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The Alpha and Omega of Hedge Fund Performance Measurement

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Abstract:

That hedge funds start gaining wide acceptance while they still remain a somewhat mysterious asset class enhances the need for a better measurement of their performance. This paper is an attempt to provide a unified picture of hedge fund managers' ability to generate abnormal returns. To alleviate the concern over model risk, we consider an extensive set of models for assessing the risk-adjusted performance of hedge fund managers. We conclude that hedge funds appear to have significantly positive alphas when normal returns are measured by an explicit factor model, even when multiple factors serving as proxies for credit or liquidity risks are accounted for. However, hedge funds on average do not have significantly positive alphas once the entire distribution is considered or implicit factors are included. While we find significantly positive alphas for a subset of hedge funds across all possible models, our main contribution is perhaps to show that (i) different models strongly disagree on the absolute risk-adjusted performance of hedge funds as evidenced by a very large dispersion of alphas across models and yet (ii) they largely agree on hedge funds'relative performance in the sense that they tend to rank order the funds in the same way.

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"At the world's Omega, as at its Alpha, lies the Impersonal" (Pierre Teilhard de Chardin)

1 Introduction

Sound investment decisions rest on identifying and selecting portfolio managers who are expected to deliver superior performance. There is ample evidence that portfolio managers following traditional active strategies on average under-perform passive investment strategies (see for example Jensen (1968), Sharpe (1966), Treynor (1966), Grinblatt and Titman (1992), Hendricks, Patel and Zeckhauser (1993), Elton, Gruber, Das and Hlavka (1993), Brown and Goeztman (1995), Malkiel (1995), Elton, Gruber and Blake (1996), or Carhart (1997), among many others). The few mutual fund managers who successfully beat the passive strategies tend to move into the arena of "alternative" investments and start their own hedge funds. Hedge funds seek to deliver high absolute returns and typically have features such as hurdle rates, incentive fees with high watermark provision which help in a better alignment of the interests of managers and the investors. This has caused many investors to seriously consider replacing the traditional active part of their portfolio with hedge funds.

A dramatic change has actually occurred in recent years in the attitude of institutional investors, banks and the traditional fund houses towards alternative investment in general, and hedge funds in particular. Interest is undoubtedly gathering pace, and the consequences of this potentially significant shift in investment behavior are far-reaching. As a result, the value of the hedge fund industry is now estimated at more than 600 billion US dollars, with more than 6,000 funds worldwide, and new hedge funds are being launched every day to meet the surging demand.

This trend towards growing institutional interest in hedge funds commands for a better understanding of the nature of hedge fund risk-adjusted performance. A variety of papers have recently been written to address this concern. Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann and Ibbotson (1999), Agarwal and Naik (2000b) and Liang (2000) use a single-factor model to estimate hedge funds' abnormal returns, or alphas. Because there is evidence that hedge fund managers are exposed to multiple rewarded sources of risk, other authors have used multi-factor models. Fung and Hsieh (1997) use an implicit multi-factor model (factor are principal components obtained through factor analysis techniques), Schneeweis and Spurgin (1999) use an explicit multi-factor model (factors are proxies for domestic and international equity and fixed-income risks, equity volatility risk, commodity risk and currency risk), Liang (1999) and Agarwal and Naik (2000a) use an explicit multi-index model (factors are return on broad-based market indices) and Edwards and Caglayan (2001) use a multi-factor model (factors are Fama-French like portfolios, including S&P 500, book-to-market, size factors, momentum-winner factors, as well as term and default factors).

One key problem with such approaches if that traditional linear factor models offer limited help in evaluating the performance of hedge funds because hedge fund returns typically exhibit non-linear option-like exposures to standard asset classes (Fung and Hsieh (1997a, 2000), Agarwal and Naik (2003), Amin and Kat (2001) or Lo (2001)) because they can use derivatives and they follow dynamic trading strategies, and also because of the explicit sharing of the upside profits (post-fee returns exhibit option-like features even if pre-fee returns do not). In the literature, one remedy has been suggested to try and capture such non-linear dependence: include new regressors with non-linear exposure to standard asset classes to proxy dynamic trading strategies in a linear regression.[1] Natural candidates for new regressors are buy-and-hold or dynamic positions in derivatives. This line of research has been pursued by Schneeweis and Spurgin (2000) or Agarwal and Naik (2003) in a systematic way, and also specifically apply to specific strategies such as pair trading (Gatev, Goetzmann and Rouwenhorst (1999)), event arbitrage (Mitchell and Pulvino (2001) or trend-following strategies (Fung and Hsieh (2001b). Alternative candidates for non linear regressors are hedge fund indices (see Lhabitant (2001)).

Because these studies are based on a variety of models for risk-adjustment, and also differ in terms of data used and time period under consideration, they yield very contrasted results.[2] As a result, an investor is left with no clear understanding of whether hedge funds are able to provide positive risk-adjusted returns. In light of this contrasted picture of hedge fund performance, the present paper can be viewed as an attempt to provide an unified picture of hedge fund managers' ability to generate superior performance. To alleviate the concern of model risk on the results of performance measurement, we consider an almost exhaustive set of pricing models that can be used for assessing the risk-adjusted performance of hedge fund managers. First, and mostly for comparison purposes, we test a standard version of the CAPM (Sharpe (1964)). We also test a single-factor model, where the return on an equally-weighted portfolio of hedge funds in the same style category is used as a factor (we perform cluster-based classification, as opposed to relying on managers' self-proclaimed styles). We also measure market beta by running regressions of returns on both contemporaneous an lagged market returns given that, in the presence of stale or managed prices, simple market model types of linear regressions may produce estimates of beta that are biased downward (Scholes

[1] Alternatively, one may allow for a non-linear analysis of standard asset classes. This is, however, a stronger departure form standard portfolio theory.

[2] The question of persistence in performance in hedge fund returns has also be addressed in the literature. Brown, Goetzmann and Ibbotson (1999), who restrict attention to performance over two consecutive periods, find little evidence of persistence in performance among offshore hedge funds. Agarwal and Naik (2000b) examine whether the nature of persistence in the performance of hedge funds is of short-term or long-term in nature by examining the series of wins and losses for two, three and more consecutive time periods. They find that the extent of persistence is sensitive to the return measurement interval. In particular, persistence decreases as the return measurement interval increases.

and Williams (1997), Dimson (1979), Asness, Krail and Liew (2001)). Because hedge fund portfolios typically involve nonlinear and/or dynamic positions in standard asset classes, we also apply Leland (1999) performance measurement for situations when the portfolio returns are highly nonlinear in the market return. In the same vein, we also test Dybvig's (1988a, 1988b) payoff distribution function model. We also use a variety of multi-factor models: (1) we consider an implicit factor model factor analysis to statistically extract the factors from the return's time-series; this is perhaps the best approach because it is free of problems such as inclusion of spurious factors and omission of true factors (see Fung and Hsiesh (1997)); (2) we use an extension of the explicit factor model in Schneeweis and Spurgin (1999) and include proxies for market risks, volatility risk, credit risk and liquidity risk; (3) we use an explicit index factor model, building on an approach initiated by Sharpe (1964, 1992). Finally, we follow Ferson and Schadt (1996) who advocate conditional performance evaluation in which the relevant expectations are conditioned on public information variables.

A preview of our results is as follows. We first conclude that hedge funds appear to have significantly positive alphas when normal returns are measured by an explicit factor model, even when multiple factors serving as proxies for credit or liquidity risks are accounted. However, hedge funds on average do not have significantly positive alphas once the entire distribution is considered or implicit factors are included. While we find significantly positive alphas for a sub-set of hedge funds across all possible models, our main finding is perhaps that the dispersion of alphas across models is very large, as can be seen from the dispersion of alphas across models. On the other hand, all pairs of models have probabilities of agreement greater than .50. In other words, while different models strongly disagree on the absolute risk-adjusted performance of hedge funds, they largely agree on their relative performance in the sense that they tend to rank order the funds in the same way.

The paper is organized as follows. In section 2, we describe the data and discuss performance biases in hedge fund return measurement. Section 3 is devoted to a simple CAPM evaluation of hedge fund alphas, as well as a careful analysis of their betas. In section 4, we adjust CAPM for the presence of stale prices in hedge fund performance reports. In section 5, we adjust CAPM for the presence of predictability in hedge fund performance and we consider a conditional performance evaluation model in which the relevant expectations are conditioned on public information variables. In section 6, we discuss two competing approaches that allow to account for nontrivial preferences about higher-order moments of hedge fund return distribution. In section 7, we introduce two types of factor models. Section 8 is devoted to a synthetic overview of the results, and the impact of various attributes such as style, age, size, fees. Section 9 concludes and provides suggestion for further research.

2 Data and Biases

Our analysis is conducted on a proprietary data base of 1,500 individual hedge fund managers, the CISDM data base, formerly known as the MAR-Zürich data base. We use the 581 hedge funds in the CISDM database that have performance data as early as 1996. It is well-known that using a specific sample from an unobservable universe of hedge funds introduces biases in performance measurement.

There are three main sources of difference between the performance of hedge funds in the data base and the performance of hedge funds in the population (see Fung and Hsieh (2001a)).

- Survivorship bias. This results when unsuccessful managers leave the industry, and their successful counterparts remain, leading to the counting of only the successful managers in the database. The inherent problem is that a database over-estimates the true returns in a strategy, because it only contains the returns of those successful, or at least of those that are currently in existence.

