Alpha and Performance Measurement: The Effect of Investor Heterogeneity

by:

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Abstract

Studies of investment performance routinely use various measures of alpha, yet the literature has not established that a positive (negative) alpha, as traditionally measured, means that an investor would want to buy (sell) a fund. However, under general conditions, when alpha is defined using the client's marginal utility function, a client faced with a positive alpha would want to buy the fund. Thus, performance measurement is inherently investor specific, and investors will disagree about the attractiveness of a given fund. We provide empirical evidence that bounds the effects of investor heterogeneity on performance measures, and study the cross sectional effects of disagreement on investors' flow response to past fund performance. The effects of investor heterogeneity are economically and statistically significant.

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Introduction

Finance researchers have an easy familiarity with alpha, which is supposed to measure the expected abnormal return of an investment. Alpha is so ubiquitous that it has become a generic, like Xerox™ or Google. Studies refer to CAPM alpha, three-factor alpha or four-factor alpha, assuming the reader hardly requires a definition. Investment practitioners routinely discuss their strategies in terms of their quest for alpha. Alpha can be active, conditional or portable. The number of investment firms with alpha in their names is truly staggering.

Despite the apparent familiarity with alpha, the current literature too often fails to think rigorously about how alphas can and should be interpreted. The contributions of this paper are three. First, we offer extensions of existing results that motivate alpha as a guide to investment selection. The conclusion is that in theory we need to define alpha in a client-specific manner in order to justify its interpretation. Second, we provide an analysis of how different client-specific alphas are expected to be from the standard alphas in the literature. We derive and estimate bounds on the extent to which a client may be expected to disagree with a traditional measure of alpha, and find that the effects of heterogeneity can be similar in importance to the choice of the performance benchmark or to the effects of statistical imprecision in traditional alphas. Third, in the cross-section of funds, we find that funds for which there is likely to be more disagreement among heterogeneous investors experience a weaker flow response to performance as measured by traditional alphas.

The next section reviews the issues with traditional alphas that motivate our analysis. Section 3 sets up the problem for client-specific alphas and Section 4 provides the main analytical results. Section 5 discusses our approach to bounding the extent to which clients may disagree about alpha. Section 6 discusses the data and Section 7 presents the empirical evidence. Section 8 concludes.

2. Problems with Traditional Alphas

There are two Fundamental Questions about the use of alphas. The first question is: When faced with a fund that has a positive (negative) alpha, should the investor want to buy (sell) that fund? The second question is: If a manager has superior information, will he or she generate a positive alpha? While the concept of alpha may be traced in some form back to Coles (1933), a substantial literature grappled with these two questions after alpha was developed within the CAPM (Sharpe, 1964) by Jensen (1968, 1972) and others. But this work, with a few exceptions, essentially died out in the late 1980s, leaving these two fundamental questions at best partially resolved. Without clean answers to these fundamental questions, it would seem that a large part of the literature on investment performance lacks a rigorous foundation. This paper provides that foundation.

As to the first question, whether an investor would wish to buy a positive-alpha fund, the literature offers some hopeful examples, but also many counterexamples. The simplest intuition for the attractiveness of a positive alpha is taught with the CAPM, where a combination of a positive-alpha fund, the market portfolio and cash can "beat the market" in a mean variance sense (higher mean return given the variance). Given an arbitrary (inefficient) benchmark, Dybvig and Ross (1985b) show (their Theorem 5), that a positive alpha measured relative to the benchmark implies that buying some of the fund *at the margin*, will result in a higher Sharpe ratio than the benchmark, if the benchmark excess return is positive.

Jobson and Korkie (1982) showed that given an inefficient index, a portfolio with weights proportional to the vector of assets' alphas, premultiplied by an inverse covariance matrix (the optimal orthogonal portfolio), can be combined with the index to generate a mean variance efficient portfolio. However, the weight in the optimal orthogonal portfolio for a positive alpha asset can be negative, and Gibbons Ross and

Shanken (1989) provide empirical examples where it is. So, even if a positive alpha is attractive at the margin to a mean-variance investor, it might not imply buying a positive alpha fund.[1]

The counterexamples to the attractiveness of a positive alpha are many. In some examples performance within the model is neutral but alpha is not zero. Jagannathan and Korajczyk (1986) and Leland (1999) show you can get nonzero CAPM alphas by trading fairly priced options with no special skill. Ferson and Schadt (1996) show you can record negative alphas when performance is neutral if you don't account for public information. Roll (1978), Dybvig and Ross (1985b) and Green (1986) give examples of nearly arbitrary alphas when there is no ability. Goetzmann et al. (2007) show how to produce positive traditional alphas through informationless trading.

These examples do not explicitly consider differential information. It seems natural to think that a portfolio manager may have better information about returns than the client investor. With differential information the problem of alpha becomes richer. The portfolio of a better-informed manager expands the opportunity set of the less-informed client, so the client would generally like to use the managed portfolio in some way. The problem is, the client might wish to short the fund even if it has a positive alpha (Chen and Knez, 1996). In summary, the existing literature suggests that the general answer to the first Fundamental Question is negative. This paper provides conditions under which the "right" alpha, defined in terms of the client's preferences, provides a reliable buy or sell indication.

