Do the Best Hedge Funds Hedge?*

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JEL Classification Codes: G11; G23
Keywords: Hedge funds; Systematic risk; Investment performance.

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1 Introduction

The size of the hedge fund industry has doubled almost every two years and currently includes more than 11,000 active funds that manage more than $2.4 trillion. With management fees averaging 1.5% and with 20% in incentive fees, the hedge fund business has been very lucrative.

To understand hedge fund performance as well as the fees that they charge it is useful to divide hedge fund returns into two components: a component that tracks an index or equivalently a passive portfolio, and an uncorrelated active component. In theory, investors should be able to get exposure to these two elements of risk separately. They can acquire the passive components through index funds, with fees that are generally less than 20 basis points, and the active components through market-neutral hedge funds, with zero exposure to systematic factors. However, in practice, most hedge funds are not market neutral, and can be viewed as a blend of the two components.

This paper describes the incentives of hedge fund managers to form portfolios that include factor risk, and empirically explores how the factor risk exposure of hedge funds relates to their performance and the fees that they charge. As our simple model illustrates, hedge fund managers with incentives to maximize the Sharpe ratios of their portfolios will choose greater exposure to priced factors if they have less confidence in their abilities to generate abnormal returns from the active component of their portfolios. Motivated by this observation, we estimate how the performance of hedge funds, as well as their fees and new inflows of assets under management, relate to their exposure to factor risk.

Our study examines a comprehensive sample of hedge funds, from 6 different data bases, over the January 1994 – December 2005 time period. The sample is free of survival bias and our study has been designed to minimize the effect of backfilling, which is a potential problem in this literature. Consistent with our hypothesis, we find that funds with less systematic factor exposure, which we measure as the R-square of returns on systematic factors, tend to have higher Sharpe ratios in present as well as in future periods. Specifically, we rank funds by the R-squares generated by regressing hedge fund returns on systematic factors, and find that those funds in the lowest R-

square quartile have annual Sharpe ratios that are 0.25 higher than funds in the highest quartile. Moreover, portfolios of funds with low past R-squares have exceptional Sharpe ratios over 1.3 .

If investors recognize that low R-square funds are likely to produce higher abnormal returns they should be able to charge higher fees. Our evidence is consistent with this hypothesis; the funds in the lowest R-square quartile charge, on average, 12 basis point more in management fees and 385 basis points more in incentive fees than the funds in the highest R-square quartile. This relation between R-squares and fees holds even after controlling for past performance and for various fund characteristics.

This study contributes to the growing hedge fund literature that suggests that hedge funds have generated excess returns over the past 15 years. This research includes studies by Fung and Hsieh (1997a), Liang (2000, 2001) and more recently by Kosowski, Naik and Teo (2007) and Fung, Hsieh, Naik and Ramadorai (2008). Our paper is especially close in motivation to recent papers that suggest that certain types of funds realize systematically better performance than others. Most notably, Aragon (2007) finds that funds with longer lock-up periods generate superior performance, which is consistent with the idea that these funds are able to generate abnormal performance by taking less liquid positions. Since these funds also tend to have lower R-squares than other funds it is possible that the relation between R-square and future Sharpe ratios is generated by this same liquidity effect. As we show, although Aragon's results hold in our broader sample, the relation between abnormal performance and R-square is not subsumed by the lock-up effect.

In addition, our results contribute to the literature that examines the relation between past performance and inflows. This literature includes Goetzmann, Ingersoll and Ross (2004), Agarwal, Daniel and Naik (2004), and Ding, Getmansky, Liang and Wermers (2007). Our evidence indicates that when investors evaluate hedge funds they do more than simply examine their past performance. Specifically, we find that low R-square funds tend to attract more assets under management even after controlling for past performance.

Our finding that low R-square hedge funds realize higher returns is also related to the recent evidence that indicates that mutual funds that take more active risk tend to perform better. For example, Kacperczyk, Sialm and Zheng (2005) find that mutual funds that overweight particular industries tend to perform better, while Cremers and Petajisto (2006) find that funds with portfolios that deviate more from their benchmarks also tend to perform better. Although Cremers and

Petajisto (2006) emphasize that active risk and tracking error are not the same thing, funds with higher tracking error, and hence lower R-squares, do tend to take more active risk.

The paper is organized as follows: Section 2 outlines the framework and our hypotheses, Section 3 describes the data, Section 4 focuses on how hedge funds performance is adjusted for risk and defines the R-squares, Section 5 tests that low R-squares are related to the outperformance of hedge funds, Section 6 tests whether investors recognize the low R-square funds and Section 7 concludes.

2 Framework and Hypotheses

To illustrate the relation between managerial ability and systematic risk exposure we assume that a hedge fund manager chooses between three investments: a risk-free asset, a publicly available index F and a proprietary strategy A_i for which

$$\begin{array}{rlrl} \mathbf{E}[F - r_f] & = \mu > 0; & std[F] & = \sigma \\ \mathbf{E}[A - r_f] & = \alpha > 0; & std[A] & = TE \\ Corr(A, F) & = 0 & & . \end{array}$$

We denote by w_F and w_A the weights allocated by the manager to his respective investment choices. The excess returns of the manager are given by $R - r_f = w_A(A - r_f) + w_F(F - r_f)$, and his Sharpe ratio by

$$SR(w_F, w_A) = \frac{\mathbf{E}[R - r_f]}{std[R]} = \frac{\alpha + \beta\mu}{\sqrt{TE^2 + \beta^2\sigma^2}}, \tag{1}$$

where $\beta = w_F/w_A$.

If the manager maximizes the portfolio's Sharpe ratio, he solves

$$\max_{w_F, w_A} SR(w_F, w_A).$$

The solution to the above optimization problem is given by

$$\begin{cases} \beta^* & = \frac{\mu/\sigma^2}{\alpha/TE^2} \\ w_F^* & = \beta^* w_A^* \end{cases}$$

and the Sharpe ratio of the optimal portfolio is

$$SR^* = \sqrt{\left(\frac{\alpha}{TE}\right)^2 + \left(\frac{\mu}{\sigma}\right)^2}.$$

To estimate the systematic risk exposures of the fund, one can regress $R - r_f$ on the systematic factor returns F; the R-square of such a regression would equal

$$\text{R-square} = \frac{\beta^{*2}\sigma^2}{TE^2 + \beta^{*2}\sigma^2} = \frac{1}{1 + \frac{(\alpha/TE)^2}{(\mu/\sigma)^2}}.$$

From the above equation we see that if hedge funds have the ability to generate abnormal returns then R-square decreases with the information ratio α/TE of the proprietary strategy. This leads to the following proposition:

Proposition 1 *If a hedge fund is maximizing its Sharpe ratio, then the R-square of the regression of the hedge fund's excess returns on systematic factors is inversely related to the fund's Sharpe ratio and information ratio.*

The main focus of this paper is on testing the above proposition that low R-square funds outperform high R-square funds. In addition, we examine whether investors recognize that low R-square funds are better. Specifically we test whether,

1. Hedge fund fees are positively related to funds' past R-squares.

2. Smaller R-square funds attract larger inflows than large R-square funds.

3 Data

3.1 Hedge Funds

There are a number of data bases that track hedge fund returns and our data comes from a combination of several of them. These include Altvest, Hedge Funds Research (HFR), HedgeFund.net (now part of Lipper HedgeWorld), Lipper TASS, mHedge and a confidential (and very small) database of funds tracked by a fund of hedge funds. Although there is substantial overlap between the databases, they do include different funds, so we believe the combination of the databases are more representative of the population of hedge funds than any individual database.[1] The intersection between these databases (i.e. the degree to which they overlap) is described in Figure 1. For each of the databases, the graveyards, i.e. data on the funds that ceased reporting, were also obtained.[2] Although there is data available starting in January 1972, for a variety of reasons the data prior to 1994 is less reliable,[3] so the data for this study starts in January 1994. In addition, since hedge funds are sometimes late reporting, our data set ends in 2005. Merging these databases results in a universe of 12,112 funds that are managed by 4,290 companies. While this is our starting database, as we discuss below, we focus on a smaller subset of funds that have more reliable data.

The industry coverage of the data is given in Figure 2. At the end of December 2005 our database covers over 8,500 existing funds with more than $1.5 trillion assets under management. Given that this number is consistent with industry estimates of the hedge fund universe at this time, we believe that our sample includes most active hedge funds.[4] To the best of our knowledge this is the most comprehensive hedge funds database used in the academic literature.

3.2 Potential Biases in Hedge Funds Data

It should be noted that for a variety of reasons the data used in hedge fund research is not as clean as the data used in mutual fund research and there are potential biases that can arise with the use of this data. In putting together our data, we tried to minimize the effects of the following potential biases.

Survivorship bias. Reporting to these databases is voluntary, and funds may stop reporting for a variety of reasons. This may be caused by the fund going out of business or alternatively, by the fund closing to new investments and no longer having an incentive to report. Fung and Hsieh (2000) estimate the difference in performance between the portfolio of all surviving funds and the portfolio of all the funds to be 3% annually. Similar estimates are found in Brown, Goetzmann, Ibbotson and

[1] To briefly examine the degree to which different databases contain statistically different funds, for each two of the databases we merge we perform a Kolmogorov-Smirnov test of whether the average net returns and assets under management of the funds in the two databases are drawn from the same distribution. The hypothesis that data are drawn from the same distribution can be rejected at better than a 5% confidence level in most cases. Hence, using different merged data sets seems to be necessary when generalizations of results to the entire hedge funds universe are sought.

[2] To the best of our knowledge this is the first study using the Altvest graveyard. Graveyards may be subject to non-disclosure agreements prohibiting the release of a fund's identity once the fund has stopped reporting.

[3] For example, most of the data vendors did not keep records of defunct funds prior to 1994.

[4] See for example the Financial News article "Big managers dominate $1 trillion hedge fund market" on March 27, 2006. The article estimates the size of the industry at above $1.5 trillion. The most recent-to-date survey, published by HedgeFund.net, covering Q1 2007, lists the assets under management in hedge funds at $2.67 trillion.

Ross (1999). Survivorship bias was a problem before 1994, when data vendors generally discarded funds who ceased reporting. However, after 1994 we have what is referred to as a "graveyard" sample, which includes the prior returns of the funds who ceased reporting. By including this graveyard sample, we have a sample without survival bias.

Self selection bias. The reporting is voluntary, so a bad fund has no reason to report, and a fund that is very good closes quickly and does not have any reason to "advertise."[5] Fung and Hsieh (1997b) claim that these effects offset each other, and should not create a bias in our empirical tests. Nevertheless, this bias is somewhat mitigated by our use of a comprehensive database.

Backfilling bias. Funds generally report to a database somewhat after the date it begins operating. Since the fund is free to backfill its historical returns when it starts to report, this produces an upward bias in the reported performance of hedge funds, (since funds are unlikely to backfill if their past performance is bad). Issues related to backfilling are especially problematic when individual managers can launch multiple funds. For example, a manager may start several small funds and only report the returns of the successful funds.

We are particularly concerned about backfilling bias and reduce our sample considerably to mitigate its effect. First, since we think the problem is especially prevalent among smaller funds, we eliminate all funds with less than $30 million under management. Specifically, if a fund starts with less than $30 million, but later has $30 million in assets, the fund is included in the sample starting at the date in which the assets under management reach $30 million and is kept in the sample as long as the fund exists (regardless of its assets under management).

In addition, we eliminate the first 27 months from the history of each fund. We arrived at our choice of 27 months by comparing various hedge fund indexes, which are not subject to backfilling biases, to indexes that we formed by using funds whose n initial monthly returns were excluded. By experimenting with the number of initial returns from the history of each fund that are excluded, we can build an index that closely matches the index reported by the database. Specifically, we find that the distance between the index reported by HFR and the indices computed by us after discarding n months of history is minimized when we choose n = 27 months. This is consistent with

[5]Reporting to a database may be an indirect form of advertising.

Jagannathan, Malakhov and Novikov (2007) who conclude that the optimal number of months to exclude is 25 months.

A particular case of back-filling bias is caused by funds being late in reporting to the databases. For example, a fund may report in month t, then wait until month $t+k$ at which time they report for all the months $t+1,...,t+k$. This enables funds going out of business to stop reporting while their returns are still good and biases the returns in the database. It may also increase the attrition rate of the data, as funds that are simply reporting late may appear to have exited the sample. By looking at different snapshots of the databases taken at various time periods we found that funds may be as late as eight months in reporting to databases, and hence we used only data until December 2005, which we constructed from data we received in August 2006.

