly, we calculated the value added at the active management level as the difference between the return of FoHF and the return of their strategy benchmarks[5]. The total value added by FoHF is equal to the sum of these two added-value measures. The results are presented in the following illustrations[6].

Exhibit 3: Estimation of FoHFs' added value

As can be seen in illustration 3, FoHF create value on average (i.e. 0.89%). However, when we go into more detail we observe that the reality is a bit more complicated since they tend to add value through strategic style allocation (i.e. 1.55% p.a.), but destroy value through active management (i.e. -0.65%). It is worth noting that FoHF not only destroy value through active management but also significantly increase volatility (i.e. the volatility of FoHF is on average 24% higher than the volatility of benchmarks). Indeed, while over 88% of FoHF succeed in creating value by choosing a good strategy benchmark, only around 31% do so through style rotation and/or fund picking. On average, the former added 2.10% and the latter 3.25%. Active management therefore appears to be a risky bet. It may pay off in certain cases, but in most cases it costs a lot (-2.40% on average). In the end, 56.7% of FoHF add value above an equally weighted portfolio (3.50% on average). Consequently, investors might wonder why FoHF do not simply give up on active management. Indeed, if they focused on strategic allocation, and as a result, stopped charging investors high incentive fees, FoHF would create much more value than they currently do.

How much of the variation in returns among funds is explained by differences in value added through passive/active management?

Interestingly, as in Henriksson [1984], or Jagannathan and Korajczyk [1986], we find that there is a negative cross-sectional correlation between value added through strategic allocation and active management (i.e. -0.30). To find what best explains the cross-sectional dispersion of FoHF performance, we regressed FoHF returns successively onto the value added by these FoHF at the strategic allocation and active management levels. While the low coefficient of determination of the first regression (less than 1%) indicates that strategic allocation is not a discriminating factor, the high coefficient of determination obtained in the second regression (87%) clearly suggests that the difference of performance observed between FoHF is mainly due to active management.

Exhibit 4: Cross-sectional dispersion of value added by FoHF through Active Management

This result is not surprising when considering illustration 3, since the cross-sectional dispersion of FoHF value added through active management appears to be significantly higher than that added through passive management (i.e. standard deviation of 3.50% versus 1.38%). However, given the fact that most FoHF appear to destroy value with active management, we can conclude that value added through active management is a good discriminating factor especially on the downside (i.e. it explains more poor FoHF performance than good FoHF performance).

Investors Should Invest in FoHF

The value proposition of FoHF initially consists of providing investors with access to a diversified basket of hedge funds with reasonable liquidity (monthly to quarterly as opposed to quarterly to annually for hedge funds). It then involves providing investors with: (i) optimal portfolio construction, (ii) efficient active management and (iii) relevant information on a regular basis. While FoHF clearly provide investors with increased liquidity in comparison with single hedge funds, the results of our study are more balanced with regard to their added value in terms of portfolio construction and active management. Empirical results indicate that around 89% of FoHF succeed in creating value at the strategic allocation level. However, it turns out that only 31% of FoHF succeed in creating value through active management. In the end, only 20% of FoHF add value at the strategic allocation level and through active management. In other words, if picking best performing funds is a challenging task, picking best performing FoHF appears to be equally difficult. Empirical results indicate that though less ambitious, focusing on FoHF adding value at the strategic allocation level could turn out to be a more rewarding strategy than striving to identify those FoHF generating alpha through active management.

Appendix I: Construction Methodology for the Edhec Hedge Fund Indices

The difficulties related to the development of indices, which are already evident in the traditional universe, are exacerbated in the alternative investment world. Due to the scarcity of information, the logic of representativity through market capitalization is difficult to apply to the alternative universe. Finding a benchmark that is representative of a particular management universe is therefore not a trivial problem. Given that it is impossible to come up with an objective judgment on what the best existing index is, a natural idea consists of using some combination of competing indices (i.e. the different indices representative of a given investment style available on the market) to reach a better understanding of what the common information about a specific investment style would be. One straightforward method would involve computing an equally-weighted portfolio of all competing indices. Since competing hedge fund indices are based on different sets of hedge funds, the resulting portfolio of indices would be more exhaustive than any of the competing indices it is extracted from. One might however want to push the logic one step further. An optimal solution involves using factor analysis techniques to generate a set of alternative indices that can be thought of as the best possible one-dimensional summaries of information conveyed by competing indices for a given style, in the sense of the largest fraction of the variance explained. Technically speaking, this amounts to using the first component of a Principal Component Analysis of competing indices (5 to 9 depending on the strategy). The composition of the series of Edhec index of indices is obtained with a simple normalization of the weights of the first component (see Amenc et al. (2004) for further details). The composition of the Edhec indices is rebalanced every 3 months using a 36-month rolling window calibration period.

