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Investing in hedge funds when returns are predictable*

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Abstract

We evaluate investment strategies in hedge funds that incorporate predictability in managerial skills, factor loadings, and benchmark returns. We find that predictability in managerial skills is the dominant source of outperformance. Long-only strategies that allow for predictability in managerial skills outperform their Fung and Hsieh (2004) benchmarks by over 12 percent per year. Moreover, the overperformance is strongest during market downturns. These findings are robust to adjustments for backfill bias, incubation bias, illiquidity-induced serial correlation, fund fees and different rebalancing horizons.

JEL codes: G11, G12, G14, G23

Keywords : Hedge Funds, Time-Varying Managerial Skills, Asset Allocation

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According to the 2005 HFR report, there were more than 7000 hedge funds globally managing over US$970 billion in assets at the end of 2004, compared to 530 hedge funds managing US$39 billion in 1990. Despite the phenomenal growth in assets managed by hedge funds, the extant academic research has cast a pall over the possibility of active management skills in this industry. For example, Malkiel and Saha (2005) report that after adjusting for various hedge fund database biases, hedge funds on average significantly underperform their benchmarks. Brown, Goetzmann, and Ibbotson (1999) show that annual hedge fund returns do not persist. Fuelling the debate, Getmansky, Lo, and, Makarov (2004) argue that whatever persistence at quarterly horizons documented by Agarwal and Naik (2000) and others in hedge funds can be simply traced to illiquidity-induced serial correlation in hedge fund returns. These results do not bode well for hedge funds and the high performance fees[1] that they charge.

Recent work on hedge funds offers more sanguine evidence on the existence of active management skills amongst hedge fund managers. Kosowski, Naik, and Teo (2007) demonstrate, using a bootstrap approach, that the alpha of the top hedge funds cannot be explained by luck or sample variability. Their bootstrap approach explicitly accounts for the fact that the top performers are drawn from a large cross-section of funds, which increases the potential for some managers to do well purely by chance. They further show that after overcoming the short sample problem inherent in hedge fund data with the seemingly unrelated assets Bayesian approach of Pástor and Stambaugh (2002a), hedge fund risk-adjusted performance persists at annual horizons. By sorting on past two-year Bayesian posterior alpha, they are able to achieve an alpha spread of 5.5 percent per annum in the out-of-sample period.

[1] Most hedge funds levy a management fee equal to 2 percent per annum and a performance fee equal to 20 percent of any performance over and above their benchmarks. However, some stellar hedge funds charge even more. For example, James Simons' extremely successful Renaissance Technologies Medallion fund charges a management fee of 5 percent and a performance fee of 44 percent ("Really Big Bucks" Alpha Magazine, May 2006).

This paper adds to the debate on hedge fund performance by analyzing performance of portfolio strategies that invest in hedge funds. These strategies exploit predictability in (i) manager asset selection and benchmark timing skills, (ii) hedge-fund risk loadings, and (iii) benchmark returns. By examining the ex-post out-of-sample opportunity set, we show that there exist subgroups of hedge funds that deliver significant overperformance. Our analysis leverages on the Bayesian framework proposed by Avramov and Wermers (2006) who study the performance of optimal portfolios of mutual funds that utilize fund return predictability.[2] They find that predictability in managerial skills is the dominant source of investment profitability. In particular, long-only strategies that incorporate predictability in managerial skills outperform their Fama and French (1993) and momentum benchmarks by 2-4 percent per year by timing industries over the business cycle, and by an additional 3-6 percent per year by choosing funds that outperform their industry benchmarks. We argue that the framework developed by Avramov and Wermers (2006) is even more relevant to the study of hedge fund performance because hedge funds are typically viewed as pure alpha bets. That is, managerial skills (if any) as opposed to risk factor loadings should explain a larger component of hedge fund returns. Hence, the payoff to predicting managerial skills should be larger with hedge funds than with mutual funds. Yet, at the same time, because hedge funds are much less constrained in their investment activities than mutual funds (i.e., hedge funds can short-sell, leverage, and trade in derivatives), predicting hedge fund managerial skills may be a far more challenging task.

Our results are broadly supportive of the value of active management in the hedge fund industry. A real time investor who allows for predictability in hedge fund alpha, beta, and benchmark returns can earn a Fung and Hsieh (2004) alpha of 12.34 percent per annum out-of-

[2] The Avramov-Wermers (2006) methodology extends the asset allocation framework developed by Avramov (2004) and Avramov and Chordia (2006).

sample. This is over 4 percent per annum higher than those earned by investors who do not allow for predictability in managerial skills, and over 9 percent per annum higher than that earned by the investor who completely excludes hedge fund return predictability and the possibility of managerial skills. We show that conditioning on macroeconomic variables, especially some measure of market volatility, is important in forming optimal portfolios that outperform out of sample. In contrast, the naïve strategy that invests in the top ten percent of funds based on past alpha only achieves an ex-post alpha of 6.60 percent per year. These results are robust to adjustments for backfill and incubation bias (Fung and Hsieh, 2004), illiquidity-induced serial correlation in fund returns (Getmansky, Lo, and Makarov, 2004), fund fees and realistic annual rebalancing horizons.

The outperforming portfolios which take into account predictability in managerial skill differ from other portfolios in terms of age and investment style composition. They tend to hold funds that are of intermediate age – funds that may have established a track record but that may not have yet suffered any adverse effects potentially associated with maturity. The winning strategies also tend to contain a larger (smaller) proportion of funds in investment objectives such as directional trader (relative value) where some of the most (least) impressive performance from strategies based on predictable skill can be found. An investigation by investment objective reveals that strategies that incorporate predictability in managerial skills significantly outperform the other strategies within the equity long/short, directional trader, multi-process and security selection fund groups. Strategies based on predictable skill are relatively less successful within the relative value and fund of funds groups. Furthermore, the optimal strategy that allows for predictability in managerial skills is particularly attractive as it pays off handsomely during stock market downturns. Consistent with the results in Avramov and Wermers (2006), this optimal portfolio performs reasonably well during the bull market of the 1990s and performs exceptionally well during the post-2000 market downturn. An initial investment of $10,000 in this optimal portfolio translates to over $32,000 at the end of our sample period (January 1996 – December 2002). Conversely, the same initial investment in the S&P 500 yields less than $16,000. Clearly, active fund management is particularly attractive to investors with concave utility functions over wealth.

The rest of the paper is structured as follows. Section 1 reviews the methodology used in the analysis. Section 2 describes the data. Section 3 presents the empirical results. Section 4 concludes and offers suggestions for future research.

1. Methodology

Our approach follows that of Avramov and Wermers (2006). In particular, we assess the economic significance of predictability in hedge fund returns as well as the overall value of active management. Our experiments are based on the perspectives of three types of Bayesian optimizing investors who differ with respect to their beliefs about the potential for hedge fund managers to possess asset selection skills and benchmark timing abilities. Specifically, the three types of investors differ in their views on the parameters governing the following hedge fund return generating model:

$$r_{it} = \alpha_{i0} + \alpha_{i1}' z_{t-1} + \beta_{i0}' f_t + \beta_{i1}' \left(f_t \otimes z_{t-1} \right) + \upsilon_{it} , \qquad (1)$$

$$f_t = a_f + A_f z_{t-1} + \upsilon_{ft} , \qquad (2)$$

$$z_t = a_z + A_z z_{t-1} + \upsilon_{zt} , \qquad (3)$$

where r_{it} is the month-*t* hedge fund return in excess of the risk free rate, z_{t-1} is the information set which contains *M* business cycle variables observed at end of month t-1, f_t is a set of *K* zero-cost benchmarks, β_{i0} (β_{i1}) is the fixed (time-varying) component of fund risk loadings, and υ_{it} is a fund-specific event assumed to be uncorrelated across funds and over time, as well as normally distributed with mean zero and variance ψ_i. The modelling of beta variation with information variables has been used in Shanken (1990) while the modelling of business cycle variables using a vector autoregression of order one in an investment context has been adopted by Kandel and Stambaugh (1996), Barberis (2000), Avramov (2002, 2004), and Avramov and Chordia (2006), among others.

Note that there are two potential sources of timing-related fund returns that are correlated with public information. First, fund risk-loadings may be predictable. This predictability may stem from changing asset level risk loadings, flows into the funds, or manager timing of the benchmarks. Second, the benchmarks, which are return spreads, may be predictable. Such predictability is captured through the time-series regression in Eq. (2). Since both of these timing components can be easily replicated by an investor, we do not consider them to be based on managerial "skill." Rather, the expression for managerial skill is $\alpha_{i0} + \alpha_{i1}^{'} z_{t-1}$ which captures benchmark timing and asset selection skills that exploit only the private information possessed by a fund manager. Needless to say, this private information can be correlated with the business cycle. This is indeed what we show in the empirical results.

