Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis*

Robert Kosowski[a], Narayan Y. Naik[b,**], Melvyn Teo[c]

[a]*INSEAD*
[b]*London Business School*
[c]*School of Business, Singapore Management University*

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Abstract

Using a robust bootstrap procedure, we find that top hedge fund performance cannot be explained by luck, and that hedge fund performance persists at annual horizons. Moreover, we show that Bayesian measures, which help overcome the short-sample problem inherent in hedge fund returns, lead to superior performance predictability. Relative to sorting on OLS alphas, sorting on Bayesian alphas yields a 5.5 percent per year increase in the alpha of the spread between the top and bottom hedge fund deciles. Our results are robust, and relevant to investors, as they are neither confined to small funds, nor driven by incubation bias, backfill bias or serial correlation.

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**Corresponding author: London Business School, Sussex Place, Regent's Park, London NW1 4SA, United Kingdom. E-mail: nnaik@london.edu, Tel: +44-20-7262 5050, extension 3579 and Fax: +44-20-7724 3317.

1. Introduction

Are stellar hedge funds like George Soros' Quantum Fund just lucky and their existence to be expected with such a large sample of hedge funds in existence? If not, does their abnormal performance persist and can it be exploited by means of trading strategies? These questions are of great relevance to institutional and retail investors who have recently raised their portfolio allocations to hedge funds in particular,[1] and to the issue of market efficiency in general. Our paper answers these questions by employing innovative statistical techniques on a large database of hedge funds.

Evaluating the significance and persistence of hedge fund returns is fraught with many difficulties. First, top performers are drawn from a large cross-section of hedge funds, which increases the potential for some managers to do particularly well by chance. Second, hedge fund performance measures do not typically follow parametric normal distributions given the funds' dynamic trading strategies and holdings of derivatives securities like options.[2] Third, the complexity of hedge fund strategies makes benchmarking their returns particularly challenging and raises the possibility of model mis-specification. Fourth, hedge fund return series are often short; hence, traditional performance measures (e.g., multi-variate generalization of Jensen's alpha) may be measured imprecisely. Fifth, hedge fund portfolio holdings are highly confidential and rarely, if at all, available to researchers. Methods using portfolio holdings to assess fund performance are not applicable in hedge fund space.

In this paper, we address these difficulties by employing robust bootstrap methodologies proposed by Kosowski, Timmermann, Wermers and White (2005) (henceforth KTWW) and the Bayesian approach of Pástor and Stambaugh (2002a) (henceforth PS). The non-parametric bootstrap approach of KTWW permits a comprehensive examination of hedge fund performance that explicitly controls for luck, minimizes the potential bias from mis-specification (Horowitz, Härdle, and Kreiss, 2003), and avoids having to parametrically model the joint distribution of hedge fund performance across thousands of funds, most of which are sparsely overlapping. The seemingly unrelated assets (henceforth SURA) Bayesian approach of PS is also robust to model

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[1] About one-third of institutional investors, including CalPERS in the United States, plan to increase their allocations to hedge funds. See "For the fortunate few," The Economist, 3rd July 2003. Also, the hedge fund industry has expanded considerably over the last decade. The 2005 HFR report indicates that there were 530 hedge funds managing under US$39 billions in 1990, while there are over 7000 hedge funds managing over US$970 billions by the end of December 2004.

[2] See, e.g., Fung and Hsieh (2001), Mitchell and Pulvino (2001) and Agarwal and Naik (2004).

mis-specification. More importantly, it takes advantage of information in seemingly unrelated assets to overcome short sample problems and improve on the precision of performance estimates. Both these approaches have been applied with some success to mutual fund returns [see KTWW and Busse and Irvine (2005)] but not to hedge fund returns. Given their complex and dynamic trading strategies, we believe that hedge funds are more likely to suffer from return non-normality, model mis-specification, and short sample problems, as compared to mutual funds. Therefore, these approaches should be even more relevant for hedge funds.

Our empirical results are striking. According to our bootstrap estimates, the performance of the top hedge funds ranked by the *t*-statistic of alpha (which is similar to sorting by the information ratio often used to rank fund managers) cannot be attributed to sample variability or luck alone. This is true across all fund investment categories, and is robust to controlling for incubation and backfill bias (Ackermann, McEnally, and Ravenscraft, 1999; Fung and Hsieh, 2000; Malkiel and Saha, 2004; Ibbotson and Chen, 2005), short-term serial correlation in returns (Getmansky, Lo, and Makarov, 2004), and structural breaks (Bai and Perron, 1998). However, the bootstrap estimates also indicate that the performance of funds with high alphas cannot be distinguished from luck. Further investigation reveals that the OLS alphas of the top funds are often imprecisely estimated and overstate hedge fund performance. Our results empirically validate the industry practice of ranking fund managers on their information ratios as opposed to their Jensen's alpha.

The bootstrap results also have implications for hedge fund return persistence. We report that funds sorted on alpha *t*-statistic formed over the past two years persist more than funds sorted on alpha over the same period. More importantly, relative to sorting on OLS performance measures, sorting on Bayesian performance measures dramatically improves predictability in hedge fund returns. The sort on past two-year Bayesian posterior alpha yields a decile spread with an economically and statistically significant alpha of 5.81 percent per annum (*t*-statistic = 2.65) which is 5.48 percent greater than that from the sort on OLS alpha. Moreover, the alpha of the top decile portfolio from the Bayesian alpha sort is 8.21 percent per annum (*t*-statistic = 4.35) and 54 percent higher than that from the OLS alpha sort. Indeed, we observe a similar phenomenon when we sort funds on *t*-statistic of Bayesian alpha versus *t*-statistic of OLS alpha. The Bayesian approach increases the magnitude of the alphas for both the top decile portfolio and the spread portfolio relative to the Frequentist approach. In particular, the sort on *t*-statistic of Bayesian alpha yields a decile spread with an alpha of 3.15 percent per annum (*t*-statistic = 1.76) and a one-percentile spread with an alpha of 6.53 percent per annum (*t*-statistic = 2.30).

Collectively, the persistence results suggest that the top hedge fund managers (at least based on the more precise Bayesian performance measures) possess asset selection skill and one can take advantage of this via simple trading strategies. We consider alternative explanations like persistence in fund fees and short-term serial correlation in fund returns. However, our results suggest that they cannot explain the bulk of the performance persistence. For instance, we obtain even stronger results with pre-fee returns. We explicitly show that our results are not driven by serial correlation, which we adjust for using various approaches. Sensitivity tests indicate that our results are of particular relevance to investors as they are neither driven by incubation and backfill bias, nor are they confined solely to small funds. Our findings are also robust to varying the formation and evaluation periods used to form portfolios of hedge funds.

The results challenge the classical finance theory view that the top hedge funds are just lucky and that hedge fund returns do not persist. In doing so, we build on several themes. Fung and Hsieh (1999, 2000, 2001), Mitchell and Pulvino (2001) and Agarwal and Naik (2004) show that hedge fund returns relate to conventional asset class returns and option-based strategy returns[3]. They find that a significant part of the variation in hedge fund returns over time can be explained by these systematic risk factors. We build on their pioneering work and show that after controlling for hedge fund exposures to these systematic risk factors, the managerial specific component of fund returns persist, and for the top funds, cannot be attributed to luck. Brown, Goetzmann and Ibbotson (1999), Agarwal and Naik (2000), and Liang (2000) conclude that hedge funds persist at quarterly horizons but not at longer horizons. Getmansky, Lo, and Makarov (2004) ascribe the short-term persistence to illiquidity in stock returns. Our Bayesian persistence results suggest that one reason why they do not find long-term persistence is that they rely on relatively imprecise frequentist performance measures. KTWW and Busse and Irvine (2005) apply the bootstrap and Bayesian methodologies, respectively, to mutual fund returns. We adopt both these complementary approaches in analyzing hedge fund returns. The results in KTWW indicate that performance of the top alpha mutual funds cannot be attributed to sampling variability. We show that due to the extreme variability of hedge fund returns, hedge fund alphas do not convey as much information about future returns as do mutual fund alphas. Busse and Irvine (2005) report that, with mutual funds, Bayesian sorts improve on the equal-weighted decile spread by at most

[3] Fung and Hsieh (1999, 2001) show that Global Macro funds deliver "collar" like payoffs while Trend Follower funds exhibit "look-back straddle" like payoffs. Mitchell and Pulvino (2001) and Agarwal and Naik (2004) demonstrate that a number of equity-based hedge fund strategy payoffs resemble those obtained from writing an uncovered put option on the equity market.

100 percent relative to Frequentist sorts [see Table 1 in Busse and Irvine (2005)]. Our results indicate that, with hedge funds, the spread portfolio alpha increases by sixteen-fold with Bayesian alpha versus OLS alpha based sorts, and suggest that Bayesian methods are even more powerful in hedge fund studies given the severity of the small sample problem

Our study joins a nascent body of work that applies Bayesian methodology to the study of fund performance.[4] Baks, Metrick, and Wachter (2001) estimate mutual funds' alphas based on informative prior beliefs about individual fund alphas. Pástor and Stambaugh (2002b) develop and implement a Bayesian framework in which prior views and empirical evidence about pricing models and managerial skill can be incorporated into the investment decision. Stambaugh (2003) shows how Baysian methods can help the inference about the returns on a fund that has survived while others have failed due lower returns. Jones and Shanken (2005) take advantage of prior beliefs about aggregate fund performance to estimate individual mutual fund performance. Similar information pooling across funds takes place in the approach developed by Cohen, Coval, and Pástor (2005) in which the historical returns and holdings of other mutual funds are used to evaluate the performance of a single mutual fund. Avramov and Wermers (2005) present a Bayesian technique to select mutual funds in the presence of general forms of stock return predictability. None of these papers apply Bayesian methods to the study of hedge funds.

The rest of the paper is structured as follows. Section 2 describes the data while Section 3 presents the bootstrap and Bayesian performance measures. Section 4 reports the empirical results including the bootstrap analysis, a comparison of Bayesian and standard performance measures, and the Bayesian performance measure based persistence tests. Section 5 concludes.

2. Data

We evaluate the performance of hedge funds using monthly net-of-fee[5] returns of live and dead hedge funds reported in the TASS, HFR, CISDM, and MSCI datasets over January 1990 to December 2002 - a time period that covers both market upturns and downturns, as well as relatively calm and turbulent periods. The union of the TASS, HFR, CISDM, and MSCI databases represents that largest known dataset of the hedge funds to date.

[4] In a similar vein, Huij and Verbeek (2003) find that shrinkage estimators which exploit information in the cross-section of fund returns are useful in analyzing mutual fund performance and persistence.
[5] Our results are robust to using pre-fee returns.

In our fund universe, we have a total of 6,392 live hedge funds and 2,946 dead hedge funds. However, due to concerns that funds with assets under management (henceforth AUM) below US$20 million may be too small for many institutional investors, we exclude such funds from the analysis.[6] This leaves us with a total of 4,300 live hedge funds and 1,233 dead hedge funds. The breakdown of funds by database is illustrated in Figure 1. The Venn diagram in Figure 1 reveals that the funds are roughly evenly split among TASS, HFR, and CISDM/MSCI[7]. While there are overlaps among the databases, there are many funds that belong to only one specific database. For example, there are 1,410 funds and 1,513 funds peculiar to the TASS and HFR databases, respectively. This highlights the advantage of obtaining our funds from a variety of data vendors.

[Figure 1 here]

Although the term "hedge fund" originated from the Long/Short Equity strategy employed by managers like Alfred Winslow Jones, the new definition of hedge funds covers a multitude of different strategies. There does not exist a universally accepted norm to classify hedge funds into different strategy classes. We follow Agarwal, Daniel, and Naik (2005) and group funds into five broad investment categories: Directional Traders, Relative Value, Security Selection, Multi-process, and Fund of Funds. Directional Trader funds usually bet on the direction of market, prices of currencies, commodities, equities, and bonds in the futures and cash market. Relative Value funds take positions on spread relations between prices of financial assets and aim to minimize market exposure. Security Selection funds take long and short positions in undervalued and overvalued securities respectively and reduce systematic risks in the process. Usually they take positions in equity markets. Multi-process funds employ multiple strategies usually involving investments in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations, and share buybacks. Fund of Funds invest in a pool of hedge funds and typically have lower minimum investment requirements. We also single out Long/Short Equity funds, which are a subset of Security Selection funds, for further scrutiny as this strategy has grown considerably over time (now representing the single largest strategy according to HFR) and has the highest alpha in Agarwal

[6] The AUM cutoff is implemented every month. Since there may be concerns that this may bias the sample in favor of finding alpha, we also redo the basic bootstrap and persistence tests with the full sample of fund return observations and obtain even stronger results.
[7] The CISDM and MSCI databases are combined in Figure 1 to facilitate illustration. A further breakdown of funds into each database is available upon request.

and Naik (2004, Table 4). For rest of the paper, we focus on the funds for which we have investment style information.

It is well known that hedge fund data are associated with many biases (Fung and Hsieh, 2000). These biases are driven by the fact that due to lack of regulation, hedge fund data are self-reported, and hence are subject to self-selection bias. For example, funds often undergo an incubation period during which they build up a track record using manager's/sponsor's money before seeking capital from outside investors. Only the funds with good track records go on to approach outside investors. Since hedge funds are prohibited from advertising, one way they can disseminate information about their track record is by reporting their return history to different databases. Unfortunately, funds with poor track records do not reach this stage, which induces an incubation bias in fund returns reported in the databases. Independent of this, funds often report return data prior to their listing date in the database, thereby creating a backfill bias. Since well performing funds have strong incentives to list, the backfilled returns are usually higher than the non-backfilled returns. To ensure that our findings are robust to incubation and backfill biases, we repeat our analysis by excluding the first 12 months of data. In addition, since most database vendors started distributing their data in 1994, the datasets do not contain information on funds that died before December 1993. This gives rise to survivorship bias. We mitigate this bias by focusing on January 1994 onward data.

3. Methodology

3.1. Factor benchmarks and performance measure α

In order to examine the abnormal performance of hedge funds, we regress the net-of-fee monthly excess return (in excess of the risk free rate) of a hedge fund on the excess returns earned by traditional buy-and-hold and primitive trend following strategies. That is, we use as performance benchmarks the seven-factor model developed by Fung and Hsieh (2004)[8]. The Fung and Hsieh (2004) factors are S&P 500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the 10-year Treasury (BD10RET), change in the spread of Moody's Baa minus the 10-year Treasury (BAAMTSY),

[8] Similar results obtain when we measure performance relative to the Agarwal and Naik (2004) option-based factor model.

bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS denotes primitive trend following strategy. Fung and Hsieh (2004) show that their factor model strongly explains variation in individual hedge fund returns.

