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Model Uncertainty and Mutual Fund Investing

BY

Yee Cheng Loon

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

Of

Doctor of Philosophy

In the Robinson College of Business

Of

Georgia State University

GEORGIA STATE UNIVERSITY
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ACCEPTANCE

This dissertation was prepared under the direction of the Yee Cheng Loon's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctoral of Philosophy in Business Administration in the Robinson College of Business of Georgia State University.

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DISSERTATION COMMITTEE

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ABSTRACT

Model Uncertainty and Mutual Fund Investing

BY

Yee Cheng Loon

August 6, 2007

Committee Chair: Dr. Vikas Agarwal

Major Academic Unit: Department of Finance

Model uncertainty exists in the mutual fund literature. Researchers employ a variety of models to estimate risk-adjusted return, suggesting a lack of consensus as to which model is correct. Model uncertainty makes it difficult to draw clear inference about mutual fund performance persistence. We explicitly account for model uncertainty by using Bayesian model averaging techniques to estimate a fund's risk-adjusted return. Our approach produces the Bayesian model averaged (BMA) alpha, which is a weighted combination of alphas from individual models. Using BMA alphas, we find evidence of performance persistence in a large sample of US equity, bond and balanced mutual funds. Funds with high BMA alphas subsequently generate higher risk-adjusted returns than funds with low BMA alphas, and the magnitude of outperformance is economically and statistically significant. We also find that mutual fund investors respond to the information content of BMA alphas. High BMA alpha funds receive subsequent cash inflows while low BMA alpha funds experience subsequent cash outflows.

Model Uncertainty and Mutual Fund Investing

1. Introduction

Model uncertainty exists when there are many plausible models and a decision maker is not sure which model is correct. Model uncertainty is important in financial economics. Investors' concerns about model uncertainty result in an additional risk premium in security prices (Hansen, Sargent and Tallarini (1999); Hansen, Sargent and Wang (2002); Anderson, Hansen and Sargent (2003); Hansen and Sargent (2006)). In asset allocation, ignoring model uncertainty leads to perceived utility loss as high as 4.8% per year (Avramov, 2002).[1]

Model uncertainty exists in the mutual fund literature.[2] Researchers employ a variety of mutual fund return generating models, suggesting a lack of consensus as to which model is correct.[3] Mutual fund return generating models are used to address a number of research questions. One question of interest to both fund investors and researchers is whether fund performance persists. Performance persistence is the notion that past performance continues into the future. Funds that performed better (worse) than other funds continue to do so in the future. If markets are efficient, then mutual fund returns should not be predictable using past information (Fama, 1991). On the other hand, since a mutual fund sells its shares at net asset value, superior fund management skill, the source of performance, may not be priced. Thus, fund returns may be predictable (Gruber, 1996). Fund investors care about performance persistence. If performance

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[1] Avramov (2002) investigates return predictability by explicitly accounting for model uncertainty. He does not consider estimation error of the explanatory variables in the predictive regressions.

[2] According to the Investment Company Institute, institutions and individuals invested approximately $6.2 trillion in U.S. equity, bond and balanced open-end mutual funds at the end of 2004 (Mutual Fund Fact Book 2006, Table 41). Clearly, mutual funds have become popular investment vehicles for both institutional and retail investors. Given the large sums involved, the behavior of mutual funds naturally attracts the attention of researchers.

[3] We provide a quick overview of mutual fund return generating models in section 2. Appendix A contains details of each model.

persists, then investors should invest in consistently good performers and take money out of consistently poor performers.

Prior research in performance persistence investigates persistence conditional on a particular model of fund return. The general research methodology can be summarized by the following steps. The researcher specifies a mutual fund return generating model and uses the chosen model to compute a fund's risk-adjusted return, or "alpha". The researcher then checks if funds with high (low) alphas in the past have high (low) alphas in the future. Consequently, inference regarding performance persistence is potentially sensitive to the choice of mutual fund return generating model. This approach does not account for model uncertainty.

The extant literature on performance persistence has produced mixed findings. Grinblatt and Titman (1992), Hendricks, Patel, and Zeckhauser (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Elton, Gruber and Blake (1996a), Bollen and Busse (2005), among others, demonstrate some degree of predictability in fund returns. However, the momentum effect in stock returns and survivorship bias seem to account for return predictability (Carhart, 1997; Brown et al, 1992). Model uncertainty is one possible factor contributing to the mixed findings. For instance, using a conditional version of the CAPM, Brown and Goetzmann (1995) find evidence consistent with performance persistence. On the other hand, using a 4-factor model that attributes fund performance to the market, size, growth and momentum, Carhart (1997) concludes that there is little evidence of persistence in managerial ability.

In this paper, we investigate mutual fund performance persistence by explicitly accounting for model uncertainty. Specifically, we measure a fund's alpha as a weighted combination of alphas from a wide variety of models employed in the mutual fund literature. This technique places higher (lower) weights on the alphas of models with higher (lower) posterior model probabilities. Roughly speaking, models that fit fund data better have higher posterior model probabilities and their alphas receive bigger weights. This makes sense because if a model fits the data better than other models, its alpha estimate should contain more information about future returns. By weighting individual model alphas, our approach pools information from a range of plausible return generating models. This represents a departure from past studies which implicitly rely on complete certainty in specific models. We employ Bayesian econometric techniques to compute the posterior model probabilities and so our alpha measure is a Bayesian model averaged (BMA) alpha.

Using our BMA alpha, we test for fund return predictability in a large sample of US actively managed mutual funds comprising of equity, balanced, and bond funds. To include bond funds in our study, our BMA alpha pools information from models of equity and bond fund returns.[4] Since balanced funds invest in equities and bonds, our BMA alpha seems highly suited to predicting balanced fund returns. Hence, we include balanced funds in our sample. We sort funds into deciles based on their BMA alphas, placing the highest (lowest) BMA alpha funds into the top (bottom) decile. We then track the subsequent monthly decile returns. We find that BMA alphas are able to predict fund risk-adjusted return (as measured by BMA alphas) for all three categories of actively managed mutual funds.[5] High BMA alpha funds outperform low BMA alpha funds in the post-ranking period. In our equity fund sample, the difference in risk-adjusted return between the top and bottom deciles ranges from 4.56% to 5.52% per year. BMA alphas also demonstrate an ability to forecast balanced fund returns. The difference in risk-adjusted return between the top and bottom deciles ranges from 2.64% to 5.04% per year. In the bond fund

[4] Between 1991 – 2003, US equity funds invested an average of 2.6% of their portfolios in long-term US government bonds and corporate bonds (Investment Company Institute, 2006 Table 29). Thus, the factors used to model bond fund returns may also be useful for equity funds.

sample, the difference in risk-adjusted return between the top and bottom deciles ranges from 2.52% to 3.12% per year. We obtain these results when we employ a one-month post-ranking period and reform the decile portfolios every month. When we extend the post-ranking period to six months and re-form the decile portfolios every six months, BMA alphas continue to exhibit predictive ability. Similarly, reforming decile portfolios every twelve months does not change our findings qualitatively. When we extend the post-ranking period up to 60 months, we continue to find evidence of predictability. We do observe that the performance differential between the top and bottom deciles narrows with the length of the post-ranking period. For example, in our balanced fund sample, as the post-ranking period increases from one month to sixty months, the difference in risk-adjusted return between the top and bottom deciles declines from 2.64% per year to 0.60% per year.[6]

Extant research shows that mutual fund investors respond to past performance, which is typically measured as raw returns, market-adjusted returns or alphas defined by individual models (see, e.g., Sirri and Tufano (1998) and Chevalier and Ellison (1997)). This approach is restrictive because it assumes that investors behave as if they use a single mutual fund return generating model to measure past performance. A more plausible assumption is that investors behave as if they employ a variety of models to measure past performance. In the aggregate, we would expect fund flows to respond to a performance measure that combines information contained in a variety of mutual fund return generating models. The BMA alpha is such a performance measure because it is a weighted combination of alphas from a range of models. To investigate whether aggregate flow behavior is consistent with fund investors using a range of

[5] Avramov (2002), Cremers (2002) and Tang (2003) show that Bayesian model averaging techniques improve the forecasting of stock indexes and passive portfolios.

models to evaluate fund performance, we relate past BMA alphas to subsequent fund flows. We find that investors respond strongly to the information contained in BMA alphas by adjusting their fund allocations. Funds with high BMA alphas receive cash inflows while funds with low BMA alphas experience cash outflows in the post-ranking period.[7] For example, in our equity fund sample, the difference in monthly flow between the top and bottom deciles ranges from 3.11% to 4.11%. In addition, Spearman rank correlations exceed 0.9, indicating a close correlation between BMA alphas and future fund flows. Furthermore, investors respond to BMA alphas up to sixty months after decile formation. Results for balanced and bond funds are similar, indicating that investors respond to the BMA alphas of a wide range of mutual funds. Our finding of significant cash outflows from poorly performing funds contrasts with the low sensitivity of flows to poor past performance documented in Sirri and Tufano (1998, Table 1).[8] Across all three fund types, we find that flows into good past performers exceed flows out of poor past performers in magnitude. This is consistent with the asymmetric relation between flows and past performance as documented by Sirri and Tufano (1998), Chevalier and Ellison (1997), Huang, Wei and Yan (2007), among others.

Our study relates to recent articles that examine various ways of incorporating additional information for predicting mutual fund returns. Cohen, Coval and Pastor (2005) show that stock holdings and trades of mutual funds provide additional information that helps to predict future returns. Busse and Irvine (2006) demonstrate that seemingly unrelated passive assets also provide

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[6] These results are based on BMA alphas estimated with a skeptical prior belief in managerial skill and a 36-month estimation window. Using an alternative prior belief or a longer estimation window does not change our conclusions qualitatively.

[7] Flow is defined as new cash flow divided by lagged total net assets.

[8] Gruber (1996) also reports outflows from poorly performing funds. To sort funds into deciles, he uses a model that attributes fund return to the equity market, the bond market, a size factor and a growth factor.

useful information for forecasting.[9] Avramov and Wermers (2006) find that conditioning on macroeconomic indicators also help to predict future returns. Cremers and Petajisto (2006) show that the actively managed portion of equity fund portfolios also predict fund performance. In contrast, we consider the pooling of information from different return generating models for predicting fund returns. Furthermore, we examine not just equity mutual funds, but also balanced and bond funds.

The rest of the article proceeds as follows. In section 2, we briefly discuss the mutual fund return models that contribute information to the BMA alpha. We defer the details of these models to Appendix A. In section 3, we describe the econometric framework and the computation of BMA alphas. We provide detailed derivations in Appendix B. In section 4, we describe the construction of our data set. In section 5, we present return forecasting results using BMA alphas and in section 6, we provide evidence of investors' cash flow response to BMA alphas. We conclude the paper in section 7.

2. Mutual fund return generating models

We consider 26 separate mutual fund return generating models that have been employed in the mutual fund literature. In this section, we provide the reader with a quick overview of the models and defer details to Appendix A.

Jensen (1968) is probably one of the earliest to use a linear return model to explain equity mutual fund returns. Specifically, he uses the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) to evaluate mutual fund performance.[10] More recently, Elton, Gruber, Das and Hlavka (1993) and Elton, Gruber and Blake (1996b) propose a 3-factor model that

[9] Pastor and Stambaugh (2002a) use seemingly unrelated passive assets to evaluate equity mutual fund performance. Kosowski, Naik and Teo (2007) find that the methodology of Pastor and Stambaugh (2002a) also helps to predict

captures the risk from holding S&P 500 stocks (i.e., large capitalization stocks), non-S&P 500 stocks (i.e., small capitalization stocks) and bonds. Carhart (1997) employs the Fama and French (1993) 3-factor model to evaluate mutual fund performance. He also proposes a 4-factor model, which is a combination of the Fama and French (1993) 3-factor model and an additional factor that captures the momentum effect documented by Jegadeesh and Titman (1993). Jones and Shanken (2005) augment the Carhart model with three factors designed to capture industry effects in mutual fund returns. Elton, Gruber and Blake (1996a) and Gruber (1996) introduce a 4-factor model which attributes fund return variations to the overall market, the return differential between large and small stocks, the return differential between growth and value stocks and the returns from corporate and government bonds. These models are unconditional models in the sense that the regression coefficients do not depend on observable quantities. In contrast, Ferson and Schadt (1996), Brown and Goetzmann (1995), and Koski and Pontiff (1999) employ conditional models in which the regression coefficients are modeled as functions of macroeconomic indicators and fund characteristics. Besides security selection, actively managed mutual funds can add value by market timing, i.e., shifting allocations between cash and risky assets at opportune moments. Thus, we also consider the market timing models of Treynor and Mazuy (1996), Henriksson and Merton (1981) and Goetzmann et al (2000). We also include the conditional versions of the Treynor-Mazuy and Henriksson-Merton models as implemented by Ferson and Schadt (1996). We complete our collection of models by adding bond mutual fund models employed by Blake et al (1993), Elton et al (1995) and Khorana et al (2001).

3. Econometric framework

3.1 Prior and Likelihood

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hedge fund returns.

Our study pools information from 26 separate models for predicting mutual fund returns. We use the subscript *j* to index mutual fund models, so that *j* = 1, 2,…, 26. We specify equal prior probability for each of the 26 models. An alternative approach is to identify the set of possible factors that affect mutual fund return. If there are *K* factors, then there are 2^K possible models of mutual fund return.[11] Each of these models receives equal prior probability equal to $1/2^K$ (see, e.g., Avramov, 2002; Cremers, 2002). Given our large sample and the number of potential factors, such an approach is too computationally intensive to be feasible.

We illustrate our econometric framework for the *j*th model, M_j. The same econometric framework applies to all other models under consideration. Specifically, for each model, we have the linear regression model,

$$r_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} x_k + u_{i,t} \tag{1}$$

where $r_{i,t}$ is fund *i*'s month *t* net return in excess of the risk free rate, α_i ("alpha") is the intercept, x_k is the *k*th explanatory variable, $\beta_{i,k}$ is fund *i*'s regression coefficient with respect to the *k*th factor and $u_{i,t}$ is the disturbance term, which is assumed to be normally, independently and identically distributed, i.e., $u_{i,t} \sim N\left(0, \sigma_u^2\right) \forall t$. Thus, the likelihood function of $r_{i,t}$ is normal.

To simplify the econometric analysis, we make the following assumptions. We assume the disturbance terms ($u_{i,t}$'s) are uncorrelated across funds, which implies that the likelihood functions are independent across funds. In addition, we assume that prior beliefs on the regression coefficients in (1) are independent across funds. Prior and likelihood independence imply that we can conduct our analysis on a fund by fund basis. Jones and Shanken (2005) and

[10] Ippolito (1989) also uses the CAPM in evaluating mutual fund performance.
[11] All such models contain an intercept term.

