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Investing in mutual funds when returns are predictable ☆

Doron Avramov*, Russ Wermers

R.H. Smith School of Business, University of Maryland, College Park, MD 20742, USA

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Abstract

This paper forms investment strategies in US domestic equity mutual funds, incorporating predictability in (i) manager skills, (ii) fund risk loadings, and (iii) benchmark returns. We find predictability in manager skills to be the dominant source of investment profitability—long-only strategies that incorporate such predictability outperform their Fama-French and momentum benchmarks by 2 to 4%/year by timing industries over the business cycle, and by an additional 3 to 6%/year by choosing funds that outperform their industry benchmarks. Our findings indicate that active management adds significant value, and that industries are important in locating outperforming mutual funds.

JEL classification: G11; G12; C11

Keywords: Equity mutual funds; Asset allocation; Time-varying managerial skills

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*Corresponding author. Tel.: +1 301 405 0400; fax: +1 301 4050359.
E-mail address: davramov@rhsmith.umd.edu (D. Avramov).

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1. Introduction

About $4 trillion is currently invested in U.S. domestic equity mutual funds, making them a fundamental part of the average U.S. investor's overall portfolio. Since about 90% of these funds are actively managed, researchers have devoted extensive efforts in studying their performance and have found that, on average, active management underperforms passive benchmarks. For example, Wermers (2000) finds that the average U.S. domestic equity fund underperforms its overall market, size, book-to-market, and momentum benchmarks by 1.2%/year over the 1975–1994 period. Recent articles show more optimistic evidence of active management skills among subgroups of funds. For instance, Baks et al. (2001) find that mean-variance investors who are skeptical about active management skills can identify mutual funds that generate ex ante positive alphas.

Moskowitz (2000) provides further evidence on the value of active management during different phases of the business cycle, demonstrating that actively managed funds generate an additional 6%/year during recessions versus expansions. A related body of work by Avramov (2004) and Avramov and Chordia (2005b) demonstrates the real-time profitability of investment strategies that condition on business cycle variables, such as the dividend yield and the default spread, to allocate funds across equity portfolios as well as individual stocks.[1] Both of these areas of research suggest that business cycle variables may be useful in identifying outperforming actively managed equity funds.

This paper studies portfolio strategies that invest in equity mutual funds, incorporating predictability in (i) manager selectivity and benchmark timing skills, (ii) fund risk loadings, and (iii) benchmark returns. Ultimately, we provide new evidence on the promise of equity mutual funds by assessing both the ex ante investment opportunity set and the ex post out-of-sample performance delivered by predictability-based strategies. Our framework for forming investment strategies builds on methodologies developed by Avramov (2004) and Avramov and Chordia (2005b). We do bring several methodological contributions, however, especially in modeling manager skills. Overall, our proposed framework is quite general and is applicable to investment decisions in real time. For one, moments used to form optimal portfolios obey closed-form expressions. This facilitates the implementation of formal trading strategies across a large universe of mutual funds. In addition, our strategies employ long-only positions in mutual funds, which implies long-only positions in the underlying stocks (since almost no mutual funds short-sell stocks)—thus, our models derive performance from strategies that could potentially be implemented by investing in mutual funds or in their underlying stock choices.

Our investment-based approach for studying the value of active management is especially appropriate in mutual fund markets because no-load retail funds are available for large-scale share purchases or redemptions on a daily basis, essentially without trading frictions. To elaborate, since essentially all open-end mutual funds traded in U.S. markets are marked-to-market each day at 4:00 p.m. (New York time), and since all buy or sell orders for these open-end funds are executed at that day's net asset value (the market value of portfolio securities at the close of the New York Stock Exchange, per mutual fund

[1] See also Kandel and Stambaugh (1996) who show that the optimal equity-versus-cash allocation can depend strongly on the current values of business cycle variables, and Barberis (2000) who finds that, as the investment horizon increases, strong predictability leads to a higher investment in equities.

share, minus any fund liabilities), any predictability that is present in these markets would imply a low-cost investment opportunity to capture it.[2]

We provide several new insights about the value of active management and the economic significance of fund return predictability through an analysis of the optimal portfolios of mutual funds prescribed by our framework at the end of the sample period (December 31, 2002). In particular, consider an investor who completely rules out predictability in fund returns, as well as active management skills. Not surprisingly, this investor heavily weights index funds, such as the Vanguard Total Stock Market Index fund. However, if this investor allows for the possibility of predictability in fund risk loadings and benchmark returns, she allocates her entire wealth to actively managed funds in the communication, technology, and other industry sectors. Thus, even though this investor disregards any possibility of active management skills, she holds actively managed funds to capitalize on predictability in benchmark returns and fund risk loadings in a way that cannot be accomplished via long-only index fund positions. Next, consider an investor who allows for predictability in active management skills. At the end of 2002, this investor optimally selects actively managed precious metals funds. Moreover, this investor would suffer a 1% per-month utility loss if forced to hold the mutual funds that are optimally selected by an investor who allows for active management skills, but not predictability in such skills. It is also worth noting that predictability-based strategies generate considerably larger Sharpe ratios than pure index fund strategies.

We also assess the out-of-sample performance of optimal portfolios of mutual funds, using the time series of realized returns generated by various trading strategies. These strategies are formed each month by allocating investments across a total of 1301 domestic equity funds over the December 1979 through November 2002 period. We find that performance is statistically indistinguishable from zero (and often negative) for strategies that ignore fund return predictability. This suggests that investment opportunities based on independent and identically distributed (i.i.d.) mutual fund returns that may be ex ante attractive, as advocated by Baks et al. (2001), do not translate into positive out-of-sample performance. In contrast, investment strategies that incorporate predictable manager selectivity and benchmark timing skills consistently outperform static and dynamic investments in the benchmarks. Specifically, such strategies yield an alpha (benchmark-adjusted performance) of 9.46% (10.52%) per year when investment returns are adjusted using a model with a fixed (time-varying) market beta. Using the Fama and French (1993) (Carhart, 1997) benchmarks, the corresponding alphas are 12.89% and 14.84% (8.46% and 11.17%).

To examine whether our proposed portfolio strategies are unique, we compare their performance to that of three competing strategies that use information in past returns as well as flows: (1) the "hot-hands" strategy of Hendricks et al. (1993); (2) the four-factor

[2]Specifically, only about 6% of open-end U.S. mutual funds charge fees that discourage short-term roundtrips, and most of these are funds that invest in non-U.S. markets, which we exclude from our analysis. For domestic equity funds—other than the brokerage cost of purchasing fund shares (which is negligible)—the buyer of no-load open-end fund shares does not pay the full trading costs and management fees incurred in selecting and buying the underlying portfolio securities. That is, since most securities are already in place, trades must be made by the mutual fund manager only to accommodate the new cash inflow, and the cost of these trades is shared pro-rata among all shareholders, new and old. Thus, the buyer of fund shares may take advantage of any predictability in the future returns of the underlying securities at a far lesser cost than would be incurred by trading these securities separately through a broker.

Carhart (1997) alpha strategy; and (3) the "smart money" strategy of Zheng (1999). Specifically, we form portfolios that pick the top 10% of funds based on their (1) 12-month compounded prior returns, (2) alpha based on the Fama-French and momentum benchmarks computed over the prior three-year period, limited to funds that have at least 30 monthly returns available, and, (3) cash inflows during the prior three months. We show that some of these strategies may generate positive performance (albeit not of the magnitude of our own proposed trading strategies) with respect to the Fama-French benchmarks, but performance becomes insignificant (or even negative) when controlling for momentum.

In contrast, the superior performance of optimal portfolios that incorporate predictable manager skills is robust to adjusting investment returns by the Fama-French and momentum benchmarks. Moreover, it is also robust to adjusting investment returns by the size, book-to-market, and momentum characteristics per Daniel et al. (1997). We demonstrate further that our predictable skill strategies perform best during recessions, but also quite well during expansions, generating positive and significant performance in absolute terms as well as relative to benchmarks. In addition, the predictable skill strategies are able to identify the very best performing funds during both expansions and recessions.

Next, we analyze the stockholdings implied by the strategies examined here. The evidence shows that predictability-based strategies hold mutual funds with similar size, book-to-market, and momentum characteristics as their no-predictability counterparts. Predictability-based strategies also hold stocks with characteristics similar to those of the holdings of the three previously studied strategies noted earlier. Indeed, the overall attributes of the funds selected by strategies that account for predictable manager skills are quite normal—it is their level of performance that is remarkable.

So, how can we explain the superior performance of strategies that account for predictable manager skills? The answer lies in examining inter- and intraindustry asset allocation effects. Specifically, we compute, for each investment month and for each strategy considered, industry-level and industry-adjusted returns. We demonstrate that, for a strategy that incorporates manager skill predictability, these industry-level returns are 2–4%/year higher than those of a passive strategy that merely holds the time-series average industry allocation of that same strategy. In contrast, such industry timing performance is virtually nonexistent for the other competing strategies that do not account for predictable manager skills. Moreover, strategies that account for predictable active management skills tilt more heavily toward mutual funds that overweight technology and energy stocks during recessions, and financial and metals stocks during expansions, indicating that business cycle variables are key to timing these industries. Remarkably, predictable skill strategies also choose individual mutual funds within the outperforming industries that, in turn, substantially outperform their industry benchmarks, even though these industry benchmarks do not account for any trading costs or fees. Specifically, an investor who allows for predictable manager skills optimally selects mutual funds that outperform their overall industry returns by 7.1%/year *more* than their fees and trading costs. Thus, strategies that search for funds with predictable skills are able to capitalize on the varying inter- and intraindustry timing skills of these funds over the business cycle.

To summarize, this paper is the first to show that incorporating predictability in manager skills yields meaningful implications for the choice of optimal portfolios of equity funds. Moreover, we clearly demonstrate in this setting that, although the average actively managed mutual fund underperforms its benchmarks, one can exploit business cycle variables to, ex ante, identify from the vast cross-section of equity funds, those fund managers with superior skills during changing business conditions. Investors who use business cycle information to choose mutual funds derive their robust performance from two important sources. First, they successfully vary their allocations to industries over the business cycle. Second, they vary their allocations to individual actively managed mutual funds within the outperforming industries. Neither source of performance is particularly correlated with the four Fama-French benchmarks, indicating that the private skills identified by these predictability-based strategies are based on characteristics of funds that are heretofore undocumented by the mutual fund literature.

The remainder of this paper proceeds as follows. Section 2 sets forth an econometric framework for studying investments in mutual funds when business cycle variables may predict future returns. Section 3 describes the data used in the empirical analysis, and Section 4 presents the findings. Conclusions and avenues for future research are offered in Section 5. Unless otherwise noted, all derivations are presented in the appendix.

2. A dynamic model of mutual fund returns

In this section, we derive a framework within which we assess the economic significance of predictability in mutual fund returns as well as the overall value of active management from the perspective of three types of Bayesian optimizing investors who differ with respect to their beliefs about the potential for mutual fund managers to possess stock picking skills and benchmark timing abilities. Specifically, the investors differ in their views about the parameters in the mutual fund return generating model, which is described as

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

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

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

In this system of equations, r_{it} is the month-t mutual fund return in excess of the risk-free rate, z_{t-1} is the information set, which contains M business cycle variables observed at the end of month $t-1$, f_t is a set of K zero-cost benchmarks, β_{i0} (β_{i1}) is the fixed (time-varying) component of fund risk loadings, and v_{it} is a fund-specific event, assumed to be uncorrelated across funds and over time, as well as normally distributed with mean zero and variance ψ_i. Modeling beta variation with information variables goes back to Shanken (1990). Modeling business cycle variables using a vector autoregression of order one in an investment context has also been applied by Kandel and Stambaugh (1996), Barberis (2000), Avramov (2002, 2004), and Avramov and Chordia (2005b).

The expression $\alpha_{i0} + \alpha'_{i1} z_{t-1}$ in Eq. (1) captures manager skills in stock selection and benchmark timing, which may vary in response to changing economic conditions.[3] Superior performance is defined as the fund's expected return (above T-bills), in excess of that attributable to a dynamic strategy with the same time-varying risk exposures that

[3]We assume that the benchmarks price all passive investments. Pastor and Stambaugh (2002a,b) note that if benchmarks do not price all passive assets, then a manager could achieve a positive alpha in the absence of any skill by investing in nonbenchmark passive assets with historically positive alphas. Thus, they distinguish between skill and mispricing, which is beyond the scope of this work.

exploit benchmark return predictability. Hence, the measure $\alpha_{i0} + \alpha_{i1}' z_{t-1}$ separates timing- and selectivity-based manager skills from fund returns that are related to predictability in benchmark returns as well as the response of fund risk loadings to changing business conditions.

In particular, note that there are two potential sources of timing-related fund returns that are correlated with public information. The first, predictable fund risk-loadings, may be due to changing stock-level risk loadings, to flows into the funds, or to manager timing of the benchmarks. The second exploits predictability in the benchmark returns themselves. Such predictability is captured through the time-series regression in Eq. (2). Because both of these timing components are assumed to be easily replicated by an investor, we do not consider them to be based on manager "skill." That is, the expression $\alpha_{i0} + \alpha_{i1}' z_{t-1}$ captures benchmark timing and stock picking skills that exploit only the private information possessed by a fund manager. Of course, this private information can be correlated with the business cycle, which is indeed what we show in the empirical section below.

To illustrate the important differences between stock-level predictability, documented by Avramov (2004) and Avramov and Chordia (2005b), and predictability in mutual fund returns, we demonstrate that the return dynamics in Eq. (1) may obtain even when stock-level alphas are zero and stock-level betas are time invariant. In particular, assume that fund i invests in S individual stocks whose return dynamics conform to the constant-beta model $r_{st} = \beta_s' f_t + v_{st}$, where f_t evolves according to Eq. (2) and $\mathrm{E}(v_{st}|z_{t-1}) = 0$. That is, this setup assumes that there is no stock-level return predictability based on public information, beyond that implied by the predictability of the benchmarks. Now, let r_t^S, β^S, and v_t^S be the corresponding S-stock versions of r_{st}, β_s, and v_{st}. At time $t-1$, the fund invests in individual stocks using the strategy $\omega_{it-1} = \omega_{i1}(z_{t-1}) + \omega_{i2}(p_{it-1})$, where ω_{it-1} is an S-vector describing the fractions (of total invested wealth) allocated to individual stocks, p_{it-1} denotes private (fund-specific) information available at time $t-1$, and $\omega(x)$ is some function of x. That is, the fund shifts weights across stocks based on public and private information. The time-t return on fund i is $r_{it} = \omega_{it-1}' r_t^S$. It follows that $\mathrm{E}(r_{it}|z_{t-1}) = \mathrm{E}[\omega_{i2}(p_{it-1})'\beta^S f_t | z_{t-1}] + \mathrm{E}[\omega_{i2}(p_{it-1})' v_t^S | z_{t-1}] + \beta_i(z_{t-1})' \mathrm{E}(f_t|z_{t-1})$.[4] Note that the expression $\alpha_{i0} + \alpha_{i1}' z_{t-1}$ is related to the first two terms of this equation. That is, even when each stock conforms to a constant-beta model in the absence of private information, private manager skills can induce risk loadings and managerial skills that vary with evolving business conditions. Further, note that abnormal performance is attributed to two sources, $\mathrm{E}[\omega_{i2}(p_{it-1})'\beta^S f_t | z_{t-1}]$ and $\mathrm{E}[\omega_{i2}(p_{it-1})' v_t^S | z_{t-1}]$, reflecting benchmark timing skills and stock picking skills, respectively (the dichotomy between timing and selectivity abilities is analyzed by, among others, Merton, 1981; Admati et al., 1986).

Implicit in the above analysis is the assumption that there is significant dependence, either linear or nonlinear, between private (fund-specific) information and the set of publicly available information variables z_t. Empirically, Moskowitz (2000) documents the relation between fund performance and the state of the economy. This relation can be

[4]We treat private manager skills as an unknown stochastic quantity, thus, we form the conditional expected value by conditioning only on public information. Of course, the manager who has a finer information set (private skills) does not perceive stock-level alphas to be zero. That is, the true model that assumes zero stock-level alphas does not condition on private skills.

expected if managers in different sectors possess specialized skills that best apply under certain states of the economy. For example, precious metals fund managers may best differentiate among metals–industry stocks during recessionary periods, whereas technology fund managers may best choose technology stocks during economic expansions. Thus, using macro variables could potentially help investors identify, ex ante, the best performing managers in different economic states.

