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Hedge funds, managerial skill, and macroeconomic variables ☆

Doron Avramov [a,b], Robert Kosowski [c], Narayan Y. Naik [d,*], Melvyn Teo [e]

[a] Hebrew University of Jerusalem, Israel
[b] R.H. Smith School of Business, University of Maryland, MD, USA
[c] Imperial College Business School, Imperial College London, UK
[d] London Business School, UK
[e] Singapore Management University, Singapore

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ABSTRACT

This paper evaluates hedge fund performance through portfolio strategies that incorporate predictability based on macroeconomic variables. Incorporating predictability substantially improves out-of-sample performance for the entire universe of hedge funds as well as for various investment styles. While we also allow for predictability in fund risk loadings and benchmark returns, 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% 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, fund termination, and style composition.

1. Introduction

The year 2008 was a difficult one for hedge funds. Many hitherto successful hedge fund managers who had consistently delivered stellar returns were hit with significant losses. Investors long conditioned to expect high alpha from such financial cognoscenti were sorely disappointed and withdrew funds en masse. For example, despite illustrious multi-year track records, both Kenneth Griffin of Citadel Investment Group and Daniel Ziff of Och-Ziff Capital Management posted significant losses in 2008. As a result of Citadel's poor performance, Griffin was forced to waive management fees and erect gates to stanch the massive wave of redemptions.[1] Have hedge fund managers lost their edge or are they simply victims

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* Corresponding author. Tel.: +44 20 7262 5050;
fax: +44 20 7724 3317.
E-mail address: nnaik@london.edu (N.Y. Naik).

[1] See, for example, "Hedge Fund Selling Puts New Stress on Market," The Wall Street Journal, 7 November 2008, and "Crisis on Wall Street: Citadel Freezes Its Funds Through March," The Wall Street Journal, 13 December 2008. Another star fund manager who suffered losses in 2008 is James Simons whose Renaissance Institutional Futures Fund and Renaissance Institutional Equities Fund slumped 12% and 16%, respectively. See "Renaissance Waives Fees on Fund That Gave Up 12%," The Wall Street Journal, 5 January 2009.

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of the prevailing market conditions? How should fund managers be evaluated given that their performance could be affected by macroeconomic factors? The fact that some investment styles such as global macro and managed futures thrive under the volatile conditions while others do not, suggests that conditioning on the economy could be important when evaluating hedge fund performance.[2]

In this paper, we confront these issues by analyzing the performance of portfolio strategies that invest in hedge funds. These strategies exploit predictability, based on macroeconomic variables, in fund manager asset selection and benchmark timing skills, hedge fund risk loadings, and benchmark returns. By examining the out-of-sample investment opportunity set, we show that allowing for predictability based on macroeconomic variables is important in ex ante identifying subgroups of hedge 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 equity mutual funds that utilize conditional return predictability. In particular, they find that long-only strategies that incorporate predictability in managerial skills outperform their Fama and French (1993) and momentum benchmarks by 2–4% per year by timing industries over the business cycle and by an additional 3–6% per year by choosing funds that outperform their industry benchmarks.

We argue that the Avramov and Wermers framework is even more relevant to the study of hedge fund performance because hedge funds engage in a much more diverse set of strategies than do mutual funds. Hedge funds trade in different markets, with different securities, and at different frequencies. They could employ leverage, complex derivatives, and short-selling. The multitude of hedge fund strategies include global macro, managed futures, convertible arbitrage, short selling, statistical arbitrage, equity long/short, and distressed debt. Anecdotal evidence suggests that the success of these strategies hinges on the behavior of various economic indicators such as the credit spread and volatility.[3] In contrast, the mutual fund universe is much less diverse. Equity mutual funds, for instance, differ mainly according to the style of securities that they invest in (e.g., small cap versus large cap and value versus growth). Therefore, macroeconomic variables are likely to be more important for explaining the cross-sectional variation in managerial skill for hedge funds.

To adjust for risk, we employ the methodology of 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, Fung and Hsieh (2004) show that their parsimonious asset-based style factor model can explain up to 80% of the variation in global hedge fund portfolio returns. The Fung and Hsieh (2004) factor model includes bond factors derived from changes in term and credit spreads. We adjust these factors appropriately for duration so that they represent returns on traded portfolios. In sensitivity tests, to account for hedge funds' exposure to emerging market equities, distress risk, stock momentum, and illiquidity, we augment the Fung and Hsieh (2004) model with the MSCI emerging markets index excess return, the Fama and French (1993) high-minus-low (HML) book-to-market factor, the Jegadeesh and Titman (1993) momentum factor, and the Pástor and Stambaugh (2003) liquidity factor, respectively. We also redo the analysis using option-based factors from the Agarwal and Naik (2004) model to ensure that our results are not artifacts of the risk model we use.

Our results suggest that fund manager performance should be evaluated conditional on various macroeconomic variables. Allowing for predictability in managerial skills based on macroeconomic variables, especially the default spread and some measure of volatility, is important for forming optimal portfolios that outperform ex post. Between 1997 and 2008, an investor who allows for predictability in hedge fund alpha, beta, and benchmark returns can earn a Fung and Hsieh (2004) alpha of 17.42% per annum out-of-sample. This is over 10% per annum higher than that earned by an investor who does not allow for predictability and over 13% per annum higher than that earned by an investor who completely excludes all predictability and the possibility of managerial skills. In contrast, the naïve strategy that invests in the top 10% of funds based on past three-year alpha achieves an ex post alpha of only 5.25% per year. The macroeconomic variables we condition on include the credit spread and the Chicago Board Options Exchange (CBOE) volatility index or the VIX. 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), and illiquidity-induced serial correlation in fund returns (Getmansky, Lo, and Makarov, 2004). The results also remain qualitatively unchanged when we allow for realistic rebalancing horizons or remove funds that are likely to be closed to new investments.

We find that strategies that incorporate predictability in managerial skills significantly outperform other strategies most within the following broad investment style categories: equity long/short, directional trader, security selection, and multi-process. They are less successful within relative value and funds of funds. One view is that by diversifying across various hedge funds, funds of funds become less dependent on economic conditions. The optimal portfolios of hedge funds that allow for predictability in managerial skills do differ somewhat from the other portfolios in terms of investment style composition. Given the within-style results, it is not surprising that the winning strategies also tend to contain a larger proportion of funds from the directional trader and security selection

[2] According to the 2008 Hedge Fund Research report, the average global macro fund gained 4.84% in 2008. In contrast, the average equity long/short fund lost 26.28% over the same period. Indeed, some macro-focused hedge fund families took advantage of the volatile market in 2008 to raise capital and set up new funds. See "Brevan Howard to Raise Dollars 500m with New Fund," The Financial Times, 6 March 2008.

[3] For example, Lowenstein (2000) provides a vivid account of how a flight to quality, brought about by the Russian ruble default, caused Long-Term Capital Management to simultaneously lose money on its risk arbitrage, relative value, and fixed income arbitrage trades.

styles in which conditioning on managerial skills generates the greatest payoffs. Conversely, they also tend to contain fewer funds from the relative value style in which 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 its relative performance 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 5.90% per annum. The alpha spread between the optimal portfolio and this style-mimicking portfolio is 11.52% per annum, which is still 13.39% per annum higher than the style-adjusted alpha spreads for the strategy that does not allow for predictability and the possibility of managerial skills. 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.

What is the economic importance of conditioning managerial skills on macroeconomic variables? We find that the optimal strategy that allows for predictability in managerial skills performed decently during the bull market of the 1990s, reasonably well during the 2001–2002 market downturn, and exceptionally well during the stock market run up from 2003–2007. An initial investment of $10,000 in this optimal portfolio translates to over $110,000 at the end of our sample period (1997–2008). In contrast, the same initial investment in the S&P 500, in the top 10% of hedge funds based on past three-year alpha, or in the strategy that does not allow for predictability and managerial skill, all yield less than $30,000.[4] Some of the impressive returns generated by the optimal strategy in 2003, 2006, and 2007 can be traced to positions in hedge funds operating in emerging markets. However, as we show in our analysis, the strategy outperforms not because of its exposure to specific geographical regions but rather because it selects the right funds investing within those regions that deliver alpha in the out-of-sample period. This holds true even after controlling for time-varying exposure to the MSCI emerging markets index.

The findings in this paper resonate with the literature on the value of active management in the hedge fund industry. Malkiel and Saha (2005) report that, after adjusting for various hedge fund database biases, on average hedge funds significantly under-perform 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, shown by Agarwal and Naik (2000) and others in hedge funds, can be traced to illiquidity-induced serial correlation in fund returns. Recent papers offer 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. They also show that after overcoming the short sample problem inherent in hedge fund data with the Bayesian approach of Pástor and Stambaugh (2002), hedge fund risk-adjusted performance persists at annual horizons. Finally, Aggarwal and Jorion (2010) show using a novel event time approach that emerging funds and managers outperform other hedge funds and that strong early performance can persist up to five years.

We show that conditioning on macroeconomic variables is important in capturing fund managerial skill. The out-of-sample performance of the optimal portfolio that allows for predictability, based on macroeconomic variables, in managerial skills is substantially higher than that for the top decile of funds sorted on the Kosowski, Naik, and Teo (2007) Bayesian alpha or on Ordinary Least Squares (OLS) alpha. We believe that our methodology improves performance by ex ante selecting good managers who were unfortunate victims of economic circumstance while avoiding bad managers who were lucky beneficiaries of economic circumstance. For example, in 2003, the optimal strategy that allows for predictability and managerial skill placed large weights on two funds: an emerging markets fund and a long bias fund. Based on their past three-year OLS alpha, these funds were not very impressive. Yet in the out-of-sample period (i.e., 2003), their returns easily surpassed most of the top funds in our sample ranked by past three-year OLS alpha. One caveat is that the optimal strategy is fairly concentrated in small to mid-size hedge funds. On average, there are nine funds in the portfolio while the median fund assets under management (AUM) is $187 million. Given the capacity constraints (Berk and Green, 2004) that hedge funds face, this suggests that a significant amount of capital cannot be put to work in this strategy.

The rest of the paper is structured as follows. Section 2 reviews the methodology used in the analysis, and Section 3 describes the data. Section 4 presents the empirical results. Section 5 concludes.

2. Methodology

We assess the economic significance of predictability in hedge fund returns as well as the overall value of active hedge fund management.[5] Our experiments are based on the perspectives 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. The investors differ in their views about the parameters governing the following hedge fund return generating model:

$$r_{it} = \alpha_{i0} + \alpha'_{i1} z_{t-1} + \beta'_{i0} f_t + \beta'_{i1} (f_t \otimes z_{t-1}) + \upsilon_{it}, \tag{1}$$

[4] A comparison of the optimal strategy portfolio with just the S&P 500 might not be very insightful as hedge funds, by virtue of their low market betas, tend to outperform stocks in down markets. Therefore, we include other portfolios of hedge funds in the analysis.

[5] See Avramov and Wermers (2006) for a more detailed discussion of the methodology.

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

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

where r_{it} is the month-t hedge fund return in excess of the risk free rate, z_{t-1} contains M business cycle variables observed at end of month $t-1$, f_t is a set of K zero-cost benchmarks typically used to assess hedge fund performance, $\beta_{i0}(\beta_{i1})$ is the fixed (time-varying) component of fund risk loadings, and v_{it} is an idiosyncratic event assumed to be uncorrelated across funds and through time. We assume that this residual is normally distributed with zero mean and variance equal to ψ_i.

Two potential sources of timing-related hedge fund returns are correlated with public information. First, fund risk-loadings could be predictable. This predictability could stem from changing asset level risk loadings, flows into the funds, or manager timing of the benchmarks. Second, the benchmarks, which are return spreads, could be predictable. Such predictability is captured through the predictive regression in Eq. (2). Because both of these timing components can be easily replicated by any investor, we do not consider them to be based on managerial skill. Instead, 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. This private information can be correlated with the business cycle, as captured by the predictive variables. This is 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 investors, who differ in their views about 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), and 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 harbors 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 over-performance or under-performance 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 macroeconomic variables should be ignored; 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%.