Friesen (2004) relax the prior independence assumption by specifying a hierarchical prior for fund alphas. A complete relaxation of the prior independence assumption requires the specification of hierarchical priors for both the fund alpha and regression coefficients. Such priors result in analytically intractable posterior distributions and require the use of Markov Chain Monte Carlo simulation techniques (see e.g., Koop, 2003).

The identities of the explanatory variables depend on the specific model under consideration. If the model is the CAPM, then α_i is the measure of abnormal performance proposed by Jensen (1968), K = 1 and x_1 is the market risk premium. Alternatively, if the model is the Fama and French (1993) three factor model, then α_i is the abnormal return with respect to that model, K = 3 and the three explanatory variables are the market risk premium, MKT, the size factor, SMB and the book-to-market factor, HML. Equation (1) can be written more compactly as:

$$r_i = Z_i \phi_i + u_i \tag{2}$$

where r_i is the $S \times 1$ vector containing the S observations of $r_{i,t}$ (we assume the fund has monthly returns for S months); $Z_i = (l_S, X_i)$ is the $S \times (K+1)$ matrix containing l_S, the $S \times 1$ unit vector in the leftmost column and X_i, the $S \times K$ matrix containing the explanatory variables specific to the *j*th model; $\phi_i = (\alpha_i, \beta_{i,1}, \ldots, \beta_{i,K})$, the $(K+1) \times 1$ coefficient vector and u_i is the $S \times 1$ vector containing the disturbance terms. To facilitate subsequent exposition, define the $(K \times 1)$ sub-vector, $b_i = (\beta_{i,1}, \ldots, \beta_{i,K})$. Following Pastor and Stambaugh (2002a), we employ the natural conjugate normal-inverted gamma prior for σ_u^2 and ϕ_i. Specifically, the prior for σ_u^2 follows an inverted gamma distribution (Zellner, 1971),

$$\sigma_u^2 \sim IG(\underline{\nu}, \underline{s}^2) \tag{3}$$

where "*IG*" stands for inverted gamma and $\underline{\nu}$ and $\underline{s}^2$ are parameters of the inverted gamma distribution. Conditional on σ_u^2, α_i and b_i are normally distributed

$$\alpha_i \mid \sigma_u^2 \sim N\left(\underline{\alpha_i}\ , \frac{\sigma_u^2}{E\left(\sigma_u^2\right)}\underline{\sigma_\alpha^2}\right) \tag{4}$$

$$b_i \mid \sigma_u^2 \sim N\left(\underline{b_i}\ , \frac{\sigma_u^2}{E\left(\sigma_u^2\right)}\underline{V_b}\right) \tag{5}$$

where $\underline{\alpha_i}$ is the prior mean of α_i, $\underline{b_i}$ is the prior mean vector of b_i, $\underline{\sigma_\alpha^2}$ is the marginal prior variance of α_i ("prior variance of alpha") and $\underline{V_b}$ is the marginal prior covariance matrix of b_i. We assume α_i and b_i are independent of each other. Given this assumption, ϕ_i is multivariate normal

$$\phi_i \mid \sigma_u^2 \sim N\left(\underline{\phi_i}\ , \sigma_u^2 \underline{V_\phi}\right) \tag{6}$$

where $\phi_i = (\underline{\alpha_i}, \underline{b_i}')'$ and $\underline{V_\phi}$ is defined as

$$\underline{V_\phi} = \frac{1}{E\left(\sigma_u^2\right)}\begin{bmatrix} \underline{\sigma_\alpha^2} & 0 \\ 0 & \underline{V_b} \end{bmatrix} \tag{7}$$

The diagonal structure of $\underline{V_b}$ stems from the assumed independence of α_i and b_i. To implement Bayesian estimation, we need to specify values for the prior hyperparameters $\underline{\alpha_i}$, $\underline{\sigma_\alpha^2}$, $\underline{s}^2$, $\underline{\nu}$, $\underline{b_i}$, and $\underline{V_b}$. We follow Pastor and Stambaugh (2002b) and set $\underline{\alpha_i}$ to

$$\underline{\alpha_i} = -\frac{1}{12}\text{expense}_i \tag{8}$$

where expense_i is fund *i*'s average annual expense ratio. Following Pastor and Stambaugh (2002b), we specify two values for $\underline{\sigma_\alpha}$ to reflect different prior beliefs about a fund manager's skill. Thus, we can investigate the sensitivity of our results to different beliefs about managerial skill.[12] Specifically, we set $\underline{\sigma_\alpha}$ to 0.01 to represent a skeptical prior belief in skill and we set $\underline{\sigma_\alpha}$ to 0.03 to represent a less skeptical prior belief in skill. A value of 0.01 implies a tighter distribution of α_i centered around the fund's monthly expense and is consistent with the view that it's hard for a fund's net return to exceed its expense. In contrast, a value of 0.03 implies a less tight distribution around the fund's monthly expense. Such a specification admits a stronger possibility that a fund's net return can exceed its expenses. In short, a larger prior variance of alpha represents a greater willingness to entertain the possibility of skill.

We employ an empirical Bayes approach in specifying values for $\underline{s}^2$, $\underline{\nu}$, $\underline{b_i}$, $\underline{V_b}$. In general, the empirical Bayes approach means that researchers use the data to obtain values for the prior hyperparameters. This is an attractive and practical solution to researchers who do not wish to use non-informative (diffuse) priors but have difficulty in eliciting subjective informative priors.[13] Each fund is viewed as a draw from the cross section of funds with the same investment objective. Thus, prior uncertainty about a fund's parameter is driven by the cross sectional variation in that parameter. For each investment objective, we select all funds having at least 60

[12] It would be interesting to conduct further sensitivity analysis by considering a wider range of prior beliefs about fund managerial skill.

[13] See Carlin and Louis (2000) for a detailed discussion of the empirical Bayes approach. Studies that employ this method include Fama and French (1997), Frost and Savarino (1986), Pastor and Stambaugh (1999, 2002a, 2002b). To apply this approach, we adopt the procedure in Pastor and Stambaugh (2002a).

months of data and compute the OLS estimate of b_i for each fund.[14] Then we set $\underline{b}_i$ equal to the sample mean of the OLS estimates and $\underline{V}_b$ equal to the covariance matrix of the OLS estimates. Each OLS regression also yields $\hat{\sigma}_u^2$, the estimate of σ_u^2. To explain how we specify $\underline{s}^2$ and $\underline{\nu}$, we introduce the first and second moments of σ_u^2. Based on Zellner (1971, p.371 – 372),

$$E(\sigma_u^2) = \frac{\underline{\nu}\underline{s}^2}{\underline{\nu} - 2} \tag{9}$$

$$Var(\sigma_u^2) = \frac{2\underline{\nu}\underline{s}^2}{(\underline{\nu} - 2)^2(\underline{\nu} - 4)} \tag{10}$$

By substituting, (9) into (10), we can express $\underline{\nu}$ as

$$\underline{\nu} = 4 + \frac{2(E(\sigma_u^2))^2}{Var(\sigma_u^2)} \tag{11}$$

We insert the cross sectional mean and variance of $\hat{\sigma}_u^2$ into the right-hand side of (11) and evaluate that expression. $\underline{\nu}$ is set equal to the next largest integer of the resulting value on the right-hand side of (11). Once we have solved for $\underline{\nu}$, we use that value, the cross sectional mean of $\hat{\sigma}_u^2$ and (9) to solve for $\underline{s}^2$.

By combining the prior and likelihood, we obtain the posterior distribution of the regression parameters (see Appendix B for the derivations). For the *j*th model, the Bayesian estimate of alpha is the mean of the posterior distribution of α_i, $E(\alpha_i \mid D, M_j)$.

3.2 Bayesian model averaged alpha

The Bayesian model averaged alpha of fund *i* is

[14] In section 4, we provide details of the mutual fund investment objectives.

$$E(\alpha_i \mid D) = \sum_{j=1}^{M} E(\alpha_i \mid D, M_j) \times p(M_j \mid D) \tag{12}$$

where $p(M_j \mid D)$ is the posterior model probability of the *j*th model (see Appendix B). For example, if the model in question is the four-factor model of Carhart (1997), then $E(\alpha_i \mid D, M_j)$ is the posterior mean of the intercept term in this model. For brevity, we shall refer to $E(\alpha_i \mid D)$ as fund *i*'s BMA alpha. The BMA alpha incorporates model uncertainty by weighing the alpha of each model by its respective probability. In this way, the BMA alpha combines information contained in different model alphas in an intuitively appealing manner. It places higher (lower) weights on the alphas of models with higher (lower) posterior model probabilities. Roughly speaking, models that fit the fund data better have higher posterior model probabilities and their alphas receive bigger weights. This makes sense because if a model fits the data better than other models, its alpha estimate should contain more information about future returns.

4. Data

We obtain US mutual fund data through December 2003 from the CRSP Mutual Fund Database. Our sample consists of three types of mutual funds: equity, bond and balanced funds. We identify mutual funds using investment objective information from Wiesenberger, ICDI and Strategic Insight (available in the CRSP Database). To identify balanced funds, we also use the POLICY variable in the CRSP Database. Equity mutual funds include funds with the following investment objectives: small company growth, other aggressive growth, growth, income, growth and income, and maximum capital gain. Bond funds consist of funds with the following objectives: government bonds, mortgage-backed securities and corporate bonds. We exclude index funds from our sample.

Since 1980, many mutual funds started offering multiple share classes to investors. In a multi-class fund, the underlying portfolio of assets is common to all share classes. Share classes differ in terms of loads (sales charge) and fees (Reid and Rea, 2003). The CRSP Mutual Fund Database contains information on every share class of the same fund. In this study, our basic unit of analysis is a specific fund, not a specific share class. When a fund has multiple share classes, we consolidate them into one fund. Furthermore, for multi-class funds, we compute value-weighted monthly net returns, expenses, loads, 12b-1 fees and turnover (Wermers, 2000; Nanda, et al, 2004). Each share class's weight is its total net assets divided by the sum of the total net assets of all share classes. For fund characteristics reported on an annual basis (expense ratio, turnover, various load fees and 12b-1 fees), the value-weighted characteristic is computed using the calendar year-end total net assets. We compute value-weighted monthly net returns using monthly total net assets when available. The CRSP Mutual Fund Database reports total net assets on an annual basis between 1961 and 1969, on a quarterly basis between 1970 and 1991 and on a monthly basis starting from 1991.[15] Given this reporting pattern, we obtain monthly total net assets in the following manner: when total net assets are reported on an annual basis, we assign that total net assets figure to every month in that year. When total net assets are reported on a quarterly basis, we assign the quarter end total net assets figure to the other months in the same quarter.

Our study requires the factors from all return generating models to be available for the same period of time. This turns out to be from 1/1980 - 12/2003, a period of 288 monthly observations. Thus, we restrict our data set to this interval. Our empirical analysis uses fund net returns (net of fees and expenses). We retain funds with at least 37 months of returns and with

[15] In the CRSP Database, not all funds switched to monthly reporting of total net assets starting from 1991. In our own sample, two funds reported only quarterly total net assets in 1991 - Seligman Frontier Fund and Lazards

available data on expense, turnover and load. We need 36 months of returns for estimation and at least 1 month of returns for the forecasting analysis. Our selection process yields a final sample of 3,619 funds between 1/1980 and 12/2003. Of these, 256 are balanced funds, 2,235 are equity funds and 1,128 are bond funds.

5. Predicting mutual fund returns

To examine the predictability of BMA alphas, we adopt a portfolio approach. We sort funds into decile portfolios based on their BMA alphas estimated using data from the previous 36 months and then we observe subsequent fund returns over post-ranking periods ranging from 1 month to 60 months. With the 1-month post-ranking period, at the end of every month, we sort funds into deciles based on their past BMA alphas. Decile 1 contains funds with the lowest BMA alphas and Decile 10 contains funds with the highest BMA alphas. We then compute the equally-weighted monthly BMA alpha of each decile portfolio during the next month. By repeating this process till the end of the sample period, we obtain the time series of monthly BMA alphas for each decile portfolio starting in January 1983 and ending in December 2003. We form the first set of decile portfolios at the end of December 1982 and the last set of decile portfolios at the end of November 2003. We also form the 10-1 portfolio, which is long Decile 10 and short Decile 1. We employ the same procedure with the 3-, 6-, 12-, 24-, 36-, 48-, and 60-month post-ranking periods, except that we rebalance the decile portfolios every 3, 6, 12, 24, 36, 48, and 60 months respectively.

For each post-ranking month *t*, a fund's BMA alpha is the posterior model probability weighted average risk-adjusted return. Specifically, for fund *i* and model *j*, the risk-adjusted return in post-ranking month *t* is calculated as

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Funds:Equity Portfolio.

$$\alpha_{i,j,t} = r_{i,t} - x'_{i,j,t}\overline{b}_{i,j} \tag{13}$$

where $\alpha_{i,j,t}$ is model *j*'s risk-adjusted return for fund *i* in post-ranking month *t*, $r_{i,t}$ is fund *i*'s excess return (in excess of the riskfree rate), $x_{i,j,t}$ is the vector of explanatory variables specific to model *j* during post-ranking month *t* and $\overline{b}_{i,j}$ is the posterior mean of the regression coefficients (excluding the intercept) obtained in the decile formation month. We then calculate fund *i*'s BMA alpha in post-ranking month *t* as

$$\alpha_{i,t} = \sum_{j=1}^{M} \alpha_{i,j,t} \times p(M_j \mid D) = \sum_{j=1}^{M} (r_{i,t} - x'_{i,j,t}\overline{b}_{i,j}) \times p(M_j \mid D) \tag{14}$$

where $p(M_j \mid D)$ is the posterior model probability of model *j* and all other variables have been defined above. We compute the decile equally-weighted BMA alpha in post-ranking month *t* by averaging the BMA alphas of funds belonging to that decile. When the post-ranking period spans multiple months (e.g., a post-ranking period of 3 months), we calculate each month's model-specific risk-adjusted return ($\alpha_{i,j,t}$) using the fund return ($r_{i,t}$) and explanatory variables ($x_{i,j,t}$) from that month, but we apply the posterior mean of the regression coefficients obtained in the decile formation month. Similarly, in calculating the BMA alpha, we apply the posterior model probabilities obtained in the decile formation month. Thus, the BMA alpha is an out-of-sample measure of risk-adjusted return.