Overall, the model for hedge fund returns described by Eqs. (1) – (3) captures potential predictability in managerial skills $(\alpha_{i1} \neq 0)$, hedge fund risk loadings $(\beta_{i1} \neq 0)$, and benchmark returns $(A_f \neq 0)$. We now introduce our three types of investors, who possess very different views concerning the existence of manager skills in timing the benchmarks and in selecting securities:

The first investor is the dogmatist who rules out any potential for fixed or time varying manager skill. The dogmatist believes that a fund manager provides no performance through benchmark timing or asset selection skills, and that expenses and trading costs are a deadweight loss to investors. We consider two types of dogmatists. The "no-predictability dogmatist (ND)" rules out predictability, and sets the parameters β_{i1} and A_f in Eqs. (1) and (2) equal to zero. The "predictability dogmatist (PD)" believes that hedge fund returns are predictable based on observable business cycle variables. We further partition the PD investor into two types. The PD-1 investor believes that fund risk loadings are predictable (i.e., β_{i1} is allowed to be nonzero) while the PD-2 investor believes that fund risk loadings and benchmark returns are predictable (i.e., both β_{i1} and A_f are allowed to be nonzero).

The second investor is the skeptic who harbours more moderate views on the possibility of active management skills. The skeptic believes that some fund managers can beat their benchmarks, though her beliefs about overperformance or underperformance are bounded, as we formalize below. As with the dogmatist, we also consider two types of skeptics: the "no-predictability skeptic (NS)" and the "predictability skeptic (PS)." The former believes that macro economic variables should be ignored while the latter believes that fund risk loadings, benchmark returns, and even managerial skills are predictable based on changing macroeconomic conditions. For the NS investor, α_{i1} equals zero with probability one, and α_{i0} is normally distributed with a mean equal to –expense/12 and a standard deviation equal to 1%. For the PS investor, the prior mean of α_{i1} is zero and the prior mean of α_{i0} equals –expense/12. Further, the prior standard errors of these parameters depend on T_0. Following Avramov and Wermers (2006), the choice of T_0 is determined by the following equation:

$$T_0 = \frac{s^2}{\sigma_\alpha^2}\left(1 + M + SR_{\max}^2\right), \tag{4}$$

where $SR_{\max}^2$ is the largest attainable Sharpe ratio based on investments in the benchmarks only (disregarding predictability), M is the number of predictive variables, s^2 is the cross-fund average of the sample variance of the residuals in Eq. (1), and σ_α is set equal to 1%

The third investor is the agnostic who allows for managerial skills to exist but has completely diffuse prior beliefs about the existence and level of skills. Specifically, the skill level $\alpha_{i0} + \alpha_{i1}^{'} z_{t-1}$ has a mean of –expense/12 and unbounded standard deviation. As with the other investors, we further subdivide the agnostic into the "no predictability agnostic (NA)" and the "predictability agnostic (PA)."

[Please insert Table 1 here]

Overall, we consider 13 investors including three dogmatists, five sceptics, and five agnostics. Table 1 summarizes the different investor types and the beliefs they hold. For each of these 13 investors, we form optimal portfolios of hedge funds. The time-*t* investment universe comprises N_t firms, with N_t varying over time as funds enter and leave the sample through closures and terminations. Each investor type maximizes the conditional expected value of the following quadratic function

$$U\left(W_t, R_{p,t+1}.a_t, b_t\right) = a_t + W_t R_{p,t+1} - \frac{b_t}{2} W_t^2 R_{p,t+1}^2, \tag{5}$$

where W_t denotes wealth at time *t*, b_t is related to the risk aversion coefficient (see below), and $R_{p,t+1}$ is the realized excess return on the optimal portfolio of mutual funds computed as $R_{p,t+1} = 1 + r_{ft} + w_t^{'} r_{t+1}$, with r_{ft} denoting the risk free rate, r_{t+1} denoting the vector of excess fund returns, and w_t denoting the vector of optimal allocations to hedge funds.

By taking conditional expectations on both sides of Eq. (5), letting $\gamma_t = (b_t W_t)/(1 - b_t W_t)$ be the relative risk-aversion parameter, and letting $\Lambda_t = [\Sigma_t + \mu_t \mu_t']^{-1}$, where μ_t and Σ_t are the mean vector and covariance matrix of future fund returns, yields the following optimization

$$w_t^* = \arg\max_{w_t} \left\{ w_t' \mu_t - \frac{1}{2(1/\gamma_t - r_{ft})} w_t' \Lambda_t^{-1} w_t \right\}. \tag{6}$$

We derive optimal portfolios of hedge funds by maximizing Eq. (6) constrained to preclude short-selling and leveraging. In forming optimal portfolios, we replace μ_t and Σ_t in Eq. (6) by the mean and variance of the Bayesian predictive distribution

$$p(r_{t+1} \mid D_t, I) = \int_\Theta p(r_{t+1} \mid D_t, \Theta, I) p(\Theta \mid D_t, I) \, d\Theta, \tag{7}$$

where D_t denote the data (hedge fund returns, benchmark returns, and predictive variables) observed up to and including time *t*, Θ is the set of parameters characterizing the processes in Eq. (1) – (3), $p(\Theta \mid D_t)$ is the posterior density of Θ, and *I* denotes the investor type (recall, there are 13 investors considered here). Such expected utility maximization is a version of the general Bayesian control problem pioneered by Zellner and Chetty (1965) and has been extensively used in portfolio selection problems.

Our objective is to assess the potential economic gain, both ex-ante and out-of-sample, of incorporating fund return predictability into the investment decision for each investor type. For each of the investors, we derive optimal portfolios and evaluate performance relative to the Fung and Hsieh (2004) seven factor model:

$$\begin{aligned} r_{i,t} &= a_i + b_i SNPMRF_t + c_i SCMLC_t + d_i BD10RET_t + e_i BAAMTSY_t \\ &+ f_i PTFSBD_t + g_i PTFSFX_t + h_i PTFSCOM_t + \varepsilon_{i,t} \end{aligned} \tag{8}$$

where $r_{i,t}$ is the monthly return on portfolio *i* in excess of the one-month T-bill return, *SNPMRF* is the S&P 500 return minus risk free rate, *SCMLC* is the Wilshire small cap minus large cap return, *BD10RET* is the change in the constant maturity yield of the 10 year treasury, *BAAMTSY* is the change in the spread of Moody's Baa - 10 year treasury, *PTFSBD* is the bond PTFS, *PTFSFX* currency PTFS, *PTFSCOM* is the commodities PTFS, where PTFS is primitive trend following strategy [see Fung and Hsieh (2004)]. 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. Building on this pioneering work, Fung and Hsieh (2004) propose an asset based style (henceforth ABS) factor model that can explain up to 80 percent of the monthly variation in hedge fund portfolios. Their ABS model, which features option based factors, avoids using a broad based index of hedge funds to model hedge fund risk since a fund index can inherit errors that were inherent in hedge fund databases. Other papers that measure hedge fund performance relative to the Fung and Hsieh (2004) model include Kosowski, Naik, and Teo (2007) and Fung, Hsieh, Ramadorai, and Naik (2007).

2. Data

We evaluate the performance of hedge funds using monthly net-of-fee[3] 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 the largest known dataset of the hedge funds to date.

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)

[3] Our results are robust to using pre-fee returns.

below US$20 million may be too small for many institutional investors, we exclude such funds from the analysis.[4] This leaves us with a total of 4,300 live hedge funds and 1,233 dead hedge funds. 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.

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

[4] The AUM cutoff is implemented every month.

alpha in Agarwal 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 examining the period from January 1994 onwards in our baseline results.

3. Empirical results

In this section, we analyze the ex-post out-of-sample performance of the optimal portfolios for our 13 investor types. The portfolios are formed based on the past 24 months of data and are reformed every twelve months. We do not reform more frequently, as in Avramov and Wermers (2006), in response to concerns that the long lock-up and redemption periods for hedge funds make more frequent reforming infeasible. Nonetheless, we shall show that reforming every six months or every quarter delivers similar results. Given our sample period, the first portfolio is formed on January 1996 based on data from January 1994 to December 1995, and the last portfolio is formed on January 2002 based on data from January 2000 to December 2001.

For each portfolio, we report various summary statistics, including the mean, standard deviation, annualized Sharpe ratio, skewness, and kurtosis. We also evaluate its performance relative to the Fung and Hsieh (2004) seven-factor model. We first consider fund return predictability based on the same set of business cycle variables used in Avramov and Wermers (2006), namely, the dividend yield, the default spread, the term spread, and the Treasury yield. These are the instruments that Keim and Stambaugh (1986) and Fama and French (1989) identify as important in predicting U.S. equity returns. The dividend yield is the total cash dividends on the value-weighted CRSP index over the previous 12 months divided by the current level of the index. The default spread is the yield differential between Moody's Baa-rated and Aaa-rated bonds. The term spread is the yield differential between Treasury bonds with more than ten years to maturity and Treasury bills that mature in three months.

