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Abstract

This paper evaluates hedge fund performance through portfolio strategies that incorporate predictability in managerial skills, fund risk loadings, and benchmark returns. Incorporating predictability substantially improves performance for the entire universe of hedge funds as well as for various investment styles. The outperformance is strongest during market downturns when the marginal utility of consumption is relatively high. Moreover, the major source of investment profitability is predictability in managerial skills. In particular, long-only strategies that incorporate predictability in managerial skills outperform their Fung and Hsieh (2004) benchmarks by over 17 percent per year. The economic value of predictability obtains for different rebalancing horizons and alternative benchmark models. It is also robust to adjustments for backfill bias, incubation bias, illiquidity-induced serial correlation, fund fees, and style composition.

JEL classifications: G11; G12; G14; G23

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According to the 2008 HFR report, there were more than 10,000 hedge funds globally managing over US$1.87 trillion in assets at the end of 2007, 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, on average hedge funds 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 traced to illiquidity-induced serial correlation in fund returns. These results do not bode well for hedge funds and the high fees[1] that they charge.

Recent work on hedge funds has offered more sanguine evidence on the existence of active management skills amongst hedge fund managers. Fung, Hsieh, Naik, and Ramadorai (2008) split their sample of Funds of Funds into have-alpha and beta-only funds. They find that have-alpha funds exhibit better survival rates and experience steadier inflows than do beta-only funds. 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 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.

This paper adds to the debate on hedge fund performance by analyzing the performance of portfolio strategies that invest in hedge funds. These strategies exploit predictability, based on aggregate economic variables, in (i) fund manager asset selection and benchmark timing skills, (ii) hedge-fund risk loadings, and (iii) benchmark returns. By examining the out-of-sample investment opportunity set, we show that there exist subgroups of ex-ante identifiable hedge

[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).

funds that deliver significant outperformance. 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 mutual fund return predictability.[2] In particular, Avramov and Wermers find that predictability in managerial skills is the dominant source of investment profitability. 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 Avramov-Wermers framework 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 as well as the cross-sectional dispersion in hedge fund performance. 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 are 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. Between 1997 and 2004, an investor who allows for predictability in hedge fund alpha, beta, and benchmark returns can earn a Fung and Hsieh (2004) alpha of 17.98 percent per annum out-of-sample. This is over 10 percent per annum higher than that earned by an investor who does not allow for predictability in managerial skills, and over 13 percent per annum higher than that earned by an investor who completely excludes all 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 ex-post. 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 4.37 percent per year. Our findings about the economic value of predictability in hedge fund returns 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), and fund fees. The results also remain qualitatively unchanged when we

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

allow for realistic rebalancing horizons, remove funds that may be closed, or adjust for risk using alternative benchmark models.

We find that strategies that incorporate predictability in managerial skills significantly outperform other strategies most within the Equity Long/Short, Directional Trader, Security Selection fund style groups. They are less successful within the Multi-process and Relative Value groups, and not successful within Funds of Funds. The optimal portfolios of hedge funds which allow for predictability in managerial skills do differ somewhat from the other portfolios in terms of age and investment style composition. The former tend to hold funds that are relatively young – funds that have established a track record but may have not yet suffered any adverse effects potentially associated with maturity. Given the above-mentioned within style results, it is not surprising that the winning strategies also tend to contain a larger proportion of funds from the Directional Trader style where conditioning on managerial skills generates the greatest payoffs. Conversely, they also tend to contain fewer funds from the Relative Value style where the payoffs from conditioning on managerial skills are lower. Nonetheless, a style-based decomposition of the optimal portfolio strategy reveals that only a small part of the 17.98 percent alpha can be explained by the strategy's allocation to investment styles. In particular, a portfolio that mimics the optimal portfolio's allocations to fund styles delivers an alpha of only 6.44 percent per annum. The 11.54 percent per annum alpha spread between the optimal portfolio and the style-mimicking portfolio is economically large and statistically significant. Hence, the outperformance of the predictability based strategy cannot be simply explained by the potentially time-varying style composition of the optimally selected fund portfolio.

Consistent with Avramov and Wermers (2006), the strategy that conditions on predictable managerial skills performs reasonably well during the bull market of the 1990s and performs exceptionally well during the post-2000 market downturn. To illustrate, an initial investment of \$10,000 in this optimal portfolio translates to over \$62,000 at the end of our sample period (1997-2004). In contrast, the same initial investment in the S&P 500 yields less than \$22,000. The optimal strategy that allows for predictability in managerial skills is particularly attractive to investors with concave utility as it pays off handsomely during stock market downturns when the marginal utility of consumption is relatively high.

The rest of the paper is structured as follows. Section 1 reviews the methodology used in the analysis while Section 2 describes the data. Section 3 presents the empirical results. Section 4 concludes.

1. Methodology

Our approach follows Avramov and Wermers (2006). 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:

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

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

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

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} $\left(\beta_{i1}\right)$ 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), Brandt (1999), Barberis (2000), and Avramov (2002, 2004), 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 zero 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 zero. Further, the prior standard errors of these parameters depend on the parameter T_0. Following Avramov and Wermers (2006), the choice of T_0 is determined by the following relation

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

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, the prior uncertainty about managerial skill, is set equal to 1% per month.

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 zero 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 hedge fund 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 $\gamma_t = \left(b_t W_t\right)/\left(1 - b_t W_t\right)$ be the relative risk-aversion parameter, and letting $\Lambda_t = \left[\Sigma_t + \mu_t \mu_t^{'}\right]^{-1}$, where μ_t and Σ_t are the mean vector and covariance matrix of future fund returns, yields the following optimization

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

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). For each investor type, the mean and variance of the predictive distribution obey analytic reduced form expressions and are displayed in Avramov and Wermers (2006). 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 (see e.g., Pastor (2000), Pastor and Stambaugh (2000), Avramov (2004), and Avramov and Chordia (2006)).

Our objective is to assess the economic value, 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:

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

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 appropriately adjusted for duration, *BAAMTSY* is the change in the spread of Moody's Baa minus the 10–year Treasury also adjusted for duration, *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 (2008). In sensitivity tests, to account for hedge fund exposure to emerging market equities and to the value factor, we augment the Fung and Hsieh (2004) model with the MSCI emerging markets benchmark excess return (EM) and the Fama and French (1993) high-minus-low book-to-market factor (HML), respectively.

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 2004 - 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.

Our initial fund universe contains a total of 8,852 live hedge funds and 3,964 dead hedge funds. 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.[4] This leaves us with a total of 6,356 live hedge funds and 1,764 dead hedge funds. While there are overlaps among the hedge fund 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 (2008) and group funds into five broad investment categories: Directional Traders, Relative Value, Security

[3] Our results are robust to using pre-fee returns.
[4] The AUM cutoff is implemented every month.

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. Funds of Funds invest in a pool of hedge funds and typically have lower minimum investment requirements. We also single out Long/Short Equity, which is a subset of Security Selection, 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 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 or 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. Another concern is that the results may be confined to funds that are still reporting to the databases but are effectively closed to new investors. Since funds may not always report their closed status, we use fund monthly inflows to infer fund closure. In sensitivity tests, we exclude funds with inflows between zero and two percent per month to account for the possibility that they are effectively closed to new investors.

3. Empirical results

3.1. Out-of-sample performance

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 funds with at least 36 months of data and are reformed every twelve months. We do not reform more frequently, as in Avramov and Wermers (2006), since 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 the sample period of our baseline tests, the first portfolio is formed on January 1997 based on data from January 1994 to December 1996, and the last portfolio is formed on January 2004 based on data from January 2001 to December 2003.

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), 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 and bond 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 relatively modest Fung and Hsieh (2004) alpha of 4.47 percent per year. In contrast, the PD-1 and PD-2 portfolios generate highly statistically significant (at any conventional significance level) alphas of 9.12 and 7.12 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 10.64 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, which we confirm below, 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, Macro, 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 rerun 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, i.e., default spread, term spread, and Treasury bill yield, with VIX range also delivers similar results. The results are reported in Panel B of Table 2. The evidence indicates that hedge fund investors are highly rewarded for incorporating predictability in managerial skills, at least when part of the predictable variation in hedge fund returns 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 17.98 percent per year. This is over 13 percent per year higher than the alpha of the investor who excludes predictability altogether (ND), and over 7 percent per year higher than the alphas of 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 strategy that invests in the top ten percent of funds based on past 36-month OLS alpha (henceforth T10) or on past two-year Bayesian posterior alpha (henceforth KNT). Relative to our PA-3 and PA-4 investors, the T10 and KNT[5] investors earn lower ex-post Fung and Hsieh (2004) alphas of 4.37 and 8.21 percent per year, respectively.

3.2. Results by investment style

One concern is that our results may not be robust across investment styles. That is, the benefits to predicting managerial skills 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 for each of our major investment styles including Equity Long/Short, Directional Trader, 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 Fund of Funds. For example, for Equity Long/Short funds, the NA strategy generates an alpha of 7.09 percent per year while the PA-4 strategy achieves an alpha of 16.69 percent per year. Similarly, for Directional Trader funds, the PA-4 strategy generates an alpha (16.38 percent per year) that is much higher than that generated by the NA strategy (4.22 percent per year). The same can be said for Security Selection funds. For Relative Value and Multi-process funds, while the PA-4 strategy no longer generates

[5] We note that their sample period, which ends in 2002, is shorter than ours. Please see the results in Panel A, Table 5 of Kosowski, Naik, and Teo (2007). To be more consistent with their paper, the KNT portfolios are constructed based on two-year Bayesian posterior alpha. The results remain qualitatively unchanged when they are constructed based on three-year Bayesian posterior alpha or when we compare their results to the performance of the PA-4 portfolio between 1997 and 2002.

impressive alphas, the PA-3 strategy still delivers strong out-of-sample performance relative to the NA strategy.

