Hedge Funds: Performance, Risk and Capital Formation[*]

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Abstract

We use a comprehensive dataset of funds-of-funds to investigate performance, risk and capital formation in the hedge fund industry over the decade from 1995-2004. We first confirm that there are high systematic risk exposures in the returns of funds-of-funds in our data. We then divide up the ten years into three distinct sub-periods and demonstrate that the average fund-of-funds has only delivered alpha in the short second period from October 1998 to March 2000. In the cross-section, however, we are able to identify funds-of-funds capable of delivering alpha. We find that these alpha producing funds-of-funds experience far greater and steadier capital inflows than their less fortunate counterparts. In turn, these capital inflows adversely affect their ability to produce alpha in the future. These findings strongly support Berk and Green's (2004) rational model of active portfolio management, in which diminishing returns to scale combined with the inflow of new capital into better performing funds leads to the erosion of superior performance over time.

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Hedge funds are considered by some to be the epitome of active management. They are lightly regulated investment vehicles with great trading flexibility, and they often pursue highly sophisticated investment strategies. Hedge funds promise ‘absolute returns’ to their investors, leading to a belief that they hold factor-neutral portfolios. They have grown in size noticeably over the past decade and have been receiving increasing portfolio allocations from institutional investors.[1] According to press reports, a number of hedge fund managers have been enjoying compensation that is well in excess of U.S.$ 10 million per annum.

How much of the hype is true? We are aware from a variety of past research papers that there are risks inherent in hedge fund returns.[2] However, in the course of active portfolio management, risk exposures are bound to change with market conditions. Can we capture the time variation in these risks? Can we characterize interesting differences in risk-adjusted performance (alpha) in the cross-section of hedge funds? Can we use these differences to forecast the future alpha generated by a set of hedge funds? What is the relationship between capital flows, cross-sectional and time-series movements in risk-adjusted hedge fund performance? Do capital inflows adversely affect the risk-adjusted performance of hedge funds over time? In this paper, we investigate these important questions. In doing so, we provide a body of evidence that lends strong support to Berk and Green’s (2004) rational model of active portfolio management.

Berk and Green’s (2004) model has three key features. First, investors competitively provide capital to funds. Second, managers have differential ability to generate high risk-adjusted returns, but face decreasing returns to scale in deploying their ability. Third, investors learn about managerial ability from past risk-adjusted performance and direct more capital towards funds with superior performance. This leads to zero risk-adjusted returns in equilibrium. We demonstrate that these features are evident in the hedge fund industry. In particular, we show that there large differences in the cross-section in the ability of funds to deliver statistically positive risk-adjusted returns (or alpha). Those funds capable of delivering alpha experience far greater and steadier capital inflows than their less fortunate counterparts. Finally, we demonstrate that capital flows adversely affect the future risk-adjusted performance of funds.

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[1] According to the TASS Asset Flows report, aggregate hedge fund assets under management have grown from U.S. $72 billion at the end of 1994 to over $670 billion at the end of 2004.

[2] See Agarwal and Naik (2005) for a comprehensive survey of the hedge fund literature.

Before one can use the data on hedge funds to examine these issues, one has to minimize the biases in these data. These biases arise from a lack of uniform reporting standards, as hedge funds have historically been largely unregulated. For example, hedge fund managers can elect whether to report performance at all, and if they do, they can decide the database(s) to which they report. They can also elect to stop reporting at their discretion.[3] This biases the returns reported in hedge fund indexes (constructed as averages of reported hedge fund returns) upwards.

Furthermore, real-life constraints make hedge fund index returns difficult to replicate. For example, some hedge funds included in an index may be closed to new money, or may even be returning money to investors. In addition, hedge funds often impose constraints on the withdrawal of capital, using lockup periods, redemption and notice periods. Moreover, the returns of hedge fund indexes do not reflect the cost of accessing the constituents of the index (e.g., search costs, due diligence costs, selection and monitoring costs). In order to obviate real-life constraints and to incorporate these costs into performance measures, producers of hedge fund indexes have come up with "investable" counterparts of their hedge fund indexes. Unfortunately, the performance of these investable counterparts has been quite poor (both in terms of the level of returns as well as tracking error) relative to the indexes they are supposed to track. This suggests that the costs of accessing the funds and costs imposed by real-life constraints are substantial and highly variable, and need to be taken into account for a true assessment of the performance of hedge funds.

To mitigate these problems, Fung and Hsieh (2000) suggest that inspecting the performance of funds-of-funds (hedge funds that invest in portfolios of other hedge funds) may be preferable to analyzing the returns of hedge fund indexes. This is because fund-of-fund returns better reflect the investment experience of investors, and incorporate the costs of managing a portfolio of hedge funds.[4] Their reasoning is very intuitive: consider the case of a hedge fund that stops reporting to data vendors several months before going belly up. As soon as it stops reporting, it is excluded from the hedge fund return index, and as a result, the index does not reflect the full extent of losses incurred by investors. In contrast, a fund-of-funds investing in the hedge fund, as a diversified portfolio, has a high chance of

[3] See, for example, Fung and Hsieh (2000) and Liang (2000) for more in-depth insights into the potential measurement errors that can arise as a result of voluntary reporting.
[4] The recent availability of hedge fund investable indices enables a perfunctory comparison: these indices have returns that are far lower than those of the reported average hedge fund indices. In comparison, the reported average fund-of-funds indices are quite close in magnitude to the investable indices, and have a high correlation with them in recent years.

surviving the collapse of one of its investments. Therefore its return (albeit indirectly) will reflect losses experienced by investors to a greater extent. Second, unlike hedge fund index returns, fund-of-fund returns reflect the cost of real-life constraints (hedge funds being closed or imposing delays to capital withdrawal). Finally, in contrast to the returns on hedge fund indexes, fund-of-fund returns are generally reported net of an additional layer of fees (i.e., the cost of managing a portfolio of underlying hedge funds), and are therefore more representative of the true investment experience of hedge fund investors.

In light of all these reasons, we use funds-of-funds in our analysis. We consolidate the main databases with these data: CSFB/Tremont TASS, HFR and CISDM. After carefully removing duplication, we have a total of 1603 funds-of-funds, over a ten-year period (January 1995 to December 2004). This data represents the most comprehensive set of funds-of-funds that is publicly available. We use this data to test the implications of Berk and Green's (2004) model and to investigate performance, risk and capital formation in the hedge fund industry.

Our analysis uncovers many interesting findings. First, there exist significant cross-sectional differences in the risk-adjusted performance (or alpha) of funds, suggesting substantial differences in ability across funds. Second, funds that produce alpha receive far greater inflows of capital than funds that only exhibit factor exposures. The capital flows into the alpha producing funds are steady, and do not significantly respond to recent past returns, while the flows into the remaining funds are characterized by return-chasing behavior. This suggests the presence of a clientele effect in the hedge fund industry, a conjecture that we explore further in the paper. Third, capital inflows significantly and adversely affect the ability of alpha producing funds to deliver alpha in the future. Interestingly, this also seems to manifest itself at the level of the industry: the level of alpha delivered by the average alpha producing fund has declined substantially in recent years. All these findings lend strong support to Berk and Green's (2004) rational model of active portfolio management.

Contracts in the hedge fund industry are currently structured to reward managers for generating returns above pre-specified benchmarks. This contract design, with minor variations, has survived the past few decades of hedge fund evolution. Our findings highlight the limitations of a contract design that does not reflect the preference of investors for superior risk-adjusted performance.[5] To circumvent this limitation, investors appear to be voting with their feet, rewarding alpha producers with a steady inflow of capital – an experience not shared by funds that failed to deliver alpha. We conjecture that the divergent ability to attract capital between alpha producing funds and the rest will ultimately translate into a revision of the hedge fund contract. Funds that do not produce alpha may be tempted to lower their fees to compete with those who do. In other words, we believe that the apparent differences in the ability of the two groups of funds (alpha producers and the rest) to attract investor capital will ultimately manifest itself in the differential pricing of services offered by these two groups of funds.

The organization of the paper is as follows: Section 2 introduces the data. Section 3 describes our methodology. Section 4 reports the results. Section 5 concludes.

2. Data

The main databases with data on funds-of-funds are: Hedge Fund Research, which supplies the HFR family of indices; the Center for International Securities and Derivatives Markets database, which produces the CISDM family of indices, and TASS. We merge and consolidate data from the HFR, CISDM and TASS databases. Duplicate funds from different database vendors are eliminated, as are substantially similar series of the same funds offered as different share classes for regulatory and accounting reasons. Our final set consists of 1603 funds, and our sample period runs from January 1995 to December 2004.

We classify funds into three categories: alive, liquidated, and stopped reporting (these last are live funds). Each year, the data vendors report which funds were 'defunct.' In some cases they provide reasons for applying this tag to a fund. Where the vendors report that defunct funds are either liquidated or that they stopped reporting, we use the vendor classification. In the few cases in which vendors do not provide a reason for 'defunct', we inspect the AUM and returns of the funds in question. If the final AUM reported by a fund is very low relative to the maximum AUM over the fund's lifetime, and if the returns in the final months of the fund's history are below the industry

[5] See Brown, Goetzmann and Liang (2004) for inefficiencies from improper structuring of fees on fees in fund-of-funds contracts, and Goetzmann, Ingersoll and Ross (2003) for incentive implications of high-water mark provision in hedge fund contracts.

average return, we classify the fund as liquidated, otherwise we classify it as a fund that has stopped reporting (but alive). For each fund classified using our procedure, we cross-check our classification with industry sources.