The results in Panel A of Table 2 indicate that incorporating predictability in hedge fund risk loadings and benchmark returns delivers much better out-of-sample performance. For example, the ND portfolio that excludes all forms of predictability yields a Fung and Hsieh (2004) alpha of 2.59 percent per year that is statistically indistinguishable from zero at the ten percent level. In contrast, the PD-1 and PD-2 portfolios generate statistically significant (at the five percent level) alphas of 6.19 and 6.21 percent per year, respectively. However, compared to mutual funds (Avramov and Wermers, 2006), there is much less evidence to indicate that incorporating predictability in managerial skills results in superior ex-post performance. The agnostic that incorporates predictability in alpha, betas, and benchmarks (i.e., PA-4) can harvest an alpha of 9.29 percent per year, which is only somewhat better than the dogmatist who allows for predictability in betas and benchmarks (i.e., PD-2).

[Please insert Table 2 here]

One view is that incorporating predictability in managerial skills is more important when investing in mutual funds than when investing in hedge funds. Another view is that the macroeconomic variables best suited for predicting hedge fund managerial skills differ from those best suited to mutual funds. One such macroeconomic variable may be VIX or the Chicago Board Options Exchange Volatility Index. VIX is constructed using the implied volatilities of a wide range of S&P 500 index options and is meant to be a forward looking measure of market risk. According to anecdotal evidence from the financial press, some hedge fund investment styles (e.g., convertible arbitrage and trend following) outperform at times of high market volatility while others perform better at times of low market volatility. Hence, conditioning on VIX may allow one to better predict managerial skills by timing the performance of hedge fund investment styles over the volatility cycle.

To test this, we replace one of the business cycle variables (dividend yield) with a measure of VIX, i.e., the lagged one-month high minus low VIX (henceforth VIX range), and redo the out-of-sample analysis. Similar inferences obtain when using contemporaneous monthly VIX, lagged one-month VIX, or standard deviation of VIX. Replacing the other business cycle variables with VIX range also delivers similar results. The results reported in Panel B of Table 2 indicate that hedge fund investors are rewarded for incorporating predictability in managerial skills, at least when part of that predictability is conditioned on some measure of market volatility. After including VIX range in the set of macroeconomic variables, the PA-4 agnostic who allows for predictability in alpha, betas, and benchmarks, can achieve an out-of-sample alpha of 12.34 percent per year. This is over nine percent per year higher than the alpha for the investor who excludes predictability altogether (ND), and over four percent per year higher than the alphas for investors who allow for predictability in betas and benchmarks only (PD-1, PD-2, PS-1, PS-2, PA-1, and PA-2). By comparing our results with those of Kosowski, Naik, and Teo (2007) who evaluate the out-of-sample performance of a similar set of hedge funds, we find that the PA-4 investor also outperforms the investor who invests in the top ten percent of funds based on past two-year OLS alpha (henceforth T10) or on past two-year Bayesian posterior alpha (KNT). Relative to our PA-3 and PA-4 investors, the T10 and KNT investors earn lower ex-post Fung and Hsieh (2004) alphas of 6.60 and 8.21 percent per year, respectively.[5]

One concern is that our results may not be robust across investment styles. That is, the benefits to predicting managerial skills in hedge fund space may be driven by predictability in the performance of a certain investment style only. To check this, we redo the out-of-sample optimal portfolio analysis on each of our major investment styles including Equity long/short, Directional traders, Multi-process, Relative value, Security selection, and Fund of Funds. The results reported in Table 3 reveal that incorporating predictability in managerial skills (PA-3, PA-4, PS-3, and PS-4) is important in identifying hedge funds that outperform their peers within the same investment style. This is true for all investment styles except for Relative Value and Fund of Funds. For example for Equity long/short funds, the NA strategy generates a statistically insignificant alpha of -3.70 percent per year while the PA-4 strategy achieves a statistically

[5] Please see the results in Panel A, Table 5 of Kosowski, Naik, and Teo (2007).

significant (at the five percent level) alpha of 9.84 percent per year. Similarly, for Directional trader funds, the PA-4 strategy generates an alpha that is more than twice that generated by the NA strategy. The same can be said of Security Selection funds. For Multi-process fund, while the PA-4 strategy no longer generates impressive alphas, the PA-3, PS-3, and PS-4 strategies still deliver strong out-of-sample performance. Strategies based on predictable skills perform worse within the Relative Value than the groups examined above. For Relative Value funds the PA-4, PS-3, and PS-4 strategies underperform many of the other strategies.

The superior performance of the PA-4 strategy for Directional Trader compared with the Relative Value funds is consistent with differences in the investment approach of these groups described in Section 2. Directional Trader funds usually bet on the direction of various markets while Relative Value funds take positions on spread relations between prices and aim to minimize market exposure. The set of predictor variables appears to allow investors to achieve superior performance when exploiting predictability in the skill of Directional Trader funds but the same is not true for Relative Value funds.

Similarly, for Fund of Funds, the strategies that exclude predictability but allow for the possibility of managerial skills (i.e., NS and NA) do well relative to the other strategies. Hence, one gets considerably less mileage when predicting the returns of Fund of Funds with the volatility measure we consider. This is consistent with previous studies that show that investments in Funds of Funds perform relatively poorly and that this may be due to the additional level of fees that they charge.

[Please insert Table 3 here]

One can also quibble about how our results are tainted by the various self-selection induced biases (Ackermann, McEnally, and Ravenscraft, 1999; Fung and Hsieh, 2004) affecting hedge fund data. By focusing on the post-1993 period, we sidestep most of the survivorship issues with hedge fund data since the databases include dead funds after December 1993. However, we have yet to address backfill and incubation bias which tends to inflate the early return observations of each fund. Moreover, there are concerns that the alpha *t*-statistics and Sharpe ratios of the optimal portfolios may be inflated due to illiquidity-induced serial correlation (Getmansky, Lo, and Makarov, 2004). The idea is that funds have some discretion in pricing their illiquid securities and the tendency is to artificially smooth prices so as to inflate risk-adjusted measures like the Sharpe ratio. Finally, the imputation of fund fees may cloud the analysis. The Bayesian optimization algorithm may, in a perverse fashion, pick out funds with low fees and, hence, high post-fee returns. To address these issues, we redo the analysis for pre-fee fund returns, for unsmoothed returns using the Getmansky, Lo and Makarov (2004) algorithm,[6] and after dropping the first 12 months of returns for each hedge fund. The results in Table 4 indicate that our baseline results are not, for the most part, driven by fund fees, illiquidity-induced serial correlation, or backfill and incubation bias. Whether we conduct the out-of-sample analysis on pre-fee returns, unsmoothed returns, or backfill and incubation bias adjusted returns, we find that the investors who allow for predictability in managerial skills (e.g., PA-3 and PA-4) significantly outperform those who do not allow for any predictability in managerial skills (e.g., NA, PA-1, and PA-2). As a final robustness check, we redo the analysis with portfolios formed every six months and every quarter, and report the results in Table 5. Since the portfolios are now based on more recent data, it is not surprising that many of the ex-post alphas increase when the portfolios are reformed more frequently. We note that allowing for predictability in managerial skills matters whether or not we reform every year, every six months

[6] 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. The appendix details how we map the Getmansky, Lo, and Makarov (2004) fund categories to our categories.

or every quarter. With semi-annual or quarterly reforming, the PA-4 strategy still dominates the NA, PA-1, and PA-2 strategies.

[Please insert Tables 4 and 5 here]

It is interesting to evaluate the characteristics of the funds in each of the 13 optimal portfolios. If we find that for each portfolio, funds are chosen from a variety of investment styles, then it provides additional evidence against the assertion that the high portfolio returns are driven by anomalous returns in a specific style. Table 6 reports the investment style composition, the average (over time) assets under management, and the average fund age for each of the 13 portfolios. The results suggest that each portfolio includes funds from a variety of investment styles but that the most successful strategies (PA-4, PS-3, PS-4) have a relatively higher weight in Directional Traders and a relatively lower weight in Relative Value funds. As we saw in Table 3, some of the most (least) impressive performance can be achieved by applying strategies based on skill predictability within the Directional Traders (Relative Value) group. Thus, the relatively large holding of Directional Traders goes some way towards explaining the superior performance of the best strategy (PA-4). Moreover, the portfolios that incorporate predictability in managerial skill differ somewhat from the other portfolios in terms of the age profile. The more successful strategies tend to hold funds that are of intermediate age and that may have established a good track record but that have not yet suffered any adverse effects potentially associated with maturity. Differences in performance can be further explained by going beyond fund characteristics.