The intercept ($\hat{\alpha}^i$) from the regression below represents the abnormal performance of the manager of hedge fund *i* after controlling for her risk exposures. In particular, to evaluate the performance of hedge funds, we run the following regression:

$$r_t^i = \hat{\alpha}^i + \sum_{k=1}^{K} \hat{\beta}_k^i F_{k,t} + \hat{\varepsilon}_t^i \qquad (1)$$

where r_t^i is net-of-fees excess return (in excess of the risk free rate) on an individual hedge fund *i* for month *t*, $\hat{\alpha}^i$ is alpha performance measure or the abnormal performance of hedge fund *i* over the regression time period, $\hat{\beta}_k^i$ is the factor loading of hedge fund *i* on factor *k* during the regression period, $F_{k,t}$ is the return for factor *k* for month *t*, and $\hat{\varepsilon}_t^i$ is the error term.

As a prelude to the bootstrap analysis, in Table 1, we report tests of normality, heteroskedasticity, and serial correlation on hedge fund residuals to examine the behavior of fund returns in our sample broken down by investment category. The first column in Table 1 reveals that the average seven-factor model alpha is positive[9] and about 0.42 percent per month (5.04 percent per year) across all funds. The average alpha *t*-statistic (1.43) is low and indicates that on average the alphas are not statistically different from zero at the 10 percent significance level. However, this does not rule out the possibility of finding performance persistence or top hedge funds with statistically significant performance.

[Table 1 here]

Looking across fund categories, Long/Short Equity funds in particular appear to have residuals that are highly negatively skewed, while Relative Value funds exhibit high kurtosis or fat tails. In addition, many funds fail the test for normality. For two investment categories: Long/Short

[9] One reason why the average fund alpha is not closer to zero may be because incubation and backfill bias artificially inflates hedge fund returns. Hence, we include tests that control for the effects of incubation and backfill bias in both the bootstrap and the Bayesian analyses.

Equity and Directional Traders, the null hypothesis of normality is rejected with the Jarque Bera test for over 50 percent of funds. Clearly, non-parametric methods, like the bootstrap, which avoid imposing assumptions of normality on hedge fund returns, are useful in evaluating hedge funds. Table 1 also reveals that fund returns are often serially correlated and fund residuals often heteroscedastic. Directional Traders fund returns appear to be most serially correlated while Long/Short Equity fund residuals are most prone to heteroscedasticity. The former is not surprising given that Directional Traders often exploit momentum-based strategies that bet on the continuation of price trends.

3.2. The bootstrap approach

The bootstrap is a non-parametric approach to statistical inference.[10] It is especially relevant to the study of top hedge fund performance for three reasons. First, the bootstrap allows the researcher to avoid having to make a priori assumptions about the shape of the distribution from which individual fund alphas are drawn. As shown in Table 1, the empirical distribution of residuals from multi-factor performance regressions is non-normal for many hedge funds. Thus, the distribution of $\hat{\alpha}$ may be poorly approximated by the normal distribution and its statistical significance is better evaluated using a non-parametric approach, such as the bootstrap. Second, the bootstrap frees the researcher from having to estimate the entire covariance matrix characterizing the joint distribution of individual funds. Specifically, the distribution of the maximum alpha depends on this covariance matrix, which is generally impossible to estimate with precision. Even if individual fund residuals are adequately approximated by a normal distribution, the very large dimension of this matrix with thousands of funds and the entry and exit of funds (which imply that many funds do not even have overlapping return records) all conspire to make estimation infeasible. Third, refinements of the bootstrap (which we will implement) provide a general approach for dealing with unknown time-series dependencies that are due, for example, to heteroscedasticity or serial correlation in the residuals from performance regressions.

The basic intuition underlying the bootstrap implementation is simple. We seek to compare the observed top fund performance to the performance of top funds in artificially generated data samples where variation in fund performance is entirely due to sample variability or luck. To

[10] Our approach is based on the bootstrap introduced by Efron (1979). For a detailed discussion of the properties of the bootstrap, see, for example, Efron and Tibshirani (1993) or Hall (1992).

prepare for our bootstrap procedure, for each fund i, we measure performance relative to the multi-factor model in Equation (1). The coefficient estimates $\left\{ \hat{\alpha}_i , \hat{\beta}_i \right\}$, t-statistic of alpha $\hat{t}_{\hat{\alpha}_i}$ [11], and time-series of estimated residuals $\left\{ \hat{\varepsilon}_{i,t} , t = 1,..., T_i \right\}$ are then saved.

For the baseline residual only resampling bootstrap, we draw a sample with replacement from the fund i residuals that are saved in the first step, creating a time-series of resampled residuals $\left\{ \hat{\varepsilon}^b_{i,t} , t = s^b_1 , s^b_2 ,..., s^b_{T_i} \right\}$, where b=1 (for bootstrap resample number one). The sample is drawn such that it has the same number of residuals (e.g., the same number of time periods T_i) as the original sample for each fund i. This resampling procedure is repeated for the remaining bootstrap iterations b = 2,...,B (in all of our bootstrap tests, we set B = 1,000). Next, for each bootstrap iteration b, a time-series of (bootstrapped) monthly net returns is constructed for this fund, imposing the null hypothesis of zero true performance ($\alpha_i = 0$, or equivalently, $t_{\alpha_i} = 0$):

$$r^b_{i,t} = \sum_{k=1}^{K} \hat{\beta}^i_k F_{k,t} + \hat{\varepsilon}^b_{i,t} , \;\; t = s^b_1 , s^b_2 ,..., s^b_{T_i} \tag{2}$$

where $s^b_1 , s^b_2 ,..., s^b_{T_i}$ is the time reordering imposed by resampling the residuals in bootstrap iteration b. As indicated by Equation (2), this sequence of artificial returns has a true alpha (and t-statistic of alpha) of zero, since the residuals are drawn from a sample that is mean zero by construction. However, when we next regress the returns for a given bootstrap sample, b, on the multi-factor model, a positive estimated alpha (and t-statistic) may result, since that bootstrap may have drawn an abnormally high number of positive residuals, or, conversely, a negative alpha (and t-statistic) may result if an abnormally high number of negative residuals are drawn.

Repeating these steps across funds i = 1,...,N, and bootstrap iterations b = 1,...,B, we then build the cross-sectional distribution of the alpha estimates $\hat{\alpha}^b_i$, or their t-statistics $\hat{t}^b_{\hat{\alpha}_i}$, resulting purely from sampling variation, as we impose the null of no abnormal performance. If we find that very few of the bootstrap iterations generate as large values of $\hat{\alpha}$ or $\hat{t}_{\hat{\alpha}}$, as those observed in the

[11] We estimate $\hat{t}_{\hat{\alpha}}$ using the Newey and West (1987) heteroskedasticity and autocorrelation consistent estimate of the standard error.

actual data, this suggests that sampling variation (luck) is not the source of performance, but that genuine asset selection skills may exist.

Given the superior statistical properties of alpha *t*-statistic, in addition to evaluating top funds ranked on alpha, we also evaluate top funds based on the alpha *t*-statistic. Although alpha measures the economic size of abnormal performance, it has a relatively high coverage error in the construction of confidence intervals. Also, funds with a shorter history of monthly net returns will have an alpha estimated with less precision, and will tend to generate alphas that are outliers. The alpha *t*-statistic provides a correction for these spurious outliers by normalizing the estimated alpha by the estimated precision of the alpha estimate. Moreover, the *t*-statistic is related to the well-known information ratio of Treynor and Black (1973), which is commonly used by practitioners to rate fund managers. For the interested reader, KTWW provides further details on the bootstrap procedure and the rationale for sorting on alpha *t*-statistic.

3.3. The Bayesian approach

The average hedge fund has a short time series. This necessarily reduces the precision with which performance measures such as alpha can be estimated. However, as PS point out, it is possible to substantially improve on the alpha estimates by using historical returns on seemingly-unrelated assets not used in the definition of the alpha performance measure. These so-called non-benchmark passive assets have longer time series than the benchmark series and are correlated with hedge fund returns. The correlation between the hedge fund and non-benchmark passive returns can be exploited to improve our alpha estimates independent of whether these passive returns are priced by the benchmarks. PS use seemingly unrelated asset returns to improve the precision of alpha estimates of mutual funds.[12]

Given that the average hedge fund has a much shorter returns series than the average mutual fund, this methodology is even more relevant to hedge funds than to mutual funds. By using information on passive non-benchmark returns, we can in fact double the length of the time series used for estimating alphas. Stambaugh (1997) shows how assets with longer historical time series provide information about the moments of assets with shorter histories. We follow the PS

[12] They find a median difference between their Bayesian posterior alphas and the OLS alphas of 2.3 percent per annum and 8.1 percent per annum for all funds and small-company growth funds, respectively.

methodology and regress non-benchmark passive returns on benchmark returns. Let $F_{m,t}^{N}$ denote the m × 1 vector of non-benchmark passive asset returns in month t regressed on the k benchmark returns $F_{k,t}^{B}$:

$$F_t^N = \hat{\alpha}^N + \sum_{k=1}^{K} \hat{\beta}_k^N F_{k,t}^B + \hat{\varepsilon}_t^N \,. \tag{3}$$

Importantly $\hat{\varepsilon}_t^i$ in Equation (1) and $\hat{\varepsilon}_t^N$ in Equation (3) are allowed to be correlated. PS show that the improvement in the estimation of alpha performance measure does not depend on whether the benchmarks $F_{k,t}^{B}$ perfectly price the non-benchmark passive assets $F_{m,t}^{N}$ or not. We also define the regression of a fund i's return on p $(= m + k)$ benchmark and non-benchmark assets:

$$R_t^i = \hat{\delta}^i + \sum_{m=1}^{M} \hat{c}_m'^{iN} F_{m,t}^N + \sum_{k=1}^{K} \hat{c}_k^{iB} F_{k,t}^B + \hat{u}_t^i, \;\; i = 1,\ldots,L \,. \tag{4}$$

Using Equation (1) and the fact that $F_{k,t}^{B}$ is uncorrelated with both $\hat{\varepsilon}_t^N$ and $\hat{u}_t^i$, PS show that

$$\alpha_i = \delta_i + c_{iN}' \alpha_N \,. \tag{5}$$

PS also show how to derive the posterior estimate $\tilde{\alpha}_i$ of α_i in Equation (5) from the posterior moments of δ_i, c_{iN}', and α_N. PS provide analytical expressions for the posterior moments $\tilde{\alpha}_i$, $\tilde{\delta}_i$, $\tilde{c}_{iN}'$, and $\tilde{\alpha}_N$. As we shall show, the mean posterior alpha estimate $\tilde{\alpha}_i$ is below the mean OLS alpha $\hat{\alpha}^i$ from Equation (1) for hedge funds.

We follow PS and apply an "empirical" Bayesian approach to estimate the prior distribution of various variables. The prior distribution of the covariance matrix of $\hat{\varepsilon}_t^N$ in Equation (3) denoted by Σ is specified as an inverted Wishart distribution,

$$\Sigma^{-1} \sim W(H^{-1}, \nu).$$

We follow PS in specifying the empirical estimates of the priors. We set the degrees of freedom $v = m + 3$ which implies that the prior contains very little information about Σ. Moreover, we specify $H = s^2(v - m - 1)I_m$, and $E(\Sigma) = s^2 I_m$. The value of s^2 is set equal to the average of the diagonal elements of the sample estimates of Σ obtained using OLS regressions in Equation (3). The parameters in Equation (4) are specified as follows: The prior for σ_u^2, the variance of $u_{i,t}$, is an inverted gamma distribution or

$$\sigma_u^2 \sim \frac{v_0 s_0^2}{\chi_{v_0}^2}, \tag{6}$$

where $\chi_{v_0}^2$ represents a chi-square variate with v_0 degrees of freedom. We define $c_L = (c'_{LN} c'_{LB})'$. Conditional on σ_u^2, the priors for δ_L and c_L are set to be normal distributions, independent of each other:

$$\delta_L \mid \sigma_u^2 \sim N\left(\delta_0, \left(\sigma_u^2 \big/ E(\sigma_u^2)\right)\sigma_\delta^2\right). \tag{7}$$

Following PS, all of our estimates are based on diffuse or completely non-informative priors.[13] In the application of the Bayesian framework, decisions regarding the non-benchmark series need to be made. As non-benchmark passive assets we use the HFR style index for each respective investment objective. For example, Long/Short Equity funds are matched with the HFR Long/Short Equity index. The limited number of benchmark factors is motivated by the observation of PS that if the number of non-benchmark assets increases without a sufficient increase in R^2 then the posterior alpha estimate may be less precise. Thus we use the same set of non-benchmark assets for funds that share the same investment objective. As PS point out, the non-benchmark passive factor should be highly correlated with fund returns, a condition fulfilled by the respective HFR style indices. To raise the explanatory power of our regressors without unduly increasing the number of non-benchmark passive assets, we also include the HFR Fund of Funds index as an additional non-benchmark passive asset for all individual funds since Fund of

[13] As PS point out the Bayesian framework can also accommodate informative beliefs.

Funds hold a variety of hedge funds in their portfolios.

4. Empirical results

4.1. A bootstrap analysis of top hedge fund performance

The first order of business is to evaluate the statistical significance of top hedge fund performance with the bootstrap. Panel A of Table 2 displays the results from our application of the bootstrap algorithm. As we require sufficient return data to estimate the factor loadings, only funds with at least 24 months of return data are included in the bootstrap sample.[14] This yields a sample of 2,734 funds for which we have investment style information. All funds are ranked in two different ways. The first two rows of Panel A rank funds according to their estimated alphas. The third and fourth rows rank funds based on the estimated alpha *t*-statistics. The results are displayed for the extreme top 5 and bottom 5 funds as well as funds at the 1st, 3rd, 5th, and 10th percentiles on both ends of the alpha and alpha *t*-statistic spectra.