- Selection bias. It occurs if the hedge funds in the database are not representative of those in the universe. Information on hedge funds are not easily available. This is because hedge funds are often offered as a way of private placement, and no obligation of disclosure is imposed in the US. As a result, information is collected by database vendors only on those hedge fund managers who cooperate.

- Beside, when a hedge fund enters into a vendor data base, the fund history is generally backfilled. This gives rise to an instant history bias (Park (1995)). Since we expect that hedge fund with good record to report their performance to data vendors, this may result in upward-biased estimates of returns for newly introduced funds

The standard procedure to measure survivorship bias (see Malkiel (1995)) is to take a difference on the period under consideration between the average return on a population and the average return on the surviving funds. Fung and Hsieh (2000), using the TASS database finds that the surviving portfolio had an average return of 13.2 % from 1994 to 1998, while the observable portfolio had an average return of 10.2 % during this time, from which a 3% survivorship bias per year for hedge funds (a similar number is obtained in Park et a. (1999).

The attrition rate, defined as the percentage of dead funds in the total number of funds has been reported by Agarwal and Naik (2000b) as a 3.62%, 2.10% and 2.22% using quarterly, half-yearly and yearly returns, which is consistent with an average annual attrition rate of 2.17% in HFR database reported by Liang (1999) during 1993-97. These attrition rates are much lower than the annual attrition rate of about 14% for offshore hedge funds during 1987-96 reported by Brown, Goetzmann and Ibbotson (1999) and 8.3% in TASS database during 1994-98 as reported by Liang (1999).

Bias	Park, Brown and Goetzmann (1999)	Fung and Hsiesh (2000)
Survivorship	2.6%	3.0%
Selection	1.9%	1.4%
Total	4.5%	4.4%

Table 1: Survivorship and Selection Biases in Hedge Fund Returns. This table provides a measure of survivorship and selection biases in hedge fund returns , for various academic studies on the subject.

Overall, it is probably a safe assumption to consider that these biases account for a total approaching at least 4.5% annual (see Park, Brown and Goetzmann (1999) and Fung and Hsiesh (2000)), as can be seen from Table 1.

3 CAPM as a Benchmark Model for Measuring the Performance of Hedge Fund Returns

While there has been some notable advance in the theory of performance measurement, most practice in the industry is still firmly rooted in the approach of the Capital Asset Pricing Model (CAPM). In the CAPM world, the appropriate measure of risk of any asset or portfolio i is given by its beta

$$\beta_i = \frac{cov\left(r_i, r_M\right)}{var\left(r_M\right)}$$

where r_i and r_M are random returns on portfolio i and on the market, respectively. Based on the well-known CAPM equilibrium relationship, the incremental expected return resulting from managerial superior information or skills (e.g., stock picking or market timing) can be represented as

$$\alpha_i = \overline{r_i} - \beta_i\left(\overline{r_M} - r_f\right) - r_f$$

where r_f is the risk-free rate. It can be estimated by a time series regression of a fund's excess return on the market excess return.

In this study, we use the return on the S&P 500 as a proxy for the market portfolio. We are of course aware of the unreliability of alpha measures when the market portfolio proxy is not mean-variance efficient (Roll (1978)) and this first take at hedge fund performance evaluation merely serves the purpose of benchmarking the results of further, more advanced, performance measures. We also test a pragmatic version of the market model, where an equally-weighted portfolio of all assets is used as the single index.

3.1 CAPM Alphas

The performance of hedge funds as measured with CAPM is given in Table 2. In this table, the standard error of alpha is found by computing an average fund return (equally weighted average of all funds) for each time period and regressing these excess returns on the market excess returns. The standard error is then taken from OLS standard error in the intercept term. This value is then used in the significance test.[3]

Note that the average alpha across all funds is significantly positive. Examining the hedge funds individually, we find that the majority of hedge funds have positive alphas, and about a third are statistically significant. Very few funds have significantly negative alphas.

Statistic	Value under CAPM
Alpha (average fund)	5.83%
Std. Err. Alpha (average fund)	2.85%
p-value (for average alpha not 0)	0.045
St.Dev. Alpha (across funds)	10.02%
% of funds with alpha significantly > 0	31.3%
% of funds with alpha significantly < 0	0.7%

Table 2: Performance of Hedge Funds as Measured with CAPM.

A histogram of CAPM alphas is given in figure 1 below. Note that the majority of funds fall into 6 bins with positive alphas ranging from 0% to 12%. Approximately 4.6% of funds had alphas outside the range of this plot and are not included here.

3.2 CAPM Betas

One important issue in hedge fund investing is the impact a particular fund would have on an existing equity portfolio. This can be measured by the CAPM beta. General statistics on our CAPM betas are shown in Table 3. While the mean beta is significantly lower than the total market beta of 1, it is still significantly positive, and the majority of funds have significantly positive betas.

A histogram showing the distribution of betas is given in figure 2 below. Note that the majority of funds have betas in the range of about 0 to 0.7. Approximately 1.5% of funds were omitted from this plot because their values were outside the convenient display range.

Of course, conditional correlations matter as much as unconditional correlations. While it has been documented that international diversification fails when it is most needed, i.e.,

[3]This method is preferable to using a one-sample t-test using the set of individual fund alphas as the sample, because individual funds' returns are correlated with each other.

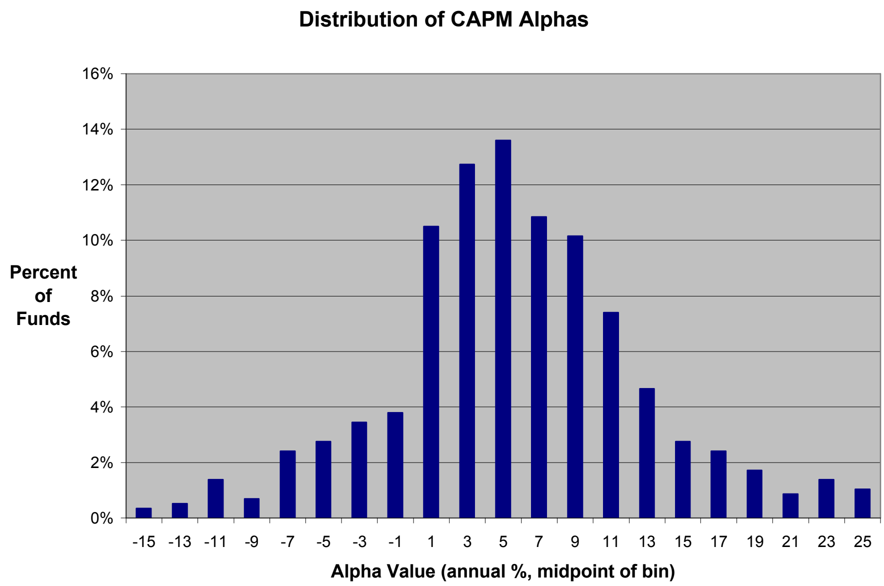

Figure 1: Distribution of CAPM alphas

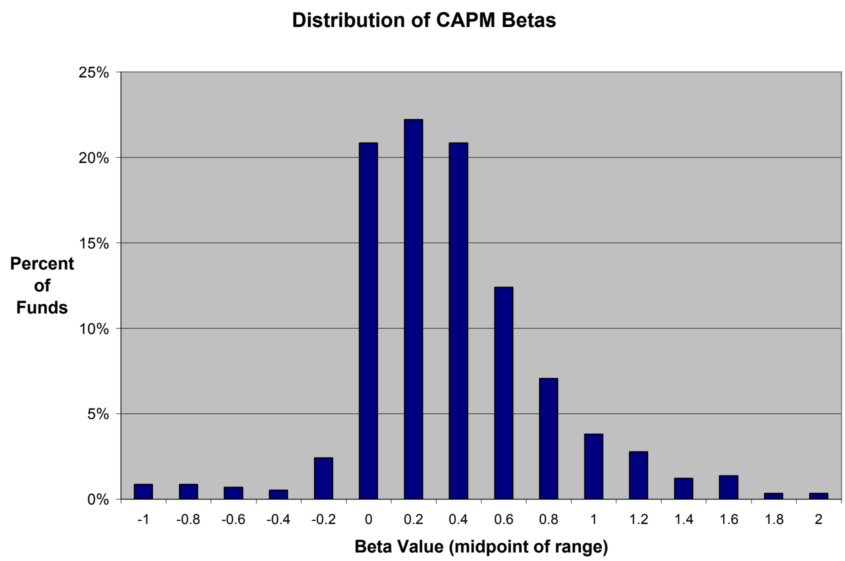

Figure 2: Distribution of CAPM betas

Statistic	Value
Mean Beta (annual rate)	0.373
Std. Dev. Beta (across funds)	0.514
p-value (for mean beta not 0)	< 0.001
% of funds with beta significantly > 0	71.2%

Table 3: CAPM Betas for Hedge Funds.

in periods of crisis (see for example Longin and Solnik (1995)), there is some evidence that conditional correlations of at least some hedge strategies with respect to stock and bond market indexes tend to be stable across various market conditions (Schneeweis and Spurgin (1999)). For the sake of brevity, and because this is not the main focus of the present paper, we do not report the results of a conditional correlation analysis here.[4]

Even though CAPM might help us obtain a first understanding of risk-adjusted hedge fund returns, there are a variety of reasons why a naive use of a CAPM model is not suited to measure hedge fund abnormal performances (see next three sections). In what follows, we consider alternative models in an attempt to alleviate the concerns about the inability of CAPM to correctly measure the risk-adjusted performance of hedge fund managers.