Overall, the dynamic model for mutual fund returns described by Eqs. (1)–(3) captures potential predictability in managerial skills ($\alpha_{i1} \neq 0$), mutual fund risk loadings ($\beta_{i1} \neq 0$), and benchmark returns ($A_f \neq 0$). Indeed, as noted by Dybvig and Ross (1985) and Grinblatt and Titman (1989), among others, using an unconditional approach to modeling mutual fund returns may lead to unreliable inference about performance—for example, assigning negative performance to a successful market-timer. In turn, this could lead to a suboptimal selection of mutual funds; we demonstrate this below when we apply our proposed framework to our sample of equity mutual funds.

We now turn to our three types of investors, who bring distinct prior beliefs to the mutual fund investment decision. Specifically, they have very different views concerning the existence of manager skills in timing the benchmarks and in selecting securities.

2.1. The "dogmatist"

Our first investor, the dogmatist, has extreme prior beliefs about the potential for manager skill. The dogmatist rules out any potential for skill, either fixed or time varying, for any fund manager. That is, the dogmatist's view is that α_{i0} is fixed at $-\frac{1}{12}(expense + 0.01 \times turnover)$ and that α_{i1} is fixed at zero, where *expense* and *turnover* are the fund's reported annual expense ratio and turnover, and where we assume a round-trip total trade cost of 1% (this prior specification is similar to Pastor and Stambaugh (2002a,b)). The dogmatist believes that a fund manager provides no performance through benchmark timing or stock selection skills, and that expenses and trading costs are a deadweight loss to investors.

We consider two types of dogmatists. The first is a "no-predictability dogmatist (ND)," who rules out predictability, additionally setting the parameters β_{i1} and A_f in Eqs. (1) and (2) equal to zero. The second is a "predictability dogmatist (PD)," who believes that mutual fund returns are predictable based on observable business cycle variables. We further partition our PD investor into two types: PD-1, who believes that fund risk loadings are predictable (i.e., β_{i1} is potentially nonzero), and PD-2, who believes that both risk loadings and benchmark returns are predictable (i.e., β_{i1} and A_f are both allowed to be nonzero). Note that our PD investors believe that asset allocation decisions can be improved by exploiting predictability in mutual fund returns based on public information, but cannot be improved through seeking managers with private skills.

2.2. The "skeptic"

Our second investor, the skeptic, brings more moderate views to the mutual fund selection mechanism. This investor allows for the possibility of active management skills, time-varying or otherwise. The skeptic accepts the idea that some fund managers may beat their benchmarks—even so, her beliefs about outperformance (or underperformance) are somewhat bounded, as we formalize below. Analogous to our partitioning of the dogmatists, we consider two types of skeptics, a "no-predictability skeptic (NS)," who believes that macroeconomic variables should be disregarded, and a "predictability skeptic (PS)," who believes that fund risk loadings, benchmark returns, and perhaps even manager skills are predictable based on evolving macroeconomic variables. Specifically, the NS investor looks for managers with potential skills in the absence of macroeconomic variables, while the PS manager believes that asset allocation can be improved by exploiting macroeconomic variables that potentially forecast fund risk loadings, benchmark returns, and private skills of mutual fund managers.

Starting with our NS investor, we model prior beliefs similarly to Pastor and Stambaugh (2002a,b). In brief, for this investor, α_{i1} equals zero with probability one, and α_{i0} is normally distributed with a mean equal to $-\frac{1}{12}expense$ and a standard deviation equal to 1%. Note that the NS investor believes that there is no relation between turnover and performance.

Moving to our PS investor, we first note that earlier papers that model informative priors in the presence of i.i.d. mutual fund returns essentially assume that manager private skills do not vary over time. In our framework, potential time variation in skills, as specified in Eq. (1), calls for a different prior. Specifically, when skill may vary, an investor's prior can be modeled as if that investor has observed a (hypothetical) sample of T_0 months in which there is no manager skill based on either public or private information—the idea of using a hypothetical sample for eliciting prior beliefs is suggested by Kandel and Stambaugh (1996) and implemented by Avramov (2002, 2004). Formally, this implies that the prior mean of α_{i1} is zero and the prior mean of α_{i0} equals $-\frac{1}{12}expense$. The prior standard errors of these parameters depend upon T_0. An investor who is less willing to accept the existence of skill is perceived to have observed a long sequence of observations from this hypothetical prior sample. At one extreme, $T_0 = \infty$ corresponds to dogmatic beliefs that rule out skill, i.e., our dogmatist of the previous section. At the other, $T_0 = 0$ corresponds to completely agnostic beliefs, which we model in the next section. To address the choice of T_0, we establish an exact link (derived in Section C.2) between the prior uncertainty about skills, denoted by σ_α, and T_0, which is given by

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

where $SR_{\max}$ is the largest attainable Sharpe ratio based on investments in the benchmarks only (disregarding predictability), M is the number of predictive variables, and s^2 is the cross-fund average of the sample variance of the residuals in Eq. (1). This exact relation gives our prior specification the skill uncertainty interpretation employed by earlier work. To apply our prior specification for the PS investor in the empirical section, we compute s^2 and $SR_{\max}^2$, and set $\sigma_\alpha = 1\%$. Then, T_0 is obtained through Eq. (4).

2.3. The "agnostic"

Our last investor is the agnostic. The agnostic resembles the skeptic in that he allows for manager skills to exist, but the agnostic has completely diffuse prior beliefs about the existence and level of skills (i.e., $T_0 = 0$ in our discussion of the previous section). Specifically, the skill level $\alpha_{i0} + \alpha_{i1}' z_{t-1}$ has mean $-\frac{1}{12}(expense)$ and unbounded standard deviation. Effectively, this means that prior beliefs are noninformative. Hence, the agnostic allows the data to completely determine the existence of funds that have managers with stock selection and/or benchmark timing skills. As with the dogmatist and the skeptic, we further subdivide the agnostic into two types, the "no-predictability agnostic (NA)" and the "predictability agnostic (PA)."

Overall we consider 13 investors: three dogmatists, five skeptics, and five agnostics. Table 1 summarizes the investor beliefs and the different strategies that they represent.

2.4. Optimal portfolios of mutual funds

We form optimal portfolios of no-load, open-end U.S. domestic equity mutual funds for each of our 13 investor types. The time-t investment universe comprises N_t funds, with N_t varying over time as funds enter and leave the sample through merger or termination. Each of the various investor types maximizes the conditional expected value of the quadratic utility 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 the time-t invested wealth, b_t reflects the absolute risk aversion parameter, 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 riskless rate, r_{t+1} denoting the vector of excess fund returns, and w_t denoting the vector of optimal allocations to mutual funds.

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

Table 1
List of investors: 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 in a few dimensions, namely, their belief in the possibility of active management skills, their belief of whether these skills are predictable, and their belief of whether fund risk loadings and benchmark returns are predictable. Predictability refers to the ability of the four macro variables, the dividend yield, the default spread, the term spread, and the Treasury yield to predict future fund returns. The dogmatists completely rule out the possibility of active management skills, the agnostics are completely diffuse about that possibility, and the skeptics have prior beliefs reflected by $\sigma_\alpha = 1\%$ per month. Here are the investor types.

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

optimization

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

We derive optimal portfolios of mutual 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

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

where $\mathscr{D}_t$ denotes the data (mutual 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), $p(\Theta|\mathscr{D}_t)$ is the posterior density of Θ, and $\mathscr{I}$ denotes the investor type. Such expected utility maximization is a version of the general Bayesian control problem developed by Zellner and Chetty (1965). Pastor (2000) and Pastor and Stambaugh (2000, 2002b) compute optimal portfolios in a framework in which returns are assumed to be i.i.d., while Kandel and Stambaugh (1996), Barberis (2000), Avramov (2002, 2004), and Avramov and Chordia (2005b) analyze portfolio decisions when returns are potentially predictable.

The optimal portfolio of mutual funds does not explicitly account for Merton (1973) hedging demands. Nevertheless, for a wide variety of preferences, hedging demands are small, or even nonexistent, as demonstrated by Ait-Sahalia and Brandt (2001), among others. Indeed, in unreported tests, we explicitly derive the hedging demands, following Fama's (1996) intuition about Merton's ICAPM. In particular, we derive an optimal ICAPM portfolio by maximizing Eq. (6) subject to the constraint that the optimal portfolio weights times the vector of the factor loadings (corresponding to all benchmarks excluding the market portfolio) is equal to the desired hedge level. For a large range of desired hedge levels, we confirm that the mean-variance portfolio component overwhelmingly dominates any effect from the hedge portfolio component. Let us also note that earlier studies (e.g., Moskowitz, 2003) examine optimal portfolios in the presence of return predictability, focusing on mean-variance optimization excluding hedging demands.

We also note that maximizing a quadratic utility function such as that in Eq. (5) ultimately could lead to optimal portfolios that are not only conditionally efficient, but also unconditionally efficient in the sense of Hansen and Richard (1987), who generalize the traditional mean-variance concept of Markowitz (1952, 1959). To see this, note that the conditionally unconstrained optimal portfolio that solves Eq. (6) is given by

$$w_t = (1/\gamma - r_f)\Lambda_t \mu_t.$$

This conditionally efficient portfolio is equivalent to the unconditionally efficient portfolio presented in Eq. (12) of Ferson and Siegel (2001), when $\gamma = 1/(\mu_p/\zeta + r_f)$, where μ_p is the excess expected return target and

$$\zeta = \mathbb{E}(\mu_t'\Lambda_t\mu_t) = \mathbb{E}\left[\frac{\mu_t'\Sigma_t^{-1}\mu_t}{1 + \mu_t'\Sigma_t^{-1}\mu_t}\right],$$

with $\mathbb{E}$ denoting the expected value taken with respect to the unconditional distribution of the predictors. Since we pre-specify γ, our resulting portfolio is both conditionally and unconditionally efficient to an investor whose expected return target is given by $\mu_p = \zeta(1/\gamma - r_f)$.

What distinguishes our 13 investor types is the predictive moments of future fund returns used in the portfolio optimization. Specifically, different views about the existence and scope of manager skills or about the existence and sources of predictability imply different predictive moments, and, therefore, imply different optimal portfolios of mutual funds. Our objective here is to assess the potential economic gain, both ex ante and out-of-sample, of incorporating fund return predictability into the investment decision for each investor type.

For each of the 13 investors, we derive optimal portfolios considering three benchmark specifications, (i) MKT, (ii) MKT, SMB, HML, and (iii) MKT, SMB, HML, WML, where MKT stands for excess return on the value-weighted CRSP index, SMB and HML are the Fama and French (1993) spread portfolios pertaining to size and value premiums, and WML is the winner-minus-loser portfolio intended to capture the Jegadeesh and Titman (1993) momentum effect. The importance of model specification in mutual fund research is discussed theoretically by Roll (1978) and documented empirically by Lehmann and Modest (1987). By considering three benchmark specifications under various prior beliefs about manager skills and fund return predictability, we attempt to address concerns about model misspecification.

3. Data

Our sample contains a total of 1301 open-end, no-load U.S. domestic equity mutual funds, which include actively managed funds, index funds, sector funds, and ETFs (exchange traded funds). Monthly net returns, as well as annual turnover and expense ratios for the funds, are obtained from the Center for Research in Security Prices (CRSP) mutual fund database over the sample period January 1975–December 2002. Additional data on fund investment objectives are obtained from the Thomson/CDA Spectrum files. In Appendix A, we provide both the process for determining whether a fund is a domestic equity fund as well as a description of the characteristics of our investable equity funds.

Table 2 reports summary statistics on the 1301 funds partitioned by self-declared Thomson investment objectives and by the length of the fund's return history (which roughly corresponds to the fund's age). Our investment objectives are "Aggressive Growth," "Growth," "Growth and Income," and "Metal and Others." The last classification includes precious metals funds, other sector funds (such as health care funds), ETFs, and a small number of funds that have missing investment-objective information in the Thomson files (but that we identify as domestic equity through their names or other information, as explained in the appendix). Note also that the investment objective for a given fund may change during its life, although this is not common. In such cases, we use the last available investment objective for that fund as the fund's objective throughout its life.

In each objective/return–history category, the first row reports the number of funds, the second row displays the cross-sectional median of the time-series average of monthly returns (in %), and the third row shows the cross-sectional median of the time-series average of total net assets (TNA in \$ millions). The total number of funds in each age category ranges from 239 to 278. Overall, the sample is roughly balanced between newer and more seasoned funds.

Table 2
Summary statistics for no-load equity mutual funds

The table reports summary statistics for 1301 open-end, no-load U.S. domestic equity mutual funds partitioned by the intersection of the fund's return history length and by the following Thompson investment objectives: "Aggressive Growth," "Growth," "Growth & Income," and "Metal and Others." The last classification includes precious metal funds, other sector funds (such as health care funds), exchange-traded funds (ETFs), and a small number of funds that have missing investment objective information in the Thomson files (but that we identify as domestic equity through the fund name and/or through the CRSP investment objective). If the investment objective for a given fund changes during its life, we assign the last investment objective available for that fund as the fund's objective throughout its life. A fund is included in the investment universe if it contains at least 48 consecutive return observations through the investment period, where investments are made on a monthly basis starting at the end of December 1979 and ending at the end of December 2002. In each objective-history category, the first row reports the number of funds, the second displays the cross-sectional median of the time-series average annual return (in %), and the third describes the cross-sectional median of the time-series average total net assets (TNA, in $ million).

Investment objective	Fund's return history in months					
	48–66	67–84	85–108	109–156	157–336	All
Aggressive Growth	8	19	26	24	44	121
	15.2	10.6	11.3	11.5	14.4	12.6
	58.2	35.2	36.1	162.6	264.7	123.1
Growth	146	216	155	144	146	807
	5.7	8.9	10.2	10.3	12.8	10.1
	41.4	69.8	116.6	185.1	267.7	100.0
Growth & Income	19	28	49	72	57	225
	5.4	6.3	10.7	9.8	11.6	10.0
	40.4	151.7	96.8	336.2	249.0	165.4
Metal and Others	99	15	9	10	15	148
	2.1	5.6	8.4	10.5	12.0	5.2
	45.8	54.5	73.9	345.6	139.1	67.4
Total # of Funds	272	278	239	250	262	1301

Instruments used to predict future mutual fund returns include the aggregate dividend yield, the default spread, the term spread, and the yield on the three-month T-bill, variables identified by Keim and Stambaugh (1986) and Fama and French (1989) as important in predicting U.S. equity returns. The dividend yield is the total cash dividends on the value-weighted CRSP index over the previous 12 months divided by the current level of the index. The default spread is the yield differential between Moodys BAA-rated and AAA-rated bonds. The term spread is the yield differential between Treasury bonds with more than ten years to maturity and T-bills that mature in three months.

4. Results

We measure the economic significance of incorporating predictability into the investment decisions of our investor types, i.e., the dogmatists, the skeptics, and the agnostics. Predictability is examined from both ex ante and ex post out-of-sample perspectives. Our ex ante analysis is based upon the formation of optimal portfolios, by each investor type, among 890 equity funds at the end of December 2002, which is the end of our sample period. Predictive moments are based on prior beliefs for each investor type, revised by sample data that is observed from January 1975 to December 2002. Our out-of-sample analysis relies on a portfolio strategy based on a recursive scheme that invests in 1301 funds over the December 1979–November 2002 period, with monthly rebalancing for each investor type, for a total of 276 monthly strategies.

The ex ante and out-of-sample analyses rely on portfolio strategies formed by maximizing Eq. (6) (subject to no short-selling of funds), while replacing μ_t and Σ_t (for each month, for each investor type) by the updated Bayesian predictive moments that account for estimation risk. Closed-form expressions for the Bayesian moments are derived in the appendix for dogmatists, skeptics, and agnostics when benchmark returns and fund risk loadings are potentially predictable (Appendix B), and for skeptics and agnostics when, in addition, manager skills are potentially predictable (Appendix C). Several other scenarios are examined as well (e.g., i.i.d. fund returns), all of which are nested cases. We pick a level of risk aversion that guarantees that, if the market portfolio and a risk-free asset are available for investment in December 2002, an investor's entire wealth will be allocated to the market portfolio.[5]

4.1. Optimal portfolios of equity mutual funds

In this section, we analyze the value of active management and the overall economic significance of predictability in mutual fund returns from an ex ante perspective. In particular, Table 3 provides optimal portfolio weights across equity mutual funds for each of the 13 investors described in Table 1. Optimal weights obtain, assuming these investors use the market benchmark to form moments for asset allocation. That is, f_t in Eq. (2) represents the excess return on the value-weighted CRSP index. Weights are shown for the end of December 2002; at this date, the investment universe consists of 890 no-load, open-end equity mutual funds with at least four years of return history. Weights not reported are zero for all investor types. In unreported results (available upon request), we confirm that qualitatively identical findings obtain using the three Fama-French benchmarks as well as the four Carhart benchmarks.