[Table 2 here]

The results in Panel A of Table 2 indicate that the performance of the top alpha hedge funds can be attributed to sampling variability. Both bootstrapped p-values for the top two funds ranked on fund alphas are greater than 0.1 suggesting that we cannot reject the null hypothesis that their alphas are driven by sampling variability at the 10 percent level of significance. In contrast, to the performance of top alpha hedge funds, the performance of the top alpha *t*-statistic hedge funds cannot be attributed to sampling variability. Their bootstrapped p-values are all below 0.01. Indeed, this is not surprising given the superior statistical properties of the alpha *t*-statistic. By penalizing the high alpha funds which have short investment histories and high standard deviations, the alpha *t*-statistic better discriminates between funds that generate superior performance through skill and funds that are simply lucky. According to our bootstrap estimates, of the 2,734 funds in our sample, by chance alone we would expect at most three funds to achieve alpha *t*-statistics of at least 4.67. In reality, 155 hedge funds exceed this alpha *t*-statistic. It is important to note that most of the top funds sorted on alpha have bootstrapped p-values below

[14] As a robustness check, we also perform the bootstrap on funds with at least 30 and at least 48 months of return data and find qualitatively similar results. These results are available upon request.

0.1. Also, in contrast to the performance of the top hedge funds, the performance of the bottom funds can be explained by sampling variability or rather, bad luck, to be precise.

To examine potential differences in performance between investment objectives, we report the statistical significance of performance measures by investment objective in Panels B to G of Table 2. To group funds by broad investment category, we use the six broad investment categories discussed in Section 2. The results displayed in Table 2 suggest that top alpha *t*-statistic funds consistently outperform their benchmarks in every investment category. We also note that the best and worst funds in the sample are Directional Trader funds. These funds make aggressive bets on the direction of the market and it is no coincidence that the top alpha, top alpha *t*-statistic, bottom alpha, and bottom alpha *t*-statistic funds are all Directional Trader funds. Fund of Funds (reported in Panel G) appear to perform worse than other investment objectives. The top Fund of Funds generates an alpha of 1.6 percent per month (19.2 percent per year) compared to the top Long/Short Equity fund that achieves an alpha of 4.1 percent per month (49.2 percent per year). The performances of the right tail funds in the Fund of Funds category appear statistically less significant than those in other investment objectives as their higher p-values show. The relatively poor performance of Funds of Funds may be due to the fact that Funds of Funds charge an additional layer of fees for combining individual hedge funds into a portfolio. Another interpretation is that due to selection bias, the individual hedge funds that are not in the database but held by Fund of Funds, have lower returns than the hedge funds in the database.[15]

To further illustrate the baseline results of the bootstrap, we plot the kernel density estimate of the bootstrapped and actual alpha *t*-statistic distributions for all funds in Figure 2. The two densities are rather different. The distribution of the alpha *t*-statistics has much more mass on the right tail than the bootstrapped alpha *t*-statistic distribution. This suggests that we are likely to find funds in the right tail with superior alpha *t*-statistics that cannot be explained by random resampling alone.

[Figure 2 here]

To gauge the robustness of our bootstrap results, we control for various issues peculiar to hedge fund returns: Incubation and backfill bias, short-term serial correlation, and structural breaks. Hedge funds often incubate their funds with the manager's own money before seeking outside

[15] We thank an anonymous referee for this important insight. In results available upon request, we redo the entire bootstrap analysis without Fund of Funds and obtain almost identical results.

investors. Also, hedge funds often report returns for their entire history in the fund databases, including back dated returns for the period prior to a funds' listing on the database. Since hedge fund inclusion in databases is done on a voluntary basis, hedge funds with poor track records will have a disincentive to report to databases while hedge funds with good track records will have an incentive to report to databases. In response to these concerns, we control for incubation and backfill bias in our bootstrap analysis. That is, we exclude the first 12 months of each fund's history, regardless of whether that history is backfilled or not (since incubation bias may occur in a fund's history even though it is not backfilled). Then, we bootstrap the residuals of the funds from the incubation and backfill bias-adjusted sample.

Other hedge fund studies have documented that hedge fund returns are often highly serially correlated, in contrast to mutual fund returns, for example. According to Getmansky, Lo, and Makarov (2004), the most likely reason for this serial correlation is funds' illiquidity exposure: hedge funds trade in securities which are not actively traded and whose market prices are not readily available. To remove the effects of artificial serial correlation induced by illiquidity exposure, we adopt the methodology in Getmansky, Lo, and Makarov (2004) to unsmooth hedge fund returns and reduce serial correlation. In particular, we map the fund categories in Table 8 of Getmansky, Lo, and Makarov (2004) to our fund categories and use the average θ_0, θ_1, and θ_2 estimates for each fund category from their Table 8 to unsmooth fund returns. Then, we re-do the bootstrap analysis on the unsmoothed sample of hedge fund returns. The appendix details how we map the Getmansky, Lo, and Makarov (2004) fund categories to our categories.

If the regression coefficients in hedge fund performance regressions exhibit structural breaks over time then constant coefficient regressions and bootstrap results are likely to be mis-specified. Recent papers have documented time-variation in the return characteristics of hedge funds (Fung and Hsieh, 2004; Fung, Hsieh, Naik, and Ramadorai, 2005). There is evidence that hedge funds change their loadings on different risk factors over time. Anecdotal evidence suggests that hedge funds suffer from sudden shocks such as the Asian and Russian crises which can lead to structural breaks in their return series. Bai and Perron (1998) provide a least-squares method for optimally determining the unknown breakpoints. We apply the Bai and Perron (1998) test to HFR hedge fund return indices and find that most categories have a common structural break in December 2000.[16] The structural break in December 2000 coincides with the height of the bull market in the

[16] HFR hedge fund returns indices are regressed on factor benchmarks. Factor benchmarks are determined

late 90s. Based on the structural break evidence in December 2000, we repeat our bootstrap procedure allowing for a break in the beta slope coefficients using a dummy regression.

[Table 3 here]

Panels A, B, and C of Table 3 indicate that similar bootstrap results obtain when we control for incubation and backfill bias, short-term serial correlation in returns, and the presence of a structural break in December 2000, respectively. Whether we confine the analysis to incubation and backfill bias-adjusted return data, or to unsmoothed hedge fund returns[17], or allow for variation in beta coefficients before and after December 2000, one cannot explain the performance of the top alpha *t*-statistic funds with sample variability or luck.

The bootstrap results thus far have relied on the simple residual only resampling bootstrap. Given the complexity of hedge fund strategies, there may be concerns that their return series may not satisfy the assumptions underlying the simple bootstrap approach. In particular, the fund residuals may be cross-sectionally dependent. This could arise from funds holding the same securities or from funds following the same trading strategies. To take into account the potential cross-sectional dependence between fund returns we apply a cross-sectional bootstrap. This procedure differs from the algorithm described in Section 3.2 in that, for a given bootstrap, we now employ the same bootstrap index across all funds. Rather than drawing sequences of time periods, t_i, that are unique to each fund, *i*, we draw T time periods from the set (t = 1,...,T), then resample residuals for this reindexed time sequence across all funds, thus preserving any cross-sectional correlation in the residuals. Since some funds may as a result be allocated bootstrap index entries from periods when they did not have a return, we drop a fund if it did not have at least 24 observations after applying the bootstrap index. The results in Panel D of Table 3 indicate that our basic bootstrap results are not driven by cross-sectional dependence in fund returns. The p-values show that the performance of the best alpha *t*-statistic funds cannot be explained by sampling variation.

Other deviations from the assumptions underlying the simple bootstrap approach can occur. First, there may be correlation between the factor returns and regression residuals. This correlation

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for each hedge fund index category by means of the regression approach described in Section 3.1 above. Both the intercept and the slope coefficients are allowed to vary.

[17] Inferences also do not change when we use the methodology of Okunev and White (2003) to eliminate return serial correlation of up to order two.

could occur if the hedge fund managers trade in securities that have a return co-skewness with the factor returns. Second, there may exist an omitted factor that is not accounted for by the Fung and Hsieh (2004) multi-factor model. If the reason why funds have high alpha *t*-statistics is because they load on this omitted factor then we may be led erroneously to conclude that fund managers have security selection ability if we do not include the omitted factor in our performance measurement model. Third, conditional on factor realizations, the fund residuals may not be independently distributed across time.

To address these concerns, we adopt the alternative bootstrap extensions described in KTWW. Namely, we perform the factor-residual resampling bootstrap that accommodates correlation between factor returns and fund regression residuals, run Monte Carlo simulations for a persistent omitted factor, and adopt the stationary bootstrap procedure of Politis and Romano (1994) to allow for time-series dependence in fund residuals. The results from these bootstrap extensions, which are available upon request, confirm that our conclusion of significant security selection ability amongst top hedge fund managers is robust to the choice of bootstrap methodology.

4.2. Bayesian hedge fund performance measures

The bootstrap results in the previous section suggest that standard OLS fund alpha may not be as indicative of fund manager performance as OLS fund alpha *t*-statistics. The bootstrapped p-values of top funds sorted on alpha are typically higher than those for top funds sorted on alpha *t*-statistics. One reason may be that the OLS fund alphas are estimated imprecisely. In this section, we introduce the Bayesian posterior fund alpha and compare it to the standard OLS fund alpha. If the standard OLS alpha is measured imprecisely, the Bayesian alpha (which is more precisely measured) should differ significantly from it. In turn, this suggests that one may get greater mileage from sorting on Bayesian fund alpha than from sorting on standard OLS fund alpha in persistence tests.

Table 4 reports the estimates of the Bayesian posterior alpha $\tilde{\alpha}_i$ and the OLS alpha $\hat{\alpha}^i$ (from Equation 1). In Panel A, the first column reports the Bayesian alpha estimate. The second and third columns report the OLS alpha estimate and the mean difference between the Bayesian and OLS alpha. As column three shows, the mean Bayesian alpha is very similar to the mean OLS alpha. However, with the top percentile and decile funds (ranked by OLS alpha) the OLS alpha tends to overestimate performance relative to the Bayesian alpha. Conversely, with bottom percentile and decile funds, the OLS alpha tends to underestimate performance relative to the Bayesian alpha. Moreover, column five reveals that this is because the Bayesian alphas are measured more precisely than the OLS alphas. The mean standard error of the Bayesian alpha is lower than that of the OLS alpha for each portfolio of funds. Columns seven and eight show that in general, similar results obtain for different priors of σ_{α_N} .[18]

Panel B of Table 4 shows the analogous statistics for Long/Short Equity funds. We single out Long/Short Equity funds as their strategies are particularly easy to understand and their risks easily captured by the multi-factor model. With this group of funds, the OLS alpha tends to mildly overestimate the true fund performance on average. The mean Bayesian alpha is 0.4 percent per year lower than the mean OLS alpha. More importantly, we find that the OLS alpha overestimates the performance of the top funds (ranked by OLS alpha) and underestimates the performance of the bottom funds. Moreover, the Bayesian alphas are also measured more precisely than the OLS alphas with this group of funds.

To get a sense of the difference between the Bayesian and OLS alphas for the top funds, Panel C of Table 4 reports the Bayesian alphas for the top 20 Long/Short Equity funds ranked by OLS alpha. For this group of funds, the Bayesian alpha is on average 8.4 percent per year below the OLS alpha. The reduction in particularly pronounced for funds with relatively short sample periods. It is interesting to note that many of the top funds have very short return histories, reflecting the severity of the short sample problem in hedge fund studies. Moreover, the difference in standard errors reported in column five indicates that the Bayesian alpha is more precisely estimated than the OLS alpha for all funds.

Overall, Table 4 shows that the longer time series of the HFR style indices (our choice for the seemingly unrelated assets) provide important information. By neglecting such information, the OLS alphas often overestimate the performance of the top funds and underestimate the performance of the bottom funds. Moreover, the Bayesian estimates are almost always measured with greater precision. Since the Bayesian alpha measure provides a more accurate estimate of

[18] The baseline prior σ_{α_N} of 0.02 is based on Pastor and Stambaugh (2002b). In results available from the authors upon request we carry out a sensitivity analysis to various prior values between zero and infinitiy. We found that the results were qualitative similar to those with the baseline value of 0.02 and thus our conclusions not sensitive to this particular choice of prior.

performance, it should also be better at picking the good and bad funds, and generating performance persistence.

4.3. A Bayesian analysis of hedge fund performance persistence

The results thus far have shown that the performance of the top hedge funds (at least when sorted on alpha *t*-statistic) cannot be explained by luck. Also, relative to the standard Frequentist approach, the Bayesian SUR approach yields more precise and conservative performance estimates. However, those results may not be relevant to investors if they cannot be parlayed into trading profits.

In this section, we test whether hedge fund performance persists using the Bayesian SUR approach. Concretely, we rank funds on their Bayesian posterior alphas and alpha *t*-statistics, and evaluate the abnormal performance of the resultant spreads and top portfolios. The use of the Bayesian performance measures alleviates the short sample problem and maximizes the power of the persistence tests. By analyzing performance persistence, we are ostensibly measuring the profits that may be harvested by investors from simple performance based trading strategies. Since it is well-known that Fund of Funds have lower average returns than individual hedge funds (Table 1 confirms this), we do not include Fund of Funds in any of our baseline persistence tests so as not to inflate the spreads from those tests.

Performance persistence has been extensively studied in the mutual fund literature. Hendricks, Patel, and Zeckhauser (1993) among others show that mutual fund returns persist in the medium term (one to three years). However Carhart (1997) argue that this is either due to managers adopting momentum strategies or to the persistence of fund expenses. However, recent studies like Mamaysky, Spiegel, and Zhang (2005), Cohen, Coval, and Pastor (2005), and KTWW show that more sophisticated econometric methods allow one to pick out funds whose returns cannot be explained by four-factor covariation or expense ratios. With hedge funds though, previous studies have found little evidence of persistence in returns. Agarwal and Naik (2000) show that hedge fund returns only persist in the short term (one to three months). Getmansky, Lo, and Makarov (2004) credit that to the illiquidity induced by assets that hedge funds trade. Like Agarwal and Naik (2000), Brown, Goetzmann, and Ibbotson (1999) and Liang (2000) find no evidence of persistence in hedge fund returns at annual horizons. What of hedge fund alphas?

As a prelude to the Bayesian analysis of fund performance persistence, we first investigate performance persistence with the standard Frequentist performance measures. Specifically, we follow Carhart (1997) and sort hedge funds on January 1 each year (from 1996 to 2002) into decile portfolios, based on their Fung and Hsieh (2004) seven-factor alphas estimated over the prior two years.[19] The portfolios are equally weighted monthly, so the weights are readjusted whenever a fund disappears. Funds with the highest past two-year alpha comprise decile 1, and funds with the lowest past two-year alpha comprise decile 10. The resulting decile portfolios and annualized performance measures are reported in Panel A of Table 5. We also sort funds based on their alpha *t*-statistics estimated over the past two years and report the performance of the resultant portfolios in Panel B of Table 5. Given the superior statistical qualities of the alpha *t*-statistic (see Table 2), we expect performance persistence to be stronger with these sorts than with the sorts on fund alpha.

