Does Idiosyncratic Risk Matter in Hedge Fund? Institutional Investor's View

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ABSTRACT

Recent research [1] in the field of hedge-fund risk exposures and performance have produced ideas that challenge traditional theories. The traditional CAPM theory states that only market risk should be incorporated into asset prices and command a risk premium. However, this theory may not hold, especially in the hedge fund industry, if some investors can not hold the market portfolio. Therefore, idiosyncratic risk could also be considered to compensate rational investors for an inability to hold the market portfolio. In this study, we address an issue related to the risk management performed by institutional investors in hedge funds, as opposite to that performed by the funds themselves. The purpose of this paper is to explore information contents of the idiosyncratic risk of hedge funds to better quantify the relationship between hedge funds performance and their risk factors. We document that hedge funds with lower systematic risk exposures have both higher risk adjusted performance and higher probability to succeed. And this result is statistically and economically significant. This study contributes to the current debate on the hedge fund transparency needs of the institutional investors of hedge funds. Hedge funds do not disclose their positions and institutional investors may only use returns to infer the risks embedded in their hedge funds. However, we show that a good manager's risk exposures cannot be inferred only from the monthly returns of the fund. Return-based risk management is problematic if the hedge funds have talented managers and provide only monthly returns, and additional transparency may be required by the institutional investors of these funds.

[1] See the Appendix for the summary of selected literatures.

I. Introduction

Hedge funds are said to be rewarding investments because they have favorable risk-return characteristics on a stand alone basis, and offer valuable diversification with respect to traditional stock and bond markets. On the other hand, hedge fund returns have a number of characteristics that make their quantitative analysis difficult: distributions are often asymmetric and have an increased tendency towards extreme outcomes (fat-tails), and dependence structures with respect to traditional markets are often complex. Moreover, quality and quantity of available data may be limited.

The size of hedge fund industry is doubling almost every two years, contains more than 9,000 active funds, and manages more than $ 1.3 trillion. Hedge funds, on average, charge 1% ~ 2% management fees and 15% ~ 30% incentive fees, and have low barriers of entry. Thus, hedge funds are a very lucrative industry. Given this explosive growth, identifying talented managers has become an increasingly daunting task for the investor.

This study tests the hypothesis that hedge funds which bear less systematic risk outperform. The returns of any fund can be divided into two parts: systematic and idiosyncratic. Since the talent is unobservable, a fund wants its investors to have high confidence in its ability to generate returns. The investors' t-statistic for excess returns is

$$\sqrt{(T)}\frac{(\mu - r_f)}{\sigma} \tag{1}$$

which justifies the motivation of the fund to maximize Sharpe ratios. This is also a justification of why the Sharpe ratios are often used as measures of performance by the hedge fund investors. In a simple setting in which funds maximize their Sharpe ratios, we show that while it is optimal for a manager to have some exposure to systematic risk, the proportion of the fund's variance that is systematic is inversely related to the manager's ability to generate performance. Simply put, if the manager is talented then the R-square of the regressions of the hedge fund returns on systematic factors should be small.

Consistent with this hypothesis, we find that funds whose returns have lower R-squares with respect to systematic factors have higher Sharpe ratios. For example, comparing the funds in the highest R-square tercile with the funds in the lowest, we find that the latter has a Sharpe ratio that is 0.38 higher and this difference is statistically significant. Furthermore, this relationship is economically significant: a portfolio consisting of the low past R-square tercile of hedge funds has returns around 1% per year higher, and Sharpe ratios around 0.40 higher than the portfolio of the high tercile of past R-square funds in the following year. This difference is robust to the size of the funds included in the analysis and to the frequency of rebalancing.

Low R-squares are not achieved only when the fund does not bear systematic risk but also when the fund is dynamically changing risk exposures so when averaged, these exposures are small. We separate out the funds whose systematic exposures change through time and show that on average, their Sharpe ratios are lower.

Therefore, we conclude that it is ability of managers to make investments uncorrelated with the systematic factors, rather than their ability to time these factors that is positively related to the fund's success. Strategies with no systematic risk exposures arguably exist in finite supply and may not accommodate all flows into hedge funds. Hence, the negative relationship between performance and systematic risk exposures may change when hedge funds receive inflows. This is similar to the mechanism in which the growth of a mutual fund renders the relationship between the manager's talent and his performance insignificant.

Do investors recognize the fact that low R-square funds are more talented? We document that these funds are able to charge higher fees: the funds in the lowest tercile of R-square charge, on average, 20 basis point more in management fees and 226 basis points more in incentive fees than the funds in the highest R-square tercile. Additionally, low R-square as an explanatory variable for fees dominates measures of realized performance such as the mean excess returns of the fund of the fund's Sharpe ratio.

Other measures of a fund's success also favor the low R-square funds: the funds in the lowest R-square tercile manage $ 9 million dollars more on average, live about 10 months longer and are 5% less likely to exit the sample than the funds in the highest R-square tercile.

Our paper extends the literature on understanding the sources of returns in hedge funds by focusing on the analysis of individual funds. In this respect our work differs from the literature directed at hedge fund risk adjusted performance, which studies only portfolios of funds. Instead, our research is close to earlier studies on risk factors that explain individual hedge fund returns such as Fung and Hsieh (1997), Liang (1998) or Dor and Jagannathan (2002). Additionally, it builds on more comprehensive and dynamic models, similar to Agarwal and Naik (2004), and accounts for more sophisticated statistical properties of the returns of the hedge funds than Getmansky, Lo and Makarov (2004).