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[1] In a mean variance setting, the optimal weight need not be of the same sign as the alpha because of the correlation among assets. If only a single fund is allowed, in combination with a fixed inefficient benchmark, then the optimal combination of the two does have a positive weight in the positive-alpha fund. Our results are more general, as they do not assume that the weights on the other assets are held fixed, they do not rely on mean-variance preferences, a single-period model or on many other restrictions that are imposed in the earlier studies.

The mean variance analysis of alpha in the literature typically takes place in a static, single period model under normality. But, returns are not normally distributed and mean-variance preferences are not very realistic. We provide a justification for alpha in a multiperiod setting for general investors, and consider the optimal discrete response of the investor. The cost of this general justification for alpha is that we have to confront investor heterogeneity. The previous literature that struggled to justify alpha, struggled in part because it sought alphas that all investors could agree on. But investors will not in general agree about alphas, so the same fund will look attractive to one investor but not to another. This leads us to the empirical question: How large are the effects of heterogeneity on alpha likely to be? This question motivates our derivation of bounds on the effects of investor heterogeneity and our empirical analysis of the effects.

The closest work that we know of to this is Glosten and Jagannathan (1994) and Chen and Knez (1996). Glosten and Jagannathan (1994) start with the definition of alpha studied here, based on the stochastic discount factor (SDF) implied by the client's marginal rate of substitution. They then assume that clients' SDFs are functions only of some traded benchmark portfolios and a small set of options strategies, and they focus on the resulting consensus or representative agent valuation of informed-manager strategies that may have option-like characteristics. A key focus of their analysis is to approximate the functional form of the expected payoff of the fund, given the benchmark returns. Among other things their approach provides insights about models for measuring market-timing ability. Chen and Knez (1996) characterize general classes of "admissible" and positive admissible performance measures in the presence of information, concluding that performance measurement is "essentially arbitrary." Following Grinblatt and Titman (1989) they focus on the case where the SDF is represented by a minimum variance efficient portfolio conditional on the client's information. They do not provide explicit answers to the two Fundamental Questions posed above.[2] Cochrane and Saa-Requejo (2000) study the bounds on Sharpe ratios (Sharpe, 1992) from several perspectives, and our bounds on heterogeneity rely on maximum Sharpe ratios.

3. A General Model for a Client's Alpha

This section revisits alpha using a natural definition based on the stochastic discount factor (SDF) approach. This approach was proposed in some form as early as Beja (1971), but became common in asset pricing only after the literature that tried to address the Fundamental Questions had waned. The SDF approach offers new insights on the Fundamental Questions about alpha. The insights are general, in that they are based on a multiperiod model and do not require normality. There is no need to rule out timing ability, nor is selectivity information required to be independent of timing information, security-specific or otherwise restricted as in the earlier literature. The agent is allowed to have a general consumption response to the introduction of the managed portfolio. The results are not limited to marginal changes, but consider the optimal discrete responses. Finally, a mean variance efficient benchmark is not required or used.[3]

Agents make consumption and portfolio choices at each date t, to maximize a separable lifetime utility function, represented as the indirect value function:

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[2] The version of alpha studied here is a "positive admissible" measure. Chen and Knez show that there can be funds that have positive alphas under some positive admissible measures and negative alphas under others. This foreshadows the result here that the "right" alpha is client-specific, and there is likely to be disagreement across investors about alpha. They also show that if an alpha is positive, there exists *some* agent with a monotone, concave utility function that would want to buy the fund *at the margin*. Optimal discrete responses, such as derived here, are not addressed.

[3] Ferson (2010) shows that a mean variance efficient benchmark is only appropriate under the CAPM.

$$J(W_t,\text{info}) \equiv \text{Max}_{\{c,x\}}\ u(C) + E\{\ \beta\ J(W_{t+1},s_{t+1})\ |\ \text{info}\}, \quad (1)$$

$$\text{s.t. } W_{t+1} = (W_t\text{-}C)\ x'R_{t+1},\ \ x'\underline{1}=1,$$

where W_t is the wealth at time t, C is the consumption expenditure at time t, R_{t+1} is the N-vector of gross (i.e., one plus the rate of) returns for the N assets, one of which can be risk-free, and $\underline{1}$ is an N-vector of ones. The K-vector of state variables in the model is s_t at time t and the conditioning information at time t, "info," takes one of two forms. The info is Z_t, representing public information that includes the current values of state variables s_t and the current risk-free rate if any, when referring to the client. The info is Ω_t when referring to the better-informed manager, assuming that Z_t is contained in Ω_t. The time subscripts are dropped except when needed to avoid ambiguity.[4]

Assuming that the uninformed agent is at an interior optimum in the N-asset economy, the first order conditions to the problem imply:

$$E(mR\,|\,Z) = \underline{1},\ \ \text{with } m = \beta\ J_w(W_{t+1})/u_c(C_t), \quad (2)$$

where m is the stochastic discount factor and subscripts denote derivatives. The notation $J_w(W)$ suppresses but allows for the dependence of the value function on the state variables and Z_t.