[Table 5 here]

According to Panel A of Table 5, in the sort on alpha, the top decile portfolio generates an alpha of 5.32 percent per year. As the parametric p-value in column five shows this alpha is statistically significant. The alpha of the second decile is also statistically significant. However, the top one percentile and top five percentile portfolios do not generate statistically significant alphas. This is consistent with our finding in Table 2 that the top two or three hedge funds do not generate statistically significant performance. One view is that these funds follow particularly risky strategies that fail to perform well in the future. Also, the alpha for the spread between the top and bottom deciles is not statistically different from zero indicating that fund alpha does not separate the good from the bad funds.

In Panel B of Table 5, we report persistence results for the sort on past two-year alpha *t*-statistics. As the third and fourth columns show, sorting on past alpha *t*-statistics leads not only to higher alphas but also to strongly statistically significant alphas for the top one percentile, top five percentile, and the top two deciles. The p-values are strongly statistically significant and the information ratio of the top decile more than doubles when sorting on alpha *t*-statistic compared to sorting on alpha. When sorting on alpha *t*-statistics, the alpha of the spread between the top and

[19] We require a minimum of 24 monthly net return observations for this estimate. For funds with missing observations, observations from the 12 months preceding the two-year window are added to obtain 24 observations. This ensures that funds with missing observations are not automatically excluded.

bottom decile portfolios also becomes larger, though it is still insignificant at the 10 percent level. An investor can modestly increase alpha by 1.86 percent per year by buying the top decile funds and avoiding the bottom decile funds based on alpha *t*-statistics.

Overall, we find greater persistence with the sort on alpha *t*-statistics than with the sort on alpha. This corroborates the finding in Table 2 that the performance of the top fund sorted on alpha *t*-statistics is statistically significant while that for the top fund sorted on alpha is not. Nonetheless, evidence of persistence is mild. The alpha spreads from these sorts are small and not strongly statistically significant. It may be because the sorts rely on standard Frequentist performance measures, which are imprecisely estimated due to the short sample problem. As discussed earlier, the Bayesian SUR performance measures alleviate the short sample problem by taking advantage of information embedded in seemingly unrelated assets. Hence, we perform analogous sorts on Bayesian posterior alpha and posterior alpha *t*-statistics, and report the performance of the resultant portfolios in Table 6.

[Table 6 here]

Panel A of Table 6 reports results when funds are sorted on Bayesian posterior alphas. As the fourth row of Table 6 shows the OLS alpha of the top decile portfolio goes up to 8.21 percent per year from 5.32 percent in Panel A of Table 5. Thus, sorting on Bayesian alpha increases the top decile OLS alpha by 54 percent compared to sorting on OLS alpha. More importantly, the decile spread alpha increases from a statistically insignificant 0.33 percent per year in the sort on OLS alpha to a statistically significant 5.81 percent per year in the sort on Bayesian posterior alpha. This represents a remarkable sixteen-fold increase in spread alpha and attests to the value of the Bayesian performance measures.

We obtain similar results with the sort on Bayesian posterior alpha *t*-statistics. The fourth row of Panel B in Table 6 reveals that the resulting first decile OLS alpha is 6.56 percent per year. This compares favourably with the more modest OLS alpha of 6.05 percent per year when sorting on OLS alpha *t*-statistics. The spread portfolios are also larger and more statistically significant with the sort on the Bayesian performance measure. Thus, strategies based on Bayesian performance measures (posterior alpha or posterior alpha *t*-statistic) lead to superior performance persistence relative to those based on standard Frequentist performance measures.

To further investigate the nature of the performance persistence, we report persistence results by investment objective in Table 7. Specifically, we sort funds based on past two-year Bayesian posterior alpha *t*-statistics[20] within each investment category. We find that the abnormal performance of the top decile funds is mainly driven by top decile funds in all categories. Relative to the top decile funds in the other investment categories, the top Multi-process and Long/Short Equity deciles achieve the highest alphas of 10.91 percent and 7.57 percent per year, respectively. We also find that the significance of the spread alpha is predominantly driven by Long/Short Equity, Directional Traders, and Relative Value. These categories achieve either decile spreads or one-percentile spread alphas that are statistically different from zero at the 10 percent level. In particular, the Long/Short Equity category achieves the highest decile spread alpha of 6.36 percent per year (*t*-statistic = 1.90) while the Directional Traders category attains the highest one-percentile spread alpha of 20.43 percent per year (*t*-statistic = 3.46). In contrast, Multi-process and Security Selection funds do not display as much evidence of persistence, although their spread alphas are still positive.

For the sake of completeness, we also perform the persistence tests for Fund of Funds in Panel F of Table 7 and find that as with individual funds, they persist strongly and generate reliably positive top alphas and spread alphas. Based on the decile spread, relative to other fund categories, Fund of Funds persists most reliably with a decile spread alpha of 6.29 percent per year (*t*-statistic = 4.03). Note that for reasons discussed earlier, we do not include Fund of Funds in the other sorts in the paper. The strength of the persistence among Fund of Funds suggests that including Fund of Funds in the sample will only bolster our baseline Bayesian sort results.

[Table 7 here]

One concern is that while we have found evidence of persistence in hedge fund performance, investors may not be able to take advantage of this persistence if it is confined to small funds[21] or driven by incubation and backfill bias. Hence, we perform Bayesian persistence tests for small versus large funds. Small funds are funds with assets under management (AUM) less than the median AUM at the start of each evaluation period. Large funds are funds with AUM greater than

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[20] The category by category sorts on Bayesian alphas yield qualitatively similar, albeit slightly weaker, results and are omitted for brevity.

[21] It may be difficult for large institutions, like government pension funds, to invest a non-negligible fraction of their assets under management in small hedge funds. Moreover, some small hedge funds are still under incubation and are not open to new investments from the general public.

the median AUM. Separately, we also control for the effects of incubation and backfill bias by excluding the first 12 months of returns for each fund and performing the persistence tests on the truncated sample of returns. The results from our sensitivity analysis are reported in Table 8. Panel A showcases the persistence tests based on two-year Bayesian alpha, while Panel B showcases the persistence tests based on two-year Bayesian alpha *t*-statistics. They broadly indicate that our results are not driven by incubation and instant history bias or limited to small funds. In fact, the decile spread alpha is higher for bigger funds (6.72 percent per year) than for smaller funds (4.43 percent per year). The top decile alphas (with the sorts on posterior alpha and posterior alpha *t*-statistic) and decile spread alpha (with the sort on posterior alpha *t*-statistic) are also statistically significant at the 5 percent level after excluding the first 12 months of returns for each fund. Hence, it appears that investors can take advantage of the performance persistence on hedge funds.[22] However, there may be limits as to how much money can be put to work in an investment strategy designed around hedge fund performance persistence. This is because when we perform the Bayesian analysis on high inflow verses low inflow funds, we find that the persistence is stronger with low inflow funds (see Table 8). We define low inflow funds as funds with mean inflow (as a percentage of AUM) less than the median inflow over the evaluation period. Conversely, we denote high inflow funds as funds with mean inflow greater than the median inflow.[23] The sensitivity of the Bayesian persistence results to fund inflow resonates with the Berk and Green (2002) argument that fund inflows compete away managerial alpha.

[Table 8 here]

There may also be concerns that our results are not driven by managerial ability. Rather, the persistence of fund fees and the short-term serial correlation in fund returns conspire to induce persistence in annual fund performance. We test this hypothesis by evaluating the persistence of pre-fee fund performance and the persistence of fund performance after unsmoothing fund returns. The results reported in Table 8 indicate that these explanations cannot account for the bulk of the performance persistence. Alpha spreads are stronger with pre-fee returns than with post-fee returns. The sort on Bayesian pre-fee alpha generates a spread of 7.19 percent per year, which is 1.38 percent per year higher than that generated by the sort on Bayesian post-fee alpha

[22] In unreported results we also carry out a sensitivity analysis to the choice of the factor model. We reproduce the analysis for the Agarwal and Naik (2004) factors and find qualitatively very similar results.
[23] One limitation of the fund inflow sensitivity analysis is that the sample size falls by roughly 50 percent when we limit the funds with those with fund inflows. This is because to calculate fund inflow for period *t*, we require fund AUM for periods *t* and *t*-1 and fund return for period *t*. As a result, the statistical power of our persistence tests falls with the reduced sample size.

(see Panel A, Table 6). The last rows in each panel show that serial correlation does not drive our findings. We use the Getmansky, Lo and Makarov (2004) specification for serial correlation hedge fund returns to unsmooth observed hedge fund returns and back out 'true' returns to remove the effect of serial correlation. We then repeat our persistence tests on the resulting returns. As the results show, the top decile and spread portfolio alphas continue to be statistically and economically significant.[24]

[Figure 3 here]

Finally, there are concerns that the persistence is driven by our specific choice of ranking (24 months) and evaluation (12 months) periods. We carry out a sensitivity analysis of persistence using various combinations of ranking and evaluation period lengths and report the results in Figure 3. The top panel of Figure 3 reports results for ranking periods of 24 and 36 months while the bottom panel reports results for ranking periods of 48 and 60 months. The results in the top panel indicate that while performance persistence (as reflected in the alpha spread between deciles 1 and 10) is strongest with an evaluation period of 6 months, it is similar across all other evaluation periods. The evidence of persistence is also comparable whether we use a ranking period of 24 months or a ranking period of 36 months. The bottom panel of Figure 3 indicates that the persistence is actually stronger when we use ranking periods of 48 and 60 months. Also, persistence is most pronounced for the evaluation periods of 24 and 36 months (depending on the ranking period); our baseline choice of 12 months does not lead to the most favourable persistence results. Overall, while persistence is strong when using a 12-month evaluation and a 24-month ranking period, different ranking and evaluation periods lead to quantitatively similar performance persistence results.[25] This suggests that our baseline persistence results are not merely artifacts of our specific choice of ranking and evaluation periods.

[24] In unreported returns we carry out an alternative adjustment for serial correlation. We introduce a one month gap between formation and evaluation periods and carry out our persistence tests on the resulting series. We find that again top decile and spread portfolio alphas are statistically and economically significant.

[25] The portfolios are equally weighted monthly so the weights are readjusted whenever a fund disappears. Thus, we do not impose a survivorship bias in the evaluation period since we do not require that funds have observations for every month during the evaluation period.

5. Conclusion

In classical finance theory, the post-fee abnormal performance of top hedge funds is driven purely by sample variability and hedge fund performance does not persist. Our findings challenge that view. We use powerful bootstrap and Bayesian methods to argue that the abnormal performance of top hedge funds cannot be attributed to luck and that hedge fund abnormal performance persists at annual horizons.

We are the first to document evidence of long-term performance persistence with hedge funds using Bayesian methods. The severity of the short sample problem in hedge funds implies that the Bayesian SUR approach is even more relevant for hedge funds than for mutual funds. By our estimates, relative to sorts on standard OLS fund alpha, sorts on Bayesian posterior fund alpha result in a 5.5 percent per year increase in the alpha spread between the top and bottom decile funds. Our persistence results are particularly germane to investors as they are not confined to small funds and are not driven by incubation and backfill bias. We consider alternative explanations for the persistence results including persistence in fees or short-term serial correlation in returns, but find evidence inconsistent with these explanations. One caveat is that the evidence for persistence is weaker for hedge funds with high inflow, potentially limiting the amount of funds that may be profitably invested in a trading strategy designed around hedge fund performance persistence.

The results suggest several avenues for future work. First, it will be interesting to explore why performance persistence is stronger with certain hedge fund categories, like Long/Short Equity, Directional Traders, Relative Value, and Fund of Funds, and weaker with others. Second, further insights may be obtained by applying Bayesian methods proposed by Avramov and Wermers (2005) to the study the problem of investing in hedge funds when returns are predictable.

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Appendix

Fund categories	**Getmansky, Lo and Makarov (2004) categories**
Security selection	US equity hedge, European equity hedge, Asian equity hedge, Global equity hedge
Directional trader	Dedicated shortseller, Global macro, Global opportunities, Natural resources, Pure leverage currency, Pure emerging market, Pure property
Multi-process	Event Driven
Relative value	Non-directional / Relative value
Fund of funds	Fund of funds
Others	Not categorized

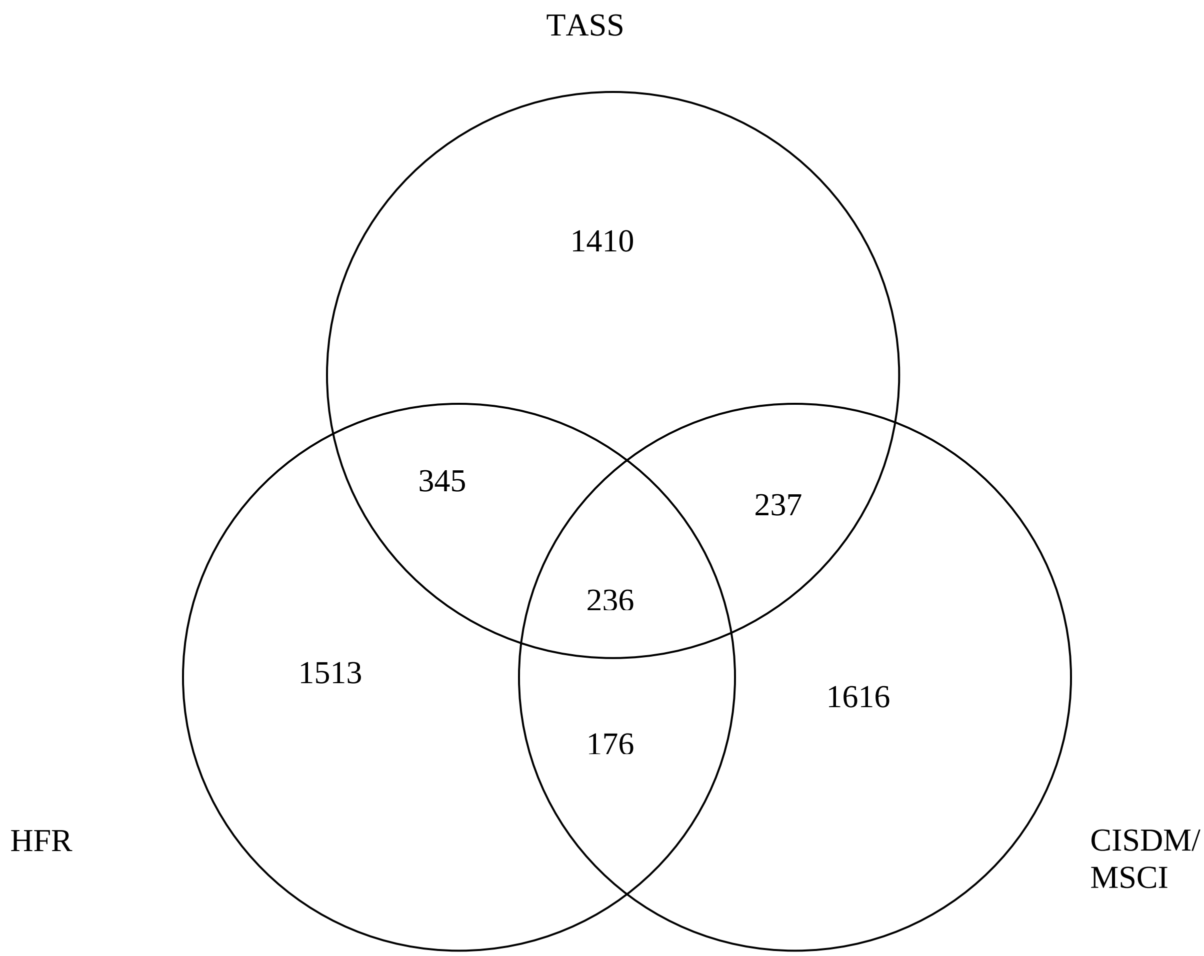

Figure 1: Composition of combined hedge fund database from January 1990 to December 2002. Funds with assets under management > US$20 million.

