Hedge Funds: Performance, Risk and Capital Formation*

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Abstract

We use a comprehensive dataset of Funds-of-Hedge-Funds (FoFs) to investigate performance, risk and capital formation in the hedge fund industry over the past ten years. We confirm the finding of high systematic risk exposures in FoF returns. We divide up the past ten years into three distinct sub-periods and demonstrate that the average FoF has only delivered alpha in the short second period from October 1998 to March 2000. In the cross-section of FoFs, however, we are able to identify FoFs capable of delivering persistent alpha. We find that these more successful FoFs experience far greater (and steadier) capital inflows than their less fortunate counterparts. Berk and Green's (2004) rational model of active portfolio management implies that diminishing returns to scale combined with the inflow of new capital leads to the erosion of superior performance over time. In keeping with this implication, we provide evidence that even successful FoFs have experienced a recent, dramatic decline in risk-adjusted performance.

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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 or alpha in the cross-section of hedge funds? Can we use these differences to predict the future performance of certain hedge funds? How have capital flows responded to cross-sectional and time-series movements in risk-adjusted hedge fund performance? Does the entry of sophisticated investors herald a reduction in the performance of hedge funds? In this paper, we investigate these important questions. In doing so, we provide a body of evidence that strongly supports Berk and Green's (2004) model of active portfolio management.

Berk and Green's model has three key features. First: investors competitively provide capital to funds. Second, managers have differential ability to generate high returns, but face decreasing returns to scale in deploying their ability. Third, investors learn about managerial ability from past performance and direct more capital towards funds with superior performance. These features, we demonstrate, are evident in the hedge fund industry, providing us with an interesting laboratory to test the predictions of their rational model of active management.

[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.

There are two main implications of the Berk and Green model. We provide evidence that these implications are indeed true in the case of hedge funds. First, we show that more successful funds experience far greater capital inflows than their less fortunate counterparts. A second implication of their model is that diminishing returns to scale combined with the inflow of new capital leads to erosion of superior performance over time. In keeping with this implication, we provide evidence that even successful funds have experienced a recent, dramatic decline in risk-adjusted performance.

Before one can use the data on hedge funds or hedge fund indexes to examine these issues, one has to minimize the biases in these data. These biases arise from a lack of uniform reporting standards given the lack of regulation. 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 by hedge fund indexes upwards.

Furthermore, real-life constraints make the hedge fund index returns difficult to replicate. For example, some hedge funds included in the index may be closed to new money, or may even be returning money. In addition, hedge funds often impose constraints on the withdrawal of money, using lockup periods, notice and redemption periods. More importantly, the hedge fund index returns 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 reduce these costs, 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 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 inspecting the performance of funds-of-hedge-funds (FoFs), which reflect the investment experience of investors and incorporate the costs of portfolio management. They suggest that analyzing FoF performance may be preferable to analyzing

[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.

the performance of an index, which may not be attainable and which does not include accessing costs.[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 index, and as a result, the index return does not reflect the full extent of losses incurred by investors. In contrast, a FoF investing in the hedge fund, being diversified, survives the collapse of the hedge fund and its return reflects, albeit indirectly, the full extent of losses experienced by investors. Second, unlike hedge fund index returns, FoF returns reflect the cost of real-life constraints (funds being closed or imposing delays to capital withdrawal) and therefore represent the true return earned by the capital invested in the underlying hedge funds. Finally, in contrast to the returns on hedge fund indexes, the FoF returns are net of all fees (i.e., after the cost of managing a portfolio of underlying hedge funds) and therefore are more representative of the true investment experience of hedge-fund investors.

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

Our analysis yields three main findings. First, there exist significant cross-sectional differences in the risk-adjusted performance (henceforth 'alpha') of FoFs, suggesting substantial differences in managerial ability. Second, the managers who produce alpha receive high and positive inflows of capital, while the rest have experienced on average zero capital inflows. Furthermore, the flows to the alpha providers are steady, and do not significantly respond to recent past returns, while the rest of the funds are characterized by trend-chasing capital flows. This may indicate a clientele effect in the hedge fund industry. Finally, the alpha of the alpha producers has significantly declined in the most recent time period in our data. All these findings are consistent with the Berk and Green model.