4 Adjusting CAPM for the Presence of Stale Prices in Hedge Fund Performance Reports

It is well-known that a fair number of hedge funds hold illiquid securities. For monthly reporting purposes, they typically price these securities using either the last available traded price or estimates of current market prices. Such non-synchronous return data can lead to understated estimates of actual CAPM market exposure, and therefore to mismeasurement of hedge fund risk-adjusted performance ((Asness, Krail and Liew (2001)). It is actually well-known that, in the presence of stale or managed prices, simple market model types of linear regressions may produce estimates of beta that are biased downward.

In the context of small firms, Scholes and Williams (1997) and Dimson (1979) propose a very simple technique to measure market beta by running regressions of returns on both

[4]We refer to Schneeweis and Spurgin (2000) and Amenc, Martellini and Vaissie (2003), who find that different strategies exhibit different patterns. They make a distinction between good, bad and stable correlation depending whether correlation is higher (resp. lower, stable) in periods of market up moves compared to periods of market down moves (see also Agarwal and Naik (2003)).

contemporaneous and lagged market returns of the following form

$$r_{i,t} - r_{f,t} = \alpha_i + \sum_{k=0}^{K} \beta_{ik} \left(r_{M,t-k} - r_{f,t-k} \right) + \varepsilon_{i,t}$$

(In this paper, we take $K = 3$.) Asness, Krail and Liew (2001) argue that, after accounting for this potentially increased market exposure, the broad universe of hedge funds does not add value. Their study, however, was conducted at the level of hedge fund indices from 1994-2000 (they use CSFB/Tremont hedge fund indices). In this paper, we conduct an analysis at the hedge fund level.

The performance of hedge funds as measured with this adjustment is given in Table 4. Note that although the average alpha is still positive, it no longer passes a test of statistical significance. Furthermore, the number of funds with alpha values significantly greater than zero has been cut in half.

Statistic	Value under CAPM	Value under Lagged CAPM
Alpha (average fund)	5.83%	2.14%
Std. Err. Alpha (average fund)	2.85%	3.21%
p-value (average fund alpha not 0)	0.045	0.51
% of funds with alpha significantly > 0	31.3%	16.9%
% of funds with alpha significantly < 0	0.7%	2.8%

Table 4: Performance of Hedge Funds under Lagged CAPM. This model adjusts for presence of stale prices.

A summary of alpha and beta values across our hedge fund database is given in table 7 below. Note that the value of beta is similar to the value obtained under CAPM. The other beta values are much smaller and in fact, when measured individually, are not statistically significant.

Statistic	Alpha	Beta	Beta1	Beta2	Beta3
Average Value	2.14%	0.386	0.075	0.095	0.060
Std. Err. in Average Fund	3.21%	0.049	.0.050	0.052	0.052
Std. Dev. across all funds	11.41%	0.520	0.152	0.171	0.147
% of funds with value significantly > 0	16.9%	72.6%	18.4%	16.7%	3.4%

Table 5: Alpha and Beta Values in Lagged CAPM Model.

A comparison of alpha distributions under the CAPM and Lagged CAPM models is shown in figure 3. Note that the CAPM model has more funds with alphas near 10%, and the Lagged CAPM model has more funds with alphas between -10% and 0.

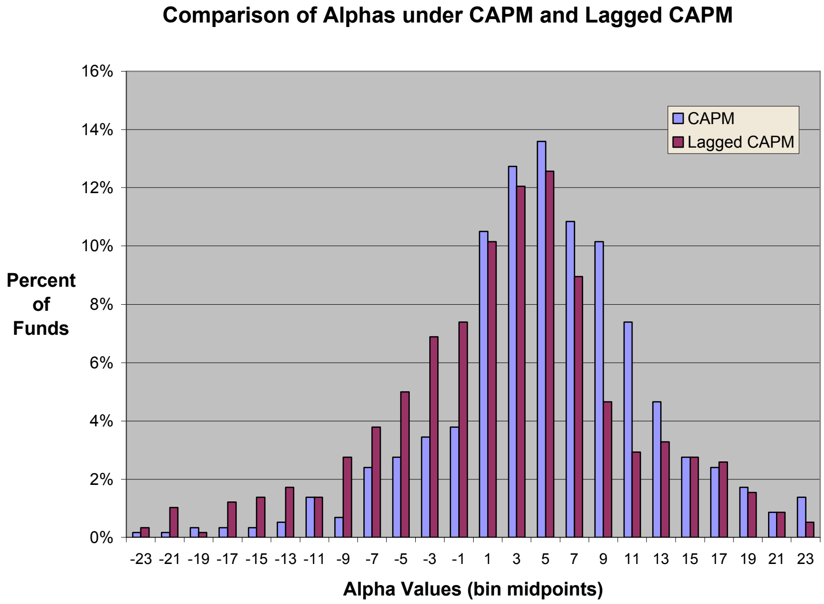

Figure 3: CAPM alphas versus lagged CAPM alphas

5 Adjusting CAPM for Predictability in Asset Returns

There are many new studies that show that stock returns at time t can be forecasted with information based at time $t-1$. For example, Harvey (1989) shows that up to 18% of the variation in U.S. stock portfolios can be forecasted on a monthly basis. Harvey (1991) finds similar results with international data (see also Ferson and Harvey (1991a) and (1991b)). More recently, Amenc, El Bied and Martellini (2001) provide strong evidence of predictability in hedge fund returns.

The use of predetermined variables to represent public information and time-variation has produced new insights about asset pricing models, and the literature on mutual fund performance has recognized that these insights can be exploited to improve on existing unconditional performance measures. In particular, Ferson and Schadt (1996) advocate conditional performance evaluation in which the relevant expectations are conditioned on public information variables (see also Christopherson, Ferson and Turner (1999) and Christopherson, Ferson and Glassman (1999)).

Following Ferson and Schadt (1996), we run the following regression

$$r_{i,t} - r_{f,t} = \alpha_i + \gamma_i \left(r_{M,t} - r_{f,t}\right) + \sum_{k=1}^{K} \delta_{ik} \left[Z_{k,t-1} \left(r_{M,t} - r_{f,t}\right)\right] + \zeta_{i,t}$$

where we use the same predictor variables as in Ferson and Schadt (1996). We normalize all independent variables to have a mean of zero and a standard deviation of one to simplify the interpretation of the regression coefficients.

- Z_1: Yield on T-Bill 3 month rate. Fama (1981) and Fama and Schwert (1977) show that this variable is negatively correlated with future stock market returns. It serves as a proxy for expectations of future economic activity.

- Z_2: Dividend yield. It has been shown to be associated with slow mean reversion in stock returns across several economic cycles (Keim and Stambaugh (1986), Campbell and Shiller (1998), Fama and French (1998)). It serves as a proxy for time variation in the unobservable risk premium since a high dividend yield indicates that dividend have been discounted at a higher rate. As a proxy for dividend yield, we use the dividend yield on S&P stocks.

- Z_3: Term spread, proxied by monthly observations of the difference between the yield on 3 months Treasuries and 10-year Treasuries.

- Z_4: Default spread. It captures the effect of default premium. Default premiums track long-term business cycle conditions; higher during recessions, lower during expansions (Fama and French (1998)). It is proxied by changes in the monthly observations of the difference between the yield on long term Baa bonds and the yield on long term AAA bonds.

The interpretation is that a manager with a significant conditional alpha term in the above regression is one whose average return is higher than the average returns of the dynamic strategies which replicate its time-varying risk exposure.

The performance of hedge funds as measured by the Conditional Model is given in Table 6. Note that the results are similar to those for CAPM. The mean alpha is slightly lower than for CAPM and only marginally significant. However, the correction for stale prices discussed in the previous section seems to have a greater impact than this correction for time-varying risk exposure.

Statistic	Value under Conditional Model
Alpha (average fund)	5.48%
Std. Err. Alpha (average fund)	3.03%
p-value (average fund alpha not 0)	0.076
% of funds with alpha significantly > 0	27.2%
% of funds with alpha significantly < 0	0.52%

Table 6: Performance of Hedge Funds under Conditional Model.

6 Adjusting CAPM for the Presence of Dynamic Trading Strategies

Leland (1999) argues that CAPM-based alpha systematically mismeasures performance when the market has i.i.d. returns. This is because the CAPM-based beta, the measure of an asset's risk, does not capture skewness and other higher-order moments of the return distribution which investors value. As a result, simple option strategies involving no skills from an investor will have their performance mismeasured. Given that it is a common practice or hedge fund managers to trade in options and/or follow dynamic trading strategies that generate non linear exposures to standard asset classes (e.g., Fung and Hsieh (1997)), it is likely that using a simple CAPM formula to measure these manager' alphas will lead to inaccurate estimates of their ability to generate superior risk-adjusted returns on the basis of superior picking or timing skills.