Table I presents descriptive statistics on our consolidated data (note that all the return data we employ is net-of-all-fees). First, mirroring the growth in AUM in the hedge fund industry, the AUM in funds-of-funds has grown from U.S. $18 billion at the end of 1995 (around 25 percent of total AUM in the hedge fund industry according to the TASS asset flows report) to around U.S. $190 billion in 2004 (close to 30 percent of the industry). Second, the data exhibit time-variation in birth, liquidation and closing rates. The average birth rate is 27 percent, the average liquidation rate is 4.7 percent, and the average rate of funds that stopped reporting despite being alive is 2.7 percent per year. Third, the equal-weighted net-of-fee mean annual returns at the end of the year average 10.3 percent over the ten years in our sample period. However, these returns vary substantially both within and across years. The table reveals that in 1998, the average return of the funds in our data is zero, which is unsurprising given the cataclysmic events that occurred in that year.

3. Methodology

3.1. Risk-Adjusted Performance Evaluation

Throughout our analysis, we model the risks of funds using the seven-factor model of Fung and Hsieh (2004a). These factors have been shown to have considerable explanatory power for fund-of-fund and hedge fund returns.[6] The set of factors consists of the excess return on the S&P 500 index (*SNPMRF*); a small minus big factor (*SCMLC*) constructed as the difference of the Wilshire small and large capitalization stock indices; the excess returns on portfolios of lookback straddle options on currencies (*PTFSFX*), commodities (*PTFSCOM*) and bonds (*PTFSBD*), which are constructed to replicate the maximum possible return to trend-following strategies on their respective underlying assets;[7] the yield spread of the US ten year treasury bond over the three month T-bill, adjusted for the duration of the ten year bond (*BD10RET*); and the change in the credit spread of the Moody's BAA bond over the 10 year treasury bond, also appropriately adjusted for duration (*BAAMTSY*). We use a linear factor model employing these factors to calculate the alpha of funds.

[6] See Fung and Hsieh (2001, 2002, 2004b). Agarwal and Naik (2004) present a factor model that includes some of the same factors as the Fung-Hsieh model.
[7] See Fung and Hsieh (2001) for a detailed description of the construction of these primitive trend-following (PTF) factors.

3.2. Time Variation and Structural Breaks

A static factor analysis of the risk structure of fund returns is not appropriate if managers change their strategies over the sample period that we investigate. Fung and Hsieh (2004a) study vendor-provided fund-of-fund indices, and perform a modified CUSUM test to find structural break points in fund factor loadings. They find that the break points coincide with extreme market events that might plausibly be expected to affect managers' risk taking behavior. These break points are the collapse of Long-Term Capital Management in September 1998, and the peak of the technology bubble in March 2000.

We employ a more formal framework in this analysis, and test for the validity of these pre-specified breakpoints using a version of the Chow (1960) test. We modify the test, replacing the standard error covariance matrix with a heteroskedasticity-consistent covariance matrix of the errors (White (1980), Hsieh (1983)). In particular, we estimate the following specification to begin with, and perform the modified Chow test:

$$\begin{aligned} &R_t = \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + (D_1 X_t)\beta_{D1} + (D_2 X_t)\beta_{D2} + (D_3 X_t)\beta_{D3} + \varepsilon_t \\ &\text{Where } X_t = [SNPMRF_t \;\; SCMLC_t \;\; BD10RET_t \;\; BAAMTSY_t \;\; PTFSBD_t \;\; PTFSFX_t \;\; PTFSCOM_t] \end{aligned} \qquad (1)$$

Here, R_t is the (equal-weighted) average excess return across all funds in month *t*, D_1 is a dummy variable set to one during the first period (January 1995 to September 1998) and zero elsewhere, D_2 is set to one during the second period (October 1998 to March 2000) and zero elsewhere, and D_3 is set to one during the third period (April 2000 to December 2004) and zero elsewhere. Thus, there are a total of 24 regressors in equation (1), including the dummy variables.

Equation (1) investigates the time variation in the equal-weighted index return, ignoring any cross-sectional heterogeneity in the set of funds. We present our method to examine cross-sectional heterogeneity in alpha-production ability across funds in the next subsection.

3.3. Cross-Sectional Differences in Funds

We conduct an exercise of solving the portfolio selection and rebalancing problem of a hypothetical real-life investor. We assume that an investor wants to allocate some money to hedge funds. The investor, as in Berk and Green's (2004) model, infers the ability of a manager by evaluating the fund's past performance. The investor selects funds that exhibit superior performance, and directs capital towards them. At annual intervals, the portfolio is rebalanced, by re-assessing the available investment opportunity set and re-selecting funds.

This exercise is implemented in the following way. At the end of 1996, we select all funds that have a full return history in the data over the previous 24 months (January 1995 to December 1996). Using Fung and Hsieh's (2004a) seven-factor model, and the non-parametric procedure of Kosowski et. al. (2006), (see Appendix A for details) we identify funds that deliver statistically positive alpha and segregate them from the remainder of the set. For expositional convenience, we denote the former set of funds as *have-alpha* funds and the remaining funds as *beta-only* funds.

We repeat the alpha estimation exercise for every rolling two-year period in our sample. Note that our selection procedure could result in a change in the identities of the *have-alpha* funds and *beta-only* funds each year, depending on the risk-adjusted performance of funds over the prior two years.

3.4. Capital Flow Analysis

We construct the quarterly net flow of capital into each of the funds in our sample. Capital flows are defined as capital contributions less withdrawals, once fund returns have been accrued. Flows are calculated under the assumption that they come in at the end of each quarter (we also experiment with the assumption that flows come in at the beginning of each quarter, and our results are invariant to this assumption):

$$F_{iq} = \frac{AUM_{iq} - AUM_{iq-1}(1 + R_{iq})}{AUM_{iq-1}} \tag{2}$$

Where F_{iq}, AUM_{iq}, R_{iq} respectively, are the flows for a fund i in quarter q expressed as a percentage of lagged AUM; the AUM of the fund i in quarter q; and the returns of fund i in quarter q. We winsorize the quarterly flows across all funds each quarter at the 1 and 99 percentile points to mitigate the effect of outliers.

To estimate the relationship between flows, past flows and past returns, we run the following regression:

$$F_{gq} = \gamma_0 + \gamma_r R_{gq-1} + \gamma_{f1} F_{gq-1} + u_{gq} \tag{3}$$

The quarterly flow measure F_{gq} is regressed on lagged quarterly flows F_{gq-1} and lagged quarterly returns R_{gq-1}. This regression is estimated separately for each sub-group *g* of funds-of-funds (*g* can be *have-alpha* or *beta-only*). We employ a Newey-West (1987) covariance matrix using four quarterly lags to account for any possible autocorrelation and heteroskedasticity in the residuals.

We then investigate whether capital providers to hedge funds behave in a similar way to those investing in mutual funds. We do so in two ways. First, we estimate a simple quintile regression separately for *have-alpha* funds and *beta-only* funds:

$$F_{iy} = \phi_1 I^1_{iy-1} + \phi_2 I^2_{iy-1} + \phi_3 I^3_{iy-1} + \phi_4 I^4_{iy-1} + \phi_5 I^5_{iy-1} + u_{iy} \tag{4}$$

Here the annual flow measure F_{iy} for a fund *i* in a year *y* is computed as a percentage of end-of-previous-year AUM, and the indicator variables I^k_{iy} represent the return quintile membership for a fund, computed across all funds in the group in the previous year. For example, if a fund *i* is a member of the top performing quintile of *have-alpha* funds in year *y-1*, $I^5_{iy-1} = 1$, and $I^4_{iy-1} = I^3_{iy-1} = I^2_{iy-1} = I^1_{iy-1} = 0$.

We then go a step further, to check whether the much-noted convexity of the responsiveness of capital flows to recent returns of mutual funds (Sirri and Tufano (1998)) is also evident in hedge funds. To do so, we regress:

$$F_{iy} = \sum_{k=1}^{5} \rho_k FRank_{iy-1}^{k} + u_{iy} \qquad (5)$$

Here, $FRank_{iy-1}^{k}$ are dummies that capture the fractional return rank for a fund *i* in a year *y-1*, computed across all funds in the group. For example, if a fund *i* is ranked 35th out of a total of 100 *have-alpha* funds in year *y-1* based on returns, $FRank_{iy-1}^{1} = 0.2$, $FRank_{iy-1}^{2} = 0.15$, and $FRank_{iy-1}^{3} = FRank_{iy-1}^{4} = FRank_{iy-1}^{5} = 0$.

In our panel specifications, we compute cross-correlation and heteroskedasticity consistent standard errors using the method of Rogers (1983, 1993). We follow the Sirri-Tufano methodology and compute Fama-MacBeth (1973) coefficients and standard errors when estimating equation (5).

Berk and Green (2004) posit that there are decreasing returns to scale in alpha production. This would imply that increases in capital flows to *have-alpha* funds will generate declines in the subsequent alpha produced by these funds. The next section outlines our methodology to investigate whether this holds true in our data.