The certainty equivalent loss (shown in Table 3 in basis points per month) is computed from the perspective of investors who use the four macro predictive variables noted earlier to choose funds, i.e., PD-, PS-, and PA-type investors, when they are constrained to hold the optimal portfolios of their no-predictability counterparts, ND, NS, and NA, respectively. The Sharpe ratio is computed for the optimal portfolio of each investor based on that investor's Bayesian predictive moments. The certainty equivalent loss and Sharpe ratio measures are based on investment opportunities perceived at the end of December 2002. We also report average values of the certainty equivalent loss and the Sharpe ratio across all 276 months, beginning December 1979 and ending November 2002, as well as for NBER expansion and recession subperiods. These optimal portfolios that invest in 1301 no-load equity funds also form the basis for our out-of-sample analysis, presented in the next section.

We first examine predictability in fund risk loadings. Note from Table 3 that incorporating predictability in fund risk loadings leaves optimal asset allocations nearly unchanged. To illustrate, consider the dogmatist who incorporates predictable fund risk

[5] Specifically, $\gamma = 2.94$. Experimenting with other values does not change our empirical findings.

Table 3

Optimal portfolios of mutual funds under the CAPM

The table provides optimal portfolio weights across equity mutual funds for each of the 13 investors described in Table 1. The optimal weights are presented assuming these investors use the market benchmark to form moments for asset allocation. Weights are provided for the end of December 2002; at this date, the investment universe consists of 890 no-load, open-end equity mutual funds with at least four years of return history. The certainty equivalent loss (in basis points per month) is computed from the perspective of investors who use predictive variables to choose funds, PD-, PS-, and PA-type investors, when they are constrained to hold the optimal portfolios of their no-predictability counterparts, ND, NS, and NA. In addition, the Sharpe ratio is computed for the optimal portfolio of each investor, based on that type's Bayesian predictive moments. These ex ante measures of the certainty equivalent loss and of Sharpe ratios are based on investment opportunities perceived at the end of December 2002. We also report average values of the certainty equivalent loss and the Sharpe ratio across all 276 months, beginning December 1979 and ending November 2002, as well as for NBER expansion and recession subperiods.

	The dogmatist			The skeptic					The agnostic				
	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4
December 2002 portfolio weights (%)													
White Oak Growth	0.0	0.0	19.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Scudder Equity 500 Index	4.7	3.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Neuberger Berman Focus	0.0	0.0	35.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Flag Investors Communications	0.0	0.0	11.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
AXP Precious Metals	0.0	0.0	0.0	0.0	0.0	0.0	10.4	7.0	0.0	0.0	0.0	18.0	6.9
Scudder Technology	0.0	0.0	3.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Pin Oak Aggressive Stock	0.0	0.0	9.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
T Rowe Price Science & Technology	0.0	0.0	14.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Scudder Gold Precious Metals	0.0	0.0	0.0	0.0	0.0	0.0	28.7	9.0	0.0	0.0	0.0	25.3	0.0
State Farm Growth Fund	13.8	20.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
USAA Precious Metals	0.0	0.0	0.0	0.0	0.0	0.0	60.9	65.6	0.0	0.0	0.0	30.8	34.4
Vanguard Institutional Index	20.7	19.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Vanguard Total Stock Market Index	60.8	55.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
PIMCO Funds PEA Innovation	0.0	0.0	0.0	0.0	0.0	2.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Munder Funds	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.7	0.0	0.0	0.0	10.8	27.5
Needham Growth Fund	0.0	0.0	0.0	3.7	13.9	3.9	0.0	0.0	0.0	16.6	5.3	0.0	0.0
Bjurman Barry Micro Cap Growth	0.0	0.0	0.0	17.0	4.0	0.0	0.0	0.0	8.6	0.0	0.0	0.0	0.0
Evergreen Small Company Value	0.0	0.0	6.4	0.0	0.0	7.4	0.0	0.0	0.0	0.0	7.2	0.0	0.0
BlackRock US Opportunities	0.0	0.0	0.0	11.6	9.9	0.0	0.0	0.0	13.6	11.4	2.9	0.0	0.0
Morgan Stanley Small Cap Growth	0.0	0.0	0.0	44.7	54.5	38.7	0.0	0.0	52.2	60.2	42.2	0.0	0.0
ProFunds UltraOTC	0.0	0.0	0.0	0.0	0.0	13.0	0.0	13.7	0.0	0.0	11.7	0.0	31.2
Rydex Srs Tr Electronics	0.0	0.0	0.0	0.0	0.0	25.0	0.0	0.0	0.0	0.0	22.7	0.0	0.0
Strong Enterprise	0.0	0.0	0.0	0.0	4.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Kinetics Internet	0.0	0.0	0.0	23.0	13.2	9.4	0.0	0.0	25.6	11.8	8.0	15.1	0.0
December 2002													
Certainty equivalent loss (bp/month)		0.0	15.1		1.3	13.7	89.1	89.6		2.0	11.9	95.0	105.5
Sharpe ratio (monthly)	0.13	0.13	0.37	0.36	0.44	0.56	0.75	0.81	0.42	0.54	0.64	1.16	1.09
December 1979– November 2002													
Average CE loss (bp/month)													
Overall		0.2	23.5		3.4	23.1	33.9	53.2		3.7	22.6	52.1	74.1
Expansions		0.2	21.1		3.1	22.4	33.6	53.7		3.3	21.8	50.9	74.8
Recessions		0.2	39.0		5.1	27.0	35.9	49.8		5.6	27.2	60.0	69.8
Average Sharpe ratio (monthly)													
Overall	0.16	0.16	0.05	0.31	0.32	0.26	0.51	0.47	0.33	0.34	0.29	0.69	0.67
Expansions	0.16	0.16	−0.04	0.31	0.30	0.18	0.50	0.42	0.33	0.33	0.21	0.68	0.60
Recessions	0.14	0.14	0.62	0.32	0.39	0.77	0.53	0.79	0.35	0.43	0.81	0.79	1.09

loadings (PD-1). Forcing this investor to hold the slightly different asset allocation of the ND does not lead to any utility loss on December 31, 2002. Also, both the ND and PD-1 investors perceive the same ex ante Sharpe ratios at this date (0.1) as well as over expansions (0.2 on average) and recessions (0.1 on average).

Next, we examine predictability in both benchmark returns and fund risk loadings. Consider the dogmatist who believes in such a predictability structure (PD-2). This investor would experience a nontrivial utility loss of 15.1 basis points per month (1.8%/year) in December 2002 if forced to hold the optimal portfolio of the ND. The utility loss is even larger over the course of all 276 monthly investments. This loss averages 21.1 (39) basis points per month over expansions (recessions).

Moreover, the optimal portfolio of the PD-2 investor consists of very different mutual funds, relative to those optimally selected by investors who disallow predictability or who allow predictability only in fund risk loadings. To illustrate, consider the ND. This investor primarily holds index funds, such as the Vanguard Institutional Index fund and the Vanguard Total Stock Market Index fund. When fund risk loading predictability is allowed (see PD-1), the same index funds are still optimally selected, albeit with slightly different weights. However, when predictability in both fund risk loadings and benchmark returns is allowed (see PD-2), the optimal portfolio consists of no index funds. Instead, a large allocation is made to growth, communication, and technology funds, such as the White Oak Growth fund and the T. Rowe Price Science & Technology fund.

Indeed, in the presence of predictability in fund risk loadings and benchmark returns, optimal portfolios consist entirely of actively managed funds even when the possibility of manager skills in stock selection and benchmark timing is ruled out. That is, actively managed funds allow the investor to capitalize on predictability in benchmarks and fund risk loadings in a way that cannot be achieved through long-only index fund positions.

We now turn to analyze predictability in manager skills. Incorporating such predictability results in asset allocation that is overwhelmingly different from the other cases examined. To illustrate, consider the agnostic who believes in predictable skills (PA-3). This investor faces an enormous utility loss of 95 basis points per month (or 11.4%/year) if constrained to hold the asset allocation of the NA. Focusing on all 276 investment periods, the average utility loss is 50.9 basis points per month over expansions and 60.0 over recessions. Monthly Sharpe ratios are also the largest for investments that allow for predictability in manager skills. The Sharpe ratio is 1.2 on December 31, 2002. The average Sharpe ratio is 0.7 (0.8) over expansions (recessions) as well as 0.7 during all 276 investment periods.

To summarize the findings of this section, we demonstrate that incorporating predictability in mutual fund returns exerts a strong influence on the composition of optimal portfolios of equity mutual funds. The economic significance of predictability is especially strong for investments that allow for predictable managerial skills. In addition, actively managed funds are much more attractive, relative to index funds, in the presence of return predictability. Specifically, the ND optimally holds index funds only, but when predictability in fund risk loadings as well as in benchmark returns is recognized, the PD-1 and PD-2 select actively managed funds. Similarly, under predictable manager skills (PS-3, PS-4, PA-3, and PA-4), all the equity funds that are optimally held are actively managed.

4.2. Out-of-sample performance

Here, we analyze the ex post, out-of-sample performance of various portfolios strategies through a sequence of investments with monthly rebalancing. Optimal portfolios are derived first using the initial 60 monthly observations, then using the first 61 monthly observations, and so on, ..., and are finally rebalanced using the first $T-1$ monthly observations, with $T=336$ denoting the sample size. Hence, the first investment is made at the end of December 1979, the second at the end of January 1980, and so on, ..., with the last at the end of November 2002. We obtain the month-t realized excess return on each investment strategy by multiplying the portfolio weights of month $t-1$ by the month-t realized excess returns of the corresponding mutual funds. This recursive scheme produces 276 excess returns on 13 investment strategies that differ with respect to the Bayesian predictive moments used in the portfolio optimization.

Table 4 reports various performance measures, described below, for evaluating portfolio strategies that are optimal from the perspective of the 13 investor types as well as for three other strategies for selecting mutual funds that have been proposed in past work. These three strategies include a "hot-hands" strategy of investing in the top decile of funds at the end of each calendar year, based on the compounded net return over that year (H–H), a strategy of investing in the top decile of funds at the end of each year, based on the Carhart alpha (α_{wml}) computed over the prior three-year period, limited to funds that have at least 30 monthly returns available (CAR), and a strategy of investing in funds, each quarter, that have above-median cash inflows (among all positive cash-inflow funds) during the prior three months (SM). The first 13 portfolio strategies are formed assuming that investors use only the market benchmark (MKT) to form moments for asset allocation.

In Table 4, μ is the average realized excess return, *SR* is the annual Sharpe ratio, *skew* is the skewness of monthly returns, α_{cpm} ($\tilde{\alpha}_{cpm}$) is the intercept obtained by regressing the realized excess returns on the market factor when beta is constant (when beta is scaled by business cycle variables), $\alpha_{\rm ff}$ and $\tilde{\alpha}_{\rm ff}$ are the same intercepts, but returns are adjusted with the Fama-French benchmarks (MKT, SMB, and HML), and α_{wml} and $\tilde{\alpha}_{wml}$ are the intercepts obtained using the Carhart benchmarks (MKT, SMB, HML, and WML); p-values are reported below the alphas. All alpha measures as well as μ are shown in % per annum. Panel A covers the entire investment period, while Panel B (C) focuses on the December 1979–December 1989 (January 1990–November 2002) investment period. The first subperiod corresponds to the time before the discovery of the macro variables by Keim and Stambaugh (1986) and Fama and French (1989). The second subperiod captures the post-discovery period.

Although we form optimal portfolios for believers in the CAPM, out-of-sample ex post performance is assessed using the CAPM, the Fama-French three-factor model, and the Carhart four-factor model. That is, we assume that the performance evaluator observes the investment returns, but does not know the model that generates the returns, and therefore, implements various performance measures. Note that a positive and significant α_{cpm} ($\tilde{\alpha}_{cpm}$) implies that the evaluated investment outperforms a static (dynamic) investment in the market benchmark, generating higher payoffs for the same fixed (time-varying) risk exposures. Performance measures under the Fama-French and Carhart models should be similarly interpreted; that is, they imply that the evaluated investment outperforms a static or dynamic investment with the same exposures to the multiple risk sources.

Table 4

Out-of-sample performance of portfolio strategies

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, as well as for three strategies for selecting mutual funds advocated in earlier work. These three strategies include a hot-hands strategy of investing in the top decile of funds at the end of each calendar year, based on the compounded net return over that year (H–H); a strategy of investing in the top decile of funds at the end of each year, based on the Carhart alpha (α_{wml}) computed over the prior three-year period, limited to funds having at least 30 monthly returns available (CAR); and a strategy of investing in funds, each quarter, that have above-median cash inflows over the prior three months (SM). 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. Performance is evaluated using 276 ex post excess returns generated using a recursive scheme. The evaluation measures are as follows: μ is the annual average realized excess return, *std* is the annual standard deviation, *SR* is the annual Sharpe ratio, *skew* is the skewness of monthly returns, α_{cpm} ($\tilde{\alpha}_{cpm}$) is the annualized intercept obtained by regressing the realized excess returns on the market factor when beta is constant (when beta is scaled by business cycle variables), α_{ff} and $\tilde{\alpha}_{\mathrm{ff}}$ are the same intercepts, but returns are adjusted with the Fama-French benchmarks, and α_{wml} and $\tilde{\alpha}_{wml}$ are the intercepts obtained using the Carhart benchmarks. *P*-values are reported below the alphas. Panel A covers the entire investment period, and Panel B (C) focuses on the December 1979–December 1989 (January 1990–November 2002) investment period.

	The dogmatist			The skeptic					The agnostic					Previously studied		
	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	H–H	CAR	SM
Panel A: *The entire investment period*																
μ	6.39	6.58	6.74	6.92	5.56	6.06	15.14	11.5	7.07	5.26	5.89	16.52	12.12	8.97	5.42	5.78
std	0.16	0.16	0.16	0.21	0.21	0.18	0.28	0.21	0.21	0.21	0.18	0.28	0.22	0.20	0.19	0.17
SR	0.39	0.41	0.43	0.33	0.27	0.34	0.55	0.54	0.33	0.25	0.33	0.59	0.54	0.44	0.28	0.34
skew	−0.71	−0.68	0.03	−0.20	−0.38	−0.28	1.13	0.32	−0.18	−0.35	−0.31	1.05	0.21	−0.52	−0.57	−0.76
α_{cpm}	−0.23	0.00	1.92	−0.38	−1.89	0.71	8.12	6.48	−0.23	−2.16	0.54	9.46	6.73	1.95	−1.86	−0.99
$P(\alpha_{cpm})$	0.66	1.00	0.38	0.88	0.36	0.79	0.07	0.08	0.93	0.31	0.84	0.04	0.08	0.39	0.26	0.32
α_{ff}	0.60	1.03	0.91	2.33	0.29	−0.51	11.14	6.86	2.49	0.06	−0.46	12.89	7.88	3.48	−0.39	−0.17
$P(\alpha_{\mathrm{ff}})$	0.22	0.04	0.68	0.22	0.87	0.85	0.01	0.05	0.20	0.97	0.86	0.00	0.03	0.04	0.74	0.81
α_{wml}	0.37	0.62	3.92	−1.30	−2.49	0.83	5.98	4.95	−1.29	−2.83	0.51	8.46	6.20	−0.99	−0.48	−1.10
$P(\alpha_{wml})$	0.46	0.22	0.07	0.45	0.13	0.76	0.14	0.17	0.47	0.10	0.85	0.04	0.10	0.46	0.69	0.06
$\tilde{\alpha}_{cpm}$	−0.09	0.14	1.85	0.14	−1.75	0.66	9.01	6.36	0.25	−1.99	0.49	10.52	6.76	1.97	−1.50	−0.99
$P(\tilde{\alpha}_{cpm})$	0.87	0.80	0.40	0.96	0.40	0.80	0.05	0.08	0.92	0.35	0.85	0.02	0.08	0.39	0.35	0.32
$\tilde{\alpha}_{\mathrm{ff}}$	0.20	0.84	0.91	2.96	1.02	0.29	13.30	9.28	3.10	1.03	0.65	14.84	9.13	4.45	0.30	0.29
$P(\tilde{\alpha}_{\mathrm{ff}})$	0.64	0.05	0.62	0.12	0.55	0.90	0.00	0.01	0.11	0.56	0.79	0.00	0.01	0.00	0.79	0.67
$\tilde{\alpha}_{wml}$	0.24	0.69	1.90	−0.84	−1.99	−0.37	9.44	7.88	−0.78	−2.01	−0.19	11.17	7.28	0.08	−0.57	−1.05
$P(\tilde{\alpha}_{wml})$	0.59	0.12	0.30	0.61	0.23	0.88	0.02	0.03	0.65	0.24	0.94	0.00	0.05	0.95	0.61	0.08
Panel B: *December 1979– December 1989*																
μ	7.18	7.68	8.43	7.57	7.88	10.82	12.83	14.85	7.57	7.61	10.78	12.39	15.21	9.40	7.51	7.81
std	0.17	0.17	0.15	0.18	0.21	0.18	0.19	0.19	0.18	0.21	0.18	0.19	0.20	0.20	0.17	0.18
SR	0.43	0.46	0.56	0.43	0.38	0.61	0.69	0.79	0.42	0.37	0.60	0.65	0.76	0.48	0.43	0.44
skew	−0.82	−0.85	−0.05	−1.36	−1.00	−0.36	−1.34	−0.07	−1.41	−1.04	−0.41	−1.36	0.01	−1.43	−0.87	−1.04
α_{cpm}	−0.73	−0.19	2.67	−0.20	−1.20	4.47	5.78	8.51	−0.33	−1.36	4.42	5.41	8.70	0.87	−0.38	−0.45
$P(\alpha_{cpm})$	0.41	0.83	0.36	0.93	0.66	0.24	0.11	0.05	0.90	0.62	0.25	0.18	0.06	0.74	0.85	0.78
α_{ff}	0.26	0.95	2.80	2.08	3.32	4.61	4.49	7.35	1.93	3.18	4.70	3.83	7.60	2.34	1.45	1.49
$P(\alpha_{\mathrm{ff}})$	0.76	0.27	0.36	0.30	0.15	0.22	0.22	0.09	0.36	0.17	0.22	0.34	0.12	0.34	0.43	0.23