[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 FoF indices are quite close in magnitude to the investable indices, and have a high correlation with them in recent years.

Taken together, our results present a challenge. On the one hand, the supply of alpha appears to have declined. On the other hand, capital chasing the producers of alpha appears to be rising steadily. This apparent mismatch between the supply of and demand for alpha is bound to generate problems unless institutional features of the industry change. In other words, the 'price' of alpha is not set correctly – there is no indexation to alpha in standard contracts in the hedge fund industry. This introduces a wedge between demand and supply in the market for alpha.

Goetzmann, Ingersoll, and Ross (2003) show that high-water mark compensation in the hedge fund industry generates pernicious risk-taking incentives for hedge fund managers. Our point is that there is another problem – the return sharing problem between investors and fund managers, which should be done on a risk-adjusted basis. Arguably, delivering alpha is far more difficult than generating returns via systematic risk exposures. Faced with a huge influx of capital, it is conceivable that hedge fund managers will attempt to generate returns by taking on more beta bets unless there is a change in the contract structure.

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 FoFs are TASS; Hedge Fund Research, which supplies the HFR family of indices; and the Center for International Securities and Derivatives Markets database, which produces the CISDM family of indices. We merge and consolidate FoF data from the HFR, TASS and CISDM 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 FoFs, and our sample period runs from January 1995 to December 2004.

Table I presents descriptive statistics on our consolidated FoF data. Note that all the return data we employ is net-of-all-fees. Mirroring the growth in AUM in the hedge fund industry, the AUM in FoFs has grown from U.S. $18 billion at the end of 1995 (around 25 percent of the hedge fund industry AUM according to the TASS asset flows report) to U.S. $190 billion in 2004 (close to 30 percent of the industry). The birth and death rates are approximately constant over time, at 27 percent and 8 percent per year, respectively.[5] The equal-weighted net-of-fee mean returns average 9.39 percent per annum over the sample period. However, these returns vary substantially both within and across years.

3. Methodology

3.1. Risk-Adjusted Performance Evaluation

Throughout our analysis, we model the risks of FoFs using the seven-factor model of Fung and Hsieh (2004a). These factors have been shown to have considerable explanatory power for FoF 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; three portfolios of lookback straddle options on currencies (*PTFSFX*), commodities (*PTFSCOM*) and bonds (*PTFSBD*), which are constructed to replicate the maximum

[5] The number of funds does not equal the previous number + births – deaths, since there are occasionally funds with missing returns on the last month of the year.

[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.

possible return to a trend-following strategy on the underlying asset, all in excess returns;[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 FoFs.

3.2. Time Variation and Structural Breaks

A static factor analysis of the risk structure of FoF returns is not appropriate if FoF managers change their strategies over the sample period that we investigate. Fung and Hsieh (2004a) study vendor-provided FoF indices, and perform a modified CUSUM test to find structural break points in FoF factor loadings. They find that the break points coincide with extreme market events that might plausibly be expected to affect FoF 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:

$$R_t^{FoF} = \alpha_1^{FoF} D_1 + \alpha_2^{FoF} D_2 + \alpha_3^{FoF} D_3 + (D_1 X_t)\beta_{D1} + (D_2 X_t)\beta_{D2} + (D_3 X_t)\beta_{D3} + \varepsilon_t \tag{1}$$

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

Here, R_t^{FoF} is the (equal-weighted) average excess return across all FoFs 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

[7] See Fung and Hsieh (2001) for a detailed description of the construction of these primitive trend-following (PTF) factors.

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 FoF index return, ignoring the cross-sectional heterogeneity in the set of FoFs. We turn to examining this heterogeneity (especially in alpha production) in the set of FoFs in the next subsection.

3.3. Cross-Sectional Differences in FoFs

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 FoFs. The investor, as in Berk and Green's model, infers the ability of the manager by evaluating the fund's past performance. He selects funds that exhibit superior performance and directs capital towards them. At annual intervals, he rebalances his portfolio by re-assessing his investment opportunity set.