Appendix II: Procedure Implemented to Mitigate Performance Measurement Biases

The measurement of hedge fund performance is made difficult by the presence of various biases. As Fung and Hsieh (2000, 2002) underline, some biases, such as the survivorship and selection biases, relate to the very nature of the alternative universe (natural biases), others, such as the backfilling (e.g. instant history bias and *pro forma* history bias) or multi-period sampling biases, relate to the way in which the main hedge fund databases or the indices themselves are constructed (spurious biases). All these biases (except perhaps the selection bias[7]) tend to artificially and significantly overestimate the performance of hedge funds and to underestimate the risks. It is therefore difficult for investors to obtain accurate information with tools that are based on biased estimators of the risk and return.

Hedge fund indices are constructed from different databases, according to diverse methods of construction and they evolve at differing paces. As a result, competing indices are differently impacted by measurement biases.

Most index providers include (at least since 1994, the creation date for major databases) dead funds in their indices which allow them to mitigate the survivorship bias. This is the case for most of the indices that enter into the composition of the Edhec indices (e.g. CSFB/Tremont, HFR, Altvest, CISDM, Van Hedge, etc.). Others, however, exclude funds that have ceased operations on an ex-post basis. They therefore suffer from significant survivorship bias (e.g. HF Net). In other words, even if a database is affected by survivorship bias because it drops defunct funds or transfers them to the "graveyard" database, the indices based on these databases do not necessarily inherit this bias. Edhec indices are not subject to ex-post adjustments on historical returns and as a result they only inherited the bias of the HF Net indices in their *pro forma* period from January 1997 through December 2000. Since January 2001, the Edhec indices are maintained on an ongoing basis and mitigate this bias by freezing returns. The Edhec indices were therefore adjusted for the survivorship bias proportionally to the weight of the HF Net indices, from January 1997 through December 2000.

When a fund is included in a database, its past performance is also integrated, which creates an instant history bias. Most index providers, however, do not include past performance of the fund in the calculation of their historical returns. Therefore, even if the underlying database is impacted by the instant history bias, the index is not. This is the case for all the indices entering into the composition of the Edhec indices except the HF Net indices (the whole history of newly included funds is backfilled and indices' historical returns are adjusted accordingly). It should be noted that instant history bias has little influence on the results of a PCA since it affects the level of returns more than their variability. As a result, the composition of the Edhec indices remains robust even if the returns of a constituent have been completely or partially subject to backfilling on the calibration period. The performance of the Edhec indices thus only needed to be adjusted proportionally to the weight of the HF Net indices, from January 1997 through December 2000 (i.e. Edhec *pro forma* history). For the same reason, despite the fact that the composition of the Edhec CTA index from January 2003 through December 2004 was calculated with *pro forma* returns for the S&P Managed Futures returns (S&P indices were primarily launched to serve as underlying assets to diverse investment vehicles, it is therefore highly probable that the performance of the selected funds over the *pro forma* period i.e. January 1998 through December 2002, is upwardly biased), we did not need to carry out any adjustment to correct for *pro forma* history bias, since the returns of the Edhec CTA index were calculated with the actual returns of the S&P Managed Futures Index from January 2003 onward (the S&P Managed Future Index was only included in the composition of the Edhec CTA Index in January 2003).

Building on Fung and Hsieh (2000, 2002), we assumed an average annual survivorship bias of 3% and an average annual instant history bias of 1.4%. The adjustment made to mitigate the impact of survivorship and instant history biases is therefore equal to 4.4% p.a. multiplied by X%, where X% is equal to the weight of HF Net in the Edhec indices of indices.

End Notes

[1] According to InvestHedge FoHF manage around 541 billons dollars and control over 50% of the hedge fund industry.

[2] We measure the significance of factor loadings with t-statistics. Factors for which the ratio of the estimated parameter and the parameter standard deviation exceeded 1.65 were selected. The others were eliminated.

[3] Calculation fees charged by providers of investable indices generally lie in a range of 40-80 bps p.a. We therefore assumed an average fee of 60 bps p.a. which we subtracted from the strategy benchmarks obtained through a return-based style analysis.

[4] It should be noted that in the absence of information on hedge funds' capitalizations, the return of an equal-weighted portfolio offers a good proxy for the performance of an uninformed investor. For the sake of consistency, we applied the same calculation fees as for strategy benchmarks, namely 60 bps p.a.