Furthermore, this study performs a comprehensive out-of-sample analysis of the validity of risk models explaining individual hedge funds. As such, this analysis is also close to the literature that links mutual funds style stability to performance. From this point of view, we extend and apply to hedge funds what Chan, Chen and Lakonishok (2002) and Brown and

Harlow (2005) did for mutual funds. Our conclusion is somewhat different from the conclusions of both of these studies: Chan, Chen and Lakonishok (2002) asserts that managers stray from their "style course" following periods of bad performance; Brown and Harlow (2005) asserts that better performance is associated with "staying the course". By contrast, our results on the relationship between performance and the extent to which funds are exposed to systematic factors show that hedge funds seem to be better off when they are orthogonal to any investment style, at any point in time.

This paper is structured as follows: Section 2 presents the model and the main hypothesis; Section 3 describes the data; Section 4 is dedicated to testing that R-squares and Sharpe ratios of the funds are inversely related; Section 5 presents and test extensions of the claim that low R-square funds are more successful; Section 6 concludes.

II. Model

Assume that a hedge fund manager i chooses between two investments: a publicly available index F and a proprietary strategy Ai for which

$$\begin{aligned} &E[F - r_f] = \mu > 0; && std[F] = \sigma \\ &E[A_i - r_f] = \alpha_i > 0; && std[A_i] = \lambda_i \\ &\rho_{A_i,F} = 0 && ,where\ \lambda_i = TE(tracking\ error) \end{aligned} \quad (2)$$

We denote by $W_{F,i}$ and $W_{A,i}$ the weights allocated by the manager to his respective investment choices. The manager is able to borrow at the risk free rate (i.e., we do not require that $W_{A,i} + W_{F,i} = 1$).

The excess returns of the manager are given by $R_i - r_f = W_{A,i}(A_i - r_f) + W_{F,i}(F - r_f)$, and his Sharpe ratio by

$$S(w_{F,i}, w_{A,i}) = \frac{E[R_i - r_f]}{std[R_i]} = \frac{\alpha_i + \beta_i \mu}{\sqrt{\lambda_i^2 + \beta_i^2 \sigma^2}} \quad (3)$$

,where $\beta_i = w_{F,i} / w_{A,i}$

If the manager maximizes his Sharpe ratio[2], he solves

[2] Hedge funds are often evaluated by their Sharpe ratios. Also a way to convince an external observer that the fund generates statistically significant excess returns is for the fund to have a high t-statistics of the excess returns. The t-statistic of the excess returns is equal to the Sharpe ratio of the fund times square root

$$\max_{w_{F,i},\, w_{A,i}} S(w_{F,i}, w_{A,i}) \tag{4}$$

The solution to the above optimization problem is given by

$$\beta_i^* = \frac{\mu / \sigma^2}{\alpha_i / \lambda_i^2} \qquad \textit{and} \qquad w_{F,i} = \beta_i^* w_{A,i} \tag{5}$$

$w_{A,i}$ remains a free choice of the manager as we do not model explicitly how hedge fund managers decide to use leverage. The optimal Sharpe ratio of the fund is

$$S_i{}^* = \sqrt{\left(\frac{\alpha_i}{\lambda_i}\right)^2 + \left(\frac{\mu}{\sigma}\right)^2} \tag{6}$$

An econometrician attempting to explain the systematic risk exposures of the fund by regressing $R_i - r_f$ on the systematic factor returns F would obtain an R^2 of the OLS regression equal to

$$(R^2)_i^* = \frac{\beta_i^{*2}\sigma^2}{\lambda_i^2 + \beta_i^{*2}\sigma^2} = \frac{1}{1 + \left(\alpha_i / \lambda_i\right)^2 / \left(\mu / \sigma\right)^2} \tag{7}$$

The first observation from the equation above is that $(R^2)_i$, like the Sharpe ratio, is independent of leverage; the second observation is that under the assumption that $\alpha_i > 0$, $(R^2)_i$ decreases with the information ratio α_i / λ_i of the proprietary strategy. As the optimal Sharpe ratio of the fund increases with the information ratio α_i / λ_i, we have the following:

If a hedge fund is maximizing its Sharpe ratio, then the R^2 of the regression of the hedge fund's excess returns on systematic factors is inversely related to the fund's Sharpe ratio.

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of the length of the fund's history. If we compare funds with histories of equal length then comparing the t-stats of their expected excess returns is equivalent to comparing their Sharpe ratios.

The main objective of this paper is to test the hypothesis that the fund's performance is inversely related to the R-squares. To obtain the R-squares, we first explain the excess returns of individual funds $R_t - r_f, t \geq t_o$,from some initial time t_0 until the time T, which is either the present period or the time the fund exited the sample, whichever is lower. Employing a factor model with K factors amounts to fitting every fund to

$$R_t - r_f = \sum_{k=1}^{K} \beta^{T,k} F_t^k + (\alpha^T + \varepsilon_t^T), \quad t = t_0, t_0 + 1, ..., T \tag{8}$$

R-square can be calculated from the above equation as

$$R^2 = 1 - \frac{Var[\varepsilon_t]}{Var[R_t]} \tag{9}$$

We estimate the overall R-squares using the entire history of the fund. By doing so, only average exposures to systematic factors observed throughout the entire life of the fund are taken into account.