Strategies based on predictable skills perform worse within the Fund of Funds group than within the other investment style groups examined above. Within 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. One possibility is that because good Fund of Funds managers successfully time hedge fund styles over the business cycle, their returns are not as correlated with macroeconomic variables and volatility.[6] Hence, one gets considerably less mileage when predicting the returns of Funds of Funds with the macroeconomic and volatility measures we consider.

[Please insert Table 3 here]

3.3. Robustness checks

One may 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 associated 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. Furthermore, some of the funds selected by the PA-4 strategy may be closed to investors following good performance without reporting a time-series variable of whether they are closed to the data providers. Exposures to emerging markets and value strategies may also require an augmented benchmark model that accounts for these exposures. Finally, the imputation of fund fees may cloud the analysis. The Bayesian

[6] To elaborate, Funds of Funds may switch into investment styles that perform well in a high volatility environment when volatility is high, and switch into investment styles that perform well in a low volatility environment when volatility is low.

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,[7] 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 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). Moreover, our results are not sensitive to either excluding funds that are closed following good performance (see Panel D) or to augmenting the Fung and Hsieh (2004) model with an emerging markets or value strategy benchmark (see Panels E and F of Table 4, respectively).[8] 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, 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]

3.4. Economic value of the optimal portfolios

To gauge the economic value 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 three-year alpha (henceforth T10), and the equal-

[7] 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.

[8] We account for closed funds by excluding fund observations when a fund has more than four monthly flows in a given calendar year that range between 0 and 2 percent. Although this may be an imperfect proxy for whether a fund has closed following good performance, we note that there is no time-series variable in the data that indicates whether a fund is closed or open in a given month. Therefore fund flows are one of the best proxies for this purpose.

weighted investment in the Fung and Hsieh (2004) seven factors (henceforth EW). We find that PA-4 strategy 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 $62,000 at the end of 2004. 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 $15,000, $22,000, and $12,000, 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.

[Please insert Figure 1 here]

3.5. The determinants of the predictability-based portfolio returns

What explains the superior performance of the PA-4 strategy? In this section, we address this question by examining each portfolio strategy's average age, size, and style composition. We seek to determine whether the PA-4 alpha can be explained by its underlying fund characteristics and style allocations.

3.5.1. Attributes of the optimal portfolios

Table 6 reports the investment style composition, the average assets under management over time, and the average fund age for each of the 13 optimal portfolios. The results suggest that each portfolio includes funds from a variety of investment styles but that the most successful strategies (PA-3, PA-4, PS-3, and PS-4) have a relatively higher weight in Directional Trader funds 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 Trader (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 their age profile. The more successful strategies (PA-3, PA-4, PS-3, and PS-4) tend to hold funds that are of intermediate age, i.e., about 5 years old. These funds may have established a good track record but may have not yet suffered any adverse effects potentially associated with maturity. Conversely, the less successful strategies (NS, PS-1, PS-2, PA-1, and PA-2) tend to hold funds that are about 7 years old. We note, however, that the less successful dogmatist portfolios (ND, PD-1, and PD-2) also hold funds that are about 5 years old.

[Please insert Table 6 here]

3.5.2. Style-based decomposition of performance

Are the differences in allocations to various hedge fund styles, e.g., Directional Trader versus Relative Value, large enough to explain the superior performance of the PA-4 strategy? To answer this question, we report in Table 7 a style-based decomposition of returns. On the first four rows of the Table 7 are the time-series average excess return (also reported in Panel B of Table 2), the average net return (μ, obtained by adding the risk-free rate to the excess return), the style return (μ_S), and the style-adjusted net return (μ -μ_S). Each month, style returns are computed by multiplying the style weight of each strategy by style level returns, which are in turn calculated as the equal-weighted average of all funds in a given investment style. The time-series average of the style-adjusted return can be interpreted as the net return achieved by each optimal portfolio over and above that generated from holding a portfolio with the same style allocation as the optimal portfolio. Clearly, the PA-4 strategy's style return of 12.98 percent per year does not explain most of the PA-4 strategy's average net return of 24.65 percent per year. In fact, the PA-4 style-adjusted net return of 11.67 percent per year is statistically different from zero at the 5 percent level.

[Please insert Table 7 here]

To understand the factors driving style return, we decompose style return into a "style passive return" ($\mu_{S,p}$), which is computed as the style-level return that accrues to a passive strategy that holds a constant allocation to each style over time and a "style timing return" (μ_S-$\mu_{S,p}$), which reflects the return earned by varying the style allocations away from the passive allocation. The results reported in Table 7 show that style passive return ($\mu_{S,p}$) is very similar across investors, ranging from 12 to 12.3 percent per year. Moreover, the difference between the passive and style return (μ_S-$\mu_{S,p}$) is insignificantly different from zero (at the 5 percent level) for all but one investor, i.e., PD-2.

So far we have not yet determined whether the superior alpha of the PA-4 strategy is explained by allocations to styles or by style-adjusted return. Therefore, we run regressions of the style and style-adjusted return on the Fung and Hsieh (2004) seven-factor benchmark model and estimate the resulting alphas. We find that for the PA-4 strategy alpha of 17.98 percent per year, only 6.44 percent per year is explained by the style level alpha. The difference of 11.54 percent is economically and statistically significant at the 5 percent level. Interestingly, the style-adjusted alpha is not significantly different from zero at the 5 percent level for all but one other strategy (i.e., the PD-1 investor). This shows that the PA-4 strategy outperforms other strategies by selecting funds within each style that deliver statistically significant alpha that is over and above that generated by the styles of the funds selected by the strategy over time.

3.5.3. Time-varying exposure to emerging markets

What else can explain the superior performance of the PA-4 portfolio? Can some of its post-2000 stellar performance be attributed to an exposure to emerging markets equities? To shed further light on the sources of outperformance of the PA-4 strategy, we decompose the excess return of the PA-4 portfolio into its alpha and beta exposure components over time. We run rolling regressions of the PA-4 portfolio excess return on the Fung and Hsieh (2004) model augmented with the MSCI emerging markets benchmark. The regressions are run with a 24-month backward looking window from December 1998 until December 2004. For each regression we save the portfolio excess return, the alpha, the beta coefficients as well as the percentage contribution of the alpha and beta exposures to the excess return.[9] Panel A of Table 8 and Figure 2 show that the alpha is time-varying, with peaks around 2000 and 2003. Moreover the exposure to emerging markets increases dramatically towards the end of the period. Panel B of Table 8 reports the average percentage contribution of alpha and beta to the excess return of the PA-4 portfolio over the 1999 to 2006 period. The table shows that most of the increase in the

[9] The alpha contribution is calculated as the monthly alpha over a 24-month rolling regression period divided by the monthly portfolio excess return. Similarly the beta contribution is calculated as the beta of benchmark multiplied by the monthly return of the benchmark during a 24-month period and divided by the average monthly portfolio excess return during the 24-month period.

PA-4 portfolio excess return between H2 2001 and H1 2003 is driven by an increase in alpha while the most of the excess return increase towards the end of the sample, i.e., H2 2003 onwards, can be explained by an exposure to emerging markets equities. These results suggest that while time-varying exposure to emerging markets may explain some of the excess returns of the PA-4 strategy, it does not explain the PA-4 strategy alpha calculated in Panel E of Table 4. In fact, the consistently high post-1999 rolling alphas reported in Panel A of Table 8 suggest that time-varying risk exposures, in general, are unlikely to explain the over performance of the PA-4 portfolio.

[Please insert Table 8 and Figure 2]

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, based on aggregate economic variables, in managerial skills is important in forming optimal portfolios of hedge funds. The strategy that allows for predictability in managerial alpha, fund betas, and benchmark returns outperforms ex-post those strategies that exclude predictability altogether or allow for predictability in betas and benchmark risk premia only. Moreover, this strategy outperforms when it is most appreciated – during market downturns. Our performance attribution analysis shows that the strategy outperforms other portfolio strategies by selecting funds that generate statistically significant alpha that is not just explained by the styles of the funds selected by the strategy over time. 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 adjustments for backfill bias, incubation bias, illiquidity-induced serial correlation, fund fees, closed funds, realistic rebalancing horizons, and alternative benchmark models.

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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 short seller, 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. Cumulative Wealth For Different Portfolio Strategies

This figure plots the cumulative wealth of an investor that invests $10,000 in four different portfolios starting in January 1997. The portfolios include the strategy PA-4 (dotted line) described in Table 1, an investment in the S&P 500 (dashed line), the strategy 'T10' that invests in the top ten percent of funds based on past three-year alpha each year (solid line), an equal-weighted investment in the seven Fung and Hsieh (2004) risk factors (dashed-dotted line). The sample period is from January 1997 to December 2004.