[Please insert Table 6 and Figure 1 here]

For a different look at the performance of the various optimal portfolios, in Figure 1, we plot the cumulative returns of the PA-4 investor against those of the S&P 500, the portfolio that invests in the top ten percent of funds based on past two-year alpha (henceforth, T10), and the equal-weighted investment in the Fung and Hsieh (2004) seven factors (henceforth, EW). We find that strategy that incorporates predictability in managerial skills (i.e., PA-4) performs reasonably well in good times (when the S&P 500 index is rising) and performs very well in bad times (when the S&P 500 index is falling). An investor who invests $10,000 in the PA-4 portfolio at the start of the sample period will be relatively insulated from the post 2000 market downturn and have over $32,000 at the end of the sample period. This is much higher than what investors who invest the same amount in the S&P 500, the T10 portfolio, or the EW portfolio will have. In particular, a $10,000 investment each in the S&P 500, the T10 portfolio, and the EW portfolio translates to about $16,000, $20,000, and $13,000, respectively, at the end of the sample period. Consistent with the results of Avramov and Wermers (2006), we find that allowing for predictability in managerial skills pays off most handsomely during bad times.

4. Conclusion

The hedge fund industry rests primarily on the premise that active fund management adds value. Yet most of the extant academic work on hedge funds suggests that hedge fund managers are bereft of active fund management skills. In particular, these studies conclude that hedge funds on average underperform their benchmarks and that hedge fund performance does not persist. By examining the optimal hedge fund portfolios of investors with different beliefs on managerial skills and predictability, we show that incorporating predictability in managerial skills is important when investing in hedge funds. The strategy that allows for predictability in managerial alpha, fund betas, and benchmark returns outperform ex-post those that exclude predictability altogether or allow for predictability in betas and factor returns only. Moreover, this strategy outperforms when it is most appreciated – during market downturns. Such overperformance is driven at least partly by the ability to identify funds in investment objectives such as directional traders where strategies based on predictable skill are particularly successful. Clearly, while not all hedge funds outperform their benchmarks, a subgroup of hedge funds do, and incorporating predictability based on macro and volatility variables is key to identifying these funds. Our results are robust to various considerations including adjustments for backfill bias, incubation bias, illiquidity-induced serial correlation, fund fees and realistic annual rebalancing horizons.

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Table 1. List of Investor Types: Names, Beliefs, and the Different Strategies They Represent

This table describes the various investor types considered in this paper following Avramov and Wermers (2006), each of which represents a unique trading strategy. Investors differ in a few dimensions, namely, their belief in the possibility of active management skills, their belief of whether these skills are predictable, and their belief of whether fund risk loadings and benchmark returns are predictable. Predictability refers to the ability of a combination of four macro variables (the dividend yield, the default spread, the term spread, and the Treasury yield) and the range of the VIX index to predict future fund returns. The dogmatists completely rule out the possibility of active management skills, the agnostics are completely diffuse about that possibility, and the skeptics have prior

1. ND:	no predictability, dogmatic about no managerial skills.
2. PD-1:	predictable betas, dogmatic about no managerial skills.
3. PD-2:	predictable betas and factors, dogmatic about no managerial skills.
4. NS:	no predictability, skeptical about no managerial skills.
5. PS-1:	predictable betas, skeptical about no managerial skills.
6. PS-2:	predictable betas and factors, skeptical about no managerial skills.
7. PS-3:	predictable alphas,skeptical about no managerial skills.
8. PS-4:	predictable alphas, betas, and factors, skeptical about no managerial skills.
9. NA:	no predictability, agnostic about no managerial skills.
10. PA-1:	predictable betas, agnostic about no managerial skills.
11. PA-2:	predictable betas and factors, agnostic about no managerial skills.
12. PA-3:	predictable alphas, agnostic about no managerial skills.
13. PA-4:	predictable alphas, betas, and factors, agnostic about no managerial skills.

Table 2. Portfolio Strategies For Different Predictor Models

The table reports various performance measures for evaluating portfolio strategies that are optimal from the perspective of the 13 investor types described in Table 1. Portfolio strategies for the 13 investor types are formed assuming these investors use the market benchmark to form expectations about future moments for asset allocation. Investors rebalance portfolios every 12 months and use the preceding 24 months to form expectations about moments. Performance is evaluated using ex post excess returns from January 1996 until December 2002 generated using a recursive scheme. The 'T10' column reports results for a strategy that selects the top 10% of funds every January based on past 24 month alphas. The evaluation measures are as follows: Mean is the annual average realized excess return, Stdv is the annual standard deviation, SR is the annual Sharpe ratio, skew is the skewness of monthly regression residuals, kurt is the kurtosis of monthly regression residuals. 'afhnr' is the annualized intercept obtained by regressing the realized excess returns on the Fung and Hsieh (2004) seven factor model. SNP, SCMLC, BD10RET BAAMTSY, PTFSBD, PTFSFX, and PTFSCOM are the slope coefficients from the seven factor model described in the text. P-values are reported below the alphas. Panel A reports results for the predictor model that includes the macro variables dividend yield, default spread, term spread and Treasury yield. Panel B reports results for the predictor model that includes the monthly range (high minus low) of the VIX, the default spread, the term spread and the Treasury yield.

Panel A. Four macro predictor variables (dividend yield, default spread, term spread and Treasury yield)

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	5.99	7.20	7.41	2.89	3.05	4.67	14.06	6.04	1.78	2.52	3.75	7.76	10.58	7.86
Stdv	15.64	5.92	5.91	14.38	9.29	8.67	17.64	14.20	16.05	9.96	10.06	9.11	12.68	9.60
SR	0.38	1.22	1.25	0.20	0.33	0.54	0.80	0.43	0.11	0.25	0.37	0.85	0.83	0.82
skew	-0.35	-0.17	-0.22	-0.28	-0.94	-0.59	-0.17	0.07	-0.02	-0.78	-0.60	-0.63	0.10	0.34
kurt	2.30	4.08	3.99	4.05	4.65	3.75	3.16	3.21	4.05	4.35	4.08	3.12	3.82	4.40
afhnr	2.59	6.19	6.21	2.62	3.16	4.49	10.97	4.60	1.49	2.33	3.13	6.24	9.29	6.60
pafhnr	0.12	0.00	0.00	0.57	0.25	0.04	0.03	0.20	0.78	0.46	0.28	0.02	0.01	0.01
SNP	0.86	0.25	0.24	0.19	0.16	0.24	0.44	0.43	0.23	0.15	0.24	0.18	0.38	0.29
SCMLC	0.30	0.19	0.20	0.31	0.13	0.17	0.54	0.48	0.36	0.14	0.18	0.27	0.43	0.40
BD10RET	0.08	0.11	0.15	-0.20	-0.25	-0.23	0.40	0.03	-0.29	-0.23	-0.21	0.20	0.08	0.20
BAAMTSY	0.06	0.14	0.23	0.97	0.68	0.52	1.12	0.66	0.84	0.72	0.62	0.68	0.49	0.34
PTFSBD	0.00	-0.01	-0.01	0.00	-0.01	-0.01	-0.02	-0.02	0.01	0.01	0.01	0.00	-0.03	-0.02
PTFSFX	0.00	0.00	0.00	-0.02	-0.01	-0.01	-0.03	0.01	-0.02	-0.02	-0.01	-0.01	0.01	0.00
PTFSCOM	0.02	0.01	0.01	0.05	0.03	0.03	0.01	0.01	0.05	0.03	0.03	0.01	0.01	0.04

Panel B. Four macro predictor variables (VIX, default spread, term spread and Treasury yield)

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	5.99	6.55	9.26	2.89	4.66	7.01	10.16	12.17	1.78	5.54	6.93	5.22	13.69	7.86
Stdv	15.64	5.92	6.62	14.38	8.10	7.11	18.28	15.84	16.05	9.52	8.56	9.56	12.99	9.60
SR	0.38	1.11	1.40	0.20	0.58	0.99	0.56	0.77	0.11	0.58	0.81	0.55	1.05	0.82
skew	-0.35	-0.22	-0.22	-0.28	-1.22	-0.46	-0.13	-0.06	-0.02	-0.77	-0.35	-0.19	0.16	0.34
kurt	2.30	4.03	3.42	4.05	6.10	3.70	2.83	3.07	4.05	4.62	4.00	2.22	2.79	4.40
afhnr	2.59	5.56	7.75	2.62	4.87	6.48	8.74	10.85	1.49	5.47	6.30	4.47	12.34	6.60
pafhnr	0.12	0.00	0.00	0.57	0.09	0.02	0.09	0.01	0.78	0.12	0.04	0.10	0.00	0.01
SNP	0.86	0.25	0.19	0.19	0.02	0.03	0.44	0.48	0.23	0.04	0.10	0.22	0.43	0.29
SCMLC	0.30	0.20	0.17	0.31	0.06	0.06	0.48	0.48	0.36	0.08	0.10	0.26	0.42	0.40
BD10RET	0.08	0.10	0.32	-0.20	-0.08	0.16	-0.20	-0.12	-0.29	-0.06	0.07	-0.10	0.02	0.20
BAAMTSY	0.06	0.10	0.24	0.97	0.61	0.54	1.00	0.68	0.84	0.69	0.58	0.65	0.45	0.34
PTFSBD	0.00	-0.01	-0.01	0.00	-0.02	-0.02	-0.01	-0.02	0.01	-0.01	-0.01	0.00	-0.02	-0.02
PTFSFX	0.00	0.00	0.00	-0.02	-0.01	0.00	0.01	0.02	-0.02	-0.01	0.01	0.00	0.02	0.00
PTFSCOM	0.02	0.01	0.00	0.05	0.02	0.00	-0.03	-0.02	0.05	0.02	0.00	0.00	0.00	0.04