Consider now presenting the client with a new investment opportunity, the managed portfolio with return $R_p = x(\Omega)'R$ where $x(\Omega)$ is the vector of the informed manager's portfolio weights. We assume that portfolio managers don't invent new

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[4] There can be another component of wealth; for example nontraded human capital, and that component can imply hedging demands as in Grinblatt and Titman (1989) without affecting any of the results.

securities, just trade the existing ones using better information. Define alpha for any portfolio R_p as:

$$\alpha_p = E(mR_p | Z) - 1. \tag{3}$$

Clearly, if the manager has no superior information in the sense that Z includes Ω, then α_p is zero by Equation (2). Let the managed portfolio return be $R_p = v_{t+1}/P_t$, where P_t is the price that the manager offers the client at time t and v_{t+1} is the random value one period later. From the definition of alpha we see that $(1+\alpha_p)P_t = E\{v_{t+1}m | Z\}$, so that if alpha is zero the client would find the offer price "fair," relative to the previous equilibrium. A positive alpha suggests a "low" price for the value. It is shown below that this intuition holds when the client's consumption and investments in all assets can change by discrete amounts in response to the introduction of the managed portfolio.[5]

4. Addressing the Fundamental Questions

4.1 Resolving the First Fundamental Question

How will the client behave when confronted with the new investment opportunity? When faced with a new investment opportunity R_p with a nonzero alpha, the client will generally adjust to new optimal consumption and portfolio choices, until the alpha is zero at the new optimum.[6] Consider a situation where we allow the client to

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[5] It is assumed, as is common in the literature starting with Mayers and Rice (1979), that the manager's trading based on superior information does not affect the market prices of the underlying assets.

[6] This is a partial normative, not a general equilibrium analysis. Berk and Green (2004) make an argument where equilibrium adjustment comes from flows of new cash across funds and diseconomies of scale in fund management, which drive informed manager's alphas to zero in equilibrium. Here, the client adjusts to a new optimal portfolio and consumption choice.

adjust current consumption and to buy or sell some amount of the manager's fund. The client feels the effects of these decisions in his future wealth, and thus the marginal utilities of current consumption and future wealth change. We assume that the client is a price-taker, so there is no effect on the market prices of assets or consumption goods. Let Δ be a reduction in current consumption used to buy the fund, leading to the random wealth at time t+1, $W(\Delta) = W_{t+1} + \Delta R_p + (W_t\text{-}C)[x(\Delta)\text{-}x]'R$, where $x(\Delta)$ is the new optimal portfolio weight vector for the N base assets, normalized to sum to 1.0, and x is the old optimal weight vector.[7] The appendix proves:

Proposition 1:

Under the assumptions described above, and also assuming regular utility functions to which the mean value theorem applies and assuming further that the response of the optimal portfolio weights on the original N assets guarantees that $[R_{pt+1} + (W_t\text{-}C_t)\,(\partial x(\Delta)/\partial\Delta)'R]\,[R_{pt+1} + (W_t\text{-}C_t)\,(x(\Delta)\text{-}x)/\Delta)'R] > 0$, Then the agent when confronted with a new investment with an alpha equal to α_p, will optimally purchase or sell the discrete amount Δ given by: $\Delta = \alpha_p \{u_c\,/(-u_{cc}^* - Q)\}$,

Where $Q = E\{\beta\, J_{ww}^*\, [R_{pt+1} + (W_t\text{-}C_t)\,(\partial x(\Delta)/\partial\Delta)'R]\,[R_{pt+1} + (W_t\text{-}C_t)\,(x(\Delta)\text{-}x)/\Delta)'R]\}<0$ and $u_{cc}^*<0$.

Proof: See the Appendix.

The sign of the optimal investment in the new fund is the same as the sign of

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[7] The client divides the beginning of period wealth W_t as follows: Δ is invested in the new fund, C-Δ is consumed and $(W_t\text{-}C)$ is invested in the old assets. At Δ=0, $W(\Delta) = W_{t+1} = (W_t\text{-}C)x'R$, and $x(\Delta)$=x. The analysis can accommodate the case where the investor does not change the current consumption, but only the portfolio weights in response to the new investment. In this case the weights $x(\Delta)$ do not sum to 1.0 and $\Delta = W_t(1\text{-}x(\Delta)'\underline{1})$.

alpha, so the investor buys (sells) a discrete amount of the fund if alpha is positive (negative). The optimal investment is zero only when alpha is zero. The optimal investment is proportional to alpha and scaled by a term which is related to "risk tolerance."

The assumption that $[R_{pt+1}+(W_t-C_t)(\partial x(\Delta)/\partial\Delta)'R][R_{pt+1}+(W_t-C_t)(x(\Delta)-x)/\Delta)'R]>0$ says that the derivatives of the optimal portfolio weights on the N base assets are adequately approximated by the discrete changes divided by the optimal Δ. This holds in the limit for small Δ. For discrete Δ there are special cases where the restriction is guaranteed to hold, such as when $x(\Delta)$ is well-approximated by a linear function of Δ or when the relative allocation to the original assets does not change very much.

It is interesting to note that while Proposition 1 relies on the definition of alpha, it does not assume that the alpha is optimally generated from the portfolio weights of an informed manager. This is important in view of the examples cited above using other definitions of alpha. The definition of alpha here precludes some of these pathologies. For example, trading within the return measurement interval, which Goetzmann et al. (2007) illustrate with several examples, can generate spurious performance with many traditional measures but does not necessarily bias the SDF alpha studied here.[8] Of course, this does not rule out statistical biases in measuring alpha. For example, return smoothing can make it difficult to estimate the true alpha because the returns of the fund are not accurately measured (e.g. Asness et al. (2000), Getmansky, Lo and Makarov, 2004).