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).

Overall, we consider 13 hedge fund investors: 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 is made up of 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:

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

where W_t denotes wealth at time t, b_t is related to the risk aversion coefficient, 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 $\boldsymbol{\Lambda}_t = [\boldsymbol{\Sigma}_t + \mu_t \mu'_t]^{-1}$, where μ_t and $\boldsymbol{\Sigma}_t$ are the mean vector and covariance matrix of future fund returns, yields the following optimization:

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

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

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

where D_t denotes 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 Eqs. (1)–(3), $p(\Theta|D_t)$ is the posterior density of Θ, and I denotes the investor type (13 investors are considered). 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

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, each of which represents a unique trading strategy. Investors differ along a few dimensions, namely, their beliefs on the possibility of active management skills, their beliefs on whether these skills are predictable, and their beliefs on whether fund risk loadings and benchmark returns are predictable. Predictability refers to the ability of a combination of macroeconomic variables (the dividend yield, the default spread, the term spread, the Treasury yield, and the range of the Chicago Board Options Exchange Volatility Index or VIX) 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 σ_α=1% per month.

Investor type	Description
ND	No predictability, dogmatic about no managerial skills
PD-1	Predictable betas, dogmatic about no managerial skills
PD-2	Predictable betas and factors, dogmatic about no managerial skills
NS	No predictability, skeptical about no managerial skills
PS-1	Predictable betas, skeptical about no managerial skills
PS-2	Predictable betas and factors, skeptical about no managerial skills
PS-3	Predictable alphas, skeptical about no managerial skills
PS-4	Predictable alphas, betas, and factors, skeptical about no managerial skills
NA	No predictability, agnostic about no managerial skills
PA-1	Predictable betas, agnostic about no managerial skills
PA-2	Predictable betas and factors, agnostic about no managerial skills
PA-3	Predictable alphas, agnostic about no managerial skills
PA-4	Predictable alphas, betas, and factors, agnostic about no managerial skills

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., Pástor, 2000; Pástor and Stambaugh, 2000; Avramov, 2004; Avramov and Chordia, 2006b).

Some concerns arise that mean variance analysis might not be relevant to hedge funds. The mean variance analysis is applicable when returns are normally distributed or investors' preferences are quadratic. Levy and Markowitz (1979) show that the mean variance analysis can be regarded as a second-order Taylor series approximation of standard utility functions. Moreover, they find that the second-order approximations are highly correlated to actual values of power and exponential utility functions over a wide range of parameter values for mutual funds. Fung and Hsieh (1997) extend the Levy and Markowitz (1979) findings to the universe of hedge funds. They argue that, even when hedge fund returns deviate from the normal distribution, the mean variance analysis of hedge funds approximately preserves the ranking of preferences in standard utility functions.

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:

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

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 ten-year Treasury appropriately adjusted for duration, *BAAMTSY* is the change in the spread of Moody's Baa minus the ten-year Treasury also adjusted for duration, *PTFSBD* is the bond PTFS, *PTFSFX* is the currency PTFS, and *PTFSCOM* is the commodities PTFS, where PTFS is primitive trend following strategy (see Fung and Hsieh, 2004). Other papers that measure hedge fund performance relative to the Fung and Hsieh (2004) model include Kosowski, Naik, and Teo (2007) and Fung, Hsieh, Naik, and Ramadorai (2008).

3. Data

We evaluate the performance of hedge funds using monthly net-of-fee returns of live and dead hedge funds reported in the TASS, HFR, CISDM, and MSCI data sets over January 1990 to December 2008—a time period that covers both market upturns and downturns, as well as relatively calm and turbulent periods.[6] The union of the TASS, HFR, CISDM, and MSCI databases represents the largest known data set of the hedge funds to date.

Our initial fund universe contains a total of 10,061 live hedge funds and 12,874 dead hedge funds. Due to concerns that funds with assets under management below $20 million could be too small for many institutional investors, we exclude such funds from the analysis.[7] This leaves us with a total of 4,225 live hedge funds and 3,982 dead hedge funds. While overlaps exist among the hedge fund databases, many funds belong to only one specific database. For example, there are 1,425 funds and 1,449 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 equity long/short strategy employed by managers such as Alfred Winslow Jones, the new definition of hedge funds covers a multitude of different strategies. A universally accepted norm to classify hedge funds into different strategy classes does not exist. We follow Agarwal, Daniel, and Naik (2009) 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.

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

[7] The AUM cutoff is implemented every month. Our baseline results remain qualitatively unchanged when we do not implement the AUM cutoff. These results are available upon request.

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 equity long/short, 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 the 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, 2009). 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. Because 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. Because 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. See Fung and Hsieh (2009) for an excellent discussion on the measurement biases in hedge fund performance data.

In addition, because most database vendors (e.g., TASS, HFR, and CISDM) started distributing their data in 1994, the data sets 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 onward in our baseline results. Moreover, we understand that MSCI started collecting hedge fund data only in 2002.[8] Hence to further mitigate survivorship bias, we drop pre-2003 data for funds that are peculiar to MSCI. Another concern is that the results could be confined to funds that are still reporting to the databases but are effectively closed to new investors. Because funds might not always report their closed status, we use fund monthly inflows to infer fund closure. In sensitivity tests, we exclude funds with inflows between 0% and 2% per month to account for the possibility that they are effectively closed to new investors.

4. Empirical results

4.1. Out-of-sample performance

In this subsection, 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 12 months.[9] We do not reform more frequently, as in Avramov and Wermers (2006), because 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 2008 based on data from January 2005 to December 2007. For each portfolio, we report various summary statistics: 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 macroeconomic variables used in Avramov and Wermers (2006), i.e., 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 US equity and bond returns. The dividend yield is the total cash dividends on the Center for Research in Security Prices (CRSP) value-weighted 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 3.89% per year. In contrast, the PD-1 and PD-2 portfolios generate economically greater alphas of 6.30% and 5.92% per year, respectively. However, compared with mutual funds (Avramov and Wermers, 2006), much less evidence exists to indicate that incorporating predictability in managerial skills results in superior ex post performance. The agnostic that incorporates predictability in alpha, betas, and

[8] We thank the anonymous referee for alerting us to the fact that MSCI started collecting data much later than 1994.

[9] We obtain somewhat weaker baseline results for portfolios formed based on funds with at least 24 months of return data. This is because, by going down to a minimum of 24 months of return observations, we get too few degrees of freedom in our large dimensional model. These results are available upon request.

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. Performance is evaluated using ex post excess returns, from January 1997 until December 2008, 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 annual Sharpe ratio, skew is the skewness of monthly regression residuals, kurt is the kurtosis of monthly regression residuals, and 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 as described in the text. Panel A reports results for the predictor model that includes the following macroeconomic 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 Chicago Board Options Exchange Volatility Index or VIX and the default spread. The alpha and alpha *t*-statistic for the PA-4 strategy are in bold.

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
Panel A: Four macroeconomic predictor variables (dividend yield, default spread, term spread, Treasury yield)														
Mean	4.73	7.16	6.63	9.15	12.46	13.70	14.04	14.24	9.97	14.64	14.91	15.75	14.89	6.10
Stdv	14.44	9.74	9.53	15.41	13.65	13.91	17.53	17.36	16.31	14.29	14.31	16.90	18.30	10.42
SR	0.33	0.74	0.70	0.59	0.91	0.99	0.80	0.82	0.61	1.02	1.04	0.93	0.81	0.59
Skew	−0.38	−0.33	−0.39	−0.19	0.14	0.27	−0.06	−0.52	−0.02	0.27	0.29	0.06	−0.23	−0.18
Kurt	2.55	3.53	3.58	4.32	2.96	3.37	3.04	3.03	4.11	3.03	3.13	3.26	3.06	3.41
Alpha	3.89	6.30	5.92	6.74	10.85	11.93	12.63	12.42	7.41	12.93	13.15	14.42	**12.74**	5.25
Alpha *t*-statistic	2.34	4.34	2.96	1.66	3.01	3.13	2.84	2.97	1.71	3.32	3.33	3.22	**2.75**	2.37
Alpha *p*-value	0.02	0.00	0.00	0.10	0.00	0.00	0.01	0.00	0.09	0.00	0.00	0.00	0.01	0.02
SNP	0.86	0.48	0.36	0.12	0.19	0.13	0.25	0.34	0.13	0.17	0.13	0.27	0.35	0.34
SCMLC	0.21	0.23	0.11	0.21	0.19	0.14	0.44	0.42	0.22	0.19	0.14	0.35	0.45	0.29
BD10RET	−0.02	0.04	−0.01	0.46	0.22	0.24	0.30	0.36	0.51	0.24	0.25	0.27	0.40	0.13
BAAMTSY	−0.12	0.11	0.29	0.84	0.48	0.56	0.61	0.68	0.82	0.48	0.57	0.45	0.45	0.25
PTFSBD	0.00	−0.01	−0.01	−0.04	−0.05	−0.05	−0.03	−0.03	−0.04	−0.05	−0.05	−0.03	−0.04	−0.01
PTFSFX	0.00	0.01	0.01	−0.01	−0.01	0.00	−0.01	−0.01	−0.01	−0.01	0.00	−0.01	−0.01	0.00
PTFSCOM	0.02	0.01	0.01	0.02	0.01	0.01	0.02	0.04	0.02	0.01	0.01	0.00	0.03	0.02
Panel B: Two macroeconomic predictor variables (VIX, default spread)														
Mean	4.73	6.56	10.03	9.15	11.58	15.41	13.91	17.03	9.97	12.13	15.21	15.61	18.50	6.10
Stdv	14.44	11.79	12.72	15.41	14.33	14.15	17.02	15.79	16.31	15.10	14.65	17.83	16.40	10.42
SR	0.33	0.56	0.79	0.59	0.81	1.09	0.82	1.08	0.61	0.80	1.04	0.88	1.13	0.59
Skew	−0.38	−0.50	0.03	−0.19	−0.33	−0.14	−0.44	−0.46	−0.02	−0.22	−0.07	−0.26	−0.44	−0.18
Kurt	2.55	3.00	5.59	4.32	4.30	4.91	3.18	3.48	4.11	3.99	4.59	3.29	3.71	3.41
Alpha	3.89	5.33	9.35	6.74	9.12	13.21	11.97	16.29	7.41	9.62	12.81	13.76	**17.42**	5.25
Alpha *t*-statistic	2.34	3.16	3.07	1.66	2.33	3.37	2.60	4.02	1.71	2.32	3.16	2.82	**4.04**	2.37
Alpha *p*-value	0.02	0.00	0.00	0.10	0.02	0.00	0.01	0.00	0.09	0.02	0.00	0.01	0.00	0.02
SNP	0.86	0.63	0.45	0.12	0.16	0.14	0.22	0.41	0.13	0.18	0.15	0.20	0.41	0.34
SCMLC	0.21	0.21	0.16	0.21	0.10	0.10	0.16	0.22	0.22	0.09	0.08	0.14	0.20	0.29
BD10RET	−0.02	0.05	0.00	0.46	0.51	0.45	0.42	0.07	0.51	0.52	0.48	0.48	0.18	0.13
BAAMTSY	−0.12	0.08	0.17	0.84	0.44	0.43	0.71	0.09	0.82	0.43	0.45	0.78	0.09	0.25
PTFSBD	0.00	−0.01	0.01	−0.04	−0.04	−0.04	−0.02	−0.04	−0.04	−0.04	−0.04	−0.01	−0.04	−0.01
PTFSFX	0.00	0.01	0.03	−0.01	−0.03	−0.02	−0.03	−0.03	−0.01	−0.03	−0.02	−0.03	−0.02	0.00
PTFSCOM	0.02	0.02	0.00	0.02	0.01	0.00	0.04	0.01	0.02	0.01	0.00	0.03	−0.01	0.02

benchmarks (i.e., PA-4) can harvest an alpha of 12.74% per year, which is somewhat smaller than the agnostic who allows for predictability in betas and benchmarks only (i.e., PA-2).