III. Data

We use a proprietary, comprehensive database consisting in a union of the Altvest, HFR and TASS databases. The proportion of funds coming from each database is described in Figure 1.
For each of the databases the lists of funds that dropped from the databases were obtained[3]. Data of various complexity is collected for a total of 8,542 funds. While smaller subsets of the database contain more information, for 7,429 funds we have monthly returns net of fees, assets under management, whether the fund is a fund of funds, and the management and incentive fees the fund is charging. Missing records for the assets under management are filled assuming that between the dates at which information is provided the funds received uniform inflows (outflows).

When a fund for which the data does not contain a name[4] is added to the merged database, we follow a procedure which eliminates the duplicates: when the correlation between the common net returns for two funds is greater than 99.9% and the correlation between the common assets under management (after filling the missing records as described above) is greater

[3] The graveyard data usually hide the names of the funds, due to non-disclosure agreements prohibiting making information on hedge funds that decided to stop reporting public.
[4] Altvest and HFR cease to report the names of the funds once the funds stop reporting to the database, so their graveyards do not include names.

that 99%, the two funds are assumed duplicates and one is eliminated. This procedure eliminates only no-name database duplicates, but if one manager runs several funds, and the names of these funds are provided, then all the funds are kept (this may result in funds with the same series of returns but different sizes being kept in the database).

The number of funds in the database is presented in Table 1, while the industry coverage of the data used is apparent in Figures 2 and 3. For December 2003, our database covers around $ 800 billion of assets under management.

Several biases have been documented to plague hedge funds data; we list them below.

Survivorship bias: Databases drop from the sample the funds that stop reporting. This may be caused either by the fund going out of business or to the fund closing to new investments and not having incentives to report any longer. 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 estimations are found in Brown, Goetzmann, Ibbotson and Ross (1999). In order to correct for this bias we included in our database the funds who ceased reporting. Inherent problems of survivorship bias exist, however, in this study, as some tests can only be run if the fund has a minimal amount of data in the database - hence, if the fund survived at least that long.

Self selection bias: The reporting is voluntary, so a bad fund has no reason to report, and a fund that is too good closes quickly and does not have any reason to “advertise”.

Backfilling bias: The moment a fund decides to report to a database might not coincide with the date the fund started, and when the fund start reporting it is free to backfill its history. Typically, hedge funds smooth their back returns; in this study we use a procedure that removes the serial autocorrelation induced by smoothing, and hence correct for this bias. Potentially, this may bias the performance of hedge funds upward.

Novikov (2004) proposes a methodology to correct for this bias which is unfortunately database dependent. For a database reporting fund indices as well, indices (which are not backfilled) may be replicated from data in which the initial histories (first month, two months, etc.) of the hedge funds were dropped. Then one can compute the number of months to be dropped which minimizes the difference between the indices reported by the database (not backfilled) and the indices replicated without using the initial histories.

In order to correct for this bias, we reproduce our analysis after we excluded 24 months of initial history of each fund, and we find our analysis robust. For a quick comparison, the median Sharpe ratio of a fund in our database, adjusted for serial autocorrelation of the returns a la Lo (2002) is 0.80. To see the impact of the backfilling bias, we eliminated 24 months from the history of each fund.

The new median Sharpe ratio (corrected for serial autocorrelation) becomes 0.73. This difference could be explained not only by the backfill bias but also by the fact that we capture only the last months of returns of some defunct funds. The small difference between the backfilled, and non-backfilled Sharpe ratios may partly be attributed to the fact that correcting for smooth returns lowers the performance of the backfilling funds.

Late reporting bias: Databases usually wait for funds to report, and a fund can be as late as 8 months in reporting. This causes a fund to appear as "defunct" while in reality it still exists and it is still willing to report. We correct for this bias using only data before December 2003, but collected in August 2004, when all the funds that are late came back to report again. This bias has not, to the best of my knowledge, been documented in the literature.

The three databases merged do not contain homogeneous fund information; Table 2 documents the differences among them. To examine the extent to which data coming from different databases are structurally different, we perform a Kolmogorov-Smirnov test that net returns and assets under management from each database were drawn from the same distribution; results are presented in Table 2; the p-values of the statistic are high when differences between Altvest and HFR are the center of attention: we cannot reject the null that Altvest and HFR net returns and respectively assets under management were drawn from the same distribution. However, we can reject at better than 5% confidence the null hypothesis that HFR and TASS, respectively Altvest and TASS were drawn from the same distribution. The TASS database seems to pick smaller funds that also have lower performance, which indicates that performance tests ran on TASS tend to produce rather pessimistic results on hedge funds compared to studies based on different databases. These differences across databases may bias the results of studies based on a single source, and make generalization from one database to the whole industry of hedge funds problematic.

Risk factors

Due to their dynamic nature, hedge fund portfolios are hard to explain by traditional buy and hold strategies, regardless of how sophisticated the latter might be. Failure of traditional risk factors to explain hedge fund returns lead to a search for nonlinear risk factors.

Two main categories of nonlinear factors surfaced:

The first category, pioneered by Glosten and Jagannathan (1994), is motivated by the observation that, unlike mutual funds, hedge funds employ derivative strategies, hence they may take asymmetrical positions relative to a factor's performance. Risk factors resembling option payoffs are hence added to the factor models designed for hedge funds.

The second category stems from an extension of the previous: if hedge funds employ derivatives, they are also cashing out or loosing on the premium that these derivatives command; such views were confirmed by detailed analysis of particular hedge fund strategies such as merger arbitrage (see Mitchell and Pulvino (2001)), whose returns resemble those of a strategy that sells "merger insurance", or more precisely, out of the money puts.