3.5. Capacity Constraints

In order to uncover the relationship between capital flows and subsequent risk-adjusted performance, we further divide the *have-alpha* funds and *beta-only* funds into two subcategories, based on the level of capital flows that they receive. In particular, in each classification period, we compute the average quarterly flow experienced by all funds in the final year of the classification period. We then sort funds based on whether they receive above the median or below the median capital flows. This gives us our two subcategories, above-median-flow and below-median-flow funds.

We then examine the future performance of the two subcategories of funds within each of the *have-alpha* and *beta-only* groups in three ways. First, we inspect the transition probabilities of these funds, i.e., the probability of above-median-flow and below-median-flow funds to be subsequently reclassified as *have-alpha* funds and *beta-only* funds in the next non-overlapping classification period, conditional on not being defunct in that period. Second, we compute the average t-statistic of alpha in the subsequent non-overlapping classification period for non-defunct above-median-flow and below-median-flow funds to get a sense of whether the 'information ratio' for a fund is affected by its level of capital flows. Finally and analogously, we compute the average level of alpha for non-defunct above-median-flow and below-median flow funds in the subsequent non-overlapping classification period. We estimate the statistical significance of the difference in these metrics for above-median-flow and below-median-flow funds using the Wald test and a cross-correlation and heteroskedasticity consistent covariance matrix (computed using the method of Rogers (1983, 1993)).

Based on the results from our analysis of capital flows in subsection 3.4 and capacity constraints in subsection 3.5, we might expect to find changes in alpha production for the average *have-alpha* or *beta-only* member over time, if capacity constraints are beginning to bite at the industry level.

3.6. Is Alpha Changing Over Time for *Have-Alpha* and *Beta-Only* Funds?

Using the identities of the *have-alpha* and *beta-only* funds that we estimated in section 3.3., we construct equally-weighted indexes of *have-alpha* and *beta-only* fund returns from January 1997 to December 2004. The indexes track the performance of the *have-alpha* funds and *beta-only* funds over the year *after* they was classified as such. Note that this means that all performance evaluation is completely out-of-sample. For example, some of the funds selected in the 1995-1996 period may die during the performance evaluation period of 1997, and therefore the 1997 out-of-sample returns would incorporate these deaths.

We then re-run equation (1), with the same structural break points, in this case successively replacing the average fund return on the left-hand side with the *have-alpha* and *beta-only* return indexes:

$$\begin{aligned} R_{gt} &= \alpha_{g1}D_1^1 + \alpha_{g2}D_2 + \alpha_{g3}D_3 + (D_1^1 X_t)\beta_{gD1} + (D_2 X_t)\beta_{gD2} + (D_3 X_t)\beta_{gD3} + \nu_{gt} \\ \text{Where } X_t &= [SNPMRF_t \;\; SCMLC_t \;\; BD10RET_t \;\; BAAMTSY_t \;\; PTFSBD_t \;\; PTFSFX_t \;\; PTFSCOM_t] \end{aligned} \qquad (6)$$

Where g represents the group, i.e., *have-alpha* or *beta-only*. The main difference between equations (1) and (6) (apart from the fact that they are run on different sets of funds) is that D_1^1 is a dummy variable that is now set to one between *January 1997* to September 1998, and zero elsewhere, to reflect the fact that the out-of-sample *have-alpha* and *beta-only* indexes begin in January 1997. The other dummies remain unchanged.

4. Results

4.1. Risk-Adjusted Performance Evaluation and Time Variation

Table II reports the results from estimating equation (1). The rows of Table II list the explanatory variables, and the columns report the sub-periods over which they are estimated. First, we test that the vectors of coefficient estimates $\hat{\beta}_{D1}, \hat{\beta}_{D2}$ are jointly different from $\hat{\beta}_{D3}$, using the heteroskedasticity-consistent covariance matrix. The χ^2 test statistic with 14 degrees of freedom is 248.4, indicating a strong rejection of the null hypothesis that the slope coefficients are the same across the three sub-periods. These results confirm that the exposures of funds to risk factors change over time. Furthermore, the way in which these exposures change suggests that the last decade consisted of three distinct sub-periods with different risk exposures. This can be seen in the strong rejection of the null hypotheses of no structural break in periods I and II.[8]

Second, the results in Table II indicate that the average fund-of-funds only exhibits statistically significant alpha during the second sub-period ($\hat{\alpha}_2$ is the only statistically significant intercept), which spans the bull market from October 1998 to March 2000. Third, Table II shows the explanatory power of the regression. The adjusted R^2 statistic is around 74 percent for the returns of the average fund. The magnitude of the R^2 statistic suggests that funds take on a significant amount of factor risk. This confirms the results extensively documented in the literature.

We tested the robustness of these results in a number of ways. First, we experimented with replacing the three PTF factors with the Agarwal and Naik (2004) out-of-the-money put option on the S&P 500. We also tried augmenting the set of factors with the excess returns on the NASDAQ technology index. As in Asness, Krail and Lew (2001), we added in lagged values of the factors, one at a time. Finally,

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[8] Specifically, we separately estimated the results in Table II in incremental form from sub-period to sub-period. Here we find that the most recent period (period three) factor loading estimates are statistically different from that of the first period in five of the seven factors. A similar comparison to the second period shows that six out of the seven factor loading estimates are statistically different. This incremental version of Table II is available from the authors on request.

we corrected individual fund returns for return-smoothing using the Getmansky, Lo and Makarov (GLM) (2004) correction. None of these changes qualitatively affected our conclusions.

Our results underscore the fact that identifying time-variation in factor loadings is important when evaluating the risk-adjusted performance of hedge funds. The results show that the average fund did not deliver alpha either in period I or in period III. However, inferences drawn from the average return series potentially hide important heterogeneity in the set of funds.

Berk and Green assume that there are significant differences in the ability of active portfolio managers. Perhaps there are funds in our sample that consistently generate alpha in all three periods, which we do not detect in our analysis of the average return. We now turn to the results from our cross-sectional analysis.

4.2. Cross-Sectional Differences in Funds

As described in section 3.3., we implement the bootstrap method of Kosowski et. al. (2006) and verify that there are funds that have statistically positive alpha in our set. We also use this technique to select *have-alpha* funds and *beta-only* funds. A detailed description of the procedure is provided in Appendix A. We also experimented with imposing parametric structure on the serial correlation of the residuals (we do this non-parametrically using the Politis-Romano (1994) stationary bootstrap), by applying the Getmansky, Lo and Makarov (2004) correction to undo any potential autocorrelation in fund returns. The results of our bootstrap experiments are qualitatively unaffected by the use of this procedure. All of these results are available on request.

The first three columns of Table III reports the number of funds included in the bootstrap experiment in each two-year period (all funds with two complete years of return history in each of the selection periods), and the percentage of the total number of funds in the *have-alpha* and *beta-only* groups. The first feature of note is that the number of funds in each of the two-year periods is steadily increasing over time. This is caused both by the increasing availability of data, and by the growth in the hedge fund industry. Second, on average across our sample period, 22 percent of the funds are classified as *have-alpha* funds, while a much larger percentage of funds do not deliver statistically positive alpha.[9]

[9] We checked whether there were any funds that delivered statistically negative alpha in the set. In each classification period, we found that fewer than five percent of the funds in the set had this property. This number is lower than the

Third, the percentage of total funds allocated to the *have-alpha* group fluctuates over time, ranging from a low of ten percent at the end of 1998 to a high of 42 percent at the end of 2000. The pattern of the fluctuation suggests that the ability of funds to deliver alpha is sensitive to market conditions.

The last four columns in Table III report transition probabilities for *have-alpha* and *beta-only* funds. In particular, the rows indicate the two-year period over which the funds were classified, while the columns indicate the percentage of funds that were classified as *have-alpha* or *beta-only* in the non-overlapping two-year classification period, as well as the percentage of funds that were liquidated or stopped reporting. Note that the final classification period is 2002-2003, since we require at least one year of out-of-sample data for our performance analysis.[10]

The results indicate that there is a greater chance for a fund to deliver alpha in the subsequent period if it is classified as a *have-alpha* fund to begin with. In particular, the overall average transition probability for a *have-alpha* fund into the subsequent *have-alpha* group is 28 percent, while that for a *beta-only* fund is 14 percent. This difference is highly statistically significant using the Wald test (using the cross-correlation and heteroskedasticity robust covariance matrix).

The average hides the fact that the year-by-year the alpha-transition probability for a *have-alpha* fund is always higher than the alpha-transition probability for a *beta-only* fund. In some years, the transition probability differential is very much higher than the average. For example, in the classification period 1997-1998 (which includes the LTCM crisis), the transition probability for a *have-alpha* fund into the *have-alpha* group of 1999-2000, is 81 percent, in contrast to the 26 percent probability for a contemporaneous *beta-only* fund. Overall, this result can be interpreted as saying that there is greater alpha persistence among the *have-alpha* group.

Table IV reports the percentage of *have-alpha* funds and *beta-only* funds that are liquidated at the end of each year over a five year post-classification period. On average, only seven percent of *have-alpha* funds are liquidated five years after classification, while for the *beta-only* funds the comparable number is 22 percent. The difference is again highly statistically significant for every post-classification year.

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significance level of our test. Therefore, we were unable to reject the hypothesis that there are no *negative alpha* funds in our data.