Table 4 (*continued*)

	The dogmatist			The skeptic					The agnostic					Previously studied		
	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	H–H	CAR	SM
α_{wml}	0.20	0.79	3.40	−0.58	0.39	4.12	0.52	5.39	−0.85	0.24	4.17	−0.16	5.17	−1.42	−0.10	−0.36
$P(\alpha_{wml})$	0.82	0.36	0.27	0.74	0.85	0.29	0.88	0.22	0.64	0.91	0.29	0.97	0.29	0.48	0.95	0.73
$\tilde{\alpha}_{cpm}$	−0.70	−0.18	1.63	−0.67	−1.48	3.33	5.56	7.08	−0.80	−1.67	3.19	5.16	7.21	0.73	−0.89	−0.74
$P(\tilde{\alpha}_{cpm})$	0.43	0.84	0.56	0.78	0.59	0.36	0.13	0.08	0.75	0.55	0.39	0.20	0.11	0.78	0.66	0.64
$\tilde{\alpha}_{\rm ff}$	−0.27	0.46	−2.30	3.54	5.25	2.39	5.26	5.47	3.35	5.33	2.63	4.98	5.24	6.28	2.14	1.79
$P(\tilde{\alpha}_{\rm ff})$	0.76	0.59	0.38	0.05	0.03	0.50	0.12	0.18	0.08	0.03	0.47	0.20	0.25	0.01	0.28	0.17
$\tilde{\alpha}_{wml}$	0.01	0.76	−1.95	0.95	1.40	1.63	0.88	2.20	0.75	1.46	1.67	0.27	1.04	1.52	−1.23	−1.04
$P(\tilde{\alpha}_{wml})$	0.99	0.39	0.46	0.55	0.54	0.63	0.79	0.61	0.65	0.52	0.63	0.94	0.83	0.48	0.51	0.32
Panel C: January 1990–November 2002																
μ	5.78	5.73	5.44	6.55	3.79	2.39	16.45	8.93	6.88	3.44	2.13	19.69	9.83	8.8	4.6	4.69
std	0.16	0.16	0.16	0.23	0.21	0.18	0.32	0.23	0.24	0.22	0.18	0.33	0.25	0.20	0.20	0.16
SR	0.36	0.36	0.34	0.28	0.18	0.13	0.51	0.39	0.29	0.16	0.12	0.59	0.40	0.43	0.23	0.29
skew	−0.61	−0.55	0.08	0.18	0.10	−0.21	1.35	0.51	0.23	0.15	−0.24	1.26	0.31	0.04	−0.44	−0.53
α_{cpm}	0.19	0.17	1.37	−0.31	−2.40	−2.14	10.10	4.90	0.03	−2.74	−2.39	12.83	5.25	2.23	−2.82	−1.62
$P(\alpha_{cpm})$	0.75	0.81	0.66	0.93	0.43	0.55	0.18	0.38	0.99	0.38	0.50	0.09	0.37	0.50	0.20	0.17
$\alpha_{\rm ff}$	0.91	1.09	0.15	2.04	−1.29	−3.63	13.68	5.47	2.42	−1.61	−3.67	16.99	6.72	3.90	−1.55	−1.04
$P(\alpha_{\rm ff})$	0.09	0.06	0.96	0.48	0.60	0.31	0.03	0.28	0.41	0.53	0.30	0.01	0.20	0.08	0.23	0.14
α_{wml}	0.51	0.45	4.91	−3.26	−4.20	−1.25	6.79	3.65	−3.01	−4.76	−1.90	11.15	5.40	−1.79	−1.25	−2.35
$P(\alpha_{wml})$	0.34	0.44	0.08	0.19	0.08	0.73	0.27	0.49	0.23	0.05	0.60	0.07	0.32	0.28	0.36	0.00
$\tilde{\alpha}_{cpm}$	0.36	0.37	1.82	0.10	−1.64	−1.48	11.90	6.14	0.43	−1.91	−1.68	14.58	6.61	2.28	−2.46	−1.40
$P(\tilde{\alpha}_{cpm})$	0.54	0.59	0.56	0.98	0.58	0.68	0.11	0.27	0.91	0.54	0.63	0.05	0.25	0.49	0.27	0.24
$\tilde{\alpha}_{\rm ff}$	0.67	1.19	1.95	1.42	−1.18	−2.62	17.39	10.28	1.97	−1.32	−2.43	19.77	9.96	3.09	−1.28	−1.04
$P(\tilde{\alpha}_{\rm ff})$	0.07	0.01	0.37	0.59	0.59	0.39	0.00	0.03	0.47	0.56	0.43	0.00	0.05	0.08	0.30	0.09
$\tilde{\alpha}_{wml}$	0.74	0.81	2.14	−3.49	−3.79	−3.66	14.23	8.76	−2.99	−3.66	−3.63	15.83	6.80	−1.21	−1.28	−2.05
$P(\tilde{\alpha}_{wml})$	0.06	0.07	0.34	0.15	0.08	0.24	0.02	0.09	0.23	0.10	0.25	0.01	0.20	0.41	0.32	0.00

Several insights about the success of the 16 (13 + 3) portfolio strategies can be inferred from Table 4. First, when business cycle variables are excluded, optimal portfolios of mutual funds yield zero and even negative performance. To illustrate, the ND realizes an insignificant alpha that ranges between −0.23% to 0.60%/year. This suggests that investment opportunities based on i.i.d. mutual fund returns that may be ex ante attractive, as advocated by Baks et al. (2001), do not translate into positive out-of-sample alphas. At the same time, we find that incorporating predictability in fund risk loadings and benchmark returns delivers much better out-of-sample performance. Specifically, a dogmatist who recognizes the possibility of predictable fund risk loadings and benchmark returns (PD-2) realizes an alpha that ranges between 0.91% ($\alpha_{\rm ff}$) and 3.92% (α_{wml}), where the latter is significant at the 7% level.

It is true that optimal portfolios that reflect predictability in fund risk loadings and benchmark returns do not always beat their benchmarks. However, when we allow for predictability in manager skills, we find that the resulting optimal portfolios consistently outperform strategies that exclude predictability, strategies that account for predictable fund risk loadings and benchmark returns only, static and dynamic investments in the Fama-French and momentum benchmarks, and the three previously studied strategies that we describe above.

To illustrate the strong performance of strategies that account for predictable manager skills, we note that the PA-3 investor selects optimal portfolios that generate $\alpha_{cpm} = 9.46\%$, $\tilde{\alpha}_{cpm} = 10.52\%$, $\alpha_{\mathrm{ff}} = 12.89\%$, $\tilde{\alpha}_{\mathrm{ff}} = 14.84\%$, $\alpha_{wml} = 8.46\%$, and $\tilde{\alpha}_{wml} = 11.17\%$, all of which are significant at the 5% level. Moreover, the out-of-sample Sharpe ratios of strategies that reflect predictability in manager skills are the largest, consistent with the ex ante results described earlier. Take, for instance, the agnostic investor. When predictability is disregarded altogether (NA), the annual Sharpe ratio is 0.33. Allowing for predictability in fund risk loadings and benchmark assets (PA-2) does not change this Sharpe ratio. However, allowing for predictability in manager skills (PA-3) delivers a much larger Sharpe ratio of 0.59.

Note, also, that the skewness of investment returns is much larger for strategies that include predictable manager skills. For instance, the level of skewness is 1.05 for investor PA-3, whereas skewness is negative for all investors who disregard predictability, such as investor NA. Although we consider only investor types who are mean-variance optimizers, the higher skewness obtained by PA-3 and other predictable skills strategies indicate that investors who directly include skewness in their preferences (such as those that have a power utility function) would prefer these optimal portfolios relative to those obtained by NA and other no-predictability strategies. That is, the higher levels of skewness indicate that predictable skills strategies may be attractive to an even broader set of investor types than those considered in this paper.

Interestingly, none of the previously studied strategies, H–H, CAR, and SM, produce performance that matches the optimal portfolios that use predictability in skills. The CAR and SM generate mostly negative alphas. The H–H strategy generates a positive and significant α_{ff} and $\tilde{\alpha}_{\mathrm{ff}}$ of 3.48% and 4.45%, respectively. However, this performance becomes insignificant when adding a momentum factor, consistent with Carhart (1997), suggesting that our portfolio strategies are unique, and that they outperform optimal strategies that exclude conditioning information as well as strategies that pick funds based on past returns and flows, as advocated previously in the mutual fund literature.

We conduct two additional experiments. First, we implement the same performance measures for two subperiods, namely, the investment period December 1979–December 1989 (Panel B, Table 4), and the investment period January 1990–November 2002 (Panel C). Second, we analyze performance (see Table 5) when optimal portfolios are formed by the 13 types of investors that believe in the Fama-French model as well as the Carhart four-factor model.

Studying two subperiods is important because the mutual fund industry has grown over time with many more funds available for investment in the second part of the sample. Moreover, through this subperiod analysis, we attempt to address data-mining concerns. Specifically, Schwert (2003) notes that the so-called financial market anomalies related to profit opportunities tend to disappear, reverse, or attenuate following their discovery. For example, he shows that the relation between the aggregate dividend yield and the equity premium is much weaker after the discovery of that predictor by Keim and Stambaugh (1986) and Fama and French (1989).

Table 5

Out-of-sample performance of optimal portfolio strategies

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, using the Fama-French model and the Carhart (1997) models to form moments for asset allocation. Performance is evaluated using 276 ex post excess returns generated using a recursive scheme. The evaluation measures are as follows: μ is the average realized excess return, α_{cpm} ($\tilde{\alpha}_{cpm}$) is the intercept obtained by regressing the realized excess returns on the market factor when beta is constant (when beta is scaled by business cycle variables), $\alpha_{\rm ff}$ and $\tilde{\alpha}_{\rm ff}$ are the same intercepts, but returns are adjusted with the Fama-French benchmarks, and α_{wml} and $\tilde{\alpha}_{wml}$ are the intercepts obtained using the Carhart benchmarks. All measures are percent per annum. The symbols * and ** reflect significance at the 5% and 10% levels, respectively.

	The dogmatist			The skeptic					The agnostic				
	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4
The Fama-French model													
μ	6.64	6.24	5.86	6.57	4.56	6.25	11.11	10.24	6.65	4.68	6.24	11.17	10.26
α_{cpm}	1.68	1.05	1.00	−0.01	−2.37	0.36	4.57	4.96	−0.10	−2.35	0.30	4.51	4.53
$\alpha_{\rm ff}$	−2.00	−1.60	−0.71	1.09	−0.99	0.77	8.35^{*}	5.00	1.37	−0.68	0.95	9.09^{*}	5.13
α_{wml}	−1.36	−2.47	−1.56	−1.50	−3.07	−0.11	2.98	3.00	−1.32	−2.65	0.12	4.11	3.10
$\tilde{\alpha}_{cpm}$	1.21	0.61	0.42	0.36	−2.00	0.62	5.67	4.96	0.30	−1.93	0.57	5.70	4.60
$\tilde{\alpha}_{\rm ff}$	−1.33	−0.51	0.82	2.34	1.22	2.92	12.38^{*}	7.67^{*}	2.77	1.65	3.04	12.80^{*}	7.41^{*}
$\tilde{\alpha}_{wml}$	−0.46	−1.30	−1.03	−0.32	−1.71	0.74	8.89^{*}	5.99	0.04	−1.21	0.87	9.35^{*}	5.13
The Carhart model													
μ	3.43	8.67	5.11	5.82	8.42	5.17	10.80	10.38	5.95	8.35	5.40	11.73	10.62
α_{cpm}	−1.48	3.25	−0.07	−0.75	2.24	−0.92	4.12	4.78	−0.75	2.08	−0.74	5.02	4.45
$\alpha_{\rm ff}$	−3.41	2.95	−0.50	0.16	4.10^{**}	0.25	7.33^{**}	5.17^{**}	0.47	4.17^{**}	0.56	9.15^{*}	5.80^{**}
α_{wml}	-5.13^{*}	0.27	−3.87	−2.12	2.42	−2.03	2.30	2.49	−1.92	2.68	−1.59	4.16	3.14
$\tilde{\alpha}_{cpm}$	−1.82	3.07	−0.27	−0.39	2.73	−0.61	5.12	4.83	−0.32	2.64	−0.42	6.18	4.67
$\tilde{\alpha}_{\rm ff}$	−2.26	3.98^{**}	1.31	1.69	4.54^{**}	2.17	10.96^{*}	6.97^{*}	2.24	4.63^{*}	2.39	12.96^{*}	6.77^{*}
$\tilde{\alpha}_{wml}$	−3.48	1.60	−2.01	−0.63	2.56	−0.55	7.71^{*}	4.77	−0.19	2.75	−0.21	9.47^{*}	4.56

Observe from Table 4, Panel C that, over the second subperiod, the PA-3 strategy produces robust performance measures. Specifically, the Sharpe ratio attributable to that strategy, 0.59, continues to be the largest across all strategies. In addition, all (annual) alphas are large and significant, given by $\alpha_{cpm} = 12.83\%$, $\tilde{\alpha}_{cpm} = 14.58\%$, $\alpha_{\rm ff} = 16.99\%$, $\tilde{\alpha}_{\rm ff} = 19.77\%$, $\alpha_{wml} = 11.15\%$, and $\tilde{\alpha}_{wml} = 15.83\%$. Indeed, much of the remarkable performance of the PA-3 strategy can be traced to this second subperiod, during which time the predictive variables are already known and available for investment, and when the investment universe contains many more funds.

Finally, observe from Table 5 that the superior performance of strategies that allow for predictability in manager skills also obtains when the three Fama-French benchmarks and the four Carhart benchmarks are used to form optimal portfolios. Such strategies consistently deliver positive alphas that are often significant at the 5% or 10% level. Also note that optimal trading strategies that exclude predictability altogether mostly generate insignificant levels of performance. Overall, the finding that predictability in manager skills is the dominant source of investment profitability still prevails under these alternative models.

We note that the findings in Moskowitz (2000) suggest that fund performance may vary with the business cycle. Moskowitz (2000) uses the NBER characterization for recessionary and expansionary periods, and documents higher performance during recessions, relative to expansions, using the difference in portfolio holdings based performance measures or the difference in net returns. Our work shows that fund performance varies predictably (and substantially) with predetermined macroeconomic variables. Moreover, explicitly incorporating predictability in manager skills using such macro variables leads to dramatically different optimal portfolios of equity mutual funds. In our framework, one can identify ex ante the best performing funds, leading to an optimal fund-of-funds that outperforms dynamic and static investments in passive benchmarks as well as other strategies previously studied in the mutual fund context. Overall, our findings suggest that active mutual fund management adds much more value than previously recognized.