Smoothed returns. Several authors (e.g. Asness, Krail and Liew (2002)) present evidence that the returns of hedge funds exhibit positive serial correlation, which is consistent with the returns being smoothed. If this is the case, the Sharpe ratios will be biased upwards. To adjust for this bias we use the correction suggested by Getmansky, Lo and Makarov (2004), which is described below.

Finally, most of the tests in this paper require that funds have at least 24 months of history left in order to be included in our final sample. Applying all the filters reduces our sample to 3,762 funds, the characteristics of which are presented in Table 1.

3.3 Risk Factors

Because hedge funds employ a wide variety of investment strategies and hold different types of assets there are potentially a large set of common factors that can influence their returns.[6] Past research by Liang (1999) consider eight different factors, Schneeweis and Spurgin (1998) consider 13 factors and Brealey and Kaplanis (2001) consider 31 factors. As described below, we consider a broader range of factors, which includes most of the factors used in the prior literature:

[6] We "explain" the returns of hedge funds only with factors that are replicable mechanically. A timing factor a la Treynor and Mazuy (1966), Henriksson and Merton (1981) or volatility factors such as the VIX index would not fit into this category as timing is a skill that cannot be replicated mechanically. However, introduction of these factors among our explanatory factors does not change our results.

Domestic Equity factors. In order to capture the common factors generating U.S. equity returns we include the Russell 3000, the NASDAQ and NAREIT indices, the Fama and French (1993) size (SMB) and value (HML) factors as well as the momentum factor (UMD) used to capture the Jegadeesh and Titman (1993) momentum effect.

International Equity. To capture international equity factors we include the FTSE 100 index, the NIKKEI 225, the Morgan Stanley Capital International (MSCI) index EAFE, the Morgan Stanley Capital International Emerging Markets Free (MSCI EMF) index as well as the DAX and CAC 40 indices.

Domestic Fixed Income. To span the securities on the domestic fixed income markets we employ the Lehman Brothers Aggregate Bond index, the Salomon Brothers 5 year index of Treasuries, the default spread (DEF) as well as duration spread (TERM) calculated by Ibbotson Associates, the Lehman Brothers Aggregate of Mortgage Backed Securities and the Lehman Brothers index of 10 year maturity Municipal Bonds.

International Fixed Income/ Foreign Exchange. The non-U.S. fixed income factors considered are the Salomon Brothers non-U.S. Weighted Government Bonds index with a 5 to 7 year duration (intermediate) and by the Salomon Brothers non-U.S. Unhedged Dollar index (a proxy for the strength of the dollar).

Commodities. Commodities are represented by the returns of the Goldman Sachs Commodity Index, the AMEX Oil index and the returns on Gold.

Nonlinear factors. Many hedge funds employ strategies that either use options or have option-like payoffs. (See for example deFigueiredo and Meredith (2005)). For example, Mitchell and Pulvino (2001) find that the returns of merger arbitrage funds resemble those of a strategy that sells "merger insurance", or more precisely, out of the money puts. To capture this possibility we include the returns of the Fung and Hsieh (2001) Primitive Trend Following Strategies (PTFS) for bonds, stock, currencies and commodities.[7] We also follow Agarwal and Naik (2004) and include portfolios of in- and out of the money calls and puts on the S&P 500 Index.

[7]These are provided by David Hsieh at http://faculty.fuqua.duke.edu/ dah7/DataLibrary/TF-FAC.xls.

Finally, as a stand-alone model we separately consider the Fung and Hsieh (2004) seven factors. These factors are the returns on the S&P 500 in excess of the risk free rate, the Wilshire small cap minus large cap return, change in the constant maturity yield of the 10 year Treasury, change in the spread between Moody's Baa yield and the 10 year Treasury and three PTFS's (for bonds, currency and commodities).

4 Factor Models

In the previous section we outlined a number of factors that can potentially explain the returns of hedge funds. These risk factors are used to estimate various multi-factor models, as described below:

$$R_t - r_f = \alpha^T + \sum_{i=1}^{K} \beta_{k_i}^T F_{k_i,t} + \epsilon_t^T, \quad t = t_0, ..., T, \tag{2}$$

where r_f is the risk free rate, K is the number of factors the fund is exposed to and all the factor returns $F_{k,t}$ represent the returns of zero-cost portfolios. Our ultimate goal is to study the relationship between performance and the R-squares generated from the above regressions.

4.1 Smoothed Returns

The problem associated with estimating equation (2) is that we do not observe the actual returns R_t. This is because hedge funds smooth their returns (Asness, Krail and Liew (2002)), either intentionally or because they hold relatively illiquid assets. Hence, as discussed in Getmansky, Lo and Makarov (2004), we observe smoothed returns, which can be expressed as a function of actual returns as follows:

$$\begin{aligned} &R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2}, \quad t = t_0, ..., T, \\ &\theta_0 + \theta_1 + \theta_2 = 1 \\ &R_t \sim \mathcal{N}(0, \sigma) \end{aligned} \tag{3}$$

where $(1 - \theta_0)$ may be interpreted as a measure of the degree to which a fund's returns are smoothed.

Combining (2) with (3) yields an equation that describes the relation between the factors and the observed smoothed returns:

$$R_t^o - r_f = \alpha^T + \sum_{i=1}^K \left[\beta_{0,k_i}^T F_{k_i,t} + \beta_{-1,k_i}^T F_{k_i,t-1} + \beta_{-2,k_i}^T F_{k_i,t-2}\right] + u_t^T, \quad t = t_0, ..., T$$

$$u_t^T = \theta_0 \epsilon_t^T + \theta_1 \epsilon_{t-1}^T + \theta_2 \epsilon_{t-2}^T \tag{4}$$

$$\theta_0 + \theta_1 + \theta_2 = 1$$

Equation (4), a regression model with $MA(2)$ disturbances, is estimated by maximum likelihood by Getmansky, Lo and Makarov (2004), Aragon (2007) and Jagannathan, Malakhov and Novikov (2007). Alternatively, Kosowski, Naik and Teo (2007) estimate equation (4) by first using previous estimates of θ, obtained by using hedge fund indices, then separately estimating (2) by OLS. We depart slightly from this literature and use a technique proposed by Choudhury, Power and St. Louis (1996) to estimate regression models with $MA(q)$ disturbances. The advantage of this method is that it does not require the maximization of the likelihood function. $\theta_{0,1,2}$ are estimated by solving a quartic algebraic equation while the rest of the parameters can be estimated via OLS from a modified model.

Once we estimate equation (4), we can map the performance statistics estimated from the observed returns to those corresponding to the real returns. In order to do so, let $\widehat{SR}^o, \widehat{IR}^o$ be the estimates of the Sharpe ratio, respectively the information ratio of the observed returns, SR, IR the true Sharpe ratio and information ratio of the equilibrium returns and $\widehat{\theta}_0$, $\widehat{\theta}_1$ and $\widehat{\theta}_2$ are estimates of $\theta_0, \theta_1, \theta_2$ from equation (4). Getmansky, Lo and Makarov (2004) show that

1. $\widehat{SR}^o \sqrt{\widehat{\theta}_0^2 + \widehat{\theta}_1^2 + \widehat{\theta}_2^2}$ is a consistent estimator of SR, and

2. $\widehat{IR}^o \sqrt{\widehat{\theta}_0^2 + \widehat{\theta}_1^2 + \widehat{\theta}_2^2}$ is a consistent estimator of IR.

Similarly it can be shown that:

3. $\widehat{\alpha}^T$ (obtained from equation (4)) is a consistent estimator of α^T from equation (2).

4. $\widehat{R}^2 := 1 - \widehat{Var(u_t^T)}/\widehat{Var(R_t^o)}$ from equation (4) is a consistent estimator of the R-square of equation (2).

4.2 Identifying the Factors

We are left with the problem of identifying the factors that are used to estimate equation (4). The problem that arises in this context is that there are a substantial number of potential factors and only a limited number of degrees of freedom for each regression. For example, to estimate a model with K factors, we need to estimate K coefficients, the intercept and two parameters describing the serial correlation in the fund's returns[8], i.e., $K + 3$ coefficients. For example, the Fung and Hsieh (2004) seven factor model requires estimates of 10 parameters. Clearly, given that in some of our tests we will be estimating the regressions with only 24 monthly observations, it is not feasible to include many more than seven factors, and it would be preferable to include somewhat fewer factors.

As we noted earlier, relative to prior studies, we consider a substantial number of factors which is necessary, given that the different hedge funds can potentially be following very different strategies that load on very different factors. However, because of limits in the degrees of freedom, it is important to limit the number of factors included in the models estimated. To do this, we follow Agarwal and Naik (2004) and use stepwise regressions to identify the factors. This method, which selects a parsimonious set of explanatory factors, by adding factors sequentially based on their F-test significance, allows the data to select a different set of factors that best explains the returns of each fund.

As an alternative specification, we also use the seven factor model of Fung an Hsieh (2004), with corrections for serial correlation.[9]

5 R-squares and Performance

This section presents estimates of the relation between the adjusted R-squares from the regressions of the hedge fund returns on the systematic factors and the future performance of the hedge funds. As we mentioned at the outset, our hypothesis is that the funds with low R-squares will perform better than those with high R-squares. Specifically, for each fund in our database, we use either the entire history of the fund or a limited time horizon, and either the seven factor model of Fung

[8]For example we need to estimate θ_0 and θ_1 as $\theta_2 = 1 - \theta_0 - \theta_1$.

[9]We have experimented with using the Fung and Hsieh ((2004) model *without* adjusting for serial correlation. The qualitative conclusions of our study continue to hold.

and Hsieh (2004) or the stepwise regression model with lags, to calculate the R-squares of each fund. We then compare the performance of the low R-square funds with those of the high R-square funds in a subsequent period.

5.1 Summary Statistics

Table 2 summarizes the R-square calculations obtained with the Fung and Hsieh and the stepwise factor models.[10] The statistics in this table indicate that the stepwise regression model with the correction for smoothed returns explains more of the variance in stock returns than the Fung and Hsieh model (median adjusted R-squares of 54% in the stepwise regression model versus 24% in the Fung and Hsieh model), which is to be expected given that the stepwise model selects the factors that maximize R-squares for each individual fund. Moreover, the step wise regression model explains the hedge fund returns with far fewer factors than the seven factor model used by Fung and Hsieh. Indeed, the median number of factors selected in this model is 3, and more than 5 factors are selected very rarely. There are a couple of interpretations of this observation. The first interpretation is that although there are very many potential factors, the factors are highly correlated with each other so that there is very little increase in explanatory power when additional factors are added. A second interpretation is that since hedge funds have focused strategies, their returns load on very few factors. The observation that the more parsimonious, but specially tailored, step wise regression model generates higher R-squares than the Fung and Hsieh factors suggests that the there is substantial independent variation in the factors we consider, and thus supports the latter interpretation.

Using estimates from the entire history of each fund, Table 3 divides the funds into R-square quartiles, and reports their average Sharpe ratios, alphas, information ratios as well as fees charged and the length of time they are in the sample. The evidence in this table indicates that the funds in the low R-square quartile outperform, on average, the funds in the highest R-square quartile. This result holds with R-squares calculated using stepwise regressions as well as with the Fung and Hsieh factors, and across each of the hedge fund strategies. In Panels C and D of Table 3, where we replicate our analysis using a subsample consisting of hedge funds with assets in excess of $200

[10]The model (4) produces estimates of $\theta_{0,1,2}$ for all but 81 funds. In Getmansky, Lo and Makarov (2004), the estimation converges for 908 funds out their database of 909. In Aragon (2007), 73 funds for which the estimated θ_0 has an absolute value greater than 5 are dropped. Our estimations requires a quartic equation to be solved in order to obtain estimations of $\theta_{0,1,2}$ and for 81 funds this equation does not have real solutions; we eliminate those from the sample, and are therefore left with 3,642 funds.

million assets under management as well as a subsample consisting of funds with assets exceeding \$1 Billion, reveal that the results hold for the large funds as well as the small funds.