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[8] The issue of bias because funds trade within the return measurement period, or interim trading, is raised by Goetzmann, Ingersoll and Ivkovic (2000) and Ferson and Khang (2002), and examined in detail by Goetzmann et al. (2007). However, Ferson, Henry and Kisgen (2006) show that if the right time-aggregated SDF is used, this problem is avoided. The definition of alpha here involves the right, time-aggregated SDF on the (perhaps heroic) assumption that investors optimize as often as managers trade.

4.2 The Second Fundamental Question

The second Fundamental Question is whether a manager with superior information will produce a positive alpha. The Appendix surveys the classical literature on this question, which concludes that the answer will not generally be "yes." The fact that Proposition 1 does not rely on alpha being generated optimally by an informed manager would seem to obviate the need to resolve the second Fundamental Question. All the client needs to know is that if her SDF alpha is positive, she should buy. Nevertheless, the model speaks to the second question, at least in special cases. For example, it follows from the definition of α_p and the client's first order condition that if R_u is any "passive" portfolio that is feasible to the client, then $\alpha_p = E[m(R_p-R_u)|Z]$. Since $m>0$ it follows that $\alpha_p>0$ if the manager's return first order stochastically dominates R_u (Chen and Knez, 1996). Indeed, any client should buy a fund that first order stochastically dominates his other investment options.

Since the uninformed portfolio is feasible for but not chosen by the informed manager, we must have for the same initial wealth, W_0 and consumption C_0, that $E[J(W^I)|\Omega] > E[J(W^u)|\Omega]$, where W^I is the future wealth of the informed manager and W^u is the future wealth without the superior information. These are related as $W^I = W^u + [W_0-C_0][x(\Omega)-x(Z)]'R$. By the mean value theorem, $J(W^I) = J(W^u) + J_w^{\#} [W_0-C_0][R_p - R_u]$, where $J_w^{\#} = J_w(aW^I + (1-a)W^u)$ for some a ε [0,1]. Substituting implies $E\{\beta J_w^{\#} [R_p - R_u]|\Omega\} = E\{\beta J_w(aW^I + (1-a)W^u) [R_p - R_u]|\Omega\} > 0$. If $a=0$ so there is no wealth effect associated with having the superior information Ω, then by the client's first order condition we have $\alpha_p > 0$. But this is not a very realistic case, as informed portfolio managers are often highly compensated for their work. A more interesting special case is:

Proposition II:

Under the assumptions of Proposition I, if the indirect value function J(.) is quadratic in wealth, an informed manager produces a positive alpha.

Proof: (See the Appendix)

Proposition II generalizes results of Mayers and Rice (1979) and Grinblatt and Titman (1989) to a multiperiod model. A quadratic J(.) function would occur in a continuous-time diffusion setting or under conditional normality of the returns given Ω. This does not require that returns appear normal from the client's perspective, which is important because x(Ω)'R will not be normal from the client's perspective even if returns are normal (Dybvig and Ross, 1985).

Proposition II also generalizes results from Ferson and Siegel (2001) to a multiperiod setting. Hansen and Richard (1987) show that a portfolio that is efficient given Ω may not be efficient given Z (conditionally efficient does not imply unconditionally efficient). However, Ferson and Siegel (2001) show that a quadratic utility agent with Ω will choose a portfolio that is also efficient given Z. Here, the agent with a quadratic indirect utility will choose a portfolio that the client using Z will also find attractive.

5. Assessing Investor Heterogeneity

We work with excess returns, $r \equiv R - R_f$, where R_f is a gross short term Treasury return. Thus, Equation (2) implies that $E(mr|Z)=0$ and equation (3) implies that $\alpha_p = E(mr_p|Z)$.[9] Consider a regression over time of r_p on the "passive" assets $\{r_j\}_j$ in r:

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[9] In theory we should be using real returns. In empirical practice, excess nominal returns are a good approximation to excess real returns for equity funds.

$$r_p = a_p + \Sigma_j \beta_j r_j + \varepsilon_p. \tag{5}$$

This is a simple, unconditional regression with constant coefficients and $E(\varepsilon_p)=E(\varepsilon_p r_j)=0$. Taking the unconditional expectation of the expression for alpha and substituting in Equation (5) we obtain:

$$E(\alpha_p) = E(m)a_p + \Sigma_j \beta_j E(mr_j) + E(m\varepsilon_p), \tag{6}$$

For all passive r_j, where the first term on the right captures the traditional, unconditional alpha that would be obtained if $\{r_j\}_j$ were used as the benchmark returns in a factor model.[10] Since $E(mr_j|Z)=0$ for the passive assets, the second term in Equation (6) is zero. Expanding the expectation of the product, mr_j, into the product of the expectations plus the covariance, we obtain:

$$\sigma(m)/E(m) = (-1/\rho_{mrj})[E(r_j)/\sigma(r_j)], \tag{7}$$

where ρ_{mrj} is the correlation between m and r_j and $\sigma(.)$ denotes the standard deviation.

The third term of Equation (6) can be expressed as $E(m\varepsilon_p) = Cov(m,\varepsilon_p) = \rho_{\epsilon m}\,\sigma(m)\,\sigma(\varepsilon_p)$, where $\rho_{\epsilon m}$ is the correlation between m and ε_p. If the correlation is zero, the traditional alpha and the expected SDF alpha for the client coincide. Investor heterogeneity about alpha arises when ε_p is correlated with the investor's marginal rate of substitution.