A refined factor model considers, as explanatory risk factors, several market indices, both from US and abroad, as well as global; payoffs on a market index I of the form Max ($R_i - k, 0$) or Min ($R_i - k, 0$).

The ideal factor model would include a minimal superset of the risk factors used in the previous research, but not to the extent to which we have factors that are collinear. Thus, this study uses to the 34 factors presented in Table 3. Although some of these factors are redundant, the procedure we use for fitting the model is insensitive to this problem.

IV. Idiosyncratic Risk and Risk-Adjusted Performance

Are Sharpe ratios negatively related to R^2s?

In this section we discuss that hedge funds performance, as expressed by the fund's Sharpe ratio, is inversely related to the extent to which systematic risk exposures explain the fund's returns.
The R-squares may be computed by estimating Equation (8) for the whole history of each individual hedge fund. However, Asness, Krail and Liew (2002) argue that hedge fund returns are autocorrelated; Getmansky, Lo and Makarov (2004) present some of the causes contributing to the serial correlation observed in hedge fund returns:

1. Hedge funds hold illiquid securities and use stale prices to compute returns;
2. Funds move their leverage ratios through time;
3. Managers smooth returns intentionally, for example by backfilling.

Getmansky, Lo and Makarov (2004) and Novikov (2004) estimate models in which the returns of the funds are autocorrelated. Following Getmansky, Lo and Makarov (2004), we estimate a model in which the observed returns of a fund follow:

$$R_t^{\,0} = (1-\theta^T)R_t + \theta^T R_{t-1}, \quad t = t_1+1,\ldots,T. \tag{10}$$

If the true returns are given by (8), then the observed returns follow:

$$\begin{aligned} &R_t^{\,0} - r_f = \alpha^T + \beta^{T,1}((1-\theta^T)F_t^{\,1} + \theta^T F_{t-1}^{\,1}) + \ldots + \beta^{T,K}((1-\theta^T)F_t^{\,K} + \theta^T F^K{}_{t-1}) + u_t^{\,T}\ ; \\ &u_y^{\,T} = (1-\theta^T)\varepsilon_t^{\,T} + \theta^T \varepsilon^T{}_{t-1}, \quad t = t_1+1, t_1+2, \ldots T. \end{aligned} \tag{11}$$

This is the factor model we estimate. In order to estimate the overall R^2 used in the Hypotheses, we take t1 = (inception of the fund) and T = min [(Dec 2003), (exit time from the database)].
Not every hedge fund is exposed to each of our 27 risk factors. To capture the factors relevant for each fund we shall use the stepwise regression to estimate the model (11). Other methodologies include principal components, or imposing a parsimonious model such as the CAPM or the Carhart (1997) 4-factors model.

The distribution of the R^2 estimates from the entire history of each fund using stepwise regressions is presented in Table 4, along with the distribution of the tracking errors and with the summary statistics of R^2 if the estimation is applied instead to mutual funds.

The quality of fit is about three times worse for hedge funds than for mutual funds - hedge fund explanatory regressions have a median adjusted R^2 of 42.10%, contrasting the 66.86% for mutual funds - consistent with the findings of Fung and Hsieh (1997a) who show that hedge funds follow dynamic strategies, and with the findings of Griffin and Xu (2005), who show that the hedge fund turnover is larger than that of mutual funds.

Consistent with Getmansky, Lo and Makarov (2004), hedge funds seem to smooth returns. Consistent with Agarwal and Naik (2004), who show that hedge fund indices are exposed to systematic risk, we find that individual hedge funds bear systematic risk as well. The median adjusted R^2 of 42.10% implies that hedge fund investors pay for quite a lot of "beta".

On average, a fund is exposed to 5 different systematic factors from our set of 27; the minimum number of factors a fund is exposed to is 0, the maximum is 10.

As a preliminary test, funds are sorted in terciles according to their R^2, and the average size, fees charged, age, probability to remain in the sample and Sharpe ratios are computed for each of the R^2 terciles. Under the null hypothesis of no relationship between the Sharpe ratios and R^2, the averages across R^2 terciles should not differ. The results are in the second column of Table 5.

V. Idiosyncratic Risk and Other Hedge Funds Characteristics

The previous section argues that low R-squares are inversely related to one measure of a fund's success: the Sharpe ratio. If low R-squares funds out-perform, do investors recognize this? If they do, we expect the low R-squares funds to be able to charge higher fees than the high R-square funds, have more assets under management, be more likely to remain in the sample (i.e., survive) and be older. In other words, several fund characteristics may influence the R^2: *the fund's age, size, the degree to which the fund smooths its returns, the number of strategies in which the fund plays and the fees charged by the fund*.

In this section we investigate the relationship between R-squares and these other measures of a fund's success: fees, assets under management, age and the likelihood to survive.

The independent variables are described below.

Size is the size of the fund. As the analysis of this section is purely cross-sectional, it is difficult to define the size of a fund (it varies through time). We transform the assets under management in December 2003 dollars, and as a proxy for size, we use the 25th percentile of the assets under management for the history of the fund. The relationship between this proxy for size and the extent to which a fund can be explained by systematic factors does not change if instead we use the 10th percentile of the 2003 assets under management or the median, but the significance decreases if we use the maximum assets under management or the mean. As habitually, we use the natural logarithm of size. Its square is included as well.