We summarize post-ranking period performance by calculating the time series average BMA alphas (in percent per month) for each decile and the 10-1 long-short portfolio. If past BMA alphas contain information about future returns, then decile 10 will outperform decile 1 during the post-ranking period. The return of the 10 – 1 portfolio will therefore be positive and statistically significant.[16] Furthermore, we would expect post-ranking period performance to improve as we move from Decile 1 to Decile 10. To test this statistically, we compute the non-parametric Spearman rank correlation. Measuring post-ranking period performance using BMA alpha allows us to account for model uncertainty in fund returns during the post-ranking period and ensures consistency across the ranking and post-ranking periods. In the subsequent discussion, we will use "BMA alpha", "alpha", "risk-adjusted return" and "return" interchangeably.[17]

5.1 Balanced funds

The rationale for using BMA alphas is that they incorporate information from a range of mutual fund return generating models, including models of stock and bond fund returns. Since balanced funds hold stocks and bonds, their returns should be most amenable to prediction by BMA alphas. Our results indicate that this is indeed the case. BMA alphas demonstrate predictive ability over varying horizons and under different estimation specifications.

In Table 1, we present the return predictability results of balanced funds where we impose a skeptical prior belief in skill (prior standard deviation of alpha is set to 0.01). For brevity, we

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[16] Throughout the paper, we use Newey and West (1987) heteroskedasticity-and-autocorrelation consistent (HAC) standard errors to compute *p*-values. The lag length is set to 6 months for computing the HAC covariance matrix. We also experiment with lag lengths of 3, 9, and 12 months and find that our findings are qualitatively unchanged. Hamilton (1994, p.282-283) describes the computation of the HAC covariance matrix and standard errors.

[17] Besides model averaging risk-adjusted returns, we also measure future fund returns in two different ways. For each decile and the 10 – 1 portfolio, we calculate the average excess return (in excess of the risk-free rate) and a risk-adjusted return (alpha) defined with respect to a specific return generating model. For balanced funds, the risk-adjusted return must account for the fact that such funds can invest in both equities and bonds. Therefore, we employ the model in Elton, et al (1996a) and Gruber (1996) because it accounts for risks in these two asset classes (see equation 20 in Appendix A.1). For equity funds, the risk-adjusted return is the alpha defined with respect to the four-factor model of Carhart (1997) (equation 17 in Appendix A.1). For bonds funds, the risk-adjusted return is the alpha defined with respect to the model in Blake, Elton and Gruber (1993) (equation 45 in Appendix A.2). Using these alternative measures of future fund returns, we find evidence of return predictability for balanced, equity and bond funds. This suggests that our findings are not due to the way we measure future fund returns. These results are available from the author upon request.

report results for Deciles 1 and 10, and the 10-1 long-short portfolio.[18] When the post-ranking period is one month (Table 1 Panel A), we find that past BMA alphas are able to predict future BMA alphas of balanced funds. High BMA alphas forecast high future BMA alphas and vice versa; the average monthly BMA alphas increase as we move from Decile 1 to Decile 10. In addition, the 10 – 1 portfolio earns a risk-adjusted return of 22 basis points per month or approximately 2.64% per year. The non-parametric Spearman rank correlation is 0.842 with a p-value smaller than 0.001, indicating that past performance is closely correlated with future performance across the deciles.

[Insert Table 1 here]

Our forecasting results suggest that BMA alphas can predict balanced fund returns over a one-month horizon. Next, we address the question of whether BMA alphas contain information about future returns over longer horizons. Looking across Table 1 Panel A, we see that BMA alphas reliably predict future returns up to 12 months after decile formation. With a 12-month post-ranking period, the 10 – 1 portfolio generates an average monthly BMA alpha of 13 basis points (approximately 1.56% per year). The Spearman rank correlation is 0.952 and highly statistically significant, which indicates predictability. Evidence of predictability weakens when we extend the post-ranking period beyond twelve months. For example, with a 24-month post-ranking period, the 10-1 portfolio does not generate any positive alpha and the Spearman correlation drops to 0.588. In general, evidence of predictability tends to weaken as the post-ranking period lengthens. As the post-ranking period increases from 1 month to 60 months, both the 10-1 portfolio return and the Spearman correlation decrease. This is a recurring pattern in our return predictability results.

[18] Results for the intermediate portfolios are available from the author upon request.

When we use a less skeptical prior belief in skill to estimate past BMA alphas, we continue to find evidence of predictability (Table 1 Panel B). In addition, across various post-ranking periods, the less skeptical belief produces larger 10-1 portfolio spreads and Spearman correlations compared to the skeptical belief. For example, when the post-ranking period is 1 month, the 10-1 portfolio return is 27 basis points per month and the Spearman correlation is 0.903 under the less skeptical belief. For the same post-ranking period, the skeptical prior produces a 10-1 portfolio return of 22 basis points per month and a Spearman correlation of 0.842. One possible explanation is that a less skeptical prior belief in skill allows estimated ranking alphas to be more dispersed. This helps to identify the worst and best out-of-sample performers and leads to both larger 10-1 spreads and higher Spearman correlations. Finally, BMA alphas estimated with the less skeptical prior belief can predict future returns over a longer horizon. Specifically, past BMA alphas can predict future returns up to 48 months after decile formation. Over this horizon, the 10-1 portfolio return is 13 basis points per month (significant at the 1% level) and the Spearman correlation is 0.867. With BMA alphas based on the skeptical belief (Panel A), the 10-1 portfolio return is statistically insignificant and the Spearman correlation is only 0.673.

We repeat the analysis using 60 months of data to estimate BMA alphas. The results are presented in Table 1 Panel C (with the skeptical prior belief) and Panel D (with the less skeptical prior belief). We continue to find evidence of predictability when we use a longer estimation window to estimate BMA alphas. The best past performers continue to outperform the worst past performers up to 60 months after decile formation. For example, when funds are sorted by past BMA alphas estimated with the less skeptical prior (Panel D), the 10-1 portfolio generates an average monthly return of 27 basis points 60 months after decile formation. The Spearman correlation is 0.721 and significant at the 5% level.

Holding prior belief constant, the longer estimation window increases 10-1 spreads across all post-ranking periods without producing a corresponding effect on Spearman correlations. This suggests that a longer estimation provides more information about the best and worst performers, but does not necessarily provide more information about the relative performance of the intermediate deciles (i.e., Deciles 2 through 9). With the skeptical prior belief (Panel C), the 10-1 portfolio generates positive returns up to 60 months after decile formation. This indicates that past BMA alphas can sort the best and worst performing funds up to 60 months into the future. In contrast, with an estimation window of 36 months, BMA alphas can only distinguish the best and worst performing funds up to 12 months into the future (Panel A). Comparing Spearman correlations in the two panels, we see that using the 60 month estimation window actually produces lower Spearman correlations over the 6-, 12- and 48-month post-ranking periods. This implies that over these post-ranking periods, using a longer estimation window does not make BMA alphas more informative about the subsequent relative performance of intermediate deciles. These conclusions remain if we examine results based on the less skeptical prior belief (i.e., compare Panels B and D).

5.2 Equity funds

Table 2 Panel A reports the forecasting performance of BMA alphas for equity funds where we impose a skeptical prior belief in skill (prior standard of alpha is set to 0.01) and use 36 months of data to estimate BMA alphas. We find that BMA alphas are able to predict future equity fund returns up to 60 months after decile formation. Decile return increases as we move from Decile 1 to Decile 10 suggesting that high BMA alphas forecast high future BMA alphas and vice versa.

Furthermore, the 10 – 1 portfolio earns an average BMA alpha ranging from 15 to 38 basis points per month. This translates into a range of 1.80% to 4.56% per year. Again, we observe that a lengthening of the post-ranking period is accompanied by a narrowing of the return differential between the top and bottom deciles and a reduction in Spearman correlation. We find stronger evidence of return predictability by using a less skeptical prior belief in skill (Table 2 Panel B). With the less skeptical prior belief, 10-1 portfolio returns and Spearman correlations tend to be larger. For example, for the 12-month post-ranking period, the skeptical belief 10-1 portfolio generates an average return of 26 basis points per month and a Spearman correlation of 0.782. The less skeptical belief 10-1 portfolio generates an average return of 31 basis points per month and a Spearman correlation of 0.964. The effect of the less skeptical prior remains if we use an estimation window of 60 months. Comparing Panels C and D reveals that 10-1 spreads and Spearman correlations tend to be larger when past BMA alphas are estimated with the less skeptical prior.

We continue to find evidence of predictability when we use a 60-month estimation window to estimate BMA alphas. The results are presented in Table 2 Panel C (with the skeptical prior belief) and Panel D (with the less skeptical prior belief). The best past performers continue to outperform the worst past performers up to 60 months after decile formation. For the same prior belief in skill, a longer estimation window provides additional information for identifying the best and worst future performers for many post-ranking periods. In addition, the longer window usually provides more information about the relative performance of intermediate deciles in the post-ranking period. For example, comparing Panels B and D, we observe that a 60-month estimation window produces 10-1 portfolio returns that equal and often exceed 10-1 portfolio returns based on a 36-month estimation window. Furthermore, Spearman correlations are often higher with a 60-month estimation window. This suggests that a longer estimation window is associated with stronger correlations between past and future performance across all fund deciles.

[Insert Table 2 here]

5.3 Bond funds

We repeat our analysis for bond funds and report the results in Table 3. We find that BMA alphas are able to predict future bond fund returns for various combinations of prior belief and estimation window. Past BMA alphas are able to predict future bond fund returns up to 60 months after decile formation. Nevertheless, evidence of predictability weakens as the post-ranking period lengthens; 10-1 portfolio return and Spearman correlation tend to decline as the post-ranking period increases from 1 month to 60 months. Holding constant the estimation window, imposing the less skeptical prior belief generally increases 10-1 portfolio returns. For example, comparing Panels A and B reveals that the less skeptical prior produces larger 10-1 portfolio return across all post-ranking periods except one (60-month).

[Insert Table 3 here]

The key finding in this section is that BMA alphas can predict the future returns of balanced, stock and bond funds over varying horizons and under different estimation specifications. Although BMA alphas are potentially useful to investors, it's not clear whether investors actually respond to the information contained in BMA alphas. We examine this issue in the next section.

6. Investors' response to model averaged alphas

Extant research on mutual fund flows shows that mutual fund investors respond to past performance, which is typically measured as raw returns or alphas defined by individual models (see, e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998)). This approach is restrictive because it assumes that investors behave as if they use a single mutual fund return generating model to measure past performance. A more plausible assumption is that investors behave as if they employ a variety of models to measure past performance. In the aggregate, we would expect fund flows to respond to a performance measure that combines information contained in a variety of mutual fund return generating models. The BMA alpha is such a performance measure because it is a weighted combination of alphas from a range of models. To investigate whether aggregate flow behavior is consistent with fund investors using a range of models to evaluate fund performance, we relate past BMA alphas to subsequent fund flows. We proceed by calculating monthly flow into a mutual fund as

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + r_{i,t})}{TNA_{i,t-1}} \tag{15}$$

where $r_{i,t}$ is fund i's month t return (without subtracting the risk-free rate), and $TNA_{i,t}$ ($TNA_{i,t-1}$) is fund i's total net assets at the end of month t ($t - 1$).

To gauge investors' respond to BMA alphas, we again apply a portfolio approach. At the end of every month, we sort funds into deciles based on their BMA alphas estimated over the previous 36 months. Decile 1 contains funds with the lowest BMA alphas and Decile 10 contains funds with the highest BMA alphas. We form the first decile portfolios at the end of December 1982 and the last decile portfolios at the end of November 2003. We then compute the equally-weighted monthly flow into each decile portfolio during the next month. Thus, the post-ranking period is 1 month. By repeating this process till the end of the sample period, we obtain the time series of monthly flows into each decile portfolio. The sample period over which cash flows are calculated is January 1983 through December 2003. To investigate the extent to which BMA alphas are related to future flows, we consider post-ranking periods of 1, 3, 6, 12, 24, 36, 48 and 60 months. That is, we reform the decile portfolios after intervals of increasing lengths. For each rebalancing scheme, we make sure that the time series of monthly flows into each decile portfolio starts in January 1983 and ends in December 2003. With a post-ranking period of 60 months, for example, we form the first decile portfolios at the end of December 1982, compute the equally weighted monthly flows into each decile over the next 60 months and reform the deciles at the end of December 1987. In this case, we form the last decile portfolios at the end of December 1998. We conduct separate analysis for balanced, equity and bond funds.

6.1 Balanced funds

We begin with the discussion of results for balanced funds. Table 4 reports the flows of decile portfolios constructed using BMA alphas estimated with a skeptical prior belief in skill (prior standard deviation of alpha is set to 0.01). For brevity, we report results for Deciles 1 and 10 and the 10-1 long-short portfolio.[19] When the post-ranking period is one month (Panel A), we find that past BMA alphas strongly predict flows into balanced funds. High BMA alphas forecast subsequent inflows and low BMA alphas forecast subsequent outflows. Decile 10, which contains funds with the highest past BMA alphas, receives an average monthly inflow of 1.9%. Decile 1, which contains funds with the lowest past BMA alphas, receives an average monthly outflow of 0.99%. The 10 – 1 portfolio has an average monthly normalized cash flow of 2.83%. The Spearman rank correlation is 0.988 indicating that BMA alphas are almost perfectly correlated with average subsequent flows of the decile portfolios. In other words, average monthly flows increase as we move from Decile 1 to Decile 10. Comparing Deciles 10 and 1, we find that flows into good past perfomers exceed flows out of poor past performers in magnitude.

[19] Results for the intermediate portfolios are available from the author upon request.

Decile 1's average monthly flow is -0.99% while decile 10's average monthly flow is 1.90%. This pattern is consistent with the asymmetric relation between flows and past performance as documented by Sirri and Tufano (1998), Chevalier and Ellison (1997), Huang, Wei and Yan (2007), among others.

BMA alphas are related to subsequent flows over periods longer than one month. Decile 1 experiences statistically significant outflows 48 months after formation while Decile 10 experiences statistically significant inflows 60 months after formation. For example, with a post-ranking period of 48 months, Decile 1's outflow is 0.49% per month, while Decile 10's inflow is 0.99% per month. The Spearman rank correlation is 0.939 and the 10-1 portfolio's flow is 1.49%. Although flows respond to past performance up to four years after decile formation, it is clear that the response weakens as the post-ranking period lengthens. Looking across Table 4 Panel A, we see that flows decrease in magnitude as the post-ranking period lengthens. This holds for Decile 1, Decile 10 and the 10-1 portfolio. In addition, the Spearman correlation also declines as the post-ranking period lengthens.