4.3. The determinants of the superior predictability-based performance

What explains the remarkable performance of strategies that account for predictable skills? In this section, we attempt to address this question. We study the attributes of these strategies at the stock holdings and net returns levels, and we explore inter- and intraindustry effects in their portfolio allocations.

4.3.1. Attributes of portfolio strategies

We first examine the attributes of our optimally selected portfolios of equity mutual funds. Table 6 provides time-series average portfolio-level and fund-level attributes across all 276 investment periods (December 1979–November 2002), as well as averages across NBER expansions only, and across NBER recessions only.

Portfolio holdings attributes of mutual funds include the time-series average characteristic selectivity performance measure of Daniel, Grinblatt, Titman, and Wermers (DGTW; 1997) in percent per year (*CS*), as well as its *p*-value, and the size (*Size*), book-to-market (*BTM*), and momentum (*MOM*) nonparametric rank characteristics of the stockholdings, as defined by DGTW. To compute the *CS* measure as well as nonparametric characteristics of the stockholdings of each fund, we follow DGTW in creating portfolios, for each stock during each year, that closely match the size, book-to-market, and momentum characteristics of that stock.[6] In turn, these portfolio holdings attributes of funds are weighted by each investor's optimal fund holdings to arrive at investor-level attributes. To illustrate, the ND investor records a *CS* measure of 0.39%/year over the entire investment period, 0.23% over expansions, and 1.25% over recessions.

These portfolio-level and fund-level attributes provide insights into the types of mutual funds that the different optimal strategies choose to hold. Let us start with the *CS* measure. There are two notable findings here. First, the *CS* measure indicates that funds selected by

[6] To be specific, we sort all CRSP stocks, conditionally, into quintiles based on their size, book-to-market, and momentum characteristics on June 30 of each year, thereby forming 125 portfolios (e.g., the portfolio identified as 5,5,5 is the large-capitalization, high book-to-market, high momentum stock portfolio). Then, the characteristic-adjusted return for each stock, from July 1 to June 30 of the following year, is the return on the stock minus the return on the value-weighted portfolio to which that stock belongs. The *CS* measure for a given fund is computed as the portfolio-weighted characteristic-adjusted return during each month of that fund's existence. The nonparametric size characteristic for a given fund is the quintile size portfolio number to which each stock belongs during a given year, weighted across all stocks held by the fund each month. The *BTM* and *MOM* nonparametric characteristics of each fund are computed similarly.

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, as well as for three strategies for selecting mutual funds that appear in previous studies, as explained in Table 4. These attributes include the portfolio-weighted characteristic selectivity measure in percent per year (*CS*), as well as its *p*-value (in parentheses), lagged net return, compounded over the 12 months prior to each portfolio formation date ($Lag_{12}(Ret)$), total net assets in millions of dollars (*TNA*) of funds, portfolio holdings-based DGTW (nonparametric) style attributes in the size (*Size*), book-to-market (*BTM*), and momentum (*MOM*) dimensions, percent monthly fund turnover, computed as annual reported turnover divided by 12 (*Turnover*), monthly percentage net cash inflows (*Flow*), computed as *TNA* minus one-quarter-lagged *TNA* (adjusted for investment returns and distributions), divided by three, fund expense ratio (*ExpenseRatio*), portfolio weight allocation to index funds (*IndexFunds*), and lead manager experience in months (*ManagerExperience*). These attributes are presented for all periods, for expansions only, and for recessions only.

	The dogmatist			The skeptic					The agnostic					Previously studied		
	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	H–H	CAR	SM
Overall																
CS	0.39	0.26	2.13	0.57	1.47	2.99	7.19	4.38	0.47	1.06	2.78	8.10	6.02	3.30	0.38	1.84
P(*CS*)	0.28	0.51	0.36	0.72	0.36	0.38	0.09	0.31	0.77	0.51	0.42	0.05	0.19	0.08	0.82	0.05
$Lag_{12}(Ret)$	7.92	8.75	8.54	26.89	22.68	17.53	37.71	28.70	26.69	22.55	17.68	38.73	29.58	29.78	19.33	19.56
TNA	388.73	343.74	201.40	343.47	296.58	224.68	170.39	149.13	318.45	286.68	216.20	146.77	139.68	175.61	195.34	243.97
Size	4.58	4.62	4.05	3.61	4.04	3.69	3.62	3.61	3.52	3.99	3.63	3.55	3.60	3.63	3.68	3.95
BTM	2.70	2.72	2.70	2.51	2.49	2.44	2.45	2.47	2.53	2.49	2.43	2.48	2.44	2.52	2.51	2.62
MOM	3.01	3.03	2.98	3.81	3.88	3.44	3.66	3.35	3.79	3.86	3.45	3.61	3.39	3.70	3.41	3.40
Turnover	1.71	1.91	3.79	9.01	9.29	7.72	8.37	7.85	9.29	9.53	8.05	8.75	7.49	8.43	8.44	7.56
Flow	2.57	2.49	3.51	5.23	4.52	4.67	6.75	6.54	5.47	4.69	4.93	7.28	6.96	5.91	4.54	6.01
ExpenseRatio	0.02	0.02	0.08	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.12	0.11	0.11	0.11	0.09
IndexFunds	0.54	0.52	0.15	0.03	0.02	0.02	0.02	0.01	0.03	0.03	0.02	0.02	0.01	0.02	0.01	0.08
ManagerExperience	85.53	88.61	123.46	155.84	179.45	120.79	120.24	111.92	148.33	171.58	117.97	108.92	106.46	99.11	105.77	97.92
Expansions																
CS	0.23	0.10	1.29	−0.93	−0.11	0.63	5.45	2.68	−0.91	−0.01	0.41	7.19	5.14	2.89	0.37	1.37
P(*CS*)	0.58	0.82	0.61	0.60	0.95	0.87	0.23	0.56	0.62	0.99	0.92	0.12	0.30	0.16	0.82	0.16
$Lag_{12}(Ret)$	8.94	9.83	10.60	28.86	25.37	20.15	41.76	32.75	28.69	25.23	20.24	42.68	33.73	31.84	21.85	21.88

TNA	403.78	354.54	194.70	375.00	316.34	233.05	180.75	159.07	347.75	304.64	223.50	154.80	144.70	182.07	201.74	250.87
Size	4.59	4.63	4.08	3.70	4.09	3.73	3.68	3.68	3.60	4.03	3.66	3.59	3.66	3.63	3.67	3.97
BTM	2.70	2.73	2.81	2.50	2.55	2.50	2.42	2.51	2.52	2.56	2.49	2.44	2.49	2.52	2.52	2.65
MOM	3.04	3.05	2.95	3.80	3.84	3.41	3.68	3.35	3.78	3.83	3.40	3.62	3.38	3.71	3.44	3.40
Turnover	1.71	1.91	3.79	9.01	9.29	7.72	8.37	7.85	9.29	9.53	8.05	8.75	7.49	8.43	8.44	7.56
Flow	2.63	2.54	3.60	4.89	4.48	4.59	6.75	6.56	5.16	4.63	4.88	7.20	7.09	5.96	4.58	6.09
ExpenseRatio	0.02	0.02	0.08	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.12	0.11	0.11	0.11	0.09
IndexFunds	0.56	0.54	0.13	0.04	0.03	0.02	0.02	0.01	0.04	0.03	0.03	0.02	0.01	0.02	0.01	0.09
ManagerExperience	89.67	91.70	120.10	160.45	176.23	117.91	120.57	111.17	152.26	167.70	114.93	105.88	105.11	96.60	102.17	95.34
Recessions																
CS	1.25	1.07	9.47	9.12	10.25	14.62	11.28	11.99	8.24	7.19	14.38	13.86	8.81	6.63	0.42	4.38
$P(CS)$	0.13	0.18	0.07	0.00	0.07	0.06	0.20	0.31	0.00	0.18	0.05	0.09	0.43	0.00	0.80	0.13
$Lag_{12}(Ret)$	1.53	2.00	−4.36	14.56	5.84	1.10	12.32	3.28	14.19	5.72	1.65	14.00	3.55	16.92	3.54	5.05
TNA	294.91	276.12	242.66	159.24	176.95	176.90	106.01	87.68	155.00	177.99	174.76	91.68	108.41	135.09	155.26	200.77
Size	4.55	4.53	3.82	3.06	3.73	3.49	3.26	3.22	2.98	3.72	3.47	3.31	3.24	3.61	3.75	3.82
BTM	2.74	2.72	2.10	2.62	2.13	2.10	2.65	2.17	2.60	2.09	2.08	2.68	2.16	2.52	2.45	2.48
MOM	2.85	2.89	3.17	3.85	4.08	3.67	3.48	3.39	3.83	4.06	3.69	3.54	3.47	3.64	3.28	3.36
Turnover	2.45	2.39	3.96	7.55	9.37	7.87	9.71	11.00	7.86	9.51	7.95	9.88	9.80	7.97	10.73	7.03
Flow	2.09	2.09	3.00	7.21	4.75	5.08	6.76	6.40	7.21	5.00	5.21	7.89	6.25	5.61	4.35	5.50
ExpenseRatio	0.03	0.03	0.08	0.10	0.10	0.10	0.11	0.11	0.11	0.11	0.11	0.11	0.10	0.11	0.11	0.09
IndexFunds	0.41	0.40	0.24	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.07
Manager Experience	59.78	68.67	147.42	127.21	199.60	139.71	118.21	116.54	124.74	195.85	137.60	129.70	115.17	114.85	128.32	114.06

almost all investor types exhibit much higher performance levels during recessions, consistent with the findings of Moskowitz (2000). Second, predictability-based strategies choose funds with higher *CS* measures during both expansions and recessions. Indeed, the highest *CS* measure over the entire investment period is recorded for the PA-3 strategy at 8.1%/year, which is significant at the 5% level. Remarkably, over recessions, the *CS* measure of the PA-2 and PA-3 strategies is 14.38% and 13.86%/year, respectively.

Interestingly, strategies that account for predictable skills, PA-3, PA-4, PS-3, and PS-4, hold funds with the highest past-year returns. This is consistent with Avramov and Chordia (2005a,b) who demonstrate the relation between time-varying alpha and momentum at the stock level. Specifically, the PA-3 investor holds funds with a prior one-year return of 38.73%, on average. The corresponding figure is 26.69% (7.92%) for the NA (ND) investor.[7] Combining the facts that both past returns and current *CS* measures are higher for investors PA-3, PA-4, PS-3, and PS-4 may indicate that these strategies identify fund managers with persistent skills. It should be noted, however, that momentum alone does not explain the entire extraordinary performance of the PA-3 strategy. Observe from Table 4 that this strategy generates an excess investment return of 16.52%/year. Adjusting investment returns by the Fama-French benchmarks yields an alpha of 12.89%; adjusting, in addition, by the momentum factor diminishes the alpha to 8.46%. That suggests that the large average investment return of investor PA-3 is partially explained by momentum. Our focus here is to explain the 8.46% residual performance that already accounts for momentum.

Related to this last point, note that the characteristics of portfolios based on stock holdings, shown by *Size*, *BTM*, and *MOM*, are similar among investor types who allow for active management skills, predictable or not. This reinforces the notion that our results are not driven by taking positions in very specialized style sectors of the market over long time-periods, such as investing in small-cap value strategies. Nor are they driven by switching investment styles over the business cycle.

Next, strategies of skeptics and agnostics involve holding smaller funds than strategies of dogmatists (see *TNA* for NS or NA as compared to ND, as well as for PS-2 or PA-2 as compared to PD-2). Further, investors who allow for predictability hold even smaller funds (e.g., see *TNA* for PA-3 as compared to NA). These findings are consistent with diseconomies of scale in active fund management (see, e.g., Chen et al., 2004).

Moving to turnover, we demonstrate that adding predictability in manager skills (PS-3, PS-4, PA-3, and PA-4) reduces the turnover level of funds optimally held relative to no-predictability strategies (NS and NA), indicating that the former strategies identify managers that have greater skills in picking underpriced stocks over longer holding periods. Note, however, that these investors hold funds with higher levels of turnover during recessions, indicating that fund managers with greater skills during downturns have shorter holding periods. Notice also that almost all investor types hold a smaller allocation of index funds during recessions. This reinforces the notion that active management is much more valuable over recessionary periods (relative to index funds), consistent with Moskowitz (2000).

[7] Indeed, some predictable skill strategies choose funds with prior returns that are higher than those of the H–H strategy. This is explained by the nature of the value weighting of the predictability-based versus the equal weighting of the H–H strategy, as well as the fact that H–H selects the top 10% of funds whereas the predictability-based strategies could select a smaller fraction.

The pattern of flows indicates that investors who believe in active management skills follow funds with higher levels of lagged net inflows, which is not surprising since they have higher allocations to funds that have high past returns, and flows and past returns have been shown to be highly correlated (see, e.g., Sirri and Tufano, 1998). However, strategies PS-3, PS-4, PA-3, and PA-4 do not merely capture the smart money effect because, as Table 4 highlights, a strategy that merely selects funds based on their flows produces negative performance relative to the Fama-French and momentum benchmarks.

The level of manager experience indicates that predictability-based strategies involve choosing fund managers with slightly less experience, but this trend does not seem especially strong.

For comparison purposes, we also present portfolio attributes for the hot-hands, Carhart, and smart money strategies discussed previously. We find that these strategies generally involve holding funds with similar fund-level and portfolio-level attributes as investors PA-3 and PA-4, but that they do not generate similar levels of CS performance. Thus, predictability-based strategies involve selecting from similar groups of funds as the more mechanical hot-hands, Carhart, and smart money strategies, but are much more successful in identifying manager talents.

We summarize the evidence emerging from this section as follows. Strategies that account for predictable manager skills outperform their characteristic-based benchmarks, especially during recessions. Such strategies pick funds with higher past one-year returns and funds with higher new money inflows. Even so, their overall extraordinary performance is unexplained by following mechanical trading strategies based on flows or momentum because the hot-hand and smart money strategies that exploit information in past returns and new money inflows do not produce such robust performance measures. In addition, the outperforming predictability-based strategies hold stocks with similar size, book-to-market, and momentum characteristics as those held by other less promising strategies. However, although the average *TNA* is different across the strategies, this does not explain the dispersion in performance. Specifically, Chen et al. (2004) find a difference in performance of only 1%/year between the smallest and largest quintiles of mutual funds. Thus, we need to look for other sources, beyond the characteristic styles, past fund returns, and new money inflows, or fund *TNA*, to explain the disparity in performance among the competing strategies. We turn to this issue next.

4.3.2. Industry allocation analysis

Specifically, we examine whether inter- and intraindustry effects can explain the dispersion in performance among trading strategies. In particular, we consider 13 industries based on the Fama-French 12-industry classification, plus a separate industry category for stocks in the metals mining and metals wholesaling businesses.[8] The 13 industries include: computer hardware, software, and other electronic equipment (Buseq); chemicals (Chems); durable goods, including autos, televisions, furniture, and household appliances (Durbl); oil, gas, and coal extraction (Enrgy); healthcare, medical equipment, and drugs (Hlth); machinery, trucks, planes, office furniture, paper, and commercial

[8]Metals stocks are extracted from the "Shops" (wholesale, retail, and some service industries) or "Other" categories of the Fama-French 12-industry classification. Stocks with SIC codes of 1000-1049, 1060-1069, and 1080-1099 are extracted from the "Other" industry category, while SIC codes of 5050-5052 are extracted from "Shops."

printing (Manuf); financials (Money); food, tobacco, textiles, apparel, leather, and toys (NoDur); wholesale, retail, and some services such as laundries and repair shops (Shops); telephone and television transmission (Telcm); utilities (Utils); metals mining and wholesaling (Metals); and all other industries (e.g., construction, building materials, transportation, hotels, business services, and entertainment).

Table 7 shows the time-series average allocations to industries over all months from December 1979 to November 2002, as well as over expansions and recessions. The allocation to a given industry during a given month is computed by multiplying the fund-level industry weight by the investor's optimal weight on that fund, then summing this product over all funds held by the investor. Fund-level industry weights are computed by assigning an industry classification to each stock in the fund's portfolio at the end of each calendar quarter. These fund-level weights are assumed to be constant until the end of the following calendar quarter, while investor-level weights are updated monthly. Quarterly holdings data for mutual funds are obtained from the Thomson/CDA database, and are described in Wermers (1999, 2000).