6.1 Power Utility Based Performance Measures

Leland (1999) proposes a simple adjustment to standard CAPM-based alpha measurement. Under the assumption that market rates of returns are identically and independently distributed and markets are perfect, the average investor will have a power marginal utility function which can be used to derive equilibrium prices (Rubinstein (1976)). Leland (1999) obtains the following performance evaluation equation

$$A_i = \overline{r_i} - B_i \left(\overline{r_M} - r_f \right) - r_f$$

This equation is formally similar to the CAPM-based alpha, the only difference being that portfolio risk is not measured by the CAPM beta but

$$B_i = \frac{cov\left(r_i, -\left(1 + r_M\right)^{-b}\right)}{cov\left(r_M, -\left(1 + r_M\right)^{-b}\right)} \tag{1}$$

where b is given by (Rubinstein (1976), Leland (1999))

$$b = \frac{\ln\left(\overline{1 + r_M}\right) - \ln\left(1 + r_f\right)}{var\left(\ln\left(1 + r_M\right)\right)} \tag{2}$$

That measure A_i is shown to deviate substantially from the CAPM α_i when the portfolio returns are highly nonlinear in the market return. The difference, however, will be relatively small when the portfolio is jointly lognormal with the market. The performance of hedge funds as measured with this model is given in Table 7. Note that the mean alpha is still positive, although it is slightly lower than that obtained with standard CAPM and higher than with the time-adjusted model. The mean B_i is also slightly higher than the betas obtained in either of the previous models.

Statistic	Value with Power-Utility Model
Mean Alpha (annual rate)	5.32%
Std. Dev. Alpha	10.16%
% of funds with alpha > 0	80%
Mean B_i	0.406
St. Dev B_i	0.537

Table 7: Performance of Hedge Funds under Power Utility Model.

6.2 Payoff Distribution Function Approach (Dybvig (1988a), (1988b))

The *payoff distribution pricing model*, introduced by Dybvig (see Dybvig (1988a, 1988b)), assigns a price to a given distribution function of consumption as the cost of the cheapest portfolio generating that function of consumption. This suggests the difference between the cost of an investor's actual portfolio and the cost of the cheapest portfolio generating the same function of consumption as a natural dollar measure of efficiency loss.[5] In a recent paper about hedge fund performance based on a continuous-time version of the payoff distribution pricing model, Amin and Kat (2001) show that hedge funds investing implies an efficiency loss of 6.42% and therefore make quite an inefficient investment.[6]

We recall their methodology.

- First step: recover the cumulative probability distribution of the monthly hedge fund payoffs as well as the S&P 500 from the available data set assuming $100 are invested at the beginning of the period. A normal distribution is assumed for the S&P 500 (i.e., we only need to estimate the mean and standard deviation of the monthly return on the S&P 500 over the period), but not for the hedge funds.

- Second step: generate payoff functions for each hedge fund. A payoff function is a function f that maps the return distribution of the S&P 500 S_T into a relevant return distribution for the hedge fund $H_T = f(S_T)$. The following example clarifies the construction of the payoff function. Suppose that the empirical distribution is such that there is a 20% probability of receiving a payoff lower than 100. We then look in the S&P 500 empirical distribution at which S&P 500 value X there is a 80% probability of finding an index value higher than X. Let us assume $X = 101$. Then, the payoff function is constructed such that when the index is at 101, the payoff would be 100.

[5]See also Pelsser and Vorst (1996) and Jouini and Kallal (2001) for extensions to the presence of transaction costs and the case of incomplete markets, respectively.

[6]They also show that 7 of the 12 hedge fund indices and 58 of the 72 individual hedge funds classified as inefficient on a stand-alone basis are capable of producing an efficient payoff profile when mixed with the S&P 500.

- Third step: we use a discrete version of a geometric Brownian motion as a model for the underlying S&P price process S and generate 20,000 end-of-month values using

$$S_{t+\varepsilon} = S_t \exp\left[\left(r - \frac{\sigma^2}{2}\right)\epsilon + \sigma\xi_t\right]$$

where the ξ_t are independent identically distributed Gaussian variables with mean zero and variance ε, r is the risk-free rate and σ the S&P volatility. From these 20,000 values, we generate 20,000 corresponding payoffs for each hedge fund, average them, and discount them back to the present to obtain a fair price for the payoff. This "price" thus obtained can be thought of the minimum initial amount that needs to be invested in a dynamic strategy involving the S&P and cash to generate the hedge fund payoff function $H_T = f(S_T)$. If the price thus obtained is higher than 100, this means that more than \$100 needs to be invested in S&P to generate a random terminal payoff comparable to the one obtained from investing a mere \$100 in the hedge fund. We therefore take this as evidence of superior performance. On the other hand, if the price obtained is lower than \$100, we conclude that one may achieve a payoff comparable to that of the hedge fund for a lower initial amount. The percentage difference is computed as a relative measure of efficiency loss.

Figure 4 compares the cumulative probability distributions for the S&P 500 with the average hedge fund. Note that the slope for the average hedge fund is much steeper than for the S&P 500, indicating a much narrow distribution of returns.

In Figure 5, we illustrate the performance of some high-rated and low-rated funds (according to PDPM). Note that the low-rated fund has a wide distribution of returns. Top rated funds were found to be of two types: high volatility funds with some exceptionally high returns, and low volatility funds. This plot illustrates one of each type; we have used the adjectives "high risk" and "low risk", simply based on the observed performance data.

The distribution of the relative measure of efficiency gain or loss is given in the following graph.

The performance of hedge funds as measured with PDPM is given in Table 8. Note that under this performance measurement scheme, on average, hedge funds do not outperform the market. However, the statistics are influenced by a few funds with large negative efficiencies. Over half of the funds have positive efficiency measures.

Note that in the implementation of PDPM, we must make an assumption about the volatility of the S&P 500. In the results presented here, we used the volatility as measured during the time period of the data. This volatility was about 16% on an annual basis. When we repeated the analysis with a higher volatility of 20%, the average hedge fund has a slightly higher efficiency and is no longer significantly different from zero. Thus, we would not claim