[Insert Table 4 here]

Next, we address the question of whether investors' cash flow response is sensitive to the choice of prior belief in skill. Table 4 Panel B reports the flows of decile portfolios constructed using BMA alphas estimated with a less skeptical prior belief in skill (prior standard deviation of alpha is set to 0.03). For post-ranking periods ranging from 1 month to 24 months, past BMA alphas strongly predict cash flows into balanced funds. Funds with good performance experience subsequent inflows while funds with poor performance experience subsequent outflows. For example, when the post-ranking period is one month, Decile 1's average monthly flow is -0.89% while Decile 10's average monthly flow is 1.82%. The Spearman correlation is 0.976 indicating that average monthly flow increases as we move from Decile 1 to Decile 10. We continue to observe an asymmetric response of fund flows to past performance. As in Panel A, the response of flows to past performance weakens over longer post-ranking periods. Results based on the less skeptical prior are generally consistent with those based on the skeptical prior. Nevertheless, a comparison of Panels A and B reveals stronger and more persistent flows when BMA alphas are estimated with the skeptical prior belief in skill. Take, for instance, flows over the 36 month post-ranking period. With the skeptical prior, Deciles 1 and 10 have statistically significant flows. The 10-1 portfolio has an inflow of 2.10% per month and the Spearman correlation is 0.976. In contrast, with the less skeptical prior, decile 1's outflow is not statistically significant. The 10-1 portfolio's monthly inflow decreases to 1.44% and the Spearman correlation is lower at 0.927.

Finally, we consider whether the length of the estimation window affects our findings. We repeat our analysis using BMA alphas estimated with 60 months of data rather than 36 months of data. Panel C reports results based on a skeptical prior belief in skill while Panel D reports results based on a less skeptical prior belief in skill. For both prior beliefs, we find that BMA alphas predict future flows up to 48 months after decile formation. We document outflows from the worst performing funds and inflows into the best performing funds. The response of flow to performance is asymmetric as the magnitude of inflow into Decile 10 is usually larger than the magnitude of outflow from Decile 1. Thus, using a longer return history to estimate BMA alphas does not change our findings.

6.2 Equity and bond funds

We repeat the cash flow analysis for equity funds and report the results in Table 5. Table 5 Panel A contains results based on a skeptical prior belief in skill (prior standard of alpha is 0.01) while Table 5 Panel B contains results based on a less skeptical prior belief in skill (prior standard deviation of alpha is 0.03). In both panels, we use 36 months of data to estimate BMA alphas. Our findings are robust to different prior beliefs in skill and so, for brevity, we will focus our discussion on Panel A. Investors respond strongly to BMA alphas, directing cash to high BMA alpha funds and withdrawing cash from low BMA alpha funds. With a one-month post-ranking period, decile flows increase as we move from decile 1 to decile 10. The 10 – 1 portfolio receives an average monthly flow of 4.11%. The Spearman rank correlation equals 1 indicating perfect correlation between rankings based on past BMA alphas and future cash flows. Our findings are unchanged when we extend the post-ranking period up to 48 months. With a 48-month post-ranking period, Decile 1 (10) has an average monthly flow of -0.31% (1.30%), the 10-1 portfolio's average monthly flow is 1.62% and the Spearman correlation is 0.988. Again, we observe an asymmetric response of flow to past performance measured using BMA alpha. For example, with a 12-month post-ranking period, the worst performing funds experience an outflow of 0.73% per month while the best performing funds experience an inflow of 2.45% per month. The same conclusion applies to other post-ranking periods ranging from 1 to 48 months. Although investors appear to respond to past performance over a span of years, the strength of the response weakens as the post-ranking period lengthens. This is most apparent by examining the 10-1 portfolio's average monthly flow, which declines from 4.11% (1-month post-ranking period) to 1.62% (48-month post-ranking period).

Our results are essentially unchanged when we use BMA alphas estimated over the previous 60 months. We continue to document outflows from funds with poor performance and inflows into funds with good performance; the flow response is asymmetric and the strength of the response declines as the post-ranking period lengthens. The flow response is statistically significant up to 60 months after decile formation. For example, in Table 5 Panel C, deciles 1 and

10 have statistically significant flows with a 60-month post-ranking period. In Panel A and for the same post-ranking period, Decile 1's outflow is not statistically different from zero. This suggests that using a longer time series to estimate BMA alphas provides more information about subsequent flows.

[Insert Table 5 here]

Repeating the analysis for bond funds produces broadly similar results (Table 6). Bond funds with higher (lower) BMA alphas subsequently receive higher (lower) cash flows. The flow response is asymmetric with good performers receiving flows of greater magnitudes. The intensity of the flow response declines as the post-ranking period lengthens. We obtain these results for post-ranking periods ranging from 1 month to 36 months when we use BMA alphas estimated with 36 months of data (Table 6 Panels A and B). The pattern extends to 60 months after decile formation when we use BMA alphas estimated with 60 months of data (Table 6 Panels C and D). In the case of bond funds, using a longer return history makes BMA alphas more informative about future flows. One notable difference from the earlier analyses is the absence of statistically significant flows for Decile 1 in the bond sample. This is apparent for virtually all post-ranking periods regardless of prior belief and estimation window. The explanation lies in the measurement of flow. Our current measure, which is used in the extant literature, normalizes new money invested in a fund by the prior month's total net assets. As Gruber (1996, p.798-799) points out, this *normalized* cash flow measure tends to magnify the flows of small funds. In unreported work, we repeat our analysis using dollar cash flow, i.e., new money invested in a fund without dividing by prior month total net assets. Dollar cash flow magnifies the flows of large funds as these funds tend to have larger absolute dollar flows. Using dollar cash flow reveals statistically significant outflows from Decile 1 up to 60 months after decile formation. Cash flows into Decile 10 are also significant up to 60 months after decile formation. Thus, investors do respond to the poor performance of bond funds by taking their money out of those funds. However, this behavior is captured using dollar cash flow rather than normalized cash flow. The implication is that cash outflows are concentrated in the larger bond funds. As a robustness check, we repeat the flow analysis using dollar cash flow for the balanced and equity fund samples as well. Using dollar cash flow does not change our findings for balanced and equity funds.[20]

To sum up, our results indicate that investors seem to react to the information contained in BMA alphas. Investors direct cash flows to mutual funds with high BMA alphas and withdraw cash flows from mutual funds with low BMA alphas. Furthermore, investors respond to BMA alphas up to sixty after decile formation.

[Insert Table 6 here]

6.3 Multivariate analysis

Thus far, we have investigated investors' cash flow response to past BMA alphas in a univariate setting. It is possible that the flow-performance relation that we document could be due to factors other than past performance as measured by BMA alphas. In this section, we estimate the effect of past BMA alphas on subsequent flows after controlling for other relevant factors. Specifically, we use our entire sample of equity, bond and balanced funds and estimate the flow regressions reported in Sirri and Tufano (1998, Table II). The first specification is

$$\begin{aligned} Flow_{i,y} = b_0 + b_1 Logltna_{i,y} + b_2 Grpflow_{i,y} + b_3 Sdret_{i,y} + b_4 Totalfee_{i,y} + \\ b_5 Qrank1_{i,y} + b_6 Qrank2_{i,y} + b_7 Qrank3_{i,y} + b_8 Qrank4_{i,y} + b_9 Qrank5_{i,y} + e_{i,y} \end{aligned} \tag{16}$$

[20] Findings based on dollar cash flow are available from the author upon request.

where $Flow_{i,y}$ is the annual flow of fund i in year y, $Logltna_{i,y}$ is the natural log of fund i's total net assets in the previous year. $Grpflow_{i,y}$ is the flow for all funds belonging to the same investment objective,[21] $Sdret_{i,y}$ is the standard deviation of fund i's monthly returns in the previous year[22] and $Totalfee_{i,y}$ is the total annual fee incurred by an investor in fund i. Following Sirri and Tufano (1998), we compute total annual fee as the sum of the expense ratio and one-seventh of the front end load, if any. $Qrank1_{i,y}$, $Qrank2_{i,y}$, $Qrank3_{i,y}$, $Qrank4_{i,y}$ and $Qrank5_{i,y}$ are quintile performance ranks defined with respect to fund i's BMA alpha estimated over the previous 36 months with a skeptical prior belief in skill. We follow Sirri and Tufano (1998) in constructing these performance ranks. For each investment objective and year, we sort all funds based on their BMA alphas and calculate each fund's fractional performance rank. The fractional rank ranges from 0 (worst performance; lowest BMA alpha) to 1 (best performance; highest BMA alpha). Using the fractional rank, we create quintile performance ranks with $Qrank1_{i,y}$ representing the top performance quintile and $Qrank5_{i,y}$ representing the bottom performance quintile. For fund i in year y, $Qrank5_{i,y}$ is min($Rank_{i,y}$, 0.2), where $Rank_{i,y}$ is fund i's fractional rank for year y. The other four quintile performance ranks are computed as

$$\begin{aligned}
Qrank4_{i,y} &= \min(Rank_{i,y} - Qrank5_{i,y}, 0.2) \\
Qrank3_{i,y} &= \min(Rank_{i,y} - Qrank5_{i,y} - Qrank4_{i,y}, 0.2) \\
Qrank2_{i,y} &= \min(Rank_{i,y} - Qrank5_{i,y} - Qrank4_{i,y} - Qrank3_{i,y}, 0.2) \\
Qrank1_{i,y} &= \min(Rank_{i,y} - Qrank5_{i,y} - Qrank4_{i,y} - Qrank3_{i,y} - Qrank2_{i,y}, 0.2)
\end{aligned}$$

The quintile ranks lends flexibility to the estimation by allowing different levels of past performance to have different effects on subsequent flows. We also estimate an alternative

[21] As mentioned in section 4, we assign equity funds to one of six investment objectives: small company growth, other aggressive growth, growth, income, growth, growth and income and maximum capital gain. Bond funds fall into one of three investment objectives: government bonds, mortgage-backed securities, and corporate bonds. Balanced funds represent a single investment objective.

specification of the flow-performance relation that reduces the five performance variables to three,

$$\begin{aligned} Flow_{i,y} = b_0 + b_1 Logltna_{i,y} + b_2 Grpflow_{i,y} + b_3 Sdret_{i,y} + b_4 Totalfee_{i,y} + \\ b_5 HIGHPERF_{i,y} + b_6 MIDPERF_{i,y} + b_7 LOWPERF_{i,y} + e_{i,y} \end{aligned} \tag{17}$$

Where $HIGHPERF_{i,y}$ is equal to $Qrank1_{i,y}$, $LOWPERF_{i,y}$ is equal to $Qrank5_{i,y}$ and $MIDPERF_{i,y}$ is equal to min ($Rank - LOWPERF_{i,y}$, 0.6). Following Sirri and Tufano (1998), we estimate equations (14) and (15) by the method of Fama and MacBeth (1973) and report the results in Table 7.

[Insert Table 7 here]

After controlling for the influence of fund size, fees, risk and investment category flow, we continue to find that investors respond to past performance as measured by BMA alphas. Table 7 Column 1 reports Fama and MacBeth regression coefficients for equation (14). Consistent with Sirri and Tufano (1998, Table II), we find that lagged fund size ($Logltna_{i,y}$) and fees ($Totalfee_{i,y}$) have negative and statistically significant effects on fund flows while the aggregate flow into the investment category has a positive and statistically significant impact on fund flows. Fund risk, as measured by $Sdret_{i,y}$, has a negative, though insignificant coefficient. All five quintile performance variables have positive coefficients indicating that good past performance increases subsequent flows, and vice versa. Of the five coefficients, the coefficients of the fourth, third and top quintiles are statistically significant at the 1% level. Consistent with Sirri and Tufano (1998) and our univariate analyses, we observe an asymmetric response of flows to past performance. Specifically, the coefficient of the top quintile is 1.812 while coefficients for the other four quintiles range from 0.226 to 0.394. We obtain similar findings with equation (15).

[22] We compute standard deviation only if a fund has a complete record of twelve monthly returns in a year.

The coefficients of $Logltna_{i,y}$ and $Totalfee_{i,y}$ continue to be negative and significant while the coefficient of $Grpflow_{i,y}$ continues to be positive and significant. All three performance variables ($LOWPERF_{i,y}$, $MIDPERF_{i,y}$, and $HIGHPERF_{i,y}$) have positive and significant coefficients. Again, we note that $HIGHPERF_{i,y}$ has a much larger coefficient indicating an asymmetric response of flows to performance.

To check the robustness of our findings, we create quintile performance ranks using BMA alphas estimated over the previous 36 months with a less skeptical prior view of skill. We re-estimate equations (14) and (15) and find that our results are qualitatively similar. As an additional check, we use BMA alphas estimated over the previous 60 months to create quintile performance ranks. Using these performance ranks do not change our findings qualitatively. We still observe inflows into funds with good past performance and outflows from funds with poor past performance. The respond of flows to past performance continues to be asymmetric.

7. Conclusion

This paper proposes a Bayesian approach for combining information contained in different models of mutual fund returns. Our approach produces the Bayesian model averaged (BMA) alpha, which is a weighted combination of alphas from individual models. This approach places higher (lower) weights on the alphas of models with higher (lower) posterior model probabilities. Roughly speaking, models that fit fund data better have higher posterior model probabilities and their alphas receive bigger weights. This makes sense because if a model fits the data better than other models, its alpha estimate should contain more information about future returns. Our approach pools information from a range of plausible return generating models of fund returns. This represents a departure from past studies which implicitly rely on complete certainty in specific models.

We use BMA alphas to forecast returns for a large sample of US equity, bond and balanced mutual funds. Combining information from a variety of models helps predict fund returns. Funds with high BMA alphas subsequently generate higher risk-adjusted returns than funds with low BMA alphas, and the magnitude of outperformance is economically and statistically significant. For example, in our equity fund sample, the difference in risk-adjusted return between the top and bottom deciles ranges from 4.56% to 5.52% per year. We also find that mutual fund investors respond to the information content of BMA alphas. High BMA alpha funds receive subsequent cash inflows while low BMA alpha funds experience subsequent cash outflows.

Appendix A: Mutual fund return generating models

In this appendix, we describe the return generating models considered in our study. For additional details, we direct interested readers to the references cited below. Table A1 summarizes all the models. We start with models of equity mutual fund returns, followed by models of bond fund returns. Unless otherwise stated, all return series are in excess of the one-month T-bill return (from Ibbotson and Associates, Inc.), the subscript *t* indexes time (expressed in months) and the subscript *i* indexes mutual funds.

<u>Appendix A.1 Equity mutual fund models</u>

CAPM-based model (Jensen (1968)):

$$r_{i,t} = \alpha_i + \beta_i MKT_t + u_{i,t} \tag{18}$$

where $r_{i,t}$ is the return of mutual fund *i*, and MKT_t is the return of the CRSP value-weighted portfolio of all NYSE, AMEX and Nasdaq stocks.

Fama and French (1993) three factor model:

$$r_{i,t} = \alpha_i + \beta_{i,1} MKT_t + \beta_{i,2} SMB_t + \beta_{i,3} HML_t + u_{i,t} \tag{19}$$

where SMB_t is the equal-weighted return on three small portfolios minus the equal-weighted return on three big portfolios, and HML_t is the equal-weighted return on two value portfolios minus the equal-weighted return on two growth portfolios. See Fama and French (1993) for complete descriptions of SMB_t and HML_t.