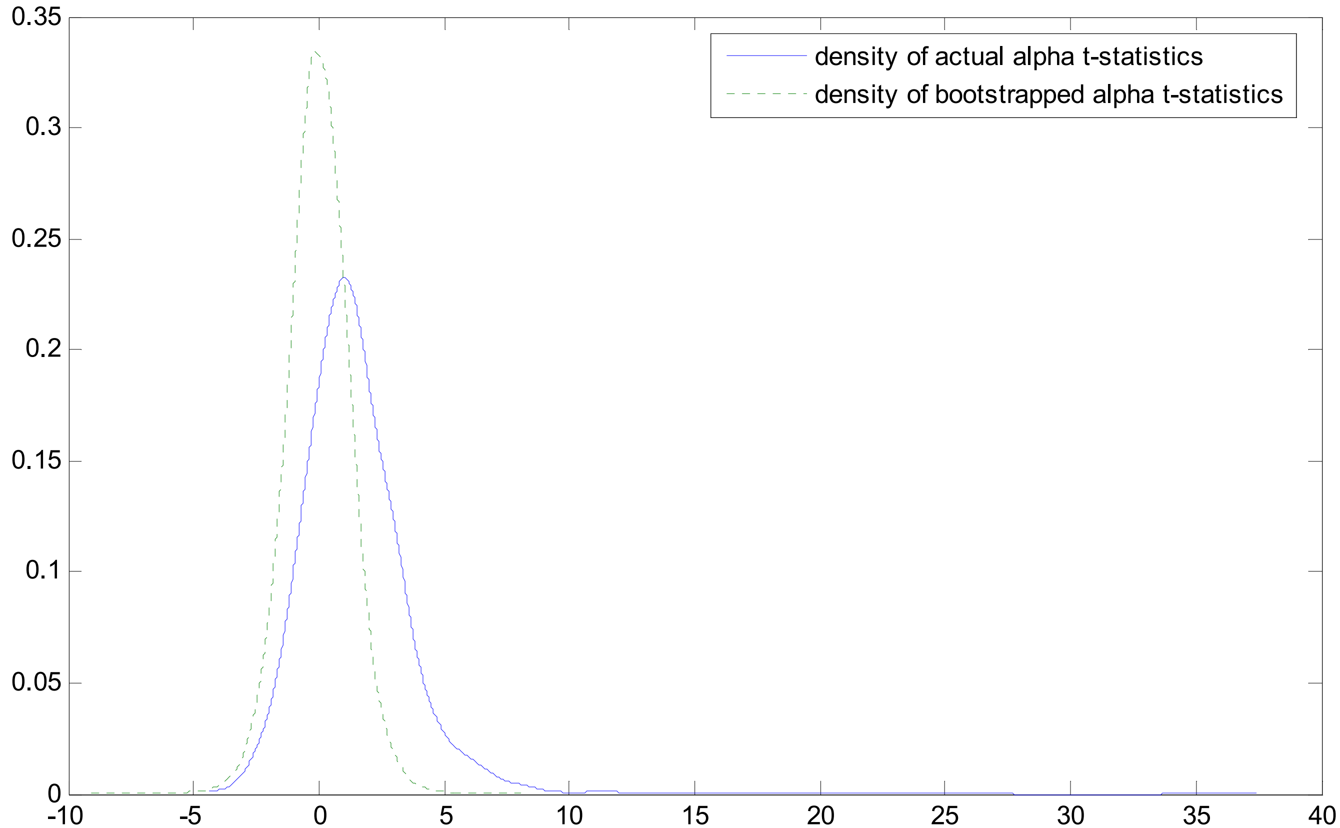

Figure 2. Kernel density estimate of the bootstrapped and the actual alpha *t* -statistic distribution for all funds. The sample period is from January 1994 to December 2002.

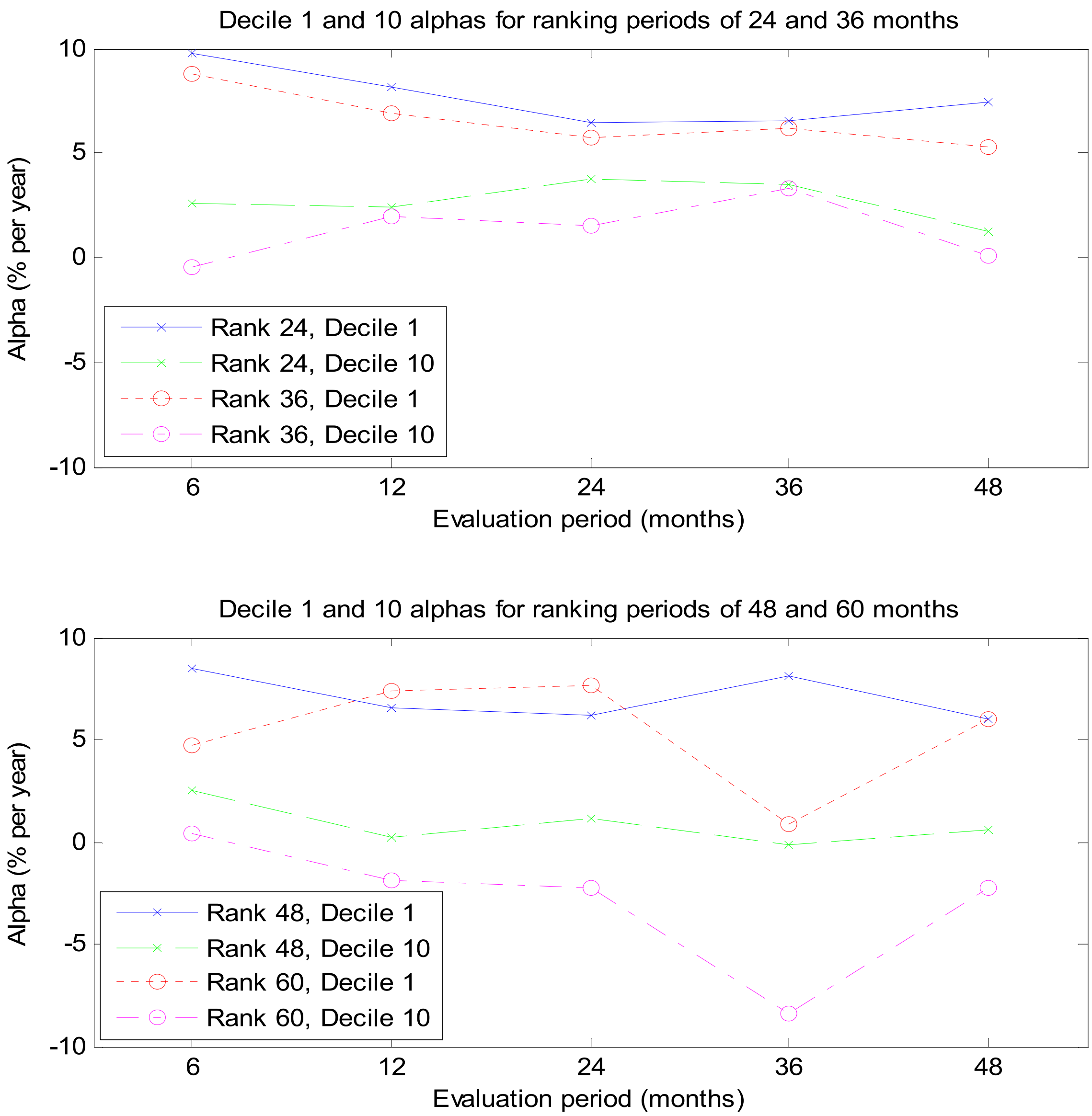

Figure 3. Sensitivity analysis of decile alpha to length of ranking and evaluation periods. This figure shows the relationship between the alphas of the decile 1 and decile 10, and the length of the ranking and evaluation periods. The ranking period is the number of monthly return observations needed to generate the alphas used to rank funds. The evaluation period is the number of months for which ranked hedge funds are held in the sort. Funds are sorted on fund Bayesian posterior alpha. The fund sample size is 757, 566, 428, and 322 for the 24 month, 36 month, 48 month, and 60 month ranking period sorts (with an evaluation period of 12 months), respectively.

Table 1

Summary Statistics and Tests of Normality, Heteroskedasticity, and Serial Correlation on Hedge Fund Residuals

This table reports the distributional properties of hedge fund return residuals by investment objective. Columns one and two report the mean of the Fung and Hsieh (2004) seven-factor model monthly alpha and the t-statistic of alpha, respectively, across funds in each category. Columns three and four report the mean kurtosis and skewness of hedge fund residuals. Column five reports the percentage of funds for which the null hypothesis of normally distributed residuals is rejected by the Jarque Bera test. Column six reports the percentage of funds for which the the Breusch Pagan test rejects the null hypothesis of homoskedastic return. Column seven reports the percentage of funds for which the Ljung-Box statistic rejects the null hypothesis of no first order autocorrelation. All tests are conducted on fund residuals. The percentage of funds with *p* -values which reject the null at the 10% confidence level is reported in each test. Fund residuals are obtained by regressing fund returns in excess of the risk free rate on the Fung and Hsieh (2004) factors. The sample period is from January 1994 to December 2002. Note that Long/short equity is a subset of Security selection.

	mean					test of normality	test of heteroscedasticity	test of serial correlation
	number of funds	alpha (%)	alpha *t* -stat	kurtosis	skewness	% of funds with Jarque Bera p <0.1	% of funds with Breusch Pagan p <0.1	% of funds with Ljung Box p <0.1
Long/short equity funds	711	0.51	1.16	3.69	-0.99	69.01	69.01	40.85
Directional trader funds	539	0.41	1.05	3.96	-0.20	51.04	37.50	61.46
Multi-process funds	278	0.37	1.72	4.25	-0.10	33.33	25.00	16.67
Relative value funds	546	0.42	2.06	5.27	-0.02	22.52	18.02	26.13
Security selection funds	951	0.50	1.14	3.75	0.00	33.96	30.19	33.96
Fund of funds	420	0.27	1.54	4.70	-0.05	39.21	36.56	32.16
All funds	2734	0.42	1.43	4.29	0.04	38.63	30.03	30.47

Table 2

Statistical Significance of The Best and Worst Hedge Funds' Performance By Investment Objective

Panel A reports the statistical significance of performance measures for all funds. Panels B to G showcase the results for the subsamples of funds in specific investment style categories. In each panel, the first and second rows reports the ranked OLS estimate of alpha in percent per month and the bootstrapped *p* -value of alpha. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The third and fourth rows report the ranked *t* -statistic of alpha based on heteroskedasticity and autocorrelation consistent standard errors as well as the bootstrapped *p* -value of the *t* -statistic. The first column on the left (right) reports funds with the lowest (highest) alpha and *t* statistic followed by results for the funds with the second lowest (highest) alpha and *t* -statistic and marginal funds at different percentiles in the left (right) tail of the distribution. The *p* -value is based on the distribution of the best (worst) funds in 1000 bootstrap resamples. The Fung and Hsieh (2004) factors are S&P 500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the 10 year treasury (BD10RET), change in the spread of Moody's Baa - 10 year treasury (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. The sample period is from January 1994 to December 2002.