5.2 Predictive Tests

The summary statistics in the previous section indicate that funds with lower R-squares tend to have better performance. In this section we examine whether estimated R-squares can be used to predict hedge fund performance in subsequent periods. Specifically, for every month t from January 1996 to December 2004 we calculate the R-square of each fund using an estimation period of two years (from month $t-23$ to month t). We then study the relationship between these estimated R-squares and performance in the subsequent year (from month $t+1$ to month $t+12$). The choice of the 24 month test period was based on two considerations: on the one hand we need enough data to estimate the Fung and Hsieh model, which requires estimates of 10 parameters, i.e., seven factor coefficients, two coefficients of smoothing (the third may be estimated using the fact that their sum is equal to one), and an intercept. On the other hand we would like the estimation period to be short, since hedge fund factor loadings are likely to change through time.[11]

Specifically, the timeline of the tests is outlined below:

$t-23$ $\qquad$ t $\quad$ $t+1$ $\qquad$ $t+12$

$\underbrace{\qquad\qquad\qquad\qquad}_{\text{estimate } R\text{-square: } R^2_{t-23:t}} \,|\cdots|\, \underbrace{\qquad\qquad}_{\text{test relationship between } R^2_{t-23:t} \text{ and performance on } [t+1;t+12]}$

In the predictive tests the measures of future performance we employ are the Sharpe ratio and the raw returns of the funds. We prefer these estimates because in contrast with performance measures such as alphas or information ratios, they are independent of any model and can be directly calculated from the raw returns of the fund.

[11] Fung, Hsieh, Naik and Ramadorai (2008) perform Chow tests to assess whether hedge fund factor loading change over time and the evidence supports such changes.

5.3 Past R-squares and Future Performance: Fama-MacBeth Regressions

To test the relationship between past R-squares and future performance we estimate Fama-MacBeth regressions. Specifically, for each month t from December 1996 to January 2005, we calculate the R-square of each fund using returns data on the estimation time interval from $t-23$ to t (the past two years), using both the stepwise regression model and the Fung and Hsieh model. We then calculate the Sharpe ratio or the raw returns $Perf_{i,t+1:t+12}$ of each fund on the testing time interval from $t+1$ to $t+12$ and regress these ratios on past R-squares and other control variables as described below:

$$\begin{aligned} Perf_{i,t+1:t+12} &= b_0 + b_1 R^2_{i,t-23:t} + b_2 Std_{i,t-23:t} + b_3 \widetilde{SR}_{i,t-23:t} + b_4 \widetilde{Ret}_{t,t-23:t} \\ &+ b_5 \log(AUM_{i,t}) + b_6 \log(Age_{i,t}) \\ &+ b_7 FOF_i + b_8 mfee_i + b_9 ifee_i + b_{10} Offshore_i + b_{11} \log(1 + LockupPeriod_i) \\ &+ b_{12} Dir_i + b_{13} RelVal_i + b_{14} SecSel_i + b_{15} Multiproc_i + \epsilon_{i,t}, \end{aligned} \tag{5}$$

where:

- $R^2_{i,t-23:t}$ is the R-square of fund i calculated using the past two years of history of the fund.
- $Std_{i,t-23:t}$ is the standard deviation of fund i calculated using the past two years of history.

The reason for using past volatilities as controls comes from our concern that the Sharpe ratio estimates are likely to be upwardly biased because of a combination of estimation error in the variances and Jensen's inequality.[12] This can potentially cause a problem in our regression analysis if past R-squares are somehow correlated with the standard error of our variance estimates, since higher standard errors are associated with greater biases in the Sharpe ratio. It is likely that the potential for this type of bias is directly related to the return variance, and for this reason we include the standard deviation as an additional explanatory variable.

[12] To understand this, assume that both the true standard deviation and excess return is 15% so the true Sharpe ratio is 1. Assume also that our standard deviation estimate is equally likely to be 10% or 20%. If this is the case, then the expected Sharpe ratio estimate will be (15/10 + 15/20) / 2 = 1.125.

- $\widetilde{SR}_{i,t-23:t}$ is the past Sharpe ratio of fund i orthogonalized to past R-squares obtained by running a cross-sectional regression of the Sharpe ratio calculated in period $t-23:t$ on the R-square of the fund calculated from the same time period. The residuals from this regression are denoted by $\widetilde{SR}_{i,t-23:t}$. This first pass regression removes the dependence between the past R-squares and the past Sharpe ratio, which is apparent from the simple sorts of Section 5.1.

- $\widetilde{Ret}_{i,t-23:t}$ are residuals from a similar first pass regressions of past returns on past R-squares.

The reason for including past performance in our regressions is because of evidence from Jagannathan, Malakhov and Novikov (2007) that hedge fund performance is persistent.

- $\log(AUM_{i,t})$ is the log of the size of the fund at the end of the estimation period.

- $\log(Age_{i,t})$ is the log of the fund's age at time t.

- FOF_i is a dummy equal to one if the fund is a fund of funds.

- $mfee_i$ and $ifee_i$ are the management fee and the incentive fee charged by the fund in percent.

- $Offshore_i$ is a dummy equal to one if the fund if offshore.

- $\log(1 + LockupPeriod_i)$ is the log of one plus the lockup period of the fund (in months). The lock-up period includes also the redemption notice period (also measured in months). For example, if the redemptions notice period is 30 days while the lock-up period is 4 months, the variable $LockupPeriod = 5$.

One of our concerns is that the relation between past R-squares and future returns is generated because the funds holding less liquid investments generate higher returns, (because of an illiquidity premium), and also have low estimated R-squares, because their returns are more likely to be smoothed. By adding the lock-up as a control variable we partly control for this possibility. However, it is worth noting that the correlation between R-squares and lock-ups is actually positive (1.16% when the R-squares are calculated from the stepwise regression model and 8.57% from the Fung and Hsieh model). This suggests that correcting for serial correlation in fund returns does a reasonable job eliminating the downward bias in R-squares that may be due to the smoothing of the returns.

- $Dir_i, RelVal_i, SecSel_i$ and $Multiproc_i$ are strategy dummies (representing Directional, Relative Value, Security Selection and respectively Multiprocess).

5.4 Results

This subsection presents evidence that indicates that low R-square funds outperform high R-square funds. In the first part of the subsection we report the results of Fama-MacBeth regressions that estimate the relation between performance and R-square after controlling for a number of other variables that are likely to also predict performance. In the second part of the subsection we examine portfolios of hedge funds that are formed based on their past R-squares. Specifically we compare the performance of a portfolio that consists of hedge funds with the highest past R-squares with the performance of a portfolio that consists of hedge funds with the lowest past R-squares.

5.4.1 Fama-MacBeth Regressions.

Table 4 reports the results of the Fama-MacBeth regressions. Consistent with our hypothesis, we find a significant negative relationship between past R-squares and future performance. The Fama-MacBeth regressions imply that, ceteris paribus, a 10% drop in the R-square (with the stepwise regression model) is associated with an annual increase in returns of about 60 basis points and an increase in the annual Sharpe ratio of about 0.05.[13]

These regressions also provide evidence of performance persistence, but the evidence is mixed: past Sharpe ratios are strongly persistent (even after correcting for past R-squares), however, raw returns do not seem to be persistent. In addition, larger funds have better Sharpe ratios but not better raw returns, perhaps, reflecting the better diversification of larger funds. Finally, funds with longer lockups appear to outperform in the future even after controlling for their R-squares. This is consistent with the results in Aragon (2007) who suggests that funds with lock up restrictions may be able to exploit a return premium by buying less liquid assets.

5.4.2 Portfolios of High and Low R-square Funds.

This subsection compares the returns of portfolios of high and low R-square hedge funds. Specifically, to assess the economic significance of the difference in performance between the low R-square

[13] Similarly, a 10% drop in returns with respect to the Fung and Hsieh model is associated with an increase of the next year Sharpe ratio of about 0.04 and an increase in returns of the next year of 61 basis points.

and high R-square funds, we directly compare the performance of a portfolio consisting of funds in the low R-square quartile with the performance of a portfolio of funds in the high R-square quartile. Specifically, we form portfolios as follows: starting in December 1996, for each month t we use the previous two years of each fund's history to calculate their R-squares. We rank funds based on these R-squares and form a portfolio consisting of funds with the lowest quartile of past R-squares, as well as a portfolio consisting of funds with the highest quartile of past R-squares. These portfolios are rebalanced at frequencies of 1, 3, 6 and 12 months. The portfolios run from January 1997 to December 2005. We report results for both value-weighted and equally-weighted portfolios.

The Sharpe ratios, alphas and the R-squares of the portfolios are reported in Table 5. The portfolio alphas and R-squares are calculated using the Fung and Hsieh benchmark portfolios. As we expect, the portfolio consisting of low R-square hedge funds have lower R-squares than the portfolio consisting of high R-square hedge funds.[14] In addition, the Sharpe ratios and alphas are higher for the portfolio consisting of low R-square hedge funds. The differences between the Sharpe ratios are quite large, generally greater than 0.6, and are generally statistically significant. To test for the statistical significance of the difference between the Sharpe ratios of these portfolios we use a Jobson and Korkie (1981) test with the correction of Memmel (2003), and adjust the variances and covariances for serial autocorrelation using Newey-West estimators. All the z_{JK} statistics of the differences (which are normally distributed) are in excess of 4.98.

The differences between the alphas of the low and high R-square hedge fund portfolios are also fairly large. In most cases, the alpha of the low R-square fund is very strongly significant and the portfolio of the high R-square portfolio is either insignicant or just marginally significant. However, because the alpha of the high R-square hedge fund portfolio is not estimated very precisely, the difference between these two alphas are not statistically significant.

[14]Note that the portfolio R-squares are actually lower than the R-squares of the individual hedge funds. This is somewhat surprising since in most cases the R-square of a portfolio is higher than the R-squares of most of its components because the idiosyncratic components of returns are diversified away. However, in this particular case the reported R-squares are not directly comparable, since for the individual funds the R-squares are computed over 24 months and for the portfolio of funds the R-square is computed over all the 108 months in which such portfolio can be formed. In general, R-squares are higher when the sample period is shorter.

5.5 Robustness

Although the results up to this point provide support for our hypothesis, as we have stressed, there are problems with the hedge fund data that is due to the fact that hedge funds invest in lots of different assets, some of which are difficult to benchmark. Some of the assets held by hedge funds are not included in any of our benchmark portfolios, (e.g., airplane leases), and many of the assets are illiquid, (e.g., bank loans). In addition, the payoffs of some assets are non-linearly related to the benchmark portfolios, (e.g., options). While we have tried to address these issues in our empirical methodology, it should be noted that there are a relatively small number of funds in which the effect of these measurement issues are considerably less of a problem. In this section we explore the relation between R-square and performance for this more select sample of hedge funds, and show that despite the small sample, the evidence supports our result that low R-square hedge funds outperform high R-square hedge funds.

Specifically, we will consider a subsample of 70 funds that satisfy the following conditions:

1. the fund reaches at least $30 million AUM at least once during the sample;
2. 100% of the fund is dedicated to equity long-short strategies;
3. the fund uses no options (including options on futures or options on options) or warrants;
4. at least 75% of the fund is focused on the U.S. (no fund reported a 100% U.S. focus).

Since these are primarily U.S. equity funds, we measure their R-squares as well as their performance using the four factor portfolios from Ken French's web site, i.e., MKT, SMB, HML, and UMD. These factors, on average, explain about 47% of the variance of these funds.

Following our previous methodology we rank each fund by their R-squares measured over the previous 24 months, and form portfolios consisting of hedge funds in the lowest and the highest R-square quartiles. These portfolios are then held for 1, 3, 6 or 12 months. As we show in Table 6, the average Sharpe ratio of the funds in the lowest R-square quartile is 1.23 annually and in the highest R-square quartile is 0.68, the difference between these Sharpe ratios is reliably different than zero. To further test whether the low R-square funds outperform the high R-square funds we compare the alpha of the portfolio of the low R-square funds with the alphas of the high R-square funds. For the value weighted portfolios, the average alpha of the low R-square portfolio is

11.65% annually while the alpha of the high R-square portfolio is -0.23% annually. This difference is statistically significant for all the rebalancing periods for the value weighted portfolios.

6 Do Investors Prefer Low R-square Funds?

Our simple model suggests that portfolio managers with more ability will choose a lower R-square strategy. Hence, sophisticated investors should consider past R-squares as well as past performance as an indicator of managerial ability. To examine whether investors do in fact account for differences in R-squares we consider two tests. The first estimates the extent to which funds with lower R-squares charge higher fees. The second estimates the extent to which funds with lower R-squares attract additional investors.