[10] We do not report death rates in 2004, as some of the databases have not updated their data up to December of that year.

The results strongly indicate that the *have-alpha* funds have a greater ability to avoid liquidation, regardless of the length of the post-classification period. These results are unchanged if we also control for the length of any individual fund's history prior to classification, suggesting that they are not driven by backfill bias.

The results in Tables III and IV provide strong evidence in support of an essential feature of Berk and Green's (2004) model, that there are significant differences in ability in the cross-section of active portfolio managers. In the hedge fund industry, high quality funds appear to distinguish themselves by their higher propensity to persistently deliver alpha, as well as their lower liquidation rates.

4.2. Capital Flow Analysis

Table V reports the equally weighted average annual flow into *have-alpha* and *beta-only* funds in each year following their classification. On average, the *have-alpha* funds experience a statistically significant inflow of 29.7 percent per annum in the year following classification, in contrast to the far lower inflows experienced by the *beta-only* funds. Indeed, the overall average level of flow for the *beta-only* funds is not statistically different from zero at the ten percent level of significance.

Figure 1 confirms this analysis. The figure is created by indexing December 1996 to 100, and multiplying this level by the compounded growth in out-of-sample equal-weighted quarterly flows each year for each group. For example, at the end of 1997, the *have-alpha* flow index takes on a value of 106.8, which is the product of the four quarterly equal-weighted flow observations in 1997 that were experienced by the average *have-alpha* fund classified in 1995-1996.

The figure is shown on a logarithmic scale to accommodate the significant differences between the two groups. The *have-alpha* flow index reaches a level of 448 at the end of December 2004. In sharp contrast, the *beta-only* flow index ends up at a level of 106. Although these statistics are stark, they mask a more intriguing set of time patterns. Reading from Table V, in 1997, which roughly corresponds with the first sub-period (pre-LTCM crisis), *have-alpha* funds and *beta-only* funds experienced significant inflows (9.1 and 10.5 percent per annum respectively). In 1998, the year of the LTCM crisis, we see that the *beta-only* funds experienced significant outflows of 6.1 percent, as compared to the statistically significant 9.7 percent inflows experienced by the *have-alpha* funds. In the year following the LTCM crisis, *beta-only* funds continued to experience dramatic outflows of 17.4 percent, while for the *have-alpha* funds, there seems to be sufficient continuing interest to offset the impacts of capital flight induced by the LTCM crisis. On net, this results in positive but statistically insignificant flows to the *have-alpha* funds in 1999. These patterns may be due to the fact that the LTCM crisis forced investors to look more carefully at the quality of funds.

This pattern continued in 2001, following the NASDAQ crash. *Have-alpha* funds experienced 32.4 percent inflows, while *beta-only* funds received statistically zero flows in this year. Finally, between 2002 and 2004, although both groups saw significant inflows, the *have-alpha* funds on average enjoyed three times the level of the inflows experienced by *beta-only* funds.

Are there other differences between the flows into *have-alpha* funds and *beta-only* funds? Table VI inspects the flow-return relationship for each group. The results here show that the flows into *have-alpha* funds show no statistical evidence of return-chasing behavior – the coefficient of quarterly flows on lagged quarterly returns is not statistically significant. However, this is not true for the flows into the *beta-only* funds. For the *beta-only* funds, high (low) returns over a quarter precede statistically significant increases (decreases) in capital flows in the subsequent quarter. This provides confidence that the results in Table V and figure 1 are not merely driven by return-chasing behavior on the part of capital providers to *have-alpha* funds.

The results in Table VI are consistent with a scenario in which less discriminating positive-feedback investors are attracted to *beta-only* funds, and more discriminating investors with a preference for absolute returns are attracted to *have-alpha* funds, providing capital that is unaffected by temporary movements in returns. There is evidence that two important groups of institutional investors,[11] defined benefit pension funds and university endowments, have increased their allocation to hedge funds over the 2000 to 2005 period.[12] This represents a significant shift, as press accounts suggest that

[11] There is a growing literature that suggests that institutional investors may be more discriminating than individual investors (two recent examples are Cohen, Gompers and Vuolteenaho (2001) and Froot and Ramadorai (2005)).

[12] The National Association of College and University Business Officers (NACUBO) shows that university endowments have increased their allocation to hedge funds from 6.1 percent of their endowment (U.S.$ 14.4 BN) in 2001 to 16.6 percent in 2005 (U.S.$ 49.6 BN). Over the same period, the top 200 defined benefit pension plans increased their allocation from U.S.$ 3.2 BN to U.S.$ 29.9 BN (source: www.pionline.com).

hedge fund demand in the early part of our sample was primarily dominated by high net-worth individuals.

Our finding that capital flows into the *have-alpha* funds are steadily increasing, while flows to the *beta-only* funds have stagnated could be generated by this evolving clientele shift in the demand side of hedge funds. It is worth noting here that *have-alpha* funds also have exposure to the seven factors in the Fung-Hsieh (2004) model. Several of these factors offer diversification attributes to a conventional asset allocation profile and could therefore be worth something to investors with such conventional profiles. However, in their quest for alpha, discriminating investors may be forced to overpay for these factor risks, since there is currently no readily available strategy to extract pure alpha from the returns of *have-alpha* funds.

Table VII takes the logic of a possible clientele difference between capital providers to *have-alpha* funds and *beta-only* funds one step further, presenting estimates of equations (4) and (5) separately for the two groups of funds. Panel A of the table reveals that the *have-alpha* funds in the top four return-quintiles experience greater inflows than the bottom quintile of funds ranked on returns. However, across these top four return quintiles of *have alpha* funds, there is not much variation in the response of capital flows to returns. In contrast, there is a monotonically increasing response of capital flows to return differences between *beta-only* funds, a fact consistent with the findings in Table VI. Indeed, the lowest return quintile *beta-only* funds experience statistically significant outflows of 8.5 percent in the year following classification, while the *beta-only* funds in the top two quintiles enjoy high, statistically positive capital flows of around 18 percent in the year following classification. Panel B of Table VII estimates the specification of Sirri and Tufano (1998) on the capital flows and returns of *have-alpha* funds and *beta-only* funds. The table reveals that there is no real convexity in the response of hedge fund investors to returns regardless of the quality of funds.

We perform a final exercise to shed light on the behaviour of *have-alpha* investors. We re-estimate equations (4) and (5), now ranking *have-alpha* funds using the t-statistic of alpha, and separately, the level of alpha. The results in Table VIII indicate that there is not much variation in the flows across quintiles of t-statistic of alpha or level of alpha. Capital providers to *have-alpha* funds seem to provide capital in equal measure to all funds regardless of how much risk-adjusted return they deliver.

Furthermore, there is no evidence of convexity in the response of the flows to *have-alpha* funds to either the t-statistic of alpha or the level of alpha.

Does the observed behavior of capital flows affect the ability of *have-alpha* funds to deliver alpha in the future? According to the Berk and Green (2004) model, investors continue to direct capital flows to managers with superior ability (*have-alpha* funds), generating declines in the risk-adjusted performance of such funds. The next sub-section discusses the results of our exercise to detect whether capital flows adversely impact future risk-adjusted performance for *have-alpha* and *beta-only* funds.

4.3. Capacity Constraints

Table IX conditions the two-year transition probabilities of *have-alpha* funds based on the inflows experienced in the final year of the classification period. The results indicate that above-median-flow funds have lower (higher) transition probabilities to the *have-alpha* (*beta-only*) group in the subsequent classification period. Across all years, an above-median-flow *have-alpha* fund has a 22 (72) percent probability of being classified as a *have-alpha* (*beta-only*) fund in the subsequent non-overlapping classification period. In contrast, for the below-median-flow *have-alpha* funds, there is a 34 (55) percent probability of being classified as a *have-alpha* (*beta-only*) fund in the subsequent non-overlapping classification period. These differences are statistically significant at the one percent level.

We repeat the same analysis for the *beta-only* funds in Table X. Apart from a slight increase in the ability of above-median-flow *beta-only* funds to transition to alpha relative to the below-median-flow *beta-only* funds (11 versus ten percent), there is no real evidence that capacity constraints are relevant for *beta-only* funds.

We also condition the future t-statistic of alpha and the future level of alpha on the level of capital flows experienced by the *have-alpha* and *beta-only* funds. Table XI reveals that for the *have-alpha* funds, the adverse effects of high capital flows on future risk-adjusted performance manifest themselves in reductions in the average t-statistic of alpha. Above-median-flow *have-alpha* funds exhibit an average t-statistic of alpha of 1.47, while for the below median flow *have-alpha* funds, the comparable number is 1.84. This difference is statistically significant at the one percent level. While the difference also manifests itself in the level of alpha, and is consistent with the results for the t-statistic of alpha, the higher variance in the level of alpha in the cross-section of *have-alpha* funds renders this difference statistically insignificant. Table XII reveals, akin to the results for the transition probabilities in Table X, that there are no real effects of capital flows on the future risk-adjusted performance of *beta-only* funds.

The results in this section indicate that conditioning the future performance of a fund on its current level of capital inflows is helpful in predicting future movements in alpha. These findings provide strong support for Berk and Green's (2004) rational model of active portfolio management. Taken together, our findings thus far indicate that capital flows have primarily gone into *have-alpha* funds, and that this has had an adverse effect on their risk-adjusted performance. The next section refines the analysis of averages that we conducted in Table II, shedding light on the inter-temporal variation in the performance of the average *have-alpha* and average *beta-only* fund.