We operationalize this exercise in the following way. At the end of 1996, we select all FoFs that have a full return history 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 FoFs that deliver statistically positive alpha and segregate them from the remainder of the set. For expositional convenience, we denote the former as *have alphas* and the remainder as *have betas*.

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 alphas* and *have betas* depending on their risk-adjusted performance over the past two years.

3.4. Capital Flow Analysis

We construct the monthly net flow of assets into each of the FoFs in our sample. Capital flow is defined as capital contribution less withdrawals, once returns have been accrued. Flows are calculated as coming in at the end of the month (we also experiment with the assumption that flows come in at the beginning of the month, and the results are invariant to this assumption):

$$F_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1}(1+R_{it})}{AUM_{i,t-1}} \qquad (2)$$

Where $F_{i,t}$, $AUM_{i,t}$, $R_{i,t}$ respectively are the flows, assets under management and returns of the *i*'th FoF for month *t*,

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

$$F_{g,t} = \gamma_0 + \gamma_r \left(\sum_{k=1}^{3} R_{g,t-k} \right) + \gamma_{f1} \left(\sum_{k=1}^{3} F_{g,t-k} \right) + u_{g,t} \qquad (3)$$

where $F_{g,t}$, $R_{g,t}$ are, respectively, the equally-weighted average flow and the equally-weighted average return in month *t* across all FoFs in group *g*, where $g \in \{have\ alphas,\ have\ betas\}$. Note that the regression is a monthly regression with overlapping three-month lagged flows and returns on the right-hand side. Withdrawal notice and redemption periods will artificially restrict flow responsiveness to past return movements if the regression were merely run using monthly lags. To enable easier interpretation of the coefficients, we impose the restriction that monthly flows and returns in the prior quarter have the same coefficient. We employ a Newey-West (1987) covariance matrix using 12 monthly lags to account for the autocorrelation potentially induced by the use of overlapping observations.

3.5. Is Alpha Changing Over Time for *Have Alphas* and *Have Betas*?

Using the identities of the *have alphas* and *have betas* that we estimated in section 3.3., we construct an equally-weighted index of *have alpha* and *have beta* returns from January 1997 to December 2004. The index tracks the performance of each of the *have alphas* and *have betas* over the year *after* it was classified. Note that this means that all performance evaluation is completely out-of-sample. For example, some of the FoFs 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 FoF return on the left-hand side with the *have alpha* and *have beta* return indexes:

$$R_t^g = \alpha_1{}^g D_1^1 + \alpha_2{}^g D_2 + \alpha_3{}^g D_3 + (D_1^1 X_t)\beta_{D1}^g + (D_2 X_t)\beta_{D2}^g + (D_3 X_t)\beta_{D3}^g + \nu_t^g \quad (4)$$
$$\text{Where } X_t = [SNPMRF_t \;\; SCMLC_t \;\; BD10RET_t \;\; BAAMTSY_t \;\; PTFSBD_t \;\; PTFSFX_t \;\; PTFSCOM_t]$$

Here, $g \in \{have\ alphas,\ have\ betas\}$. The main difference between equations (1) and (4) (apart from the fact that they are run on different sets of FoFs) 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 *have beta* indexes begin in January 1997.

Based on the results from the capital flow analysis in section 3.4., we would correspondingly expect to find changes in alpha production for the groups in different sub-periods. For example, Berk and Green would suggest that an increase in capital flows experienced by an alpha producer would result in a decline in subsequent alpha production.

4. Results

4.1. Risk-Adjusted Performance Evaluation and Time Variation

Table II reports the results from estimating the regression in 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 $\widehat{\beta}_{D1}, \widehat{\beta}_{D2}$ are jointly different from $\widehat{\beta}_{D3}$, using the heteroskedasticity-consistent covariance matrix. The χ^2 test statistic with 14 degrees of freedom is 248.42, 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 FoFs 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 FoF only exhibits statistically significant alpha during the second sub-period ($\hat{\alpha}_2^{FoF}$ is the only statistically significant intercept), which spans the bull market from October 1998 to March 2000.