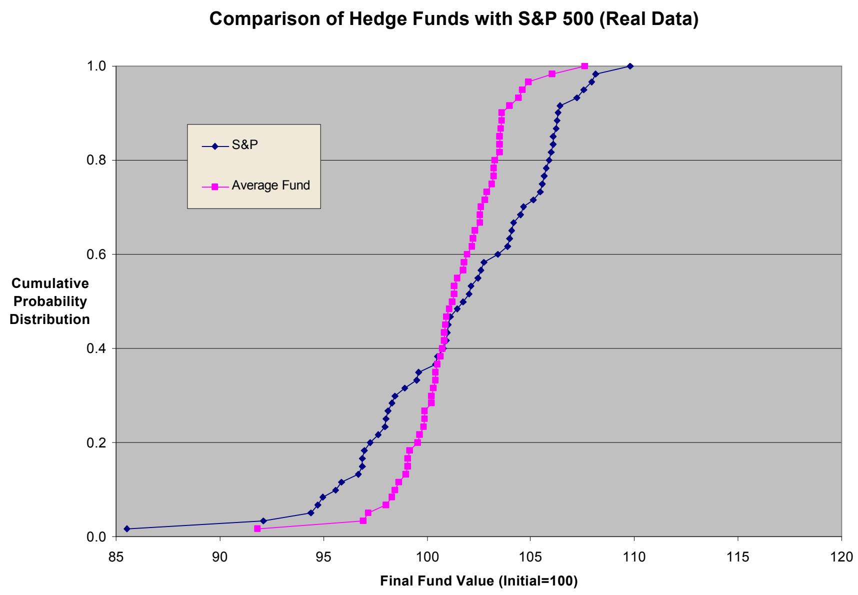

Figure 4: Comparison of hedge funds with S&P

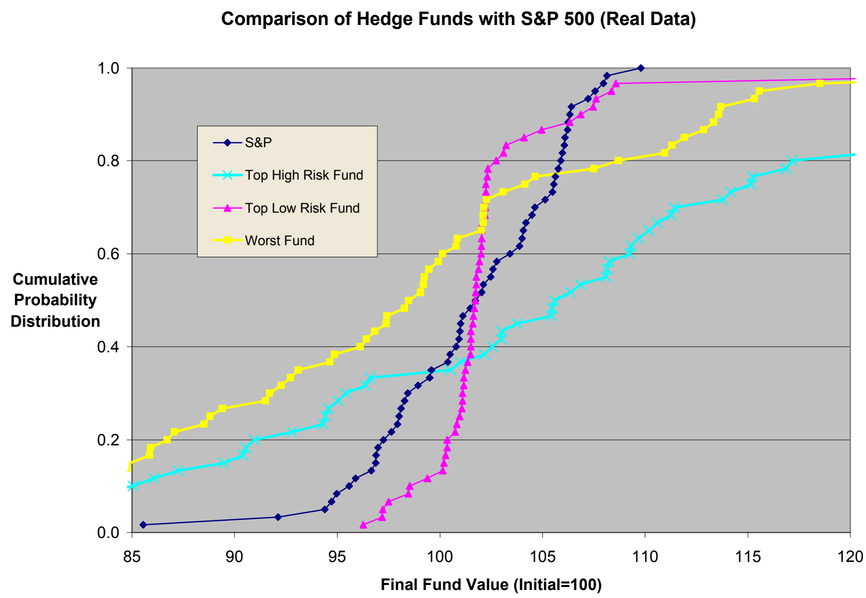

Figure 5: Comparison of hedge funds with S&P

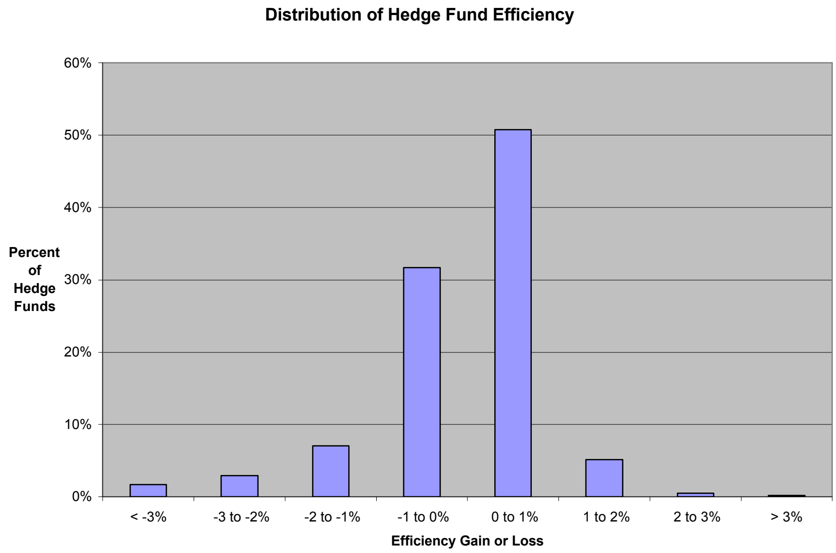

Figure 6: Distribution of hedge funds efficiency

	PDPM
Mean Efficiency (annual rate)	-0.92%
St.Dev. Efficiency	10.66%
% of funds with efficiency > 0	58%

Table 8: Performance of Hedge Funds under PDPM.

that hedge funds as a group underperform the market under PDPM, only that they fail to outperform it.

7 Adjusting CAPM for the Presence of Multiple Rewarded Risk Factors

In the classical CAPM framework, the expected return on an asset is related to the beta of the asset with respect to market portfolio. Because hedge funds are typically exposed to a variety of risk sources including volatility risks, credit or default risks, liquidity risks, etc., on top of standard market risks, a single factor (i.e., the market portfolio) may not be capable to properly measure the riskiness of various asset classes. In particular, a CAPM-based performance measurement will overestimate the abnormal return of a manager with positive exposure to nonmarket risk factors, and underestimate the abnormal return of a manager with negative exposure to nonmarket risk factors. For this reason we propose the use of a multifactor model for measuring the risk premium of various asset classes.

The theoretical foundations of the model are based on the Arbitrage Pricing Theory (Ross (1976)). The basic model of risk premium that serves as the foundation of our empirical estimates is given by

$$\overline{r_i} - r_f = \sum_{k=1}^{K} \beta_{ik} \lambda_k \tag{3}$$

where $\overline{r_i}$ is the expected return on asset i, is the riskless rate, β_{ik} is the exposure of asset i to factor k, and λ_k is the risk premium associated with factor k. Therefore, the risk premium on asset i is related to its exposures to various sources of risk and the corresponding risk premiums.

More generally, under the assumption that actively managed portfolios (here, hedge funds) earn a premium in excess of the risk premium represented by the portfolio's factor loadings and the associated factor premiums, we write

$$\overline{r_i} - r_f = \alpha_i + \sum_{k=1}^{K} \beta_{ik} \lambda_k \tag{4}$$

To try and mitigate model risk, we have tested the two following models, an implicit factor model and an explicit-multi-index model. We have also tested an explicit multi-factor based on proxies for market risks, volatility risk, credit risk and liquidity risk, as in Schneeweis and Spurgin (1999), but not report the detailed results here in the interest of brevity (see section 8 for a synthetic comparison of all results).

7.1 Implicit Factor Model

We use factor analysis to statistically extract the factors from the returns' time-series. This is perhaps the best approach because it is free of problems such as inclusion of spurious factors and omission of true factors. More specifically, we use Principle Component Analysis (PCA) to extract a set of implicit factors. The PCA of a time-series consists in studying the correlation matrix of successive shocks. Its purpose is to explain the behavior of observed variables using a smaller set of unobserved implied variables. Since principal components are chosen solely for their ability to explain risk, a given number of implicit factors always capture a larger part of asset return variance-covariance than the same number of explicit factors. One drawback is that implicit factors do not have a direct economic interpretation (except for the first factor, which is typically highly correlated with the market index). From a mathematical standpoint, it consists in transforming a set of N correlated variables into a set of orthogonal variables, or implicit factors, which reproduces the original information present in the correlation structure. Each implicit factor is defined as a linear combination of original variables.

The main challenge is to select a number of factors K such that the first K factors capture large fraction of asset return variance, while the remaining part can be regarded as statistical noise. A sophisticated test by Connor and Corajczyk (1993) finds between 4 to 7 factors for the NYSE and AMEX over 1967-1991, which is roughly consistent with Roll and Ross (1980). Ledoit (1999) uses a 5 factors model. In this paper, we select the relevant number of factors by applying some explicit results from the theory of random matrixes (Laloux et al. (1999)).[7]

The performance of hedge funds as measured with the Implicit Factor Model is given in Table 9. Note that the mean alpha is less than zero under this model. This suggests that there are factors influencing hedge fund performance that are captured in the Implicit Factor Model but not captured in CAPM.

Statistic	Value under Implicit Factor Model
Mean Alpha (annual rate)	-1.04%
Std. Dev. Alpha	12.59%
p-value (for mean alpha not 0)	0.047
% of funds with alpha > 0	44%

Table 9: Performance of Hedge Funds under Implicit Factor Model.

7.2 Explicit Multi-Index Model

Since hedge fund returns exhibit non-linear option-like exposures to standard asset classes (Fung and Hsieh (1997, 2000)), traditional linear factor models offer limited help in evaluating the performance of hedge funds. In the literature, one remedy has been suggested to try and capture such non-linear dependence: include new regressors with non-linear exposure to standard asset classes to proxy dynamic trading strategies in a linear regression. Natural candidates for new regressors are buy-and-hold positions in derivatives (Schneeweis and Spurgin (2000), Agarwal and Naik (2003) or Fung and Hsieh (2001)), or hedge fund indices (Lhabitant (2001)).

In this section, we follow the latter approach and use the CSFB/Tremont indexes which is currently the industry's only asset-weighted hedge fund index.[8] We measure risk-adjusted performance as the intercept (with T-statistic for assessment of statistical significance) of an

[7] The idea is to compare the properties of an empirical covariance matrix (or equivalently correlation matrix since asset return have been normalized to have zero mean and unit variance) to a null hypothesis purely random matrix as one could obtain from a finite time-series of strictly independent assets.

[8] Amenc and Martellini (2001) have introduced a set of "pure style indices" and tested their superior power in the context of style analysis. We do not, however, use these pure style indices because data is not available before 1998.

unconstrained regression of the fund's excess return on the different indices' excess return. In order to avoid over-fitting and multi-colinearity problems, we select, for each fund, of the subset of sub-indices which have been identified as more than marginally contributing to explaining the fund return (e. g., style weights larger than 10%). In particular, we use different models (i.e., different sets of indices) for different groups, but the same model (i.e., same set of indices) within a given group.

To achieve such peer grouping representation, we first use Sharpe's (1988, 1992) style analysis technique and represent each fund by a vector of the fund's style weights. This technique involves a constrained regression that uses several asset classes to replicate the historical return pattern of a portfolio, where the constraints are imposed to enhance an intuitive interpretation of the coefficients. First, to interpret the coefficients as weights within a portfolio the factor loadings are required to add up to one. Second, coefficients should be positive to reflect the short-selling constraint most fund managers are subject to. A non-linear regression analysis is proposed to arrive at point estimates for the portfolio weights. We then perform cluster-based peer grouping by minimizing intra-group and maximizing extra-group distance between funds, where distance is defined in terms of an appropriate metric in the space of fund's style weights.

Next, we describe the results of our peer grouping process and then the analysis of excess returns. Our clustering process resulted in eight groups, with the largest group having approximately half of the funds. To illustrate the nature of each cluster, we also computed, for each cluster, the average weighting on each index among the funds in that cluster. These results are shown in the table below. Each line represents a hedge fund and each column represents a cluster. Bold font indicates the largest entry in either a row or a column and tends to indicate that funds of that type dominate the cluster. For example, cluster 2 is dominated by emerging market funds (or more specifically, funds that are well predicted by the emerging market index). Cluster 3 is dominated primarily by fixed income arbitrage funds, but also includes managed futures. Cluster 5, the largest cluster, is dominated by Market Neutral funds.

cluster	1	2	3	4	5	6	7	8
Conv. Arb.	0.02	0.04	0.02	**0.61**	0.08	0.01	0.06	0.16
Short	0.02	0.06	0.07	0.07	0.08	**0.30**	0.06	0.04
Emerging Market	0.14	**0.85**	0.06	0.02	0.03	0.04	0.06	0.03
Mkt Neutral	0.04	0.00	0.11	0.06	**0.58**	0.23	0.19	0.03
Event Driven	0.03	0.02	0.07	0.04	0.06	0.04	**0.49**	0.03
Fixed Inc Arb	0.02	0.00	**0.38**	0.06	0.05	0.01	0.06	0.02
Global Macro	0.03	0.00	0.02	0.03	0.00	0.00	0.00	**0.53**
Long/Short	**0.68**	0.04	0.05	0.03	0.08	**0.34**	0.04	0.15
Managed Futures	0.02	0.00	**0.23**	0.08	0.03	0.02	0.04	0.00

It is also instructive to compare the primary indexes for each cluster with the self-proclaimed style of each fund in the cluster. Unfortunately, the self-proclaimed style information we have does not match 1-1 with the set of market indexes we have, and for many of our funds, no self-proclaimed style information is available. Nevertheless, a table of the information we do have is given below. Each row indicates a cluster and the number of funds with the given self-claimed style are indicated in each column. The column "0" indicates funds for which we do not have self-proclaimed style information.