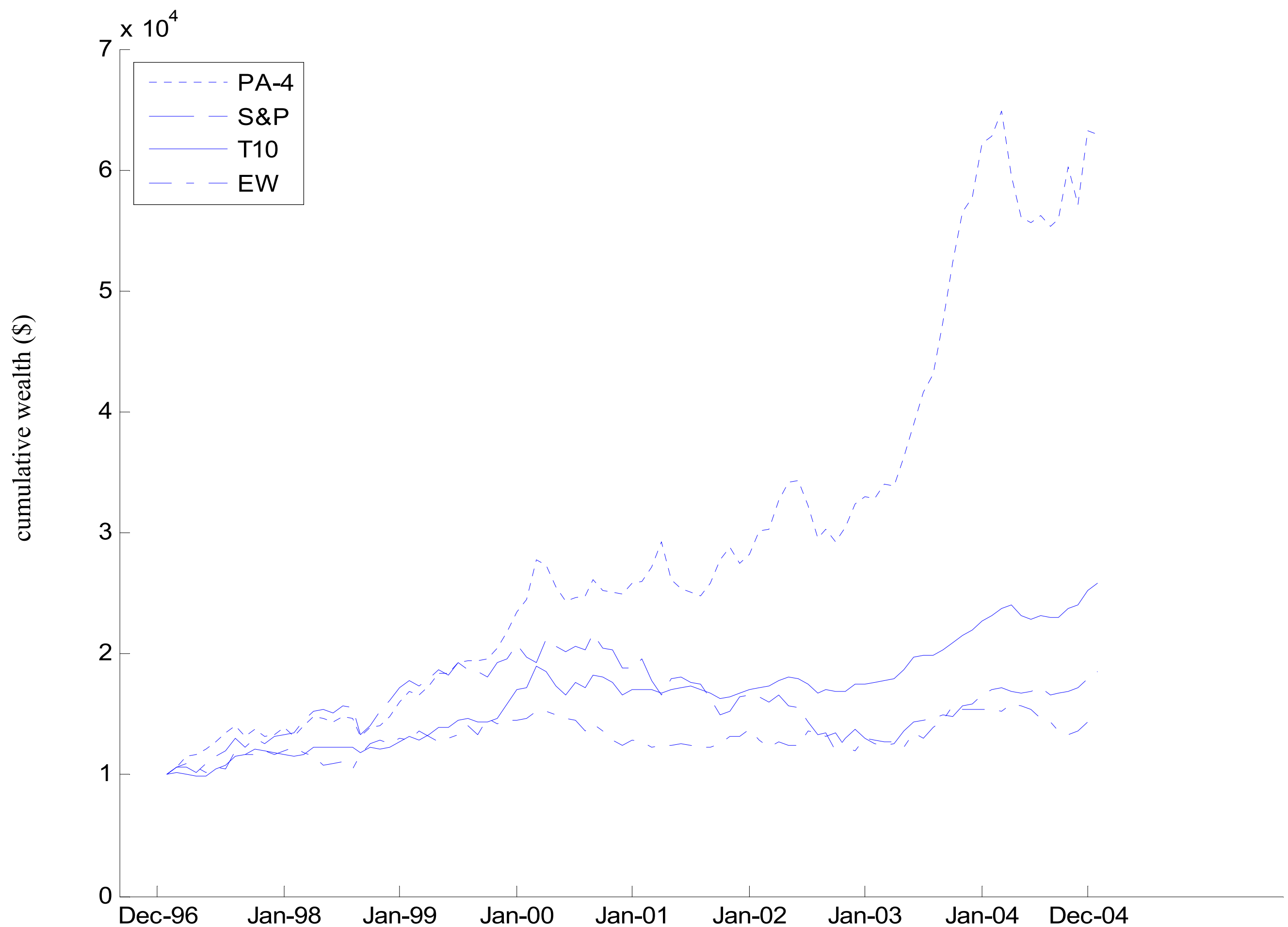

Figure 2. PA-4 Strategy Portfolio Alpha

This figure plots the alpha of the PA-4 strategy over time based on the augmented Fung and Hsieh (2004) benchmark model that includes the MSCI emerging markets benchmark. We decompose the excess return of the PA-4 portfolio into alpha and beta exposures by running rolling regressions with a 24-month backward looking window each month from December 1998 until December 2004. For each rolling regression and 24-month period, we save the monthly alpha of the PA-4 portfolio The figure reports the alpha for each month from December 1998 until December 2004.

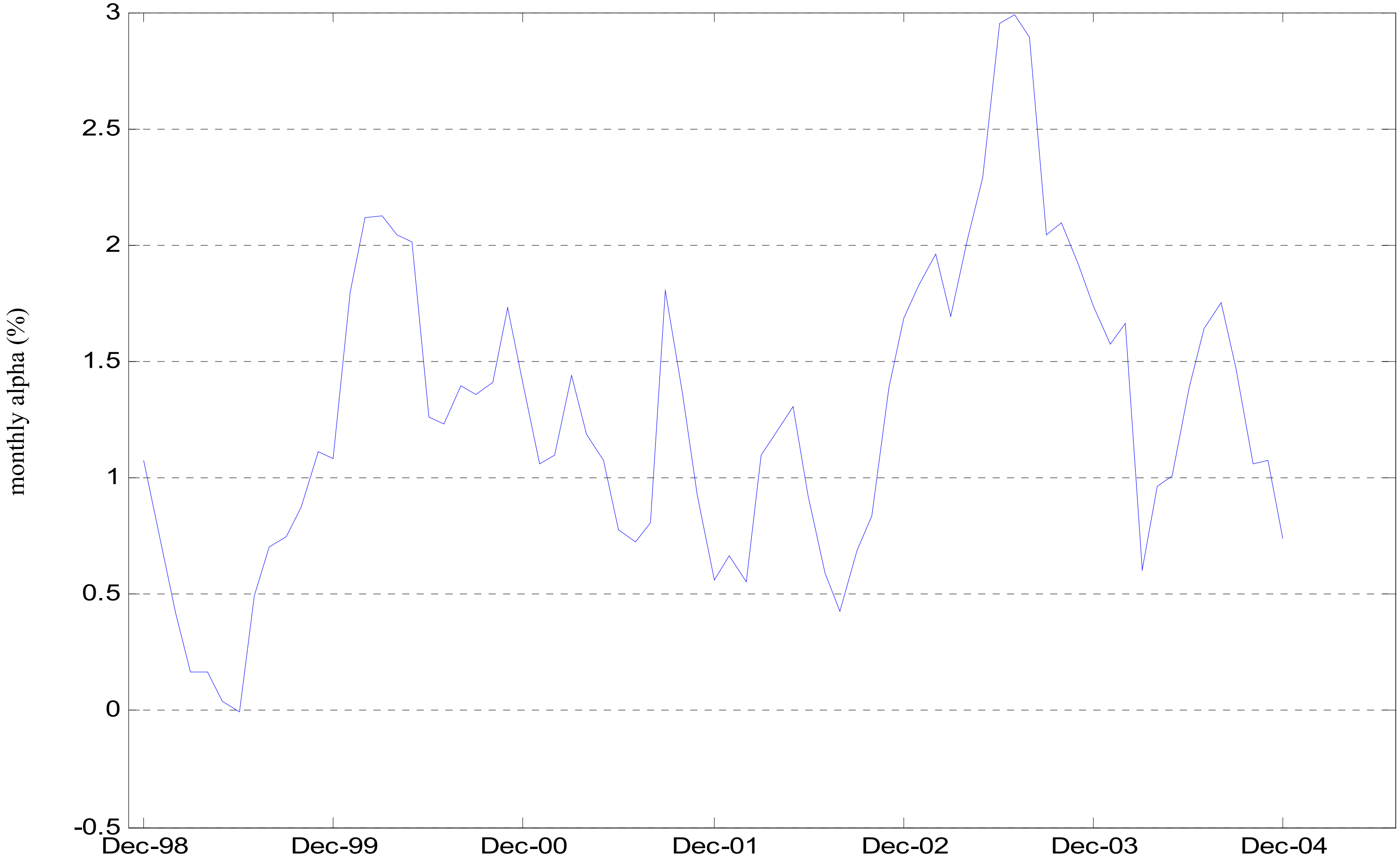

Table 1: List of Investor Types

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 beliefs on the possibility of active management skills, on whether these skills are predictable, and on 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 beliefs reflected by $\sigma\alpha$= 1% per month.

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. Performance of Portfolio Strategies with Different Predictor Variables

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. Performance is evaluated using ex-post excess returns from January 1997 until December 2004 that are 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 36-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 annualized Sharpe ratio; skew is the skewness of monthly regression residuals; kurt is the kurtosis of monthly regression residuals; alpha 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. Panel A reports results for the predictor model that includes the dividend yield, the default spread, the term spread, and the 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, 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	10.46	13.51	10.51	7.07	8.72	9.39	15.90	15.73	6.71	9.36	10.01	14.94	14.60	8.95
stdv	15.49	10.21	7.68	11.94	11.04	10.24	16.85	16.51	12.49	11.38	10.99	15.24	16.49	10.18
SR	0.68	1.32	1.37	0.59	0.79	0.92	0.94	0.95	0.54	0.82	0.91	0.98	0.89	0.88
skew	-0.34	-0.21	-0.61	-0.82	-0.44	-0.65	-0.06	-0.37	-0.70	-0.47	-0.48	-0.05	-0.20	0.35
kurt	2.35	3.41	4.86	5.17	2.70	3.43	3.13	2.68	4.69	2.78	3.13	2.62	2.61	3.64
alpha	4.47	9.12	7.12	1.82	3.07	4.15	12.45	9.87	1.45	3.82	4.80	12.59	10.64	4.37
alpha *t*-statistic	3.12	5.77	4.22	0.47	0.95	1.32	2.25	1.97	0.36	1.10	1.38	2.42	2.03	2.08
alpha *p*-value	0.00	0.00	0.00	0.64	0.34	0.19	0.03	0.05	0.72	0.27	0.17	0.02	0.05	0.04
SNP	0.90	0.51	0.34	0.11	0.21	0.12	0.24	0.36	0.12	0.18	0.13	0.28	0.36	0.38
SCMLC	0.26	0.28	0.16	0.23	0.20	0.11	0.50	0.49	0.24	0.18	0.10	0.39	0.49	0.41
BD10RET	0.08	0.12	0.13	0.48	0.38	0.40	0.23	0.45	0.46	0.38	0.37	0.12	0.38	0.32
BAAMTSY	0.07	0.19	0.23	0.88	0.95	0.97	0.17	0.51	0.88	0.96	1.00	-0.12	-0.07	0.17
PTFSBD	0.01	-0.01	0.00	-0.02	-0.03	-0.02	-0.03	-0.01	-0.02	-0.02	-0.02	-0.02	-0.04	0.00
PTFSFX	0.00	0.01	0.01	0.00	-0.01	0.00	-0.03	-0.03	0.00	0.00	0.00	-0.01	-0.02	0.01
PTFSCOM	0.01	0.01	-0.01	0.03	0.00	-0.02	0.02	0.03	0.04	0.00	-0.02	0.00	0.04	0.01