The third important observation from Table II is the explanatory power of the regression. The adjusted R^2 statistic is around 74 percent for the returns of the average FoF. The magnitude of the R^2 statistic suggests that FoFs take on a significant amount of factor risk. This confirms the results 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, we corrected individual FoF 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 time-variation is an important dimension to consider when computing risk-adjusted performance of hedge funds. Our analysis reveals that the average FoF 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 FoFs.

Berk and Green assume that there are significant differences in the ability of active portfolio managers. Perhaps there are FoFs in our sample that consistently generate alpha in all three periods,

[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.

which we do not detect in our analysis of the average return. We now turn to the results from our cross-sectional analysis of FoFs.

4.2. Cross-Sectional Differences in FoFs

As described in section 3.3., we implement the bootstrap method of Kosowski et. al. (2006) and verify that there are FoFs that have statistically positive alpha in our set of funds. We also use the technique to select *have alpha* and *have beta* 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), applying the GLM correction to undo any potential autocorrelation in FoF returns, and then re-doing the bootstrap experiments. Our results 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 FoFs 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 FoFs in the *have alpha* and *have beta* groups. The first feature of note is that the number of FoFs 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, 22.5 percent of the FoFs are classified as *have alphas*, while a much larger percentage of FoFs do not deliver statistically positive alpha. Third, the percentage of total FoFs allocated to the *have alphas* fluctuates over time, ranging from a low of 10 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 FoFs to deliver alpha is sensitive to market conditions.

The last three columns in Table III report transition probabilities for the *have alphas* and *have betas*. In particular, the rows indicate the two-year period over which the FoFs were classified, while the columns indicate the percentage of the funds that were classified as *have alphas* and *have betas* in the non-overlapping two-year classification period, as well as the percentage of FoFs that were defunct.

Note that the final classification period is 2002-2003, since we require at least one year of out-of-sample data for the performance analysis that follows.[9]

The results indicate that there is a greater likelihood of a FoF delivering alpha in the subsequent period if it is classified as a *have alpha* fund. In particular, the average transition probability for a *have alpha* fund into the subsequent *have alpha* group is 34 percent, while that for a *have beta* fund is 12 percent. This average hides the fact that in some years, the transition probability differential is much higher. 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 selected in 1999-2000 is 81 percent, in contrast to the 26 percent probability for a contemporaneous *have beta* 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 alphas* and *have betas* that remain in business at the end of each year over a five year post-classification period. The results strongly indicate that the *have alphas* have a greater ability to survive, 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 model, that there are significant differences in ability in the cross-section of active portfolio managers. This quality differential manifests itself in the hedge fund industry in the form of higher survival rates and higher probability of persistently delivering alpha.

4.2. Capital Flow Analysis

The top panel of Table V reports the average monthly equally weighted flow into *have alphas* and *have betas*. On average, the *have alphas* experience a statistically significant inflow of 1.5 percent per month (approximately 18 percent per annum), in contrast to the statistically zero inflows experienced by the *have betas*. Figure 1 confirms this analysis of averages. The figure indexes January 1997 to 100, and plots the compounded growth in flows over the entire sample period for both groups. The

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

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 424 at the end of December 2004. In sharp contrast, the *have beta* flow index ends up at a level of 111. Although these statistics are stark, they mask a more intriguing set of time patterns.

When we examine the flows into the two groups during the three sub-periods, we observe the following. During the first sub-period (pre-LTCM crisis) *have alphas* experienced significant inflows (0.9 percent per month), while *have betas* did not. In the second sub-period (the bull-market period) we see that the *have betas* experienced significant outflows, as compared to the statistically zero flows experienced by the *have alphas*. This may be due to the fact that during the bull-market period, and following the LTCM crisis, equities may have been far more attractive to investors. Nevertheless, on aggregate they seemed to pull money only out of *have betas*. Finally, in the most recent sub-period, both groups experienced significant inflows. However the flows into *have alphas* are more than four times the magnitude of those into *have betas* (2.2 percent a month versus 0.5 percent per month).