Count of number	Self-claimed style											
Cluster #	0	EVENT-DRIV	GL MACRO	GLOBAL EMER	GLOBAL EST	GLOBAL INTL	LONG ONLY	MEDIAN	MKT NEUTRAL	SECTOR	SHORT-SALES a	Grand Total
1	5	16	3	3	23	6	1		16	2		75
2	2			1	5		1					9
3	24	3		1	13	2		1	4			48
4	10	3	1	4	12				5	1	1	37
5	88	26	14	12	43	9	2	6	49	15	4	268
6	7	5	2		9	1		1	13	4	2	44
7	21	12	8	4	19	1	1	6	14	5	1	92
8	4	1		2	1	1						9
(blank)												
Grand Total	161	66	28	27	125	20	5	14	101	27	8	582

Overall, the results do not indicate as much correlation between self-proclaimed style and cluster as one might hope. For example, only about half of the market neutral funds make it into the market neutral cluster (#5); yet overall, about half of the funds make it into that cluster. So a self-claimed market neutral fund is no more likely to be in the market neutral cluster than a fund with a different claimed type. These observations show that one should have some concern about managers' style purity potentially caused by managers' style drifts (see for example Bares, Gibson and Gyger (2001) for similar evidence on hedge fund managers, and DiBartolomeo and Witkowski (1997), Brown and Goetzmann (1997) or Kim, Shukla and Tomas (1999) for evidence of serious misclassifications if self-reported *mutual fund* investment objectives are compared to actual styles).

Next, we measure the excess return of hedge funds using the primary indexes appropriate to each cluster as factors in the model. We call this the Multi-Index model, a factor model similar in spirit to the one used by Elton et al. (1993). The performance of hedge funds under the Multi-Index model is shown in Table 10. Note that the mean hedge fund has alpha not significantly different from zero. These results suggest that the CSFB indexes effectively capture risk factors that are not captured by the standard CAPM, and that fund managers with positive CAPM alphas are often not outperforming hedge fund indexes.

Statistic	Value under Multi-Index Model
Mean Alpha (annual rate)	0.79%
Std. Dev. Alpha	16.27%
p-value (for mean alpha not 0)	0.24
% of funds with alpha $>$ 0	57%

Table 10: Performance of Hedge Funds under Multi Index Model.

Next, we regress hedge fund excess returns $r_{it} - r_f$ on the excess return of the equally-weighted portfolio of all hedge funds within a cluster. This is formally similar to Sharpe's (1963) single-index model (see also Ledoit (1999)).

The performance of hedge funds under this cluster-index model is shown in Table 11. Comparing this cluster-index model to the multi-index model presented above, we find that the results are similar. Note that the cluster-index model has an average alpha very close to zero. This should not be surprising since the same funds are used in the computation of the index as are used for computation of alpha.

Statistic	Value under Cluster-Index
Mean Alpha (annual rate)	0.06%
St.Dev. Alpha	15.02%
p-value (for mean alpha not 0)	0.92
% of funds with alpha > 0	60%

Table 11: Performance of Hedge Funds under a Cluster-Based Single Index Model.

8 Performance Analysis

We next use the multiple models presented in this paper to draw conclusions concerning the performance of hedge funds.

8.1 A Synthesis

First, we summarize the information presented earlier on average alphas by method in Table 12 (refer to earlier sections for further details on statistical significance). Each line lists one of the models discussed earlier; the final line simply lists the average return over the time period we used, unadjusted for risk. The standard deviations are across funds (not across time periods).

We conclude that hedge funds appear to have significantly positive alphas for CAPM-like models, even when multiple factors are considered. However, hedge funds on average do not have significantly positive alphas once the entire distribution is considered (PDPM) or implicit factors are included (PCA). Nevertheless, many individual funds do have significantly positive alphas.

To get a better insight about average alpha measures across models, we compute the cross-sectional distribution of average alphas across all models (see figure 7). The mean of that distribution is 4.07%, the standard deviation is 9.56%. This seems to indicate that the average hedge fund is likely to generate positive risk-adjusted return, when the risk-adjustment is performed with an average of asset pricing models. The conclusion that hedge funds yield on average positive alpha needs, however, to be balanced by the presence of survivorship,

	Average	St. Dev.	% > 0
CAPM	5.8%	10%	82.3%
Stale	2.1%	11.4%	65.2%
Cond	5.5%	10.2%	80.2%
Leland	5.3%	10.3%	78.7%
PPDM	-0.9%	10.7%	58.3%
PCA	-1%	12.6%	43.9%
Macro	7.3%	9.8%	86.7%
Index	0.8%	16.3%	56.5%
Cluster	0.1%	15%	59.4%
Av. Return	15.7%	9.8%	97.1%

Table 12: Mean Alphas by Model. This table summarizes the average alpha values for each model discussed in this paper. Reported mean differences may not exactly equal differences between reported means due to rounding.

selection and instant history biases, which account for a total approaching at least 4.5% annual, as recalled earlier. Therefore, the average alpha net of these biases is a negative $-.43\% = 4.07\% - 4.5\%$. On the other hand, 276 (out of 581 hedge funds) have an average alpha across methods larger than 4.5%, which seems to indicate the presence of positive abnormal return for at least some funds in the sample, even after accounting for the presence of the biases.

In the same vein, we compute the distribution of standard deviation of alpha across the sample of hedge funds (figure 8). The mean of that distribution is 7.66%, the standard deviation is 4.60%. It should be noted that one fund has a dispersion of alpha across methods larger than 40%!

Second, we wish to know whether funds that are rated highly by one method tend to also be rated highly by other methods. There are many different ways of investigating this. One of the most obvious is the correlation between alphas across methods, as shown in Table 13.

Note that the CAPM-related methods (CAPM, Stale, Conditional, Leland, and Macro) are highly correlated with each other, indicating that the adjustments have small effects. The implicit factor model has a smaller correlation with the other methods, indicating that it is picking up other factors not present in the explicit factors used in the other models. The clustering based methods also have lower correlation with the CAPM-related methods, indicating that they also pick up different factors.

Another way of examining the relationship between different models is to look at pairs of funds and ask whether the different models tend to rank order the funds in the same way. We call this the probability of agreement between any two models. Specifically, for any two models, it is the probability that the two models will agree on the rank order of a randomly-chosen

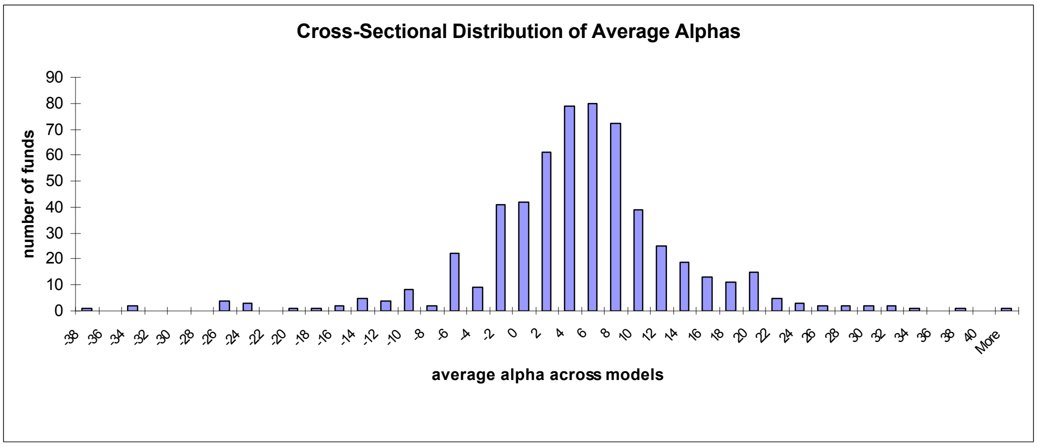

Figure 7: Cross-Section of Average Alphas. The mean of that distribution is 4.07%, the standard deviation is 9.56%.