The evidence shows that no-predictability investors who differ in their outlook toward the value of active management, i.e., ND, NS, and NA, hold similar allocations to industries, both overall, as well as during expansions and recessions. Since the ND investor, who rules out any possibility of active management skills, has industry allocations that are similar to the less dogmatic NS and NA investors, active management skills do not seem to be particularly concentrated in funds with a certain industry tilt when one disregards business cycle variations.

However, predictability-based strategies yield significantly different industry allocations relative to their no predictability counterparts, both during expansions and recessions. For example, investors PA-1, PA-2, PA-3, and PA-4 hold much higher allocations to energy (enrgy), utilities (utils), and especially metals (metals), and a lower allocation to computers and other business equipment (buseq) than investor NA. Moreover, predictability-based strategies do change their industry tilts over the business cycle. For instance, the PA-3 agent invests about 18% in metals during expansions, and only 8% during recessions. We also formally test whether industry allocations differ more for predictability-based approaches, and find support for this hypothesis.

To summarize, unlike their no-predictability counterparts, investors that use information variables in forming their optimal portfolios exhibit large variation in industry tilts over the business cycle. This suggests that such investors consider a mutual fund's industry orientation as an important characteristic in predicting and ultimately improving performance. Our findings here invite further inquiry into such investor strategies. For example, it is unclear why industry variation enhances performance. It is also unclear whether managers are able to pick funds within the selected industries that ultimately outperform their industry benchmarks. The next section addresses these issues.

4.3.3. Industry attribution analysis

Table 8 exhibits performance measures based on an industry-level attribution. The first three rows of the table present time-series average net returns ($\tilde{\mu}$, obtained by adding the annual risk-free rate to μ as reported in Table 4), industry-level returns ($\tilde{\mu}^{\mathrm{I}}$), and industry-adjusted net returns ($\tilde{\mu} - \tilde{\mu}^{\mathrm{I}}$). Industry-level returns are computed for each month by multiplying the industry allocations implied by each strategy's holdings of mutual funds by industry-level returns. The reported time-series average of industry-adjusted net returns is

Table 7
Industry allocations of optimal portfolios

The table reports the industry allocations of portfolio strategies that are optimal from the perspective of the 13 investor types described in Table 1, as well as for three strategies for selecting mutual funds that appear in previous studies, as explained in Table 4. The industries presented include 13 industries, based on the 12 Fama-French industry classification, plus a separate industry category for stocks in metals mining and metals wholesaling. These metals–industry stocks are extracted from the "energy" or "other" categories of the Fama-French 12 industry classification. The 13 industries include computer hardware, software, and other electronic equipment (Buseq); chemicals (Chems); durable goods, including autos, televisions, furniture, and household appliances (Durbl); oil, gas, and coal extraction (Enrgy); healthcare, medical equipment, and drugs (Hlth); machinery, trucks, planes, office furniture, paper, and commercial printing (Manuf); financials (Money); food, tobacco, textiles, apparel, leather, and toys (NoDur); wholesale, retail, and some services such as laundries and repair shops (Shops); telephone and television transmission (Telcm); utilities (Utils); metals mining and wholesaling (Metals); and, all other industries (e.g., construction, building materials, transportation, hotels, business services, and entertainment). These allocations are computed using the portfolio holdings of the mutual funds, then weighting these fund-level industry characteristics by each investor's optimal portfolio each month. This table shows the time-series average allocations over all months from December 1979 to November 2002, as well as over expansions and recessions.

	The dogmatist			The skeptic					The agnostic					Previously studied		
	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	H–H	CAR	SM
Overall																
Buseq	0.24	0.20	0.11	0.19	0.19	0.11	0.17	0.11	0.20	0.19	0.11	0.17	0.12	0.18	0.20	0.16
Chems	0.06	0.07	0.02	0.02	0.03	0.01	0.02	0.01	0.02	0.03	0.01	0.02	0.01	0.03	0.03	0.04
Durbl	0.02	0.03	0.02	0.03	0.03	0.02	0.02	0.01	0.03	0.03	0.02	0.02	0.01	0.03	0.03	0.04
Enrgy	0.07	0.08	0.09	0.04	0.07	0.15	0.08	0.14	0.03	0.08	0.16	0.09	0.14	0.07	0.07	0.07
Hlth	0.13	0.13	0.06	0.10	0.09	0.05	0.07	0.04	0.10	0.09	0.05	0.07	0.04	0.10	0.10	0.08
Manuf	0.12	0.11	0.06	0.11	0.09	0.08	0.09	0.06	0.11	0.09	0.08	0.08	0.06	0.11	0.10	0.12
Money	0.13	0.12	0.24	0.22	0.21	0.25	0.18	0.24	0.22	0.20	0.25	0.18	0.23	0.17	0.16	0.17
NoDur	0.07	0.08	0.04	0.07	0.06	0.06	0.05	0.05	0.06	0.06	0.05	0.04	0.05	0.06	0.07	0.07
Shops	0.05	0.05	0.07	0.09	0.10	0.06	0.05	0.04	0.09	0.10	0.07	0.05	0.04	0.10	0.09	0.10
Telcm	0.04	0.05	0.03	0.06	0.06	0.04	0.06	0.05	0.06	0.06	0.04	0.06	0.05	0.04	0.05	0.04
Utils	0.02	0.04	0.17	0.01	0.01	0.07	0.07	0.07	0.01	0.01	0.07	0.07	0.07	0.04	0.03	0.05
Metals	0.00	0.02	0.11	0.01	0.06	0.17	0.15	0.24	0.01	0.06	0.17	0.16	0.23	0.05	0.07	0.02
Others	0.05	0.05	0.07	0.10	0.10	0.08	0.09	0.09	0.09	0.10	0.08	0.08	0.09	0.10	0.10	0.10
Expansions																
Buseq	0.25	0.21	0.09	0.19	0.18	0.08	0.17	0.09	0.20	0.18	0.09	0.17	0.11	0.19	0.20	0.17
Chems	0.06	0.07	0.03	0.02	0.03	0.01	0.02	0.01	0.02	0.03	0.01	0.02	0.01	0.03	0.03	0.04
Durbl	0.02	0.03	0.02	0.03	0.03	0.02	0.02	0.01	0.03	0.03	0.02	0.02	0.01	0.03	0.03	0.04
Enrgy	0.06	0.07	0.08	0.03	0.06	0.14	0.08	0.14	0.03	0.07	0.15	0.09	0.13	0.06	0.06	0.06
Hlth	0.13	0.13	0.05	0.09	0.08	0.04	0.06	0.03	0.09	0.08	0.04	0.06	0.03	0.10	0.10	0.08
Manuf	0.11	0.11	0.06	0.11	0.09	0.08	0.08	0.06	0.11	0.09	0.08	0.07	0.06	0.11	0.10	0.11
Money	0.14	0.13	0.26	0.23	0.22	0.28	0.19	0.26	0.24	0.22	0.27	0.19	0.26	0.17	0.16	0.17
NoDur	0.07	0.08	0.05	0.07	0.06	0.06	0.05	0.05	0.07	0.06	0.05	0.04	0.05	0.06	0.07	0.07
Shops	0.04	0.05	0.06	0.08	0.10	0.06	0.05	0.03	0.09	0.10	0.06	0.05	0.03	0.10	0.09	0.09
Telcm	0.04	0.05	0.03	0.06	0.06	0.04	0.07	0.05	0.06	0.06	0.04	0.06	0.06	0.04	0.05	0.05
Utils	0.02	0.04	0.20	0.01	0.01	0.08	0.07	0.08	0.01	0.01	0.08	0.07	0.08	0.04	0.03	0.05
Metals	0.00	0.01	0.11	0.01	0.06	0.18	0.16	0.26	0.01	0.06	0.19	0.18	0.25	0.05	0.07	0.02
Others	0.05	0.05	0.06	0.09	0.10	0.08	0.08	0.08	0.09	0.10	0.08	0.07	0.09	0.10	0.10	0.10
Recessions																
Buseq	0.20	0.16	0.25	0.19	0.23	0.23	0.19	0.23	0.19	0.23	0.23	0.16	0.22	0.13	0.18	0.15
Chems	0.05	0.05	0.02	0.03	0.02	0.01	0.02	0.02	0.03	0.02	0.01	0.02	0.02	0.03	0.03	0.04
Durbl	0.03	0.03	0.01	0.02	0.01	0.01	0.03	0.01	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.03

Table 7 (*continued*)

	The dogmatist			The skeptic					The agnostic					Previously studied		
	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	H–H	CAR	SM
Enrgy	0.12	0.18	0.19	0.08	0.14	0.19	0.11	0.20	0.09	0.15	0.20	0.12	0.21	0.12	0.13	0.10
Hlth	0.11	0.11	0.11	0.17	0.13	0.12	0.11	0.10	0.17	0.12	0.11	0.11	0.11	0.09	0.09	0.09
Manuf	0.14	0.13	0.07	0.12	0.09	0.08	0.11	0.07	0.11	0.09	0.08	0.11	0.07	0.11	0.11	0.13
Money	0.11	0.11	0.08	0.10	0.08	0.10	0.13	0.09	0.11	0.08	0.10	0.15	0.10	0.17	0.13	0.13
NoDur	0.08	0.07	0.03	0.06	0.05	0.03	0.07	0.02	0.05	0.04	0.03	0.07	0.02	0.07	0.05	0.07
Shops	0.07	0.07	0.09	0.10	0.09	0.09	0.08	0.07	0.10	0.09	0.09	0.08	0.08	0.10	0.10	0.10
Telcm	0.03	0.04	0.04	0.05	0.07	0.05	0.05	0.04	0.05	0.07	0.05	0.05	0.04	0.03	0.05	0.04
Utils	0.03	0.03	0.01	0.04	0.02	0.02	0.06	0.02	0.04	0.01	0.02	0.06	0.02	0.05	0.03	0.05
Metals	0.01	0.08	0.09	0.02	0.05	0.06	0.09	0.13	0.02	0.06	0.06	0.08	0.11	0.04	0.08	0.02
Others	0.06	0.07	0.11	0.13	0.10	0.10	0.15	0.11	0.13	0.11	0.10	0.15	0.11	0.13	0.12	0.11

obtained as the difference between $\tilde{\mu}$ and $\tilde{\mu}^{\mathrm{I}}$, and represents the net returns accomplished by each strategy above that accomplished through their allocations to industries.

The industry-level returns explain some of the variation in net returns across investor types. For example, investor PA-3 generates an average net return that is 9.3% higher than that of investor NA (22.82–13.48%). Of this 9.3% difference, 3.6% is due to higher returns generated by industry selection. The remaining 5.7% difference is due to higher returns earned in excess of industry allocations, as shown by the industry-adjusted net returns. That is, investor PA-3 uses business cycle information first to choose industries that significantly outperform those chosen by NA, and then to select individual mutual funds within those well-performing industries that are able to outperform their industry benchmarks. This latter point is especially noteworthy, since the industry benchmarks are gross of any trading costs of implementing such an industry-level mimicking strategy. Specifically, PA-3 chooses individual mutual funds, using business cycle information, that outperform their industry benchmarks by 7.1%/year more than the level of fees and trading costs of the funds.

Next, we break down the monthly industry-level returns ($\tilde{\mu}^{\mathrm{I}}$) into two components. The first component, the "industry passive return" ($\tilde{\mu}^{\mathrm{I}p}$), is computed as the industry-level return that accrues to a passive strategy that merely holds the allocation to each industry constant over time (at its time-series average for a given investor). The second, the "industry timing return" ($\tilde{\mu}^{\mathrm{I}} - \tilde{\mu}^{\mathrm{I}p}$), is the difference between the total industry return and the industry passive return. This second component represents the industry-level return earned by timing the industries through holdings of mutual funds, since this return component can only reflect time-series variations in industry allocations relative to passive strategies that merely hold the average allocations.

The evidence shows that the industry passive return component is comparable across all investor types. On the other hand, investors that account for predictability in manager skills actively time industries to enhance performance; for example, PA-3 exhibits an industry timing return of almost 3%/year, while NA exhibits a negative industry timing return. In general, investors using business cycle information generate industry timing returns of 2–4%/year.

At this stage, it is an open question as to whether these industry-level returns and/or industry-adjusted returns reflect strategies already documented in previous work, such as

Table 8
Industry 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, as well as for the additional three strategies for selecting mutual funds that appear in previous studies, as explained in Table 4. The first three rows of the table present time-series average net returns ($\tilde{\mu}$, the same μ reported in Table 4 plus the average annual risk-free rate), industry-level returns, based on a 13-industry classification of the stocks held by funds, weighted by the optimal investor holdings of these funds ($\tilde{\mu}^{\mathrm{I}}$), and industry-adjusted net returns ($\tilde{\mu} - \tilde{\mu}^{\mathrm{I}}$), computed as the difference between these first two return items (its time-series p-value is also shown). The next three rows break down industry-level returns ($\tilde{\mu}^{\mathrm{I}}$) into two components namely, the "industry passive return" ($\tilde{\mu}^{\mathrm{I}_P}$), which is the industry-level return that accrues to holding the allocation to each industry constant over time (at its time-series average for a given investor), and the "industry timing return" ($\tilde{\mu}^{\mathrm{I}} - \tilde{\mu}^{\mathrm{I}_P}$), which is the difference between the industry-level return and the industry passive return (its time-series p-value is also shown). The following three sections report the Carhart alpha (α_{wml}) and associated p-values for investor net returns, as previously reported in Table 4, industry-level returns, and industry-adjusted net returns. Slope coefficients for the Carhart model, as well as their p-values, are also shown for industry-level and industry-adjusted returns (β_{mkt}, β_{size}, β_{btm}, and β_{mom} represent loadings on the market, size, book-to-market, and momentum factors).