6.1 R-squares and Fees

This section tests the hypothesis that funds with lower R-squares charge higher fees. As we mentioned earlier, we have data on the fees for each hedge fund in the last year of the fund's history, (i.e., the latest year for funds that are still alive). Given this, our tests examine the relation between R-squares, calculated in the past, and the most recent fees.

To test our hypothesis we first sort funds based on their R-squares over their entire history and compare the fees charged by the funds in the low R-square quartile with the fees charged by the funds in the high R-square quartile. As we show in Table 3 (Panel A1), with the stepwise regression model the average Management Fee of the low R-square quartile of funds is 12 basis points higher than the average management fee of the high R-square quartile. This difference is significant at better than the 1% level. When the Fung and Hsieh (2004) model is used to calculate the R-squares, the difference is less (8 basis points in Panel B1), but is still statistically significant (at the 1% level). We also observe differences between the Incentive Fees of low and high R-square funds. The low R-square funds (as calculated from stepwise regressions) charge on average 385 basis points more than the high R-square funds (Panel A1 of Table 3) and 184 basis points more when the Fung and Hsieh (2004) model is used. These differences are statistically significant in both cases.

In our multivariate analysis we regress fees on the past R-squares along with past performance and other fund characteristics, such as size, age, investment style and the presence of share restrictions. To enable comparisons between the importance of past R-squares versus measures of performance in determining the fees, we normalize both the R-squares and the measures of performance in these regressions, transforming them into standard normal variables with a mean of zero and a standard deviation of one. These regressions, which we present in Table 7, indicate that R-squares are strongly negatively related to fees (both management and incentive fees), even after controlling for these other characteristics. The magnitude of the coefficient of the past R-square rank is about twice as large as that of the coefficients on past Sharpe ratios, about the same magnitude as the coefficient on past returns, and in some of the models adding R-square as an explanatory variable completely subsumes the statistical significance of the performance measures (e.g. in the Models 3 and 4 of Incentive Fees where the R-square are calculated relative to the Fung and Hsieh (2004) model).

6.2 R-squares and Flows

This subsection tests the hypothesis that lower R-square funds attract more investors. To do so, we analyze the relationship between the R-squares calculated using the prior two years of history of each fund, and the net flows into the fund in the subsequent year. Specifically, we run a Fama-MacBeth regression, similar to regressions estimated in Sirri and Tufano's (1998) analysis of inflows into mutual funds, that includes the past R-squares along with controls for past and current performance, strategy, age of the fund, past volatility, size and whether the fund has lock-ups.

The estimates from these regressions, presented in Table 8, indicate that funds with lower past R-squares attract more new capital. These estimates indicate that a decrease of 10% in the R-square leads to a 1 percentage point increase in the subsequent year's flow. To understand the magnitude of this effect, we note first that the annual inflows in our sample, calculated from January-to-December each year, have a mean of about 29% of assets under management (median of 23%) across the years 1996 to 2005. Hence our results on the relationship between inflows may be interpreted as follows: for two funds that are otherwise identical except for the estimate R-square of one is 10% lower, and managing \$100 million each, the average flow next year will be \$29 million; the lower R-square fund, however, will get \$1 million more than the higher R-square fund. A 10% drop in R-square, therefore, is associated with a $1/29 \approx 3.45\%$ relative difference in flows.

7 Conclusions

As the hedge fund industry grows there is an increased interest in developing criteria for picking talented hedge fund managers. Given that special ability, if it exists, should persist, past performance is likely to be the most important criteria for selecting a hedge fund. However, it is not the only criteria that is used in practice.

In practice, fund of funds and consultants that evaluate hedge funds consider a number of characteristics that can potentially be indicators of future performance. Most of these indicators are based on relatively soft information, like the integrity of the hedge fund managers, and cannot be evaluated in a back test. However, the extent to which funds hedge out their factor risk is something that can be estimated, and as we argue in this paper, hedge fund managers with more confidence in their abilities will expose their investors to less factor risk.

We tested this hypothesis and found that the degree to which hedge funds hedge their factor exposures is indeed indicative of future performance. Furthermore, the evidence suggests that there are investors who recognize that low R-square funds are likely to be better performers. Specifically, we found that lower R-square funds charge higher fees and attract more capital, even after controlling for their past performance.

There were a couple of issues raised in this study that may warrant further research. The first issue stems from the observation that a portfolio of low R-square funds still has substantial volatility that cannot be explained by our common factors. This evidence suggests that although these low R-square funds seem to have very low correlation with the large group of common factors that we have included in our study, the funds tend to be correlated with each other. This observation is consistent with the presence of additional common factors that the hedge funds tend to be exposed to, or alternatively, to hedge funds following similar strategies that time their exposures to the factors.

Finally, we postulated and tested that the ability to hedge systematic factor exposures is an indicator of a manager's talent and should thus be reflected in the manager's performance. Hedging is a skill that sophisticated investors are likely to possess. Future research may identify other such skills, that contribute to the investment process, that can be back tested as performance predictors.

Bibliography

Agarwal, V. and N. Naik, 2004, 'Risks and Portfolio Decisions Involving Hedge Funds', *Review of Financial Studies*, 17, 63-98.

Agarwal, V., N.D. Daniel and N. Naik, 2006, 'Role of managerial incentives and discretion in hedge fund performance', *SSRN working paper*

Aragon, G., 2007, 'Share restrictions and asset pricing: evidence from the hedge fund industry', *Journal of Financial Economics*, 83, 33-58

Almazan, A., K. C. Brown, M. Carlson and D. A. Chapman, 2004, 'Why Constrain your Mutual Fund Manager?', *Journal of Financial Economics*, 73, 289-321

Amenc, N., S. Curtis and L. Martellini, 2003, 'The Alpha and the Omega of Hedge Funds Performance', *working paper*, EDHEC

Asness, C., Krail, R. and J. Liew, 2002, 'Do Hedge Funds Hedge?', *The Journal of Portfolio Management* 28, 6–19

Berk, J. and Green, R., 2004, 'Mutual Fund Flows and Performance in Rational Markets', *Journal of Political Economy* 112, 1269-1295.

Boyson, N., 2004, 'Hedge Fund Career Concerns', *working paper*, Northeastern University

Brealey, R. and E. Kaplanis, 2001, 'Changes in Factor Exposures of Hedge Funds', *working paper*, London School of Business

Brown, S., Goetzmann, W., Ibbotson, R. and S. Ross, 1992, 'Survivorship Bias in Performance Studies', *Review of Financial Studies* 5, 553–580.

Brown, S., Goetzmann, W. and J. Park, 2001, 'Careers and Survival: Competition and Risks in the Hedge Fund and CTA Industry', Journal of Finance 56, 1869–1886.

Brown, K. C. and W. V. Harlow, 2006, 'The Right Answer to the Wrong Question: Identifying Superior Active Portfolio Management', *Journal of Investment Management*, Fourth Quarter

Carhart, M., 1997, 'On Mutual Funds Performance Persistence', *Journal of Finance*, 52, 57-82

Choudhury, A. H., S. Power and R. D. St. Louis, 1996, 'Convenient Methods for Estimation of Linear Regression Models with MA(q) Disturbances', *The Canadian Journal of Economics*, 29, 309-317

Cremers, M., and A. Petajisto, 2006, 'How Active is Your Fund Manager?: A New Measure That Predicts Performance', *Working* paper, Yale School of Management.

Daniel, K., M. Grinblatt, S. Titman and R. Wermers, 1997, 'Measuring mutual fund performance with characteristic-based benchmarks', *Journal of Finance* 52, 1-33

deFigueiredo, R and R. Meredith, 2005, 'Understanding Hedge Fund Returns: A Factor Approach', *working paper*, Citigroup Alternative Investments.

De Souza, C. and S. Gokcan, 2003, 'How Hedge Fund Characteristics Impact Performance', *AIMA Journal*

Ding, B., M. Getmansky, B. Liang and R. Wermers, 2007, 'Investor Flows and Share Restrictions in the Hedge Funds Industry', *working paper*

Fama, E. F. and K.R. French, 1993, 'Common risk factors in the returns on stocks and bonds', *Journal of Financial Economics* 33, 3-56

Fung, W. and D. Hsieh, 1997a, 'Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds', *Review of Financial Studies* 10, 275–302.

Fung, W. and D. Hsieh, 1997b, 'Investment Style and Survivorship Bias in the Returns of CTAs: The Information Content of Track Records', *Journal of Portfolio Management* 24, 30–41.

Fung, W. and D. Hsieh, 1999, 'A Primer on Hedge Funds', *Journal of Empirical Finance* 6, 309–31.

Fung, W. and D. Hsieh, 2000, 'Performance Characteristics of Hedge Funds and Commodity Funds: Natural versus Spurious Biases', *Journal of Financial and Quantitative Analysis* 35, 291–307.

Fung, W. and D. Hsieh, 2001, 'The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers', *Review of Financial Studies* 14, 313–341.

Fung, W. and D. Hsieh, 2002, 'Asset-Based Style Factors for Hedge Funds', *Financial Analysts Journal* 58, 16–27.

Fung, W. and D. Hsieh, 2004, 'Hedge Fund Benchmarks: A Risk Based Approach', *Financial Analyst Journal*, 60, 65-80

Fung, W., D. Hsieh, N. Y. Naik and T. Ramadorai, 2008, 'Hedge Funds: Performance, Risk and Capital Formation', *Forthcoming in the Journal of Finance*

Glosten, L.R. and R. Jagannathan (1994), 'A Contingent Claim Approach to Performance Evaluation', *Journal of Empirical Finance* 1, 133-160

Goetzmann, W., Ingersoll R. and S. Ross (2004), 'High-Water Marks and Hedge Fund Management Contracts', *Journal of Finance* 58, 1685-1717

Gregoriou, G. N. and F. Rouah, 2002, 'Large Versus Small Hedge Funds: Does Size Affect Performance?', *The Journal of Alternative Investments*

Griffin, J, and Xu, J, 2008, 'How smart are the smart guys?', *Forthcoming in the Review of Financial Studies*

Henriksson, R.D. and Merton, R.C., 1981, 'On Market Timing and Investment Performance II: Statistical Procedure for Evaluating Forecasting Skills', *Journal of Business* 54, 513-533.

Jagannathan, R., A. Malakhov and D. Novikov, 2007, 'Do Hot Hands Exist Among Hedge Fund Managers? An Empirical Evaluation ', *NBER working paper*

Jegadeesh, N. and S. Titman, 1993, 'Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency', *Journal of Finance* 48, 65-91

Jobson, J. D. and B. M. Korkie, 1981, 'Performance Hypothesis Testing with the Sharpe and Treynor Measures', *Journal of Finance* 36, 889-908

Kacperczyk, M., C. Sialm, and L. Zheng, 2005, 'On the Industry Concentration of Actively Man- aged Equity Mutual Funds', *J*ournal of Finance 60, 1983–2012.

Kat, A. and F. Menexe, 2003, 'Persistence in Hedge Fund Performance: the True Value of a Track Record', *Journal of Alternative Investments*

Kazemi, H., G. Martin and T. Schneeweis, 2002, 'Understanding Hedge Funds Performance: Research Issues Revisited', *The Journal of Alternative Investments*, Winter 2002

Kazemi, H. and T. Schneeweis, 2003, 'Conditional Performance of Hedge Funds', *University of Massachussetts at Amherst working paper*

Koh, F., W. T. H. Koh and M. Teo, 2003, 'Asian Hedge Funds: Return Persistence, Style and Fund Characteristics', *working paper*

Kosowski, R., N. Y. Naik and M. Teo, 2007, 'Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Approach', *Journal of Financial Economics*, 84, 229-264

Liang, B., 1999, 'On the Performance of Hedge Funds', *Financial Analysts Journal* 55, 72–85.

Liang, B., 2000, 'Hedge Funds: The Living and the Dead', *Journal of Financial and Quantitative Analysis* 35, 309–326.

Liang, B., 2001, 'Hedge Fund Performance: 1990 — 1999', *Financial Analysts Journal* 57, 11–18.

Lo, A., 2001, 'Risk Management For Hedge Funds: Introduction and Overview',*Financial Analysts Journal* 57, 16–33.

Lo, A., 2002, 'The Statistics of Sharpe Ratios', *Financial Analysts Journal* 58, 36–50.

Memmel, C.,2003, 'Performance Hypothesis Testing with the Sharpe Ratio', *Finance Letters* 1, 2123.