Panel B. Four macro predictor variables (VIX, default spread, term spread, 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	10.46	13.16	14.44	7.07	9.88	13.58	18.84	17.72	6.71	10.07	12.64	18.20	21.17	8.95
stdv	15.49	10.97	12.66	11.94	11.35	11.96	16.72	15.26	12.49	12.06	12.29	16.20	17.09	10.18
SR	0.68	1.20	1.14	0.59	0.87	1.14	1.13	1.16	0.54	0.84	1.03	1.12	1.24	0.88
skew	-0.34	-0.29	0.23	-0.82	-0.60	-0.52	-0.27	-0.36	-0.70	-0.52	-0.53	-0.19	-0.42	0.35
kurt	2.35	2.97	3.93	5.17	3.18	2.93	2.91	2.56	4.69	3.10	3.06	3.00	2.77	3.64
alpha	4.47	8.41	9.04	1.82	4.46	8.42	13.64	13.17	1.45	4.81	7.47	14.46	17.98	4.37
alpha *t*-statistic	3.12	5.28	2.70	0.47	1.23	2.23	2.37	3.04	0.36	1.21	1.87	2.49	3.44	2.08
alpha *p*-value	0.00	0.00	0.01	0.64	0.22	0.03	0.02	0.00	0.72	0.23	0.07	0.01	0.00	0.04
SNP	0.90	0.58	0.50	0.11	0.19	0.22	0.21	0.51	0.12	0.18	0.20	0.18	0.49	0.38
SCMLC	0.26	0.28	0.20	0.23	0.10	0.17	0.26	0.40	0.24	0.08	0.14	0.22	0.44	0.41
BD10RET	0.08	0.17	0.28	0.48	0.46	0.34	0.49	0.28	0.46	0.43	0.37	0.36	0.24	0.32
BAAMTSY	0.07	0.12	0.37	0.88	0.89	0.85	0.68	0.01	0.88	0.90	0.85	0.37	-0.43	0.17
PTFSBD	0.01	-0.01	-0.01	-0.02	-0.04	-0.04	-0.05	-0.04	-0.02	-0.03	-0.04	-0.05	-0.07	0.00
PTFSFX	0.00	0.01	0.03	0.00	-0.01	0.00	-0.03	-0.01	0.00	-0.01	0.00	-0.01	0.02	0.01
PTFSCOM	0.01	0.02	0.00	0.03	0.02	0.03	0.05	0.04	0.04	0.02	0.03	0.03	0.05	0.01

Table 3. Performance of Portfolio Strategies within Investment Styles

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. Performance is evaluated using ex-post excess returns from January 1997 until December 2004 that are 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 36-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 annualized Sharpe ratio; skew is the skewness of monthly regression residuals; kurt is the kurtosis of monthly regression residuals; alpha 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. The predictor model includes the monthly range (high minus low) of the VIX, the default spread, the term spread, and the Treasury yield. Panels A-F report results by investment style for styles that 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	10.68	13.64	11.53	11.81	16.14	17.49	23.10	18.87	10.88	15.73	17.89	19.45	20.00	12.19
stdv	15.63	12.11	12.80	12.08	10.91	11.13	14.80	14.09	12.05	11.28	11.14	14.53	14.85	11.91
SR	0.68	1.13	0.90	0.98	1.48	1.57	1.56	1.34	0.90	1.39	1.61	1.34	1.35	1.02
skew	-0.35	-0.18	-0.02	0.26	0.45	0.37	0.15	-0.29	0.19	0.35	0.43	-0.25	0.00	0.99
kurt	2.39	2.73	2.95	2.71	2.71	3.13	2.93	2.90	2.52	2.55	2.91	2.82	2.84	4.38
alpha	4.77	8.81	6.60	7.68	11.97	13.43	18.55	14.22	7.09	11.85	13.85	16.59	16.69	8.58
alpha *t*-statistic	3.34	5.51	2.56	2.28	4.17	4.51	4.42	4.09	2.03	3.58	4.26	3.30	3.68	2.44
alpha *p*-value	0.00	0.00	0.01	0.03	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.02
SNP	0.91	0.67	0.66	0.34	0.36	0.38	0.49	0.54	0.32	0.32	0.33	0.27	0.48	0.37
SCMLC	0.25	0.29	0.27	0.40	0.34	0.35	0.41	0.44	0.37	0.30	0.30	0.25	0.35	0.31
BD10RET	0.06	0.15	0.33	0.24	0.26	0.31	0.17	0.17	0.15	0.22	0.32	0.07	0.22	0.17
BAAMTSY	0.05	-0.01	-0.20	0.20	0.19	0.04	0.13	0.06	0.29	0.24	0.13	0.19	-0.32	0.16
PTFSBD	0.01	0.00	0.00	-0.03	-0.02	-0.02	-0.01	-0.01	-0.02	-0.03	-0.03	-0.02	-0.04	-0.01
PTFSFX	0.00	0.02	0.02	0.02	0.02	0.03	0.01	-0.01	0.01	0.02	0.03	0.01	0.00	-0.01
PTFSCOM	0.02	0.02	0.01	0.02	0.02	0.02	-0.01	0.00	0.03	0.02	0.01	-0.01	-0.01	0.03

Panel B. Directional Trader 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	11.21	12.85	13.48	9.65	10.92	15.12	18.01	17.50	10.99	10.12	13.68	20.14	20.15	10.07
stdv	14.38	11.05	12.25	13.26	12.81	13.46	19.55	15.99	13.78	14.14	14.53	19.81	17.71	11.95
SR	0.78	1.16	1.10	0.73	0.85	1.12	0.92	1.09	0.80	0.72	0.94	1.02	1.14	0.84
skew	-0.31	-0.05	0.44	-0.38	-0.28	-0.39	-0.12	-0.26	-0.31	-0.21	-0.35	-0.18	-0.19	-0.17
kurt	2.58	3.36	4.64	4.29	3.12	3.40	2.56	2.48	4.27	2.99	3.33	2.74	2.87	2.71
alpha	4.61	7.50	8.29	2.88	4.59	9.29	11.48	12.89	4.22	3.70	7.67	15.72	16.38	4.37
alpha *t*-statistic	1.81	3.15	2.26	0.81	1.26	2.42	1.82	2.66	1.09	0.87	1.79	2.28	3.02	1.32
alpha *p*-value	0.07	0.00	0.03	0.42	0.21	0.02	0.07	0.01	0.28	0.39	0.08	0.03	0.00	0.19
SNP	0.62	0.43	0.28	0.33	0.32	0.34	0.41	0.46	0.27	0.31	0.35	0.26	0.47	0.29
SCMLC	0.40	0.33	0.26	0.39	0.32	0.36	0.42	0.36	0.42	0.33	0.39	0.37	0.46	0.39
BD10RET	0.19	0.25	0.28	0.67	0.54	0.38	0.55	0.19	0.72	0.54	0.43	0.54	0.21	0.50
BAAMTSY	0.59	0.50	0.71	0.59	0.68	0.66	0.57	0.30	0.61	0.72	0.64	0.15	-0.09	0.54
PTFSBD	-0.01	-0.02	-0.02	-0.03	-0.03	-0.03	-0.04	-0.04	-0.03	-0.02	-0.03	-0.06	-0.07	0.01
PTFSFX	-0.01	0.01	0.01	-0.01	-0.01	-0.01	-0.04	-0.02	-0.01	-0.02	-0.01	-0.03	-0.01	-0.01
PTFSCOM	0.01	0.02	0.00	-0.01	0.01	0.03	0.04	0.05	-0.02	0.00	0.03	0.04	0.07	0.01

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	15.60	14.19	16.27	13.98	12.90	14.36	15.72	12.67	11.89	11.03	13.07	16.52	13.97	2.94
stdv	11.39	8.99	10.82	11.29	10.16	12.30	14.18	13.77	10.87	9.83	11.39	13.34	13.69	9.88
SR	1.37	1.58	1.50	1.24	1.27	1.17	1.11	0.92	1.09	1.12	1.15	1.24	1.02	0.30
skew	-0.77	-0.57	-0.43	-1.29	-1.33	-1.15	-0.68	-0.80	-1.38	-1.49	-1.32	-0.26	-0.46	-1.06
kurt	4.48	5.12	3.93	7.18	7.97	5.45	5.43	5.87	7.64	8.47	5.99	3.69	4.67	7.75
alpha	11.39	10.53	11.30	11.32	9.98	9.69	11.74	8.64	9.51	8.43	8.84	12.51	9.68	-0.46
alpha *t* -statistic	6.75	6.22	4.32	2.96	3.10	2.60	2.38	1.86	2.55	2.63	2.57	2.68	2.09	-0.17
alpha *p* -value	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.07	0.01	0.01	0.01	0.01	0.04	0.87
SNP	0.56	0.39	0.42	0.17	0.17	0.30	0.18	0.30	0.17	0.17	0.29	0.16	0.30	0.15
SCMLC	0.36	0.28	0.29	0.12	0.15	0.23	0.19	0.20	0.09	0.11	0.20	0.17	0.16	0.27
BD10RET	0.07	0.10	0.35	0.00	0.00	0.25	0.27	0.34	0.01	-0.01	0.21	0.36	0.43	0.09
BAAMTSY	0.05	0.21	0.24	0.54	0.61	0.61	0.57	0.25	0.47	0.54	0.55	0.51	0.22	0.56
PTFSBD	-0.02	-0.02	-0.03	-0.03	-0.03	-0.03	-0.05	-0.05	-0.03	-0.03	-0.03	-0.05	-0.04	-0.05
PTFSFX	0.00	0.00	0.02	-0.01	-0.01	-0.02	0.01	0.01	-0.01	-0.01	-0.02	0.02	0.03	0.01
PTFSCOM	0.00	0.01	0.00	0.03	0.02	0.03	0.03	0.02	0.03	0.02	0.03	0.02	0.01	-0.01