It is important to note that we have taken the unconditional expectation of the

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[10] Using the SDF approach, α_p is measured at the beginning of the period, like an asset price. Using the traditional regressions of returns on factors, alpha is measured at the end of the period, like a return. The term E(m) translates between the two dates.

client's conditional expectation to arrive at these results, stated in terms of the expected alpha. Clients have different beliefs when they hold different Zs, and their different consumptions and portfolio choices lead to different marginal rates of substitution. As long as we can apply iterated expectations, the implications of investor heterogeneity that we examine can be represented using the unconditional expectations. [11] In this sense, our measures of the effects of heterogeneity are conservative. Differential beliefs across investors is another potential direct source of disagreement about alpha.

Equation (6) implies:

$$\begin{aligned} |E(\alpha_p)/E(m) - a_p| &= |\rho_{\epsilon m}\, \sigma(\varepsilon_p)\, [\sigma(m)/E(m)]\,| \\ &= |\rho_{\epsilon m}\, \sigma(\varepsilon_p)\, (-1/\rho_{mrj})[E(r_j)/\sigma(r_j)]|, \end{aligned} \tag{8}$$

Where the second line uses (7). The term $(-1/\rho_{mrj})[E(r_j)/\sigma(r_j)$ is positive and the same for all passive assets, so it may be replaced with $\{(-1/\rho_{mrj^*})[E(r_j^*)/\sigma(r_j^*)\}$, where r_j^* is the portfolio of passive assets that achieves the maximum Sharpe ratio, SR_{max}. With this substitution and assuming $SR_{max}>0$, we have:

$$\begin{aligned} |E(\alpha_p)/E(m) - a_p| &= |(-\rho_{\epsilon m} / \rho_{mrj^*})\, \sigma(\varepsilon_p)\ SR_{max}| \\ &= |(-\rho_{\epsilon m} / \rho_{mrj^*})|\ \sigma(\varepsilon_p)\ SR_{max} \\ &\leq \sigma(\varepsilon_p)\ SR_{max}, \end{aligned} \tag{9}$$

[11] Taking the conditional expectation of the definition of alpha delivers the expected alpha. The investor's information set is still reflected in the expected alpha to the extent that different information sets lead clients to different consumption and portfolio policies, and thus different marginal rates of substitution. The analysis also applies to conditional moments given public information known by all clients, in which case E(.), ρ and the σ's refer to these conditional moments. We will consider this case below.

where the assumption moving between the second and third lines is that $|\rho_{\epsilon m} / \rho_{mrj^*}| \leq 1$. Since the return r_j^* maximizes the Sharpe ratio, it maximizes the correlation to m, and this assumption should be innocuous.

We also have a lower bound on the effects of investor heterogeneity. From the second line of Equation (9), and using $|\rho_{mrj^*}| \leq 1$, we have:

$$|E(\alpha_p)/E(m) - a_p| \geq |\rho_{\epsilon m}| \, \sigma(\varepsilon_p) \, SR_{max.} \tag{10}$$

Equations (9) and (10) bound the effects of investor heterogeneity on alpha. The left hand side of these expressions is the difference between the expected SDF alpha for the client and a traditional measure of alpha using the passive returns as factors. The right hand side of Equation (9) expresses the upper bound in terms of variables that we can estimate using data. The lower bound in (10) also depends on the unobserved correlation, $\rho_{\epsilon m}$. A fund with a low $\sigma(\varepsilon_p)$ is a fund whose return variation is largely captured by the passive benchmark assets. For such a fund there can be little disagreement over its performance. A fund with $\rho_{\epsilon m}$=0 is a fund whose correlation with the client's marginal utility is completely captured by the passive benchmark assets. For such a fund the traditional measures capture the correct expected alpha. Equation (10) may be a conservative lower bound if $|\rho_{mrj^*}|$ is far below 1.0. Investors whose marginal utility fluctuations are not captured well by the passive asset returns will disagree more with the traditional alphas.

Our estimates of the bounds on heterogeneity rely on several assumptions. Some of these are clearly innocuous but others are not, and the failure of these assumptions may affect the results. We assume that the alphas are zero, from the client's perspective, on the passive benchmark assets r_j. It seems plausible that the investor would be at an interior optimum relative to his allocation to a broad market index, and thus the alpha of the market index would be zero. While active funds may have alphas, it seems plausible to assume that index funds and exchange traded funds (ETFs) have zero, or nearly zero, alphas. We therefore examine index funds and ETFs as examples of the passive benchmark assets. The assumption of zero alphas is less likely to hold for benchmarks like the Fama and French (1993) factors, given the highly tilted small and value stock positions they embed and the extreme short positions they imply. If the benchmark assets have nonzero alphas from the client's perspective then the second term of Equation (6) is not zero and our bounds should include a weighted average of these unobservable alphas. The weights are the active fund's betas on the benchmark assets. The weighted average of the alphas of the benchmarks may be close to zero. However, our results should be interpreted with caution in view of this issue.