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 could be the 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., macro and trend following) outperform in times of high market volatility while others perform better in times of low market volatility.[10] Hence, conditioning on VIX could allow one to better predict managerial skills by timing the performance of hedge fund investment styles over the volatility cycle.

[10] The 19 February 2008 Wall Street Journal article "Global Macro, the Strategic Sequel," reports that the global macro strategy tends to do well when volatility is high and interest rates are moving. According to the article, by betting on economic trends in currencies, interest rates and other instruments, global macro traders score big gains under such conditions. Similarly, the 5 November 2008 Wall Street Journal article "Some Trend Following Funds are Winners in Rough Market," reports that the increased volatility in markets from commodities to stocks is helping trend followers profit.

Moreover, in the presence of estimation errors, it could be judicious to work with a more parsimonious conditioning framework. For example, Jagannathan and Wang (1996), in their work on the conditional Capital Asset Pricing Model (CAPM), raise the issue of severe estimation errors in the presence of multiple predictors. To minimize estimation errors, they run a horse race across predictors and ultimately use the default spread. Avramov and Chordia (2006a) also appeal to a single predictor, i.e., the default spread. Sharp increases in the default spread are often indicative of flights to quality, which have been linked anecdotally to significant deteriorations in the performance of various hedge fund strategies (Lowenstein, 2000).

Motivated by these concerns, we consider predictability based simply on the default spread and 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. The results are reported in Panel B of Table 2. The evidence indicates that hedge fund investors are rewarded for incorporating predictability in managerial skills, at least when the predictable variation in hedge fund returns is conditioned on our parsimonious set of macroeconomic variables. The PA-4 agnostic who allows for predictability in alpha, betas, and benchmarks can achieve an impressive out-of-sample alpha of 17.42% per year. This is over 13% per year higher than the alpha of the investor who excludes predictability altogether (ND), over 7% per year higher than the alphas of investors who allow for predictability in betas only (PD-1, PS-1, and PA-1), and over 4% per year higher than the alphas of investors who allow for predictability in betas and benchmarks only (PD-2, PS-2, and PA-2). It is interesting to compare 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 replicate their methodology and find that the PA-4 investor outperforms the strategy that invests in the top 10% of funds based on past risk-adjusted performance, regardless of whether risk-adjusted performance is measured using past 36-month OLS alpha (henceforth T10) or past two-year Bayesian posterior alpha (henceforth 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 5.25% and 4.37% per year, respectively.[11]

4.2. Results by investment style

One concern is that our results might not be robust across investment styles. That is, the benefits to predicting managerial skills could 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: 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. The outperformance of the strategies that incorporate predictability is most impressive for security selection, directional traders, equity long/short, and multi-process funds. For example, for security selection funds, the NA strategy generates an alpha of 7.29% per year, and the PA-4 strategy achieves an alpha of 15.09% per year. Similarly, for directional trader funds, the PA-4 strategy generates an alpha of 16.58% per year that is much higher than the 8.64% per year alpha generated by the NA strategy. The same can be said for equity long/short and multi-process funds.

Strategies based on predictable skills are less impressive within the relative value and fund of funds groups when compared with the other investment style groups. For example, within fund of funds, the PA-4 strategy outperforms the NA strategy by only 1.46% per year. One view is that because good fund of funds managers successfully time hedge fund styles over the business cycle, their returns are not as correlated with the default spread and volatility.[12] Another view is that by diversifying across different hedge funds (some whose returns vary positively with the business cycle and some whose returns vary negatively with the business cycle), funds of funds become less dependent on economic conditions. In either case, one gets considerably less mileage when predicting the returns of funds of funds with the macroeconomic measures we consider.

4.3. Robustness checks

Another concern is that our results could be 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 because 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 could be inflated by 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 such as the Sharpe ratio. Further, some of the funds selected by the PA-4 strategy could be closed to investors following good performance. Moreover, additional factors could be required in the performance evaluation model to account for hedge fund

[11] To facilitate meaningful comparison, for the construction of the T10 and KNT portfolios, we use the same set of funds used to form our optimal strategy portfolios.

[12] To elaborate, funds of funds could 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.

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. The T10 column reports results for a strategy that selects the top 10% of funds every January based on past 36-month alphas. Performance is evaluated using ex post excess returns, from January 1997 until December 2008, that are 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, and 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 as described in the text. The predictor model includes the monthly range (high minus low) of the Chicago Board Options Exchange Volatility Index or VIX and the default spread. Panels A–F report results for investment objectives, which are described in detail in the text. The alpha and alpha *t*-statistic for the PA-4 strategy are in bold.

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
Panel A: Long/short equity funds														
Mean	4.42	6.22	4.19	9.86	11.01	9.43	9.50	12.01	10.73	12.27	12.01	9.57	13.09	5.29
Stdv	14.61	12.75	11.01	13.71	13.03	12.37	15.09	13.42	14.08	13.10	12.13	14.80	14.33	10.96
SR	0.30	0.49	0.38	0.72	0.85	0.76	0.63	0.90	0.76	0.94	0.99	0.65	0.91	0.48
Skew	−0.44	−0.52	−0.33	−0.20	−0.30	−0.18	−0.34	−0.34	−0.01	−0.10	0.02	−0.26	−0.34	0.20
Kurt	2.65	3.11	4.28	2.72	2.96	3.38	3.20	3.60	2.64	2.97	3.55	3.50	4.11	3.89
Alpha	3.53	4.94	2.87	7.88	8.80	7.42	8.65	10.94	8.80	10.21	10.09	8.70	**12.05**	5.18
Alpha *t*-statistic	2.27	2.95	1.28	2.30	2.65	2.22	2.60	3.70	2.46	2.95	3.04	2.49	**3.48**	2.10
Alpha *p*-value	0.02	0.00	0.20	0.02	0.01	0.03	0.01	0.00	0.02	0.00	0.00	0.01	0.00	0.04
SNP	0.86	0.70	0.53	0.33	0.32	0.25	0.58	0.49	0.32	0.30	0.26	0.48	0.42	0.34
SCMLC	0.20	0.22	0.18	0.29	0.22	0.18	0.19	0.25	0.29	0.21	0.16	0.20	0.24	0.23
BD10RET	−0.01	0.06	0.15	0.26	0.23	0.24	0.04	0.12	0.29	0.24	0.24	0.16	0.18	0.01
BAAMTSY	−0.04	0.09	−0.10	0.35	0.17	0.11	0.25	0.27	0.39	0.14	0.04	0.40	0.40	0.28
PTFSBD	0.00	−0.01	0.00	−0.04	−0.06	−0.05	−0.01	−0.01	−0.03	−0.05	−0.05	0.01	0.00	0.00
PTFSFX	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.01	−0.01
PTFSCOM	0.02	0.02	0.01	0.02	0.01	0.00	0.01	0.00	0.03	0.01	0.00	0.01	0.00	0.02
Panel B: Directional trader														
Mean	5.69	6.49	9.41	8.74	10.51	14.19	13.54	16.47	11.03	11.45	16.63	14.29	17.68	10.57
Stdv	13.58	11.51	12.38	16.53	15.36	15.24	18.93	16.62	17.20	16.15	15.11	19.17	17.94	14.12
SR	0.42	0.56	0.76	0.53	0.68	0.93	0.72	0.99	0.64	0.71	1.10	0.75	0.99	0.75
Skew	−0.32	−0.28	0.15	−0.42	−0.44	−0.45	−0.15	−0.17	−0.27	−0.33	−0.20	−0.25	−0.36	−0.34
Kurt	2.63	2.94	5.89	4.01	3.73	4.36	2.86	3.03	3.93	3.55	4.16	2.99	3.34	3.16
Alpha	4.98	5.24	8.82	6.58	8.33	12.44	11.32	15.39	8.64	9.06	14.46	12.46	**16.58**	9.84
Alpha *t*-statistic	2.03	2.37	2.73	1.60	2.15	3.22	2.30	3.79	1.99	2.19	3.51	2.45	**3.68**	2.68
Alpha *p*-value	0.04	0.02	0.01	0.11	0.03	0.00	0.02	0.00	0.05	0.03	0.00	0.02	0.00	0.01
SNP	0.60	0.49	0.29	0.29	0.28	0.22	0.36	0.40	0.24	0.27	0.20	0.31	0.42	0.18
SCMLC	0.32	0.26	0.22	0.32	0.27	0.27	0.30	0.32	0.34	0.27	0.26	0.30	0.32	0.29
BD10RET	0.01	0.08	−0.01	0.35	0.38	0.26	0.39	0.12	0.41	0.44	0.37	0.38	0.14	0.11
BAAMTSY	0.11	0.14	0.26	0.52	0.46	0.56	0.56	0.36	0.62	0.49	0.25	0.58	0.30	0.58
PTFSBD	−0.02	−0.02	0.00	−0.07	−0.06	−0.06	−0.05	−0.05	−0.07	−0.06	−0.06	−0.04	−0.05	−0.02
PTFSFX	0.00	0.01	0.03	−0.01	−0.02	−0.01	−0.03	−0.02	−0.01	−0.02	−0.01	−0.03	−0.03	−0.01
PTFSCOM	0.01	0.03	0.01	−0.01	0.00	0.00	0.04	0.02	−0.01	0.00	−0.01	0.02	0.01	0.04
Panel C: Multi-process funds														
Mean	8.05	6.80	8.26	7.37	7.83	6.79	13.29	12.83	6.66	6.89	6.64	11.31	12.11	4.66
Stdv	11.15	9.79	8.96	12.42	12.12	12.20	14.91	15.87	12.19	11.92	11.70	14.38	15.79	8.01
SR	0.72	0.69	0.92	0.59	0.65	0.56	0.89	0.81	0.55	0.58	0.57	0.79	0.77	0.58
Skew	−0.71	−0.55	−0.47	−1.08	−0.99	−0.92	−0.39	−0.54	−1.11	−1.05	−0.88	−0.27	−0.50	−0.61