4.3. Intertemporal Variation in the Alpha of *Have-Alpha* Funds and *Beta-Only* Funds

In order to shed light on the time pattern of alphas for our two groups of funds, we estimate equation (6) and report the results in Table XIII. The first feature of note in Table XIII is that the major significant difference in risk taking behavior between the groups manifests itself in the tendency of the *beta-only* funds to take on consistently greater exposure to static risk factors (*SNPMRF*, *SCMLC*, *BAAMTSY* and *BD10RET*). Second, the adjusted R^2 statistics confirm that the Fung-Hsieh (2004a) seven-factor model continues to offer good explanatory power for the two groups of funds. Third, the structural break points utilized for the analysis of the average funds are confirmed to exist for the two groups of funds as well.

Turning to the alphas, in the first sub-period, the *have-alpha* funds delivered (out-of-sample), a statistically significant alpha of 47 basis points per month, or 5.6 percent per annum in excess of the risk-free rate. In contrast, the *beta-only* funds did not produce any detectable alpha over this period. The imprecise negative coefficient suggests that the fee component of *beta-only* returns destroyed any alpha they may have produced. During the second sub-period (the bull-market period), although both groups delivered statistically significant alpha, the alpha of the *have-alpha* funds was almost 2 ½ times that delivered by the *beta-only* funds. In the final sub-period, the alpha of the *have-alpha* funds has deteriorated. The *have-alpha* funds generate 18 basis points a month of alpha, or 2.2 percent per annum. This may be attributable to the significant capital inflows experienced by the *have-alpha* funds and the attendant declines in alpha that these inflows presage.

5. Concluding Remarks

In this paper, we use data from the hedge fund industry to test key implications of Berk and Green's (2004) rational model of active portfolio management. Consistent with the assumptions of the model, we find that there are significant differences in the ability of funds to deliver alpha. We also find that investors perceive these ability differentials, and in response, direct a steady stream of capital to the funds that exhibit superior risk-adjusted performance. This inflow of capital is associated with a decline in the alpha produced by funds. Finally, we find that following significant inflow of capital in the industry, the level of alpha has come down substantially in recent years. These findings lend strong support to Berk and Green's (2004) model.

Our findings suggest that there is an apparent mismatch between the supply and demand for alpha. On the one hand, capital appears to be seeking alpha. On the other hand, the supply of alpha appears to be drying up.   We believe that the divergent ability to attract capital between the alpha producing funds and their less fortunate counterparts will ultimately translate into a revision of the hedge fund contract. Funds that fail to produce alpha may be tempted to lower their fees in order to attract investors' capital. This would result in different prices for the services offered by these two groups of funds.

Appendix A: Bootstrap Experiment.

Consider the following simple example, which closely follows Kosowski et. al. (2006). In a set of 1,000 independent standard normal random variables, if we apply a test at the ten percent level of significance, then, even under the null, we would observe ten percent of the tests being rejected. Thus, for 307 funds-of-funds in the 1997-1998 group, we would expect around 15 (five percent) to reject the null (of zero alpha in a regression of their returns on risk factors), in the upper tail using a five percent one-sided test. However, this is only true if the in-sample distribution of the t-statistics roughly corresponds to the asymptotic standard normal distribution. This will only be true if the residuals from the regressions of fund-of-fund returns on risk factors are homoskedastic, serially uncorrelated and cross-sectionally independent. This is an assumption that is very likely to be violated, given the much noted non-normality of hedge fund returns.

The literature on order statistics and the bootstrap are useful in this context. Returning to the hypothetical example of 1,000 random outcomes X_1, X_2, …, X_{1000}, denote the order statistics as $X_{(1)} \leq X_{(2)} \leq \ldots \leq X_{(1000)}$. Under the assumption of independence, and using the fact that the $X_{(i)}$ are drawn from a standard normal distribution, the probability that $X_{(950)} > 3.884$ is five percent. Hence, if in the sample, we find the 95th percentile of the t-statistic is greater than 3.884, then there exist funds-of-funds with positive alpha.

However our order statistics are not drawn from a standard normal distribution. We can use the bootstrap to relax the assumptions of independence and normality to find the correct critical value for the 95th percentile order statistic. A description of the bootstrap experiment follows:

Cross-sectional bootstrap:

Step1: For each fund *i*, regress the excess return on risk factors:

$$r_{i,t} = \hat{\alpha}_i + x_t^{'} \hat{\beta}_i + \hat{\varepsilon}_{i,t}, t = 1,...,T .$$

Save the $\hat{\beta}_i$, $\hat{\varepsilon}_{i,t}$ and the t-statistics of $\hat{\alpha}_i, \hat{t}(\hat{\alpha}_i)$, which can be calculated using standard OLS, or using Newey-West or other standard errors. Do this for all funds $i = 1,...,I$. Save the t-statistics, as well as quantiles of the cross-sectional distribution of the t-statistics, e.g. the 95th quantile, $\hat{t}_{0.95}$.

Step 2: Draw *T* periods with replacement from $t = 1,...,T$. Call the resampled periods $\{t = s_1^b,...,s_T^b\}$, where *b=1* is bootstrap number 1. For each fund, create the resampled observations:

$$r_{i,t}^b = x_t^{'}\hat{\beta}_i + \hat{\varepsilon}_{i,t}, \text{ for } t = s_1^b,...,s_T^b$$

These draws impose the null that the alpha is zero; preserve the cross-sectional correlation of the residuals $\hat{\varepsilon}_{i,t}$ across funds; and preserve the higher order correlation of the regressors and the residuals. For each fund *i* that has data for all resampled periods (this is true of all funds in each of the 1997-1998 and 1999-2000 periods), run the regression:

$$r_{i,t}^b = \hat{\alpha}_i^b + x_t^{'}\hat{\beta}_i^b + \hat{\varepsilon}_{i,t}^b \text{ for } t = s_1^b,...,s_T^b$$

Save the t-statistic of $\hat{\alpha}_i^b, \hat{t}^b(\hat{\alpha}_i^b)$. In each resample, save all the simulated t-statistics of the constant terms, $\hat{t}^b(\hat{\alpha}_i^b)$, across all funds (307 in the 1997-1998 period). Second, in each resample, inspect the cross-sectional distribution of the t-statistics. Suppose we are interested in the 95th percentile of the cross-sectional t-statistics. Then after each resample, we can look at the 95th percentile of $\{\hat{t}^b(\hat{\alpha}_i^b)\}$ over all 307 funds. Call this $\hat{t}_{0.95}^b$

Step 3: Repeat **Step 2** for $b = 1,...,B$. This gives two distributions, one for $\{\hat{t}^b(\hat{\alpha}_i^b)\}$, and another one for $\{\hat{t}_{0.95}^b\}$.

Step 4: For each fund i, if $\hat{t}(\hat{\alpha}_i)$ is in the upper decile of the distribution of the simulated t-statistics, {$\hat{t}^b(\hat{\alpha}_i^b)$}, we call it a *have-alpha* fund. Otherwise, we call it a *beta-only* fund. We also inspect where $\hat{t}_{0.95}$ is in the distribution of {$\hat{t}_{0.95}^b$}.

Stationary Bootstrap: We use the stationary bootstrap of Politis and Romano (1994) to allow for weakly dependent correlation over time. Here, replace Step 2 as follows: first, draw randomly from the sample $t = 1,...,T$. For the second resample observation, draw a uniform random variable from *[0,1]*. If it is less than *Q*, then use the next observation. If we are at the end of the sample, start from the beginning again. If greater than *Q*, draw a new observation. We do this for *Q=0, 0.1, 0.5*. We report results for *Q=0.5* in the main body of the paper. The other two choices for *Q* do not materially affect our results.

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Table I
Summary Statistics

For each year represented in a row, in columns we present the total number of funds-of-funds in the data at the end of the year, the number of funds that entered the data during the year, the number that were liquidated during the year, the number that stopped reporting during the year, the total AUM in billions of U.S. dollars of the funds alive at the end of each year; and the mean, median and standard deviation of the annual return at the end of the year across all funds.

Year	**Number of Funds**	**Born**	**Liquidated**	**Stopped Reporting**	**Total AUM (U.S.$ BN)**	**Mean Return**	**Median Return**	**Std Return**
1995	248	57	9	4	18.4	0.14	0.13	0.16
1996	336	107	13	6	26.0	0.15	0.15	0.09
1997	415	103	19	5	43.0	0.17	0.16	0.11
1998	487	111	22	17	37.6	0.00	0.02	0.15
1999	575	124	23	13	42.3	0.24	0.20	0.20
2000	657	127	26	19	49.4	0.08	0.10	0.14
2001	763	167	36	25	60.5	0.05	0.06	0.08
2002	898	174	25	14	77.8	0.02	0.02	0.07
2003	1036	208	48	22	123.1	0.12	0.10	0.11
2004	1158	203	35	46	194.6	0.07	0.07	0.04

Table II
The Changing Risks of Funds-of-Hedge-Funds

The top panel of this table contains estimates of:

$$R_t = \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + (D_1 X_t)\beta_{D1} + (D_2 X_t)\beta_{D2} + (D_3 X_t)\beta_{D3} + \varepsilon_t$$

Where $X_t = [SNPMRF_t \;\; SCMLC_t \;\; BD10RET_t \;\; BAAMTSY_t \;\; PTFSBD_t \;\; PTFSFX_t \;\; PTFSCOM_t]$

Here, R_t , the dependent variable, is the (equal-weighted) average annualized excess return across all funds in month *t*, D_1 is a dummy variable set to one during the first period (January 1995 to September 1998) and zero elsewhere, D_2 is set to one during the second period (October 1998 to March 2000) and zero elsewhere, and D_3 is set to one during the third period (April 2000 to December 2004) and zero elsewhere. The regressors *X* are described in section 3.1 of the text. The bottom panel contains estimates of Chow structural break test Chi-squared statistics. White heteroskedasticity consistent standard errors are reported below coefficients.