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	3.73	6.87	8.89	9.37	11.08	11.66	15.30	13.26	9.50	10.96	11.61	16.22	13.29	7.92
stdv	13.81	8.70	10.01	9.06	7.58	7.72	8.02	8.56	8.94	7.45	7.76	8.50	9.02	6.05
SR	0.27	0.79	0.89	1.03	1.46	1.51	1.91	1.55	1.06	1.47	1.50	1.91	1.47	1.31
skew	-0.29	-0.03	-0.17	-1.60	-0.81	-0.65	-0.14	-0.74	-1.59	-0.83	-0.66	-0.37	-0.86	-0.73
kurt	3.05	3.77	3.73	10.40	5.08	3.97	2.50	5.79	11.08	5.08	4.02	2.89	5.93	5.36
alpha	-0.41	3.70	4.04	8.16	9.77	9.68	12.15	9.87	8.55	9.91	9.91	13.70	10.42	6.04
alpha *t* -statistic	-0.18	1.84	1.66	2.49	3.89	3.93	4.60	3.90	2.65	3.98	3.93	4.65	3.59	2.92
alpha *p* -value	0.85	0.07	0.10	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
SNP	0.72	0.42	0.45	-0.02	0.06	0.13	0.16	0.29	-0.05	0.04	0.12	0.10	0.26	0.09
SCMLC	0.09	0.05	0.03	0.00	-0.03	-0.02	0.01	0.07	0.00	-0.03	-0.02	-0.05	0.04	0.06
BD10RET	-0.06	0.11	0.36	-0.08	-0.12	-0.02	0.17	0.25	-0.10	-0.14	-0.05	0.16	0.22	0.14
BAAMTSY	0.04	0.12	0.33	0.58	0.53	0.48	0.52	0.20	0.57	0.49	0.45	0.42	0.14	0.26
PTFSBD	0.02	0.01	0.01	-0.01	-0.03	-0.03	-0.01	-0.02	-0.02	-0.03	-0.03	-0.02	-0.02	-0.02
PTFSFX	-0.02	0.00	0.01	0.01	0.00	0.00	0.02	0.02	0.01	0.00	0.00	0.03	0.02	-0.01
PTFSCOM	-0.02	0.01	0.01	0.02	0.02	0.01	-0.02	-0.01	0.02	0.01	0.01	-0.03	-0.03	0.00

Panel E. Security Selection 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	10.93	13.97	12.45	11.22	14.81	16.38	23.09	17.10	10.37	14.43	16.54	19.46	18.59	3.58
stdv	15.66	12.15	12.82	11.96	10.49	10.91	14.87	13.89	12.02	10.84	10.86	14.39	14.35	13.79
SR	0.70	1.15	0.97	0.94	1.41	1.50	1.55	1.23	0.86	1.33	1.52	1.35	1.30	0.26
skew	-0.32	-0.20	-0.01	0.22	0.39	0.31	0.14	-0.07	0.14	0.39	0.36	-0.19	-0.12	0.29
kurt	2.37	2.77	3.06	2.60	2.59	2.92	2.80	2.62	2.22	2.52	2.73	2.69	2.58	3.57
alpha	4.93	9.12	7.42	6.88	10.57	12.27	18.51	12.54	6.17	10.35	12.27	16.66	14.93	3.70
alpha *t* -statistic	3.50	5.96	2.94	2.25	3.90	4.25	4.44	3.98	1.95	3.36	3.99	3.40	3.69	0.91
alpha *p* -value	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.36
SNP	0.91	0.68	0.67	0.39	0.37	0.39	0.49	0.57	0.39	0.34	0.36	0.29	0.50	0.50
SCMLC	0.28	0.31	0.28	0.40	0.29	0.31	0.43	0.47	0.36	0.25	0.26	0.28	0.40	0.42
BD10RET	0.08	0.15	0.34	0.22	0.26	0.29	0.17	0.15	0.12	0.22	0.30	0.06	0.21	0.15
BAAMTSY	0.02	-0.03	-0.19	0.19	0.21	0.08	0.11	-0.02	0.32	0.29	0.21	0.11	-0.27	-0.06
PTFSBD	0.01	0.00	0.00	-0.03	-0.02	-0.02	-0.01	-0.02	-0.03	-0.03	-0.02	-0.02	-0.03	-0.02
PTFSFX	0.00	0.02	0.03	0.02	0.03	0.03	0.01	0.00	0.01	0.03	0.03	0.01	0.01	0.01
PTFSCOM	0.01	0.01	0.01	0.01	0.02	0.01	-0.01	0.01	0.02	0.02	0.01	-0.02	-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	8.45	9.42	7.64	12.09	8.20	8.03	10.41	9.67	12.06	8.17	8.33	10.28	9.55	6.09
stdv	10.78	9.72	10.73	8.67	8.80	9.18	11.38	11.01	8.34	8.88	9.15	10.71	11.27	15.72
SR	0.78	0.97	0.71	1.39	0.93	0.88	0.91	0.88	1.45	0.92	0.91	0.96	0.85	0.39
skew	-0.01	0.10	-0.03	0.66	-0.31	-0.41	0.54	0.14	0.50	-0.32	-0.38	0.45	0.42	0.83
kurt	4.08	3.94	3.66	4.86	7.69	7.43	4.71	5.39	4.55	7.56	7.58	4.00	6.09	6.36
alpha	3.81	4.91	2.72	9.23	5.24	4.47	7.09	6.37	9.28	5.23	4.86	8.07	6.28	1.55
alpha *t* -statistic	1.76	2.18	0.90	3.27	1.96	1.64	2.08	2.17	3.43	1.93	1.77	2.36	2.07	0.29
alpha *p* -value	0.08	0.03	0.37	0.00	0.05	0.10	0.04	0.03	0.00	0.06	0.08	0.02	0.04	0.77
SNP	0.46	0.35	0.30	0.16	0.13	0.15	0.25	0.28	0.15	0.12	0.14	0.20	0.27	0.37
SCMLC	0.31	0.30	0.27	0.22	0.28	0.28	0.38	0.41	0.22	0.28	0.28	0.35	0.43	0.14
BD10RET	0.14	0.20	0.33	0.27	0.20	0.26	0.18	0.17	0.27	0.20	0.26	0.18	0.18	0.42
BAAMTSY	0.33	0.46	0.57	0.17	0.32	0.43	0.23	0.15	0.17	0.32	0.41	-0.04	0.12	0.32
PTFSBD	-0.01	-0.01	-0.01	0.02	-0.02	-0.03	-0.01	-0.04	0.01	-0.02	-0.03	0.01	-0.04	0.03
PTFSFX	0.01	0.01	0.00	0.02	0.01	0.01	0.00	0.00	0.02	0.01	0.01	0.01	0.01	0.02
PTFSCOM	0.02	0.03	0.04	-0.01	0.00	0.02	0.04	0.04	-0.01	0.00	0.01	0.04	0.03	0.09

Table 4. Robustness Tests

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. Performance is evaluated using ex-post excess returns from January 1997 until December 2004 that are 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 36-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 annualized Sharpe ratio; skew is the skewness of monthly regression residuals; kurt is the kurtosis of monthly regression residuals; alpha 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. 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 reports the baseline results from Panel B of Table 2. Panel B reports results after adjusting returns for serial correlation based on the procedure outlined in Getmansky, Lo and Makarov (2004). Panel C reports results after adjusting for backfill and incubation bias by excluding the first 12 monthly return observations for each fund. Panel D reports results for funds that we believe, based on fund flow, to be still open to new investments. Panels E and F report results for an augmented factor model consisting of the Fung and Hsieh (2004) model and the MSCI Emerging Markets and HML factor, respectively.

Panel A. Baseline Scenario (see Panel B, 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	10.46	13.16	14.44	7.07	9.88	13.58	18.84	17.72	6.71	10.07	12.64	18.20	21.17	8.95
stdv	15.49	10.97	12.66	11.94	11.35	11.96	16.72	15.26	12.49	12.06	12.29	16.20	17.09	10.18
SR	0.68	1.20	1.14	0.59	0.87	1.14	1.13	1.16	0.54	0.84	1.03	1.12	1.24	0.88
skew	-0.34	-0.29	0.23	-0.82	-0.60	-0.52	-0.27	-0.36	-0.70	-0.52	-0.53	-0.19	-0.42	0.35
kurt	2.35	2.97	3.93	5.17	3.18	2.93	2.91	2.56	4.69	3.10	3.06	3.00	2.77	3.64
alpha	4.47	8.41	9.04	1.82	4.46	8.42	13.64	13.17	1.45	4.81	7.47	14.46	17.98	4.37
alpha *t*-statistic	3.12	5.28	2.70	0.47	1.23	2.23	2.37	3.04	0.36	1.21	1.87	2.49	3.44	2.08
alpha *p*-value	0.00	0.00	0.01	0.64	0.22	0.03	0.02	0.00	0.72	0.23	0.07	0.01	0.00	0.04
SNP	0.90	0.58	0.50	0.11	0.19	0.22	0.21	0.51	0.12	0.18	0.20	0.18	0.49	0.38
SCMLC	0.26	0.28	0.20	0.23	0.10	0.17	0.26	0.40	0.24	0.08	0.14	0.22	0.44	0.41
BD10RET	0.08	0.17	0.28	0.48	0.46	0.34	0.49	0.28	0.46	0.43	0.37	0.36	0.24	0.32
BAAMTSY	0.07	0.12	0.37	0.88	0.89	0.85	0.68	0.01	0.88	0.90	0.85	0.37	-0.43	0.17
PTFSBD	0.01	-0.01	-0.01	-0.02	-0.04	-0.04	-0.05	-0.04	-0.02	-0.03	-0.04	-0.05	-0.07	0.00
PTFSFX	0.00	0.01	0.03	0.00	-0.01	0.00	-0.03	-0.01	0.00	-0.01	0.00	-0.01	0.02	0.01
PTFSCOM	0.01	0.02	0.00	0.03	0.02	0.03	0.05	0.04	0.04	0.02	0.03	0.03	0.05	0.01