Kurt	4.15	3.89	4.71	5.36	4.99	5.56	4.14	4.49	5.50	5.12	5.29	4.17	4.44	5.58
Alpha	7.37	5.95	6.75	6.62	7.12	5.96	12.53	11.61	5.96	6.22	5.80	10.54	**11.01**	4.16
Alpha *t*-statistic	4.36	3.74	3.71	2.05	2.30	1.90	3.12	2.73	1.87	2.02	1.92	2.65	**2.58**	2.23
Alpha *p*-value	0.00	0.00	0.00	0.04	0.02	0.06	0.00	0.01	0.06	0.05	0.06	0.01	0.01	0.03
SNP	0.54	0.44	0.35	0.16	0.16	0.18	0.17	0.24	0.16	0.16	0.18	0.15	0.23	0.15
SCMLC	0.30	0.27	0.21	0.10	0.12	0.14	0.17	0.17	0.08	0.09	0.12	0.14	0.16	0.21
BD10RET	0.03	0.06	0.22	−0.05	−0.05	−0.01	−0.01	0.06	−0.06	−0.05	−0.01	0.04	0.04	0.00
BAAMTSY	0.03	0.15	0.15	0.59	0.59	0.49	0.65	0.61	0.56	0.56	0.48	0.56	0.60	0.27
PTFSBD	−0.02	−0.02	−0.02	−0.04	−0.04	−0.05	−0.04	−0.04	−0.04	−0.04	−0.05	−0.03	−0.04	−0.03
PTFSFX	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00
PTFSCOM	0.01	0.01	0.00	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.02	0.02	0.02	0.01
Panel D: Relative value funds														
Mean	−2.07	0.69	3.42	2.90	3.30	3.72	3.76	4.55	2.84	3.24	3.65	3.62	4.80	4.09
Stdv	12.86	9.12	9.03	9.74	8.70	8.58	9.57	10.12	9.61	8.71	8.53	10.13	10.64	5.66
SR	−0.16	0.08	0.38	0.30	0.38	0.43	0.39	0.45	0.30	0.37	0.43	0.36	0.45	0.72
Skew	−0.52	−0.48	−0.50	−1.56	−1.41	−1.20	−2.01	−1.94	−1.61	−1.39	−1.22	−1.83	−1.74	−1.19
Kurt	3.61	4.04	4.91	8.45	7.23	7.08	10.18	9.38	8.85	7.20	7.19	8.62	8.50	7.18
Alpha	−1.69	0.49	2.43	2.39	3.01	3.19	3.22	3.64	2.38	3.03	3.21	2.84	**3.75**	3.98
Alpha *t*-statistic	−0.91	0.32	1.33	0.93	1.43	1.49	1.38	1.48	0.95	1.43	1.51	1.14	**1.42**	2.92
Alpha *p*-value	0.37	0.75	0.18	0.35	0.16	0.14	0.17	0.14	0.35	0.15	0.13	0.26	0.16	0.00
SNP	0.67	0.44	0.39	0.01	0.04	0.05	0.13	0.22	−0.01	0.04	0.04	0.13	0.23	0.06
SCMLC	0.05	0.03	0.04	−0.04	−0.06	−0.04	−0.07	−0.02	−0.05	−0.07	−0.05	−0.08	−0.03	0.03
BD10RET	−0.17	−0.03	0.16	0.00	−0.08	−0.01	−0.11	−0.04	−0.02	−0.10	−0.03	−0.10	−0.03	−0.02
BAAMTSY	−0.06	0.18	0.20	0.75	0.70	0.68	0.58	0.41	0.76	0.70	0.68	0.59	0.39	0.41
PTFSBD	0.00	0.01	0.01	−0.02	−0.03	−0.03	−0.04	−0.04	−0.03	−0.03	−0.03	−0.05	−0.05	−0.01
PTFSFX	−0.02	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.00
PTFSCOM	−0.02	0.00	−0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.00
Panel E: Security selection														
Mean	4.38	6.55	4.48	8.44	9.30	6.72	11.67	14.13	9.10	10.44	9.05	11.93	15.77	8.60
Stdv	14.65	12.79	10.98	13.22	12.42	11.93	14.88	14.73	13.56	12.63	12.04	14.90	14.64	16.29
SR	0.30	0.51	0.41	0.64	0.75	0.56	0.78	0.96	0.67	0.83	0.75	0.80	1.08	0.53
Skew	−0.41	−0.52	−0.27	−0.31	−0.44	−0.24	−0.36	−0.31	−0.13	−0.19	−0.02	−0.29	−0.41	0.47
Kurt	2.62	3.19	4.22	2.78	3.27	3.54	3.50	3.85	2.63	3.24	3.63	3.51	3.91	3.97
Alpha	3.49	5.35	3.18	6.64	7.49	5.10	10.86	13.51	7.29	8.67	7.45	11.23	**15.09**	6.52
Alpha *t*-statistic	2.23	3.21	1.45	2.10	2.46	1.60	3.09	3.70	2.22	2.70	2.30	3.10	**4.01**	2.04
Alpha *p*-value	0.03	0.00	0.15	0.04	0.02	0.11	0.00	0.00	0.03	0.01	0.02	0.00	0.00	0.04
SNP	0.87	0.70	0.54	0.36	0.35	0.27	0.51	0.45	0.36	0.34	0.28	0.43	0.39	0.59
SCMLC	0.23	0.24	0.20	0.29	0.23	0.18	0.23	0.26	0.29	0.21	0.16	0.25	0.23	0.40
BD10RET	0.00	0.05	0.16	0.24	0.23	0.26	0.06	0.07	0.30	0.27	0.29	0.20	0.12	0.20
BAAMTSY	−0.06	0.10	−0.12	0.30	0.15	0.10	0.16	0.08	0.36	0.13	0.05	0.41	0.18	0.56
PTFSBD	0.01	−0.01	0.00	−0.04	−0.05	−0.04	−0.01	−0.02	−0.02	−0.04	−0.03	0.01	−0.01	−0.02
PTFSFX	0.00	0.01	0.01	0.00	0.00	−0.01	0.00	−0.01	0.00	−0.01	−0.01	−0.01	−0.01	0.03
PTFSCOM	0.02	0.02	0.00	0.01	0.00	0.00	0.00	−0.01	0.03	0.01	0.00	0.01	−0.01	0.04
Panel F: Funds of funds														
Mean	2.65	1.45	1.19	6.68	4.40	3.63	9.49	8.52	6.77	4.92	4.38	11.14	8.23	4.27
Stdv	11.49	10.40	8.88	10.25	10.06	9.44	10.75	10.29	9.92	9.95	9.22	11.09	10.56	14.87
SR	0.23	0.14	0.13	0.65	0.44	0.38	0.88	0.83	0.68	0.49	0.48	1.00	0.78	0.29
Skew	−0.46	−0.54	−0.43	0.09	−0.25	−0.18	0.83	0.53	0.16	−0.19	−0.10	0.85	0.57	1.07

Table 3 (*continued*)

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
Kurt	3.72	3.91	4.02	3.94	4.01	4.20	4.74	5.47	3.82	4.06	4.14	4.47	6.35	7.04
Alpha	1.64	0.53	−0.03	5.97	3.43	2.58	9.64	7.87	6.07	3.99	3.39	10.60	**7.53**	3.15
Alpha *t*-statistic	0.77	0.25	−0.02	2.18	1.29	1.04	3.24	2.94	2.25	1.49	1.37	3.44	**2.76**	0.76
Alpha *p*-value	0.44	0.80	0.99	0.03	0.20	0.30	0.00	0.00	0.03	0.14	0.17	0.00	0.01	0.45
SNP	0.45	0.34	0.22	0.19	0.17	0.14	0.15	0.22	0.17	0.15	0.13	0.19	0.23	0.31
SCMLC	0.25	0.21	0.17	0.16	0.19	0.18	0.29	0.31	0.15	0.18	0.17	0.28	0.33	0.09
BD10RET	0.04	0.06	0.18	0.10	0.13	0.13	−0.06	0.03	0.10	0.14	0.13	0.06	0.03	0.29
BAAMTSY	0.35	0.43	0.38	0.34	0.36	0.35	−0.18	−0.33	0.31	0.32	0.30	−0.17	−0.33	0.16
PTFSBD	−0.02	−0.01	−0.01	0.00	−0.01	−0.02	−0.01	−0.04	0.00	−0.01	−0.02	−0.01	−0.04	0.05
PTFSFX	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00
PTFSCOM	0.02	0.03	0.02	0.02	0.02	0.03	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.05

exposure to emerging markets, distress risk (Fama and French, 1993), stock momentum (Jegadeesh and Titman, 1993), and illiquidity (Pástor and Stambaugh, 2003).

To address these issues, we redo the analysis for unsmoothed returns using the Getmansky, Lo and Makarov (2004) algorithm and after dropping the first 12 months of returns for each hedge fund.[13] The results in Table 4 indicate that our baseline results are not, for the most part, driven by illiquidity-induced serial correlation or backfill and incubation bias. Whether we conduct the out-of-sample analysis on unsmoothed returns or backfill and incubation bias adjusted returns, we find that the investor who allows for full predictability, including predictability in managerial skills (i.e., PA-4), significantly outperforms 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 C) or to augmenting the Fung and Hsieh (2004) model with the MSCI emerging markets factor, the Fama and French (1993) HML (high minus low) value factor, the Jegadeesh and Titman (1993) momentum factor, or the Pástor and Stambaugh (2003) liquidity factor (see Panels D–G of Table 4).[14]

To further allay concerns that the results are artifacts of our risk model, we augment our model with the out-of-the-money put and call option-based factors from the Agarwal and Naik (2004) factor model. These option-based factors nicely account for the fact that many hedge fund strategies deliver returns that resemble those from writing put options on equity indices (Agarwal and Naik, 2004). The results with this augmented model are qualitatively similar to our baseline results and are reported in Panel H of Table 4.[15] As an additional robustness check, we redo the analysis with portfolios formed every six months and every quarter. The results are reported in Table 5. We note that allowing for predictability in managerial skills matters whether or not we reform every year, every six months, or every

[13] 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.

[14] 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%. Although this could be an imperfect proxy for whether a fund has closed following good performance, no time series variable in the data indicates whether a fund is closed or open in a given month. Therefore, fund flows are one of the best proxies for this purpose. To capture exposure to stock momentum, we use Kenneth French's UMD (up minus down) momentum factor. Our results with the Pástor and Stambaugh (2003) factor question the findings of Gibson and Wang (2010) who argue that hedge funds do not deliver abnormal returns once liquidity risk is accounted for. Unlike us, Gibson and Wang do not measure performance relative to the Fung and Hsieh model.

[15] We also augment the Fung and Hsieh model with the emerging markets factor, HML, the momentum factor, the liquidity factor, the OTM (out-of-the-money) call factor, and the OTM put factor simultaneously, and we find that the results are qualitatively unchanged. The alpha of the PA-4 strategy with this augmented model is 13.85% per annum (t-statistic=3.20).

Table 4
Robustness checks.

This table reports robustness checks after adjusting for serial correlation, backfill bias, fund closure, and alternative benchmark models. It includes 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. The T10 column reports results for a strategy that selects the top 10% of funds every January based on past 36-month alphas. Performance is evaluated using ex post excess returns, from January 1997 until December 2008, that are 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, and 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 as described in the text. The predictor model includes the monthly range (high minus low) of the Chicago Board Options Exchange Volatility Index or VIX, the default spread, the term spread, and the Treasury yield. Panel A reports results after adjusting returns for serial correlation as in Getmansky, Lo, and Makarov (2004). Panel B reports results after adjusting returns for backfill bias (by excluding the first 12 monthly return observations for each fund). Panel C reports results for funds that are open based on a fund flow proxy. Panels D–H report results when performance is evaluated relative to augmented Fung and Hsieh (2004) models that include emerging market, value, momentum, liquidity, and option-based factors, respectively. The alpha and alpha *t*-statistic for the PA-4 strategy are in bold.