Do these flows reduce the propensity of FoFs to deliver alpha? According to Berk and Green's model, investors would continue to direct capital flows to managers with superior ability (*have alphas*), and this will result in a deterioration of performance of such funds over time. The startlingly high flows experienced by *have alphas* in the final sub-period, therefore, may result in a decline in their ability to produce alpha. We investigate the issue of whether alpha has declined in magnitude for the *have alpha* FoFs in the next section. However, we begin with looking at transition probabilities conditional on FoF inflows.

Table VI conditions the two-year transition probabilities of *have alpha* FoFs based on the inflows experienced in the year post-classification. The results indicate that across all funds with available flow data, FoFs that experienced above the median inflow have lower (higher) transition probabilities to the *have alpha* (*have beta*) group in the subsequent classification period. Across all years, an above median inflow *have alpha* FoF has a 25 (69) percent probability of being classified as a *have alpha* (*have beta*) FoF in the subsequent non-overlapping classification period. This is contrasted with the 31 (60) percent probability of being classified as a *have alpha* (*have beta*) FoF in the subsequent non-overlapping classification period for the below median inflow *have alpha* FoFs.

Before we turn to the next section, there is just one more point worth noting. Table VII shows results from estimating equation (3). The results here show that the flows into *have alphas* show no statistical evidence of return-chasing behavior - the coefficient of flows on lagged returns is not significant. However, this is not true for the flows into *have betas*. For the *have betas*, high (low) returns over a quarter precede increases (decreases) in capital flows in the subsequent month.

This observation is consistent with a scenario in which positive-feedback investors are attracted to *have betas*. Perhaps more sophisticated investors with a preference for absolute returns are attracted to *have alphas*, and provide capital that is unaffected by temporary movements in returns.

There is a growing literature that suggests that institutional investors can be characterized as sophisticated (two recent examples are Cohen, Gompers and Vuolteenaho (2001) and Froot and Ramadorai (2005)). There is evidence that two important groups of institutional investors, defined benefit pension funds and university endowments, have increased their allocation to hedge funds over the 2000 to 2004 period.[10] Our finding that capital flows into the *have alphas* are steadily increasing, while flows to the *have betas* have stagnated could be generated by this evolving clientele shift in the demand side of hedge funds. We now turn to identifying time variation in the alphas of *have alphas* and *have betas*.

4.3. Intertemporal Variation in the Alpha of *Have Alphas* and *Have Betas*

In order to shed light on the time pattern of alphas for our two groups of FoFs, we estimate equation (4) and report the results in Table VIII.

The first feature of note in Table VIII is that the major significant difference in risk taking behavior between the groups manifests itself in the tendency of the *have betas* to take on consistently greater exposure to static risk factors (*SNPMRF*, *SCMLC*, *BAAMTSY* and *BD10RET*). Second, the adjusted R-squared statistics confirm that the Fung-Hsieh (2004a) seven-factor model continues to offer good

[10] 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 14.7 percent in 2004 (U.S.$ 39.2 BN). Over the same period, the top 200 defined benefit pension plans increased their allocation from U.S.$ 3.2 BN to U.S.$ 21.1 BN (source: www.pionline.com).

explanatory power for the two groups of FoFs. Third, the structural break points utilized for the analysis of the average FoF are confirmed to exist for the two groups of FoFs as well.

Turning to the alphas, in the first sub-period, the *have alphas* delivered (on an out-of-sample basis) a statistically significant alpha of 0.47 percent per month. In contrast, the *have betas* did not produce any detectable alpha over this period. The imprecise negative coefficient suggests that the fee component of *have beta* 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 *have alphas* generated almost 2 ½ times the amount generated by the *have betas*.

In the final sub-period, the predictions of Berk and Green seem to be borne out. The steady inflows of capital experienced by the *have alphas* and *have betas* during this period appear to have wiped out the potential of both groups to deliver statistically significant alpha.