Carhart (1997) augment the Fama French three factor model with an additional factor designed to capture the momentum effect documented by Jegadeesh and Titman (1993).

Carhart (1997) four factor model:

$$r_{i,t} = \alpha_i + \beta_{i,1} MKT_t + \beta_{i,2} SMB_t + \beta_{i,3} HML_t + \beta_{i,4} UMD_t + u_{i,t} \tag{20}$$

where UMD_t is the equal-weighted return on the two high prior return portfolios minus the equal-weighted return on the two low prior return portfolios. We are grateful to Ken French for providing the data on *MKT*, *SMB*, *HML*, and *UMD*.

Jones and Shanken (2005) use a seven factor model consisting of the four factors in Carhart's model and three industry factors. These industry factors are constructed to explain industry return covariation orthogonal to *MKT*, *SMB*, *HML*, and *UMD*.

Jones and Shanken (2005) seven factor model:

$$\begin{aligned} r_{i,t} = \alpha_i &+ \beta_{i,1} MKT_t + \beta_{i,2} SMB_t + \beta_{i,3} HML_t + \beta_{i,4} UMD_t + \\ &\beta_{i,5} IP1_t + \beta_{i,6} IP2_t + \beta_{i,7} IP3_t + u_{i,t} \end{aligned} \tag{21}$$

where $IP1_t$, $IP2_t$, $IP3_t$ are the first, second and third industry factors respectively. We construct these factors following the description in Jones and Shanken (2005).

Elton, et al (1993) and Elton, et al (1996b) specify a three factor model in which mutual fund return is a function of the returns on three passive portfolios: a large cap portfolio, a small cap portfolio and a bond portfolio.

Elton et al (1993)-Elton et al (1996b) three factor model:

$$r_{i,t} = \alpha_i + \beta_{i,1}SP_t + \beta_{i,2}OSP_t + \beta_{i,3}B1_t + u_{i,t} \tag{22}$$

where SP_t is the return on the S&P 500 index, OSP_t is the return on a small stock index which has been made orthogonal to the S&P 500 index, and $B1_t$ is the return on a passive debt portfolio consisting of 80% intermediate government bonds and 20% long-term corporate bonds. $B1_t$ is orthgonalized to remove the effects of SP_t and OSP_t.

Elton, et al (1996a) and Gruber (1996) specify a four factor model in which mutual fund excess return is a function of the returns on a large cap portfolio, a portfolio that is long small stocks and short large stocks, a portfolio that is long growth stocks and short value stocks, and a bond portfolio.

Elton, et al (1996a)-Gruber (1996) four factor model:

$$r_{i,t} = \alpha_i + \beta_{i,1}SP_t + \beta_{i,2}SL_t + \beta_{i,3}GV_t + \beta_{i,4}B2_t + u_{i,t} \tag{23}$$

where SL_t is the difference in return between a small-cap portfolio and a large-cap stock portfolio based on Prudential-Bache indices, GV_t is the difference in return between a high growth portfolio and a value portfolio based on Prudential-Bache indices, and $B2_t$ is a par-weighted combination of the Lehman Brothers Aggregate bond index and a high-yield bond index.

Treynor and Mazuy (1966)'s market timing model:

$$r_{i,t} = \alpha_i + \beta_i MKT_t + \gamma_i MKT_t^2 + u_{i,t} \tag{24}$$

where MKT_t^2 is the squared of MKT_t.

Henriksson and Merton (1981)'s market timing model:

$$r_{i,t} = \alpha_i + \beta_i MKT_t + \gamma_i MKT_t^+ + u_{i,t} \tag{25}$$

where MKT_t^+ is defined as max(0, MKT_t). In both models, γ_i captures the portfolio manager's market timing ability. Goetzmann, et al (2000) refine the Henriksson-Merton model by recognizing that mutual funds can time the market on a daily basis even though fund returns are measured on a monthly basis. Goetzmann, et al (2000) propose two market timing models:

$$r_{i,t} = \alpha_i + \beta_i SP_t + \gamma_i P_t + u_{i,t} \tag{26}$$

$$r_{i,t} = \alpha_i + \beta_{i,1}SP_t + \gamma_i P_t + \beta_{i,2}SMB_t + \beta_{i,3}HML_t + u_{i,t} \tag{27}$$

With

$$P_t = \left[\left(\prod_{\tau\in\mathrm{month(t)}}^{t} \max\left(1 + SP_\tau + r_{f,\tau}\ , 1 + r_{f,\tau}\right)\right) - 1\right] - SP_t \tag{28}$$

where SP_τ is the S&P 500 excess return for day τ in month t and $r_{f,\tau}$ is the simple daily rate that, over the number of calendar days in the month, compounds to the 1-month T-bill return from Ibbotson and Associates, Inc. We thank Ken French for providing data on $r_{f,\tau}$.

Ferson and Schadt (1996) propose two conditional models: a one factor model and a four factor model. In both models, the conditioning information variables are:

1. Lagged level of the one-month Treasury bill yield, $r_{f,t-1}$
2. Lagged dividend yield of the value-weighted CRSP index of NYSE and AMEX stocks, $DIV1_{t-1}$
3. Lagged measure of the slope of the term structure, $TERM_{t-1}$
4. Lagged quality spread in the corporate bond market, DEF_{t-1}
5. Dummy variable taking the value of 1 if the month is January and 0 otherwise, JAN_t

Their conditional one factor model (based on the CAPM):

$$r_{i,t} = \alpha_i + \beta_i MKT_t + u_{i,t} \tag{29}$$

$$\begin{aligned}\beta_i &= \delta_0^{MKT} + \delta_1^{MKT} r_{f,t-1} + \delta_2^{MKT} DIV1_{t-1} + \\ &\quad \delta_3^{MKT} TERM_{t-1} + \delta_4^{MKT} DEF_{t-1} + \delta_5^{MKT} JAN_t \\ &= \delta_0^{MKT} + \delta^{MKT\prime} z_{t-1}\end{aligned} \tag{30}$$

Where δ^{MKT} is the (5×1) vector,

$$\delta^{MKT} = \left(\delta_1^{MKT}, \delta_2^{MKT}, \delta_3^{MKT}, \delta_4^{MKT}, \delta_5^{MKT}\right)' \tag{31}$$

and z_{t-1} is the (5×1) vector of conditioning information variables,

$$z_{t-1} = \left(r_{f,t-1}, DIV1_{t-1}, TERM_{t-1}, DEF_{t-1}, JAN_t\right)' \tag{32}$$

Using the same conditioning variables, Ferson and Schadt also implement a four factor conditional model:

$$r_{i,t} = \alpha_i + \beta_{i,1} SP_t + \beta_{i,2} S_t + \beta_{i,3} GB_t + \beta_{i,4} LB_t + u_{i,t} \tag{33}$$

where the definitions of $\beta_{i,1}, \beta_{i,2}, \beta_{i,3}$, and $\beta_{i,4}$ follow (30) and (31), SP_t is the return on S&P 500 index, S_t is the return on the Ibbotson Small Firm Total Return index, GB_t is the return on the Ibbotson Long-Term Government Bond Return index and LB_t is the return on a below investment grade bond index.

Ferson and Schadt (1996) also implement conditional forms of the market timing models of Treynor and Mazuy (1966) and Henriksson and Merton (1981).

Brown and Goetzmann (1995) propose two conditional models: a one factor model and a three factor model. In contrast to Ferson and Schadt, Brown and Goetzmann use fund characteristics (reported on an annual basis) as conditioning variables. In addition, both the *intercept* and regression coefficients are modeled as linear functions of the conditioning variables. The conditioning variables are:

1. Natural logarithm of last year's total net assets, *LTNA*.
2. Last year's reported expense ratio, *EXP*.

3. Fund's length of existence (age), *TIME*. The CRSP Mutual Fund Database only reports the year in which the fund was organized. Thus, we measure *TIME* as the number of years between the year of inception and the most recent calendar year.

The Brown and Goetzmann conditional one factor model:

$$r_{i,t} = \alpha_i + \beta_i MKT_t + u_{i,t} \tag{34}$$

α_i is now defined as:

$$\begin{aligned} \alpha_i &= \delta_0 + \delta_1 LTNA + \delta_2 EXP + \delta_3 TIME \\ &= \delta_0 + \delta' z_{t-1} \end{aligned} \tag{35}$$

where δ is the (3×1) vector

$$\delta = \left(\delta_1, \delta_2, \delta_3\right)' \tag{36}$$

and β_i is now defined as:

$$\begin{aligned} \beta_i &= \delta_0^{MKT} + \delta_1^{MKT} LTNA + \delta_2^{MKT} EXP + \delta_3^{MKT} TIME \\ &= \delta_0^{MKT} + \delta^{MKT\prime} z_{t-1} \end{aligned} \tag{37}$$

where δ^{MKT} is the (3×1) vector

$$\delta^{MKT} = \left(\delta_1^{MKT}, \delta_2^{MKT}, \delta_3^{MKT}\right)' \tag{38}$$

and z_{t-1} is the (3×1) vector of conditioning information variables

$$z_{t-1} = \left(LTNA, EXP, TIME\right)' \tag{39}$$

Brown and Goetzmann also employ a conditional form of the Elton et al (1993) three factor model (see (22)).

$$r_{i,t} = \alpha_i + \beta_{i,1} SP_t + \beta_{i,2} OSP_t + \beta_{i,3} B1_t + u_{i,t} \tag{40}$$

where the definition of α_i follows (35) and (36) and the definitions of $\beta_{i,1}, \beta_{i,2}$ and $\beta_{i,3}$ follow (37) and (38).

Koski and Pontiff (1999) employ a three factor conditional model in which mutual fund excess returns are a function of the general stock market's performance, the return differential between small-cap and large cap stocks and the returns of corporate bonds. Their choice of conditioning information variables include both marketwide and fund specific variables. Three conditioning variables are:

1. Risk-free rate at month t, $r_{f,t}$.
2. Lagged dividend yield of the CRSP value-weighted index, $DIV2_{t-1}$.
3. Lagged return difference between the mutual fund's return and the CRSP value-weighted index return, $PERF_{i,t-1}$.

The Koski and Pontiff model:

$$r_{i,t} = \alpha_i + \beta_{i,1} MKT_t + \beta_{i,2} CAP_t + \beta_{i,3} BOND_t + u_{i,t} \tag{41}$$

where MKT_t is the excess return of the CRSP value-weighted portfolio of all NYSE, AMEX and Nasdaq stocks, CAP_t is the difference between the return on the 10*th* decile (small firm) CRSP capitalization portfolio and the 1*st* decile (large firm) capitalization portfolio and $BOND_t$ is the excess return of a long-term corporate bond index.

Pontiff and Koski only model the regression betas as a function of $r_{f,t}$, $DIV2_{t-1}$ and $PERF_{i,t-1}$. Specifically, $\beta_{i,1}$ is defined as:

$$\begin{aligned} \beta_{i,1} &= \delta_0^{MKT} + \delta_1^{MKT} r_{f,t} + \delta_2^{MKT} DIV2_{t-1} + \delta_3^{MKT} BOND_{t-1} \\ &= \delta_0^{MKT} + \delta^{MKT\prime} z_{t-1} \end{aligned} \tag{42}$$

where δ^{MKT} is the (3×1) vector

$$\delta^{MKT} = \left(\delta_1^{MKT}, \delta_2^{MKT}, \delta_3^{MKT}\right)' \tag{43}$$

and z_{t-1} is the (3×1) vector of conditioning information variables

$$z_{t-1} = \left(r_{f,t}, DIV2_{t-1}, BOND_{t-1}\right)' \tag{44}$$

$\beta_{i,2}$ and $\beta_{i,3}$ are defined in a similar fashion as $\beta_{i,1}$.

Appendix A.2 Bond mutual fund models

Blake, Elton and Gruber (1993) employ four models of bond fund returns. The simplest is a single index model:

$$r_{i,t} = \alpha_i + \beta_i GC_t + u_{i,t} \tag{45}$$

where $r_{i,t}$ is the return of mutual fund *i*, and GC_t is the return of the Lehman Brothers government/corporate bond index. Khorana (2001) and Jayaraman, Khorana and Nelling (2002) also employ this single-index model. The next model is a three factor model:

$$r_{i,t} = \alpha_i + \beta_{i,1} GC_t + \beta_{i,2} MBS_t + \beta_{i,3} LB_t + u_{i,t} \tag{46}$$

where GC_t is the return of the Lehman Brothers government/corporate bond index, MBS_t is the return on the Lehman Brothers mortgage-backed securities index and LB_t is the return on a below investment grade bond index. Another three factor model accounts for differences in bond maturities:

$$r_{i,t} = \alpha_i + \beta_{i,1} ITG_t + \beta_{i,2} LTG_t + \beta_{i,3} LB_t + u_{i,t} \tag{47}$$

where ITG_t is the return on the Lehman Brothers intermediate government bond index, LTG_t is the return on the Lehman Brothers long-term government bond index and LB_t is the return on a below investment grade bond index. The intermediate bond index is market-weighted and contains government bonds with maturities between 1 and 10 years. The long-term bond index contains bonds with maturities beyond 10 years. The authors also employ a six-factor model intended to capture differences in maturity range and risk premiums between securities.

$$r_{i,t} = \alpha_i + \beta_{i,1} ITG_t + \beta_{i,2} LTG_t + \beta_{i,3} ITC_t + \beta_{i,4} LTC_t + \beta_{i,5} MBS_t + \beta_{i,6} LB_t + u_{i,t} \tag{48}$$

where ITC_t is the Lehman Brothers intermediate corporate bond index, LTC_t is the return on the Lehman Brothers long-term corporate bond index. The other variables are as defined previously.

Khorana (2001) and Jayaraman, et al (2002) employ a four-index model:

$$r_{i,t} = \alpha_i + \beta_{i,1} GC_t + \beta_{i,2} MBS_t + \beta_{i,3} LTG_t + \beta_{i,4} ITG_t + u_{i,t} \tag{49}$$

where the GC_t, MBS_t, LTG_t, ITG_t are as defined previously.

Elton, Gruber and Blake (1995) employ 4 different models. The simplest is a one-factor model,

$$r_{i,t} = \alpha_i + \beta_{i,1} B2_t + u_{i,t} \tag{50}$$

where $B2_t$ is the aggregate bond market return as defined previously.