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
Panel A: Serial correlation adjusted returns														
Mean	5.03	6.66	9.67	9.16	11.53	14.56	11.81	16.75	10.51	12.44	15.11	14.60	19.48	5.80
Stdv	14.69	11.97	12.74	15.58	14.62	14.45	17.26	16.63	17.04	15.47	15.06	18.11	17.06	11.00
SR	0.34	0.56	0.76	0.59	0.79	1.01	0.68	1.01	0.62	0.80	1.00	0.81	1.14	0.53
Skew	−0.37	−0.47	0.00	−0.35	−0.48	−0.28	−0.43	−0.43	−0.12	−0.33	−0.18	−0.28	−0.44	−0.10
Kurt	2.53	2.89	5.13	4.33	4.33	4.84	3.23	3.50	4.15	4.05	4.63	3.50	3.79	3.48
Alpha	4.17	5.38	8.90	6.78	8.96	12.42	10.20	16.13	7.91	9.89	12.67	12.82	**17.97**	4.83
Alpha *t*-statistic	2.56	3.25	2.99	1.66	2.26	3.09	2.19	3.90	1.74	2.34	3.04	2.60	**4.06**	2.02
Alpha *p*-value	0.01	0.00	0.00	0.10	0.03	0.00	0.03	0.00	0.08	0.02	0.00	0.01	0.00	0.05
SNP	0.88	0.65	0.48	0.13	0.18	0.16	0.27	0.48	0.14	0.18	0.16	0.22	0.44	0.36
SCMLC	0.24	0.23	0.18	0.21	0.10	0.09	0.16	0.25	0.23	0.09	0.07	0.14	0.22	0.31
BD10RET	0.01	0.08	0.03	0.44	0.50	0.40	0.28	0.05	0.53	0.51	0.47	0.43	0.28	0.17
BAAMTSY	−0.17	0.04	0.13	0.79	0.45	0.39	0.57	0.04	0.83	0.47	0.47	0.78	0.24	0.22
PTFSBD	0.00	−0.01	0.01	−0.05	−0.05	−0.05	−0.04	−0.04	−0.04	−0.05	−0.05	−0.01	−0.03	−0.01
PTFSFX	0.00	0.01	0.02	−0.01	−0.03	−0.02	−0.03	−0.03	−0.01	−0.03	−0.02	−0.03	−0.02	0.00
PTFSCOM	0.02	0.02	0.00	0.01	0.01	0.00	0.04	0.01	0.02	0.01	0.00	0.03	0.00	0.02
Panel B: Backfill bias adjusted returns														
Mean	4.23	6.36	7.03	7.92	10.09	12.90	11.07	14.91	7.97	11.81	15.89	14.39	16.16	6.60
Stdv	14.39	11.85	10.76	17.02	15.49	15.27	17.34	16.26	17.80	14.85	14.22	18.63	17.30	11.08
SR	0.29	0.54	0.65	0.47	0.65	0.84	0.64	0.92	0.45	0.80	1.12	0.77	0.93	0.60
Skew	−0.39	−0.47	−0.50	−0.10	−0.36	−0.18	−0.35	−0.25	0.02	0.04	0.27	−0.24	−0.26	−0.12
Kurt	2.58	3.04	4.67	3.24	3.60	3.83	3.23	2.85	3.29	3.08	3.63	3.42	3.34	3.63
Alpha	3.49	5.21	5.92	5.76	7.53	10.35	9.58	13.83	5.77	9.12	13.09	13.17	**14.36**	5.68
Alpha *t*-statistic	2.13	3.09	2.87	1.39	1.97	2.65	2.07	3.42	1.32	2.42	3.42	2.64	**3.30**	2.41
Alpha *p*-value	0.03	0.00	0.00	0.17	0.05	0.01	0.04	0.00	0.19	0.02	0.00	0.01	0.00	0.02
SNP	0.85	0.62	0.51	0.33	0.31	0.26	0.18	0.37	0.31	0.28	0.22	0.17	0.36	0.35
SCMLC	0.22	0.23	0.19	0.38	0.26	0.25	0.17	0.27	0.37	0.26	0.25	0.20	0.25	0.31
BD10RET	−0.03	0.04	0.09	0.39	0.38	0.37	0.17	0.04	0.39	0.44	0.48	0.19	0.19	0.15
BAAMTSY	−0.10	0.10	0.03	0.68	0.56	0.48	0.79	0.37	0.78	0.49	0.27	0.95	0.60	0.31
PTFSBD	0.00	−0.01	0.00	−0.04	−0.06	−0.07	−0.05	−0.06	−0.04	−0.05	−0.05	−0.03	−0.05	−0.01
PTFSFX	0.00	0.01	0.02	−0.01	−0.01	0.00	−0.02	−0.02	0.00	−0.01	0.00	−0.03	−0.01	0.00
PTFSCOM	0.02	0.02	0.01	0.02	0.02	0.00	0.07	0.03	0.02	0.02	0.01	0.06	0.03	0.03

Table 4 (*continued*)

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
Panel C: Open funds														
Mean	4.34	6.38	9.72	8.55	11.01	14.52	13.26	16.26	9.57	11.64	14.21	14.49	17.49	6.05
Stdv	14.43	11.87	12.55	15.74	14.61	14.33	17.00	15.96	16.55	15.24	14.86	17.68	16.34	10.72
SR	0.30	0.54	0.78	0.54	0.75	1.01	0.78	1.02	0.58	0.76	0.96	0.82	1.07	0.56
Skew	−0.40	−0.50	0.00	−0.18	−0.32	−0.10	−0.46	−0.45	-0.01	−0.20	−0.03	−0.23	−0.39	−0.16
Kurt	2.58	2.97	5.13	4.16	4.09	4.71	3.15	3.44	3.99	3.88	4.39	3.33	3.72	3.28
Alpha	3.48	5.16	8.95	6.31	8.65	12.48	11.30	15.28	7.12	9.17	11.95	12.56	**15.99**	4.84
Alpha *t*-statistic	2.12	3.04	3.00	1.54	2.20	3.21	2.49	3.77	1.64	2.22	2.96	2.63	**3.73**	2.10
Alpha *p*-value	0.04	0.00	0.00	0.13	0.03	0.00	0.01	0.00	0.10	0.03	0.00	0.01	0.00	0.04
SNP	0.86	0.63	0.45	0.16	0.21	0.20	0.24	0.43	0.16	0.21	0.21	0.21	0.41	0.34
SCMLC	0.19	0.21	0.16	0.23	0.12	0.12	0.17	0.24	0.24	0.11	0.11	0.16	0.20	0.24
BD10RET	−0.02	0.04	0.01	0.45	0.49	0.43	0.42	0.10	0.51	0.51	0.46	0.49	0.24	0.13
BAAMTSY	−0.11	0.09	0.17	0.86	0.46	0.43	0.70	0.05	0.85	0.46	0.45	0.77	0.09	0.33
PTFSBD	0.00	−0.01	0.00	−0.04	−0.04	−0.04	−0.02	−0.05	−0.03	−0.04	−0.04	−0.01	−0.04	−0.02
PTFSFX	0.00	0.01	0.03	−0.01	−0.03	−0.02	−0.03	−0.03	−0.01	−0.03	−0.03	−0.03	−0.02	0.00
PTFSCOM	0.02	0.02	0.00	0.02	0.01	0.00	0.05	0.02	0.02	0.01	0.00	0.04	0.00	0.03
Panel D: Fung and Hsieh model augmented with the MSCI emerging markets factor														
Mean	4.73	6.56	10.03	9.15	11.58	15.41	13.91	17.03	9.97	12.13	15.21	15.61	18.50	6.10
Stdv	14.44	11.79	12.72	15.41	14.33	14.15	17.02	15.79	16.31	15.10	14.65	17.83	16.40	10.42
SR	0.33	0.56	0.79	0.59	0.81	1.09	0.82	1.08	0.61	0.80	1.04	0.88	1.13	0.59
Skew	−0.38	−0.50	0.03	−0.19	−0.33	−0.14	−0.44	−0.46	−0.02	−0.22	−0.07	−0.26	−0.44	−0.18
Kurt	2.55	3.00	5.59	4.32	4.30	4.91	3.18	3.48	4.11	3.99	4.59	3.29	3.71	3.41
Alpha	3.67	5.04	9.06	6.37	8.64	12.69	11.52	15.70	7.02	9.13	12.28	13.36	**16.79**	4.96
Alpha *t*-statistic	2.41	3.49	3.10	1.63	2.37	3.52	2.61	4.31	1.67	2.35	3.28	2.82	**4.35**	2.44
Alpha *p*-value	0.02	0.00	0.00	0.11	0.02	0.00	0.01	0.00	0.10	0.02	0.00	0.01	0.00	0.02
SNP	0.71	0.44	0.26	−0.13	−0.16	−0.20	−0.07	0.02	−0.13	−0.15	−0.20	−0.07	−0.01	0.15
SCMLC	0.16	0.15	0.11	0.14	0.01	0.00	0.07	0.11	0.15	−0.01	−0.02	0.06	0.08	0.24
BD10RET	−0.01	0.06	0.01	0.47	0.52	0.46	0.44	0.09	0.53	0.53	0.49	0.50	0.20	0.14
BAAMTSY	−0.23	−0.06	0.03	0.66	0.20	0.18	0.49	−0.21	0.63	0.19	0.19	0.58	−0.23	0.10
PTFSBD	0.01	−0.01	0.01	−0.03	−0.04	−0.03	−0.01	−0.03	−0.03	−0.04	−0.04	0.00	−0.02	−0.01
PTFSFX	0.00	0.01	0.03	−0.01	−0.03	−0.02	−0.03	−0.03	−0.01	−0.03	−0.02	−0.03	−0.02	0.00
PTFSCOM	0.02	0.02	0.00	0.01	0.00	−0.01	0.04	0.01	0.02	0.00	−0.01	0.02	−0.01	0.02
EM	0.14	0.19	0.19	0.24	0.30	0.33	0.28	0.38	0.25	0.31	0.33	0.26	0.41	0.19
Panel E: Fung and Hsieh model augmented with the Fama and French (1993) HML factor														
Mean	4.73	6.56	10.03	9.15	11.58	15.41	13.91	17.03	9.97	12.13	15.21	15.61	18.50	6.10
Stdv	14.44	11.79	12.72	15.41	14.33	14.15	17.02	15.79	16.31	15.10	14.65	17.83	16.40	10.42
SR	0.33	0.56	0.79	0.59	0.81	1.09	0.82	1.08	0.61	0.80	1.04	0.88	1.13	0.59
Skew	−0.38	−0.50	0.03	−0.19	−0.33	−0.14	−0.44	−0.46	−0.02	−0.22	−0.07	−0.26	−0.44	−0.18
Kurt	2.55	3.00	5.59	4.32	4.30	4.91	3.18	3.48	4.11	3.99	4.59	3.29	3.71	3.41
Alpha	4.74	5.89	10.33	7.34	9.45	13.53	11.64	16.09	7.98	9.86	13.02	13.08	**16.89**	6.01
Alpha *t*-statistic	3.11	3.60	3.49	1.81	2.40	3.43	2.51	3.94	1.83	2.36	3.18	2.67	**3.90**	2.81
Alpha *p*-value	0.00	0.00	0.00	0.07	0.02	0.00	0.01	0.00	0.07	0.02	0.00	0.01	0.00	0.01
SNP	0.78	0.58	0.36	0.06	0.13	0.11	0.25	0.43	0.08	0.16	0.13	0.26	0.46	0.27
SCMLC	0.17	0.18	0.12	0.18	0.09	0.09	0.17	0.23	0.20	0.08	0.07	0.17	0.23	0.26
BD10RET	−0.02	0.05	0.00	0.46	0.51	0.45	0.42	0.07	0.51	0.52	0.48	0.49	0.18	0.13