5. Conclusion

In this paper, we use data from the hedge fund industry, and provide a direct test of the implications of the Berk and Green (2004) rational model of active portfolio management.

Consistent with the model, we find that there are significant differences in the ability of managers to deliver alpha. Our evidence is also consistent with investors perceiving these ability differentials, and in response, directing a steady stream of capital to the managers with higher ability. This persistent inflow of capital is associated with a decline in the alpha produced in the hedge fund industry. The decline is experienced by all managers regardless of ability.

Our results also suggest that there is an apparent mismatch between the supply and demand for alpha. On the one hand, the supply of alpha appears to be drying up. On the other, capital appears to be seeking alpha. This could presage changes in the organization of the hedge fund industry. Contracts in the hedge fund industry are currently structured to reward managers for generating returns above pre-specified fixed benchmarks. The findings in this paper suggest that conditioning incentives on risk-adjusted performance may be preferable.

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 10 percent significance level, then, even under the null, we would observe 10 percent of the tests being rejected. Thus, for 307 FoFs in the 1997-1998 group, we expect around 15 (5 percent) to reject the null in the upper tail using a 5 percent one-sided significance level. However, this is only true if the in-sample distribution of the t-stats roughly corresponds to the asymptotic standard normal distribution. This is only true if the residuals of the FoF factor regressions are homoskedastic, serially uncorrelated and cross-sectionally independent.

We can use the order statistics literature and the bootstrap to help us here. Returning to the hypothetical example of 1000 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 fact that the $X_{(i)}$ come from a standard normal distribution, the probability that $X_{(950)} > 3.884$ is 5 percent. Hence, if in the sample, we find the 95th percentile of the t-stat is greater than 3.884, then there are FoFs with positive alpha. We can use a bootstrap to relax the assumption 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-stats of $\hat{\alpha}_i, \hat{t}(\hat{\alpha}_i)$, which is calculated using standard OLS, or Newey-West with 3 lags. Do this for all funds $i = 1,...,I$. Save the t-stats, 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:

$r_{i,t}^{b} = \hat{\alpha}_{i}^{b} + x_{t}^{'}\hat{\beta}_{i}^{b} + \hat{\varepsilon}_{i,t}^{b}$ 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 *all* the simulated t-statistics, { $\hat{t}^{b}(\hat{\alpha}_{i}^{b})$ }, we call it a *have alpha* fund. Otherwise, we call it a *have beta* 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 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-Hedge-Funds (FoFs) in the data in December of each year, the number of FoFs that entered the data by the end of the year, the number that exited the data by the end of 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 equal-weighted return index of all FoFs in annualized percentage points. The standard deviation is annualized by multiplying by the square root of 12 under the assumption that monthly returns are iid.

Year End	**N(Funds)**	**N(Born)**	**N(Died)**	**AUM U.S.$ BN**	$\mu(R_t^{FoF})$ annualized percent	$med(R_t^{FoF})$ annualized percent	$\sigma(R_t^{FoF})$ annualized percent
1995	248	57	13	18.208	12.164	13.268	3.931
1996	336	104	19	25.351	14.555	14.499	5.276
1997	415	103	24	43.485	15.787	19.532	6.172
1998	487	111	39	38.204	0.063	-3.130	7.049
1999	575	123	36	42.867	20.633	10.775	6.221
2000	657	118	45	51.081	7.272	1.361	6.991
2001	763	169	61	67.491	4.117	4.864	2.699
2002	898	182	39	84.081	1.550	4.857	2.255
2003	1036	202	70	124.619	11.106	9.570	2.285
2004	1158	226	94	189.405	6.665	7.389	3.700

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

The top panel of this table contains estimates of:

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

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

Here, R_t^{FoF} , the dependent variable, is the (equal-weighted) average excess return across all FoFs 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*
Adj R-squared	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 *Have Beta* FoFs