The second model consists of four factors:

$$r_{i,t} = \alpha_i + \beta_{i,1} SP_t + \beta_{i,2} DEF2_t + \beta_{i,3} OPTION_t + \beta_{i,4} B2_t + u_{i,t} \tag{51}$$

where $DEF2_t$ is the default risk factor defined as the difference in return between the below investment grade bond index and the Lehman Brothers intermediate government index, $OPTION_t$ is the difference in return between the Lehman Brothers Government National Mortgage Association (GNMA) index and a government bond series with the same duration. All other factors have been defined. The third model consists of a different collection of four factors:

$$r_{i,t} = \alpha_i + \beta_{i,1} SP_t + \beta_{i,2} B2_t + \beta_{i,3} GDP_t + \beta_{i,4} INF_t + u_{i,t} \tag{52}$$

where INF_t is the unanticipated change in inflation and GDP_t is the unexpected change in the real GDP forecast. The final model is a six-factor model,

$$r_{i,t} = \alpha_i + \beta_{i,1} SP_t + \beta_{i,2} DEF2_t + \beta_{i,3} OPTION_t + \beta_{i,4} B2_t + \beta_{i,5} GNP_t + \beta_{i,6} INF_t + u_{i,t} \tag{53}$$

Appendix B: Econometric derivation

In this appendix, we derive the posterior distribution of the regression parameters. After that, we describe the computation of the marginal likelihood and posterior model probability.

<u>Appendix B.1 Posterior distribution</u>

We derive the posterior distributions of ϕ_i and σ_u^2.[23] Given the distributional assumptions of $u_{i,t}$, the likelihood function of r_i is normal

$$p(r_i \mid Z_i, \phi_i, \sigma_u) = \frac{1}{(2\pi)^{S/2}\, \sigma_u^2} \exp\left\{ -\frac{1}{2\sigma_u^2} (r_i - Z_i\phi_i)' (r_i - Z_i\phi_i) \right\} \tag{54}$$

[23] See Zellner (1971) and Poirier (1995) for further details.

The prior pdf of σ_u^2 is

$$p(\sigma_u) = \frac{2}{\Gamma(\underline{\nu}/2)} \left(\frac{\underline{\nu}\,\underline{s}^2}{2} \right) \frac{1}{\sigma^{\underline{\nu}+1}} \exp\left\{ -\frac{\underline{\nu}\,\underline{s}^2}{2\sigma_u^2} \right\} \tag{55}$$

where $\Gamma(\cdot)$ denotes the gamma function. Conditional on σ_u, the prior pdf of ϕ_i is

$$p(\phi_i \mid \sigma_u) = \frac{1}{(2\pi)^{(k+1)/2} \left| \underline{V_\phi} \right|^{1/2} \sigma_u^{k+1}} \exp\left\{ -\frac{1}{2\sigma_u^2} \left(\phi_i - \underline{\phi_i} \right)' \left(\phi_i - \underline{\phi_i} \right) \right\} \tag{56}$$

The product of (54), (55) and (56) yields the joint posterior pdf of ϕ_i and σ_u

$$\begin{aligned} p(\phi_i, \sigma_u \mid Z_i, r_i) &\propto p(r_i \mid Z_i, \phi_i, \sigma_u)\, p(\phi_i \mid \sigma_u)\, p(\sigma_u) \\ &\propto \frac{1}{\sigma^{\underline{\nu}+1}} \times \frac{1}{\sigma_u^{k+1}} \times \frac{1}{\sigma_u^{S}} \times \exp\left\{ -\frac{1}{2\sigma_u^2} (r_i - Z_i\phi_i)'(r_i - Z_i\phi_i) \right\} \\ &\quad \times \exp\left\{ -\frac{1}{2} \left(\phi_i - \underline{\phi_i} \right)' \underline{V_\phi}^{-1} \left(\phi_i - \underline{\phi_i} \right) \right\} \times \exp\left\{ -\frac{\underline{\nu}\,\underline{s}^2}{2\sigma_u^2} \right\} \end{aligned} \tag{57}$$

Rewriting $(r_i - Z_i\phi_i)'(r_i - Z_i\phi_i) + \left(\phi_i - \underline{\phi_i} \right)' \underline{V_\phi}^{-1} \left(\phi_i - \underline{\phi_i} \right)$ as

$$r_i' r_i + \underline{\phi_i}' \underline{V_\phi}^{-1} \underline{\phi_i} + \left(\phi_i - \overline{\phi_i} \right)' \left(\underline{V_\phi}^{-1} + Z_i' Z \right) \left(\phi_i - \overline{\phi_i} \right) - \overline{\phi_i}' \left(\underline{V_\phi}^{-1} + Z_i' Z \right) \overline{\phi_i}$$

and rearranging the terms in the exponents gives us

$$p(\phi_i, \sigma_u \mid Z_i, r_i) \propto \frac{1}{\sigma_u^{k+1}} \exp\left\{ -\frac{1}{2\sigma_u^2} \left(\phi_i - \overline{\phi_i} \right)' \overline{V_\phi}^{-1} \left(\phi_i - \overline{\phi_i} \right) \right\} \times \frac{1}{\sigma^{\overline{\nu}+1}} \exp\left\{ -\frac{\overline{\nu}\,\overline{s}^2}{2\sigma_u^2} \right\} \tag{58}$$

where $\overline{V_\phi} = \left(\underline{V_\phi}^{-1} + Z_i' Z_i \right)^{-1}$, $\overline{\phi_i} = \overline{V_\phi} \left(\underline{V_\phi}^{-1} \underline{\phi_i} + Z_i' r_i \right)$, $\overline{\nu} = S + \underline{\nu}$, and $\overline{\nu}\,\overline{s}^2 = \underline{\nu}\,\underline{s}^2 + r_i' r_i + \underline{\phi_i}' \underline{V_\phi}^{-1} \underline{\phi_i} - \overline{\phi_i}' \left(\underline{V_\phi}^{-1} + Z_i' Z_i \right) \overline{\phi_i}$. Conditional on σ_u, the posterior pdf of ϕ_i is multivariate normal and the posterior pdf of σ_u is inverted gamma

$$\phi_i \mid Z_i, r_i, \sigma_u \sim N\left(\overline{\phi_i}\,,\, \sigma_u^2 \overline{V_\phi} \right) \tag{59}$$

$$\sigma_u^2 \sim IG\left(\overline{\nu}\,,\, \overline{s}^2 \right) \tag{60}$$

$$E\left(\sigma_u^2 \mid Z_i, r_i \right) = \frac{\overline{\nu}\,\overline{s}^2}{\overline{\nu} - 2} = \tilde{\sigma}_u^2 \tag{61}$$

In addition, the marginal posterior ϕ_i follows a multivariate *t* distribution with mean and variance given by [24]

$$E\left(\phi_i \mid D\right) = \overline{\phi_i} \tag{62}$$

Under model M_j, the Bayesian estimate of alpha, $E(\alpha_i \mid D, M_j)$, is the (1,1) element of $\overline{\phi_i}$.

$$Var\left(\phi_i \mid D\right) = \frac{\overline{\nu}\,\overline{s}^2}{\overline{\nu}-2}\overline{V_\phi} \tag{63}$$

Appendix B.2 Marginal likelihood and Posterior model probability

The derivation of the posterior distributions leads us nicely to the discussion of the marginal likelihood, $p\left(D \mid M_j\right)$, since it requires certain quantities from the prior and posterior distributions. Given our normal-inverted gamma natural conjugate prior, the marginal likelihood under model M_j has an analytical form[25]

$$p\left(D \mid M_j\right) = c_j\left[\left|\overline{V_{\phi_j}}\right| \Big/ \left|\underline{V_{\phi_j}}\right|\right]^{1/2}\left(\overline{\nu_j}\,\overline{s_j}^2\right)^{-\overline{\nu_j}/2} \tag{64}$$

$$c_j = \frac{\Gamma\left(\overline{\nu_j}/2\right)\left(\underline{\nu_j}\,\underline{s_j^2}\right)^{\underline{\nu_j}/2}}{\Gamma\left(\underline{\nu_j}/2\right)\pi^{S/2}} \tag{65}$$

where $\left|\underline{V_{\phi_j}}\right|$ and $\left|\overline{V_{\phi_j}}\right|$ denote the determinants of $\underline{V_{\phi_j}}$ and $\overline{V_{\phi_j}}$ respectively. The subscript *j* reminds us that the various quantities in (64) and (65) are computed under model *j*. The *j*th model's posterior model probability, $p\left(M_j \mid D\right)$, is computed as (see, e.g., Hoeting, Madigan, Raftery and Volinsky (1999))

$$p\left(M_j \mid D\right) = \frac{p\left(D \mid M_j\right)p\left(M_j\right)}{\sum_{j=1}^{M} p\left(D \mid M_j\right)p\left(M_j\right)} \tag{66}$$

where $p\left(M_j\right)$ is the prior model probability of the *j*th model. For this study, each model receives equal prior model probability, i.e., $p\left(M_j\right) = p\left(M_k\right) \forall j,k \in M$. Thus, model *j*'s posterior probability simplifies to

$$p\left(M_j \mid D\right) = p\left(D \mid M_j\right) \Big/ \sum_{j=1}^{M} p\left(D \mid M_j\right) \tag{67}$$

Note that the denominator in equation (67) need not sum to 1. To the extent that models used by researchers in the past do not capture all the models that can explain the data, the sum of the marginal likelihoods will not be 1. Posterior model probabilities are still well-defined in this

[24] As mentioned earlier, the reader should remember that these moments are with respect to a specific model.

instance. As long as a model's marginal likelihood is highest amongst all other models under consideration, it will receive the highest posterior model probability. Conversely, a model with the lowest marginal likelihood will receive the lowest posterior model probability.

[25] Poirier (1995, p.543).

Table A1: Variables in mutual fund models

This table summarizes the models considered in this paper. A “1” indicates that the model includes the variable while a “0” indicates that the model excludes the variable. MKT is the return on the CRSP value-weighted index of NYSE, AMEX and Nasdaq stocks. SMB is the small-minus-big portfolio. HML is the high-minus-low portfolio. UMD is momentum factor. SP is the S&P 500 index return. OSP is the small stock index which is orthogonal to SP. B1 is the portfolio consisting of 80% intermediate government bonds and 20% long-term corporate bonds. SL is the return differential between small-cap and large-cap stocks. GV is the return differential between growth and value stocks. B2 is a portfolio representing the aggregate bond market. MKT^2 is the squared of MKT. MKTP is max(0, MKT). P is the daily timing measure of Goetzmann et al (2000). IP1, IP2, IP3 are three industry factors. S is the Ibbotson Small Firm Total Return index, GB is the Ibbotson Long-Term Government Bond Return index. LB is a below investment grade bond index. CAP is the return differential between the 10th decile (small firm) CRSP capitalization portfolio and the 1st decile (large firm) capitalization portfolio. BOND is the Ibbotson Long-Term Corporate Bond Index. GC is the Lehman Brothers government/corporate bond index. MBS is the Lehman Brothers mortgage-backed securities index. ITG is the Lehman Brothers intermediate government bond index. LTG is the Lehman Brothers long-term government bond index. ITC is the Lehman Brothers intermediate corporate bond index. LTC is the Lehman Brothers long-term corporate bond index. DEF2 is the return differential between the below investment grade bond index and the Lehman Brothers intermediate government index. OPTION is the return differential between the Lehman Brothers Government National Mortgage Association (GNMA) index and a government bond series with the same duration. GDP is the unexpected change in the real GDP forecast. INF is the unanticipated change in inflation.

Model	Article	MKT	SMB	HML	UMD	SP	OSP	B1	SL	GV	B2	MKT^2	MKTP	P	IP1	IP2	IP3	S	GB	LB	CAP	BOND	GC	MBS	ITG	LTG	ITC	LTC	DEF2	OPTION	GDP	INF
1	Jensen (1986)	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	Fama and French (1993)	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	Carhart (1997)	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	Elton et al (1993)	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	Elton et al (1996a)	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	Treynor and Mazuy (1966)	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	Henriksson and Merton (1981)	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	Goetzmann et al (2000) I	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	Goetzmann et al (2000) II	0	1	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	Jones and Shanken (2005)	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	Ferson and Schadt (1996) I [A]	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	Ferson and Schadt (1996) II [A]	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
13	Ferson and Schadt (1996) III [A]	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	Ferson and Schadt (1996) IV [A]	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	Brown and Goetzmann (1995) I [B]	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	Brown and Goetzmann (1995) II [B]	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	Koski and Pontiff (1999) [C]	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0
18	Blake et al (1993) I	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
19	Blake et al (1993) II	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0
20	Blake et al (1993) III	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0
21	Blake et al (1993) IV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1	0	0	0	0
22	Khorana et al (2001)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0
23	Elton et al (1995) I	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	Elton et al (1995) II	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
25	Elton et al (1995) III	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
26	Elton et al (1995) IV	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1

[A] Conditional model. Conditioning variables are lagged T-bill yield, lagged dividend yield, lagged term spread, lagged default spread and January dummy.

[B] Conditional model. Conditioning variables are lagged natural log of total net assets, lagged expense ratio, and fund age.

[C] Conditional model. Conditioning variables are risk-free return, lagged dividend yield of the CRSP value-weighted index and lagged return differential between the mutual fund the CRSP value-weighted index.

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Table 1: Return predictability of balanced funds sorted by BMA alphas

We investigate the return predictability of balanced funds after accounting for model uncertainty using Bayesian model averaged (BMA) alphas. We sort funds into decile portfolios based on their BMA alphas estimated using past data and then observe fund returns over post-ranking periods ranging from 1 month to 60 months. With the 1-month post-ranking period, at the end of every month, we sort balanced funds into deciles based on their past BMA alphas. Decile 1 contains funds with the lowest BMA alphas and Decile 1 contains funds with the highest BMA alphas. We then compute the equally-weighted monthly BMA alpha of each decile portfolio during the next month. By repeating this process till the end of the sample period, we obtain the time series of monthly BMA alphas for each decile portfolio starting in January 1983 and ending in December 2003. We form the first set of decile portfolios at the end of December 1982 and the last set of decile portfolios at the end of November 2003. We also form the 10-1 portfolio, which is long decile 10 and short decile 1. We employ the same procedure with the 3-, 6-, 12-, 24-, 36-, 48-, and 60-month post-ranking periods, except that we rebalance the decile portfolios every 3, 6, 12, 24, 36, 48, and 60 months respectively. In Panels A and B (C and D), we sort funds into deciles using BMA alphas estimated over the previous 36 (60) months. In Panels A and C, we estimate past BMA alphas assuming a skeptical prior belief in skill (prior standard deviation of alpha is 0.01). In Panels B and D, we use a less skeptical prior belief in skill (prior standard deviation of alpha is 0.03). We report the time series average BMA alphas (in percent per month) for deciles 1 and 10, the 10-1 long-short portfolio and the non-parametric Spearman rank correlation of decile ranking and post-formation average BMA alphas. With the exception of the Spearman correlation, numbers in parentheses are p-values based on Newey and West (1987) heteroskedasticity-and-autocorrelation consistent (HAC) standard errors. We compute HAC covariance matrices using a lag length of 6 months. “Decile 1” refers to the bottom decile with the lowest past BMA alphas, “Decile 10” refers to the top decile with the highest past BMA alphas and “10-1” refers to the portfolio that is long Decile 10 and short Decile 1. Spearman is the non-parametric Spearman rank correlation. *, **, *** denotes statistical significance at the 10%, 5% and 1% level respectively.