BAAMTSY	−0.05	0.13	0.25	0.89	0.46	0.46	0.69	0.07	0.86	0.45	0.47	0.73	0.04	0.31
PTFSBD	−0.01	−0.01	0.00	−0.05	−0.05	−0.04	−0.02	−0.04	−0.04	−0.05	−0.05	0.00	−0.03	−0.02
PTFSFX	0.00	0.01	0.03	−0.01	−0.03	−0.02	−0.03	−0.03	−0.01	−0.03	−0.02	−0.03	−0.03	0.00
PTFSCOM	0.02	0.02	0.00	0.01	0.00	0.00	0.05	0.01	0.02	0.01	0.00	0.03	−0.01	0.02
HML	−0.20	−0.13	−0.23	−0.14	−0.08	−0.08	0.08	0.05	−0.13	−0.06	−0.05	0.16	0.13	−0.18
Panel F: Fung and Hsieh model augmented with the UMD momentum factor														
Mean	4.73	6.56	10.03	9.15	11.58	15.41	13.91	17.03	9.97	12.13	15.21	15.61	18.50	6.10
Stdv	14.44	11.79	12.72	15.41	14.33	14.15	17.02	15.79	16.31	15.10	14.65	17.83	16.40	10.42
SR	0.33	0.56	0.79	0.59	0.81	1.09	0.82	1.08	0.61	0.80	1.04	0.88	1.13	0.59
Skew	−0.38	−0.50	0.03	−0.19	−0.33	−0.14	−0.44	−0.46	−0.02	−0.22	−0.07	−0.26	−0.44	−0.18
Kurt	2.55	3.00	5.59	4.32	4.30	4.91	3.18	3.48	4.11	3.99	4.59	3.29	3.71	3.41
Alpha	3.03	4.23	7.75	6.06	8.14	12.16	11.47	15.16	7.00	8.81	11.93	13.89	**16.87**	3.55
Alpha *t*-statistic	1.88	2.66	2.63	1.48	2.07	3.09	2.46	3.74	1.59	2.11	2.92	2.81	**3.87**	1.76
Alpha *p*-value	0.06	0.01	0.01	0.14	0.04	0.00	0.02	0.00	0.11	0.04	0.00	0.01	0.00	0.08
SNP	0.88	0.66	0.49	0.13	0.19	0.17	0.24	0.44	0.14	0.20	0.17	0.20	0.43	0.38
SCMLC	0.18	0.18	0.12	0.19	0.07	0.07	0.14	0.19	0.21	0.07	0.06	0.14	0.19	0.25
BD10RET	−0.05	0.01	−0.06	0.44	0.48	0.41	0.41	0.03	0.50	0.49	0.45	0.49	0.16	0.07
BAAMTSY	−0.06	0.15	0.28	0.89	0.50	0.50	0.75	0.16	0.85	0.48	0.51	0.77	0.12	0.36
PTFSBD	0.01	0.00	0.02	−0.04	−0.04	−0.03	−0.02	−0.04	−0.04	−0.04	−0.04	−0.01	−0.03	0.00
PTFSFX	0.00	0.01	0.03	−0.01	−0.02	−0.02	−0.03	−0.03	−0.01	−0.03	−0.02	−0.03	−0.02	0.00
PTFSCOM	0.01	0.01	−0.01	0.01	0.00	−0.01	0.04	0.00	0.02	0.00	−0.01	0.03	−0.01	0.01
UMD	0.09	0.12	0.17	0.07	0.11	0.11	0.05	0.12	0.04	0.09	0.09	−0.01	0.06	0.18
Panel G: Fung and Hsieh model augmented with the Pástor and Stambaugh (2003) liquidity factor														
Mean	4.73	6.56	10.03	9.15	11.58	15.41	13.91	17.03	9.97	12.13	15.21	15.61	18.50	6.10
Stdv	14.44	11.79	12.72	15.41	14.33	14.15	17.02	15.79	16.31	15.10	14.65	17.83	16.40	10.42
SR	0.33	0.56	0.79	0.59	0.81	1.09	0.82	1.08	0.61	0.80	1.04	0.88	1.13	0.59
Skew	−0.38	−0.50	0.03	−0.19	−0.33	−0.14	−0.44	−0.46	−0.02	−0.22	−0.07	−0.26	−0.44	−0.18
Kurt	2.55	3.00	5.59	4.32	4.30	4.91	3.18	3.48	4.11	3.99	4.59	3.29	3.71	3.41
Alpha	3.61	5.00	8.97	6.15	8.60	12.78	11.49	16.02	6.86	9.15	12.41	13.57	**17.44**	4.66
Alpha *t*-statistic	2.25	3.10	2.99	1.55	2.24	3.30	2.52	3.96	1.61	2.23	3.08	2.77	**4.03**	2.32
Alpha *p*-value	0.03	0.00	0.00	0.12	0.03	0.00	0.01	0.00	0.11	0.03	0.00	0.01	0.00	0.02
SNP	0.85	0.62	0.44	0.10	0.15	0.13	0.21	0.40	0.12	0.16	0.14	0.19	0.41	0.32
SCMLC	0.16	0.15	0.10	0.11	0.01	0.03	0.08	0.18	0.13	0.01	0.02	0.10	0.21	0.19
BD10RET	−0.04	0.03	−0.03	0.42	0.47	0.41	0.39	0.05	0.47	0.48	0.45	0.47	0.18	0.08
BAAMTSY	−0.16	0.04	0.12	0.76	0.36	0.37	0.65	0.05	0.74	0.37	0.40	0.75	0.09	0.16
PTFSBD	0.01	−0.01	0.01	−0.03	−0.04	−0.04	−0.01	−0.04	−0.03	−0.04	−0.04	0.00	−0.04	0.00
PTFSFX	0.00	0.01	0.03	−0.01	−0.03	−0.02	−0.03	−0.03	−0.01	−0.03	−0.02	−0.03	−0.02	0.00
PTFSCOM	0.014	0.015	0.00	0.00	0.00	−0.01	0.04	0.01	0.01	0.00	−0.01	0.02	−0.01	0.01
LIQUIDITY	0.08	0.09	0.11	0.16	0.14	0.12	0.13	0.07	0.15	0.13	0.11	0.05	−0.01	0.16
Panel H: Fung and Hsieh model augmented with the Agarwal and Naik (2004) OTM call and put factors														
Mean	4.73	6.56	10.03	9.15	11.58	15.41	13.91	17.03	9.97	12.13	15.21	15.61	18.50	6.10
Stdv	14.44	11.79	12.72	15.41	14.33	14.15	17.02	15.79	16.31	15.10	14.65	17.83	16.40	10.42
SR	0.33	0.56	0.79	0.59	0.81	1.09	0.82	1.08	0.61	0.80	1.04	0.88	1.13	0.59
Skew	−0.38	−0.50	0.03	−0.19	−0.33	−0.14	−0.44	−0.46	−0.02	−0.22	−0.07	−0.26	−0.44	−0.18
Kurt	2.55	3.00	5.59	4.32	4.30	4.91	3.18	3.48	4.11	3.99	4.59	3.29	3.71	3.41
Alpha	3.93	5.22	7.02	3.55	5.75	9.63	10.61	14.64	3.98	6.05	9.11	11.40	**14.79**	4.97
Alpha *t*-statistic	2.18	2.84	2.10	0.80	1.34	2.25	2.14	3.27	0.84	1.34	2.07	2.20	**3.12**	2.02

Table 4 (*continued*)

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
Alpha *p*-value	0.03	0.01	0.04	0.43	0.18	0.03	0.03	0.00	0.40	0.18	0.04	0.03	0.00	0.05
SNP	0.68	0.47	0.31	−0.07	−0.10	−0.12	−0.33	0.22	−0.14	−0.16	−0.17	−0.48	0.15	0.27
SCMLC	0.20	0.20	0.15	0.19	0.08	0.08	0.14	0.21	0.20	0.07	0.06	0.11	0.18	0.29
BD10RET	0.01	0.08	0.03	0.51	0.57	0.51	0.52	0.11	0.58	0.60	0.55	0.61	0.24	0.14
BAAMTSY	−0.03	0.16	0.24	0.93	0.56	0.56	0.99	0.18	0.95	0.59	0.60	1.12	0.21	0.28
PTFSBD	0.00	−0.01	0.01	−0.03	−0.04	−0.03	−0.02	−0.04	−0.03	−0.04	−0.04	0.00	−0.03	−0.01
PTFSFX	0.00	0.01	0.03	−0.01	−0.03	−0.02	−0.04	−0.03	−0.01	−0.03	−0.02	−0.04	−0.03	0.00
PTFSCOM	0.017	0.02	0.00	0.01	0.00	−0.01	0.04	0.01	0.01	0.00	−0.01	0.02	−0.01	0.02
OTMCALL	0.01	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.02	0.00	0.00
OTMPUT	0.00	0.00	−0.01	−0.01	−0.02	−0.02	−0.02	−0.01	−0.02	−0.02	−0.02	−0.02	−0.01	0.00

quarter. With semi-annual rebalancing, the PA-4 strategy still dominates the NA, PA-1, and PA-2 strategies. With quarterly rebalancing, while the PA-4 strategy no longer dominates the PA-2 strategy, it is comforting to note that the best performing strategy is PS-4, which also allows for predictability in managerial skills.

Finally, concerns arise that because funds that drop out from our database could have terminated their operations, our results could be biased upward. This is because, when a fund in the portfolio drops out of the database, we take the equal-weighted average return of the funds in the portfolio that remain in the database. Funds drop out from databases for other reasons as well. Some funds, for instance, stop reporting as they have reached maximum capacity and are no longer open to new investors. It is difficult to fully address the termination issue because we do not observe the termination returns of funds. Because our results are robust to using shorter rebalancing periods (e.g., semi-annually and quarterly), it is unlikely that fund termination significantly affects the results.

Nonetheless, to allay concerns regarding fund termination, we experiment with setting the termination return to 0%, −30%, and −50% for funds that dropped out. We find that the results are robust to these adjustments for fund termination. In particular, if we assume that after a fund drops out, the money previously allocated to the fund earns a 0% return until the end of the year, the PA-4 strategy delivers an alpha of 16.76% per year. If we assume that for the month after it drops out the fund return is −30%, and thereafter, the money is reallocated to the remaining funds in the portfolio, the PA-4 strategy earns an alpha of 12.23% per year. Lastly, if we assume that the termination return is −50%, the PA-4 strategy generates an alpha of 9.20% per year. In all three cases, PA-4 is the best performing strategy and outperforms the ND strategy by a significant margin.

4.4. Economic value of the optimal portfolios

To gauge the economic value of the various optimal portfolios, in Fig. 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 10% of funds based on past three-year alpha (T10), the equal-weighted investment in the Fung and Hsieh (2004) seven factors (henceforth EW), and the no-predictability dogmatist or ND investor who rules out predictability and managerial skills. We find that PA-4 strategy performs remarkably well for most of the sample period. An investor who invests $10,000 in the PA-4 portfolio at the start of the sample period is relatively insulated from the 2001–2002 market downturn and has more than $110,000 at the end of 2008. This is much higher than what investors who invest the same amount in the S&P 500, the T10 portfolio, the EW portfolio, or the ND portfolio has. In particular, a $10,000 investment each in the S&P 500, the T10 portfolio, the EW portfolio, and the ND portfolio translates to about $23,000, $30,000, and $16,000, and $24,000, respectively, at the end of the sample period.

Table 5
Out-of-sample performance for strategies with alternative 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. Panels A and B report results for when investors rebalance portfolios every six and three months, respectively. The T10 column reports results for a strategy that selects the top 10% of funds every six and three months based on past 36-month alphas. Performance is evaluated using ex post excess returns, from January 1997 until December 2008, that are 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, and 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 Fung and Hsieh (2004) seven-factor model as described in the text. The alpha and alpha *t*-statistic for the PA-4 strategy are in bold.