Variable		**Variable**		**Variable**	
D1*Constant	0.0009	**D2*Constant**	**0.0093**	**D3*Constant**	0.0006
	0.0011		*0.0018*		*0.0008*
D1*SNPMRF	**0.2866**	**D2*SNPMRF**	**0.1314**	**D3*SNPMRF**	**0.1388**
	0.0323		*0.0404*		*0.0177*
D1*SCMLC	**0.1371**	**D2*SCMLC**	**0.2993**	**D3*SCMLC**	**0.1289**
	0.0637		*0.0309*		*0.0199*
D1*BD10RET	-0.0169	**D2*BD10RET**	**0.4799**	**D3*BD30RET**	**0.1603**
	0.1203		*0.1288*		*0.0303*
D1*BAAMTSY	**0.7160**	**D2*BAAMTSY**	**0.6376**	**D3*BAAMTSY**	**0.1421**
	0.1503		*0.1630*		*0.0622*
D1*PTFSBD	0.0062	**D2*PTFSBD**	**0.0576**	**D3*PTFSBD**	-0.0018
	0.0119		*0.0170*		*0.0027*
D1*PTFSFX	**0.0111**	**D2*PTFSFX**	**-0.0199**	**D3*PTFSFX**	**0.0140**
	0.0047		*0.0092*		*0.0050*
D1*PTFSCOM	**0.0269**	**D2*PTFSCOM**	**-0.0140**	**D3*PTFSCOM**	0.0120
	0.0078		*0.0044*		*0.0075*
Adjusted R^2	0.737				
N	96				

Period for Chow Structural Break Test	
Test for Period I & II Break	
Chi-sq(14)	**248.42**
Test for Period I Break	
Chi-sq(7)	**86.70**
Test for Period II Break	
Chi-sq(7)	**82.75**

Table III
Transition Probabilities of *Have-Alpha* and *Beta-Only* Funds

The rows show the two-year period in which funds are classified as *have-alpha* and *beta-only* funds. The columns are, in order, the total number of funds with two full years of return history in each of the classification periods; the percentage of the total classified as *have-alpha* funds; the percentage of the total classified as *beta-only* funds; and the percentages of *have-alpha* and *beta-only* funds that are classified in the subsequent non-overlapping period as *have-alpha*; *beta-only*; liquidated or stopped reporting. For example, in 1996-1997, of 259 total funds, 34 percent and 66 percent respectively were classified as *have-alpha* and *beta-only*, 17 percent of these *have-alpha* funds were reclassified as *have-alpha* funds in the 1998-1999 period, 74 percent as *beta-only* funds, 5 percent liquidated and 5 percent stopped reporting (numbers are rounded to the nearest percent). In contrast, 7 percent of the 1996-1997 *beta-only* funds were classified as 1998-1999 *have-alpha* funds, 73 percent were reclassified as *beta-only* funds and 13 percent liquidated and 6 percent stopped reporting. The final rows report the Wald test statistics (using a cross-correlation and heteroskedasticity robust covariance matrix) and the p-value for the hypothesis that the *have-alpha* and *beta-only* transition probabilities are the same.

Classification Period	**Number of Funds**	**Proportion**			**P(Two-Year Transition)**			
		Have-Alpha	***Beta-Only***	**From/To:**	***Have-Alpha***	***Beta-Only***	***Liquidated***	***Stopped Reporting***
1995-1996	195	0.21	0.79	***Have-Alpha***	0.24	0.68	0.02	0.05
				Beta-Only	0.04	0.82	0.10	0.04
1996-1997	259	0.34	0.66	***Have-Alpha***	0.17	0.74	0.05	0.05
				Beta-Only	0.07	0.73	0.13	0.06
1997-1998	307	0.10	0.90	***Have-Alpha***	0.81	0.16	0.00	0.03
				Beta-Only	0.26	0.58	0.09	0.07
1998-1999	374	0.17	0.83	***Have-Alpha***	0.27	0.65	0.05	0.03
				Beta-Only	0.18	0.62	0.12	0.09
1999-2000	448	0.42	0.58	***Have-Alpha***	0.24	0.64	0.06	0.06
				Beta-Only	0.09	0.70	0.12	0.09
2000-2001	506	0.22	0.78	***Have-Alpha***	0.30	0.65	0.03	0.02
				Beta-Only	0.10	0.77	0.08	0.04
2001-2002	584	0.17	0.83					
2002-2003	700	0.15	0.85					
Average	3373	0.22	0.78	***Have-Alpha***	0.28	0.65	0.04	0.03
				Beta-Only	0.14	0.69	0.11	0.06
				Wald Statistic	26.82	3.27	87.04	8.65
				p-value	0.00	0.07	0.00	0.00

Table IV
Liquidation Probabilities of *Have-Alpha* and *Beta-Only* Funds

The rows correspond to the two-year period in which funds are classified as *have-alpha* and *beta-only* funds. The columns indicate the proportion of *have-alpha* funds and *beta-only* funds that were liquidated after one, two, three, four and five years after the classification period. The top panel shows the liquidation probabilities for the *have-alpha* funds and the bottom panel for the *beta-only* funds. For example, in 1996-1997, of 259 total funds, 34 percent and 66 percent respectively were classified as *have-alpha* funds and *beta-only* funds (from the previous table), of these *have-alpha* funds 3 percent were liquidated in 1998, a total of 5 percent were liquidated by the end of 1999, and a total of 10 percent were liquidated at the end of 2002. In contrast, for the *beta-only* funds classified in 1996-1997, 8 percent were liquidated in 1998, a total of 13 percent were liquidated by the end of 1999, and a total of 24 percent were liquidated at the end of 2002. The final rows report the Wald test statistics (using a cross-correlation and heteroskedasticity robust covariance matrix) and the p-value for the hypothesis that the *have-alpha* and *beta-only* liquidation probabilities are the same.

Classification Period	***Have-Alpha* Liquidation Probabilities**				
	Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**
1995-1996	0.00	0.02	0.02	0.05	0.07
1996-1997	0.03	0.05	0.09	0.10	0.10
1997-1998	0.00	0.00	0.00	0.03	0.03
1998-1999	0.00	0.05	0.11	0.11	
1999-2000	0.04	0.06	0.09		
2000-2001	0.03	0.03			
2001-2002	0.02				
Average	0.02	0.03	0.06	0.07	0.07
	***Beta-Only* Liquidation Probabilities**				
	Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**
1995-1996	0.06	0.10	0.16	0.19	0.22
1996-1997	0.08	0.13	0.19	0.23	0.24
1997-1998	0.06	0.09	0.16	0.18	0.19
1998-1999	0.08	0.12	0.15	0.16	
1999-2000	0.11	0.12	0.14		
2000-2001	0.05	0.08			
2001-2002	0.05				
Average	0.07	0.11	0.16	0.19	0.22
Wald Statistic	36.15	87.04	42.39	100.41	53.57
p-value	0.00	0.00	0.00	0.00	0.00

Table V
Flows Into *Have-Alpha* and *Beta-Only* Funds

The rows correspond to the years in which funds are classified as *have-alpha* funds and *beta-only* funds. The columns report the average annual flow for the subsequent year across all funds in the group indicated in the column heading. Annual flows are computed as the product of quarterly flows, and quarterly flows are computed as increase in AUM less accrued returns, under the assumption that flows came in at the end of the quarter. For example, in 1996-1997, we classify funds as *have-alpha* funds and *beta-only* funds. The columns reveal that *have-alpha* funds experience an average inflow of 9.7 percent of end-1997 AUM over the subsequent year, 1998. White heteroskedasticity consistent standard errors are reported below yearly estimates, and cross-correlation and heteroskedasticity robust standard errors are reported below the pooled estimate.

Classification Period	***Have-Alpha*** **Flows(t+1)**	***Beta-Only*** **Flows(t+1)**
1995-1996	**0.091**	**0.105**
	0.047	0.041
1996-1997	**0.097**	**-0.061**
	0.040	0.021
1997-1998	0.032	**-0.174**
	0.045	0.020
1998-1999	**0.187**	-0.021
	0.050	0.019
1999-2000	**0.324**	0.041
	0.042	0.039
2000-2001	**0.349**	**0.085**
	0.062	0.020
2001-2002	**0.483**	**0.161**
	0.072	0.028
2002-2003	**0.404**	**0.244**
	0.060	0.025
Overall	**0.297**	0.082
	0.044	0.050

Table VI
Return Chasing in *Have-Alpha* and *Beta-Only* Funds

This table presents estimates of:

$$F_{gq} = \gamma_0 + \gamma_r R_{gq-1} + \gamma_{f1} F_{gq-1} + u_{gq}$$

estimated separately for each sub-group g of funds (g is *have-alpha* or *beta-only*). The quarterly flow measure F_{gq} in each case is expressed as a percentage of end-of-previous quarter AUM, and is regressed on lagged quarterly flows F_{gq-1} and lagged quarterly returns R_{gq-1}. The column headings indicate the sub-group g for which the equation is estimated. Newey-West autocorrelation and heteroskedasticity-consistent standard errors are presented below coefficients, estimated using four quarterly lags.