Panel A: Skeptical prior belief, 36-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.17***	-0.16***	-0.16***	-0.15***	-0.12***	-0.14***	-0.10**	-0.02
	(0.000)	(0.000)	(0.001)	(0.000)	(0.007)	(0.001)	(0.025)	(0.646)
Decile 10	0.04	0.01	-0.03	-0.02	-0.08	-0.06	-0.06	0.03
	(0.395)	(0.887)	(0.594)	(0.659)	(0.124)	(0.236)	(0.305)	(0.600)
10-1	0.22***	0.17***	0.13**	0.13***	0.04	0.09*	0.04	0.05
	(0.000)	(0.000)	(0.018)	(0.005)	(0.477)	(0.072)	(0.454)	(0.393)
Spearman	0.842***	0.903***	0.915***	0.952***	0.588*	0.564*	0.673**	-0.176
	(0.002)	(0.000)	(0.000)	(0.000)	(0.074)	(0.090)	(0.033)	(0.627)

Panel B: Less skeptical prior belief, 36-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.21***	-0.18***	-0.20***	-0.17***	-0.16***	-0.20***	-0.15***	-0.05
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.003)	(0.329)
Decile 10	0.06	0.03	0.01	0.01	-0.02	0.02	-0.01	0.04
	(0.203)	(0.505)	(0.787)	(0.783)	(0.694)	(0.670)	(0.831)	(0.427)
10-1	0.27***	0.21***	0.21***	0.19***	0.14**	0.22***	0.13**	0.10
	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)	(0.000)	(0.040)	(0.121)
Spearman	0.903***	0.988***	0.988***	0.964***	0.927***	0.418	0.867***	0.261
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.229)	(0.001)	(0.467)

Panel C: Skeptical prior belief, 60-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.27***	-0.26***	-0.20***	-0.18***	-0.20***	-0.13**	-0.20***	-0.10*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.038)	(0.000)	(0.089)
Decile 10	0.09	0.06	0.09	0.12**	0.03	0.04	-0.02	0.09
	(0.150)	(0.307)	(0.170)	(0.047)	(0.582)	(0.510)	(0.716)	(0.147)
10-1	0.36***	0.33***	0.29***	0.29***	0.23***	0.17***	0.18***	0.19***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.001)	(0.005)
Spearman	0.867***	0.915***	0.842***	0.758**	0.624*	0.842***	0.600*	0.527
	(0.001)	(0.000)	(0.002)	(0.011)	(0.054)	(0.002)	(0.067)	(0.117)

Panel D: Less skeptical prior belief, 60-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.29***	-0.30***	-0.24***	-0.22***	-0.21***	-0.15**	-0.20***	-0.18***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.023)	(0.002)	(0.001)
Decile 10	0.13**	0.08	0.11*	0.17***	0.06	0.08	0.00	0.10
	(0.032)	(0.202)	(0.065)	(0.007)	(0.281)	(0.187)	(0.995)	(0.132)
10-1	0.42***	0.38***	0.35***	0.39***	0.27***	0.23***	0.20***	0.27***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spearman	0.879***	0.915***	0.830***	0.576*	0.721**	0.842***	0.661**	0.721**
	(0.001)	(0.000)	(0.003)	(0.082)	(0.019)	(0.002)	(0.038)	(0.019)

Table 2: Return predictability of equity funds sorted by BMA alphas

We investigate the return predictability of equity funds after accounting for model uncertainty using Bayesian model averaged (BMA) alphas. We sort funds into decile portfolios based on their BMA alphas estimated using past data and then observe fund returns over post-ranking periods ranging from 1 month to 60 months. With the 1-month post-ranking period, at the end of every month, we sort equity funds into deciles based on their past BMA alphas. Decile 1 contains funds with the lowest BMA alphas and Decile 10 contains funds with the highest BMA alphas. We then compute the equally-weighted monthly BMA alpha of each decile portfolio during the next month. By repeating this process till the end of the sample period, we obtain the time series of monthly BMA alphas for each decile portfolio starting in January 1983 and ending in December 2003. We form the first set of decile portfolios at the end of December 1982 and the last set of decile portfolios at the end of November 2003. We also form the 10-1 portfolio, which is long decile 10 and short decile 1. We employ the same procedure with the 3-, 6-, 12-, 24-, 36-, 48-, and 60-month post-ranking periods, except that we rebalance the decile portfolios every 3, 6, 12, 24, 36, 48, and 60 months respectively. In Panels A and B (C and D), we sort funds into deciles using BMA alphas estimated over the previous 36 (60) months. In Panels A and C, we estimate past BMA alphas assuming a skeptical prior belief in skill (prior standard deviation of alpha is 0.01). In Panels B and D, we use a less skeptical prior belief in skill (prior standard deviation of alpha is 0.03). We report the time series average BMA alphas (in percent per month) for deciles 1 and 10, the 10-1 long-short portfolio and the non-parametric Spearman rank correlation of decile ranking and post-formation average BMA alphas. With the exception of the Spearman correlation, numbers in parentheses are p-values based on Newey and West (1987) heteroskedasticity-and-autocorrelation consistent (HAC) standard errors. We compute HAC covariance matrices using a lag length of 6 months. "Decile 1" refers to the bottom decile with the lowest past BMA alphas, "Decile 10" refers to the top decile with the highest past BMA alphas and "10-1" refers to the portfolio that is long Decile 10 and short Decile 1. Spearman is the non-parametric Spearman rank correlation. *, **, *** denotes statistical significance at the 10%, 5% and 1% level respectively.

Panel A: Skeptical prior belief, 36-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.37***	-0.38***	-0.37***	-0.33***	-0.33***	-0.29***	-0.31***	-0.35***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decile 10	0.01	-0.03	-0.03	-0.07	-0.09	-0.14*	-0.09	-0.05
	(0.880)	(0.642)	(0.657)	(0.264)	(0.185)	(0.060)	(0.129)	(0.455)
10-1	0.38***	0.35***	0.34***	0.26***	0.24***	0.15*	0.21***	0.29***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.060)	(0.001)	(0.002)
Spearman	0.952***	0.976***	0.952***	0.782***	0.564*	0.176	0.721**	0.915***
	(0.000)	(0.000)	(0.000)	(0.008)	(0.090)	(0.627)	(0.019)	(0.000)

Panel B: Less skeptical prior belief, 36-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.41***	-0.41***	-0.39***	-0.35***	-0.34***	-0.29***	-0.32***	-0.35***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decile 10	0.05	0.02	0.02	-0.04	-0.03	-0.09	-0.05	0.00
	(0.413)	(0.770)	(0.803)	(0.582)	(0.593)	(0.245)	(0.448)	(0.949)
10-1	0.46***	0.42***	0.41***	0.31***	0.30***	0.20**	0.27***	0.36***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.020)	(0.000)	(0.000)
Spearman	0.988***	0.976***	0.927***	0.964***	0.794***	0.382	0.903***	0.988***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.276)	(0.000)	(0.000)

Panel C: Skeptical prior belief, 60-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.37***	-0.35***	-0.34***	-0.31***	-0.33***	-0.34***	-0.34***	-0.42***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decile 10	0.02	0.02	0.00	-0.05	-0.08	-0.02	-0.09	-0.04
	(0.722)	(0.732)	(0.982)	(0.418)	(0.304)	(0.830)	(0.238)	(0.660)
10-1	0.39***	0.38***	0.34***	0.26***	0.25***	0.33***	0.25***	0.39***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.006)	(0.000)
Spearman	0.976***	0.988***	0.939***	0.867***	0.782***	0.855***	0.661**	0.988***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.008)	(0.002)	(0.038)	(0.000)

Panel D: Less skeptical prior belief, 60-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.39***	-0.39***	-0.38***	-0.36***	-0.37***	-0.38***	-0.39***	-0.46***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decile 10	0.06	0.05	0.03	-0.02	-0.05	0.01	-0.06	0.01
	(0.308)	(0.457)	(0.605)	(0.809)	(0.535)	(0.885)	(0.481)	(0.869)
10-1	0.46***	0.44***	0.42***	0.34***	0.33***	0.39***	0.33***	0.48***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spearman	0.988***	0.988***	0.964***	0.988***	0.891***	0.879***	0.855***	0.988***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)

Table 3: Return predictability of bond funds sorted by BMA alphas

We investigate the return predictability of bond funds after accounting for model uncertainty using Bayesian model averaged (BMA) alphas. We sort funds into decile portfolios based on their BMA alphas estimated using past data and then observe fund returns over post-ranking periods ranging from 1 month to 60 months. With the 1-month post-ranking period, at the end of every month, we sort bond funds into deciles based on their past BMA alphas. Decile 1 contains funds with the lowest BMA alphas and Decile 1 contains funds with the highest BMA alphas. We then compute the equally-weighted monthly BMA alpha of each decile portfolio during the next month. By repeating this process till the end of the sample period, we obtain the time series of monthly BMA alphas for each decile portfolio starting in January 1983 and ending in December 2003. We form the first set of decile portfolios at the end of December 1982 and the last set of decile portfolios at the end of November 2003. We also form the 10-1 portfolio, which is long decile 10 and short decile 1. We employ the same procedure with the 3-, 6-, 12-, 24-, 36-, 48-, and 60-month post-ranking periods, except that we rebalance the decile portfolios every 3, 6, 12, 24, 36, 48, and 60 months respectively. In Panels A and B (C and D), we sort funds into deciles using BMA alphas estimated over the previous 36 (60) months. In Panels A and C, we estimate past BMA alphas assuming a skeptical prior belief in skill (prior standard deviation of alpha is 0.01). In Panels B and D, we use a less skeptical prior belief in skill (prior standard deviation of alpha is 0.03). We report the time series average BMA alphas (in percent per month) for deciles 1 and 10, the 10-1 long-short portfolio and the non-parametric Spearman rank correlation of decile ranking and post-formation average BMA alphas. With the exception of the Spearman correlation, numbers in parentheses are p-values based on Newey and West (1987) heteroskedasticity-and-autocorrelation consistent (HAC) standard errors. We compute HAC covariance matrices using a lag length of 6 months. “Decile 1” refers to the bottom decile with the lowest past BMA alphas, “Decile 10” refers to the top decile with the highest past BMA alphas and “10-1” refers to the portfolio that is long Decile 10 and short Decile 1. Spearman is the non-parametric Spearman rank correlation. *, **, *** denotes statistical significance at the 10%, 5% and 1% level respectively.

Panel A: Skeptical prior belief, 36-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.20***	-0.20***	-0.19***	-0.18***	-0.15***	-0.13***	-0.15***	-0.11***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decile 10	0.03	0.02	0.01	0.00	-0.02	-0.04	-0.03	-0.03
	(0.343)	(0.517)	(0.766)	(0.928)	(0.646)	(0.388)	(0.539)	(0.570)
10-1	0.23***	0.22***	0.20***	0.18***	0.13***	0.10***	0.12***	0.08*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.001)	(0.088)
Spearman	0.964***	0.952***	0.770***	0.855***	0.879***	0.576*	0.624*	0.636**
	(0.000)	(0.000)	(0.009)	(0.002)	(0.001)	(0.082)	(0.054)	(0.048)

Panel B: Less skeptical prior belief, 36-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.20***	-0.20***	-0.20***	-0.18***	-0.15***	-0.14***	-0.14***	-0.10***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decile 10	0.06**	0.05	0.04	0.04	0.03	-0.00	0.04	0.00
	(0.047)	(0.114)	(0.167)	(0.147)	(0.437)	(0.905)	(0.283)	(0.920)
10-1	0.26***	0.25***	0.24***	0.23***	0.18***	0.13***	0.18***	0.11***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)
Spearman	0.952***	0.903***	0.879***	0.867***	0.879***	0.758**	0.612*	0.624*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.011)	(0.060)	(0.054)

Panel C: Skeptical prior belief, 60-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.21***	-0.20***	-0.18***	-0.18***	-0.17***	-0.17***	-0.17***	-0.15***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decile 10	-0.00	-0.01	-0.01	-0.02	-0.04	-0.04	-0.02	-0.01
	(0.933)	(0.699)	(0.740)	(0.411)	(0.213)	(0.201)	(0.626)	(0.644)
10-1	0.21***	0.19***	0.17***	0.15***	0.13***	0.13***	0.15***	0.13***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spearman	0.855***	0.903***	0.818***	0.964***	0.855***	0.648**	0.867***	0.830***
	(0.002)	(0.000)	(0.004)	(0.000)	(0.002)	(0.043)	(0.001)	(0.003)

Panel D: Less skeptical prior belief, 60-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.22***	-0.21***	-0.19***	-0.18***	-0.18***	-0.18***	-0.17***	-0.15***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decile 10	0.04*	0.03	0.03	0.02	0.00	0.01	0.01	0.03
	(0.099)	(0.237)	(0.256)	(0.539)	(0.884)	(0.821)	(0.672)	(0.346)
10-1	0.26***	0.24***	0.22***	0.20***	0.18***	0.18***	0.19***	0.18***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spearman	0.818***	0.891***	0.782***	0.976***	0.964***	0.758**	0.915***	0.770***
	(0.004)	(0.001)	(0.008)	(0.000)	(0.000)	(0.011)	(0.000)	(0.009)

Table 4: Flows into balanced funds sorted by BMA alphas

We sort balanced funds into decile portfolios based on their BMA alphas estimated using past data and then observe normalized cash flow over post-ranking periods ranging from 1 month to 60 months. With the 1-month post-ranking period, at the end of every month, we sort balanced funds into deciles based on their past BMA alphas. Decile 1 contains funds with the lowest BMA alphas and Decile 10 contains funds with the highest BMA alphas. We then compute the equally-weighted monthly normalized cash flow of each decile portfolio during the next month. By repeating this process till the end of the sample period, we obtain the time series of monthly normalized cash flow for each decile portfolio starting in January 1983 and ending in December 2003. We form the first set of decile portfolios at the end of December 1982 and the last set of decile portfolios at the end of November 2003. We also form the 10-1 portfolio, which is long decile 10 and short decile 1. We employ the same procedure with the 3-, 6-, 12-, 24-, 36-, 48-, and 60-month post-ranking periods, except that we rebalance the decile portfolios every 3, 6, 12, 24, 36, 48, and 60 months respectively. In Panels A and B (C and D), we sort funds into deciles using BMA alphas estimated over the previous 36 (60) months. In Panels A and C, we estimate past BMA alphas assuming a skeptical prior belief in skill (prior standard deviation of alpha is 0.01). In Panels B and D, we use a less skeptical prior belief in skill (prior standard deviation of alpha is 0.03). We report the time series average normalized cash flow (in percent per month) for deciles 1 and 10, the 10-1 long-short portfolio and the non-parametric Spearman rank correlation of decile ranking and post-formation average normalized cash flow. With the exception of the Spearman correlation, numbers in parentheses are p-values based on Newey and West (1987) heteroskedasticity-and-autocorrelation consistent (HAC) standard errors. We compute HAC covariance matrices using a lag length of 6 months. "Decile 1" refers to the bottom decile with the lowest past BMA alphas, "Decile 10" refers to the top decile with the highest past BMA alphas and "10-1" refers to the portfolio that is long Decile 10 and short Decile 1. Spearman is the non-parametric Spearman rank correlation. *, **, *** denotes statistical significance at the 10%, 5% and 1% level respectively.