Panel B. 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	11.59	12.92	18.34	8.27	10.51	14.47	17.39	17.18	7.41	10.31	13.02	16.45	20.77	9.43
stdv	16.00	11.35	13.99	12.36	11.44	11.95	17.33	16.54	13.20	12.36	12.49	17.11	18.68	10.54
SR	0.72	1.14	1.31	0.67	0.92	1.21	1.00	1.04	0.56	0.83	1.04	0.96	1.11	0.89
skew	-0.32	-0.32	-0.02	-0.81	-0.59	-0.46	-0.26	-0.36	-0.78	-0.56	-0.54	-0.17	-0.44	0.40
kurt	2.29	2.85	2.91	5.09	2.95	2.76	2.92	2.37	4.86	2.93	2.88	2.99	2.79	3.77
alpha	5.44	7.90	10.73	2.76	5.01	9.21	11.43	12.15	2.02	5.08	7.91	12.55	17.40	4.63
alpha *t*-statistic	3.71	5.12	3.37	0.69	1.38	2.49	2.00	2.70	0.46	1.24	1.95	2.06	3.14	2.03
alpha *p*-value	0.00	0.00	0.00	0.49	0.17	0.01	0.05	0.01	0.64	0.22	0.05	0.04	0.00	0.04
SNP	0.93	0.62	0.60	0.13	0.20	0.26	0.26	0.60	0.13	0.18	0.22	0.19	0.57	0.38
SCMLC	0.28	0.28	0.22	0.24	0.10	0.18	0.35	0.48	0.25	0.07	0.14	0.26	0.53	0.42
BD10RET	0.11	0.20	0.53	0.51	0.47	0.35	0.57	0.34	0.46	0.43	0.36	0.40	0.29	0.36
BAAMTSY	0.01	0.11	0.62	0.88	0.87	0.76	0.69	-0.12	0.91	0.90	0.80	0.36	-0.64	0.21
PTFSBD	0.01	0.00	-0.02	-0.02	-0.04	-0.04	-0.05	-0.04	-0.02	-0.04	-0.04	-0.05	-0.07	0.00
PTFSFX	0.00	0.01	0.03	0.00	-0.01	0.00	-0.04	-0.01	-0.01	-0.01	0.00	-0.01	0.02	0.01
PTFSCOM	0.01	0.02	0.01	0.03	0.02	0.03	0.06	0.04	0.03	0.02	0.02	0.04	0.05	0.02

Panel C. Backfill and Incubation 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	9.93	12.88	16.25	5.58	8.29	11.06	17.08	15.93	4.71	6.95	9.20	16.40	19.30	8.59
stdv	15.49	11.05	12.55	13.96	12.14	12.61	16.87	16.11	14.14	12.61	13.26	16.79	18.75	11.15
SR	0.64	1.17	1.30	0.40	0.68	0.88	1.01	0.99	0.33	0.55	0.69	0.98	1.03	0.77
skew	-0.35	-0.26	-0.24	-0.02	-0.20	-0.20	-0.19	-0.20	-0.04	-0.21	-0.14	-0.18	-0.14	0.34
kurt	2.40	2.99	2.82	3.19	2.53	2.61	2.77	2.48	2.89	2.47	2.52	2.98	2.47	3.45
alpha	3.94	8.08	10.76	-0.81	2.04	4.81	11.71	10.07	-1.65	0.88	2.74	12.61	14.19	3.39
alpha *t* -statistic	2.85	5.06	4.36	-0.21	0.58	1.35	2.04	2.23	-0.41	0.23	0.67	2.10	2.49	1.42
alpha *p* -value	0.01	0.00	0.00	0.83	0.56	0.18	0.04	0.03	0.68	0.82	0.50	0.04	0.01	0.16
SNP	0.89	0.58	0.62	0.35	0.29	0.34	0.21	0.51	0.32	0.25	0.28	0.16	0.52	0.40
SCMLC	0.26	0.29	0.27	0.46	0.25	0.29	0.29	0.45	0.44	0.22	0.24	0.21	0.48	0.43
BD10RET	0.06	0.17	0.29	0.50	0.56	0.52	0.46	0.45	0.50	0.55	0.61	0.37	0.53	0.34
BAAMTSY	0.10	0.14	0.12	0.63	0.75	0.68	0.77	0.24	0.70	0.80	0.79	0.48	-0.17	0.32
PTFSBD	0.01	-0.01	-0.01	-0.01	-0.03	-0.03	-0.04	-0.04	0.00	-0.03	-0.03	-0.05	-0.07	-0.01
PTFSFX	0.00	0.02	0.03	-0.01	-0.01	-0.01	-0.03	-0.01	-0.02	-0.02	-0.01	-0.02	0.01	0.02
PTFSCOM	0.01	0.02	0.02	0.02	0.02	0.03	0.06	0.05	0.03	0.02	0.02	0.06	0.08	0.02

Panel D. Adjusted for Closed 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	10.07	12.67	13.79	6.24	8.96	12.25	17.88	15.96	6.06	8.68	11.05	17.14	18.32	10.21
stdv	15.48	10.92	12.67	12.52	12.05	12.74	17.02	16.40	12.96	12.65	13.05	15.77	18.02	11.84
SR	0.65	1.16	1.09	0.50	0.74	0.96	1.05	0.97	0.47	0.69	0.85	1.09	1.02	0.86
skew	-0.36	-0.30	0.22	-0.71	-0.48	-0.44	-0.22	-0.28	-0.60	-0.38	-0.40	-0.20	-0.35	0.56
kurt	2.39	3.00	3.93	4.79	2.87	2.63	2.86	2.48	4.48	2.87	2.74	3.13	2.82	3.63
alpha	4.07	7.84	8.36	0.25	2.86	6.55	12.26	11.03	-0.03	2.73	5.46	13.33	14.31	4.58
alpha *t* -statistic	2.84	4.77	2.45	0.06	0.78	1.73	2.14	2.29	-0.01	0.68	1.35	2.35	2.64	1.60
alpha *p* -value	0.01	0.00	0.02	0.95	0.44	0.09	0.04	0.02	1.00	0.50	0.18	0.02	0.01	0.11
SNP	0.90	0.57	0.49	0.16	0.23	0.28	0.22	0.49	0.16	0.21	0.26	0.16	0.51	0.42
SCMLC	0.23	0.27	0.19	0.26	0.16	0.23	0.30	0.43	0.27	0.15	0.21	0.15	0.47	0.36
BD10RET	0.08	0.17	0.29	0.48	0.46	0.32	0.47	0.32	0.49	0.45	0.35	0.38	0.27	0.35
BAAMTSY	0.09	0.19	0.42	1.03	1.02	0.93	0.81	0.13	1.06	1.01	0.90	0.45	-0.20	0.48
PTFSBD	0.01	-0.01	-0.01	-0.01	-0.03	-0.03	-0.04	-0.06	-0.01	-0.03	-0.03	-0.05	-0.08	-0.01
PTFSFX	0.00	0.01	0.03	-0.01	-0.01	0.00	-0.03	0.00	-0.01	-0.01	-0.01	-0.01	0.02	0.02
PTFSCOM	0.01	0.02	0.00	0.04	0.03	0.04	0.05	0.05	0.04	0.04	0.04	0.03	0.06	0.04

Panel E. Fung and Hsieh (2004) Model Augmented with an Emerging Markets Benchmark

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	10.46	13.16	14.44	7.07	9.88	13.58	18.84	17.72	6.71	10.07	12.64	18.20	21.17	8.95
stdv	15.49	10.97	12.66	11.94	11.35	11.96	16.72	15.26	12.49	12.06	12.29	16.20	17.09	10.18
SR	0.68	1.20	1.14	0.59	0.87	1.14	1.13	1.16	0.54	0.84	1.03	1.12	1.24	0.88
skew	-0.37	-0.35	0.20	-0.82	-0.58	-0.51	-0.25	-0.36	-0.69	-0.49	-0.51	-0.16	-0.41	0.35
kurt	2.38	3.05	4.07	5.16	3.17	2.90	2.92	2.53	4.68	3.10	3.03	3.03	2.78	3.64
alpha	4.55	8.93	9.57	2.12	5.49	9.88	14.06	14.52	1.72	5.80	8.88	14.69	19.59	4.70
alpha *t* -statistic	3.14	5.91	2.87	0.54	1.57	2.84	2.43	3.51	0.42	1.49	2.36	2.50	3.92	2.25
alpha *p* -value	0.00	0.00	0.01	0.59	0.12	0.01	0.02	0.00	0.68	0.14	0.02	0.01	0.00	0.03
SNP	0.88	0.48	0.39	0.05	-0.01	-0.06	0.13	0.25	0.07	-0.01	-0.07	0.14	0.19	0.32
SCMLC	0.25	0.23	0.16	0.21	0.01	0.04	0.23	0.29	0.22	0.00	0.03	0.20	0.30	0.39
BD10RET	0.08	0.18	0.29	0.49	0.48	0.37	0.50	0.31	0.47	0.45	0.40	0.36	0.27	0.32
BAAMTSY	0.06	0.05	0.30	0.84	0.75	0.64	0.62	-0.18	0.85	0.76	0.65	0.34	-0.65	0.13
PTFSBD	0.01	-0.01	-0.01	-0.02	-0.03	-0.03	-0.05	-0.04	-0.02	-0.03	-0.03	-0.04	-0.06	0.00
PTFSFX	0.00	0.02	0.03	0.00	0.00	0.00	-0.03	-0.01	0.00	0.00	0.00	-0.01	0.02	0.01
PTFSCOM	0.01	0.02	0.00	0.04	0.03	0.04	0.05	0.05	0.04	0.03	0.04	0.03	0.06	0.01
EM	0.02	0.10	0.10	0.06	0.19	0.27	0.08	0.25	0.05	0.18	0.26	0.04	0.30	0.06