Age is the age of a fund, measured in months, from the time when the fund starts reporting until the minimum between December 2003 and the time the fund ceased reporting.

Alive is a dummy meant to separate funds that ceased to report from funds that were still in existence in December 2003.

Rho is the degree to which returns are serially autocorrelated. It is the smoothing coefficient from equation (11).

Complexity. There are structural differences in the fund managers' talent, determined by the complexity of the hedge funds they run; managers following certain investment strategies may have different Sharpe ratios, may grow to different sizes, or are more or less prone to smooth their returns. In order to address this problem we have to control for the investment strategy of the fund. Unfortunately most of the database used in this study does not contain information regarding the strategy of the hedge fund.

To resolve this weakness, we estimate each fund's investment strategy as follows. A Sharpe (1992) style regression is performed, having the fund's returns as dependent variable and the returns of 15 HFR strategy indices as independent variables. In this regression, some of the strategy indices have significant t-statistic. We retain the number of significant t-stats (at 5%)

from each style regression, and define that number as the complexity of the fund. If no t-statistics were significant, then the complexity of the fund is taken to be equal to 16 (highest possible value). Funds of funds are also similar to funds we call complex; we do include a control for funds of funds. This rough classification results in a distribution of the assets under management across strategies as shown in Figure 4.

FOF is fund of funds dummy.

mfee is the management fees charged by the fund in percents.

ifee is the incentive fee. Note that the returns used throughout this study are net of fees.

S is the Sharpe ratio of the fund i, adjusted for serial correlation.

With a few exceptions the variables above are relatively uncorrelated: the highest positive correlation is 30% (between Complexity and Age). The next positive correlation is 13% (between Alive and rho). The most negative correlation is -40% (between FOF and ifee). The next negative is -10% (between Life and mfee).

Consequently, we first estimate the model:

$$R_i^2 = f[size_i, size_i^2, mfee_i, ifee_i, Age_i, Alive_i, rho_i, Complexity_i, FOF_i] + \varepsilon_i \tag{12}$$

The table 5 also presents averages of other fund characteristics across different R^2 terciles.

We run a similar analysis using the tracking error as a dependent variable. Although the tracking error is not formally related to our Hypotheses, we are interested if the idiosyncratic component of the funds' returns is hedged (that is the tracking errors are small) or not by estimating the following model:

$$\begin{aligned} S_i &= f[R_i^2 - E(R_i^2), size_i, mfee_i, ifee_i, Age_i, Alive_i, rho_i, Complexity_i, FOF_i] + \varepsilon_i \\ S_i &= f[TE_i^2 - E(TE_i^2), size_i, mfee_i, ifee_i, Age_i, Alive_i, rho_i, Complexity_i, FOF_i] + \varepsilon_i \end{aligned} \tag{13}$$

The results are in the Panel A of Table 7.

Note that R^2 orthogonalized on fund characteristics (that is, $R^2 - E(R^2)$) is now an exogenous variable. We have chosen to make this assumption because there is a large body of hedge fund literature studying the relationship between Sharpe ratios and fund characteristics[5] and we had to control for the latter.

Although the tracking error does not directly enter our tests, it is descriptive of whether the idiosyncratic investments of a fund are hedged, and for comparison purposes we included in the results reported.

Results

R-squares and Fees:

*Do h*igher fees correspond to lower overall R^2?

From Table 5, we observe that as we move from the low to high R^2 terciles, the average of both incentive and management fees decrease. There is a difference of 20.29 basis points between the average management fees charged by the funds with low R^2 and the average management fees charged by the funds with high R^2. The corresponding difference is 226.39 basis points for the incentive fees and both difference are statistically significant. Furthermore, Table 6 shows a negative and statistically significant relationship between R^2 and the fees charged.

One result from Table 6 is that fees are not very strongly related to the tracking error. In fact only the management fee seems to be strongly related to the tracking error, and this is true only for the funds smaller than $ 15 million.

If the structure of the fees is what incentives the manager to take more or less risk, then mutual funds, who charge only management fees, should have a different risk taking behavior from hedge funds, whose manager extract rents from investors through mostly through the incentive fees. Under this assumption, that fees drive the risk taking, the weak link we find between the incentive fees and the tracking errors is consistent with Brown, Goetzmann and Park

[5] The relationship between size and performance has been studied by Getmansky (2004), Gregoriou and Rouah (2002), Koh, Koh and Teo (2003) among others. The relationship between performance and age of the fund has been studied by Howell (2001), Amenc, Curtis and Martellini (2003) and De Souza and Gokcan (2003) among others. The relationship between performance and fees has been studied by Kazemi, Martin and Schneeweis (2002), Koh, Koh and Teo (2003), De Souza and Gokcan (2003) and Amenc, Curtis and Martellini (2003). Other fund factors (e.g. manager tenure, redemption specifications, managerial investment in the fund) are also related to performance but we lack data on these variables.

(2001) who show that hedge funds are less likely to engage in tournament behavior than their mutual funds counterparts. Furthermore, the fact that management fees are positively related to tracking errors is then consistent with Brown, Harlow and Starks (1996), who show that mutual funds (who charge management fees) engage in tournaments behavior.

An interesting question is what do investors pay fees for. Are the hedge funds compensated for performance, Sharpe ratios, or in fact investors recognize the importance of the idiosyncratic investment ideas in the hedge fund world and compensate the managers with these ideas?

In order to answer this question, we test whether R^2 has power in explaining the fees above and beyond the power of Sharpe ratios or that of excess returns. The results are presented in Table 8.