Panel A: Skeptical prior belief, 36-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.99***	-1.01***	-1.04***	-0.90***	-0.79***	-0.74***	-0.49***	0.08
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.655)
Decile 10	1.90***	1.91***	1.88***	1.81***	1.41***	1.36***	0.99***	0.69**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)
10-1	2.83***	2.89***	2.88***	2.68***	2.20***	2.10***	1.49***	0.45
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.167)
Spearman	0.988***	1.000***	0.964***	0.988***	0.976***	0.976***	0.939***	0.806***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)

Panel B: Less skeptical prior belief, 36-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.89***	-0.93***	-0.94***	-0.74***	-0.59***	-0.27	-0.19	0.48**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.166)	(0.396)	(0.023)
Decile 10	1.82***	1.82***	1.75***	1.80***	1.50***	1.17***	1.12***	0.69**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.017)
10-1	2.69***	2.71***	2.65***	2.50***	2.09***	1.44***	1.31***	-0.01
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.981)
Spearman	0.976***	0.976***	0.988***	0.976***	0.964***	0.927***	0.964***	0.673**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.033)

Panel C: Skeptical prior belief, 60-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.83***	-0.81***	-0.73***	-0.71***	-0.65***	-0.63***	-0.77***	0.01
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.003)	(0.000)	(0.980)
Decile 10	1.85***	1.86***	1.79***	1.70***	1.11***	0.97***	0.82***	0.53*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.053)
10-1	2.68***	2.67***	2.51***	2.41***	1.76***	1.61***	1.59***	0.52
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.108)
Spearman	1.000***	0.988***	0.952***	0.976***	0.988***	0.988***	0.782***	0.624*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.054)

Panel D: Less skeptical prior belief, 60-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.72***	-0.68***	-0.53***	-0.61***	-0.58***	-0.54**	-0.79***	-0.20
	(0.000)	(0.000)	(0.007)	(0.004)	(0.007)	(0.015)	(0.000)	(0.555)
Decile 10	1.86***	1.87***	1.79***	1.75***	1.03***	0.97***	0.56**	0.45*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.044)	(0.097)
10-1	2.59***	2.55***	2.32***	2.36***	1.60***	1.52***	1.35***	0.65**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.032)
Spearman	0.988***	1.000***	0.964***	0.976***	0.952***	0.927***	0.673**	0.721**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.033)	(0.019)

Table 5: Flows into equity funds sorted by BMA alphas

We sort equity funds into decile portfolios based on their BMA alphas estimated using past data and then observe normalized cash flow over post-ranking periods ranging from 1 month to 60 months. With the 1-month post-ranking period, at the end of every month, we sort equity funds into deciles based on their past BMA alphas. Decile 1 contains funds with the lowest BMA alphas and Decile 10 contains funds with the highest BMA alphas. We then compute the equally-weighted monthly normalized cash flow of each decile portfolio during the next month. By repeating this process till the end of the sample period, we obtain the time series of monthly normalized cash flow for each decile portfolio starting in January 1983 and ending in December 2003. We form the first set of decile portfolios at the end of December 1982 and the last set of decile portfolios at the end of November 2003. We also form the 10-1 portfolio, which is long decile 10 and short decile 1. We employ the same procedure with the 3-, 6-, 12-, 24-, 36-, 48-, and 60-month post-ranking periods, except that we rebalance the decile portfolios every 3, 6, 12, 24, 36, 48, and 60 months respectively. In Panels A and B (C and D), we sort funds into deciles using BMA alphas estimated over the previous 36 (60) months. In Panels A and C, we estimate past BMA alphas assuming a skeptical prior belief in skill (prior standard deviation of alpha is 0.01). In Panels B and D, we use a less skeptical prior belief in skill (prior standard deviation of alpha is 0.03). We report the time series average normalized cash flow (in percent per month) for deciles 1 and 10, the 10-1 long-short portfolio and the non-parametric Spearman rank correlation of decile ranking and post-formation average normalized cash flow. With the exception of the Spearman correlation, numbers in parentheses are p-values based on Newey and West (1987) heteroskedasticity-and-autocorrelation consistent (HAC) standard errors. We compute HAC covariance matrices using a lag length of 6 months. "Decile 1" refers to the bottom decile with the lowest past BMA alphas, "Decile 10" refers to the top decile with the highest past BMA alphas and "10-1" refers to the portfolio that is long Decile 10 and short Decile 1. Spearman is the non-parametric Spearman rank correlation. *, **, *** denotes statistical significance at the 10%, 5% and 1% level respectively.

Panel A: Skeptical prior belief, 36-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-1.14***	-1.07***	-0.94***	-0.73***	-0.48***	-0.36***	-0.31**	-0.11
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)	(0.025)	(0.488)
Decile 10	2.96***	2.86***	2.70***	2.45***	2.06***	1.53***	1.30***	1.11***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
10-1	4.11***	3.93***	3.64***	3.19***	2.53***	1.88***	1.62***	1.21***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spearman	1.000***	1.000***	1.000***	1.000***	1.000***	0.988***	0.988***	0.939***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel B: Less skeptical prior belief, 36-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-1.05***	-0.99***	-0.87***	-0.69***	-0.44***	-0.31**	-0.29**	-0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.025)	(0.036)	(0.980)
Decile 10	2.89***	2.81***	2.64***	2.38***	2.04***	1.50***	1.32***	1.05***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
10-1	3.93***	3.80***	3.51***	3.07***	2.48***	1.81***	1.60***	1.06***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spearman	1.000***	1.000***	1.000***	1.000***	0.976***	1.000***	0.988***	0.927***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel C: Skeptical prior belief, 60-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.89***	-0.91***	-0.84***	-0.68***	-0.53***	-0.39**	-0.46***	-0.30**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.001)	(0.041)
Decile 10	2.33***	2.27***	2.10***	1.92***	1.31***	1.20***	0.85***	0.88***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
10-1	3.22***	3.17***	2.94***	2.60***	1.84***	1.59***	1.31***	1.18***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spearman	1.000***	1.000***	1.000***	1.000***	1.000***	0.964***	0.939***	0.903***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel D: Less skeptical prior belief, 60-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.83***	-0.83***	-0.78***	-0.64***	-0.47***	-0.33**	-0.40***	-0.24*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.023)	(0.003)	(0.099)
Decile 10	2.28***	2.23***	2.08***	1.88***	1.25***	1.19***	0.78***	0.79***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
10-1	3.11***	3.05***	2.85***	2.52***	1.72***	1.52***	1.18***	1.03***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spearman	1.000***	1.000***	1.000***	1.000***	0.988***	0.964***	0.988***	0.927***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 6: Flows into bond funds sorted by BMA alphas

We sort bond funds into decile portfolios based on their BMA alphas estimated using past data and then observe normalized cash flow over post-ranking periods ranging from 1 month to 60 months. With the 1-month post-ranking period, at the end of every month, we sort bond funds into deciles based on their past BMA alphas. Decile 1 contains funds with the lowest BMA alphas and Decile 10 contains funds with the highest BMA alphas. We then compute the equally-weighted monthly normalized cash flow of each decile portfolio during the next month. By repeating this process till the end of the sample period, we obtain the time series of monthly normalized cash flow for each decile portfolio starting in January 1983 and ending in December 2003. We form the first set of decile portfolios at the end of December 1982 and the last set of decile portfolios at the end of November 2003. We also form the 10-1 portfolio, which is long decile 10 and short decile 1. We employ the same procedure with the 3-, 6-, 12-, 24-, 36-, 48-, and 60-month post-ranking periods, except that we rebalance the decile portfolios every 3, 6, 12, 24, 36, 48, and 60 months respectively. In Panels A and B (C and D), we sort funds into deciles using BMA alphas estimated over the previous 36 (60) months. In Panels A and C, we estimate past BMA alphas assuming a skeptical prior belief in skill (prior standard deviation of alpha is 0.01). In Panels B and D, we use a less skeptical prior belief in skill (prior standard deviation of alpha is 0.03). We report the time series average normalized cash flow (in percent per month) for deciles 1 and 10, the 10-1 long-short portfolio and the non-parametric Spearman rank correlation of decile ranking and post-formation average normalized cash flow. With the exception of the Spearman correlation, numbers in parentheses are p-values based on Newey and West (1987) heteroskedasticity-and-autocorrelation consistent (HAC) standard errors. We compute HAC covariance matrices using a lag length of 6 months. "Decile 1" refers to the bottom decile with the lowest past BMA alphas, "Decile 10" refers to the top decile with the highest past BMA alphas and "10-1" refers to the portfolio that is long Decile 10 and short Decile 1. Spearman is the non-parametric Spearman rank correlation. *, **, *** denotes statistical significance at the 10%, 5% and 1% level respectively.

Panel A: Skeptical prior belief, 36-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.05	-0.02	0.04	0.18	0.53	0.66*	0.62	1.02***
	(0.876)	(0.946)	(0.914)	(0.630)	(0.170)	(0.091)	(0.146)	(0.009)
Decile 10	1.81***	1.75***	1.69***	1.64***	1.39***	1.19***	1.39***	0.89***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
10-1	1.86***	1.77***	1.65***	1.46***	0.86**	0.53	0.78*	-0.13
	(0.000)	(0.000)	(0.000)	(0.000)	(0.044)	(0.174)	(0.052)	(0.708)
Spearman	0.976***	0.988***	0.976***	0.927***	0.745**	0.697**	0.564*	0.285
	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.025)	(0.090)	(0.425)

Panel B: Less skeptical prior belief, 36-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.03	-0.02	-0.01	0.19	0.57	0.62	0.62	1.05***
	(0.927)	(0.946)	(0.988)	(0.615)	(0.139)	(0.117)	(0.137)	(0.008)
Decile 10	1.83***	1.76***	1.70***	1.68***	1.39***	1.08***	1.47***	0.80***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
10-1	1.86***	1.79***	1.71***	1.49***	0.83**	0.47	0.84**	-0.25
	(0.000)	(0.000)	(0.000)	(0.000)	(0.044)	(0.232)	(0.035)	(0.466)
Spearman	0.976***	0.976***	0.939***	0.903***	0.758**	0.612*	0.539	0.248
	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.060)	(0.108)	(0.489)

Panel C: Skeptical prior belief, 60-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.04	-0.01	0.06	0.05	0.18	0.16	0.36	0.06
	(0.916)	(0.977)	(0.872)	(0.883)	(0.608)	(0.656)	(0.299)	(0.862)
Decile 10	1.48***	1.48***	1.34***	1.37***	1.40***	1.08***	1.12***	0.99***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
10-1	1.52***	1.49***	1.28***	1.31***	1.21***	0.92***	0.75***	0.92***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Spearman	1.000***	0.988***	0.976***	0.952***	0.745**	0.794***	0.430	0.733**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.006)	(0.214)	(0.016)

Panel D: Less skeptical prior belief, 60-month estimation window

	Post-ranking period							
	1	3	6	12	24	36	48	60
Decile 1	-0.04	-0.02	0.07	0.06	0.19	0.16	0.33	0.08
	(0.923)	(0.967)	(0.840)	(0.862)	(0.594)	(0.653)	(0.343)	(0.829)
Decile 10	1.47***	1.47***	1.33***	1.32***	1.32***	1.00***	1.03***	0.87***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.003)	(0.008)
10-1	1.51***	1.48***	1.26***	1.25***	1.13***	0.85***	0.69***	0.79***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
Spearman	0.988***	0.988***	0.964***	0.891***	0.830***	0.806***	0.564*	0.721**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.005)	(0.090)	(0.019)

Table 7: Multivariate analysis of normalized cash flows

We estimate the impact of past fund performance as measured by BMA alpha on subsequent annual normalized cash flows, after controlling for other factors that influence flows. The sample consists of equity, bond and balanced funds between 1983 and 2003. The number of fund-year observations is 26342. The dependent variable is each fund's annual normalized cash flow. Logltna is the natural log of a fund's total net assets in the previous year. Grpflow is the normalized cash flow for all funds belonging to the same investment objective, Sdret is the standard deviation of monthly returns in the previous year. Totalfee is the total annual fee incurred by a fund investor. Following Sirri and Tufano (1998), we compute total fee as the sum of the expense ratio and one-seventh of the front end load, if any. We measure past performance using BMA alpha estimated over the past 36 months with a skeptical prior belief in skill (prior standard deviation of alpha is 0.01). We use past BMA alphas and the method described in Sirri and Tufano (1998) to construct the performance quintiles, LOWPERF, MIDPERF and HIGHPERF. The table reports regression coefficients and standard errors obtained using the method of Fama and MacBeth (1973). Avg. adjusted R^2 is the average adjusted R^2 from the 21 annual cross-sectional regressions. Standard errors are in parentheses. *, **, *** denote significance at the 10%, 5% and 1% level respectively.

	(1)	(2)
Logltna	-0.058***	-0.058***
	(0.006)	(0.006)
Grpflow	0.724***	0.725***
	(0.130)	(0.129)
Sdret	-0.091	-0.089
	(0.705)	(0.702)
Totalfee	-0.021*	-0.021*
	(0.010)	(0.010)
Bottom quintile (LOWPERF)	0.238	0.248**
	(0.141)	(0.103)
4^{th} quintile	0.310***	
	(0.103)	
3^{rd} quintile	0.394***	
	(0.119)	
2^{nd}-4^{th} quintile (MIDPERF)		0.322***
		(0.035)
2^{nd} quintile	0.226	
	(0.131)	
Top quintile (HIGHPERF)	1.812***	1.751***
	(0.229)	(0.205)
Intercept	0.204***	0.204***
	(0.045)	(0.044)
Avg. adjusted R^2	0.098	0.096
Fund-Year	26342	26342