Table 3. Portfolio Strategies by Investment Objective

This table reports performance measures for portfolio strategies described in Table 1 and applied to each hedge fund investment objective separately. Portfolio strategies for the 13 investor types are formed assuming these investors use the market benchmark to form expectations about future moments for asset allocation. Investors rebalance portfolios every 12 months and use the preceding 24 months to form expectations about moments. The 'T10' column reports results for a strategy that selects the top 10% of funds every January based on past 24 month alphas. Performance is evaluated using ex post excess returns from January 1996 until December 2002 generated using a recursive scheme. The evaluation measures are as follows: Mean is the annual average realized excess return, Stdv is the annual standard deviation, SR is the annual Sharpe ratio, skew is the skewness of monthly regression residuals, kurt is the kurtosis of monthly regression residuals. afhnr is the annualized intercept obtained by regressing the realized excess returns on the Fung and Hsieh (2004) seven factor model. SNP, SCMLC, BD10RET, BAAMTSY, PTFSBD, PTFSFX and PTFSCOM are the slope coefficients from the seven factor model described in the text. P-values are reported below the alphas. The predictor model includes the monthly range (high minus low) of the VIX, the default spread, the term spread and the Treasury yield. Panel A-F report results for investment objectives which are described in detail in the text.

Panel A. Long Short Equity Funds

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	6.75	8.48	10.55	0.48	2.30	6.73	9.76	11.01	-2.00	2.65	5.87	8.36	12.38	6.85
Stdv	16.04	7.76	8.05	13.92	6.95	7.47	16.34	12.41	18.14	8.54	8.87	12.91	12.78	11.39
SR	0.42	1.09	1.31	0.03	0.33	0.90	0.60	0.89	-0.11	0.31	0.66	0.65	0.97	0.60
skew	-0.35	-0.21	-0.19	-0.09	-0.33	-0.40	-0.40	-0.06	-0.33	-0.39	-0.58	-0.09	0.00	0.24
kurt	2.28	4.06	3.95	2.85	3.19	3.39	3.15	2.94	4.32	3.50	3.75	3.05	2.94	3.75
afhnr	3.31	6.93	8.50	-1.06	2.27	5.83	7.19	8.70	-3.70	1.92	4.40	6.33	9.84	5.86
pafhnr	0.03	0.00	0.00	0.79	0.31	0.04	0.14	0.01	0.46	0.47	0.16	0.07	0.00	0.02
SNP	0.90	0.38	0.34	0.40	0.16	0.11	0.49	0.47	0.54	0.21	0.19	0.40	0.50	0.39
SCMLC	0.30	0.23	0.20	0.47	0.18	0.16	0.41	0.38	0.46	0.16	0.15	0.38	0.39	0.53
BD10RET	0.03	0.11	0.32	-0.09	-0.08	0.21	0.13	0.21	-0.41	-0.12	0.12	0.08	0.21	0.00
BAAMTSY	0.00	0.02	0.13	0.43	0.14	0.08	0.81	0.40	0.65	0.45	0.39	0.67	0.40	0.14
PTFSBD	0.01	-0.01	-0.02	0.03	-0.01	0.00	0.01	-0.01	0.06	0.02	0.02	0.01	0.00	-0.01
PTFSFX	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.01
PTFSCOM	0.02	0.01	0.00	0.03	0.04	0.01	0.01	-0.01	0.03	0.03	0.01	0.02	0.00	0.04

Panel B. Directional Trader

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	7.27	7.06	11.01	10.82	7.42	9.45	13.62	15.97	8.80	8.07	8.88	11.76	15.52	9.93
Stdv	14.57	6.18	7.93	14.64	8.05	7.64	20.16	17.16	16.79	8.75	8.89	15.26	16.51	13.38
SR	0.50	1.14	1.39	0.74	0.92	1.24	0.68	0.93	0.52	0.92	1.00	0.77	0.94	0.74
skew	-0.17	0.62	0.62	0.06	-0.48	-0.28	-0.10	0.15	0.27	-0.45	-0.28	0.17	0.30	0.10
kurt	2.63	5.07	3.80	3.37	3.14	2.87	2.69	3.21	3.55	3.35	3.09	4.29	3.88	3.62
afhnr	4.63	6.13	9.69	8.49	6.87	8.55	11.57	14.18	6.55	7.15	7.76	10.65	14.38	8.12
pafhnr	0.12	0.00	0.00	0.03	0.00	0.00	0.04	0.00	0.16	0.01	0.00	0.03	0.00	0.06
SNP	0.60	0.19	0.06	0.43	0.11	0.06	0.46	0.50	0.44	0.13	0.15	0.28	0.47	0.24
SCMLC	0.43	0.18	0.13	0.57	0.20	0.16	0.50	0.51	0.68	0.23	0.22	0.31	0.49	0.42
BD10RET	0.18	0.11	0.36	0.30	0.02	0.13	-0.08	-0.02	0.22	0.09	0.09	-0.03	0.01	0.37
BAAMTSY	0.57	0.28	0.38	0.47	0.52	0.66	1.08	0.73	0.43	0.59	0.66	0.91	0.39	0.73
PTFSBD	-0.02	-0.01	-0.01	-0.02	-0.02	-0.01	-0.02	-0.02	-0.01	-0.02	-0.01	-0.03	-0.04	0.00
PTFSFX	-0.01	0.00	0.02	-0.01	-0.01	0.00	-0.02	-0.01	-0.02	-0.01	-0.01	-0.02	0.00	0.01
PTFSCOM	0.02	0.00	-0.01	0.01	-0.03	-0.03	-0.06	-0.01	0.00	-0.03	-0.03	-0.02	0.01	0.06

Panel C. Multi-Process Funds

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	7.73	6.98	10.90	-2.11	-0.01	0.72	11.73	7.62	-2.34	-0.12	0.70	12.09	0.92	9.72
Stdv	13.42	6.37	6.84	11.99	9.81	13.47	18.40	15.10	12.06	9.90	13.60	18.65	15.91	8.77
SR	0.58	1.10	1.59	-0.18	0.00	0.05	0.64	0.50	-0.19	-0.01	0.05	0.65	0.06	1.11
skew	-0.93	-0.30	-0.52	-1.26	-1.82	-1.04	-0.73	-0.69	-1.15	-1.80	-1.03	-0.72	-0.60	-0.52
kurt	4.33	4.92	3.74	6.33	7.65	7.32	4.37	5.41	6.43	7.49	7.14	4.24	5.04	4.99
afhnr	9.03	8.27	11.34	0.40	1.98	4.11	15.66	9.90	0.00	1.84	4.15	16.51	3.19	8.92
pafhnr	0.00	0.00	0.00	0.94	0.64	0.45	0.02	0.09	1.00	0.67	0.45	0.02	0.59	0.00
SNP	0.63	0.15	0.10	0.18	0.12	0.15	0.24	0.20	0.19	0.12	0.15	0.24	0.28	0.22
SCMLC	0.36	0.18	0.15	0.04	0.14	0.25	0.45	0.40	0.04	0.12	0.24	0.45	0.41	0.27
BD10RET	0.12	-0.07	0.27	-0.17	-0.15	-0.27	-0.17	-0.18	-0.16	-0.14	-0.28	-0.23	-0.10	0.17
BAAMTSY	0.09	0.15	0.41	0.11	0.05	0.20	0.73	0.28	0.08	0.04	0.20	0.73	0.45	0.44
PTFSBD	-0.02	-0.02	-0.03	-0.03	-0.03	-0.06	-0.07	-0.04	-0.03	-0.03	-0.06	-0.07	-0.04	-0.03
PTFSFX	0.01	-0.02	0.02	-0.02	-0.04	-0.04	-0.05	-0.06	-0.02	-0.03	-0.04	-0.04	-0.03	0.00
PTFSCOM	-0.01	0.01	0.01	0.02	0.02	0.04	0.05	0.04	0.02	0.02	0.04	0.06	0.02	0.03