We observe that the R^2 of the fund completely subsumes the power of both returns and Sharpe ratios in explaining the fees charged by the fund. This effect is even stronger in the case of incentive fees, where the R^2 is clearly the most significant explanatory variable.

This evidence suggests that hedge fund fees are set so that managers get compensated more for idiosyncratic investment ideas, rather than for their ability to generate performance subsequently. Additionally, this evidence suggests that R^2 is a better descriptor of the manager's talent, as differentiated from luck or any other apparent manifestations of talent[6].

R-squares and Assets Under Management:

Are assets under management inversely related to overall R^2?

From Table 5, we observe that funds in the low R^2 tercile are \$ 9.21 million larger on average than the funds in the high R^2 tercile. To gauge the magnitude of the difference, recall that the median size of the hedge funds is around \$ 38 million. This is evidence in favor of the hypothesis. However the difference is not statistically significant (although economically large).

There is a concave, statistically significant relationship between R^2 and size of the fund, as captured by aum25, as apparent from Table 6. Thus we reject the null of no relationship between R^2 and size of the funds. When we examine the concave relationship between R^2 and size, we observe that it becomes negative only past a certain fund size. The coefficient of aum25

[6] For example, Berk and Green (2004) imply that the proposition "talented mangers outperform" is a myth (because talented get to manage larger funds and their talent cannot materialize in performance regardless of scale). Hence, measuring manager's talent by performance may be wrong. Our results suggests that investors reward more a low R^2 manager than a outperforming one.

is 0.0107 for all funds, while the coefficient of $(aum25)^2$ is -0.0014. This means that the R^2 decreases with fund size as the fund manages more than LN (0.0107/0.0014) = $2.033772 million.

R-squares and Age:

Do Older funds have lower overall R^2?

Table 5 shows that funds with a lower R^2 have been reporting to our database 9 months more, on average, than the funds with a higher R^2. This difference is statistically significant and economically important as it represents 17% of the median age of a fund in our database (which is 53 months), and constitutes evidence in favor of Hypothesis.

The coefficient of Age in the R^2 regressions from Table 6 is negative and statistically significant, so we can reject the null of no relationship between age and R^2. The same relationship carries to larger funds although the coefficient of Age is less significant.

R-squares and Survival:

Do Funds with a lower probability to exit the sample have lower overall R^2?

From Table 5, funds with lower R^2 have 5.19% more probability to remain in the sample than funds with high R^2. Table 6, as well as Panel B in Table 7 further shows a negative, statistically significant relationship between probability to remain in the sample and the R^2. We can reject the null of no relationship.

VI. Conclusion

In recent years, as researchers have come to grips with the meaning of such events as the 1998 LTCM crisis, new lines of thought have been developed in the hedge-fund research literature concerning the concepts of performance and risk. These new ideas challenge traditional concepts, calling into question the relevance and efficacy of the conventional wisdom concerning hedge-fund evaluation.

This study contributes to the current debate on the hedge fund transparency needs of the institutional investors of hedge funds. Hedge funds do not, in general, disclose their positions and hedge fund investors may only use returns to infer the risks embedded in their hedge funds. In this study, we address an issue related to the risk management performed by institutional investors in hedge funds, as opposite to that performed by the funds themselves.

It is almost a truism of the hedge fund universe that a talented manager is one with investment idea that are “out of the box” and whose strategies are uncorrelated with publicly available indices. Intuitively, a less talented manager has to rely more on investing correlated to public indices in order to produce returns. In turn, this manager’s R-squares will be high, and a simple model shows that their performance will be low.

Consistent with the common wisdom confirmed by our simple model, we find evidence in support of this hypothesis. Our finding, that the lack of covariance with public indices is related to abnormal performance, is economically significant: we show that a portfolio of low R-square funds outperforms a portfolio of high R-square funds. In addition, we show that a portfolio of low R-square funds outperforms the average portfolio of hedge funds, and that this relationship is robust to the size of the funds considered or to the frequency of rebalancing the portfolio.

Not only do we find that funds whose strategies are more idiosyncratic have higher Sharpe ratios, but also that these funds are recognized and compensated by investors. For example, these funds have more assets under management.

Additionally, we show not only that low R-square funds are able to charge higher fees, but also that R-square dominates excess returns or Sharpe ratios as an explanatory variable of the fund fees. This relationship is stronger for incentive fees. Simply put, we show that investors pay for investment ideas with little systematic risk on top of what they pay for fund performance.

We show that if a manager is good, then his risk exposures cannot be inferred only from the monthly returns of the fund. Thus, this study has implications for the risk management performed by institutional investors holding hedge funds and attempting to understand the risks associated with them.

If institutional investors attempt to understand the systematic exposures of their funds using factor models, and succeed, then our results show that the fund manager either lacks talent, or that he is over-invested. Returns based risk management is therefore problematic if the hedge funds to be explained have talented managers and provide only monthly returns, and additional transparency may be required by the institutional investors of these funds.

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Table 1: Summary Statistics for the Hegde Funds Industry

Database started keeping track of the funds that ceased to report on after 1994.
Second panel presents cross-sectional summary statistics of the funds.