	The dogmatist			The skeptic					The agnostic					Previously studied		
	ND	PD-1	PD-2	NS	PS-1	PS-2	PS-3	PS-4	NA	PA-1	PA-2	PA-3	PA-4	H–H	CAR	SM
$\tilde{\mu}$	12.68	12.88	13.02	13.30	11.88	12.33	21.18	17.80	13.48	11.56	12.17	22.82	18.47	15.27	11.72	12.58
$\tilde{\mu}^{\mathrm{I}}$	13.03	12.96	13.93	12.41	12.94	13.40	16.72	15.11	12.13	13.06	13.43	15.72	14.14	13.13	12.81	13.19
$\tilde{\mu} - \tilde{\mu}^{\mathrm{I}}$	−0.34	−0.09	−0.91	0.89	−1.07	−1.07	4.47	2.69	1.35	−1.50	−1.26	7.10	4.33	2.13	−1.09	−0.61
$P(\tilde{\mu} - \tilde{\mu}^{\mathrm{I}})$	0.50	0.87	0.66	0.70	0.59	0.67	0.23	0.42	0.57	0.46	0.61	0.06	0.18	0.29	0.49	0.51
$\tilde{\mu}^{\mathrm{I}_P}$	13.72	13.75	13.16	13.98	13.61	13.06	12.73	12.29	13.98	13.58	13.03	12.74	12.31	13.51	13.34	13.69
$\tilde{\mu}^{\mathrm{I}} - \tilde{\mu}^{\mathrm{I}_P}$	−0.69	−0.79	0.78	−1.57	−0.67	0.34	3.98	2.82	−1.85	−0.52	0.40	2.98	1.82	−0.38	−0.53	−0.49
$P(\tilde{\mu}^{\mathrm{I}} - \tilde{\mu}^{\mathrm{I}_P})$	0.22	0.19	0.52	0.04	0.36	0.74	0.03	0.07	0.03	0.47	0.74	0.11	0.30	0.68	0.48	0.39
Net return																
α_{wml}	0.37	0.62	3.92	−1.30	−2.49	0.83	5.98	4.95	−1.29	−2.83	0.51	8.46	6.20	−0.99	−0.48	−1.10
$P(\alpha_{wml})$	0.46	0.22	0.07	0.45	0.13	0.76	0.14	0.17	0.47	0.10	0.85	0.04	0.10	0.46	0.69	0.06
Industry return																
α_{wml}	0.17	0.00	1.10	−0.79	−0.31	0.34	3.10	1.58	−0.93	−0.20	0.60	2.82	0.46	0.23	0.09	0.25
$P(\alpha_{wml})$	0.41	0.99	0.28	0.24	0.62	0.71	0.06	0.23	0.20	0.74	0.57	0.07	0.77	0.63	0.79	0.10
β_{mkt}	1.01	1.01	1.03	1.06	1.06	1.04	1.03	1.02	1.07	1.05	1.03	1.00	1.03	0.99	0.99	1.00
$P(\beta_{mkt})$	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	0.00	0.00	0.00
β_{size}	0.01	0.00	−0.06	−0.02	0.00	−0.05	0.13	0.10	−0.02	0.01	−0.04	0.13	0.09	0.07	0.02	0.00
$P(\beta_{size})$	0.22	0.67	0.03	0.37	0.77	0.04	0.00	0.00	0.28	0.61	0.13	0.00	0.02	0.00	0.01	0.72
β_{btm}	−0.01	−0.01	0.09	−0.04	−0.02	0.07	−0.03	0.09	−0.07	−0.02	0.05	−0.10	0.06	−0.07	−0.07	−0.01
$P(\beta_{btm})$	0.05	0.14	0.00	0.04	0.20	0.02	0.59	0.03	0.00	0.19	0.15	0.03	0.24	0.00	0.00	0.24
β_{mom}	0.00	0.00	−0.06	0.01	0.01	−0.04	0.05	0.00	0.00	0.01	−0.04	0.04	0.02	0.03	0.01	0.00
$P(\beta_{mom})$	0.53	0.34	0.00	0.53	0.48	0.03	0.08	0.91	0.71	0.33	0.03	0.18	0.38	0.00	0.03	0.14
Industry adjusted return																
α_{wml}	0.20	0.63	2.82	−0.51	−2.18	0.49	2.89	3.37	−0.36	−2.63	−0.09	5.64	5.73	−1.22	−0.58	−1.35
$P(\alpha_{wml})$	0.68	0.22	0.13	0.75	0.16	0.85	0.37	0.29	0.83	0.10	0.97	0.10	0.07	0.34	0.64	0.02
β_{mkt}	−0.04	−0.06	−0.27	−0.12	−0.06	−0.21	−0.21	−0.33	−0.12	−0.07	−0.21	−0.17	−0.31	−0.04	−0.02	−0.03
$P(\beta_{mkt})$	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.03	0.00	0.02	0.00	0.12	0.48	0.00
β_{size}	−0.02	−0.03	0.03	0.48	0.34	0.29	0.62	0.43	0.50	0.35	0.31	0.65	0.42	0.48	0.38	0.24
$P(\beta_{size})$	0.05	0.02	0.57	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_{btm}	−0.09	−0.12	0.00	−0.24	−0.20	0.09	−0.24	−0.07	−0.20	−0.21	0.09	−0.23	−0.15	−0.03	−0.11	−0.07
$P(\beta_{btm})$	0.00	0.00	0.96	0.00	0.00	0.23	0.01	0.49	0.00	0.00	0.24	0.02	0.12	0.46	0.00	0.00
β_{mom}	0.02	0.03	−0.17	0.26	0.20	−0.07	0.33	0.13	0.28	0.20	−0.03	0.28	0.09	0.30	−0.01	0.10
$P(\beta_{mom})$	0.05	0.01	0.00	0.00	0.00	0.13	0.00	0.02	0.00	0.00	0.43	0.00	0.09	0.00	0.60	0.00

the industry-level momentum of Moskowitz and Grinblatt (1999), or, instead, that they indicate genuine skills based on private information. To address this issue, Table 8 breaks down the net return alpha (computed using the four-factor Carhart model) into the alpha derived by industry allocations and the alpha derived by allocations to individual mutual funds, controlling for their industry exposures. Alphas are computed by regressing the excess industry-level returns as well as the industry-adjusted returns (both described above) on the four Fama-French and momentum benchmarks. Table 8 also presents the factor loadings for each of these two regressions.

We start with the industry-level regressions. We show that almost none of the industry-level timing returns are due to the investors using industry–momentum strategies. In particular, note that the industry return alpha (2.82%/year for PA-3) is very similar to the industry-timing return described previously (2.98%/year). That is, returns attributable to industry timing by strategies that incorporate predictability in manager skills survive the four-benchmark adjustment. This evidence indicates that funds selected by the PA-3 investor load on industries using private information, or at least information unrelated to the standard four benchmarks. Moreover, examining the benchmark loadings reveals no particular tilts toward any style factor.

Next, we consider regression results for the industry-adjusted net returns for each investor type. We demonstrate that the skeptics and agnostics hold mutual funds that have slightly negative market and book-to-market exposures relative to their industries, and positive size and momentum exposures, suggesting that actively managed mutual funds that load on smaller, more growth-oriented stocks that have higher past returns outperform other funds.

However, among actively managed funds, predictability-based strategies have similar exposures to benchmarks as their no-predictability counterparts, indicating that the superior performance of predictability-based strategies is not due to their taking positions in funds with different style characteristics. Further, the majority of industry-adjusted net returns is unexplained by the four benchmarks. In particular, as noted earlier, the industry-adjusted net return for PA-3 is 7.3%/year. When we adjust this return using the four benchmarks, the alpha is 5.6%/year.

To summarize the results of this section, we find that investors who use business-cycle information to choose mutual funds derive their returns from two important sources. First, they vary their allocations to industries over the business cycle. Second, they vary their allocations to individual mutual funds within the chosen industries. Neither source of returns is particularly correlated with the four Fama-French and momentum benchmarks, indicating that the private skills identified by these predictability-based strategies are based on characteristics of funds that are heretofore undocumented by the mutual fund literature.

4.4. Survivorship bias

Survivorship bias has been extensively studied in the context of mutual funds. Indeed, in the single-period investments, which are the basis for Table 3, only funds that exist in December 2002 are investable. Otherwise, funds that were liquidated or otherwise ceased to exist prior to December 2002 are excluded. This may raise survivorship bias concerns. The multiperiod out-of-sample investment analysis undertaken here seems relatively more robust to survivorship bias, because funds that did not survive until December 2002 are still part of the investment universe. Still, to be included in our tests, a mutual fund must have at least 48 consecutive months before the investment is made as well as one additional month subsequent to the investment. Hence, a relevant question is: Should performance measures be adjusted to reflect this return requirement? Below, we explain why performance measures need not be adjusted.

In the spirit of Baks et al. (2001), we assume that, conditional on the realized fund returns, the probability of survival is unaffected by conditioning on the true values of the parameters that govern the dynamics of mutual fund returns. Then, by implementing Bayes' rule and by assuming that the residual in Eq. (1) is uncorrelated across funds, conditioning on survival has no effect on the posterior distribution of the parameters. Hence, any adjustment to the reported performance measures is not needed.[9]

5. Conclusion

This paper studies predictability in mutual fund returns and the overall value of active management in an investment-based framework. Specifically, we form optimal portfolios of no-load, open-end U.S. domestic equity mutual funds in the presence of predictability (based on business cycle variables) in (i) manager selectivity and benchmark timing skills, (ii) mutual fund risk loadings, and (iii) benchmark returns. The proposed framework is both quite general and applicable to real investment strategies. For example, we are able to distinguish between public and private information-based timing and selectivity returns. Moreover, moments used for asset allocation have closed-form expressions. We apply our framework to a universe of 1301 equity funds over the 1975–2002 period. The resulting optimal portfolios provide several new insights about the value of active management and the economic significance of fund return predictability from both ex ante and out-of-sample perspectives.

Ex ante, incorporating predictability in mutual fund returns substantially changes the optimal allocations to equity funds. First, predictability makes actively managed funds appear much more attractive than index funds, as well as pushing optimal portfolios toward mutual funds with higher allocations to stocks in the energy, utilities, and metals industries, and lower allocations to stocks in the computer and other business equipment industries. In addition, predictability-based strategies generate much larger Sharpe ratios than their no-predictability counterparts. We demonstrate that an investor who believes in predictability, especially predictable manager skills, but is constrained to hold the asset allocation of her no-predictability counterpart, faces a large utility loss—exceeding, in some cases, 1% per month.

Out-of-sample optimal portfolios that exclude predictability often yield negative alphas, suggesting that investment opportunities based on i.i.d. fund returns that may be ex ante attractive, as advocated by Baks et al. (2001), do not translate into positive out-of-sample alphas. In contrast, portfolio strategies that allow for predictable manager selectivity and benchmark timing skills consistently outperform static and dynamic investments in passive

[9]Stambaugh (2003) and Jones and Shanken (2005) explore survival issues in a framework that accounts for prior dependence across funds. Under such dependence, conditioning on survival can affect the posterior distribution of the parameters. Given the vast universe of mutual funds considered here, it is nontrivial to account for such dependence. Indeed, as noted by Stambaugh (2003), further complexities can be studied as computer power allows.

benchmarks. Specifically, such strategies yield an α of 9.46% and 10.52%/year when investment returns are adjusted using a model with a fixed and with a time-varying market beta, respectively. Using the Fama-French (Carhart) benchmarks, the corresponding figures are 12.89% and 14.84% (8.46% and 11.17%).

We show that inter- and intraindustry asset allocation patterns are key to understanding the source of these superior levels of performance. Specifically, strategies that incorporate time-varying manager skills outperform their benchmarks by 2–4%/year through their ability to time industries over the business cycle. Moreover, they choose individual funds that outperform their industry benchmarks to achieve an additional 3–6%/year. These strategies choose funds that do not differ much in their size, book-to-market, and momentum styles, based on stock holdings, relative to other strategies that allow for active management skill but disallow predictability in manager skill.

We also compare the performance of strategies that incorporate predictability in managerial skills to that of competing strategies that use past returns and flows: (1) the "hot-hands" strategy of Hendricks et al. (1993); (2) the four-factor Carhart (1997) alpha strategy; and, (3) the "smart money" strategy of Zheng (1999). Specifically, we form portfolios that pick the top 10% of funds based on their (1) 12-month compounded prior returns, (2) alpha with respect to the Fama-French and momentum benchmarks, and (3) positive new cash flows. We show that, unlike our predictability-based strategies, these competing strategies generate insignificant performance relative to the Fama-French and momentum benchmarks. This suggests that our portfolio strategies are unique, and that they outperform optimal strategies that exclude information based on business cycle variables as well as previously studied strategies that pick funds based on past returns and flows.

Our paper suggests several avenues for future research. First, our framework might be extended to study optimal portfolios that incorporate predictability based on fund-level or manager-level variables. The impact of the changing characteristics of stocks held by a fund (such as the size, book-to-market, and prior-year return) on the profitability of optimal portfolios is also an open question—such characteristics have been widely used in recent studies of performance evaluation (see, e.g., Daniel et al., 1997). Examining whether these characteristics add to the predictability of fund returns may provide further insights into active management.

Appendix A. Description of mutual fund database

This part of the appendix describes the database in detail. Our procedure for building our database begins with the merged CRSP/Thomson open-end mutual fund database described by Wermers (2004). This merged database contains monthly fund net returns, self-declared investment objectives (quarterly in Thomson, annually in CRSP), annual turnover and expense ratios, and annual load charges for each shareclass of each fund (from CRSP). Our procedure for classifying and characterizing funds is as follows.

A.1. Investment objectives

We focus on open-end, no-load U.S.-headquartered domestic equity funds. We exclude balanced or flexible funds because we wish to rule out strategies that involve investments in nonequity securities, such as U.S. government or corporate bonds.

To determine whether a fund qualifies as a domestic equity fund, we proceed through several steps. Then, we determine whether, at the beginning of a given quarter, the fund has a self-declared investment objective that is consistent with investing almost exclusively in domestic equities. In particular, we check the investment objective from the Thomson database, as well as the (somewhat different) investment objective data from the CRSP files to make a first pass at a classification. In doing so, we verify investment objectives for all shareclasses of a given fund (because the data is missing in some cases from some shareclasses in CRSP). Our approach is to use Thomson investment objectives, which are less precise but rarely missing; CRSP investment objectives are more precise, but the large proportion of missing data precludes the wholesale use of these data. Nevertheless, we use CRSP objectives to refine, where possible, our inclusion of funds.

Next, we check the name of the fund for words that indicate that it has an objective other than domestic equity, such as an international growth fund. This step helps us to correct any omissions and/or errors in the Thomson or CRSP investment objectives (i.e., when the investment objective is vague, wrong, or missing). For example, we identify index funds both through CRSP investment objectives and through the names of funds, since Thomson does not identify these funds. Finally, we exclude any shareclasses for such funds that have a nonzero total load (including front-end and deferred) only during the year that the total load is nonzero. We exclude all other funds such as balanced funds, international funds, and bond funds.

A.2. Net returns

We obtain monthly net returns from the CRSP mutual fund database. To compute the net return for a given mutual fund in the linked Thomson/CRSP database, we aggregate the net returns on all no-load shareclasses that exist during that month by value-weighting the shareclass returns using beginning-of-month total net assets (TNA) for each shareclass. Thus, our monthly returns mimic the returns that would have been earned by a pro-rata investment across all no-load shareclasses of a given fund. This approach avoids any biases that might result from using only a single shareclass from a given fund.

When one or more no-load shareclasses has missing returns or total net asset information, we aggregate the net returns for remaining shareclasses that have full data. Finally, when a missing return is indicated for a fund-month for a shareclass in the CRSP files, the first nonmissing return is discarded to alleviate the CRSP approach of filling in a cumulative return at this date, which would introduce large measurement errors.

In forming "hot-hands" and "smart money" portfolios of mutual funds as well as in assessing whether the universe of equity funds provides close substitutes to the Fama-French and momentum benchmarks, we include all shareclasses, including those charging a load. In this case, we reconstruct our shareclass-averaged net returns including all no-load and load shareclasses for each fund.

A.3. Turnover and expenses

Like net returns, turnover and expenses are shareclass-averaged for each fund, with rebalancing done when a shareclass disappears or has missing data. Shareclass-specific monthly turnover and expenses are derived by dividing the annual numbers (from CRSP) by 12. Weights for shareclass averaging are based on beginning-of-month total net assets (TNA) for the shareclass.

A.4. Flows

Net flows from consumers are estimated with the change in the ratio of total net assets divided by the net asset value per share (i.e., the shares outstanding of the fund) during a month, where the effect of splits during the month are reversed from the end-of-month shares outstanding. In addition, cash distributions are all assumed to be reinvested, meaning that the growth in shares outstanding are net of all distribution-related reinvestments (which are assumed to be 100% reinvested). In other words, reinvested distributions, both capital-gain and dividend, are not counted as flows. Before 1991, total net assets are available only on a quarterly basis, so monthly flows are estimated by dividing the quarterly number by three.

In unreported tests, we compared these estimated flows with the known, actual monthly flows from a large number of funds from a given major mutual fund family. We find that the estimates based on the above procedure are very close to the known actuals for these funds (over 100 funds), which provides reassurance that our computation of flows is more broadly applicable to the universe of funds.

Appendix B. Investments when fund risk loadings and benchmark returns may be predictable

This part of the appendix derives moments for asset allocation under the case in which fund risk loadings and benchmark returns could be predictable by business cycle variables, but managerial skill is not.

B.1. Prior beliefs

First note that $\alpha_{i1} = 0$ in Eq. (1) because skill is assumed to be unpredictable. Part C of the appendix relaxes this assumption. The prior on α_{i0} is

$$p(\alpha_{i0} \mid \psi_i) \propto (\psi_i)^{-1/2} \exp\left\{ -\frac{1}{2\psi_i} (\Gamma_i - \Gamma_{i0})' \Upsilon (\Gamma_i - \Gamma_{i0}) \right\}, \tag{8}$$

where $\Gamma_{i0} = [\bar{\alpha}_{i0}, 0, \ldots, 0]'$, $\Upsilon = \Delta\Delta' s^2/\sigma_\alpha^2$, Δ is a $(KM + K + 1)$ vector whose first element is one and the rest of the elements are zero, σ_α^2 is the degree of belief about managerial skill, and s^2 is computed as the cross-sectional average of the sample variance of the residuals in Eq. (1). Note that the dogmatic (agnostic) case implies that $\sigma_\alpha = 0$ (∞). The skeptic case implies that $0 < \sigma_\alpha < \infty$. (In the empirical application, we set $\sigma_\alpha = 1\%$.) For the dogmatist, we set $\bar{\alpha}_{i0} = -\frac{1}{12}(expense + 0.01 \times turnover)$, where *expense* and *turnover* are the fund's annual average values of reported expense ratio and turnover. For the skeptic and agnostic, we set $\bar{\alpha}_{i0} = -\frac{1}{12}(expense)$. The prior beliefs about all other parameters in Eqs. (1)–(3) are taken to be noninformative. Specifically, the prior is proportional to $(\psi_i)^{-1} |\Sigma_{\mathrm{ff}}|^{-(K+1)/2} |\Sigma_{zz.rf}|^{-(M+1)/2}$.