Panel D. Relative Value Funds

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	-1.30	4.04	5.91	2.04	5.15	6.95	-1.21	0.49	1.54	5.50	7.22	8.14	3.16	8.94
Stdv	16.63	4.27	5.11	11.19	8.24	8.21	12.52	14.20	11.18	7.98	8.43	13.89	12.51	7.09
SR	-0.08	0.95	1.16	0.18	0.62	0.85	-0.10	0.03	0.14	0.69	0.86	0.59	0.25	1.26
skew	-0.32	0.20	-0.49	0.35	-0.59	0.32	-0.13	-0.49	0.31	-0.55	0.46	1.50	0.57	0.38
kurt	2.18	3.38	2.91	3.10	3.65	3.20	3.50	5.29	3.31	3.79	3.67	6.79	5.94	4.80
afhnr	0.75	3.90	4.87	1.92	5.66	7.68	-0.14	1.10	1.38	5.84	7.93	6.75	3.65	7.89
pafhnr	0.63	0.00	0.04	0.72	0.12	0.05	0.98	0.86	0.80	0.10	0.05	0.28	0.52	0.00
SNP	0.88	0.14	0.06	0.14	-0.04	0.02	0.25	0.21	0.08	-0.06	0.01	-0.06	0.14	0.19
SCMLC	0.14	0.14	0.02	0.12	0.04	0.05	0.08	0.05	0.13	0.05	0.04	0.09	0.07	0.26
BD10RET	0.15	0.09	0.25	0.36	0.08	0.16	0.29	0.07	0.32	0.08	0.18	0.49	0.11	0.25
BAAMTSY	0.14	0.04	0.24	0.13	0.16	0.17	0.78	0.66	0.14	0.12	0.19	0.48	0.51	0.15
PTFSBD	0.00	-0.01	0.00	-0.02	-0.03	-0.04	-0.03	0.00	-0.02	-0.03	-0.04	-0.04	-0.01	-0.02
PTFSFX	0.00	-0.01	0.01	0.00	-0.06	-0.02	0.05	0.08	0.00	-0.05	-0.02	0.07	0.08	0.00
PTFSCOM	0.01	0.00	-0.02	0.02	0.02	0.02	0.01	-0.03	0.02	0.02	0.02	-0.05	-0.03	0.02

Panel E. Security Selection

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	1.28	5.64	8.28	-1.16	1.72	3.54	4.91	9.80	-4.58	1.53	4.11	6.80	12.01	6.29
Stdv	16.65	7.40	7.09	15.86	8.10	9.27	19.98	13.75	18.99	10.62	9.75	17.17	13.99	10.64
SR	0.08	0.76	1.17	-0.07	0.21	0.38	0.25	0.71	-0.24	0.14	0.42	0.40	0.86	0.59
skew	-0.22	0.27	0.11	0.00	-0.58	-0.28	-0.22	-0.22	-0.09	-0.43	-0.60	-0.16	0.14	0.27
kurt	2.05	3.27	3.44	3.00	3.91	3.91	2.29	3.21	3.70	3.41	3.53	2.61	2.78	3.94
afhnr	3.43	5.74	7.46	-0.49	3.33	3.11	6.03	10.46	-2.86	2.55	3.76	6.99	12.69	5.34
pafhnr	0.12	0.00	0.01	0.93	0.31	0.48	0.36	0.03	0.68	0.53	0.39	0.20	0.00	0.03
SNP	0.86	0.31	0.15	0.37	0.21	0.13	0.70	0.47	0.46	0.27	0.20	0.47	0.50	0.37
SCMLC	0.32	0.21	-0.01	0.44	0.13	0.06	0.47	0.23	0.41	0.11	0.06	0.47	0.36	0.50
BD10RET	0.06	0.09	0.28	-0.31	-0.05	0.36	0.30	0.01	-0.58	-0.07	0.31	0.27	0.14	0.02
BAAMTSY	0.00	0.03	0.40	0.22	0.22	0.23	0.70	0.26	0.27	0.53	0.49	1.05	0.33	0.11
PTFSBD	0.00	0.00	-0.01	0.05	-0.01	-0.01	0.01	0.01	0.07	0.02	0.00	0.02	0.00	-0.01
PTFSFX	0.00	-0.01	-0.01	-0.01	0.01	0.03	0.00	0.00	-0.02	0.01	0.02	-0.02	-0.01	0.01
PTFSCOM	0.03	0.00	-0.02	0.02	0.02	0.00	0.05	-0.01	0.04	0.02	0.00	0.04	0.02	0.03

Panel F. Funds of Funds

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	0.27	2.76	4.76	5.30	4.66	2.88	-1.16	2.54	2.52	4.09	2.65	-5.30	1.58	3.68
Stdv	12.04	6.05	8.90	10.75	8.57	6.83	13.75	10.32	10.38	8.83	6.99	13.39	11.01	11.38
SR	0.02	0.46	0.53	0.49	0.54	0.42	-0.08	0.25	0.24	0.46	0.38	-0.40	0.14	0.32
skew	0.34	0.59	0.48	0.14	-0.22	-0.19	0.14	0.66	0.07	-0.09	-0.26	0.09	0.50	0.36
kurt	3.85	4.88	4.24	3.95	3.94	3.42	2.17	3.93	3.87	3.91	3.65	2.64	3.50	4.74
afhnr	1.03	2.65	3.05	4.64	3.97	2.26	-2.86	3.30	2.23	3.48	2.20	-7.02	2.27	1.09
pafhnr	0.77	0.20	0.43	0.27	0.21	0.44	0.56	0.31	0.61	0.29	0.46	0.13	0.50	0.75
SNP	0.41	0.13	0.04	0.10	0.09	0.03	0.31	0.26	0.08	0.10	0.04	0.30	0.29	0.23
SCMLC	0.40	0.23	0.14	0.32	0.29	0.15	0.48	0.36	0.26	0.31	0.17	0.47	0.42	0.25
BD10RET	0.10	0.08	0.28	0.33	0.19	0.08	0.11	-0.05	0.25	0.18	0.05	0.14	-0.02	0.65
BAAMTSY	0.19	0.08	0.34	0.67	0.36	0.26	0.31	0.27	0.67	0.35	0.22	0.48	0.23	0.81
PTFSBD	-0.02	-0.02	0.01	-0.01	-0.02	-0.01	0.05	0.00	-0.01	-0.02	-0.02	0.04	0.00	-0.01
PTFSFX	0.00	0.00	0.06	0.01	0.02	0.01	-0.01	-0.02	0.00	0.02	0.01	0.00	-0.02	0.02
PTFSCOM	0.01	-0.01	-0.03	0.01	-0.02	-0.03	0.00	0.02	0.02	-0.02	-0.03	-0.01	0.02	0.07

Table 4. Robustness Checks

This table reports robustness checks after adjusting for fund fees, serial correlation and back fill biases. The table reports various performance measures for evaluating portfolio strategies that are optimal from the perspective of the 13 investor types described in Table 1. Portfolio strategies for the 13 investor types are formed assuming these investors use the market benchmark to form expectations about future moments for asset allocation. Investors rebalance portfolios every 3 months and use the preceding 24 months to form expectations about moments. The 'T10' column reports results for a strategy that selects the top 10% of funds every January based on past 24 month alphas. Performance is evaluated using ex post excess returns from January 1996 until December 2002 generated using a recursive scheme. The evaluation measures are as follows: Mean is the annual average realized excess return, Stdv is the annual standard deviation, SR is the annual Sharpe ratio, skew is the skewness of monthly regression residuals, kurt is the kurtosis of monthly regression residuals. Afhnr is the annualized intercept obtained by regressing the realized excess returns on the Fung and Hsieh (2004) seven factor model. SNP, SCMLC, BD10RET, BAAMTSY, PTFSBD, PTFSFX and PTFSCOM are the slope coefficients from the seven factor model described in the text. P-values are reported below the alphas. The predictor model includes the monthly range (high minus low) of the VIX, the default spread, the term spread and the Treasury yield. For convenience Panel A reports the baseline results from Panel B in Table 2. Panel B reports results for returns gross of fees. Panel C reports results after adjusting returns for serial correlation based on the procedure outlined in Getmansky, Lo and Makarov (2004). Panel D reports results after adjusting returns for backfill bias (by excluding the first 12 monthly observations in a funds life).