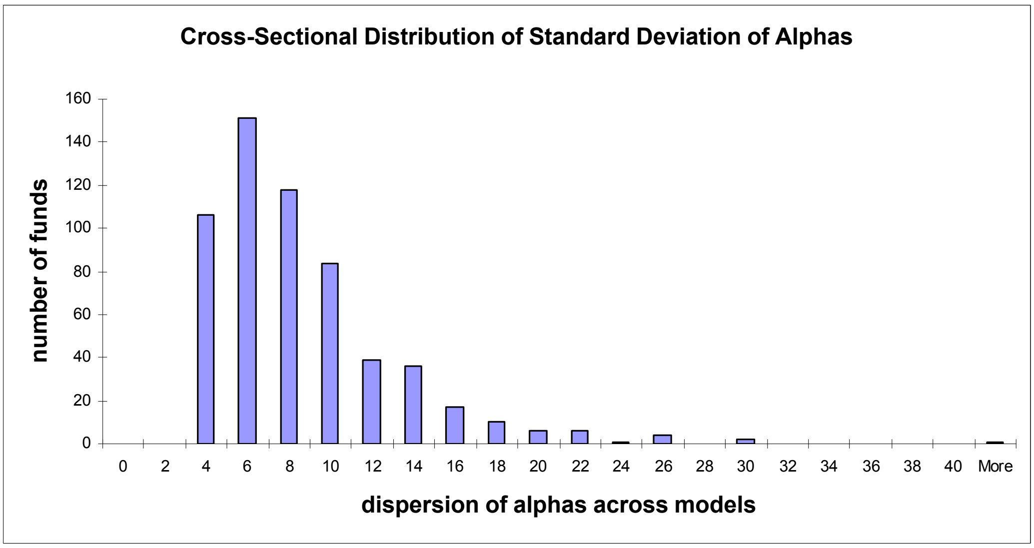

Figure 8: Cross-Section of Standard Deviation of Alphas. The mean of that distribution is 7.66%, the standard deviation is 4.60%.

	Stale	Cond	Leland	PPDM	PCA	Macro	Index	Cluster
CAPM	0.90	0.96	0.998	0.72	0.52	0.97	0.59	0.73
Stale	1.00	0.88	0.90	0.71	0.44	0.86	0.53	0.74
Cond		1.00	0.96	0.66	0.50	0.93	0.58	0.71
Leland			1.00	0.71	0.51	0.97	0.60	0.73
PPDM				1.00	0.42	0.68	0.38	0.73
PCA					1.00	0.55	0.27	0.33
Macro						1.00	0.54	0.64
Index							1.00	0.61
Cluster								1.00

Table 13: Correlation of Alphas between each pair of models.

pair of hedge funds (from our database). We calculate this statistic as follows:

$$A_{k,l} = \frac{\sum_{i=1}^{N} \sum_{j=i+1}^{N} g_{k,l}(i,j)}{N(N-1)/2}$$

where $A_{k,l}$ denotes the probability of agreement between methods k and l, and $g_{k,l}(i,j)$ is 1 if methods k and l agree on the rank order of funds i and j (i.e. $\alpha_k(i) > \alpha_k(j)$ and $\alpha_l(i) > \alpha_l(j)$, or $\alpha_k(i) < \alpha_k(j)$ and $\alpha_l(i) < \alpha_l(j)$) and is 0 otherwise.

The probability of agreement between pairs of models is given in Table14.

	Stale	Cond	Leland	PPDM	PCA	Macro	Index	Cluster	Av. Ret
CAPM	0.84	0.91	0.98	0.81	0.64	0.92	0.69	0.74	0.77
Stale	1.00	0.83	0.85	0.80	0.61	0.81	0.69	0.76	0.70
Cond		1.00	0.90	0.81	0.63	0.87	0.70	0.74	0.75
Leland			1.00	0.80	0.63	0.91	0.70	0.75	0.77
PPDM				1.00	0.62	0.77	0.66	0.77	0.70
PCA					1.00	0.65	0.57	0.56	0.67
Macro						1.00	0.67	0.70	0.80
Index							1.00	0.76	0.58
Cluster								1.00	0.60

Table 14: Probability of Agreement between each pair of models.

Note that the pairs of models with high correlations also have high probabilities of agreement. In addition, all pairs of models have probabilities of agreement > 0.50.

8.2 Impact of Fund Characteristics on Performance

We next use the multiple models presented in this paper to analyze the impact of fund characteristics on performance. Specifically, we investigate the impact of fund size, fund type, age, incentive fees, administrative fees, minimum purchase amount on fund performance. We investigate each of these characteristics using all of the models presented earlier to illustrate the impact of the choice of models on our conclusions.

8.2.1 Impact of Fund Size on Performance

First, we investigate the impact of a fund's asset size on performance. For each fund, we compute average assets over the time interval used for this study. We then divided the funds into two equal-size groups: those in the larger half in asset size and those in the smaller half. (Two funds were eliminated because we did not have asset size information.) For each group, we computed the average alpha obtained with each of the methods discussed earlier and performed a two-sample t-test to determine the significance of the differences. The results are shown in Table 15.

	Model									
	CAPM	Stale	Cond	Leland	PDPM	PCA	Macro	Index	Cluster	Avg Ret
Large Funds										
mean	6.75%	3.30%	6.30%	6.21%	0.95%	-0.50%	8.15%	1.70%	1.88%	15.94%
N	289	289	289	289	289	289	289	289	289	289
sd	9.25%	10.22%	9.09%	9.44%	8.57%	12.75%	9.34%	15.01%	12.67%	8.88%
stderr	0.54%	0.60%	0.53%	0.56%	0.50%	0.75%	0.55%	0.88%	0.75%	0.52%
Small Funds										
mean	4.96%	1.01%	4.72%	4.49%	-2.72%	-1.51%	6.39%	-0.01%	-1.72%	15.58%
N	290	290	290	290	290	290	290	290	290	290
sd	10.66%	12.79%	11.29%	10.76%	12.11%	12.43%	10.20%	17.33%	16.88%	10.63%
stderr	0.63%	0.75%	0.66%	0.63%	0.71%	0.73%	0.60%	1.02%	0.99%	0.62%
Difference										
mean	1.79%	2.29%	1.57%	1.73%	3.68%	1.01%	1.76%	1.71%	3.61%	0.36%
p value	0.03	0.02	0.07	0.04	< 0.01	0.33	0.03	0.21	< 0.01	0.66

Table 15: Impact of Asset Size on Performance. This table shows the results of two-sample t-tests conducted on mean alpha values for each model discussed in this paper. Reported mean differences may not exactly equal differences between reported means due to rounding.

Note that for all methods, the mean alpha for large funds exceeds the mean alpha for small funds. This fact, combined with the observation that most of the results are statistically significant, suggests that large funds do indeed outperform small funds on average.

8.2.2 Impact of Fund Type on Performance

Next, we investigate the impact of self-declared fund type on performance. The types considered were taken from the CISDM classification system. We omitted from the analysis approximately 160 funds for which we did not have fund type information. For each fund type, we computed the mean alpha values by model. These values are presented in Table 16. We were also particularly interested in the performance of market neutral funds, so Table 17 shows a two-sample t-test comparing market neutral funds with all other funds.

	# of Funds	CAPM	Stale	Cond	Leland	PDPM	PCA	Macro	Index	Cluster	Avg Ret
Event Driven	66	4.96%	1.05%	4.45%	4.26%	0.44%	-1.13%	6.05%	1.79%	1.95%	13.46%
GL Macro	28	4.15%	1.19%	2.56%	3.73%	-3.53%	-3.87%	5.75%	1.39%	1.79%	14.06%
Global Emerg.	27	-2.66%	-5.33%	-0.96%	-3.98%	-14.20%	-0.66%	1.07%	-11.57%	-15.14%	13.89%
Global Est.	125	6.93%	2.39%	6.71%	6.48%	-0.54%	-1.45%	8.75%	-1.04%	-3.55%	21.05%
Global Intl.	20	2.87%	-1.13%	1.77%	2.35%	-7.26%	-2.84%	5.56%	-2.23%	-7.38%	10.67%
Long Only	5	2.32%	-1.53%	-0.06%	1.53%	-3.41%	-5.18%	3.56%	-7.37%	-6.47%	18.02%
Median	14	4.87%	2.61%	4.63%	4.42%	1.89%	-2.77%	5.83%	1.25%	0.82%	11.75%
Mkt Neutral	101	9.40%	6.74%	9.28%	9.04%	2.88%	-0.52%	9.73%	8.17%	9.67%	15.48%
Sector	27	10.47%	5.57%	8.44%	9.81%	-0.73%	3.27%	12.06%	-1.14%	-2.44%	25.68%
Short Sales	8	13.65%	14.80%	15.11%	14.21%	-19.62%	-0.24%	13.34%	20.34%	-2.96%	6.45%
Unknown	160	4.20%	0.20%	3.85%	3.72%	0.05%	-0.83%	5.65%	-0.94%	-0.06%	12.96%

Table 16: Impact of Fund Type on Performance. This table shows mean alpha values by fund type for each model discussed in this paper.

	CAPM	Stale	Cond	Leland	PDPM	PCA	Macro	Index	Cluster	Avg Ret
Market Neutral										
mean	9.40%	6.74%	9.28%	9.04%	2.88%	-0.52%	9.73%	8.17%	9.67%	15.48%
st.dev.	12.76%	12.94%	14.38%	12.75%	7.51%	14.89%	11.93%	13.78%	15.37%	11.45%
Non-Market Neutral										
mean	5.52%	1.66%	5.08%	4.95%	-2.60%	-1.30%	7.27%	-0.68%	-2.91%	17.19%
st.dev.	12.76%	12.94%	14.38%	12.75%	7.51%	14.89%	11.93%	13.78%	15.37%	11.45%
Difference										
mean	3.88%	5.08%	4.20%	4.09%	5.49%	0.79%	2.46%	8.85%	12.58%	-1.71%
p-value	0.01	< 0.01	0.01	< 0.01	< 0.01	0.64	0.07	< 0.01	< 0.01	0.18

Table 17: Comparison of Market Neutral Funds with All Others.