Our analysis ignores the issues of trading costs and taxes, which can be important. The incidence of these transactions costs differ across investors, and thus are likely to contribute to investor heterogeneity. Active mutual fund returns are reported net of expense ratios and trading costs, but without regard to the client's tax costs. Passive benchmarks, on the other hand, do not reflect even their trading costs, which can be substantial (see Carino et al., 2009). A cleaner comparison would be to measure the benchmark returns after costs. Short of this ideal, we use index funds and ETFs as benchmark assets, motivated in part by their relatively low trading costs.

The maximum Sharpe ratios in Equations (9) and (10) should in theory reflect the maximum taken over all of the assets in the client's portfolio for which she is at an interior optimum. In empirical practice we can only use small subsets of the possible assets. We therefore consider several alternative groups of assets as the passive benchmark assets, in order to assess the sensitivity of the results to this choice. Since the maximum Sharpe ratio in the universe of many assets is likely to be larger than on the subsets we examine, our upper bounds on the effects of heterogeneity are conservative from this perspective.

We have explicitly conditioned out heterogeneity in investor's beliefs in our bounds. There are two ways to interpret the bounds in view of this important issue. If we assume that investors beliefs are characterized by mathematical conditional expectations and that each investor knows at least as much as our lagged conditioning variables, then we can condition each investor's Euler equation down using the law of iterated expectations and there is no problem. However, if some investors know less than our four lagged instruments or form expectations in other ways, that operation may become invalid.

6. The Data

6.1. The Fund Returns

We study monthly returns on actively managed equity mutual funds from January 1984 to December 2008. Monthly mutual fund returns are from the CRSP mutual fund database. We remove funds with less than 5 million dollars of assets under management at the end of the previous year and funds with less than twelve monthly returns. Funds that invest more than 70% in bonds plus cash at the end of previous year are also screened out.

The literature has documented a number of potential biases in the CRSP mutual fund data base. Fama and French (2010) point out a selection bias due to missing returns from about 15% of the funds on CRSP before 1984. Evans (2007) documents that incubated mutual funds overstate average performance due to backfilling. Backfilling refers to a situation where a fund's past returns are added to the database when the fund enters the database. The incubation process selects only those funds whose returns during the incubation period were high, leaving out those whose returns were low. Incubation and backfilling can bias alpha upwards. We remove fund returns before the date of fund organization and also the first year of a fund's returns. These screens leave us with a sample of 333 active equity funds in the first year, 1984, growing to 7077 funds in the final year, 2008.

6.2. Benchmark Returns

Roll (1978) and Lehmann and Modest (1987), among others, find that performance measurement is sensitive to the choice of benchmarks. Ferson and Schadt (1996) emphasize the importance of incorporating public information and time variation in fund evaluation. In our study, six alternative sets of benchmark returns are used to represent the passive assets available to investors. We choose a range in the type and number of benchmarks to help assess the sensitivity of the results to the issue of benchmark choice. Since our bounds are relative to a traditional alpha based on a given set of benchmark returns, we include performance benchmarks that have been common in the literature. Our benchmarks are: (1) a broad stock market portfolio, (2) the three Fama and French (1993) factors, (3) a set of six index mutual funds, and (4) a set of eight exchange traded funds (ETFs). We also include the equal-weighted portfolios of the index funds and of the ETFs as the final two benchmarks.

The proxy for the market portfolio is the CRSP value-weighted index of NYSE stocks. The Fama and French factors are the market excess return, SMB, and HML. SMB and HML measure the excess returns of small caps over big caps and of value stocks over growth stocks, respectively. These data are from Ken French's website[12]. Index mutual funds are selected from the CRSP database by matching fund names with the string "index". We merge index funds from CRSP with their benchmarks from Morningstar, and apply the same screens to the matched index funds as to the sample of active equity funds. This leaves us with a sample of 3 index funds in 1984, growing to 306 in 2008. To use the index funds as the passive assets we form six equally-weighted portfolios based on their stated benchmarks as reported by Morningstar. The Categories are: S&P500, S&P Midcap, Small cap, Russell, MSCI and Others.

Exchange traded funds (ETFs) now cover a wide range array of asset classes and strategies. We select the following eight ETFs based on their high trading volume and market sector coverage: SPY (large cap), MDY (mid cap), IJR (small cap), EWJ (Japan), EFA (MSCI ex-US), XLE (Energy), QQQQ (Technology), and IYR (mortgage and real estate).

Table 1 presents summary statistics for the monthly returns of the active equity funds, benchmark factors, index funds and ETFs. Equally-weighted averages of the index funds and ETF returns are included as the bottom rows. The summary statistics include the mean returns, standard deviations, minimum and maximum values, first order autocorrelations and sample Sharpe ratios. The index funds have mean returns around one half percent per month and standard deviations just under five percent. The monthly Sharpe ratios vary between 7.8% and 12.6%. The ETFs display more

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[12] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

heterogeneity, with means between -0.38% and +0.68%, standard deviations between 4.1% and 8.8% and Sharpe ratios between -6.4% and +10.6%. The Sharpe ratio of the equally-weighted portfolio of index funds is 10.9% and for the ETFs it is 8.6% per month. The autocorrelations are small, with all below 15%, the MSCI non US ETF being an exception at 35.8%.

The statistics for the active mutual fund returns summarize the cross-section by sorting the individual funds and reporting the values at various fractiles of the cross-sectional distribution. Each column is sorted separately on the statistic shown. In the presence of estimation error such sorting overstates the extremes, but there is clearly a lot of heterogeneity across the active funds. While the mean fund with at least 12 monthly observations lost about 0.17% per month over our sample period, ten percent of the funds returned 0.66% or more per month. The mean standard deviation was 5.32%, but 10 percent of the funds had standard deviations below 3.25% and ten percent were above 7.74%.