Panel A. Baseline Scenario - Net Returns (see Table 2)

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	5.99	6.55	9.26	2.89	4.66	7.01	10.16	12.17	1.78	5.54	6.93	5.22	13.69	7.86
Stdv	15.64	5.92	6.62	14.38	8.10	7.11	18.28	15.84	16.05	9.52	8.56	9.56	12.99	9.60
SR	0.38	1.11	1.40	0.20	0.58	0.99	0.56	0.77	0.11	0.58	0.81	0.55	1.05	0.82
skew	-0.35	-0.22	-0.22	-0.28	-1.22	-0.46	-0.13	-0.06	-0.02	-0.77	-0.35	-0.19	0.16	0.34
kurt	2.30	4.03	3.42	4.05	6.10	3.70	2.83	3.07	4.05	4.62	4.00	2.22	2.79	4.40
afhnr	2.59	5.56	7.75	2.62	4.87	6.48	8.74	10.85	1.49	5.47	6.30	4.47	12.34	6.60
pafhnr	0.12	0.00	0.00	0.57	0.09	0.02	0.09	0.01	0.78	0.12	0.04	0.10	0.00	0.01
SNP	0.86	0.25	0.19	0.19	0.02	0.03	0.44	0.48	0.23	0.04	0.10	0.22	0.43	0.29
SCMLC	0.30	0.20	0.17	0.31	0.06	0.06	0.48	0.48	0.36	0.08	0.10	0.26	0.42	0.40
BD10RET	0.08	0.10	0.32	-0.20	-0.08	0.16	-0.20	-0.12	-0.29	-0.06	0.07	-0.10	0.02	0.20
BAAMTSY	0.06	0.10	0.24	0.97	0.61	0.54	1.00	0.68	0.84	0.69	0.58	0.65	0.45	0.34
PTFSBD	0.00	-0.01	-0.01	0.00	-0.02	-0.02	-0.01	-0.02	0.01	-0.01	-0.01	0.00	-0.02	-0.02
PTFSFX	0.00	0.00	0.00	-0.02	-0.01	0.00	0.01	0.02	-0.02	-0.01	0.01	0.00	0.02	0.00
PTFSCOM	0.02	0.01	0.00	0.05	0.02	0.00	-0.03	-0.02	0.05	0.02	0.00	0.00	0.00	0.04

Panel B. Returns Gross of Fees

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	9.56	10.07	13.35	4.60	6.91	10.35	13.26	15.86	2.29	9.52	10.69	8.30	18.84	12.84
Stdv	15.28	5.88	6.49	15.94	8.86	7.69	18.31	15.54	18.07	9.73	8.66	9.47	12.89	10.61
SR	0.63	1.71	2.06	0.29	0.78	1.34	0.72	1.02	0.13	0.98	1.23	0.88	1.46	1.21
skew	-0.38	-0.29	-0.26	-0.21	-0.81	-0.37	-0.25	-0.22	0.05	-0.69	-0.24	-0.35	0.06	0.18
kurt	2.34	4.33	3.45	3.47	4.59	3.46	2.90	3.22	3.75	4.33	3.19	2.40	2.71	4.24
afhnr	6.41	9.19	11.95	4.15	6.97	9.66	11.48	14.41	1.78	9.36	10.04	7.60	17.17	11.52
pafhnr	0.00	0.00	0.00	0.40	0.02	0.00	0.02	0.00	0.75	0.01	0.00	0.00	0.00	0.00
SNP	0.83	0.25	0.17	0.23	0.08	0.08	0.47	0.48	0.29	0.07	0.14	0.23	0.43	0.32
SCMLC	0.28	0.19	0.15	0.39	0.12	0.11	0.49	0.45	0.49	0.13	0.15	0.25	0.41	0.44
BD10RET	0.02	0.07	0.30	-0.21	-0.10	0.12	-0.13	-0.10	-0.29	-0.03	0.05	-0.11	0.07	0.17
BAAMTSY	0.11	0.11	0.26	1.07	0.66	0.55	1.10	0.78	0.94	0.72	0.55	0.62	0.62	0.43
PTFSBD	0.00	-0.01	-0.01	0.01	-0.01	-0.01	-0.01	-0.02	0.02	-0.01	-0.01	0.00	-0.02	-0.01
PTFSFX	0.00	0.00	0.01	-0.03	-0.01	0.00	0.00	0.01	-0.02	-0.01	0.00	0.00	0.02	0.01
PTFSCOM	0.02	0.01	0.00	0.07	0.04	0.02	-0.02	-0.01	0.07	0.03	0.02	0.01	0.00	0.05

Panel C. Serial Correlation Adjusted Returns

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	6.08	6.38	8.77	2.31	4.88	7.54	10.46	13.12	1.72	5.48	6.73	5.08	14.32	7.60
Stdv	16.19	6.47	7.04	14.41	7.66	6.72	19.77	16.40	15.97	9.31	8.34	9.99	13.96	10.50
SR	0.38	0.99	1.24	0.16	0.64	1.12	0.53	0.80	0.11	0.59	0.81	0.51	1.03	0.72
skew	-0.34	-0.29	-0.33	-0.39	-1.09	-0.29	-0.11	0.03	-0.05	-0.63	-0.27	-0.15	0.16	0.45
kurt	2.20	4.05	3.30	3.95	5.24	4.19	2.64	3.04	3.98	4.16	4.24	2.24	2.81	4.69
afhnr	2.28	5.18	7.06	1.89	5.06	7.03	8.44	11.48	1.34	5.46	6.18	4.09	12.77	6.20
pafhnr	0.14	0.00	0.00	0.68	0.06	0.01	0.11	0.01	0.79	0.11	0.04	0.14	0.00	0.02
SNP	0.90	0.28	0.21	0.21	0.02	0.03	0.51	0.52	0.23	0.03	0.09	0.24	0.48	0.32
SCMLC	0.33	0.23	0.19	0.33	0.06	0.07	0.61	0.52	0.38	0.08	0.11	0.29	0.44	0.47
BD10RET	0.12	0.13	0.37	-0.21	-0.07	0.17	-0.09	-0.07	-0.27	-0.06	0.07	-0.05	0.03	0.23
BAAMTSY	0.00	0.09	0.24	0.92	0.57	0.49	1.09	0.58	0.83	0.65	0.54	0.64	0.36	0.28
PTFSBD	0.01	-0.01	-0.02	0.00	-0.02	-0.02	-0.01	-0.02	0.01	-0.01	-0.01	0.00	-0.02	-0.02
PTFSFX	0.00	0.00	0.00	-0.02	-0.02	0.00	0.00	0.01	-0.03	-0.01	0.00	0.00	0.01	0.00
PTFSCOM	0.01	0.01	0.00	0.05	0.02	0.00	-0.03	-0.02	0.05	0.02	0.00	0.00	0.00	0.05

Panel D. Backfill Bias Adjusted Returns

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	5.16	6.45	9.20	-0.78	-0.87	3.01	4.48	-0.42	-0.62	6.12	2.94	6.00	9.92	7.49
Stdv	15.64	6.19	6.76	14.78	7.99	7.22	18.22	16.92	8.92	16.73	8.04	13.05	14.33	10.02
SR	0.33	1.04	1.36	-0.05	-0.11	0.42	0.25	-0.02	-0.07	0.37	0.37	0.46	0.69	0.75
skew	-0.39	-0.12	-0.16	-0.06	-0.78	-0.49	-0.23	0.30	-0.52	-0.28	-0.25	-0.37	-0.10	0.19
kurt	2.34	3.96	3.71	3.72	4.18	3.74	2.54	4.40	3.59	3.17	3.54	3.13	2.79	4.35
afhnr	1.74	5.35	7.64	-1.50	-0.69	2.50	3.25	-0.75	-0.40	4.55	2.42	5.03	8.37	6.17
pafhnr	0.25	0.00	0.00	0.74	0.81	0.35	0.52	0.89	0.90	0.27	0.41	0.16	0.02	0.01
SNP	0.86	0.26	0.20	0.29	0.10	0.08	0.41	0.26	0.10	0.54	0.11	0.30	0.50	0.31
SCMLC	0.30	0.21	0.17	0.43	0.11	0.10	0.50	0.45	0.15	0.48	0.15	0.35	0.48	0.42
BD10RET	0.08	0.11	0.30	-0.15	-0.16	0.08	-0.25	-0.25	-0.16	-0.17	0.03	-0.24	-0.09	0.25
BAAMTSY	0.08	0.10	0.22	0.67	0.24	0.32	1.06	0.61	0.21	0.78	0.27	0.77	0.49	0.33
PTFSBD	0.00	-0.01	-0.01	0.00	-0.01	-0.01	0.00	0.00	-0.01	-0.01	-0.01	0.01	0.00	-0.02
PTFSFX	0.00	0.00	0.01	-0.02	-0.02	0.00	0.01	-0.02	-0.02	0.01	-0.01	0.00	0.01	0.00
PTFSCOM	0.02	0.01	0.00	0.04	0.02	-0.01	-0.03	0.04	0.02	0.00	-0.01	-0.01	0.01	0.05

Table 5. Out of Sample Performance for Different Rebalancing Frequencies

The table reports various performance measures for evaluating portfolio strategies that are optimal from the perspective of the 13 investor types described in Table 1. Portfolio strategies for the 13 investor types are formed assuming these investors use the market benchmark to form expectations about future moments for asset allocation. Panel A, B and C report results for when investors rebalance portfolios every 12, 6 and 3 months respectively. The 'T10' column reports results for a strategy that selects the top 10% of funds every 12, 6 and 3 months based on past 24 month alphas. Performance is evaluated using ex post excess returns from January 1996 until December 2002 generated using a recursive scheme. The evaluation measures are as follows: Mean is the annual average realized excess return, Stdv is the annual standard deviation, SR is the annual Sharpe ratio, skew is the skewness of monthly regression residuals, kurt is the kurtosis of monthly regression residuals. 'afhnr' is the annualized intercept obtained by regressing the realized excess returns on the Fung and Hsieh (2004) seven factor model. SNP, SCMLC, BD10RET BAAMTSY, PTFSBD, PTFSFX and PTFSCOM are the slope coefficients from the Fung and Hsieh (2004) seven factor model described in the text. P-values are reported below the alphas.