Year	Funds Born	Funds Died	Total Funds
1989	83	2	363
1990	159	1	520
1991	214	0	733
1992	278	1	1011
1993	404	0	1414
1994	508	61	1922
1995	506	186	2367
1996	683	182	2864
1997	722	316	3404
1998	666	497	3754
1999	667	458	3924
2000	611	381	4077
2001	803	316	4499
2002	877	174	5060
2003	767	516	5653

	Mean	Median	Std
25th Percentile of size ($ mil)	53.3589	11.945	388.083
Age	66.0582	53	50.2813
Still in sample (Alive)	72.84%	N/A	N/A
FOF	23.33%	N/A	N/A
Management Fee	1.3665	1.25	0.7657
Incentive Fee	16.5776	20	6.8582
Mean Excess Return (annual)	7.32%	6.21%	14.69%
Sharpe Ratio (annual)	0.8018	0.6657	1.5797

Table 2: Heterogeneity across net return and AUM from Altvest, HFR and TASS

Means (with standard deviations in parenthesis) and Medians of the monthly returns net of fees and AUM across Altvest, HFR and TASS, and the merged database.
A Kolmogorov-Smirnov test to check whether the distributions of AUM and net returns are similar among the databases.
Low p-values for the Kolmogorov-Smirnov statistic means that we are more likely to reject the null that the two samples are drawn from the same distribution.
TASS seems to be different than both Altvest and HFR, and seems to contain funds with lower AUM and with lower net returns.

	Altvest		HFR		TASS	
2003	**Mean**	**(Std)**	**Mean**	**(Std)**	**Mean**	**(Std)**
Net	0.0133	-0.037	0.0129	-0.0345	0.0131	-0.0388
AUM	122.52	-351.78	140.4	-815.93	99.05	-218.55

Entire database	**Mean**	**(Std)**
Net	0.0099	-0.0626
AUM	85.05	-443.95

	Altvest	HFR	TASS
2003	**Median**	**Median**	**Median**
Net	0.0088	0.0086	0.0082
AUM	32	28.6	26.4

Kolmogorov-Smirnov p-values

	Altvest-HFR	**Altvest-TASS**	**HFR-TASS**
Net	0.2922	0.0042	0.04
AUM	0.0351	0	0

Table 3: Sample Statistics for the Systematic Risk Factors Used

	Mean	Median	Std
FTSE 100	0.53	0.4	5.93
MSCI Worl ex US	0.35	0.55	4.39
MSCI EM	0.08	0.49	6.86
NAREIT Equity	1.01	1.19	3.43
NASDAQ	1.14	1.57	8.31
Russell 1000	0.98	1.38	4.59
Russell 2000	0.92	1.68	5.7
Russell 3000	1.11	0.94	3.25
Russell Midcap Value	0.89	1.41	4.34
VIXret	1.88	0.17	18.1
MSCI EAFE	0.24	0.75	4.36
SPPo	-8.99	3.8	124.22
SPPa	-85.35	3.98	1099.81
SPCo	6.01	4.16	199.61
SPCa	-9.04	3.86	463.33
DXY	-0.07	-0.12	2.21
Lehman Agg	0.57	0.66	1.15
Lehman Agg - MBS	0.56	0.61	0.9
Lehman Munis 10Y	0.51	0.71	1.34
SB Currency Hedged	0.58	0.65	0.93
SB US Gvt 1 Y	0.57	0.3	1.91
SB US Gvt 10 Y	0.52	0.48	2.14
SB US Gvt 30 Y	0.57	0.64	3.16
SB US Gvt 5 Y	0.51	0.44	1.34
CPI	0.2	0.19	0.23
AMEX Oil Index	0.8	0.4	5.25
GSCI	0.52	0.63	5.54

All Unit is percent per month.

Table 4: Summary of Factor Analysis Applied to Individual Hedge Funds

Summary statistics for R^2 and tracking errors from fitting the model is presented:
The standard errors for the hedge fund model are adjusted for serial correlation,

Hedge Funds	Mean	Stdev	25th percentile	Median	75th percentile
Adjusted R^2 (stepwise regression)	42.50%	26.89%	21.77%	42.10%	62.96%
TE	3.80%	6.10%	1.64%	2.71%	4.50%

$$R_t^{\,0} - r_f = \alpha^T + \beta^{T,1}((1-\theta^T)F_t^{\,1} + \theta^T F_{t-1}^{\,1}) + \ldots + \beta^{T,K}((1-\theta^T)F_t^{\,K} + \theta^T F^K{}_{t-1}) + u_t^{\,T}\ ;$$
$$u_y^{\,T} = (1-\theta^T)\varepsilon_t^{\,T} + \theta^T \varepsilon^T{}_{t-1}, \quad t = t_1+1, t_1+2, \ldots T.$$

Mutual Funds	Mean	Stdev	25th percentile	Median	75th percentile
Adjusted R^2 (stepwise regression)	61.34%	28.34%	48.60%	66.86%	83.45%
TE	1.82%	1.90%	0.53%	1.26%	2.61%

$$R_t - r_f = \sum_{k=1}^{K} \beta^{T,k} F_t^{\,k} + (\alpha^T + \varepsilon_t^{\,T}), \quad t = t_0, t_0+1, \ldots, T$$

Table 5: R^2 and Talent Proxies

The funds are sorted by the R^2 terciles.