	Have-Alpha **Flows**	***Beta-Only*** **Flows**
Intercept	-0.002	-0.005
	0.009	0.004
Ret (L1)	0.203	**0.325**
	0.160	0.095
Flow (L1)	**0.778**	**0.809**
	0.078	0.074
Adjusted R^2	0.466	0.717
N	32	32

Table VII
Flow-Return Regressions

This table reports the results from estimating the following two specifications separately for the *have-alpha* and *beta-only* funds.
Panel A presents estimates of:

$$F_{iy} = \phi_1 I^1_{iy-1} + \phi_2 I^2_{iy-1} + \phi_3 I^3_{iy-1} + \phi_4 I^4_{iy-1} + \phi_5 I^5_{iy-1} + u_{iy}$$

and Panel B presents estimates of:

$$F_{iy} = \sum_{k=1}^{5} \rho_k FRank^k_{iy-1} + u_{iy}$$

Here, the annual flow measure F_{iy} for a fund i in a year y is computed as a percentage of end-of-previous-year AUM. In panel A the columns represent the return quintile membership for the funds, computed across all funds in the group in the previous year. For example, if a fund i is a member of the top performing quintile of funds in year y-1, $I^5_{iy-1} = 1$, and all other indicator variables take on a value of zero. In panel B, the columns represent the fractional return ranks for the funds, computed across all funds in the group in the previous year. For example, if a fund i is ranked 35 out of a total of 100 funds in year y-1 based on returns, $FRank^1_{iy-1} = 0.2$, $FRank^2_{iy-1} = 0.15$, and $FRank^3_{iy-1}, FRank^4_{iy-1}, FRank^5_{iy-1}$ are assigned values of zero.
Cross-correlation and heteroskedasticity robust standard errors are reported below the estimates. The final column reports the adjusted R^2 statistic.

Panel A	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Adjusted R^2**
Have-Alpha						
Returns	**0.140**	**0.333**	**0.349**	**0.285**	**0.382**	0.017
	0.045	0.053	0.073	0.052	0.077	
Beta-Only						
Returns	**-0.085**	0.039	0.100	**0.176**	**0.182**	0.038
	0.031	0.049	0.078	0.058	0.054	

Panel B	**FRank1**	**Frank2**	**FRank3**	**FRank4**	**Frank5**	**Adjusted R^2**
Have-Alpha						
Returns	**0.975**	0.514	-0.230	0.099	0.343	0.053
	0.349	0.420	0.603	0.516	0.788	
Beta-Only						
Returns	-0.329	**0.502**	0.296	0.241	0.092	0.028
	0.230	0.237	0.238	0.193	0.254	

Table VIII
Flow-Alpha Regressions for *Have-Alpha* Funds

This table reports the results from estimating the following two specifications for the *have-alpha* funds.
Panel A presents estimates of:

$$F_{iy} = \phi_1 I^1_{iy-1} + \phi_2 I^2_{iy-1} + \phi_3 I^3_{iy-1} + \phi_4 I^4_{iy-1} + \phi_5 I^5_{iy-1} + u_{iy}$$

and Panel B presents estimates of:

$$F_{iy} = \sum_{k=1}^{5} \rho_k FRank^k_{iy-1} + u_{iy}$$

Here, the annual flow measure F_{iy} for a fund *i* in a year *y* is computed as a percentage of end-of-previous-year AUM. In panel A the columns represent the alpha and t-statistic of alpha quintile membership for the funds, computed across all *have-alpha* funds in the previous year. For example, if a fund *i* is a member of the highest quintile of funds in year *y-1* based on the t-statistic of alpha (or the level of alpha), $I^5_{iy-1} = 1$, and all other indicator variables take on a value of zero. In panel B, the columns represent the fractional t-statistic of alpha (or the level of alpha) ranks for the funds, computed across all *have-alpha* funds in the group in the previous year. For example, if a fund *i* is ranked 35 out of a total of 100 funds in year *y-1* based on the t-statistic of alpha (or the level of alpha), $FRank^1_{iy-1} = 0.2$, $FRank^2_{iy-1} = 0.15$, and $FRank^3_{iy-1}, FRank^4_{iy-1}, FRank^5_{iy-1}$ are assigned values of zero.
In all cases, alpha and the t-statistic of alpha for a fund *i* for year *y* are estimated over years *y-1* and *y* using the bootstrap procedure documented in the Appendix. Cross-correlation and heteroskedasticity robust standard errors are reported below the estimates. The final column reports the adjusted R^2 statistic.

	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Adjusted R^2**
Have-Alpha						
T-Statistic of Alpha	**0.299**	**0.291**	**0.299**	**0.307**	**0.288**	-0.006
	0.067	0.060	0.053	0.057	0.069	
Level of Alpha	**0.295**	**0.338**	**0.271**	**0.259**	**0.320**	-0.003
	0.064	0.067	0.050	0.087	0.057	

	FRank1	**Frank2**	**FRank3**	**FRank4**	**Frank5**	**Adjusted R^2**
Have-Alpha						
T-Statistic of Alpha	**1.628**	-0.885	0.765	-0.301	-0.190	-0.037
	0.356	0.419	0.564	0.569	0.494	
Level of Alpha	**1.554**	-0.302	-0.308	0.595	-0.544	0.000
	0.423	0.359	0.467	0.500	1.053	

Table IX
Transition Probabilities for Above and Below Median Flow *Have-Alpha* Funds

The rows correspond to the two-year period in which funds are classified as *have-alpha* funds. The columns are, in order: the group affiliation, i.e. whether the average fund classified as a *have-alpha* experienced inflows (in the second year of the classification period) that were above or below the median *have-alpha* inflow in that year; the number of *have-alpha* funds in each group; the percentage of the flow group members classified as *have-alpha* funds in the subsequent classification period; the percentage of the flow group members classified as *beta-only* funds; ; the percentage of group members that were liquidated, and the percentage that stopped reporting. For example, in 1996-1997, 43 *have-alpha* funds had above the median inflow in 1997. Of these, 12 percent were classified as *have-alpha* funds, 79 percent as *beta-only* funds, 5 percent were liquidated, and 5 percent stopped reporting in 1998-1999. Percentages may not add up to 100 because of rounding error. The final rows report the Wald test statistics (using the cross-correlation and heteroskedasticity robust covariance matrix) for the hypothesis that the above and median flow transition probabilities are identical, and the p-value.

Classification Period	**Flow Group**	**Number of Funds**	**P(Two-Year Transition)**			
			Have-Alpha	***Beta-Only***	***Liquidated***	***Stopped Reporting***
1995-1996	**above median**	20	0.20	0.65	0.05	0.10
	below median	21	0.29	0.71	0.00	0.00
1996-1997	**above median**	43	0.12	0.79	0.05	0.05
	below median	44	0.23	0.68	0.05	0.05
1997-1998	**above median**	15	0.93	0.07	0.00	0.00
	below median	16	0.69	0.25	0.00	0.06
1998-1999	**above median**	31	0.26	0.65	0.10	0.00
	below median	32	0.28	0.66	0.00	0.06
1999-2000	**above median**	93	0.17	0.77	0.03	0.02
	below median	93	0.30	0.51	0.10	0.10
2000-2001	**above median**	56	0.16	0.84	0.00	0.00
	below median	56	0.45	0.46	0.05	0.04
overall	**above median**	258	0.22	0.72	0.03	0.02
	below median	262	0.34	0.55	0.05	0.06
Wald Statistic			6.25	6.03	0.60	4.01
p-value			0.01	0.01	0.44	0.05

Table X
Transition Probabilities for Above and Below Median Flow *Beta-Only* Funds

The rows correspond to the two-year period in which funds are classified as *beta-only* funds. The columns are, in order: the group affiliation, i.e. whether the average *beta-only* fund experienced inflows (in the second year of the classification period) that were above or below the median *beta-only* inflow in that year; the number of *beta-only* funds in each group; the percentage of the flow group members classified as *have-alpha* funds in the subsequent classification period; the percentage of the flow group members classified as *beta-only* funds; the percentage of group members that were liquidated, and the percentage that stopped reporting. For example, in 1996-1997, 86 *have-alpha* funds had above the median inflow in 1997. Of these, 7 percent were classified as *have-alpha* funds, 76 percent as *beta-only* funds, 8 percent liquidated and 9 percent stopped reporting in 1998-1999. Percentages may not add up to 100 because of rounding error. The final rows report the Wald test statistics (using the cross-correlation and heteroskedasticity robust covariance matrix) for the hypothesis that the above and median flow transition probabilities are identical, and the p-value.