The last panel of Table 1 shows that requiring four years of data, as we must for some of our analysis, has a large impact on the left tail of the mean returns. At the ten percent tail the mean return values are -0.39% in the longer-surviving subset, versus -1.35% in the broader sample. The surviving funds in the left tail do much better. The effects on the standard deviations and in the right tail of average returns are much smaller. Nevertheless, this selection effect should be kept in mind when interpreting some of the results below. In particular, our bounds will use funds' (residual) standard deviations. Survivor selection seems to slightly inflate the 10% left tail (3.38% versus

3.25%) and reduce the right tail (7.42% versus 7.74%) of the standard deviations. The comparison on survivor selection using 12 versus 48 months is only suggestive, because we can't measure the standard deviations without some survivor selection. But it suggests that our upper bounds in investor heterogeneity will be conservative for the high-volatility funds, in view of survivor selection.

6.3. The Public Information Variables

Numerous studies suggest public information variables that have predictive power for asset returns and risks. We use a Treasury bill yield, default spread, term spread and a dividend yield as the lagged predictor variables.[13] We use these variables to estimate conditional versions of the bounds on heterogeneity as described below.

We use the one-month annualized Treasury bill yield from CRSP as a predictor. The excess returns are measured net of the one month return on a three-month Treasury bill, to avoid having the same variable on the right and left-hand sides of the predictive regressions. The default spread is the yield difference between Moody's Baa-rated and Aaa-rated corporate bonds. The term spread is the yield difference between a constant maturity 10-year Treasury bond and the 3-month Treasury bill. The dividend yield is the sum of dividends paid on the S&P500 index over the past 12 months divided by the current level of the index. The data for these predictors is collected from DRI Basic Economics.

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[13] See Campbell (1987), Campbell and Shiller (1988a, 1988b), Fama and French (1989) Cochrane (1991), Fama and Schwert (1977) and Ferson and Harvey (1991) for more information about the

7. Empirical Results

We first present some results about traditional estimates of alpha that we use to inform our interpretation of the bounds. The bounds are then presented, first using unconditional moments, and we then consider a number of conditional models.

7.1 *Traditional Alphas*

Table 2 summarizes estimates of traditional alphas using the various benchmarks. In panel A the alphas are the intercepts in excess return regressions on the benchmark excess returns. The benchmarks are the market portfolio proxy (Mkt), the three Fama-French factors (FF3), the vector of six index mutual funds (Idx MFs) or eight ETFs, or a single equally-weighted portfolio of index funds (EW Idx MFs) or of the exchange traded funds (EW ETFs). The cross-section is summarized as in Table 1 by sorting on each statistic and presenting the values at various fractiles. The statistics include the traditional alpha, its standard error and the residual standard deviations of the regressions.

The residual standard deviation is used below in our estimates of the bounds. The mean residual volatility varies from 1.5% using the vector of eight ETFs to 2.7% using their equally weighted portfolio. Compared to the mean volatility of the total returns in Table 1 of just under over 5%, there is a substantial fraction of the average fund's return volatility that is not captured by the traditional factors. This is the risk that investors may disagree about in their evaluation of the mutual funds. There is substantial variation in the estimated $\sigma(\epsilon_p)$ across funds, suggesting variation in the extent of investor disagreement across funds. The interquartile range under the CAPM is 1.4% to 3.1% per

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lagged predictor variables.

month. The FF3 factors narrow the range somewhat, producing an interquartile range of 1.1% to 2.5% per month. The multifactor ETF benchmarks produce the smallest residual standard errors, with an interquartile range of 0.7% to 1.6% per month.

There is also heterogeneity across the mutual funds in their traditional alpha estimates. The average standard error of the alphas varies across the models between 0.21% and 0.33% in Panel A. At the same time the point estimates at the upper and lower 10% tails are -0.55% and 0.48% for the CAPM, a range of about three to four standard errors.

Panel B of Table 2 summarizes estimates of conditional alphas, following Ferson and Schadt (1996). Their model includes the lagged public information variables, Z, in the regression as the products of Z and the benchmark excess returns. This allows for conditional betas that may vary over time as linear functions of Z. The intercepts are the conditional alphas. Because of the additional variables we restrict to the subset of funds with at least 48 months of data, as summarized in Table 1. With the additional variables in the regressions, the standard errors of the residuals are slightly smaller and the variation across models is slightly smaller. For example, in the conditional CAPM the left tail of the residual volatility distribution is similar to that in the unconditional CAPM, reflecting the offsetting effects of selection bias, which was seen in Table 1 to increase the left tail values, and the additional regressors, which reduce the values. In the right tail both effects work in the same direction and the volatilities are reduced. Across funds, the variation in the point estimates of the conditional alphas is slightly smaller than under the unconditional CAPM. The range for the 10% tails is -0.41% to +0.43%, still more than about three standard errors.

The residual volatilities are smaller in the conditional models. The smaller the residual volatility, the smaller is the investor disagreement other things equal. The extreme example with the smallest residual volatilities in Table 2 is the 8 ETF benchmark. Still, the median residual volatility in this case is 0.71% per month and 80% of the funds' residual volatilities are between 0.31% and 1.43% per month.