Panel A: All funds

	Bottom	2.	3.	4.	5.	1%	3%	4%	10%	10%	5%	3%	1%	5.	4.	3.	2.	Top
monthly alpha (%)	-3.46	-3.29	-2.93	-2.82	-2.63	-1.61	-0.88	-0.64	-0.33	1.24	1.63	2.08	2.82	3.74	3.77	3.77	4.06	4.06
p -value (bootstrapped)	0.70	0.44	0.47	0.38	0.40	0.42	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.02	0.06	0.11	0.43
t -alpha	-4.42	-4.31	-3.87	-3.78	-3.45	-2.50	-1.82	-1.41	-0.81	3.78	4.90	5.86	7.87	14.21	17.69	22.00	24.01	37.38
p -value (bootstrapped)	0.99	0.97	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel B: Long/short equity funds

	Bottom	2.	3.	4.	5.	1%	3%	4%	10%	10%	5%	3%	1%	5.	4.	3.	2.	Top
monthly alpha (%)	-2.25	-2.21	-2.15	-2.09	-1.99	-1.22	-0.84	-0.59	-0.34	1.42	1.92	2.20	2.87	3.40	3.42	3.74	3.77	4.06
p -value (bootstrapped)	0.93	0.74	0.59	0.43	0.39	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.22
t -alpha	-3.45	-2.45	-2.42	-2.39	-2.32	-2.17	-1.52	-1.28	-0.77	3.12	3.83	4.42	8.06	10.01	10.70	11.33	11.45	11.50
p -value (bootstrapped)	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel C: Directional trader funds

	Bottom	2.	3.	4.	5.	1%	3%	4%	10%	10%	5%	3%	1%	5.	4.	3.	2.	Top
monthly alpha (%)	-3.46	-3.29	-2.93	-2.82	-2.39	-2.39	-1.61	-1.13	-0.64	1.50	2.16	2.65	3.10	3.22	3.32	3.39	3.77	4.06
p -value (bootstrapped)	0.42	0.15	0.12	0.06	0.16	0.16	0.07	0.50	0.99	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.06	0.21
t -alpha	-4.42	-4.31	-3.87	-3.78	-3.34	-3.34	-2.34	-1.77	-1.12	3.17	4.14	5.18	6.38	6.38	6.38	8.80	9.25	37.38
p -value (bootstrapped)	0.62	0.29	0.28	0.17	0.39	0.39	0.74	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel D: Multi-process funds

	Bottom	2.	3.	4.	5.	1%	3%	4%	10%	10%	5%	3%	1%	5.	4.	3.	2.	Top
monthly alpha (%)	-2.24	-2.12	-0.98	-0.79	-0.72	-0.98	-0.47	-0.31	-0.19	0.89	1.25	1.49	2.24	2.01	2.24	2.53	2.73	3.32
p -value (bootstrapped)	0.13	0.02	0.66	0.88	0.91	0.66	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
t -alpha	-2.43	-2.40	-2.38	-1.87	-1.86	-2.38	-1.45	-1.17	-0.56	4.00	5.87	6.79	7.54	7.33	7.54	8.20	8.44	8.48
p -value (bootstrapped)	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel E: Relative value funds

	Bottom	2.	3.	4.	5.	1%	3%	4%	10%	10%	5%	3%	1%	5.	4.	3.	2.	Top
monthly alpha (%)	-1.64	-1.60	-1.22	-1.13	-0.97	-0.97	-0.64	-0.46	-0.25	1.11	1.44	1.78	2.18	2.29	2.32	2.56	2.84	3.49
p -value (bootstrapped)	0.83	0.54	0.84	0.82	0.94	0.94	0.94	0.98	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03
t -alpha	-2.70	-2.58	-2.54	-2.38	-2.21	-2.21	-1.62	-1.39	-0.70	4.92	6.14	7.09	12.95	13.47	14.21	17.69	22.00	24.01
p -value (bootstrapped)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel F: Security selection Funds

	Bottom	2.	3.	4.	5.	1%	3%	4%	10%	10%	5%	3%	1%	5.	4.	3.	2.	Top
monthly alpha (%)	-2.63	-2.25	-2.21	-2.15	-2.09	-1.25	-0.86	-0.65	-0.36	1.39	1.92	2.20	2.87	3.55	3.71	3.74	3.77	4.06
p -value (bootstrapped)	0.81	0.83	0.68	0.55	0.43	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.06	0.24
t -alpha	-3.45	-2.49	-2.45	-2.42	-2.40	-2.15	-1.52	-1.27	-0.77	3.08	3.77	4.32	6.53	10.01	10.70	11.33	11.45	11.50
p -value (bootstrapped)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel G: Fund of funds

	Bottom	2.	3.	4.	5.	1%	3%	4%	10%	10%	5%	3%	1%	5.	4.	3.	2.	Top
monthly alpha (%)	-1.78	-1.60	-1.55	-1.04	-1.02	-1.04	-0.69	-0.46	-0.22	0.71	0.89	1.02	1.38	1.38	1.46	1.48	1.54	1.60
p -value (bootstrapped)	0.57	0.29	0.10	0.45	0.28	0.45	0.11	0.58	1.00	0.00	0.00	0.00	0.02	0.02	0.05	0.16	0.39	0.69
t -alpha	-3.12	-2.94	-2.78	-2.76	-2.73	-2.76	-2.11	-1.68	-0.94	4.09	5.02	5.64	7.12	7.12	7.15	7.44	7.87	8.65
p -value (bootstrapped)	0.99	0.98	0.97	0.93	0.85	0.93	0.92	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01

Table 3

Bootstrap Sensitivity Analysis

Panel A reports the statistical significance of performance measures after correcting for incubation and backfill bias by removing the first 12 months of data for each fund. Panel B reports analogous estimates after correcting for serial correlation using the Getmansky, Lo and Makarov (2004) correction. Panel C allows for a structural break (identified using the Bai and Perron (1998) test) in December 2000. Panel D implements the bootstrap that allows for cross-sectional dependence in residuals. In each panel, the first and second rows reports the ranked OLS estimate of alpha in percent per month and the bootstrapped *p* -value of alpha. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The third and fourth rows report the ranked *t* -statistic of alpha based on heteroskedasticity and autocorrelation consistent standard errors as well as the bootstrapped *p* -value of the *t* -statistic. The first column on the left (right) reports funds with the lowest (highest) alpha and t-statistic followed by results for the funds with the second lowest (highest) alpha and t-statistic and marginal funds at different percentiles in the left (right) tail of the distribution. The p-value is based on the distribution of the best (worst) funds in 1000 bootstrap resamples. The Fung and Hsieh (2004) factors are S&P 500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the 10 year treasury (BD10RET), change in the spread of Moody's Baa - 10 year treasury (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. The sample period is from January 1994 to December 2002.

Panel A: Adjusting for incubation and backfill bias

	Bottom	2.	3.	4.	5.	1%	3%	4%	10%	10%	5%	3%	1%	5.	4.	3.	2.	Top
monthly alpha (%)	-3.44	-3.44	-3.31	-3.26	-3.24	-1.98	-1.01	-0.73	-0.41	1.12	1.42	1.75	2.21	2.81	2.95	3.10	3.43	3.93
p -value (bootstrapped)	0.36	0.07	0.02	0.00	0.00	0.00	0.49	0.96	1.00	0.00	0.00	0.00	0.00	0.02	0.03	0.06	0.08	0.18
t -alpha	-5.51	-4.91	-4.45	-4.26	-3.99	-3.00	-2.02	-1.61	-0.97	3.76	4.78	5.64	7.66	11.80	12.26	17.30	17.63	24.74
p -value (bootstrapped)	0.52	0.48	0.58	0.55	0.70	0.85	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel B: With unsmoothed returns using the Getmansky, Lo and Makarov (2004) correction

	Bottom	2.	3.	4.	5.	1%	3%	4%	10%	10%	5%	3%	1%	5.	4.	3.	2.	Top
monthly alpha (%)	-3.55	-3.32	-2.98	-2.90	-2.80	-1.67	-0.98	-0.73	-0.39	1.22	1.60	2.05	2.84	3.84	3.86	3.96	4.08	4.35
p -value (bootstrapped)	0.76	0.60	0.65	0.53	0.45	0.65	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.01	0.02	0.06	0.19	0.42
t -alpha	-4.38	-4.29	-3.86	-3.84	-3.48	-2.50	-1.84	-1.44	-0.89	3.55	4.58	5.55	7.31	12.69	17.21	19.97	23.21	37.31
p -value (bootstrapped)	0.99	0.96	0.99	0.98	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel C: With structural break in December 2000 identified using the Bai and Perron (1998) test

	Bottom	2.	3.	4.	5.	1%	3%	4%	10%	10%	5%	3%	1%	5.	4.	3.	2.	Top
monthly alpha (%)	-1.53	-1.18	-1.12	-1.08	-1.06	-0.68	-0.35	-0.20	-0.02	1.18	1.40	1.59	2.04	2.29	2.32	2.58	2.68	3.12
p -value (bootstrapped)	0.75	0.95	0.93	0.90	0.82	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
t -alpha	-3.06	-2.51	-2.30	-2.06	-2.04	-1.68	-0.93	-0.59	-0.08	4.69	5.97	6.70	8.30	10.86	11.13	12.81	13.43	24.90
p -value (bootstrapped)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel D: Adjusting for cross-sectional dependence in residuals

	Bottom	2.	3.	4.	5.	1%	3%	4%	10%	10%	5%	3%	1%	5.	4.	3.	2.	Top
monthly alpha (%)	-2.82	-2.15	-2.13	-2.12	-2.09	-1.32	-0.68	-0.46	-0.23	1.18	1.46	1.69	2.27	2.93	3.07	3.29	3.49	3.55
p -value (bootstrapped)	0.86	0.99	0.96	0.92	0.89	1.00	1.00	1.00	1.00	0.00	0.00	0.01	0.02	0.12	0.14	0.13	0.20	0.48
t -alpha	-4.42	-3.78	-3.17	-3.12	-2.96	-2.28	-1.49	-1.18	-0.55	3.95	5.10	5.96	8.18	12.95	14.21	17.69	22.00	24.01
p -value (bootstrapped)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 4

Bayesian Versus OLS Hedge Fund Alphas

This table reports Bayesian posterior alphas and OLS alphas in percent per month. Panel A reports summary results for all funds in the sample. Panel B reports the same measures as Panel A but for long/short equity funds only. Panel C reports the Bayesian alphas for the top 20 Long/short equity funds (ranked by OLS alpha). For each panel, column one reports the overall mean as well as the mean of different percentiles of the Bayesian posterior alpha estimate (α_{SURA}). The Bayesian posterior alpha is estimated using the seemingly unrelated assets approach of Pastor and Stambaugh (2002) for the prior of $\sigma_{\alpha N}$=0.2. Column two reports the OLS alpha. Column three shows the average difference between the Bayesian and the OLS alpha. A negative value in column three indicates that the Bayesian alpha is lower than the OLS alpha. Columns four and five report the Bayesian standard deviation of the Bayesian posterior alphas and the reduction in the standard deviation compared to the standard deviation of the OLS alpha. Column six reports the number of observations per fund. Columns seven and eight report the reduction in the Bayesian alpha relative to the OLS alpha for different prior measures (the prior of $\sigma_{\alpha N}$=0 and infinity). The sample period is from January 1994 to December 2002.

	(1)	(2)	(1) minus (2)		SURA s.e. minus OLS s.e.		(1) minus (2)	(1) minus (2)
Portfolio	Bayesian Alpha (α_{SURA})	OLS Alpha (α_{OLS})	(α_{SURA} -α_{OLS}) for $\sigma_{\alpha N}$ of 0.2	s.e. of Bayesian Alpha	s.e.(α_{SURA})-s.e.(αOLS)	nobs	(α_{SURA} -α_{OLS}) for $\sigma_{\alpha N}$ of 0	(α_{SURA} -α_{OLS}) for $\sigma_{\alpha N}$ of ∞
			Panel A: Summary results for all funds					
all funds	0.43	0.42	0.01	0.32	-0.16	55	-0.08	0.07
top 1%tile	2.76	3.28	-0.52	0.66	-0.53	35	-0.59	0.43
top decile	1.63	1.86	-0.23	0.48	-0.30	49	-0.35	0.11
bottom decile	-1.74	-2.16	0.41	0.60	-0.46	39	0.23	0.04
bottom 1%tile	-0.56	-0.80	0.24	0.43	-0.30	45	0.11	0.00
			Panel B: Summary results for all long/short equity funds					
all funds	0.48	0.52	-0.04	0.40	-0.21	52	-0.17	0.05
top 1%	2.75	3.49	-0.74	0.66	-0.68	31	-0.92	-0.62
top decile	1.73	2.07	-0.33	0.53	-0.34	44	-0.53	-0.21
bottom decile	-1.16	-1.78	0.62	0.61	-0.52	36	0.68	0.57
bottom 1%tile	-0.65	-0.74	0.09	0.43	-0.29	40	-0.09	0.20

Fund	(1) Bayesian Alpha (α_{SURA})	(2) OLS Alpha (α_{OLS})	(1) minus (2) (α_{SURA} -α_{OLS}) for $\sigma_{\alpha N}$ of 0.2	s.e. of Bayesian Alpha	SURA s.e. minus OLS s.e. s.e.(α_{SURA})-s.e.(α_{OLS})	nobs	(1) minus (2) (α_{SURA} -α_{OLS}) for $\sigma_{\alpha N}$ of 0	(1) minus (2) (α_{SURA} -α_{OLS}) for $\sigma_{\alpha N}$ of ∞
Panel C: Top 20 long/short equity funds (ranked by OLS alpha)								
1	1.23	4.06	-2.83	0.8	-1.26	26	-3.34	-2.58
2	1.78	3.77	-1.99	0.8	-0.70	24	-2.06	-1.95
3	3.08	3.74	-0.66	0.7	-0.58	33	-0.39	-0.83
4	2.04	3.42	-1.38	0.6	-0.59	34	-1.57	-1.19
5	4.44	3.40	1.04	0.8	-0.79	24	0.97	1.12
6	3.12	3.32	-0.21	0.6	-0.73	25	-0.58	0.02
7	3.25	3.29	-0.04	0.3	-0.21	40	-0.18	0.05
8	3.05	2.87	0.18	0.7	-0.59	40	-0.19	0.40
9	0.77	2.82	-2.05	0.9	-0.19	46	-2.20	-1.98
10	1.93	2.78	-0.85	0.6	-0.32	34	-1.22	-0.58
11	1.73	2.72	-0.99	0.6	-0.37	24	-1.06	-0.98
12	1.80	2.44	-0.64	0.6	-0.86	24	-0.76	-0.51
13	1.17	2.42	-1.25	0.7	-0.06	74	-2.42	-0.52
14	1.79	2.39	-0.60	0.6	-0.29	30	-0.77	-0.50
15	1.23	2.35	-1.12	1.1	-0.83	33	-2.13	-0.50
16	2.34	2.33	0.01	0.5	-0.06	78	-0.24	0.15
17	2.30	2.30	-0.01	0.5	-0.28	35	0.11	-0.10
18	2.29	2.24	0.05	0.5	-0.63	25	-0.07	0.12
19	2.18	2.24	-0.06	0.3	-0.19	45	-0.07	-0.05
20	1.59	2.21	-0.62	0.8	-1.01	28	-1.42	-0.11

Table 5

Performance Persistence Tests

Hedge funds excluding Fund of Funds are sorted on January 1 each year (from 1996 until 2002) into portfolios, based on their Fung and Hsieh (2004) OLS alphas or t-statistics of OLS alpha. We use the most recent 24 months of return observations in the 36-month window preceding the evaluation period for the alpha estimation. The portfolios are equally weighted monthly, so the weights are re-adjusted whenever a fund disappears. Funds with the highest past two-year alpha or alpha *t*-statistic comprise decile 1, and funds with the lowest comprise decile 10. The x%ile portfolio is an equally-weighted portfolio of the top x percent funds. The last three rows represent the difference in returns between the extreme deciles and the extreme 1 percentiles. Column five reports the one-tailed parametric p-value of alpha. Columns six to eight report the annualized information ratio (IR), tracking error (TE), and Sharpe ratio (SR). Columns nine to 15 report the beta coefficients for the Fung and Hsieh (2004) factors. The factors are S&P 500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the 10-year Treasury (BD10RET), change in the spread of Moody's Baa minus 10-year Treasury (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. Alpha is the intercept of the model. Column 16 reports the adjusted R-squared statistic. Column 17 reports the p-value from the Jarque Bera test of normality.