Mitchell, M. and T. Pulvino, 2001, 'Characteristics of Risk and Return in Risk Arbitrage',*Journal of Finance*

Novikov, D., 2004, 'Do Hedge Fund Managers Have Hot Hands', *working paper*, Northwestern University

Posthuma, N. and P.J. van der Sluis, 'A Reality Check on Hedge Funds Returns', *SSRN working paper*, 2003

Schneeweis, T. and R. Spurgin, 1998, 'Multi-Factor Analysis of Hedge Fund, Managed Futures and Mutual Fund Return and Risk Characteristics', *working paper*, University of Massachusetts at Amherst

Sharpe, W., 1992, 'Asset Allocation: Management Style and Performance Measurement', *Journal of Portfolio management* 18, 7-19.

Sirri, E. and P. Tufano, 1998, 'Costly Search and Mutual Fund Flows', *Journal of Finance* 53, 1589-1622.

Treynor, J. L. and F. Black, 1973, 'How to Use Security Analysis to Improve Portfolio Selection', *Journal of Business*, January, 66-88

Treynor, J.L. and K.K. Mazuy, 1966, 'Can Mutual Funds Outguess the Market?', *Harvard Business Review*, 44, July-August, 131-136

Table 1: Fund Characteristics

The table presents summary statistics of fund characteristics of the entire hedge fund universe , including defunct funds, as of December 2005. We eliminate the first 27 months from the history of each fund to correct for backfilling bias. We only include the funds which reach $ 30 million in assets only after they reach this limit. We further require each fund to have at least 24 months of history.

Variable	Mean	StdDev	Min	10%	25%	Median	75%	90%	Max
All Funds									
Management Fee (%)	1.35	0.74	0.00	0.80	1.00	1.25	1.60	2.00	15.00
Incentive Fee (%)	15.34	7.86	0.00	0.00	10.00	20.00	20.00	20.00	50.00
Size ($ mil.)	211.40	405.49	3.63	30.82	48.53	95.71	212.18	481.21	7376.91
Lockup (months)	3.96	7.29	0.00	0.00	0.00	0.00	12.00	12.00	90.00
Redemptions Notice (days)	38.10	28.00	0.00	5.00	25.00	30.00	60.00	90.00	365.00
Life in the sample (months)	63.89	31.76	24.00	27.00	36.00	57.00	89.00	118.00	167.00
No. Funds									3,762
No. Companies									1,706
Directional Traders									
Management Fee (%)	1.35	0.58	0.00	1.00	1.00	1.25	1.50	2.00	6.00
Incentive Fee (%)	17.36	6.46	0.00	5.30	20.00	20.00	20.00	20.00	50.00
Size ($ mil.)	159.53	256.74	5.71	29.33	44.66	80.39	179.96	367.50	3861.79
Lockup (months)	4.76	7.82	0.00	0.00	0.00	0.00	12.00	12.00	60.00
Redemptions Notice (days)	32.38	22.66	0.00	5.00	15.00	30.00	45.00	60.00	120.00
Life in the sample (months)	58.44	30.22	24.00	27.00	33.00	48.00	81.00	108.90	120.00
No. Funds									566
No. Companies									360

Continued on the next page ...

Table 1 (cont.): Fund Characteristics

Variable	Mean	StdDev	Min	10%	25%	Median	75%	90%	Max
Relative Value									
Management Fee (%)	1.29	0.83	0.00	0.73	1.00	1.00	1.54	2.00	15.00
Incentive Fee (%)	17.77	6.80	0.00	0.00	20.00	20.00	20.00	20.00	50.00
Size ($ mil.)	243.76	452.25	3.63	34.20	55.50	113.63	250.84	573.04	7376.91
Lockup (months)	3.92	6.62	0.00	0.00	0.00	0.00	12.00	12.00	36.00
Redemptions Notice (days)	43.18	31.95	0.00	14.00	30.00	30.00	60.00	90.00	365.00
Life in the sample (months)	61.09	30.97	24.00	28.00	35.00	51.00	89.00	112.00	139.00
No. Funds									541
No. Companies									312
Security Selection									
Management Fee (%)	1.23	0.55	0.00	1.00	1.00	1.00	1.50	2.00	4.00
Incentive Fee (%)	17.59	6.35	0.00	5.00	20.00	20.00	20.00	20.00	50.00
Size ($ mil.)	194.10	321.85	4.32	28.41	44.40	87.80	202.91	430.63	3989.42
Lockup (months)	4.33	6.44	0.00	0.00	0.00	0.00	12.00	12.00	36.00
Redemptions Notice (days)	32.48	23.47	0.00	5.00	20.00	30.00	45.00	60.00	180.00
Life in the sample (months)	66.14	30.74	24.00	29.00	38.00	60.00	87.00	119.00	120.00
No. Funds									952
No. Companies									569

Continued on the next page . . .

Table 1 (cont.): Fund Characteristics

Variable	Mean	StdDev	Min	10%	25%	Median	75%	90%	Max
Multiprocess									
Management Fee (%)	1.24	0.53	0.00	0.80	1.00	1.00	1.50	2.00	3.00
Incentive Fee (%)	17.78	6.48	0.00	5.00	20.00	20.00	20.00	20.00	50.00
Size ($ mil.)	265.11	548.51	12.44	35.35	55.44	108.02	237.38	520.30	6795.30
Lockup (months)	7.00	9.36	0.00	0.00	0.00	1.50	12.00	12.00	90.00
Redemptions Notice (days)	43.08	25.27	0.00	10.80	30.00	30.00	60.00	90.00	120.00
Life in the sample (months)	66.90	33.74	24.00	27.00	35.75	59.00	102.00	120.00	120.00
No. Funds									309
No. Companies									208
Fund of Funds									
Management Fee (%)	1.27	0.56	0.00	0.62	1.00	1.25	1.50	2.00	4.00
Incentive Fee (%)	7.75	7.02	0.00	0.00	0.00	10.00	10.00	20.00	50.00
Size ($ mil.)	266.01	535.24	30.20	41.74	63.14	117.79	249.86	570.38	7194.68
Lockup (months)	3.04	7.88	0.00	0.00	0.00	0.00	0.00	12.00	72.00
Redemptions Notice (days)	49.61	31.03	0.00	15.00	30.00	45.00	60.00	90.00	365.00
Life in the sample (months)	60.30	31.08	24.00	26.00	34.00	51.00	82.00	114.00	157.00
Number of Underlying Funds	28.17	21.02	0.00	10.00	15.00	25.00	34.25	50.80	200.00
No. Funds									855
No. Companies									793

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Table 1 (cont.): Fund Characteristics

Variable	Mean	StdDev	Min	10%	25%	Median	75%	90%	Max
Funds larger than $ 200 mil.									
Management Fee (%)	1.33	0.81	0.00	0.50	1.00	1.25	1.50	2.00	15.00
Incentive Fee (%)	15.14	8.09	0.00	0.00	10.00	20.00	20.00	20.00	33.00
Size ($ mil.)	576.08	654.80	200.09	222.94	258.10	366.95	628.30	1145.60	7376.91
Lockup (months)	3.18	6.70	0.00	0.00	0.00	0.00	0.00	12.00	72.00
Redemptions Notice (days)	40.07	34.07	0.00	5.00	20.00	30.00	60.00	90.00	365.00
Life in the sample (months)	68.35	32.93	24.00	29.00	38.00	61.00	98.00	120.00	155.00
No. Funds									1,004
No. Companies									733

Table 2: Summary statistics of factor models

The table presents summary statistics of Sharpe ratios (SR), as well as of adjusted R-squares, alphas (α), tracking errors (TE), information ratios (IR) and, when the model employed is the stepwise regression, summary statistics on the number of factors included. All the performance measures are annualized. The R-squares are calculated from the factor models of Fung and Hsieh (2004) and, respectively, stepwise regressions to the entire history of funds with more than 27 months of history and which reached more \$ 30 million in assets in our sample. Funds are divided by strategy type. We also present summary statistics for the larger funds (funds that reached \$ 200 million in assets in our sample). The model (4) cannot be estimated for 81 of our total of 3,762 funds.

	Stepwise					Fung and Hsieh				
	Mean	StDev	25%	Median	75%	Mean	StDev	25%	Median	75%
					All Funds (3,681 funds, 1,796 companies)					
R-square	0.43	0.25	0.24	0.42	0.61	0.26	0.13	0.16	0.24	0.34
SR	0.88	1.13	0.38	0.72	1.16	0.88	1.13	0.38	0.72	1.16
α	0.04	0.11	-0.00	0.03	0.06	0.05	0.11	0.01	0.04	0.08
TE	0.08	0.09	0.03	0.05	0.10	0.09	0.08	0.04	0.07	0.11
IR	0.62	1.66	-0.08	0.48	1.08	0.71	1.18	0.19	0.64	1.14
No. factors	3.29	1.85	2	3	4	–	–	–	–	–
					Directional Funds (566 funds, 360 companies)					
R-square	0.55	0.21	0.41	0.55	0.71	0.28	0.13	0.19	0.28	0.36
SR	0.69	0.64	0.32	0.63	1.02	0.69	0.64	0.32	0.63	1.02
α	0.06	0.18	0.00	0.05	0.11	0.07	0.14	0.01	0.06	0.12
TE	0.12	0.09	0.05	0.09	0.15	0.15	0.11	0.08	0.12	0.19
IR	0.56	1.44	0.04	0.54	1.08	0.50	0.93	0.15	0.50	0.91
No. factors	3.46	1.75	2	3	5	–	–	–	–	–
					Relative Value (541 funds, 312 companies)					
R-square	0.34	0.26	0.14	0.32	0.51	0.21	0.14	0.11	0.18	0.28
SR	0.86	1.10	0.28	0.74	1.25	0.86	1.10	0.28	0.74	1.25
α	0.03	0.07	-0.00	0.03	0.06	0.04	0.07	0.01	0.03	0.06
TE	0.05	0.04	0.02	0.04	0.06	0.05	0.05	0.03	0.04	0.07
IR	0.88	2.02	-0.07	0.70	1.55	0.96	1.68	0.15	0.79	1.52
No. factors	2.57	1.67	1	2	4	–	–	–	–	–
					Security Selection (952 funds, 569 companies)					
R-square	0.53	0.25	0.37	0.55	0.73	0.25	0.13	0.15	0.23	0.33
SR	0.83	0.73	0.44	0.74	1.09	0.83	0.73	0.44	0.74	1.09
α	0.05	0.13	-0.00	0.03	0.08	0.07	0.13	0.02	0.05	0.10
TE	0.08	0.07	0.04	0.06	0.10	0.11	0.09	0.06	0.09	0.14
IR	0.61	1.51	-0.05	0.55	1.28	0.73	1.08	0.26	0.66	1.12
No. factors	3.53	1.87	2	3	5	–	–	–	–	–
					Multiprocess (309 funds, 208 companies)					
R-square	0.44	0.23	0.27	0.43	0.60	0.26	0.14	0.14	0.24	0.34
SR	0.97	0.71	0.58	0.87	1.34	0.97	0.71	0.58	0.87	1.34
α	0.05	0.09	0.01	0.04	0.08	0.06	0.07	0.02	0.05	0.09
TE	0.06	0.04	0.03	0.05	0.08	0.07	0.05	0.04	0.06	0.09
IR	1.00	1.31	0.28	0.85	1.52	1.02	0.98	0.40	0.85	1.45
No. factors	3.45	1.95	2	3	4	–	–	–	–	–
					Fund of Funds (855 funds, 793 companies)					
R-square	0.64	0.24	0.48	0.67	0.85	0.28	0.12	0.19	0.26	0.34
SR	0.91	0.68	0.50	0.83	1.23	0.91	0.68	0.50	0.83	1.23
α	0.01	0.06	-0.01	0.01	0.03	0.03	0.08	0.01	0.02	0.05
TE	0.03	0.03	0.02	0.02	0.04	0.06	0.05	0.02	0.04	0.08
IR	0.16	2.10	-0.56	0.41	1.19	0.59	1.08	0.11	0.60	1.06
No. factors	3.55	1.87	2	3	5	–	–	–	–	–

Table 3: Low vs. High R-square funds

The table presents average Sharpe ratios (SR), alphas (α), information ratios (IR), fees and length of histories for funds in the low R-square quartile, respectively high R-square quartile as well as their differences. Performance statistics are annualized. t-stats of the averages as well as t-stats of the differences are reported. Wilcoxon p-values of a test of difference in medians of the Sharpe ratios, alphas, information ratios, fees and length of histories between the low and respectively the high R-square quartiles are reported as well.