The rows correspond to the two-year period in which FoFs are classified into *have alphas* and *have betas*. The columns are, in order, the total number of FoFs with two full years of return history in each of the classification periods; the number (and percentage of the total) classified as *have alphas*; the number (and percentage of the total) classified as *have betas*; and the percentages of *have alphas* and *have betas* that are classified in the subsequent non-overlapping period as *have alphas*; *have betas* or stopped reporting (defunct). For example, in 1996-1997, of 259 total funds, 34 percent and 66 percent respectively were classified as *have alphas* and *have betas*, 17 percent of these *have alphas* were reclassified as *have alphas* in the 1998-1999 period, 68 percent as *have betas*, and 7 percent stopped reporting. In contrast, 7 percent of the 1996-1997 *have betas* were classified as 1998-1999 *have alphas*, 73 percent were reclassified as *have betas* and 20 percent stopped reporting.

Classification Period	**N(FoFs)**	**N(*Have Alpha*) (% *Have Alpha*)**	**N(*Have Beta*) (% *Have Beta*)**	**From/To:**	**P(Two-Year Transition)** *Have Alpha*	***Have Beta***	**Defunct**
1995-1996	195	41	154	***Have Alpha***	24%	68%	7%
		21%	79%	***Have Beta***	4%	82%	14%
1996-1997	259	88	171	***Have Alpha***	17%	74%	9%
		34%	66%	***Have Beta***	7%	73%	20%
1997-1998	307	31	276	***Have Alpha***	81%	16%	3%
		10%	90%	***Have Beta***	26%	58%	16%
1998-1999	374	64	310	***Have Alpha***	27%	65%	8%
		17%	83%	***Have Beta***	18%	62%	21%
1999-2000	448	188	260	***Have Alpha***	24%	64%	12%
		42%	58%	***Have Beta***	9%	71%	21%
2000-2001	506	111	395	***Have Alpha***	30%	65%	4%
		22%	78%	***Have Beta***	10%	77%	12%
2001-2002	584	99	485				
		17%	83%				
2002-2003	700	105	595				
		15%	85%				
Average		22%	78%	***Have Alpha***	34%	59%	7%
				Have Beta	12%	71%	17%

Table IV
Survival Probabilities of *Have Alphas* and *Have Betas*

The rows correspond to the two-year period in which FoFs are classified into *have alphas* and *have betas*. The columns indicate the percentage of *have alphas* and *have betas* that were alive after one, two, three, four and five years after the classification period. The top panel shows the survival probabilities for the *have alphas* and the bottom panel for the *have betas*.

Classification Period	**Percentage of *Have Alpha* FoFs alive after**				
	Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**
1995-1996	100%	93%	93%	88%	73%
1996-1997	93%	91%	86%	74%	71%
1997-1998	100%	97%	97%	97%	94%
1998-1999	97%	92%	87%	86%	
1999-2000	94%	88%	84%		
2000-2001	96%	96%			
2001-2002	99%				
Average	97%	93%	89%	86%	79%

Classification Period	**Percentage of *Have Beta* FoFs alive after**				
	Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**
1995-1996	93%	86%	77%	72%	62%
1996-1997	90%	80%	73%	63%	59%
1997-1998	91%	84%	72%	67%	65%
1998-1999	92%	79%	75%	72%	
1999-2000	84%	79%	76%		
2000-2001	94%	88%			
2001-2002	93%				
Average	91%	83%	75%	69%	62%

Table V
Percentage Flows into *Have Alphas* and *Have Betas*

The rows correspond to the sub-periods: the first period is January 1995 to September 1998; the second goes from October 1998 to March 2000, and the third period from April 2000 to December 2004. Within each period, we report the average equal-weighted flow percentage (flows are computed as increase in AUM less accrued returns, under the assumption that flows came in at the end of the month), the standard error of the sample average flow, and the number of monthly observations used to compute the sample average and standard error. The columns show the group for which the flow percentages are computed; the last column reports the sample statistics for the difference in equal weighted flow percentages between the *have alpha* and *have betas*.