Panel A: Ranking funds on two-year OLS alphas (one-year holding period)

Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	*t*-stat of alpha	One-tailed parametric p-value of alpha	IR	TE	SR	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R2	p-value (Normality Test)
1%ile	0.89	15.13	-0.95	-0.19	0.43	-0.08	12.35	0.06	0.31	0.31	0.49	0.49	-0.01	0.04	0.10	0.27	0.01
5%ile	6.37	11.77	4.32	1.29	0.10	0.52	8.33	0.54	0.29	0.35	0.48	0.78	-0.02	0.03	0.06	0.45	0.00
decile 1	7.21	10.27	5.32	1.97	0.03	0.80	6.69	0.70	0.30	0.36	0.42	0.51	-0.02	0.02	0.06	0.54	0.21
decile 2	7.25	7.74	5.76	3.04	0.00	1.23	4.70	0.94	0.28	0.26	0.26	0.35	-0.02	0.02	0.02	0.60	0.22
decile 3	5.71	5.87	4.78	4.00	0.00	1.61	2.97	0.97	0.25	0.21	0.08	0.12	-0.01	0.02	0.01	0.72	0.78
decile 4	6.40	4.87	5.57	5.11	0.00	2.06	2.71	1.32	0.20	0.16	0.09	0.13	-0.01	0.00	0.00	0.66	0.39
decile 5	6.51	4.53	5.77	5.82	0.00	2.34	2.46	1.44	0.19	0.13	0.06	0.14	-0.01	0.01	0.00	0.68	0.42
decile 6	5.22	4.66	4.42	3.95	0.00	1.59	2.78	1.12	0.19	0.12	0.08	0.14	-0.01	0.01	0.01	0.61	0.82
decile 7	5.15	5.67	4.07	2.96	0.00	1.19	3.41	0.91	0.25	0.15	0.11	0.04	0.00	0.01	0.01	0.61	0.45
decile 8	5.87	6.78	4.44	2.71	0.00	1.09	4.06	0.87	0.30	0.19	0.16	0.06	-0.01	0.01	0.00	0.61	0.60
decile 9	5.54	6.46	4.24	2.56	0.01	1.03	4.12	0.86	0.27	0.15	0.11	0.13	0.01	0.02	0.02	0.56	0.66
decile 10	6.22	10.84	4.99	1.46	0.08	0.59	8.51	0.57	0.37	0.17	0.02	0.09	-0.01	0.02	0.00	0.33	0.15
95%ile	7.14	13.72	5.67	1.35	0.09	0.55	10.41	0.52	0.49	0.19	-0.03	0.01	-0.02	0.01	-0.01	0.37	0.30
99%ile	9.53	19.74	8.24	1.33	0.10	0.53	15.43	0.48	0.70	0.06	-0.33	-0.49	-0.01	0.04	-0.04	0.33	0.01
spread 10%	0.99	10.90	0.33	0.08	0.47	0.03	9.71	0.09	-0.06	0.19	0.39	0.42	-0.01	0.01	0.06	0.13	0.09
spread 1%	-8.65	23.20	-9.19	-1.15	0.13	-0.46	19.81	-0.37	-0.39	0.25	0.82	0.97	-0.01	0.00	0.14	0.20	0.06

Panel B: Ranking funds on two-year OLS *t*-statistics of alpha (one-year holding period)

Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	*t*-stat of alpha	One-tailed parametric p-value of alpha	IR	TE	SR	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R2	p-value (Normality Test)
1%tile	7.34	2.26	7.03	9.76	0.00	3.93	1.79	3.25	0.06	0.06	0.06	0.04	-0.01	0.00	0.00	0.32	0.00
5%tile	6.64	3.17	6.36	6.26	0.00	2.52	2.52	2.10	0.06	0.08	0.10	0.17	-0.01	0.00	0.02	0.31	0.00
decile 1	6.52	4.15	6.05	5.26	0.00	2.12	2.86	1.57	0.10	0.14	0.13	0.24	-0.01	0.01	0.02	0.48	0.68
decile 2	6.05	6.19	5.14	3.37	0.00	1.36	3.79	0.98	0.19	0.24	0.22	0.26	-0.02	0.01	0.03	0.59	0.97
decile 3	6.53	6.14	5.39	3.78	0.00	1.52	3.54	1.06	0.22	0.23	0.19	0.26	-0.01	0.01	0.02	0.64	0.30
decile 4	7.84	6.82	6.36	3.71	0.00	1.50	4.25	1.15	0.27	0.22	0.26	0.17	-0.01	0.02	0.02	0.58	0.08
decile 5	4.63	6.87	3.29	2.51	0.01	1.01	3.25	0.68	0.32	0.22	0.14	0.14	-0.01	0.02	0.01	0.76	0.41
decile 6	5.69	6.69	4.52	2.95	0.00	1.19	3.81	0.85	0.28	0.19	0.09	0.21	0.00	0.01	0.01	0.65	0.73
decile 7	6.08	7.14	4.78	2.84	0.00	1.14	4.18	0.85	0.32	0.17	0.07	0.14	0.00	0.02	0.01	0.63	0.82
decile 8	6.66	7.22	5.08	2.80	0.00	1.13	4.51	0.92	0.31	0.20	0.20	0.10	0.00	0.02	0.01	0.57	0.56
decile 9	5.18	7.61	3.92	1.74	0.04	0.70	5.58	0.68	0.28	0.13	0.09	0.17	0.00	0.01	0.01	0.41	0.00
decile 10	5.33	8.72	4.19	1.67	0.05	0.67	6.24	0.61	0.34	0.16	0.02	0.04	-0.01	0.02	0.00	0.44	0.09
95%ile	4.86	9.44	3.85	1.38	0.09	0.55	6.95	0.52	0.34	0.17	-0.06	0.01	-0.01	0.01	-0.02	0.41	0.34
99%ile	3.64	12.99	2.84	0.69	0.25	0.28	10.29	0.28	0.36	0.30	-0.07	0.11	-0.02	0.02	-0.03	0.32	0.12
spread 10%	1.19	7.71	1.86	0.73	0.24	0.29	6.36	0.15	-0.24	-0.02	0.11	0.20	-0.01	-0.01	0.02	0.26	0.80
spread 1%	3.70	12.50	4.19	0.98	0.16	0.40	10.57	0.30	-0.30	-0.25	0.14	-0.07	0.01	-0.02	0.03	0.22	0.11

Table 6

Bayesian Performance Persistence Tests

Hedge funds excluding Fund of Funds are sorted on January 1 each year (from 1996 to 2002) into portfolios, based on their Fung and Hsieh (2004) Bayesian posterior alphas or Bayesian posterior *t*-statistic of alphas. We use the most recent 24 months of return observations in the 36-month window preceding the evaluation period for the alpha estimation. The portfolios are equally weighted monthly, so the weights are re-adjusted whenever a fund disappears. Funds with the highest past two-year alpha or *t*-statistic of alpha comprise decile 1, and funds with the lowest comprise decile 10. The *x*%ile portfolio is an equally-weighted portfolio of the top *x* percent funds. The last three rows represent the difference in returns between the extreme deciles and the extreme 1 percentiles. Column five reports the one-tailed parametric p-value of alpha. Columns six to eight report the annualized information ratio (IR), tracking error (TE), and Sharpe ratio (SR). Columns nine to 15 report the beta coefficients for the Fung and Hsieh (2004) factors estimated using the Seemingly Unrelated Assets approach of Pastor and Stambaugh (2002). The factors are S&P500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the 10-year Treasury (BD10RET) change in the spread of Moody's Baa minus 10-year Treasury (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. Alpha is the intercept of the model. Column 16 reports the adjusted R-squared statistic. Column 17 reports the p-value from the Jarque Bera test of normality.

Panel A: Ranking funds on two-year Bayesian posterior alpha (one-year holding period)

Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	*t*-stat of alpha	One-tailed parametric p-value of alpha	IR	TE	SR	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2	p-value (Normality Test)
1%ile	12.06	11.09	11.86	3.26	0.00	1.31	9.03	1.09	0.18	0.26	0.10	0.56	-0.04	0.01	0.04	0.28	0.14
5%ile	8.24	7.78	7.37	3.47	0.00	1.40	5.28	1.06	0.26	0.21	0.11	0.31	-0.02	0.01	0.03	0.50	0.13
decile 1	9.31	7.76	8.21	4.35	0.00	1.75	4.68	1.20	0.29	0.25	0.15	0.27	-0.02	0.01	0.02	0.60	0.55
decile 2	7.93	7.15	6.93	4.36	0.00	1.76	3.94	1.11	0.28	0.27	0.10	0.08	-0.02	0.00	0.00	0.67	0.78
decile 3	6.04	5.50	5.22	4.37	0.00	1.76	2.96	1.10	0.22	0.20	0.09	0.11	-0.01	0.01	0.01	0.68	0.00
decile 4	6.15	4.87	5.54	5.78	0.00	2.33	2.38	1.26	0.20	0.16	0.04	0.15	-0.01	0.01	0.00	0.74	0.85
decile 5	5.65	4.95	4.73	4.26	0.00	1.72	2.75	1.14	0.19	0.13	0.14	0.25	-0.02	0.01	0.00	0.66	0.88
decile 6	4.67	4.60	3.79	3.64	0.00	1.47	2.59	1.01	0.19	0.12	0.12	0.19	-0.01	0.01	0.01	0.65	0.81
decile 7	5.23	5.78	4.18	3.51	0.00	1.41	2.96	0.91	0.25	0.15	0.11	0.17	-0.02	0.00	0.01	0.71	0.78
decile 8	5.14	6.20	4.32	3.20	0.00	1.29	3.35	0.83	0.26	0.18	0.02	0.14	-0.01	0.01	0.01	0.68	0.86
decile 9	5.13	8.92	3.57	2.09	0.02	0.84	4.24	0.58	0.41	0.27	0.09	0.19	-0.01	0.02	0.02	0.75	0.45
decile 10	4.84	13.18	2.40	0.88	0.19	0.35	6.76	0.37	0.59	0.40	0.07	0.24	0.01	0.00	0.01	0.71	0.02
95%ile	5.82	14.93	3.30	1.02	0.16	0.41	8.06	0.39	0.66	0.44	0.02	0.15	0.01	0.01	0.02	0.68	0.03
99%ile	6.24	16.46	4.61	0.88	0.19	0.35	13.03	0.38	0.53	0.33	-0.06	0.12	0.00	0.01	0.01	0.32	0.15
spread 10%	4.47	7.84	5.81	2.65	0.01	1.07	5.45	0.57	-0.30	-0.16	0.08	0.03	-0.03	0.00	0.01	0.47	0.46
spread 1%	5.83	16.12	7.25	1.21	0.12	0.49	14.86	0.36	-0.35	-0.07	0.15	0.45	-0.04	-0.01	0.03	0.07	0.20

Panel B: Ranking funds on two-year Bayesian posterior *t*-statistics of alpha (one-year holding period)

Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	*t*-stat of alpha	One-tailed parametric p-value of alpha	IR	TE	SR	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2	p-value (Normality Test)
1%ile	8.77	4.26	8.58	5.94	0.00	2.40	3.58	2.06	0.06	0.09	0.06	0.21	-0.02	-0.01	0.01	0.23	0.02
5%ile	7.34	5.15	6.98	5.03	0.00	2.03	3.44	1.43	0.14	0.18	0.05	0.17	-0.02	0.00	0.01	0.51	0.13
decile 1	7.25	5.61	6.56	4.96	0.00	2.00	3.28	1.29	0.20	0.21	0.11	0.14	-0.02	0.00	0.01	0.63	0.08
decile 2	6.71	5.81	5.97	4.92	0.00	1.98	3.01	1.16	0.23	0.21	0.10	0.15	-0.02	0.00	0.01	0.71	0.49
decile 3	8.51	5.35	7.74	6.65	0.00	2.68	2.89	1.59	0.22	0.17	0.04	0.11	-0.01	0.00	0.00	0.68	0.00
decile 4	5.55	5.75	4.57	3.14	0.00	1.27	3.61	0.97	0.21	0.17	0.17	0.21	-0.02	0.01	0.01	0.57	0.16
decile 5	7.05	6.27	6.10	4.34	0.00	1.75	3.48	1.13	0.25	0.20	0.11	0.19	-0.02	0.02	0.00	0.66	0.08
decile 6	4.93	6.17	3.77	2.83	0.00	1.14	3.31	0.80	0.26	0.16	0.12	0.23	-0.01	0.01	0.01	0.69	0.88
decile 7	6.27	6.71	5.06	3.56	0.00	1.44	3.53	0.94	0.29	0.16	0.10	0.23	-0.01	0.00	0.01	0.70	0.00
decile 8	4.33	7.65	3.28	2.20	0.02	0.89	3.69	0.57	0.34	0.26	0.03	0.10	-0.01	0.01	0.01	0.75	0.68
decile 9	4.33	9.08	2.58	1.45	0.08	0.58	4.43	0.48	0.41	0.25	0.11	0.29	0.00	0.01	0.02	0.74	0.93
decile 10	5.18	9.85	3.41	1.74	0.04	0.70	4.85	0.53	0.45	0.32	0.04	0.14	0.00	0.01	0.01	0.74	0.00
95%ile	4.52	10.12	2.99	1.27	0.10	0.51	5.83	0.45	0.42	0.34	-0.01	0.03	0.01	0.01	0.00	0.64	0.00
99%ile	2.88	9.17	2.04	0.70	0.24	0.28	7.27	0.31	0.28	0.25	0.13	-0.11	-0.03	0.03	-0.01	0.31	0.00
spread 10%	2.07	6.36	3.15	1.76	0.04	0.71	4.44	0.33	-0.25	-0.11	0.06	0.00	-0.02	-0.01	0.00	0.47	0.07
spread 1%	5.89	8.13	6.53	2.30	0.01	0.93	7.05	0.72	-0.22	-0.15	-0.07	0.32	0.01	-0.03	0.02	0.18	0.00

Table 7

Bayesian Performance Persistence Tests - By Fund Category

Hedge funds, excluding Fund of Funds, by fund category, are sorted on January 1 each year (from 1996 to 2002) into portfolios, based on their Fung and Hsieh (2004) Bayesian posterior alpha *t*-statistics. We use the most recent 24 months of return observations in the 36-month window preceding the evaluation period for the alpha estimation. The portfolios are equally weighted monthly, so the weights are re-adjusted whenever a fund disappears. Funds with the highest past t-statistic of alpha comprise decile 1. The 1%ile portfolio is an equally-weighted portfolio of the top 1 percent funds. Spread 10% is the spread between the extreme deciles. Spread 1% is the spread between the top 1 percent and bottom 1 percent of funds. Column five reports the one-tailed parametric p-value of alpha. Columns six to eight report the annualized information ratio (IR), tracking error (TE), and Sharpe ratio (SR). Columns nine to 15 report the beta coefficients for the Fung and Hsieh (2004) factors estimated using the Seemingly Unrelated Assets approach of Pastor and Stambaugh (2002). The factors are S&P500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the 10-year Treasury (BD10RET), change in the spread of Moody's Baa minus 10-year Treasury (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. Alpha is the intercept of the model. Column 16 reports the adjusted R-squared statistic. Column 17 reports the p-value from the Jarque Bera test of normality.

Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	t-stat of alpha	One-tailed parametric p-value of alpha	IR	TE	SR	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2	p-value (Normality Test)
Panel A: Long/short equity funds																	
1%	4.15	10.74	3.06	0.90	0.19	0.36	8.43	0.39	0.34	0.24	0.05	0.12	-0.01	0.03	-0.01	0.33	0.00
decile 1	8.14	6.30	7.57	4.13	0.00	1.66	4.55	1.29	0.20	0.22	0.01	0.03	-0.01	0.01	0.01	0.43	0.14
spread 10%	4.19	10.84	6.36	1.90	0.03	0.77	8.30	0.39	-0.36	-0.28	-0.19	-0.15	-0.02	0.01	-0.01	0.36	0.74
spread 1%	6.68	13.83	7.07	1.34	0.09	0.54	13.12	0.48	0.09	-0.17	-0.23	0.45	-0.01	0.03	-0.01	0.02	0.72
Panel B: Directional trader funds																	
1%	13.73	14.09	11.96	2.81	0.00	1.13	10.58	0.97	0.35	0.48	0.20	0.31	-0.02	0.00	-0.02	0.38	0.00
decile 1	8.12	9.96	6.57	2.60	0.01	1.05	6.26	0.82	0.34	0.34	0.25	0.36	-0.03	0.00	0.02	0.57	0.17
spread 10%	2.13	9.70	2.41	0.67	0.25	0.27	8.86	0.22	-0.16	0.02	0.27	0.05	-0.02	-0.01	0.02	0.09	0.04
spread 1%	20.21	15.78	20.43	3.46	0.00	1.40	14.64	1.28	0.15	0.29	0.04	0.15	-0.05	0.00	0.01	0.06	0.00
Panel C: Multi-process funds																	
1%	8.17	3.61	7.82	5.91	0.00	2.38	3.28	2.27	0.04	0.03	0.02	0.21	0.01	0.00	0.01	0.10	0.01
decile 1	11.00	6.65	10.91	4.88	0.00	1.97	5.55	1.65	0.16	0.11	-0.01	0.06	-0.03	0.00	0.02	0.24	0.00
spread 10%	1.43	6.10	1.42	0.58	0.28	0.23	6.07	0.23	0.01	0.03	-0.04	-0.01	0.01	0.00	0.00	-0.08	0.18
spread 1%	6.42	13.17	7.25	1.45	0.08	0.58	12.43	0.49	-0.11	-0.28	-0.18	0.21	0.00	-0.03	0.03	0.03	0.00

Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	t-stat of alpha	One-tailed parametric p-value of alpha	IR	TE	SR	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2	p-value (Normality Test)
Panel D: Relative value funds																	
1%	5.14	7.37	5.87	2.16	0.02	0.87	6.74	0.70	-0.09	-0.01	-0.07	0.55	-0.02	0.00	0.02	0.09	0.00
decile 1	6.37	4.66	6.68	4.20	0.00	1.69	3.94	1.37	-0.03	0.05	0.01	0.37	-0.02	-0.01	0.02	0.22	0.00
spread 10%	2.40	5.61	3.04	1.61	0.06	0.65	4.69	0.43	-0.18	-0.01	0.00	0.22	0.00	-0.02	0.01	0.24	0.00
spread 1%	5.81	8.94	6.31	1.87	0.03	0.75	8.39	0.65	-0.10	-0.09	-0.01	0.60	-0.02	-0.01	0.02	0.04	0.00
Panel E: Security selection funds																	
1%	3.88	10.90	2.40	0.90	0.19	0.36	6.59	0.36	0.49	0.35	-0.07	-0.47	0.01	0.01	-0.02	0.60	0.97
decile 1	6.39	8.18	4.93	2.80	0.00	1.13	4.37	0.78	0.37	0.28	0.13	-0.06	-0.01	0.01	0.00	0.69	0.74
spread 10%	2.66	9.31	3.66	1.11	0.14	0.45	8.19	0.29	-0.18	-0.16	0.04	-0.23	-0.02	0.01	-0.01	0.15	0.29
spread 1%	5.08	14.77	4.12	0.75	0.23	0.30	13.66	0.34	0.26	0.07	-0.26	-0.76	0.06	0.00	-0.04	0.07	0.00
Panel F: Funds of funds																	
1%	10.45	12.88	8.11	1.79	0.04	0.72	11.22	0.81	0.25	0.17	0.57	0.61	-0.03	0.00	0.01	0.17	0.00
decile 1	8.77	6.56	7.44	3.79	0.00	1.53	4.87	1.34	0.20	0.19	0.25	0.18	-0.01	0.01	0.02	0.40	0.23
spread 10%	6.66	4.00	6.29	4.03	0.00	1.62	3.87	1.66	0.04	0.04	0.08	-0.13	0.00	0.00	0.00	-0.02	0.33
spread 1%	10.29	13.32	8.32	1.64	0.05	0.66	12.61	0.77	0.13	0.07	0.47	0.67	-0.01	0.00	0.01	0.02	0.00

Table 8

Bayesian Performance Persistence Tests - Sensitivity Analysis

This table reports a sensitivity analysis of the performance persistence tests in Table 6. In Panel A, the portfolios are formed based on past two-year Bayesian posterior alpha. In Panel B, the portfolios are formed based on past two-year *t*-statistics of Bayesian posterior alpha. In both panels, funds are held for one year. For comparison purposes, the first row of each panel reproduces parts of Table 6 from the corresponding panel. The next four rows report results for subgroups of funds. Small (large) funds are funds with assets under management or AUM below (above) the median AUM of funds in existence. Low (high) inflow funds are funds with an average inflow below (above) the median inflow of funds in existence. The third last row reports results corrected for incubation and backfill bias by removing the first 12 months of reported returns. The second last row reports results on pre-fee fund returns. The last row reports results after accounting for serial correlation by unsmoothing returns using the Getmansky, Lo and Makarov (2004) specification for serial correlation. Column five reports the one-tailed parametric p-value of alpha. Columns six to eight report the annualized information ratio (IR), tracking error (TE), and Sharpe ratio (SR). Columns nine to 15 report the beta coefficients for the Fung and Hsieh (2004) factors estimated using the Seemingly Unrelated Assets approach of Pastor and Stambaugh (2002). The factors are S&P500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the 10-year Treasury (BD10RET), change in the spread of Moody's Baa minus 10-year Treasury (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. Alpha is the intercept of the model. Column 16 reports the adjusted R-squared statistic.

Panel A: Ranking funds on two-year Bayesian posterior alpha (one year holding period)

Sensitivity test	Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	*t*-stat of alpha	One-tailed parametric p-value of alpha	IR	TE	SR	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2
Baseline results	decile 1	9.31	7.76	8.21	4.35	0.00	1.75	4.68	1.20	0.29	0.25	0.15	0.27	-0.02	0.01	0.02	0.60
	spread 10%	4.47	7.84	5.81	2.65	0.01	1.07	5.45	0.57	-0.30	-0.16	0.08	0.03	-0.03	0.00	0.01	0.47
Small funds	decile 1	11.44	9.24	10.36	4.15	0.00	1.67	6.19	1.24	0.36	0.20	0.06	0.18	-0.02	0.02	0.01	0.51
	spread 10%	3.25	8.09	4.43	1.69	0.05	0.68	6.51	0.40	-0.24	-0.21	0.03	0.11	-0.02	0.01	0.01	0.29
Large Funds	decile 1	7.02	7.74	5.79	3.02	0.00	1.22	4.75	0.91	0.26	0.28	0.21	0.31	-0.02	0.00	0.02	0.59
	spread 10%	5.74	7.49	6.72	3.22	0.00	1.30	5.17	0.77	-0.31	-0.08	0.12	0.09	-0.02	-0.01	0.00	0.48
Low inflow funds	decile 1	8.96	10.52	7.82	2.51	0.01	1.01	7.72	0.85	0.29	0.33	0.23	0.25	-0.04	0.00	0.02	0.41
	spread 10%	6.32	8.64	7.30	2.46	0.01	0.99	7.36	0.73	-0.21	-0.02	0.12	-0.21	-0.03	0.00	-0.01	0.21
High inflow funds	decile 1	8.60	6.66	8.01	3.69	0.00	1.49	5.38	1.29	0.20	0.14	0.06	0.09	-0.01	0.01	0.01	0.29
	spread 10%	3.74	11.23	5.21	1.43	0.08	0.58	9.03	0.33	-0.34	-0.13	0.09	-0.20	-0.02	0.00	0.00	0.29
Incubation/	decile 1	7.58	7.72	6.44	3.73	0.00	1.50	4.28	0.98	0.31	0.27	0.17	0.16	-0.02	0.01	0.02	0.66
backfill bias	spread 10%	2.56	8.51	3.73	1.50	0.07	0.60	6.17	0.30	-0.29	-0.16	0.14	-0.06	-0.03	0.01	0.00	0.43
Pre-fee returns	decile 1	13.98	8.09	12.86	6.58	0.00	2.65	4.85	1.73	0.31	0.26	0.12	0.24	-0.02	0.01	0.02	0.61
	spread 10%	6.22	6.56	7.19	3.81	0.00	1.54	4.68	0.95	-0.24	-0.10	0.12	0.03	-0.03	0.00	0.01	0.44
Serial correlation	decile 1	9.14	8.17	7.82	4.01	0.00	1.61	4.84	1.12	0.32	0.27	0.18	0.24	-0.02	0.01	0.02	0.62
adjusted returns	spread 10%	3.89	8.68	5.22	2.17	0.02	0.87	5.97	0.45	-0.33	-0.19	0.11	0.03	-0.03	0.01	0.00	0.48

Panel B: Ranking funds on two-year t-statistics of Bayesian posterior alpha (one year holding period)

Sensitivity test	Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	*t* -stat of alpha	One-tailed parametric p-value of alpha	IR	TE	SR	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2
Baseline results	decile 1	7.25	5.61	6.56	4.96	0.00	2.00	3.28	1.29	0.20	0.21	0.11	0.14	-0.02	0.00	0.01	0.63
	spread 10%	2.07	6.36	3.15	1.76	0.04	0.71	4.44	0.33	-0.25	-0.11	0.06	0.00	-0.02	-0.01	0.00	0.47
Small funds	decile 1	8.51	6.67	7.42	4.91	0.00	1.98	3.75	1.28	0.28	0.23	0.15	0.04	-0.02	0.01	0.00	0.66
	spread 10%	1.20	6.18	1.71	0.80	0.21	0.32	5.32	0.19	-0.13	-0.10	0.14	0.00	-0.02	0.00	0.01	0.19
Large Funds	decile 1	7.28	5.41	6.85	4.74	0.00	1.91	3.59	1.34	0.14	0.18	0.09	0.20	-0.02	-0.01	0.01	0.52
	spread 10%	5.81	6.89	7.23	4.41	0.00	1.78	4.07	0.84	-0.32	-0.09	0.01	-0.01	-0.02	-0.01	-0.01	0.62
Low inflow funds	decile 1	8.16	6.59	7.10	3.92	0.00	1.58	4.50	1.24	0.21	0.21	0.18	0.26	-0.02	0.00	0.01	0.49
	spread 10%	4.56	7.78	5.11	2.15	0.02	0.87	5.88	0.59	-0.25	-0.10	0.17	-0.04	-0.01	0.01	0.00	0.38
High inflow funds	decile 1	6.41	4.85	6.02	4.43	0.00	1.78	3.37	1.32	0.15	0.16	0.06	0.08	-0.02	0.01	0.01	0.47
	spread 10%	2.93	6.96	3.80	1.79	0.04	0.72	5.26	0.42	-0.22	-0.05	0.10	-0.24	-0.02	-0.01	-0.01	0.38
Incubation/	decile 1	6.97	5.78	6.39	4.77	0.00	1.92	3.33	1.21	0.20	0.21	0.08	0.13	-0.02	0.00	0.01	0.64
backfill bias	spread 10%	2.49	6.72	3.66	2.04	0.02	0.82	4.45	0.37	-0.27	-0.13	0.07	0.00	-0.03	0.00	-0.01	0.52
Pre-fee returns	decile 1	10.77	4.88	10.24	8.39	0.00	3.38	3.03	2.21	0.15	0.17	0.08	0.17	-0.02	0.00	0.01	0.58
	spread 10%	2.34	7.06	3.57	1.96	0.03	0.79	4.52	0.33	-0.30	-0.13	0.07	0.01	-0.02	-0.01	0.00	0.55
Serial correlation	decile 1	8.14	6.46	7.16	5.18	0.00	2.09	3.44	1.26	0.25	0.25	0.15	0.17	-0.02	0.00	0.01	0.69
adjusted returns	spread 10%	3.41	6.56	4.53	2.40	0.01	0.97	4.69	0.52	-0.25	-0.11	0.06	-0.04	-0.03	0.00	0.00	0.44