Panel F. Fung and Hsieh (2004) Model Augmented with the Fama and French (1993) HML Factor

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	10.46	13.16	14.44	7.07	9.88	13.58	18.84	17.72	6.71	10.07	12.64	18.20	21.17	8.95
stdv	15.49	10.97	12.66	11.94	11.35	11.96	16.72	15.26	12.49	12.06	12.29	16.20	17.09	10.18
SR	0.68	1.20	1.14	0.59	0.87	1.14	1.13	1.16	0.54	0.84	1.03	1.12	1.24	0.88
skew	-0.37	-0.35	0.20	-0.82	-0.58	-0.51	-0.25	-0.36	-0.69	-0.49	-0.51	-0.16	-0.41	0.35
kurt	2.38	3.05	4.07	5.16	3.17	2.90	2.92	2.53	4.68	3.10	3.03	3.03	2.78	3.64
alpha	5.41	9.16	11.19	2.61	4.75	8.93	11.37	12.86	2.12	4.89	7.76	11.85	17.38	5.70
alpha *t* -statistic	3.92	5.80	3.47	0.66	1.28	2.31	1.98	2.89	0.51	1.20	1.89	2.05	3.25	2.82
alpha *p* -value	0.00	0.00	0.00	0.51	0.20	0.02	0.05	0.00	0.61	0.24	0.06	0.04	0.00	0.01
SNP	0.85	0.54	0.39	0.07	0.17	0.19	0.32	0.53	0.09	0.17	0.19	0.32	0.53	0.31
SCMLC	0.22	0.25	0.13	0.21	0.09	0.15	0.35	0.42	0.22	0.08	0.13	0.31	0.46	0.36
BD10RET	0.09	0.18	0.29	0.48	0.46	0.34	0.48	0.28	0.47	0.43	0.37	0.34	0.24	0.32
BAAMTSY	0.06	0.11	0.34	0.87	0.89	0.84	0.71	0.01	0.88	0.90	0.85	0.41	-0.42	0.16
PTFSBD	0.01	-0.01	-0.02	-0.02	-0.04	-0.04	-0.03	-0.04	-0.02	-0.03	-0.04	-0.03	-0.06	-0.01
PTFSFX	0.00	0.02	0.03	0.00	-0.01	0.00	-0.04	-0.01	0.00	-0.01	0.00	-0.01	0.02	0.02
PTFSCOM	0.01	0.02	-0.01	0.03	0.02	0.03	0.06	0.04	0.03	0.02	0.03	0.04	0.05	0.01
HML	-0.11	-0.09	-0.25	-0.09	-0.03	-0.06	0.26	0.04	-0.08	-0.01	-0.03	0.30	0.07	-0.15

Table 5. Performance of Portfolio Strategies within 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. Investors rebalance portfolios every 12 months. Performance is evaluated using ex-post excess returns from January 1997 until December 2004 that are 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 36-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 annualized Sharpe ratio; skew is the skewness of monthly regression residuals; kurt is the kurtosis of monthly regression residuals; alpha 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. The predictor model includes the monthly range (high minus low) of the VIX, the default spread, the term spread, and the Treasury yield. In Panel A, portfolios are rebalanced once a year in January. In Panel B, portfolios are rebalanced twice a year in January and July. In Panel C, portfolios are rebalanced four times a year in January, April, July, and October.

Panel A. Baseline Scenario - 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	10.46	13.16	14.44	7.07	9.88	13.58	18.84	17.72	6.71	10.07	12.64	18.20	21.17	8.95
stdv	15.49	10.97	12.66	11.94	11.35	11.96	16.72	15.26	12.49	12.06	12.29	16.20	17.09	10.18
SR	0.68	1.20	1.14	0.59	0.87	1.14	1.13	1.16	0.54	0.84	1.03	1.12	1.24	0.88
skew	-0.34	-0.29	0.23	-0.82	-0.60	-0.52	-0.27	-0.36	-0.70	-0.52	-0.53	-0.19	-0.42	0.35
kurt	2.35	2.97	3.93	5.17	3.18	2.93	2.91	2.56	4.69	3.10	3.06	3.00	2.77	3.64
alpha	4.47	8.41	9.04	1.82	4.46	8.42	13.64	13.17	1.45	4.81	7.47	14.46	17.98	4.37
alpha *t*-statistic	3.12	5.28	2.70	0.47	1.23	2.23	2.37	3.04	0.36	1.21	1.87	2.49	3.44	2.08
alpha *p*-value	0.00	0.00	0.01	0.64	0.22	0.03	0.02	0.00	0.72	0.23	0.07	0.01	0.00	0.04
SNP	0.90	0.58	0.50	0.11	0.19	0.22	0.21	0.51	0.12	0.18	0.20	0.18	0.49	0.38
SCMLC	0.26	0.28	0.20	0.23	0.10	0.17	0.26	0.40	0.24	0.08	0.14	0.22	0.44	0.41
BD10RET	0.08	0.17	0.28	0.48	0.46	0.34	0.49	0.28	0.46	0.43	0.37	0.36	0.24	0.32
BAAMTSY	0.07	0.12	0.37	0.88	0.89	0.85	0.68	0.01	0.88	0.90	0.85	0.37	-0.43	0.17
PTFSBD	0.01	-0.01	-0.01	-0.02	-0.04	-0.04	-0.05	-0.04	-0.02	-0.03	-0.04	-0.05	-0.07	0.00
PTFSFX	0.00	0.01	0.03	0.00	-0.01	0.00	-0.03	-0.01	0.00	-0.01	0.00	-0.01	0.02	0.01
PTFSCOM	0.01	0.02	0.00	0.03	0.02	0.03	0.05	0.04	0.04	0.02	0.03	0.03	0.05	0.01

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	10.93	13.57	15.60	7.24	11.44	13.09	21.14	16.69	6.48	11.95	13.10	20.13	18.40	11.38
stdv	15.76	10.92	12.36	11.52	10.94	10.99	16.82	15.16	12.22	11.62	11.54	15.85	16.07	10.04
SR	0.69	1.24	1.26	0.63	1.05	1.19	1.26	1.10	0.53	1.03	1.14	1.27	1.15	1.13
skew	-0.32	-0.13	0.28	-0.54	-0.54	-0.46	0.23	0.16	-0.51	-0.45	-0.49	0.15	-0.16	0.39
kurt	2.35	2.93	3.92	3.73	2.97	2.98	2.69	2.73	3.55	2.76	2.87	2.62	2.67	3.80
alpha	4.79	8.69	10.61	1.74	5.88	7.53	15.06	11.55	0.83	6.19	7.25	15.19	14.07	6.61
alpha *t*-statistic	3.34	5.10	2.73	0.51	1.78	2.18	2.83	2.45	0.22	1.72	1.99	2.99	2.75	3.02
alpha *p*-value	0.00	0.00	0.01	0.61	0.08	0.03	0.01	0.02	0.82	0.09	0.05	0.00	0.01	0.00
SNP	0.92	0.55	0.35	0.14	0.19	0.13	0.33	0.36	0.14	0.18	0.14	0.35	0.32	0.34
SCMLC	0.26	0.25	0.19	0.30	0.16	0.18	0.38	0.39	0.30	0.16	0.18	0.35	0.45	0.40
BD10RET	0.09	0.14	0.36	0.43	0.43	0.55	0.33	0.31	0.42	0.44	0.56	0.22	0.17	0.33
BAAMTSY	0.08	0.28	0.43	0.91	0.88	0.83	0.81	0.45	0.98	0.96	0.90	0.46	0.35	0.33
PTFSBD	0.01	-0.01	0.00	-0.02	-0.03	-0.03	0.01	0.00	-0.02	-0.02	-0.02	-0.01	-0.02	0.00
PTFSFX	0.00	0.01	0.02	-0.01	0.00	0.01	-0.02	-0.02	-0.01	0.00	0.00	0.02	0.00	0.00
PTFSCOM	0.02	0.01	-0.01	0.01	-0.01	-0.01	-0.02	0.00	0.02	-0.01	-0.01	-0.03	-0.02	0.01