	R^2	SR	mfee	ifee	aum25	Age	Pr(Alive)
Low R^2	12.14%(10.02%)	1.0197(2.3064)	1.4763(0.8905)	17.7291(6.3577)	57.53(439.8348)	69.2829(50.2678)	0.7473(0.4346)
Med R^2	41.66%(7.65%)	0.7564(0.9997)	1.3525(0.7485)	16.5727(6.8616)	54.38(416.6248)	69.0009(45.6930)	0.7436(0.4367)
High R^2	72.79%(12.60%)	0.6344(1.0644)	1.2734(0.6254)	15.4652(7.1362)	48.32(294.6952)	60.0744(53.8956)	0.6954(0.4604)
Low-High Mean	-0.6065	0.3853	0.2029	2.2639	9.21	9.2085	0.0519
Low-High t-test	-6.0499	7.1255	8.7329	11.0641	0.81	5.8381	3.8358

Table 6: The relationship between R^2 , TE and Fund Characteristics

Determinants of the ability to explain the risks specific to individual funds.
For every fund, a spetwise regression is performed; this procedure generates a benchmark for the fund.
The adjusted R^2 and stdev of the error term (TE) are stored.
Then, cross-sectional regressions:

$$R_i^2 = f[\,fund_i\ characteristics\,] + \varepsilon_i$$
$$TE_i = f[\,fund_i\ characteristics\,] + \varepsilon_i$$

Dependent Variable	**TE**		**R^2**			**TE**		**R^2**	
	All Funds (6526 obs)					***Funds over $15 mil (4528 obs)***			
Independent Variable	**Coefficien**	**t-test**	**Coefficien**	**t-test**		**Coefficien**	**t-test**	**Coefficien**	**t-test**
cons	0.0371	4.6203	0.6126	29.4416		0.0338	4.6101	0.6197	17.5849
aum25	-0.0062	-7.2702	0.0107	2.859		-0.0088	-2.1628	0.0029	0.1085
(aum25)2	0.0003	2.0468	-0.0014	-1.977		0.0007	1.4966	-0.0007	-0.2514
Age	0.0001	2.1397	-0.0005	-4.0246		0	0.0539	-0.0001	-0.3353
Alive	-0.0097	-5.6438	-0.0226	-2.9282		-0.0095	-4.1099	-0.0216	-1.73
rho	0.0344	5.0552	-0.1645	-10.0601		0.0254	3.625	-0.1821	-6.3751
Complexity	0.0008	0.4514	0.0004	0.0868		0.0036	4.6738	-0.0089	-1.3008
FOF	-0.0203	-8.321	0.0621	6.6304		-0.0205	-6.6159	0.0868	6.0016
mfee	0.003	3.4015	-0.0351	-5.365		0.0016	1.6696	-0.0287	-4.1779
ifee	0.0002	0.9971	-0.0044	-7.6269		-0.0002	-0.8376	-0.0034	-3.8812
Adjusted R^2		5.75%		6.62%			8.36%		7.60%

Table 7: The relationship between R^2 , TE and Fund Performance, measured as SR adjusted for serial correlation.

For every fund, a srepwise regression is performed and the R^2 and TE are stored.
The cross-sectional regression of SR on [R^2 - E(R^2)] and [TE - E(TE)] are conducted, controlling for fund characteristics.
E(R^2) and E(TE) are estimations of R^2 and TE from the model:

$$R_i^2 = f[size_i, size_i^2, mfee_i, ifee_i, Age_i, Alive_i, rho_i, Complexity_i, FOF_i] + \varepsilon_i$$

Dependent Variable	**SR**		**SR**	
	All Funds (6526 obs)			
Independent Variable	**Coefficient**	**t-test**	**Coefficient**	**t-test**
cons	0.44	3.9009	0.2416	2.291
R^2 - *E* (R^2)	-0.3068	-4.5121		
TE - *E* (TE)			0.2593	0.8672
aum25	0.0007	0.0633	0.0006	0.0504
Age	-0.0001	-0.2694	0	0.0052
Alive	0.4192	10.2083	0.4289	10.4109
rho	2.2341	32.5069	2.2753	33.1188
Complexity	-0.0982	-4.4663	-0.0985	-4.4748
FOF	-0.133	-2.5702	-0.1464	-2.8148
mfee	-0.0085	-0.3634	0.0016	0.0709
ifee	0.0028	0.8857	0.0041	1.3108
Adjusted R^2		18.53%		18.28%

Table 8: R^2 as a dominant explanatory variable of the fund's fees

**Regressions of fund fees on mean excess returns, SR and R^2 of the fund are conducted.
R^2 of the fund dominates returns and fees as an explanatory variable.**

Panel A: Management Fee

	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
const	1.3617	128.5552	1.3695	128.8227	1.4793	80.4386	1.493	79.4446	1.4887	78.0203
Mean Excess Returns	0.0645	0.9992			0.0492	0.7665			0.0882	1.3048
Sharpe Ratio (SR)			-0.0038	-0.6452			-0.009	-1.5124	-0.0116	-1.8445
Fund R^2					**-0.2739**	-7.803	**-0.2806**	-7.9492	**-0.2808**	-7.955
Adjusted R^2 of regression		0.00%		0.00%		0.91%		0.94%		0.95%

Panel B: Incentive Fee

	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
const	16.2893	172.299	16.554	173.8508	17.8324	109.2369	18.1744	108.579	17.2791	101.2086
Mean Excess Returns	**3.9366**	6.8332			**3.7368**	6.5487			**2.1271**	3.6205
Sharpe Ratio (SR)			0.0294	0.547			-0.039	-0.7295	6.0416	10.2451
Fund R^2					**-3.596**	-11.5375	**-3.683**	-11.7134	**-4.0003**	-12.8324
Adjusted R^2 of regression		0.00%		0.00%		2.67%		2.03%		4.19%