Panel A1. The stepwise regression model - all funds

R^2 percentile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	1.04	1.10	0.06	1.41	16.84	86.59
75%	Mean	0.78	-0.13	0.00	1.29	12.99	55.50
25 − 75%	Mean Dif.	0.25	1.23	0.06	0.12	3.85	31.09
	tstat	6.83	16.76	14.37	3.90	10.75	18.18
25 − 75%	Wilcoxon p	0.000	0.000	0.000	0.000	0.000	0.000

Panel B1. The Fung and Hsieh seven factors model - all funds

R^2 percentile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	0.98	0.93	0.06	1.41	16.20	84.59
75%	Mean	0.76	0.57	0.04	1.32	14.36	60.44
25 − 75%	Mean Dif.	0.23	0.36	0.02	0.08	1.84	24.16
	tstat	5.96	7.58	4.09	2.50	5.02	13.20
25 − 75%	Wilcoxon p	0.000	0.000	0.000	0.000	0.000	0.000

Panel A2. The stepwise regression model - Security Selection

R^2 percentile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	1.13	1.17	0.07	1.43	17.75	89.42
75%	Mean	0.77	-0.00	0.01	1.26	16.57	64.35
25 − 75%	Mean Dif.	0.36	1.18	0.06	0.17	1.18	25.07
	tstat	4.68	8.91	6.65	2.94	1.79	6.78
25 − 75%	Wilcoxon p	0.001	0.000	0.000	0.007	0.005	0.000

Panel B2. The Fung and Hsieh seven factors model - Security Selection

R^2 percentile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	1.05	1.10	0.09	1.40	18.08	92.57
75%	Mean	0.72	0.63	0.07	1.19	17.39	68.11
25 − 75%	Mean Dif.	0.33	0.48	0.02	0.21	0.69	24.46
	tstat	5.15	5.59	1.54	3.98	1.16	6.38
25 − 75%	Wilcoxon p	0.000	0.000	0.110	0.000	0.101	0.000

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Table 3 (cont.): Low vs. High R-square funds

Panel A3. The stepwise regression model - Directional

R^2 percentile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	0.67	0.66	0.10	1.76	18.71	95.35
75%	Mean	0.87	0.41	0.01	1.38	16.15	52.69
25 − 75%	Mean Dif.	-0.20	0.25	0.09	0.38	2.57	42.67
	tstat	-1.10	1.64	5.92	4.51	3.71	11.17
25 − 75%	Wilcoxon p	0.301	0.071	0.000	0.000	0.003	0.000

Panel B3. The Fung and Hsieh seven factors model - Directional

R^2 percentile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	0.83	0.61	0.10	1.48	18.03	91.67
75%	Mean	0.59	0.51	0.06	1.57	17.69	62.37
25 − 75%	Mean Dif.	0.24	0.10	0.04	-0.09	0.34	29.30
	tstat	3.82	1.11	2.63	-0.96	0.51	6.94
25 − 75%	Wilcoxon p	0.000	0.094	0.061	0.778	0.946	0.000

Panel A4. The stepwise regression model - Multiprocess

R^2 percentile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	1.11	1.20	0.08	1.35	19.38	83.18
75%	Mean	0.88	1.13	0.03	1.09	16.90	68.43
25 − 75%	Mean Dif.	0.23	0.07	0.05	0.26	2.47	14.75
	tstat	2.92	0.32	3.81	3.01	2.31	2.16
25 − 75%	Wilcoxon p	0.097	0.401	0.000	0.006	0.012	0.000

Panel B4. The Fung and Hsieh seven factors model - Multiprocess

R^2 percentile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	1.16	1.31	0.08	1.39	19.10	82.13
75%	Mean	0.79	0.72	0.03	1.07	16.90	60.35
25 − 75%	Mean Dif.	0.36	0.59	0.05	0.32	2.19	21.78
	tstat	3.09	4.03	5.82	3.57	2.00	3.44
25 − 75%	Wilcoxon p	0.006	0.000	0.000	0.000	0.016	0.000

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Table 3 (cont.): Low vs. High R-square funds

Panel A5. The stepwise regression model - Relative Value

R^2 percentile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	1.07	1.23	0.05	1.54	18.67	73.13
75%	Mean	0.82	0.87	0.02	1.46	17.50	50.77
25 − 75%	Mean Dif.	0.25	0.36	0.03	0.08	1.17	22.35
	tstat	2.99	1.52	3.72	0.62	1.65	5.90
25 − 75%	Wilcoxon p	0.078	0.002	0.000	0.083	0.028	0.000

Panel B5. The Fung and Hsieh seven factors model - Relative Value

R^2 percentile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	0.99	1.11	0.05	1.50	18.30	62.84
75%	Mean	0.96	0.92	0.03	1.41	18.08	55.08
25 − 75%	Mean Dif.	0.03	0.18	0.01	0.09	0.22	7.76
	tstat	2.27	1.09	1.48	0.77	2.30	2.00
25 − 75%	Wilcoxon p	0.076	0.225	0.389	0.002	0.023	0.000

Panel A6. The stepwise regression model - Fund of Funds

R^2 prrcrntile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	1.17	1.18	0.04	1.27	7.86	91.61
75%	Mean	0.72	-1.02	-0.02	1.31	8.60	45.95
25 − 75%	Mean Dif.	0.45	2.20	0.06	-0.03	-0.74	45.66
	tstat	7.55	14.35	10.35	-0.63	-1.16	17.54
25 − 75%	Wilcoxon p	0.000	0.000	0.000	0.481	0.081	0.000

Panel B6. The Fung and Hsieh seven factors model - Fund of Funds

R^2 percentile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	0.88	0.60	0.02	1.29	9.14	77.39
75%	Mean	0.82	0.44	0.02	1.24	8.36	52.07
25 − 75%	Mean Dif.	0.06	0.16	0.01	0.05	0.79	25.32
	tstat	2.94	3.82	2.22	0.86	1.22	3.77
25 − 75%	Wilcoxon p	0.065	0.086	0.004	0.061	0.187	0.000

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Table 3 (cont.): Low vs. High R-square funds - large funds, stepwise regression model

Panel C. Over $ 200 million assets under management (1,081 funds)

R^2 percentile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	1.17	1.31	0.06	1.35	16.31	87.43
75%	Mean	0.84	0.14	0.01	1.27	13.04	60.33
25 − 75%	Mean Dif.	0.33	1.17	0.05	0.08	3.27	27.11
	tstat	4.79	9.68	8.04	1.41	4.84	8.19
25 − 75%	Wilcoxon p	0.000	0.000	0.000	0.307	0.000	0.000

Panel D. Over $ 1 billion assets under management (107 funds)

R^2 percentile		**SR**	**IR**	α	**M.Fee** (in %)	**I.Fee** (in %)	**Life** (in mths.)
25%	Mean	1.15	1.39	0.07	1.39	15.26	101.89
75%	Mean	0.92	0.75	0.02	1.06	10.43	80.15
25 − 75%	Mean Dif.	0.23	0.64	0.05	0.33	4.83	21.74
	tstat	1.04	1.52	2.60	1.71	2.30	1.98
25 − 75%	Wilcoxon p	0.307	0.097	0.005	0.153	0.012	0.000

Table 4: Past R-squares and Future Performance: Fama-MacBeth regressions

The table presents the results of running a Fama-MacBeth regression of model (5).
Each month t, we run stepwise regressions on the returns of each hedge fund on the time interval $[t-23:t]$ on the returns of the explanatory factors on the time interval $[t-23:t]$ (with unsmoothing). The R-squares of these regressions are denoted by $R^2_{t-23:t}$. We then ran Fama-MacBeth regressions of the performance $Perf$ of each fund on the time period $[t+1:t+12]$ on $R^2_{t-23:t}$. $Perf$ may be the Sharpe ratio or the raw returns of the fund. The controls are as follows: $Std_{t-23:t}$ is the volatility of the fund on the interval $[t-23:t]$. The controls for past returns and past Sharpe ratios, $\widetilde{Ret}_{t-23:t}$ and $\widetilde{SR}_{t-23:t}$, respectively are obtained by taking the residuals from regressions of past returns $Ret_{t-23:t}$ and respectively past Sharpe ratios $SR_{t-23:t}$ on the past R-squares $R^2_{t-23:t}$. $\log(AUM_t)$ is the logarithm of the assets under management at time t. $\log(Age_t)$ is the logarithm of the age of the fund at time t. FOF is a fund of funds dummy. $mfee$ and $ifee$ represent the management, respectively the incentive fees charged by the fund. $Offshore$ a dummy variable equal to 1 if the fund if an Offshore fund. $LockupPeriod$ represents the logarithm of $(1+lockup)$, where $lockup$ is expressed in months. Four strategy dummies are included (Directional, Relative Value, Security Selection and Multiprocess). The fifth category of funds is the funds not classified. The regressions include a constant term. t-statistics are Newey-West.

Panel A. The stepwise regression model with unsmoothing

Dependent Variable: **Sharpe ratio** on $[t+1:t+12]$

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$R^2_{t-23:t}$	-0.1239	-0.1093	-0.1460	-0.1592	-0.1546	-0.1349
t-stat	-2.7962	-2.5751	-3.1762	-4.5029	-4.2624	-4.4271
$Std_{t-23:t}$	-2.7965	-3.8827	-1.6018	-1.3552	-1.9073	-1.3499
t-stat	-5.8854	-6.7821	-3.0477	-2.9777	-3.6507	-2.8288
$\widetilde{SR}_{t-23:t}$			0.5071	0.5019	0.4851	0.4998
t-stat			24.0851	22.9923	12.6677	11.2627
$\widetilde{Ret}_{t-23:t}$		0.2138				
t-stat		4.8810				
$\log(AUM_t)$				0.0110	0.0103	0.0100
t-stat				2.8134	2.4653	2.5951
$\log(Age_t)$				0.0774	-0.0414	-0.0416
t-stat				1.1631	-1.6045	-1.6943
Fixed Fund Characts.						
FOF				0.0614	0.0521	0.0537
t-stat				2.1986	1.8836	1.9013
$mfee$				-0.0140	-0.0081	-0.0027
t-stat				-1.0733	-0.8747	-0.4030
$ifee$				0.0012	0.0012	0.0011
t-stat				1.4492	1.5659	1.4856
Offshore					0.0153	0.0134
t-stat					1.5984	1.4052
LockupPeriod					0.0083	0.0052
t-stat					1.4910	1.0297
Category Dummies						
Dir.						-0.0824
t-stat						-2.6032
Rel. Val.						0.0197
t-stat						0.4870
Sec. Sel.						-0.0751
t-stat						-1.8517
Multiproc.						0.0206
t-stat						0.4801
Avg. adj. R^2	4.66%	8.90%	17.29%	20.03%	18.73%	22.92%

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Table 4 (cont.): Past R-squares and Future Performance: Fama-MacBeth regressions

Panel B. The stepwise regression model with unsmoothing

Dependent Variable: **Returns** on $[t+1:t+12]$

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$R^2_{t-23:t}$	-0.0514	-0.0415	-0.0555	-0.0448	-0.0223	-0.0199
t-stat	-2.7268	-2.2625	-2.8589	-2.2483	-2.3652	-2.8711
$Std_{t-23:t}$	1.8786	0.9879	2.1960	1.1428	1.2122	1.2730
t-stat	3.3276	2.5277	3.2774	2.6556	2.9839	2.7807
$\widetilde{SR}_{t-23:t}$			0.1293			
t-stat			2.6785			
$\widetilde{Ret}_{t-23:t}$		0.1734		0.1521	0.0356	0.0302
t-stat		2.7019		2.8111	1.8680	1.7926
$\log(AUM_t)$				0.0015	-0.0052	-0.0050
t-stat				0.9704	-2.6627	-2.7168
$\log(Age_t)$				0.0969	0.0077	0.0048
t-stat				1.7675	0.5916	0.3895
Fixed Fund Characts.						
FOF				0.0241	-0.0052	-0.0061
t-stat				2.3466	-0.7563	-1.0644
$mfee$				-0.0054	0.0031	0.0059
t-stat				-0.5192	0.6265	1.5272
$ifee$				0.0008	0.0001	0.0001
t-stat				2.2066	0.4755	0.4575
Offshore					0.0102	0.0127
t-stat					1.9227	3.0144
LockupPeriod					0.0101	0.0091
t-stat					3.3279	3.0856
Category Dummies						
Dir.						-0.0142
t-stat						-0.8375
Rel. Val.						0.0007
t-stat						0.0991
Sec. Sel.						0.0196
t-stat						1.2232
Multiproc.						0.0067
t-stat						0.8214
Avg. adj. R^2	5.87%	9.29%	9.29%	18.43%	12.85%	16.46%