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	11.48	14.23	14.96	11.92	16.86	20.31	20.58	18.03	13.98	19.59	21.97	23.69	26.17	12.98
stdv	15.94	10.97	14.12	12.75	11.54	13.93	15.03	14.94	14.54	13.11	14.82	17.14	17.65	10.28
SR	0.72	1.30	1.06	0.93	1.46	1.46	1.37	1.21	0.96	1.49	1.48	1.38	1.48	1.26
skew	-0.31	-0.08	-0.30	-0.25	-0.07	0.02	-0.16	-0.07	-0.16	0.15	0.11	0.33	0.54	0.34
kurt	2.31	2.97	4.62	2.97	2.76	4.01	2.74	2.74	3.07	2.94	3.49	3.26	3.65	3.89
alpha	5.22	9.69	9.68	5.53	11.16	14.02	16.89	13.75	6.88	13.00	15.03	18.59	19.85	7.98
alpha *t* -statistic	3.50	5.60	2.09	1.44	3.11	3.00	3.36	2.71	1.54	3.13	3.06	3.12	3.29	3.48
alpha *p* -value	0.00	0.00	0.04	0.15	0.00	0.00	0.00	0.01	0.13	0.00	0.00	0.00	0.00	0.00
SNP	0.92	0.56	0.35	0.16	0.19	0.09	0.26	0.29	0.19	0.19	0.10	0.19	0.15	0.35
SCMLC	0.26	0.24	0.19	0.27	0.12	0.12	0.30	0.31	0.29	0.12	0.12	0.26	0.28	0.39
BD10RET	0.09	0.09	0.52	0.51	0.42	0.68	0.04	0.34	0.58	0.50	0.68	0.33	0.61	0.36
BAAMTSY	0.10	0.20	0.32	1.07	0.96	1.03	0.48	0.26	1.18	1.16	1.21	0.74	0.86	0.37
PTFSBD	0.01	-0.01	0.00	-0.04	-0.04	-0.03	0.00	-0.01	-0.04	-0.03	-0.03	-0.02	-0.03	0.00
PTFSFX	0.00	0.01	0.04	0.01	0.01	0.04	0.02	0.02	0.02	0.02	0.05	0.03	0.05	0.01
PTFSCOM	0.02	0.01	0.00	0.02	0.00	0.02	-0.03	0.01	0.03	0.00	0.01	-0.03	0.00	0.02

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 investment styles, the averaged assets under management (AUM) in millions of US$, the average age of the funds, and the mean number of funds in each of the portfolios over time.

	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4
Panel A: Style Allocations													
Long/Short Equity	56%	42%	39%	22%	21%	23%	23%	30%	23%	20%	23%	24%	25%
Directional Trader	10%	19%	26%	39%	42%	41%	56%	49%	38%	42%	42%	53%	50%
Multi-process	3%	10%	9%	6%	8%	7%	8%	8%	8%	9%	8%	11%	12%
Relative Value	14%	15%	15%	26%	23%	23%	10%	7%	23%	21%	21%	10%	10%
Security Selection	18%	14%	12%	6%	7%	6%	4%	5%	7%	8%	7%	3%	3%
Fund of Funds	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Panel B: Portfolio Characteristics													
AUM (US$ million)	183	159	139	90	119	164	318	185	63	79	130	179	83
fund age (years)	4.8	5.0	5.2	7.2	7.2	6.9	5.3	5.2	7.5	7.4	7.2	4.9	5.4
mean number of funds	158	350	282	8	13	17	11	18	6	11	15	12	16

Table 7: Style-based Decomposition of Optimal Portfolio Strategy Returns

This table decomposes the net investment returns generated by portfolio strategies that are optimal from the perspective of the 13 investor types described in Table 1. The first four rows of the table present time-series average excess return reported in Panel B of Table 2, the time-series average net return (μ), i.e., the excess return plus the risk-free rate, style level returns based on the returns weighted by the optimal investor allocations to each style (μ_S), and style-adjusted net returns (μ-μ_S), computed as the difference between the second and third row. The time-series *p* -value of the style-adjusted return is shown in the fifth row. The next three rows break down style-level returns into two components, namely, the style passive return ($\mu_{S,p}$), which is the style-level return that accrues to holding the allocation to each style constant over time (at its time-series average for a given investor), and the style timing return (μ_S - $\mu_{S,p}$), which is the difference between the style-level return and the style passive return. The time-series *p* -value of the style timing return is also shown. The remaining rows report the Fung and Hsieh (2004) seven-factor model alphas and associated *p* -values for the excess return, style-level return and style-adjusted return.

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4
mean excess return	10.46	13.16	14.44	7.07	9.88	13.58	18.84	17.72	6.71	10.07	12.64	18.20	21.17
mean net return, μ	13.94	16.64	17.92	10.54	13.36	17.06	22.31	21.20	10.18	13.55	16.11	21.68	24.65
style return, μ_S	12.29	12.31	12.82	11.55	11.67	11.95	11.69	12.67	11.48	11.72	11.91	11.42	12.98
style-adjusted return, μ-μ_S	1.65	4.32	5.10	-1.01	1.69	5.11	10.63	8.53	-1.29	1.83	4.20	10.25	11.67
style-adjusted return *p* -value	0.63	0.02	0.10	0.77	0.58	0.09	0.04	0.03	0.72	0.59	0.20	0.05	0.02
passive style return, $\mu_{S,p}$	12.29	12.06	12.12	12.01	12.06	12.06	12.25	12.27	12.03	12.06	12.06	12.22	12.24
style timing return, μ_S-$\mu_{S,p}$	0.00	0.25	0.70	-0.46	-0.39	-0.11	-0.56	0.40	-0.55	-0.34	-0.15	-0.80	0.73
style timing return *p* -value	1.00	0.12	0.04	0.48	0.37	0.80	0.31	0.28	0.43	0.44	0.75	0.13	0.09
alpha	4.47	8.41	9.04	1.82	4.46	8.42	13.64	13.17	1.45	4.81	7.47	14.46	17.98
alpha *p* -value	0.00	0.00	0.01	0.64	0.22	0.03	0.02	0.00	0.72	0.23	0.07	0.01	0.00
style alpha	5.95	6.01	6.26	4.99	5.13	5.38	5.17	6.13	4.81	5.14	5.31	4.95	6.44
style alpha *p* -value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
style-adjusted alpha	-1.48	2.40	2.78	-3.17	-0.67	3.03	8.47	7.04	-3.36	-0.33	2.17	9.51	11.54
style-adjusted alpha *p* -value	0.19	0.02	0.37	0.36	0.83	0.33	0.12	0.07	0.36	0.93	0.52	0.09	0.02

Table 8. Return Decomposition for Best Portfolio Strategy (PA-4)

This table reports a decomposition of the excess return of the PA-4 portfolio into alpha and beta exposures. The sample period is from January 1997 to December 2004. In Panel A we decompose the excess return of the PA-4 portfolio into alpha and beta exposures by running rolling regressions with a 24-month backward looking window each month (with the first window ending December 1998). For each rolling regression and 24-month period, the average monthly excess return of the PA-4 portfolio, the alpha, and the beta coefficients are saved. The semi-annual time-series averages of these variables are reported. In Panel A, Column 1 reports the semi-annual averages of the rolling alphas. Alpha is measured relative to an augmented Fung and Hsieh (2004) model that includes an emerging markets benchmark (EM). Columns 2-9 report the semi-annual averages of the betas. Similarly, Panel B reports the semi-annual average percentage contribution of alpha and beta exposures to the excess return of the PA-4 strategy. The alpha contribution is calculated as the monthly alpha over a 24-month rolling regression period divided by the monthly portfolio excess return. The beta contribution is calculated as the beta of benchmark multiplied by the monthly benchmark return and divided by the average monthly portfolio excess return during the 24-month period.

Panel A. Semi-Annual Average of Monthly Rolling Regression Coefficients

Period	Alpha (% per month)	SNP	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	EM
H1 1999	0.26%	0.75	0.27	-0.35	-0.37	0.03	-0.08	0.13	0.10
H2 1999	0.84%	0.64	0.29	0.16	0.30	0.01	-0.03	0.06	0.11
H1 2000	1.89%	0.55	0.55	0.21	0.25	0.01	-0.02	-0.01	0.05
H2 2000	1.42%	0.57	0.56	0.11	-0.01	0.05	0.01	-0.01	0.08
H1 2001	1.11%	-0.02	0.38	0.47	-0.87	-0.01	0.02	-0.01	0.33
H2 2001	1.03%	-0.35	0.23	0.83	-0.77	-0.05	0.05	0.10	0.44
H1 2002	0.96%	-0.41	0.22	0.59	-0.38	-0.03	0.06	0.14	0.31
H2 2002	0.94%	0.02	0.53	-0.04	-1.50	-0.09	-0.05	0.08	0.16
H1 2003	2.12%	0.37	0.58	0.40	-0.46	-0.13	-0.03	0.14	0.08
H2 2003	2.28%	0.31	0.46	0.34	-0.33	-0.07	0.00	0.07	0.35
H1 2004	1.20%	0.16	0.01	0.34	-0.02	0.06	0.04	-0.03	0.76
H2 2004	1.29%	0.17	-0.28	0.26	0.37	0.10	0.04	-0.04	0.71

Panel B. Semi-Annual Average of Alpha and Beta Percentage Contributions to Excess Return

Period	Excess return (% per month)	Alpha contribution	SNP	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	EM
H1 1999	1.36%	18%	104%	-26%	-12%	2%	5%	5%	15%	-11%
H2 1999	1.48%	56%	62%	-27%	0%	-1%	3%	4%	7%	-3%
H1 2000	2.19%	87%	27%	-15%	-1%	-2%	3%	0%	-1%	3%
H2 2000	2.07%	70%	23%	3%	-1%	0%	2%	-1%	1%	3%
H1 2001	1.34%	86%	6%	25%	4%	-2%	0%	-3%	1%	-17%
H2 2001	0.85%	118%	45%	31%	51%	2%	5%	-11%	-59%	-81%
H1 2002	0.72%	218%	157%	32%	160%	-4%	-5%	-105%	-197%	-156%
H2 2002	0.68%	132%	20%	76%	-10%	-2%	-38%	4%	-42%	-40%
H1 2003	1.24%	194%	-44%	31%	28%	-14%	-39%	-2%	-49%	-5%
H2 2003	2.80%	85%	-3%	15%	5%	-7%	-8%	1%	-5%	19%
H1 2004	2.58%	46%	3%	1%	7%	0%	-2%	5%	0%	40%
H2 2004	2.77%	47%	7%	-8%	2%	12%	-13%	1%	-3%	54%