B.2. The likelihood function

The sample contains T_i monthly returns of fund i (overall, the investment universe contains $N = 1301$ no-load, open-end, equity mutual funds) and T monthly observations of K benchmark returns and M business cycle variables. Fund i enters the sample at time t_i and leaves at time $t_i + T_i - 1$, following a merger or termination. The fund may remain until the end of our sample period, December 2002. Let r_i denote the T_i-vector of excess returns on fund i, let $G_i = [G'_{t_i}, \ldots, G'_{t_i+T_i-1}]'$, where $G_t = [1, f'_t, f'_t \otimes z'_{t-1}]'$, let $\Gamma_i = [\alpha_{i0}, \beta'_{i0}, \beta'_{i1}]'$, let $Z = [z'_1, \ldots, z'_T]'$, let $F = [f'_1, \ldots, f'_T]'$, let $X = [x'_0, \ldots, x'_{T-1}]'$, where $x_0 = [1, z'_0]'$ with z_0 being the first observation of the macro predictors, let $V_f = [v'_{f1}, \ldots, v'_{fT}]'$, let $V_Z = [v'_{z1}, \ldots, v'_{zT}]'$, let V_{rz} be a $T \times N$ matrix whose ith column contains T_i values of v_{it} when returns on fund i are recorded and $T - T_i$ zeros when such returns are missing, let $A_Z = [a_z, A_z]'$, let $A_F = [a_f, A_f]'$, let $Q_{G_i} = I_{T_i} - G_i(G'_iG_i)^{-1}G'_i$, let $Q_X = I_T - X(X'X)^{-1}X$, let $W_Z = [X, V_f, V_{rz}]$, and let $Q_Z = I_T - W_Z\left(W'_ZW_Z\right)^{-1}W'_Z$. The processes for fund returns, benchmark returns, and business cycle predictors characterized in Eqs. (1)–(3) can be rewritten as $r_i = G_i\Gamma_i + v_i, F = XA_F + v_f$, and $Z = XA_Z + v_z$, respectively. Then, the likelihood can be factored as

$$\mathscr{L} \propto \left[\prod_{i=1}^{N}(\psi_i)^{-T_i/2}\exp\left\{-\frac{1}{2\psi_i}(r'_iQ_{G_i}r_i + (\Gamma_i - \hat{\Gamma}_i)'G'_iG_i(\Gamma_i - \hat{\Gamma}_i))\right\}\right]$$
$$\times|\Sigma_{\mathrm{ff}}|^{-T/2}\exp\left\{-\frac{1}{2}\operatorname{tr}[\Sigma_{\mathrm{ff}}^{-1}(F'Q_XF + (A_F - \hat{A}_F)'X'X(A_F - \hat{A}_F)]\right\}$$
$$\times|\Sigma_{zz.r.f}|^{-T/2}\exp\left\{-\frac{1}{2}\operatorname{tr}[\Sigma_{zz.r.f}^{-1}(Z'Q_ZZ + (\xi - \hat{\xi})'W'_ZW_Z(\xi - \hat{\xi})]\right\}, \tag{9}$$

where $\xi = [A'_Z, \Sigma_{zf}\Sigma_{\mathrm{ff}}^{-1}, \Sigma_{zr}\Psi^{-1}]'$, Ψ is a diagonal matrix whose (i,i)th element is ψ_i, $\Sigma_{zz.r.f} = \Sigma_{zz} - \Sigma_{zr}\Sigma_{rr}^{-1}\Sigma_{rz} - \Sigma_{zf}\Sigma_{\mathrm{ff}}^{-1}\Sigma_{fz}$, Σ_{fz} is the covariance between v_{ft} and v_{zt}, Σ_{zz} is the variance of v_{zt}, and Σ_{rz} is an $N \times M$ matrix whose ith row contains the covariance between v_{it} and v_{zt}, $\hat{\Gamma}_i = (G'_iG_i)^{-1}G'_ir_i, \hat{A}_F = (X'X)^{-1}X'F,$ and $\hat{\xi} = (W'_ZW_Z)^{-1}W'_ZZ$.

B.3. The predictive moments

The first two moments of the Bayesian predictive distribution displayed in Eq. (7), say at time T, are

$$\mathbb{E}\{r_{T+1}|\mathscr{D}_T\} = \tilde{\alpha}_0 + \tilde{\beta}_T\tilde{A}'_Fx_T, \tag{10}$$

$$\mathbb{V}\{r_{T+1}|\mathscr{D}_T\} = (1 + \delta_T)\tilde{\beta}_T\hat{\Sigma}_{\mathrm{ff}}\tilde{\beta}'_T + A_T, \tag{11}$$

where $\tilde{\alpha}_0$ and $\tilde{\beta}_T$ are the all-fund versions of $\tilde{\alpha}_{i0}$ and $\tilde{\beta}_i(z_T)$ $[\tilde{\beta}_i(z_T) = \tilde{\beta}_{i0} + (I_K \otimes z'_T)\tilde{\beta}_{i1}]$, $\tilde{\alpha}_{i0}, \tilde{\beta}_{i0}$, and $\tilde{\beta}_{i1}$ are the first element, the next K elements, and the last KM elements in the vector $\tilde{\Gamma}_i = (G'_iG_i + \Upsilon)^{-1}(G'_ir_i + \Upsilon\Gamma_{i0})$, $\delta_T = \frac{1}{T}[1 + (\bar{z} - z_T)'\hat{V}_z^{-1}(\bar{z} - z_T)]$, $\tilde{A}_F = \hat{A}_F$, $\hat{\Sigma}_{\mathrm{ff}} = F'Q_XF/(T - K - M - 2)$, and A_T is a diagonal matrix whose (i,i) element is

$$\tilde{\psi}_{i1}(1 + \operatorname{tr}[\hat{\Sigma}_{\mathrm{ff}}\tilde{\Omega}_i](1 + \delta_T) + \Omega_i^{11} + 2[\Omega_i^{12} + \Omega_i^{13}(I_K \otimes z_T)]\tilde{A}'_Fx_T + \operatorname{tr}[\tilde{A}'_Fx_Tx'_T\tilde{A}_F\tilde{\Omega}_i]). \tag{12}$$

In (12), $\tilde{\psi}_{i1} = \tilde{\psi}_i/(T_i - K - KM - 2)$, $\tilde{\psi}_i = r_i'r_i + \Gamma_{i0}'\Upsilon\Gamma_{i0} - \tilde{\Gamma}_i'(G_i'G_i + \Upsilon)\tilde{\Gamma}_i$, $\tilde{\Omega}_i = \Omega_i^{22} + \Omega_i^{23}(I_K \otimes z_T) + (I_K \otimes z_T')\Omega_i^{32} + (I_K \otimes z_T')\Omega_i^{33}(I_K \otimes z_T)$, and Ω_i^{mn} is a partition of $(G_i'G_i + \Upsilon)^{-1}$ (based on the partitions of $G_{it} = [1;f_t';f_t' \otimes z_{t-1}']'$) given by

$$(G_i'G_i + \Upsilon)^{-1} = \begin{pmatrix} \Omega_i^{11} & \Omega_i^{12} & \Omega_i^{13} \\ \Omega_i^{21} & \Omega_i^{22} & \Omega_i^{23} \\ \Omega_i^{31} & \Omega_i^{32} & \Omega_i^{33} \end{pmatrix}. \tag{13}$$

Appendix C. Investments when skills may be predictable

Here we study the agnostic and skeptic investors. Of course, the dogmatist rules out skill, both fixed and time-varying.

C.1. The agnostic

The agnostic investor allows the data to determine the magnitude of skill, both fixed and time-varying. Under that assumption of diffuse priors, the Bayesian predictive mean and variance are given by

$$\mathbb{E}\{r_{T+1}|\mathscr{D}_T\} = \tilde{\alpha}_0 + \tilde{\alpha}_1 z_T + \tilde{\beta}_T \tilde{A}_F' x_T, \tag{14}$$

$$\mathbb{V}\{r_{T+1}|\mathscr{D}_T\} = (1 + \delta_T)\tilde{\beta}_T \hat{\Sigma}_{\mathrm{ff}} \tilde{\beta}_T' + A_T, \tag{15}$$

where the (i, i) element of the diagonal matrix A_T is given by

$$\begin{aligned} &\tilde{\psi}_{i2}(1 + \mathrm{tr}[\hat{\Sigma}_{\mathrm{ff}}\tilde{\Omega}_i](1 + \delta_T) + x_T'\Omega_i^{11}x_T + 2x_T[\Omega_i^{12} + \Omega_i^{13}(I_K \otimes z_T)]\tilde{A}_F'x_T \\ &\quad + \mathrm{tr}[\tilde{A}_F'x_T x_T'\tilde{A}_F\tilde{\Omega}_i]), \end{aligned} \tag{16}$$

$\tilde{\psi}_{i2} = \tilde{\psi}_i/(T_i - K - M - KM - 2)$, and the quantities $\tilde{\psi}_{i2}$ and Ω_i^{mn} are based upon the partitions of $G_{it} = [1, z_{t-1};f_t';f_t' \otimes z_{t-1}']'$.

C.2. The skeptic

Here, prior beliefs about time-varying skill are informative. To simplify the analysis we study the case in which risk premia and fund risk loadings are constant. That is, $\beta_{i1} = 0$ and $A_f = 0$ with probability one. When skill varies over time the investor's prior is modeled as if a hypothetical sample of T_0 months has been observed. In this sample, there is no manager skill in benchmark timing and stock selection based on either public or private information. The mean and variance of fund returns, benchmark returns, and predictive variables in the hypothetical sample are equal to those in the actual sample. Thus, based on that hypothetical sample, the prior on Γ_i is modeled as

$$\Gamma_i|\psi_i \sim \mathrm{N}[\Gamma_{i0}, \psi_i[G_{i0}'G_{i0}]^{-1}], \tag{17}$$

where $\Gamma_{i0} = [\bar{\alpha}_{i0}, 0', \bar{\beta}'_{i0}]'$, $\bar{\alpha}_{i0} = -\frac{1}{12}(expense)$, $\bar{\beta}_{i0} = (f'f)^{-1}(f'r_i) - T_i(f'f)^{-1}\bar{f}\bar{\alpha}_{i0}$, and

$$[G'_{i0}G_{i0}]^{-1} = \frac{1}{T_0}\begin{bmatrix} 1+\bar{z}'\hat{V}_z^{-1}\bar{z}+\bar{f}'\hat{V}_f^{-1}\bar{f} & -\bar{z}'\hat{V}_z^{-1} & -\bar{f}'\hat{V}_f^{-1} \\ -\hat{V}_z^{-1}\bar{z} & \hat{V}_z^{-1} & 0 \\ -\hat{V}_f^{-1}\bar{f} & 0 & \hat{V}_f^{-1} \end{bmatrix}. \tag{18}$$

To address the choice of T_0, we establish an exact link between σ_α (the skill uncertainty entertained by Pastor and Stambaugh (2002a,b)) and T_0. The link is given by

$$T_0 = \frac{s^2}{\sigma_\alpha^2}(1 + M + SR_{\max}^2), \tag{19}$$

where $SR_{\max}$ is the largest attainable Sharpe ratio based on investments in the benchmarks only (disregarding predictability), M is the number of macroeconomic variables that are potentially useful in predicting fund returns, and s^2 is the cross-fund average of the sample variance of the residuals in Eq. (1). This exact link gives our prior specification the skill uncertainty interpretation employed by earlier work. To apply our prior specification for the predictability skeptic investor in the empirical section, we compute s^2 and $SR_{\max}^2$, and set $\sigma_\alpha = 1\%$. Then, we obtain T_0 through Eq. (19).

The derivation of the link displayed in Eq. (19) is presented below. First note that based on the hypothetical sample, the prior of $\alpha_i = [\alpha_{i0}, \alpha'_{i1}]'$ is given by

$$\alpha_i|\psi_i \sim \mathrm{N}\left(\bar{\alpha}_i, \frac{\psi_i}{T_0}\begin{bmatrix} 1+\bar{z}'\hat{V}_z^{-1}\bar{z}+\bar{f}'\hat{V}_f^{-1}\bar{f} & -\bar{z}'\hat{V}_z^{-1} \\ -\hat{V}_z^{-1}\bar{z} & \hat{V}_z^{-1} \end{bmatrix}\right), \tag{20}$$

where $\bar{\alpha}_i = [-\frac{1}{12}(expense), 0_{1,M}]'$ and $0_{1,M}$ is an M-row vector of ones. Then, we derive the prior variance of $\alpha_{i0} + \alpha'_{i1}z_{t-1}$ using the steps

$$\begin{aligned} \mathrm{var}(\alpha_{i0} + \alpha'_{i1}z_{t-1}|\psi_i, \mathscr{D}_0) &= \mathrm{E}[\alpha_{i0}^2 + \alpha_{i1}z_{t-1}z'_{t-1}\alpha'_{i1} + 2\alpha_{i0}\alpha'_{i1}z_{t-1}] - \bar{\alpha}_{i0}^2 \\ &= \frac{\psi_i}{T_0}(1 + \bar{z}'\hat{V}_z^{-1}\bar{z} + \bar{f}'\hat{V}_f^{-1}\bar{f}) + \frac{\psi_i}{T_0}\,\mathrm{tr}\{[\hat{V}_z + \bar{z}\bar{z}'][\hat{V}_z^{-1}]\} \\ &\quad - \frac{2\psi_i}{T_0}\bar{z}'\hat{V}_z^{-1}\bar{z} \\ &= \frac{\psi_i}{T_0}[1 + M + \bar{f}'\hat{V}_f^{-1}\bar{f}] \\ &= \frac{\psi_i}{T_0}[1 + M + SR_{\max}^2], \end{aligned} \tag{21}$$

where $\mathscr{D}_0$ stands for the information in the hypothetical sample, tr denotes the trace operator, and $\bar{f}'\hat{V}_f^{-1}\bar{f}$ is the square of the maximal admissible Sharpe ratio obtained by investing in benchmarks only. The link in Eq. (19) follows by comparing the unconditional variance derived in Eq. (21) with that of Pastor and Stambaugh (2002a,b), which is given by $\psi_i\sigma_\alpha^2/s^2$.

Next, we form posterior densities by combining the hypothetical prior sample with the noninformative prior $\psi_i^{-1}|\Sigma_{\mathrm{ff}}|^{-(K+1)/2}|\Sigma_{zz.r.f}|^{-(M+1)/2}$ and the actual data. We then find that the Bayesian predictive mean and variance are

$$\mathbb{E}\{r_{T+1}|\mathscr{D}_T\} = \tilde{\alpha}_0 + \tilde{\alpha}_1 z_T + \tilde{\beta}\bar{f}, \tag{22}$$

$$\mathbb{V}\{r_{T+1}|\mathscr{D}_T\} = \left(1 + \frac{1}{T^*}\right)\tilde{\beta}\tilde{V}_f\tilde{\beta}' + A_T, \tag{23}$$

where $\tilde{\alpha}_0, \tilde{\alpha}_1$, and $\tilde{\beta}$ are the all-fund versions of $\tilde{\alpha}_{i0}, \tilde{\alpha}_{i1}$, and $\tilde{\beta}_i$, obtained as the first column, the next M columns, and the last K columns of $\tilde{\Gamma}_i = \left(G_i'G_i + G_{i0}'G_{i0}\right)^{-1}\left(G_i'r_i + [G_{i0}'G_{i0}]\Gamma_{i0}\right)$,

$$A_T(i,i) = \tilde{\psi}_{i3}\left(1 + \mathrm{tr}[\tilde{V}_f\Omega_i^{22}]\left(1 + \frac{1}{T^*}\right) + x_T'\Omega_i^{11}x_T + 2x_T\Omega_i^{12}\bar{f} + \mathrm{tr}[\bar{f}\bar{f}'\Omega_i^{22}]\right), \tag{24}$$

$$T_i^* = T_i + T_0, \quad T^* = T + T_0, \quad \tilde{\psi}_{i3} = \frac{(T_i^*/T_i)r_i'r_i - \tilde{\Gamma}_i'(G_i'G_i + G_{i0}'G_{i0})\tilde{\Gamma}_i}{T_i^* - K - M - 2},$$

$$\tilde{V}_f = \frac{T^*\hat{V}_f}{T^* - K - 3},$$

and the Ω_i^{mn} matrices are obtained by partitioning $(G_i'G_i + G_{i0}'G_{i0})^{-1}$.

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