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Table 4 (cont.): Past R-squares and Future Performance: Fama-MacBeth regressions

Panel C. The Fung Hsieh model

Dependent Variable: **Sharpe ratio** on $[t+1:t+12]$

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$R^2_{t-23:t}$	-0.1043	-0.0912	-0.1224	-0.1267	-0.1375	-0.1161
t-stat	-2.5718	-2.5380	-2.8516	-3.5648	-2.8773	-2.8251
$Std_{t-23:t}$	-2.8964	-3.9626	-1.6206	-1.3788	-2.0373	-1.5037
t-stat	-5.8728	-6.9309	-3.0097	-2.8669	-3.4121	-2.9796
$\widetilde{SR}_{t-23:t}$			0.5077	0.5041	0.4840	0.4997
t-stat			23.5616	22.8248	11.7451	10.7115
$\widetilde{Ret}_{t-23:t}$		0.2143				
t-stat		4.7912				
$\log(AUM_t)$				0.0109	0.0098	0.0100
t-stat				2.8096	2.2130	2.4044
$\log(Age_t)$				0.0768	-0.0317	-0.0328
t-stat				1.1600	-1.4121	-1.5146
Fixed Fund Characts.						
FOF				0.0608	0.0305	0.0381
t-stat				2.1706	1.2496	1.4764
$mfee$				-0.0127	0.0010	0.0047
t-stat				-0.9005	0.0954	0.6537
$ifee$				0.0013	0.0004	0.0005
t-stat				1.4874	0.4682	0.5467
Offshore					0.0154	0.0142
t-stat					1.5758	1.4225
LockupPeriod					0.0189	0.0154
t-stat					2.6464	2.4233
Category Dummies						
Dir.						-0.0783
t-stat						-2.6709
Rel. Val.						0.0177
t-stat						0.4360
Sec. Sel.						-0.0742
t-stat						-1.6875
Multiproc.						0.0072
t-stat						0.1701
Avg. adj. R^2	4.25%	8.60%	17.07%	19.93%	19.23%	23.38%

Continued on the next page ...

Table 4 (cont.): Past R-squares and Future Performance: Fama-MacBeth regressions

Panel D. The Fung Hsieh model

Dependent Variable: **Returns** on $[t+1:t+12]$

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$R^2_{t-23:t}$	-0.0760	-0.0656	-0.0801	-0.0674	-0.0452	-0.0361
t-stat	-2.5824	-2.1985	-2.6892	-2.0700	-3.0539	-3.9953
$Std_{t-23:t}$	1.8653	0.9980	2.1935	1.1577	1.2307	1.2818
t-stat	3.2212	2.4455	3.2099	2.5824	2.8177	2.5634
$\widetilde{SR}_{t-23:t}$			0.1263			
t-stat			2.7159			
$\widetilde{Ret}_{t-23:t}$		0.1720		0.1509	0.0172	0.0078
t-stat		2.7109		2.8300	0.9483	0.3482
$\log(AUM_t)$				0.0018	-0.0005	-0.0003
t-stat				1.0954	-0.4151	-0.3206
$\log(Age_t)$				0.0976	-0.0127	-0.0160
t-stat				1.7765	-1.5067	-1.7309
Fixed Fund Characts.						
FOF				0.0252	0.0011	-0.0003
t-stat				2.3905	0.2548	-0.0700
$mfee$				-0.0050	-0.0026	0.0027
t-stat				-0.4734	-0.2934	0.5694
$ifee$				0.0008	0.0006	0.0007
t-stat				2.0566	1.9684	1.8840
Offshore					-0.0001	0.0036
t-stat					-0.0163	0.6443
LockupPeriod					0.0003	0.0037
t-stat					2.0311	1.4687
Category Dummies						
Dir.						-0.0148
t-stat						-0.6346
Rel. Val.						-0.0097
t-stat						-1.7230
Sec. Sel.						0.0203
t-stat						1.0152
Multiproc.						0.0047
t-stat						0.5367
Avg. adj. R^2	5.80%	9.21%	9.21%	18.50%	12.47%	16.69%

Table 5: Portfolios constructed based on past R-squares

Each month t we sort funds based on their R-square calculated on the period from $t-23$ to t. We form the portfolio of the high, respectively low past R-square funds by taking the funds in the top quartile, respectively the bottom quartile and either equally-weighting or value-weighting them. Portfolio are rebalanced every 1, 3, 6 or 12 months. We report the annual alphas and the annual Sharpe ratios of these portfolios. We also report the average cutoff for low or high R-squares, as well as the R-square of the low/high R-square portfolios. We perform a mean test of differences in alphas and a Jobson and Korkie (1981) test with Memmel (2003) correction of differences in Sharpe ratios between the two portfolios. Panels A and B present these results when the model use to calculate the R-square of the funds is the Stepwise regression; Panels C and D present these results when the rolling R-squares are calculated using the the Fung and Hsieh model. In all the panels, we use the Fung and Hsieh model to estimate the alphas of the resulting portfolios. Each portfolio runs from January 1997 to December 2005.

	1 month				3 months				6 months				12 months			
	av. cutoff	α	SR	port. R^2	av. cutoff	α	SR	port. R^2	av. cutoff	α	SR	port. R^2	av. cutoff	α	SR	port. R^2
Panel A: Stepwise R-squares, Fung and Hsieh portfolio alphas – Value-weighted portfolios																
low R^2 ($R^2 \leq$ cutoff)	37.82%	0.06	1.64	20.45%	37.72%	0.06	1.55	18.54%	37.99%	0.05	1.40	26.27%	37.76%	0.05	1.42	22.13%
t-stat		5.29				5.00				4.48				4.51		
high R^2 ($R^2 \geq$ cutoff)	76.86%	0.03	0.82	30.19%	76.81%	0.03	0.87	29.08%	76.99%	0.03	0.80	28.67%	77.01%	0.02	0.80	30.94%
t-stat		1.28				1.45				1.24				1.12		
low − high R^2		0.03	0.82			0.03	0.68			0.02	0.60			0.03	0.63	
t-stat		1.11				1.00				0.82				1.13		
z_{JK}-stat			5.79				5.49				5.35				5.12	
Panel B: Stepwise R-squares, Fung and Hsieh portfolio alphas – Equally weighted portfolios																
low R^2 ($R^2 \leq$ cutoff)	37.82%	0.07	1.86	23.63%	37.72%	0.07	1.76	27.27%	37.99%	0.07	1.82	27.88%	37.76%	0.07	1.83	27.03%
t-stat		6.12				5.71				5.95				5.88		
high R^2 ($R^2 \geq$ cutoff)	76.86%	0.05	1.06	32.55%	76.81%	0.05	1.09	31.75%	76.99%	0.05	1.05	30.55%	77.01%	0.04	1.01	30.88%
t-stat		2.43				2.50				2.31				2.16		
low − high R^2		0.02	0.80			0.02	0.67			0.02	0.78			0.03	0.82	
t-stat		0.93				0.76				0.89				1.24		
z_{JK}-stat			6.53				6.65				7.18				6.98	
Panel C: Fung and Hsieh R-squares and portfolio alphas– Value-weighted portfolios																
low R^2 ($R^2 \leq$ cutoff)	33.47%	0.05	1.42	22.20%	33.50%	0.05	1.35	20.95%	33.18%	0.05	1.26	25.01%	33.11%	0.05	1.23	20.28%
t-stat		4.02				3.83				3.35				3.14		
high R^2 ($R^2 \geq$ cutoff)	58.05%	0.03	0.99	35.11%	58.02%	0.04	1.12	33.13%	57.89%	0.04	1.08	31.12%	57.56%	0.03	1.02	30.44%
t-stat		1.93				2.43				2.36				2.12		
low − high R^2		0.02	0.43			0.01	0.23			0.01	0.18			0.02	0.21	
t-stat		0.98				0.63				0.46				0.88		
z_{JK}-stat			5.58				4.88				4.67				5.23	
Panel D: Fung and Hsieh R-squares and portfolio alphas– Equally weighted portfolios																
low R^2 ($R^2 \leq$ cutoff)	33.47%	0.07	1.80	26.43%	33.50%	0.07	1.72	25.78%	33.18%	0.07	1.67	27.02%	33.11%	0.07	1.72	25.57%
t-stat		5.88				5.66				5.49				5.41		
high R^2 ($R^2 \geq$ cutoff)	58.05%	0.05	1.20	35.98%	58.02%	0.05	1.27	35.02%	57.89%	0.05	1.25	33.08%	57.56%	0.05	1.19	30.68%
t-stat		2.70				2.93				2.84				2.64		
low − high R^2		0.02	0.60			0.02	0.45			0.02	0.42			0.03	0.52	
t-stat		1.09				0.91				0.87				1.20		
z_{JK}-stat			7.78				7.42				7.21				8.89	

Table 6: Portfolios constructed based on past R-squares – robustness tests

This table is based on a subsample of funds database which are 100% dedicated to equity long short strategies, are focused on U.S. equities in a proportion larger than 75% and do not use derivatives (except futures). Each month t we sort the funds based on their R-square calculated on the period from $t-23$ to t, using the Fama and French (1993) factors along with the Carhart (1994) momentum factor, without corrections for serial correlation. We form the portfolios of the high, respectively low past R-square funds by taking the funds in the top quartile, respectively the bottom quartile and either equally-weighting or value-weighting them. Portfolio are held then rebalanced every 1, 3, 6 or 12 months. We report the annual alphas and the annual Sharpe ratios of these portfolios. We also report the average cutoff for low or high R-squares, as well as the R-square of the low/high R-square portfolios. We perform a mean test of differences in alphas and a Jobson and Korkie (1981) test with Memmel (2003) correction of differences in Sharpe ratios between the two portfolios. Each portfolio runs from January 1997 to December 2005.

	1 month				3 months				6 months				12 months			
	av. cutoff	α	SR	port. R^2	av. cutoff	α	SR	port. R^2	av. cutoff	α	SR	port. R^2	av. cutoff	α	SR	port. R^2
Panel A: Value-weighted portfolios																
low R^2 ($R^2 \leq$ cutoff)	28.03%	0.12	1.19	11.54%	27.36%	0.13	1.34	15.63%	26.86%	0.10	1.24	17.08%	24.76%	0.11	1.13	26.00%
t-stat		2.88				3.14				2.67				2.42		
high R^2 ($R^2 \geq$ cutoff)	66.98%	0.00	0.61	78.94%	66.80%	-0.00	0.50	72.37%	65.94%	-0.00	0.54	71.34%	63.59%	-0.01	0.51	75.88%
t-stat		0.18				-0.15				-0.14				-0.24		
low − high R^2		0.12	0.58			0.13	0.84			0.11	0.70			0.12	0.62	
t-stat		2.53				2.76				2.32				2.26		
z_{JK}-stat			2.98				3.48				3.16				3.30	
Panel B: Equally weighted portfolios																
low R^2 ($R^2 \leq$ cutoff)	28.03%	0.10	1.14	12.23%	27.36%	0.10	1.16	15.94%	26.86%	0.12	1.46	20.85%	24.76%	0.16	1.67	26.09%
t-stat		2.55				2.50				3.36				4.28		
high R^2 ($R^2 \geq$ cutoff)	66.98%	0.01	0.62	69.56%	66.80%	0.00	0.48	63.37%	65.94%	0.01	0.53	62.13%	63.59%	-0.01	0.49	66.51%
t-stat		0.43				0.01				0.16				-0.19		
low − high R^2		0.09	0.53			0.10	0.68			0.11	0.92			0.16	1.18	
t-stat		1.83				1.92				2.29				3.31		
z_{JK}-stat			2.81				2.90				3.59				4.41	

Table 7: Fees and R-squares.