Classification Period	**Flow Group**	**Number of Funds**	**P(Two-Year Transition)**			
			Have-Alpha	***Beta-Only***	***Liquidated***	***Stopped Reporting***
1995-1996	**above median**	77	0.04	0.79	0.09	0.08
	below median	77	0.04	0.84	0.12	0.00
1996-1997	**above median**	86	0.07	0.76	0.08	0.09
	below median	86	0.07	0.71	0.19	0.03
1997-1998	**above median**	138	0.27	0.58	0.09	0.06
	below median	138	0.25	0.59	0.09	0.07
1998-1999	**above median**	155	0.20	0.64	0.08	0.08
	below median	156	0.15	0.60	0.15	0.10
1999-2000	**above median**	130	0.08	0.82	0.08	0.03
	below median	131	0.10	0.60	0.16	0.15
2000-2001	**above median**	197	0.15	0.75	0.06	0.05
	below median	197	0.06	0.79	0.11	0.04
Overall	**above median**	783	0.11	0.75	0.08	0.06
	below median	785	0.10	0.68	0.14	0.08
Wald Statistic			4.05	0.63	18.32	0.16
p-value			0.04	0.43	0.00	0.69

Table XI
Quantitative Measures of Alpha for Above and Below Median Flow *Have-Alpha* Funds

The rows correspond to the two-year period in which funds are classified as *have-alpha* funds. The columns are, in order: the group affiliation, i.e. whether the average *have-alpha* fund experienced inflows (in the second year of the classification period) that were above or below the median *have-alpha* inflow in that year; the number of *have-alpha* funds in each group; the average t-statistic of alpha for these funds in the subsequent classification period; the annual average magnitude of alpha for these funds in the subsequent classification period; For example, in 1996-1997, 43 *have-alpha* funds had above the median inflow in 1997. For the ones that survived (see Table VI for details), the average t-statistic of alpha in the 1998-1999 classification period was 0.929, and the average annual alpha magnitude was 3.2 percent over the risk-free rate. The final rows report the Wald test statistics (using the cross-correlation and heteroskedasticity robust covariance matrix) for the hypothesis that the above and median flow average t-statistic of alpha and average magnitude of alpha are identical, and the p-value.

Classification Period	**Flow Group**	**Number of Funds**	***T-Statistic of Alpha***	***Level of Alpha***
1995-1996	**above median**	20	1.61	0.047
	below median	21	1.44	0.045
1996-1997	**above median**	43	0.93	0.032
	below median	44	1.45	0.068
1997-1998	**above median**	15	4.42	0.109
	below median	16	4.30	0.108
1998-1999	**above median**	31	1.38	0.044
	below median	32	1.39	0.018
1999-2000	**above median**	93	1.03	0.023
	below median	93	1.52	0.036
2000-2001	**above median**	56	1.72	0.031
	below median	56	2.59	0.062
overall	**above median**	258	1.47	0.035
	below median	262	1.84	0.047
Wald Statistic			5.97	2.31
p-value			0.01	0.13

Table XII
Quantitative Measures of Alpha for Above and Below Median Flow *Beta-Only* Funds

The rows correspond to the two-year period in which funds are classified as *beta-only* funds. The columns are, in order: the group affiliation, i.e. whether the average *beta-only* fund experienced inflows (in the second year of the classification period) that were above or below the median *beta-only* inflow in that year; the number of *beta-only* funds in each group; the average t-statistic of alpha for these funds in the subsequent classification period; the annual average magnitude of alpha for these funds in the subsequent classification period; For example, in 1996-1997, 86 *beta-only* funds had above the median inflow in 1997. For the ones that survived (see Table VII for details), the average t-statistic of alpha in the 1998-1999 classification period was 0.804, and the annual average alpha magnitude was 5.3 percent. The final rows report the Wald test statistics (using the cross-correlation and heteroskedasticity robust covariance matrix) for the hypothesis that the above and median flow average t-statistic of alpha and average magnitude of alpha are identical, and the p-value.

Classification Period	**Flow Group Final Year**	**Number of Funds**	***T-Statistic of Alpha***	***Level of Alpha***
1995-1996	**above median**	77	-0.09	-0.028
	below median	77	-0.17	-0.040
1996-1997	**above median**	86	0.80	0.053
	below median	86	0.89	0.061
1997-1998	**above median**	138	1.69	0.050
	below median	138	1.60	0.042
1998-1999	**above median**	155	0.78	0.018
	below median	156	0.52	-0.011
1999-2000	**above median**	130	-0.02	-0.005
	below median	131	0.18	0.001
2000-2001	**above median**	197	1.10	0.029
	below median	197	0.78	0.024
Overall	**above median**	783	0.82	0.020
	below median	785	0.73	0.013
Wald Statistic			1.13	2.00
p-value			0.29	0.16

Table XIII
The Changing Risks of *Have-Alpha* and *Beta-Only* Funds

The top panel of this table contains estimates of:

$$R_{gt} = \alpha_{g1}D_1^1 + \alpha_{g2}D_2 + \alpha_{g3}D_3 + (D_1^1 X_t)\beta_{gD1} + (D_2 X_t)\beta_{gD2} + (D_3 X_t)\beta_{gD3} + \nu_{gt}$$

$$\text{Where } X_t = [SNPMRF_t \;\; SCMLC_t \;\; BD10RET_t \;\; BAAMTSY_t \;\; PTFSBD_t \;\; PTFSFX_t \;\; PTFSCOM_t]$$

Here, R_{gt} , the dependent variable, is the (equal-weighted) average annualized excess return across all funds in group *g* in month *t* (*g* is *have-alpha* or *beta-only*), D_1 is a dummy variable set to one during the first period (January 1995 to September 1998) and zero elsewhere, D_2 is set to one during the second period (October 1998 to March 2000) and zero elsewhere, and D_3 is set to one during the third period (April 2000 to December 2004) and zero elsewhere. The regressors *X* are described in section 3.1 of the text. The columns report the estimates for each the regression for each group. The bottom panel contains estimates of Chow structural break test Chi-squared statistics for each group. White heteroskedasticity consistent standard errors are reported below coefficients.

Variable	***Have-Alpha***	***Beta-Only***	**Variable**	***Have-Alpha***	***Beta-Only***	**Variable**	***Have-Alpha***	***Beta-Only***
D1*Constant	**0.0047**	-0.0017	**D2*Constant**	**0.0160**	**0.0066**	**D3*Constant**	**0.0018**	-0.0002
	0.0013	*0.0022*		*0.0016*	*0.0024*		*0.0010*	*0.0009*
D1*SNPMRF	**0.1449**	**0.3896**	**D2*SNPMRF**	-0.0514	**0.1916**	**D3*SNPMRF**	**0.1069**	**0.1535**
	0.0187	*0.0356*		*0.0347*	*0.057*		*0.0245*	*0.0193*
D1*SCMLC	**0.1438**	0.0901	**D2*SCMLC**	**0.2871**	**0.3173**	**D3*SCMLC**	**0.1192**	**0.1433**
	0.0528	*0.0814*		*0.0229*	*0.041*		*0.0339*	*0.0234*
D1*BD10RET	-0.0500	**-0.3517**	**D2*BD10RET**	**0.5764**	**0.4707**	**D3*BD30RET**	**0.1678**	**0.1685**
	0.0768	*0.1293*		*0.0557*	*0.1774*		*0.0391*	*0.0331*
D1*BAAMTSY	**0.7828**	0.4475	**D2*BAAMTSY**	**0.2945**	**0.8022**	**D3*BAAMTSY**	**0.2062**	**0.1394**
	0.1822	*0.2992*		*0.0740*	*0.2304*		*0.0775*	*0.0680*
D1*PTFSBD	0.0013	0.0336	**D2*PTFSBD**	**0.0631**	**0.0663**	**D3*PTFSBD**	-0.0052	-0.0008
	0.0089	*0.0188*		*0.0132*	*0.0218*		*0.0038*	*0.0034*
D1*PTFSFX	0.0081	0.0104	**D2*PTFSFX**	**-0.0278**	-0.0209	**D3*PTFSFX**	0.0092	**0.0159**
	0.0059	*0.0098*		*0.0048*	*0.0133*		*0.0070*	*0.0045*
D1*PTFSCOM	0.0029	**0.0622**	**D2*PTFSCOM**	**-0.0266**	-0.0101	**D3*PTFSCOM**	0.0169	0.0117
	0.0162	*0.0202*		*0.0048*	*0.0069*		*0.0102*	*0.0072*
Adjusted R^2	0.733	0.752						
N	96	96						

Period for Chow Structural Break Test	***Have-Alpha***	***Beta-Only***
Test for Period I & II Break		
Chi-sq(14)	**55.21**	**113.88**
Test for Period I Break		
Chi-sq(7)	**159.51**	**50.50**
Test for Period II Break		
Chi-sq(7)	**358.35**	**212.77**

Figure 1
Cumulative Flows for *Have-Alpha* and *Beta-Only* Funds

The X-axis shows the month for which the flow index is plotted on a logarithmic scale on the Y-axis. The index begins at a value of 100 in December 1996 and successive values are given by $Index_{gq} = Index_{gq-1} * (1 + F_{gq})$ where F_{gq} is the flow percentage for group *g* (*g* is *have-alpha* or *beta-only*), for quarter *q*.