[5] The return of the strategy benchmark and the equally-weighted portfolio were adjusted for index calculation fees of 60 bps p.a.

[6] Red bars in the graphics indicate break-even thresholds.

[7] The selection bias is the net effect of two sources of biases, namely self-selection from hedge fund managers and selection criteria imposed by database managers. Fund managers might decide to refrain from reporting because they have posted bad performance or conversely because they have achieved excellent returns and do not need to draw new investors. In the same vein, some criteria imposed by database managers on track record length or assets under management might either induce an under- or over-estimation of hedge fund returns. In sum, upward and downward biases due to selection bias are generally assumed to cancel out, and the selection bias to be not economically significant.

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Exhibits

Exhibit 1: Range of Time Series Regression R^2 Values

Percentile	FoHF	Mutual Funds*
5	24.75%	46.90%
25	43.06%	79.80%
50	59.57%	87.60%
75	69.63%	91.40%
95	82.83%	94.10%
Average	56.17%	81.40%

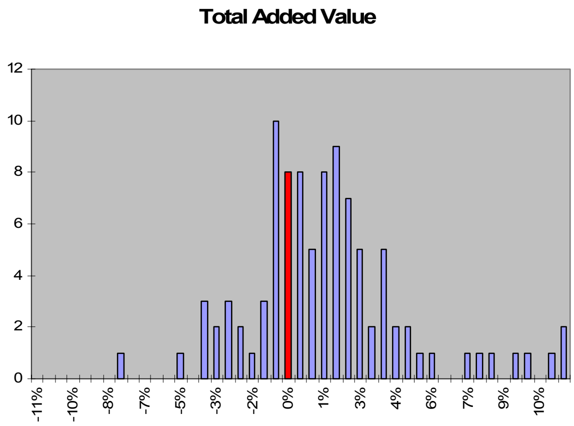
* *Results are taken from Ibbotson and Kaplan (2000)*

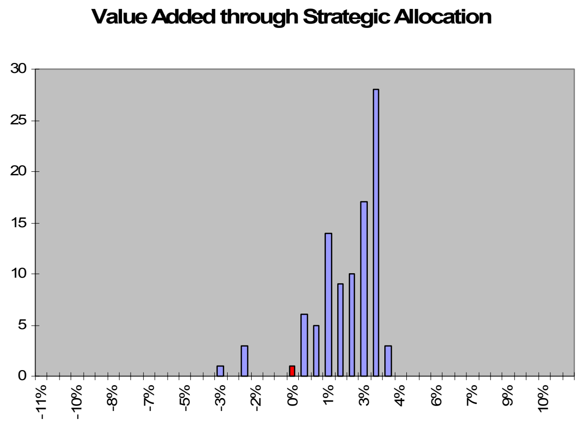
Exhibit 2: Percentage Range of Total Return Level Explained by Policy Return

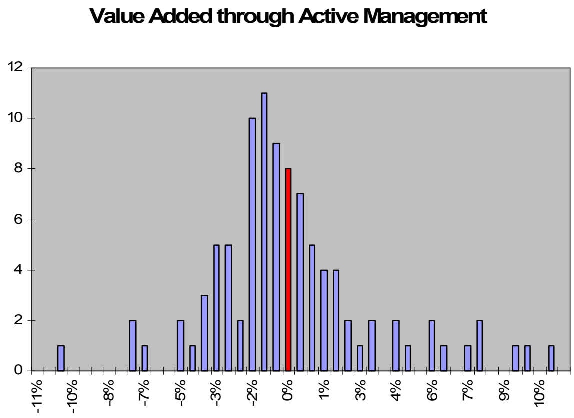
Percentile	FoHF	Mutual Funds*
5	55.99%	82.00%
25	93.98%	94.00%
50	113.79%	100.00%
75	135.92%	112.00%
95	213.00%	132.00%
Average	129.06%	104.00%

* *Results are taken from Ibbotson and Kaplan (2000)*

Exhibit 3: Estimation of FoHFs' added value







Annual Added Value	Total	Strategic Allocation	Active Management
Average	0.89%	1.55%	-0.65%
Standard Deviation	3.35%	1.38%	3.50%
Skewness	0.84	-1.54	0.81
Exc. Kurtosis	1.52	3.10	1.69
Nbr of positive (in %)	56.70%	88.66%	30.93%
Average Added Value	3.50%	2.10%	3.25%
Nbr of negative (in %)	43.30%	11.34%	69.07%
Average Added Value	-1.36%	-0.46%	-2.40%

Exhibit 4: Cross-sectional dispersion of value added by FoHF through Active Management