The table presents regressions of fees on R-squares ranks, past fund performance ranks (based on past returns *Ret* or past Sharpe ratios *SR*) and fund characteristics. The fund characteristics used as controls are logarithm of *Age*, logarithm of assets under management *AUM* taken at the time when the fund enters the sample and translated into December 2005 U.S. $, strategy as well as funds of funds dummies and a dummy variable *Locked* which takes the value 1 if the fund has lock-up restrictions. R-squares, returns and Sharpe ratios are standardized variables. The t-statistics are Newey-West.

	Dependent Variable: Incentive Fee							
	Stepwise Regression Model				Fung and Hsieh Model			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Ret	0.4419		0.4410		0.3466		0.3274	
t-stat	3.0955		3.0918		2.3066		2.1800	
SR		0.1598		0.1507		0.1107		0.0684
t-stat		1.3353		1.2599		0.8626		0.5312
R^2			-0.3007	-0.2977			-0.3817	-0.3854
t-stat			-2.7694	-2.7375			-3.2530	-3.2690
$log(Age)$	-0.3199	-0.2546	-0.2536	-0.1899	-0.4662	-0.4013	-0.6425	-0.5902
t-stat	-1.9835	-1.5825	-1.5567	-1.1685	-2.2671	-1.9430	-3.0251	-2.7554
$log(AUM)$	-0.1416	-0.1497	-0.1433	-0.1505	-0.1086	-0.1157	-0.1057	-0.1077
t-stat	-1.1326	-1.1907	-1.1473	-1.1979	-0.8148	-0.8613	-0.7945	-0.8026
$Directional$	0.2327	0.5020	0.3426	0.6096	0.3301	0.5478	0.5542	0.7597
t-stat	0.4370	0.9534	0.6421	1.1554	0.5885	0.9891	0.9819	1.3643
$RelativeValue$	0.4462	0.3736	0.4113	0.3388	0.5333	0.4803	0.4982	0.4499
t-stat	0.8304	0.6952	0.7658	0.6309	0.9424	0.8486	0.8815	0.7960
$SecuritySelection$	0.2126	0.3526	0.2622	0.4011	0.3899	0.5096	0.5361	0.6528
t-stat	0.4109	0.6833	0.5067	0.7774	0.7157	0.9396	0.9822	1.2014
$Multiprocess$	0.6606	0.6795	0.7316	0.7508	0.5991	0.6236	0.7667	0.7991
t-stat	1.1063	1.1368	1.2251	1.2559	0.9529	0.9910	1.2172	1.2669
FOF	-8.6997	-8.7412	-8.6002	-8.6427	-8.6588	-8.6919	-8.4580	-8.4836
t-stat	-17.1037	-17.1752	-16.8797	-16.9530	-16.1831	-16.2324	-15.7244	-15.7535
$Locked$	1.6350	1.6652	1.6903	1.7220	1.6863	1.7164	1.7596	1.7969
t-stat	6.4151	6.5087	6.6170	6.7141	6.2801	6.3763	6.5390	6.6567
Regr. adj. R-square	29.66 %	29.53 %	29.78 %	29.64 %	29.46 %	29.37 %	29.65 %	29.56 %
	Dependent Variable: Management Fee							
Ret	0.0270		0.0269		0.0242		0.0226	
t-stat	1.8775		1.8726		1.5746		1.4689	
SR		0.0259		0.0249		0.0217		0.0183
t-stat		2.1529		2.0695		1.6531		1.3852
R^2			-0.0340	-0.0334			-0.0324	-0.0314
t-stat			-3.1097	-3.0555			-2.6915	-2.5983
$log(Age)$	-0.0186	-0.0132	-0.0111	-0.0059	-0.0180	-0.0106	-0.0329	-0.0260
t-stat	-1.1437	-0.8164	-0.6757	-0.3639	-0.8520	-0.5020	-1.5113	-1.1848
$log(AUM)$	-0.0245	-0.0266	-0.0247	-0.0267	-0.0220	-0.0244	-0.0218	-0.0237
t-stat	-1.9450	-2.1059	-1.9626	-2.1152	-1.6124	-1.7702	-1.5961	-1.7238
$Directional$	0.2055	0.2232	0.2179	0.2352	0.2050	0.2210	0.2240	0.2383
t-stat	3.8348	4.2160	4.0596	4.4362	3.5655	3.8965	3.8704	4.1757
$RelativeValue$	0.0864	0.0826	0.0825	0.0787	0.0653	0.0607	0.0623	0.0583
t-stat	1.5983	1.5285	1.5265	1.4574	1.1254	1.0479	1.0749	1.0060
$SecuritySelection$	0.0005	0.0095	0.0061	0.0150	-0.0266	-0.0191	-0.0142	-0.0074
t-stat	0.0101	0.1836	0.1176	0.2886	-0.4768	-0.3441	-0.2539	-0.1338
$Multiprocess$	-0.0251	-0.0259	-0.0171	-0.0179	-0.0598	-0.0610	-0.0456	-0.0467
t-stat	-0.4177	-0.4306	-0.2843	-0.2976	-0.9280	-0.9458	-0.7054	-0.7221
FOF	-0.0486	-0.0508	-0.0373	-0.0398	-0.0546	-0.0583	-0.0375	-0.0413
t-stat	-0.9485	-0.9931	-0.7277	-0.7760	-0.9950	-1.0628	-0.6804	-0.7488
$Locked$	-0.0712	-0.0734	-0.0650	-0.0670	-0.0701	-0.0712	-0.0639	-0.0646
t-stat	-2.7766	-2.8529	-2.5282	-2.5993	-2.5484	-2.5819	-2.3161	-2.3360
Regr. adj. R-square	2.38 %	2.41 %	2.59 %	2.61 %	2.39 %	2.40 %	2.56 %	2.56 %

Table 8: R-squares and inflows.

Each month from January 1997 to December 2004 we calculate the R-square using the previous two years of each fund's returns. The R-squares are calculated using either the stepwise regression model or the Fung and Hsieh model. We then calculate the net inflows into the fund for the next year, setting the inflow to -1 if the fund becomes extinct in the next period. $LowPer, MidPerf$ and $HighPerf$ are defined as in Sirri and Tufano (1998). $Ret_{t+1:t+12}$ represent the performance of the fund in the testing period ("next year"). Age and AUM are the age of the fund (in months) and the assets under management (in \$ mil.). $\widetilde{Std}$ represents the component of volatility that is orthogonal on the R-square in each cross-section (it is obtained by running a cross-sectional regression on volatility on R-square in each cross-section, and then taking the residuals of that regression). $mfee$ and $ifee$ are the incentive, respectively the management fees charged by the fund. We include strategy and funds of funds dummies as well as lock-up dummy equal to 1 if the fund has lock-ups.

	Stepwise regression				Fung and Hsieh model			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
$Rsqr_{t-23:t}$	-0.1574	-0.1414	-0.1413	-0.1394	-0.0929	-0.1047	-0.1055	-0.1031
t-stat	-6.2565	-9.8604	-10.9505	-11.0923	-3.5893	-4.4735	-4.7369	-4.9109
$LowPerf_{t-23:t}$	1.6654	1.4131	1.4164	1.4169	1.6142	1.3810	1.3838	1.3839
t-stat	5.5455	5.1337	5.3359	5.2539	5.5650	5.0800	5.3324	5.2734
$MedPerf_{t-23:t}$	2.6989	2.8087	2.8460	2.8924	2.5294	2.6294	2.6688	2.7126
t-stat	4.0453	3.8260	3.8525	3.9897	4.0978	3.8872	3.9385	4.1101
$HighPerf_{t-23:t}$	-0.2256	-0.2102	-0.1991	-0.1968	-0.1984	-0.1947	-0.1846	-0.1836
t-stat	-0.9486	-1.0174	-0.9600	-0.9418	-0.8529	-0.9457	-0.8936	-0.8840
$Ret_{t+1:t+12}$	0.5226	0.5407	0.5365	0.5373	0.6408	0.6616	0.6573	0.6582
t-stat	13.1764	14.0134	14.1462	14.0852	9.8451	11.8571	11.4591	11.5408
$\widetilde{Std}_{t-23:t}$	-1.8196	-1.7410	-1.7506	-1.7409	-2.1289	-1.9995	-2.0086	-1.9967
t-stat	-6.5036	-5.5844	-5.6154	-5.5374	-5.9207	-5.0712	-5.0745	-5.0019
$log(Age)_t$		-0.2289	-0.2270	-0.2296		-0.2320	-0.2297	-0.2324
t-stat		-2.6384	-2.7378	-2.7149		-2.6198	-2.7121	-2.6899
$log(AUM)_t$		-0.0370	-0.0370	-0.0377		-0.0373	-0.0373	-0.0378
t-stat		-4.7917	-4.7023	-4.7995		-4.8414	-4.7331	-4.8214
$Directional$		-0.0441	-0.0498	-0.0512		-0.0460	-0.0521	-0.0534
t-stat		-2.4646	-2.5005	-2.4976		-2.5463	-2.6083	-2.5987
$RelativeValue$		0.0134	0.0136	0.0147		0.0178	0.0176	0.0188
t-stat		0.3965	0.3886	0.4232		0.5411	0.5189	0.5550
$SecuritySelection$		-0.0502	-0.0500	-0.0486		-0.0473	-0.0473	-0.0459
t-stat		-1.3921	-1.3530	-1.3352		-1.3401	-1.3072	-1.2855
$Multiprocess$		0.0003	-0.0001	0.0043		0.0022	0.0015	0.0058
t-stat		0.0094	-0.0033	0.1315		0.0681	0.0448	0.1737
FOF		-0.0088	-0.0274	-0.0262		-0.0153	-0.0320	-0.0306
t-stat		-0.2563	-0.9541	-0.9451		-0.4591	-1.1444	-1.1371
$mfee$			0.0108	0.0101			0.0115	0.0108
t-stat			1.9092	1.8061			2.0608	1.9731
$ifee$			-0.0017	-0.0016			-0.0015	-0.0014
t-stat			-1.5881	-1.4386			-1.4670	-1.3161
$Locked$				-0.0211				-0.0200
t-stat				-1.9076				-1.8139
avg. adj. $\bar{R}^2$	13.09 %	16.06 %	16.08 %	16.09 %	14.26 %	17.36 %	17.38 %	17.39 %

Figure 1: Database Coverage - December 2005

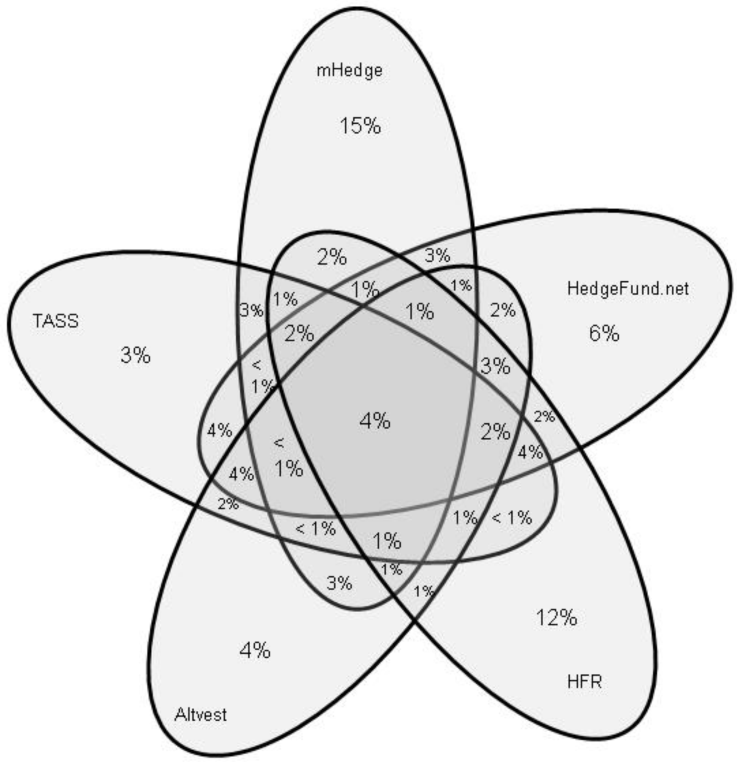

Figure 2: Number of funds and assets under management in the hedge funds industry

The figure represents the number of hedge funds across time, between 1994 and 2005. The total number of funds is measured at the end of each year. The number of funds are on the right Y-axis and the number of funds are illustrated by the line plots. The bar plot represents the year-end assets under management in the industry. These amounts are on the left Y-axis and are in $ mil.