From these tables, we note the following:

1. The CAPM models rate short-selling funds the highest, although other models did not. Short-selling funds tend to have negative betas, so even absolute performance near the risk-free rate will result in positive CAPM alphas. Conversely, the PDPM, which looks at the complete probability distribution of returns but not the correlation with market performance, rates these funds very low.

2. Most models rate market neutral funds as outperforming the average of other funds at a statistically significant level. However, two of the factor models do not. Presumably a typical market neutral fund has a favorable probability distribution of returns but is subject to some implicit or macroeconomic risks not well captured by the other models.

8.2.3 Impact of Fund Age on Performance

Next, we investigate the impact of a fund's age on performance. Here, age is defined as the length of time in operation prior to the beginning of our study. We divided the funds into two groups of approximately equal size: newer funds (age of one or two years) and older funds. For each group, we computed the average alpha obtained with each of the methods discussed earlier and performed a two-sample t-test to determine the significance of the differences. The results are shown in Table 18.

	CAPM	Stale	Cond	Leland	PDPM	PCA	Macro	Index	Cluster	Avg Ret
Newer Funds										
mean	7.34%	2.90%	6.88%	6.84%	-0.02%	-0.50%	8.67%	2.40%	1.63%	17.65%
st.dev.	11.67%	13.11%	12.21%	11.74%	11.16%	14.62%	11.30%	16.75%	16.91%	11.41%
Older Funds										
mean	4.59%	1.43%	4.27%	4.10%	-1.50%	-1.66%	6.03%	-0.26%	-0.95%	13.99%
st. dev.	8.16%	10.10%	8.19%	8.37%	10.05%	10.39%	8.13%	15.54%	12.97%	7.75%
Difference										
mean	2.76%	1.47%	2.61%	2.74%	1.48%	1.16%	2.63%	2.66%	2.58%	3.66%
p-value	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	0.289846	< 0.01	0.011266	< 0.01	< 0.01

Table 18: Impact of Fund Age on Performance. This table shows the results of two-sample t-tests conducted on mean alpha values for each model discussed in this paper. Reported mean differences may not exactly equal differences between reported means due to rounding.

Note that for all methods, the mean alpha for newer funds exceeds the mean alpha for older funds. The differences vary in significance across the methods. The most significant results are obtained with the CAPM and Explicit Factor models.

8.2.4 Impact of Fees on Performance

Next, we investigate the impact of incentive fees paid to the fund manager on fund performance. For each fund, we obtained the incentive fees, expressed as a percentage of profit. We then divided the funds into two groups: those with incentive fees >=20% (most were exactly 20%) and those with incentive fees < 20%. (We eliminated all funds with incentive fee values of zero in the database, assuming that these values represented unreported data rather than zero incentive fees.) For each group, we computed the average alpha obtained with each of the methods discussed earlier and performed a two-sample t-test to determine the significance of the differences. The results are shown in Table 19.

	CAPM	Stale	Cond	Leland	PDPM	PCA	Macro	Index	Cluster	Avg Ret
High Incentive Funds (N=334)										
mean	6.11%	2.40%	5.56%	5.64%	-0.66%	-1.10%	7.57%	2.49%	0.55%	15.48%
st. dev.	8.43%	9.97%	8.22%	8.52%	10.57%	11.58%	8.60%	15.30%	13.29%	9.12%
Low Incentive Funds (N=99)										
mean	0.73%	-2.81%	0.45%	0.04%	-4.38%	-2.54%	2.55%	-5.23%	-4.76%	12.02%
st.dev.	8.26%	10.75%	7.85%	8.56%	10.99%	11.12%	8.03%	12.27%	13.82%	8.27%
Difference										
mean	5.38%	5.22%	5.10%	5.60%	3.72%	1.44%	5.02%	7.72%	5.32%	3.46%
p-value	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	0.26	< 0.01	< 0.01	< 0.01	< 0.01

Table 19: Impact of Incentive Fees on Performance. This table shows the results of two-sample t-tests conducted on mean alpha values for each model discussed in this paper. Reported mean differences may not exactly equal differences between reported means due to rounding.

Note that for all methods, the mean alpha for high incentive funds exceeds the mean alpha for low incentive funds. A strong significant effect is obtained with almost all of the methods. The lack of significant difference found with the implicit factor method suggests the possibility that managers of high-incentive funds take on some risks not well captured by the other models.

We have also investigated the impact of a fund's administrative fees on performance by dividing the funds into two groups: those with administrative fees $>= 2\%$ and those with fees $< 2\%$. None of the differences we obtain (but not report here in the interest of brevity) is significant at the 0.05 level. This suggests that there is no significant difference between funds with higher or lower administrative fees.

8.2.5 Impact of Minimum Purchase Amount on Performance

Finally, we investigate the impact of the minimum purchase amount on performance. Minimum purchase amounts for the hedge funds in our study ranged from 0 to \$25 million. For this analysis, we divided the funds into two groups: those with a minimum purchase amount $>=$ \$300,000 and those with smaller amounts. (We discarded funds with zero reported minimum purchase amount, but the conclusions do not change if these funds are added back in.) The results are shown in Table 20.

Note that for all methods, the mean alpha for funds with the larger minimum purchase amounts exceeds the mean alpha for the other funds. Furthermore, the differences are statistically significant for all methods examined in this study. Note, however, that this does not

	CAPM	Stale	Cond	Leland	PDPM	PCA	Macro	Index	Cluster	Avg Ret
High Mininum Purchase Funds (N=285)										
mean	7.47%	4.34%	7.32%	7.00%	0.44%	0.17%	8.66%	3.00%	2.01%	16.98%
st. dev.	10.60%	11.52%	11.23%	10.67%	10.25%	12.94%	10.41%	16.93%	16.39%	10.43%
Low Minimum Purchase Funds (N=251)										
mean	3.63%	-0.58%	3.19%	3.09%	-2.80%	-2.69%	5.28%	-1.92%	-2.46%	14.09%
st.dev.	0.63%	0.68%	0.67%	0.63%	0.61%	0.77%	0.62%	1.00%	0.97%	0.62%
Difference										
mean	3.84%	4.93%	4.13%	3.91%	3.24%	2.86%	3.38%	4.92%	4.47%	2.89%
p-value	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	0.01	< 0.01	< 0.01	< 0.01	< 0.01

Table 20: Impact of Minimum Purchase Size on Performance. This table shows the results of two-sample t-tests conducted on mean alpha values for each model discussed in this paper. Reported mean differences may not exactly equal differences between reported means due to rounding.

imply causality: it may be that funds that have been very successful have no trouble attracting investors and are therefore more likely to raise their minimum purchase amounts.

9 Conclusion and Suggestions for Further Research

Conflicting evidence about alphas can be found in the burgeoning literature on hedge fund performance measurement. Our contribution is to provide an unified picture of hedge fund managers to generate superior performance. To alleviate the concern of model impact on the results of performance measurement, we consider an almost exhaustive set of pricing models that can be used for assessing the risk-adjusted performance of hedge fund managers. Because we test such a large array of methods in a unified environment, we are able to quantify how different models agree or disagree in terms of relative or absolute performance evaluation. If ten different methods conclude that the risk-adjusted performance of a given fund exceeds that of another fund, then we should have some confidence as to whether the first fund did actually dominate the second fund. Similarly, if ten different methods conclude that the risk-adjusted performance of a given fund is significantly positive, then we should have some confidence about the result. While we find positive alphas for a sub-set of hedge funds across all possible models, our main conclusion is perhaps that the dispersion of alphas across models is very large, as can be seen from the dispersion of alphas across models. The magnitude of the disagreement among competing models is perhaps one of the most striking result of our study. In that sense, our results may actually be regarded as a test of model performance as much as a test of fund performance. One may actually use the information contained in the empirical distribution of alphas across various strategies as an input in an active asset allocation models (see Cvitanic et al. (2003)). On the other hand, all pairs of models have probabilities of agreement greater than .50, even a trivial model that only computes the average return. In other words, while different models strongly disagree on the absolute risk-adjusted performance of hedge funds, they largely agree on their relative performance in the sense that they tend to rank order the funds in the same way.

In the light of the empirical research on hedge fund performance, it is therefore a safe assumption to conclude that alphas on active strategies, if they exist, are not easy to measure with any degree of certainty. This is sharp contrast with the fact that there is some evidence that conditional correlations of at least some hedge strategies with respect to stock and bond market indexes tend to be stable across various market conditions (Schneeweis and Spurgin (1999)).[9] Hedge fund are exposed to a variety of risk factors, and, as a result, generate normal, as opposed to abnormal, returns.

The hedge fund industry should perhaps focus on promoting the beta-benefits of hedge fund investing, which are significant and less arguable, as opposed to promoting the alpha-benefits of hedge fund investing, which are very hard to measure with any degree of accuracy. This also suggests that the future of alternative investments may lie in "the impersonal", i.e., in passive indexing strategies.

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[9] In a follow up paper, Schneeweis and Spurgin (2000) find that different strategies exhibit different patterns. They make a distinction between good, bad and stable correlation depending whether correlation is higher (resp. lower, stable) in periods of market up moves compared to periods of market down moves. Agarwal and Narayan (2001) also report evidence of higher correlation between some hedge fund returns and equity market returns when conditioning upon equity market down moves as opposed to conditioning upon up moves.

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