Panel A. Annual Rebalancing

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	5.99	6.55	9.26	2.89	4.66	7.01	10.16	12.17	1.78	5.54	6.93	5.22	13.69	7.86
Stdv	15.64	5.92	6.62	14.38	8.10	7.11	18.28	15.84	16.05	9.52	8.56	9.56	12.99	9.60
SR	0.38	1.11	1.40	0.20	0.58	0.99	0.56	0.77	0.11	0.58	0.81	0.55	1.05	0.82
skew	-0.35	-0.22	-0.22	-0.28	-1.22	-0.46	-0.13	-0.06	-0.02	-0.77	-0.35	-0.19	0.16	0.34
kurt	2.30	4.03	3.42	4.05	6.10	3.70	2.83	3.07	4.05	4.62	4.00	2.22	2.79	4.40
afhnr	2.59	5.56	7.75	2.62	4.87	6.48	8.74	10.85	1.49	5.47	6.30	4.47	12.34	6.60
pafhnr	0.12	0.00	0.00	0.57	0.09	0.02	0.09	0.01	0.78	0.12	0.04	0.10	0.00	0.01
SNP	0.86	0.25	0.19	0.19	0.02	0.03	0.44	0.48	0.23	0.04	0.10	0.22	0.43	0.29
SCMLC	0.30	0.20	0.17	0.31	0.06	0.06	0.48	0.48	0.36	0.08	0.10	0.26	0.42	0.40
BD10RET	0.08	0.10	0.32	-0.20	-0.08	0.16	-0.20	-0.12	-0.29	-0.06	0.07	-0.10	0.02	0.20
BAAMTSY	0.06	0.10	0.24	0.97	0.61	0.54	1.00	0.68	0.84	0.69	0.58	0.65	0.45	0.34
PTFSBD	0.00	-0.01	-0.01	0.00	-0.02	-0.02	-0.01	-0.02	0.01	-0.01	-0.01	0.00	-0.02	-0.02
PTFSFX	0.00	0.00	0.00	-0.02	-0.01	0.00	0.01	0.02	-0.02	-0.01	0.01	0.00	0.02	0.00
PTFSCOM	0.02	0.01	0.00	0.05	0.02	0.00	-0.03	-0.02	0.05	0.02	0.00	0.00	0.00	0.04

Panel B. Semi-Annual Rebalancing

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	6.58	9.35	8.83	10.08	9.13	8.62	14.25	16.78	11.70	10.28	9.27	12.96	19.95	9.10
Stdv	15.96	8.26	8.94	14.92	9.91	9.33	16.76	14.98	16.28	11.65	10.96	13.38	13.88	9.30
SR	0.41	1.13	0.99	0.68	0.92	0.92	0.85	1.12	0.72	0.88	0.85	0.97	1.44	0.98
skew	-0.34	0.29	-0.56	-0.11	-0.80	-0.32	-0.16	0.04	-0.04	-0.59	-0.32	-0.21	-0.08	0.31
kurt	2.25	3.22	6.32	2.90	3.78	2.59	3.40	2.93	2.71	3.07	2.56	2.73	2.82	4.78
afhnr	1.90	7.32	7.55	8.09	8.45	7.84	10.71	12.86	9.76	9.57	8.19	10.35	15.77	7.99
pafhnr	0.25	0.00	0.02	0.09	0.02	0.03	0.02	0.00	0.08	0.03	0.04	0.01	0.00	0.00
SNP	0.88	0.35	0.20	0.31	0.10	0.03	0.35	0.41	0.30	0.09	0.09	0.25	0.43	0.27
SCMLC	0.28	0.25	0.23	0.31	0.11	0.12	0.40	0.47	0.32	0.12	0.17	0.24	0.44	0.37
BD10RET	0.00	0.08	0.15	-0.21	-0.15	-0.01	-0.17	0.11	-0.26	-0.22	-0.10	-0.21	0.27	0.17
BAAMTSY	0.09	0.16	-0.08	0.59	0.34	0.35	1.13	0.69	0.49	0.40	0.44	0.80	0.53	0.41
PTFSBD	0.01	-0.02	0.00	0.01	0.00	0.00	0.00	-0.01	0.03	0.02	0.01	0.02	-0.01	-0.02
PTFSFX	0.00	0.00	0.01	-0.02	-0.02	-0.01	-0.02	-0.01	-0.02	-0.01	0.00	-0.03	-0.01	0.00
PTFSCOM	0.02	0.00	0.01	0.03	0.01	0.01	-0.01	-0.02	0.03	0.00	0.00	-0.01	-0.01	0.04

Panel C. Quarterly Rebalancing

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	T10
Mean	7.69	7.71	9.78	8.83	9.70	9.20	14.57	17.62	11.47	9.85	9.08	17.21	18.38	10.39
Stdv	16.08	9.52	9.41	16.22	11.42	10.56	15.96	14.30	17.65	12.54	12.14	15.15	13.65	9.16
SR	0.48	0.81	1.04	0.54	0.85	0.87	0.91	1.23	0.65	0.79	0.75	1.14	1.35	1.13
skew	-0.31	-0.14	0.02	-0.43	-0.45	-0.44	0.09	0.24	-0.34	-0.37	-0.44	0.56	-0.03	0.25
kurt	2.22	3.89	4.87	3.80	3.13	3.31	3.55	3.30	3.47	2.69	2.78	4.16	3.32	4.97
afhnr	3.11	5.10	7.70	6.93	8.23	8.19	11.64	14.49	9.55	8.40	7.65	14.59	15.05	9.09
pafhnr	0.07	0.00	0.01	0.20	0.05	0.04	0.03	0.00	0.13	0.07	0.09	0.01	0.00	0.00
SNP	0.88	0.43	0.25	0.33	0.12	0.09	0.25	0.35	0.28	0.14	0.17	0.23	0.33	0.25
SCMLC	0.27	0.29	0.27	0.37	0.11	0.10	0.29	0.34	0.34	0.14	0.16	0.31	0.29	0.37
BD10RET	-0.02	0.05	0.24	-0.16	-0.06	-0.02	-0.13	0.08	-0.15	-0.10	-0.08	0.14	0.23	0.23
BAAMTSY	0.07	0.22	0.18	0.44	0.59	0.37	0.57	0.40	0.46	0.47	0.36	0.24	0.54	0.50
PTFSBD	0.01	-0.02	-0.02	0.00	0.00	0.00	0.03	0.01	0.01	0.02	0.02	-0.01	-0.03	-0.02
PTFSFX	0.00	0.01	0.03	-0.01	-0.02	-0.01	-0.03	-0.01	-0.01	-0.01	-0.01	-0.04	-0.01	0.01
PTFSCOM	0.02	0.00	-0.01	0.03	0.01	0.01	-0.03	-0.01	0.02	0.01	0.02	-0.03	-0.02	0.03

Table 6. Attributes of Optimal Portfolios

The table reports several attributes of the portfolio strategies that are optimal from the perspective of the 13 investor types described in Table 1. The results are based on the baseline scenario described in Panel B of Table 2. These attributes include the percentage allocation of each strategy to different hedge fund categories, the averaged assets under management (AuM) in million USD as well as the age of the fund (measured as weighted fund start date minus 1988).

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4
LSE	58%	28%	30%	27%	32%	39%	22%	24%	32%	31%	37%	37%	33%
DT	13%	21%	22%	23%	27%	21%	57%	44%	24%	29%	22%	31%	36%
MP	3%	16%	15%	5%	8%	10%	6%	8%	4%	8%	11%	5%	7%
RV	18%	27%	25%	37%	30%	27%	11%	14%	31%	27%	25%	21%	16%
SS	9%	8%	7%	8%	3%	3%	5%	9%	9%	4%	4%	5%	8%
AuM (mil. $)	234	281	295	538	792	1326	283	331	557	476	825	226	259
Fund Age	4.6	4.7	4.8	6.6	6.4	6.1	5.6	5.4	7.0	6.6	6.4	5.1	5.6

Figure 1. Cumulative Wealth For Different Portfolio Strategies

This figure plots the cumulative wealth of an investor that invests $10,000 in four different strategies in January 1996. The strategies include the strategies PA-4 (dotted line) described in Table 1, the strategy 'T10' that invests in the top 10% of funds each year (dashed line), an investment in the S&P 500 (solid line), an equal weighted investment in the 7 Fung and Hsieh (2004) risk factors (dashed-dotted line).