Sub-period	*Have Alpha Flows*	*Have Beta Flows*	*Have Alpha-Have Beta*
Period I			
Average	**0.009**	0.003	**0.006**
Std Error	0.002	0.002	0.002
N	21	21	21
Period II			
Average	0.002	**-0.014**	**0.015**
Std Error	0.003	0.003	0.003
N	18	18	18
Period III			
Average	**0.022**	**0.005**	**0.017**
Std Error	0.002	0.001	0.001
N	57	57	57
Full Sample			
Average	**0.015**	0.001	**0.014**
Std Error	0.002	0.001	0.001
N	96	96	96

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

The rows correspond to the two-year period in which FoFs are classified as *have alphas*. The columns are, in order: the group affiliation, i.e. whether the average FoF classified as a *have alpha* fund experienced inflows over the next year that were above or below the median *have alpha* FoF inflow in that year; the number of *have alpha* FoFs in each group; the percentage of the flow group members classified as *have alphas* in the subsequent classification period; the percentage of the flow group members classified as *have betas*; and the percentage of group members that stopped reporting (defunct). For example, in 1996-1997, 42 *have alpha* FoFs had above the median inflow in 1998. Of these, 14 percent were classified as *have alphas*, 74 percent as *have betas*, and 12 percent stopped reporting in 1997-1998.

Year	**Flow Group Year +1**	**N(FoFs)**	**P(Two-Year Transition)**		
			Have Alphas	***Have Betas***	**Defunct**
1995-1996	**above median**	19	21%	68%	11%
	below median	20	25%	70%	5%
1996-1997	**above median**	42	14%	74%	12%
	below median	43	19%	77%	5%
1997-1998	**above median**	15	80%	20%	0%
	below median	15	80%	13%	7%
1998-1999	**above median**	31	23%	74%	3%
	below median	31	29%	58%	13%
1999-2000	**above median**	90	21%	71%	8%
	below median	90	28%	58%	14%
2000-2001	**above median**	55	25%	73%	2%
	below median	55	35%	60%	5%
overall	**above median**	252	25%	69%	6%
	below median	254	31%	60%	9%

Table VII
Flow Trend-Chasing Regressions

This table presents estimates of:

$$F_{g,t} = \gamma_0 + \gamma_r \left(\sum_{k=1}^{3} R_{g,t-k} \right) + \gamma_{f1} \left(\sum_{k=1}^{3} F_{g,t-k} \right) + u_{g,t}$$

estimated separately for each sub-group of FoFs. The monthly flow measure $F_{g,t}$ in each case is expressed as a percentage of end-of-previous month AUM. The column headings indicate the FoF sub-group g for which the equation is estimated. Newey-West autocorrelation and heteroskedasticity-consistent standard errors are presented below coefficients.

	***Have Alpha* Flows**	***Have Beta* Flows**
Intercept	-0.001	-0.002
	-0.003	-0.001
Ret (L1-L3)	0.089	**0.125**
	0.055	0.020
Flow (L1-L3)	**0.279**	**0.295**
	0.025	0.018
Adj R-squared	0.434	0.630
N	96	96

Table VIII
The Changing Risks of *Have Alpha* and *Have Beta* Funds-of-Hedge-Funds

The top panel of this table contains estimates of:

$$R_t^g = \alpha_1^g D_1^1 + \alpha_2^g D_2 + \alpha_3^g D_3 + (D_1^1 X_t)\beta_{D1}^g + (D_2 X_t)\beta_{D2}^g + (D_3 X_t)\beta_{D3}^g + \nu_t^g$$

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

Here, R_t^g, the dependent variable, is the (equal-weighted) average excess return across all FoFs in group *g* 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 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	***Alphas***	***Betas***	**Variable**	***Alphas***	***Betas***	**Variable**	***Alphas***	***Betas***
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*
Adj R-squared	0.733	0.752						
N	96	96						

Period for Chow Structural Break Test	***Have Alphas***	***Have Betas***
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 Alphas* and *Have Betas*

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 $Index_t^g = Index_{t-1}^g * (1 + F_t^g)$ where F_t^g is the flow percentage for group $g \in \{Have\ Alphas,\ Have\ Betas\}$, for month *t*.