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
Panel A: Semi-annual rebalancing														
Mean	4.36	6.67	8.68	7.13	12.23	14.65	14.00	15.84	6.88	12.68	14.25	12.24	13.90	8.87
Stdv	14.87	12.32	12.18	15.54	15.16	14.46	17.70	15.50	16.37	15.80	15.39	18.02	16.53	10.68
SR	0.29	0.54	0.71	0.46	0.81	1.01	0.79	1.02	0.42	0.80	0.93	0.68	0.84	0.83
Skew	−0.42	−0.57	−0.13	−0.18	−0.21	−0.04	−0.36	−0.43	0.04	−0.04	0.01	−0.28	−0.36	−0.17
Kurt	2.65	3.25	5.26	3.79	3.52	3.73	2.77	3.21	3.58	3.36	3.64	2.79	2.97	3.48
Alpha	3.49	5.76	7.64	5.35	10.11	12.65	12.35	15.22	5.03	10.57	12.23	11.12	**13.52**	8.03
Alpha *t*-statistic	2.13	3.50	2.42	1.32	2.54	3.16	2.76	3.84	1.16	2.49	2.88	2.33	**3.11**	3.46
Alpha *p*-value	0.04	0.00	0.02	0.19	0.01	0.00	0.01	0.00	0.25	0.01	0.00	0.02	0.00	0.00
SNP	0.87	0.64	0.36	0.14	0.19	0.08	0.34	0.30	0.14	0.19	0.10	0.31	0.31	0.31
SCMLC	0.21	0.21	0.14	0.23	0.14	0.11	0.16	0.18	0.24	0.13	0.10	0.10	0.14	0.29
BD10RET	−0.01	0.02	0.16	0.32	0.36	0.40	0.14	0.04	0.38	0.42	0.45	0.10	−0.02	0.14
BAAMTSY	−0.05	0.19	0.19	0.79	0.72	0.70	0.82	0.50	0.81	0.72	0.75	0.75	0.50	0.34
PTFSBD	0.00	−0.01	0.01	−0.05	−0.05	−0.03	−0.04	−0.04	−0.04	−0.04	−0.02	−0.03	−0.03	−0.01
PTFSFX	0.00	0.01	0.02	−0.01	−0.01	−0.01	−0.01	−0.03	−0.02	−0.02	−0.02	−0.02	−0.02	0.00
PTFSCOM	0.02	0.01	0.00	0.01	0.01	0.01	0.06	0.04	0.02	0.01	0.01	0.04	0.02	0.02
Panel B: Quarterly rebalancing														
Mean	4.85	7.39	7.99	10.07	13.30	15.57	14.92	16.70	9.42	13.53	14.48	13.17	14.22	9.74
Stdv	14.95	12.29	12.90	15.39	14.45	14.42	18.44	17.60	16.40	15.20	15.22	18.50	17.79	10.64
SR	0.32	0.60	0.62	0.65	0.92	1.08	0.81	0.95	0.57	0.89	0.95	0.71	0.80	0.92
Skew	−0.41	−0.35	−0.05	−0.03	0.00	0.11	−0.28	−0.34	0.08	0.12	0.13	−0.26	−0.24	−0.15
Kurt	2.64	3.04	4.54	3.50	3.34	3.52	2.69	2.98	3.33	3.11	3.37	2.81	3.00	3.66
Alpha	4.08	6.50	6.51	8.25	11.37	13.49	12.55	14.12	7.52	11.47	12.38	11.34	**12.01**	8.74
Alpha *t*-statistic	2.53	3.61	1.94	2.00	2.94	3.29	2.64	3.00	1.68	2.76	2.85	2.26	**2.44**	3.69
Alpha *p*-value	0.01	0.00	0.05	0.05	0.00	0.00	0.01	0.00	0.09	0.01	0.01	0.03	0.02	0.00
SNP	0.88	0.65	0.37	0.12	0.17	0.05	0.37	0.32	0.14	0.17	0.07	0.28	0.29	0.30
SCMLC	0.20	0.22	0.16	0.23	0.10	0.08	0.15	0.15	0.26	0.09	0.07	0.09	0.12	0.28
BD10RET	−0.04	0.00	0.23	0.34	0.25	0.31	0.40	0.53	0.40	0.33	0.35	0.33	0.42	0.16
BAAMTSY	−0.06	0.04	0.26	0.66	0.60	0.63	0.89	0.68	0.63	0.62	0.64	0.84	0.60	0.34
PTFSBD	0.00	−0.01	0.01	−0.05	−0.06	−0.04	−0.02	0.00	−0.04	−0.05	−0.04	−0.01	−0.02	−0.01
PTFSFX	0.00	0.01	0.02	−0.01	−0.01	0.00	0.00	−0.01	−0.02	−0.02	0.00	−0.01	−0.01	0.00
PTFSCOM	0.02	0.01	0.01	0.01	0.01	0.02	0.04	0.05	0.02	0.02	0.02	0.03	0.03	0.03

During the turmoil of 2008, while the PA-4 strategy was not the best performing strategy, it outperformed most of the other strategies including the no predictability dogmatist strategy (ND) and all the non dogmatist strategies that do not allow for predictability in managerial skills (NS, PS-1, PS-2, NA, PA-1, and PA-2).

4.5. *The determinants of the predictability-based portfolio returns*

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

4.5.1. *Attributes of the optimal portfolios*

Table 6 reports the investment style composition, the median assets under management averaged 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 and security selection funds and a relatively lower weight in relative value funds. As in Table 3, some of the most impressive performances can be achieved by applying strategies based on skill predictability within the directional trader and security selection groups. Conversely, skill predictability based strategies within the relative value group delivered the least impressive performance. Thus, the relatively large holding of directional trader and security selection funds goes some way toward explaining the superior performance of the best strategy (PA-4).

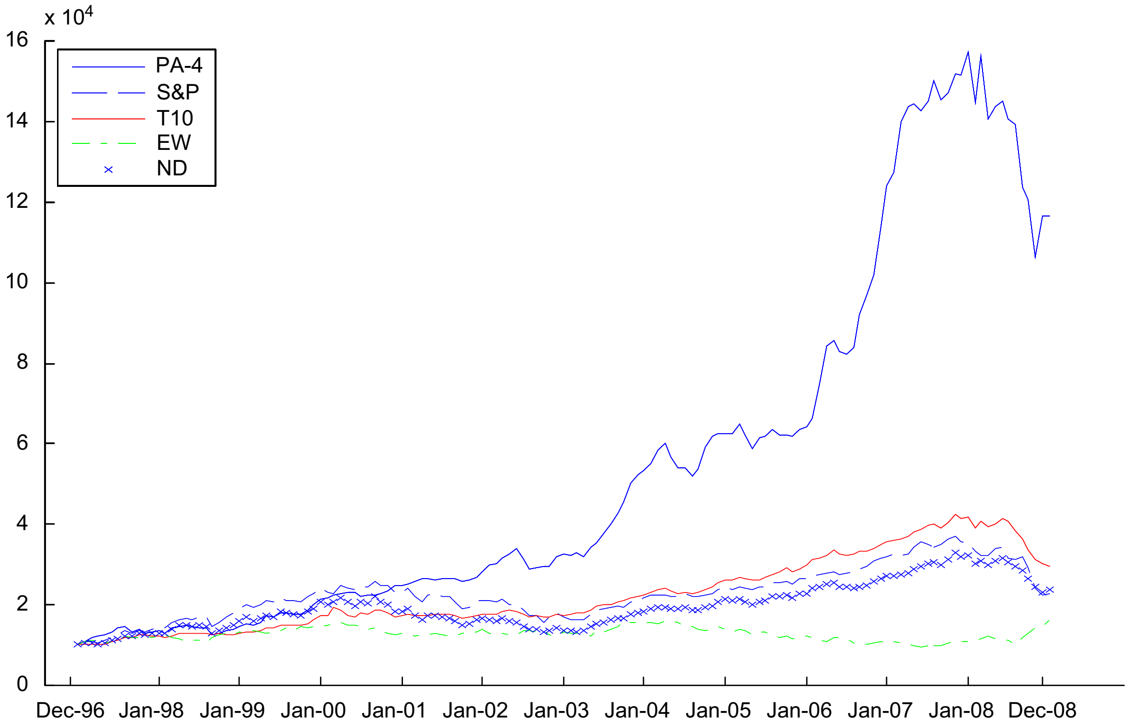

Fig. 1. Cumulative wealth for different portfolio strategies. This figure plots the cumulative wealth of an investor that invests $10,000 in five different strategies starting in January 1997. The strategies include PA-4 (dotted line) and ND (asterisked line) described in Table 1, the strategy T10 that invests in the top 10% of funds each year (dashed line), the strategy S&P that invests in the S&P 500 (solid line), and the strategy EW that is an equal-weighted investment in the seven Fung and Hsieh (2004) risk factors (dashed-dotted line).

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 median assets under management (AUM) in millions of US dollars averaged over time, the age of the fund in years, and the number of funds in each of the portfolios averaged over time.

Style/parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4
Long/short equity	56%	49%	38%	26%	23%	26%	20%	22%	25%	23%	27%	22%	27%
Directional traders	13%	17%	25%	48%	53%	53%	53%	41%	49%	53%	53%	51%	38%
Multi-process	8%	11%	11%	4%	5%	4%	6%	11%	5%	6%	4%	5%	7%
Relative value	9%	10%	15%	17%	15%	15%	9%	9%	15%	13%	12%	8%	9%
Security selection	15%	13%	11%	5%	3%	3%	13%	17%	5%	4%	4%	14%	19%
AUM (millions of US dollars)	108	111	133	121	135	118	195	221	116	113	165	203	187
Fund age (years)	7.1	7.1	7.4	8.3	8.7	9.2	8.1	8.5	9.1	9.3	9.5	8.1	8.6
Number of funds (mean)	320	418	516	5	7	8	8	9	4	6	7	8	9

We find that the portfolios that incorporate predictability in managerial skill do not differ significantly 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 between 8.1 to 8.6 years old. The less successful non dogmatist strategies (NS, PS-1, PS-2, PA-1, and PA-2) tend to hold funds that are marginally older, i.e., between 8.3 to 9.5 years old, while the less successful dogmatist portfolios (ND, PD-1, and PD-2) tend to hold funds that are marginally younger, i.e., between 7.1 to 7.4 years old. The optimal strategy that allows for predictability and managerial skill (PA-4) is fairly concentrated in small to mid-size hedge funds. On average, there are nine funds in the portfolio and the median fund AUM is $187 million. Given the capacity constraints (Berk and Green, 2004) that hedge funds face, this suggests that not a lot of capital can be put to work in this strategy.

4.5.2. 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

Table 7
Style attribution analysis.
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 five rows of the table present time series average excess return (reported in Table 2), the time series average net return μ (the excess return plus the risk-free rate), style level returns based on the five hedge fund investment objectives (LSE, DT, MP, RV, and SS) returns weighted by the optimal investor allocations to each style (μ_S), the style-adjusted net returns ($\mu - \mu_S$) computed as the difference between the second and third row, and its time series p-value. The next three rows break down style-level returns (μ_S) 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 ($\mu_S - \mu_{S,p}$), which is the difference between the style-level return and the style passive return (its time series p-value is also shown). The following three sections report the Fung and Hsieh (2004) seven-factor model alpha (α_{FH}) and associated p-value for investor net returns, style-level returns, and style-adjusted returns. β (SNP, SCMLC, BD10RET, BAAMTSY, PTFSBD, PTFSFX, and PTFSCOM) represent loadings on the seven factors.

Parameter	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4
Excess return	4.73	6.56	10.03	9.15	11.58	15.41	13.91	17.03	9.97	12.13	15.21	15.61	18.50
Average net return μ	8.20	10.03	13.50	12.62	15.05	18.88	17.38	20.50	13.44	15.61	18.68	19.08	21.97
Style return μ_S	9.77	9.75	10.19	9.83	9.99	10.02	8.91	9.69	9.77	9.77	9.83	9.02	10.06
$\mu - \mu_S$	−1.58	0.28	3.31	2.79	5.05	8.86	8.47	10.81	3.66	5.83	8.85	10.06	11.91
$p(\mu - \mu_S)$	0.52	0.86	0.22	0.46	0.15	0.01	0.04	0.00	0.36	0.12	0.02	0.03	0.00
Passive style $\mu_{S,p}$	9.72	9.52	9.62	9.87	9.83	9.88	9.85	9.69	9.88	9.81	9.92	9.87	9.65
$\mu_S - \mu_{S,p}$	0.05	0.22	0.57	−0.03	0.17	0.14	−0.94	0.00	−0.10	−0.04	−0.10	−0.85	0.41
$p(\mu_S - \mu_{S,p})$	0.72	0.12	0.04	0.95	0.64	0.70	0.03	0.99	0.85	0.93	0.81	0.06	0.21
Net return $\alpha_{FH,Net}$	3.89	5.33	9.35	6.74	9.12	13.21	11.97	16.29	7.41	9.62	12.81	13.76	17.42
$p(\alpha_{FH,Net})$	0.02	0.00	0.00	0.10	0.02	0.00	0.01	0.00	0.09	0.02	0.00	0.01	0.00
Style return $\alpha_{FH,S}$	5.76	5.67	6.01	5.71	5.86	5.89	4.67	5.57	5.69	5.71	5.76	4.74	5.90
$p(\alpha_{FH,S})$	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
β_{SNP}	0.35	0.32	0.31	0.24	0.25	0.26	0.26	0.28	0.24	0.25	0.26	0.27	0.28
β_{SCMLC}	0.18	0.18	0.17	0.13	0.13	0.13	0.13	0.14	0.13	0.13	0.13	0.14	0.15
$\beta_{BD10RET}$	0.03	0.04	0.06	0.06	0.05	0.04	0.04	0.03	0.06	0.03	0.03	0.05	0.04
$\beta_{BAATMSY}$	0.10	0.12	0.14	0.30	0.26	0.24	0.30	0.24	0.30	0.26	0.24	0.29	0.23
β_{PTFSBD}	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	0.00	−0.01	−0.01	−0.01	−0.01
β_{PTFSFX}	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
$\beta_{PTFSCOM}$	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Style-adjusted return $\alpha_{FH,\ Net\text{-}S}$	−1.87	−0.35	3.35	1.03	3.26	7.32	7.30	10.72	1.72	3.91	7.05	9.02	11.52
$p(\alpha_{FH,Net\text{-}S})$	0.09	0.71	0.22	0.78	0.34	0.04	0.08	0.00	0.67	0.29	0.05	0.05	0.00
β_{SNP}	0.51	0.31	0.14	−0.13	−0.09	−0.11	−0.04	0.12	−0.11	−0.07	−0.11	−0.07	0.13
β_{SCMLC}	0.02	0.03	0.00	0.09	−0.03	−0.02	0.03	0.08	0.09	−0.04	−0.05	−0.01	0.05
$\beta_{BD10RET}$	−0.05	0.01	−0.06	0.40	0.46	0.41	0.38	0.04	0.46	0.49	0.45	0.44	0.14
$\beta_{BAATMSY}$	−0.22	−0.04	0.04	0.54	0.17	0.19	0.42	−0.15	0.52	0.17	0.21	0.49	−0.14
β_{PTFSBD}	0.01	0.00	0.02	−0.04	−0.03	−0.03	−0.01	−0.03	−0.03	−0.03	−0.04	0.01	−0.02
β_{PTFSFX}	0.00	0.01	0.02	−0.01	−0.03	−0.03	−0.04	−0.04	−0.02	−0.03	−0.03	−0.04	−0.03
$\beta_{PTFSCOM}$	0.01	0.02	0.00	0.00	−0.01	−0.02	0.04	0.00	0.00	−0.01	−0.01	0.02	−0.02

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 ($\mu - \mu_S$). 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 10.06% per year does not explain most of the PA-4 strategy's average net return of 21.97% per year. In fact, the PA-4 style-adjusted net return of 11.91% per year is statistically different from zero at the 5% level.

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 ($\mu_S - \mu_{S,p}$), 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 9.52% to 9.92% per year. Moreover, the difference between the passive and style return ($\mu_S - \mu_{S,p}$) is economically insignificant for all investors.

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 17.42% per year, only 5.90% per year is explained by the style-level alpha. The difference of 11.52% is economically and statistically significant at the 5% level. Interestingly, the style-adjusted alpha is not significantly different from zero at the 5% level for many other strategies. 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. More important, the PA-4 strategy outperforms the ND strategy on a style- and

Table 8
Return decomposition for best portfolio strategy.

This table reports a decomposition of the excess return of the PA-4 portfolio into alpha and beta exposures from January 1997 until December 2008. Panel A decomposes 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 the rows of this table. In Panel A, row 1 of Column 1 reports the average alpha of the PA-4 strategy portfolio return for rolling regressions ending between January 1999 and June 1999 (H1 1999). The alpha is based on an augmented Fung and Hsieh (2004) model that includes an emerging markets benchmark. Columns 2–9 report the semi-annual averages of the betas. Panel B reports the semi-annual average percentage contribution of alpha and beta exposures to the excess return of the PA-4 strategy between January 1999 and December 2008. 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 return of the benchmark during a 24-month period and divided by the average monthly portfolio excess return during the 24-month period. Row 1 of Column 1 reports the average monthly excess return on the PA-4 strategy for rolling regressions ending between January 1999 and June 1999 (H1 1999). Column 2 reports the average percentage contribution of alpha to the total PA-4 excess return during this time period. Columns 3–10 report the percentage contribution of beta exposures.

Panel A: Semi-annual average of monthly rolling regression coefficients

Year	Alpha (percentage per month)	SNP	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	EM
H1 1999	0.15	0.63	0.20	−0.42	−0.30	0.04	−0.10	0.12	0.25
H2 1999	0.86	0.47	0.33	0.07	0.40	0.01	−0.02	0.04	0.23
H1 2000	1.25	0.40	0.22	0.13	0.47	0.00	0.02	−0.02	0.18
H2 2000	1.38	0.21	0.08	−0.35	−0.20	−0.02	0.01	−0.04	0.18
H1 2001	1.55	−0.17	−0.07	−0.16	−0.12	0.00	0.03	−0.05	0.21
H2 2001	1.04	−0.19	−0.05	−0.34	−0.53	−0.01	0.00	−0.07	0.19
H1 2002	0.90	−0.28	−0.04	−0.52	−0.53	0.00	0.00	−0.08	0.17
H2 2002	0.83	0.01	0.36	−0.51	−0.59	−0.05	−0.08	−0.05	0.05
H1 2003	1.42	0.09	0.42	0.16	−0.11	−0.07	−0.03	0.09	0.33
H2 2003	1.56	−0.15	0.35	−0.11	−0.33	−0.05	0.00	0.04	0.61
H1 2004	1.56	−0.42	0.35	−0.06	−0.33	−0.04	0.00	0.00	0.87
H2 2004	1.46	−0.59	0.38	−0.07	−0.10	0.00	0.03	−0.07	0.92
H1 2005	0.83	−0.37	0.56	0.16	0.59	0.06	−0.02	−0.03	0.68
H2 2005	0.12	0.11	0.71	0.39	0.64	0.05	−0.01	0.02	0.34
H1 2006	0.98	0.38	0.79	−0.17	1.00	0.06	−0.05	0.00	0.00
H2 2006	2.40	1.36	0.58	−0.48	1.00	0.10	−0.06	−0.01	−0.26
H1 2007	3.64	0.86	0.81	0.20	1.17	0.12	0.00	−0.09	−0.09
H2 2007	4.51	−0.24	0.86	0.78	0.87	0.06	0.02	−0.13	0.26
H1 2008	2.92	−0.58	0.84	1.17	0.99	0.01	0.00	−0.11	0.78
H2 2008	0.56	−0.72	0.30	0.74	0.29	−0.01	−0.05	−0.04	0.78

Panel B: Semi-annual average of alpha and beta percentage contributions to excess return

Year	Excess return (percentage per month)	Alpha	SNP	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	EM
H1 1999	0.90	13	134	−29	−23	2	12	10	21	−41
H2 1999	1.12	78	64	−43	−1	−2	3	5	6	−10
H1 2000	1.63	76	26	−8	−1	−2	−1	0	−1	11
H2 2000	1.94	72	13	0	4	0	−1	0	3	10
H1 2001	1.60	98	5	−4	−1	0	0	−4	8	−2
H2 2001	1.08	91	16	−4	−14	4	2	1	30	−26
H1 2002	1.11	80	31	−2	−20	−1	0	−3	35	−20
H2 2002	0.89	92	2	37	−41	1	−15	6	23	−5
H1 2003	1.01	147	−14	24	12	−4	−21	−2	−32	−10
H2 2003	2.37	68	1	14	−2	−8	−6	0	−4	37
H1 2004	2.45	64	−7	8	−1	−9	1	−2	−1	47
H2 2004	2.78	53	−24	10	−1	−3	0	−1	−5	70
H1 2005	2.52	34	−19	16	0	17	−16	−1	−2	71
H2 2005	1.15	0	7	24	7	27	−31	1	0	66
H1 2006	1.31	47	11	32	1	27	−28	0	1	9
H2 2006	2.14	114	39	9	2	12	−45	−3	−1	−28
H1 2007	3.24	112	19	1	−2	5	−32	0	4	−6
H2 2007	3.43	132	−5	−31	0	0	−12	0	−3	18
H1 2008	2.34	120	−1	−66	23	−14	−1	0	−10	49
H2 2008	0.59	−45	−930	61	−234	−478	−12	758	−85	1066

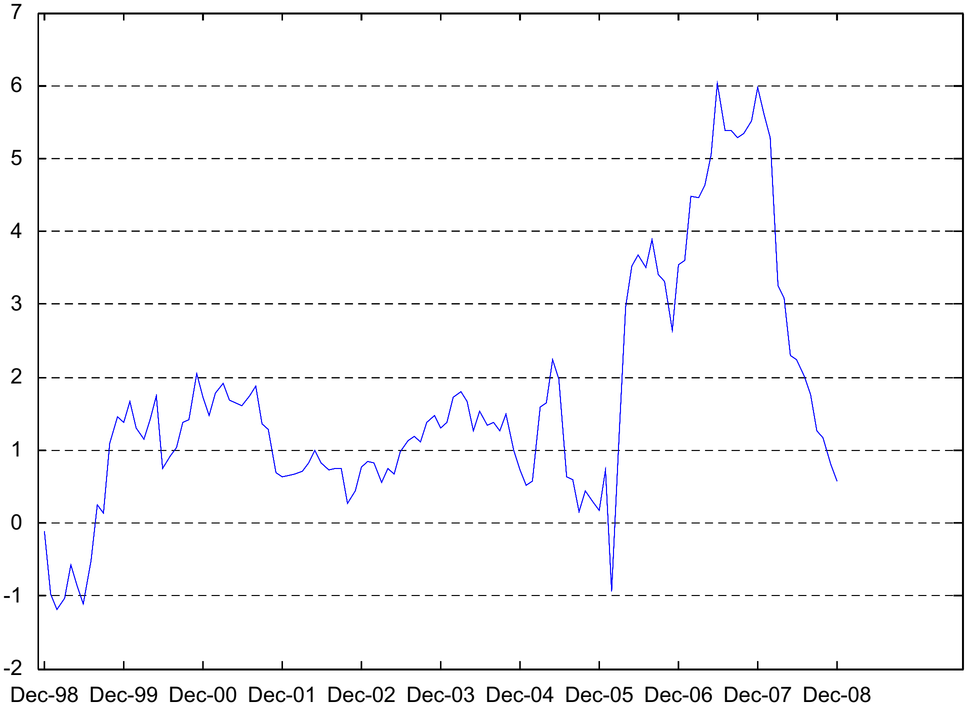

Fig. 2. PA-4 strategy portfolio alpha. This figure plots the rolling 24-month alpha of the PA-4 strategy over time based on the augmented Fung and Hsieh (2004) benchmark model that includes the MSCI emerging markets benchmark. We decompose the excess return of the PA-4 portfolio into alpha and beta exposures by running rolling regressions with a 24-month backward-looking window each month from December 1998 until December 2008. For each rolling regression and 24-month period, we save the monthly alpha of the PA-4 portfolio. See Table 1 for investor type description.

risk-adjusted basis by an economically significant 13.39% per year. Hence, differences in style allocation cannot explain the relative outperformance of the PA-4 strategy.

4.5.3. *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 2008. For each regression we save the portfolio excess return, the alpha, and the beta coefficients as well as the percentage contribution of the alpha and beta exposures to the excess return.[16] Panel A of Table 8 and Fig. 2 show that the alpha is time-varying, with peaks around 2000, 2004, and 2007. Exposure to emerging markets also varied significantly over the sample 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 1999–2008 period. The table shows that while most of the excess return increase between H2 2003 to H2 2005 can be explained by an exposure to emerging markets equities, most of the increase in the PA-4 portfolio excess return between H2 2001 to H1 2003 and between H1 2006 to H1 2008 is driven by an increase in alpha. These results suggest that while time-varying exposure to emerging markets could explain some of the excess returns of the PA-4 strategy, it does not explain the PA-4 strategy alpha calculated in Panel D 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.

5. Conclusion

The hedge fund industry rests primarily on the premise that active fund management adds value. Yet, the recent poor performance of several hitherto stellar fund managers has severely dented investor confidence. Many hedge fund investors have withdrawn their funds, calling into question the value of active fund management skills. We show that hedge fund managers should be evaluated in light of macroeconomic variables such as the default spread and volatility. By examining the optimal hedge fund portfolios of investors with different beliefs on

[16] 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.

managerial skills and predictability, we find that incorporating predictability in managerial skills is important in forming optimal portfolios of hedge funds. The key feature of our model is that predictability is based on the default spread and the VIX. 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. Our performance attribution analysis shows that the strategy outperforms other portfolio strategies by selecting funds that generate statistically significant alpha. Its relative outperformance cannot simply be explained by the styles of the funds selected by the strategy over time. Our results are robust to various adjustments for backfill bias, incubation bias, illiquidity, fund closure, realistic rebalancing horizons, and alternative benchmark models.

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