In the unconditional FF3 model, a common model for alpha in the current literature, the median residual volatility is 1.7% per month. A conservative estimate for the monthly maximum Sharpe ratio is 10%, so a conservative upper bound on the effects of investor heterogeneity on alpha is about 0.17% per month, or 2% per year for the median fund. The median standard error of the FF3 alpha is 0.2% or about 2.5% per year. This suggests that the effects of heterogeneity can be similar in magnitude to about one standard error of estimation uncertainty.

Panel C of Table 2 provides another point of comparison. It shows the range of traditional alpha estimates across the six models. For each fund, the range is the difference between the largest and the smallest alpha estimate across the six models, and the distribution of the range is summarized across the funds. The median range of the unconditional alphas across the six models is 0.43% per month, or about 5.2% per year. This suggests that the impact of investor heterogeneity on alpha could be comparable in magnitude to the choice of benchmark model. The next section takes these comparisons up more in more detail.

7.2 Bounds on the Effects of Investor Heterogeneity using Unconditional Models

Table 3 summarizes estimates of the upper bound on investor disagreement about alphas given in Equation (9) using "unconditional" models. The bounds are computed by running regressions of the excess fund returns on the benchmark excess returns and capturing the regression residual, ε_p. The upper bounds are calculated as the product $\sigma(\varepsilon_p)$ $SR_{max,}$ where $\sigma(\varepsilon_p)$ is the unconditional standard deviation of ε_p and SR_{max} is the square root of the maximum squared unconditional Sharpe ratio in the benchmark assets. It is well known that estimates of maximum Sharpe ratios are upwardly biased in finite samples (e.g. Jobson and Korkie, 1982). We adjust the maximum Sharpe ratio estimates for finite sample bias following Ferson and Siegel (2003).[14]

Table 3 shows that the mean upper bound varies from 0.23% to 0.43% per month across the benchmark models, or about 3% to 5% per year. The upper 10% tail ranges from 0.39% to 0.70% per month, and the lower 10% tail ranges from 0.09% to 0.14% per month across the models. To evaluate the potential economic significance of these values, we compare the upper bounds with the ambiguity in traditional alphas associated with the choice of benchmark, as summarized in Table 2. A representative example is the FF3 benchmark. Here the median upper bound is 0.31% per month. In comparison, for the median fund, the range of alphas across the six benchmarks is 0.43% per month. The effects of investor disagreement could potentially be comparable in magnitude to the issue of benchmark choice.

Another way to assess the importance of investor heterogeneity is in comparison with the ambiguity in the traditional alphas associated with estimation error. Consider the CAPM for example. For the median fund the standard error of the CAPM alpha is Table 2 is 0.25%. In Table 3 the median upper bound in the CAPM is 0.22% per month. Thus, investors may disagree on the performance of the median fund, as measured by CAPM, by an amount similar to the standard error of the traditional alpha.

7.3 Conditional Models

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[14] The adjustment for finite sample bias is $SR^2_{adjusted} = [(T-N-2)/T]\ SR^2 - N/T$, where N is the number of benchmark assets, T is the length of the time series and SR^2 is the maximum likelihood estimate of the maximum squared Sharpe ratio under normality. We do not apply the correction when N=1.

Our assessment of the potential impact of heterogeneity in Table 3 may be affected by the use of unconditional moments. On the one hand, the conditional residual volatility of a fund is likely to be smaller than the unconditional volatility. On the other hand the conditional maximum Sharpe ratio is likely to be higher than the unconditional one, so the net effect of conditioning is not a priori clear. This section presents results using several conditional models to assess the sensitivity of the upper bounds to this issue.

Table 4 presents results for models that assume that the funds and the benchmark assets have fixed conditional second moments and first moments that are time-varying as linear functions of the lagged public information, Z. Under these assumptions the unconditional variance of the residual for a fund return in a regression on the benchmark returns and the lagged Z is the expected value of the conditional residual variance given Z. The conditional Sharpe ratio is time varying. The expected value of the upper bound on heterogeneity is therefore the fixed $\sigma(\varepsilon_p)$ multiplied by the expected Sharpe ratio, which we estimate using the sample mean of the time-varying ratio. We find that the upper bounds on the effects of investor heterogeneity appear larger in the conditional models, indicating that the larger maximum Sharpe ratio dominates the smaller residual variance. For example, in the FF3 factor benchmark, the median estimate of the bound is 0.61%, compared with the 0.31% we found in Table 3. At the same time the median range of the alpha estimates across the benchmarks is similar, as shown in Table 2, so the importance of heterogeneity relative to benchmark choice is almost twice as large as before. The effects of heterogeneity now exceed the range of alphas across the benchmark models at each fractile of the distribution across funds.

Comparing these results with the standard errors of the traditional alphas for the conditional models in Table 2, we find that the effects of investor heterogeneity seem larger relative to the effects of statistical imprecision in the conditional models than in the unconditional models. For example, in the conditional CAPM the heterogeneity effect is a little less than two standard errors of alpha, and in the FF3 factors it is more than three standard errors. The heterogeneity effect generally appears even more important relative to statistical precision in the other multifactor benchmarks.

In Table 4 we assume that $\sigma(\varepsilon_p)$ is fixed over time and the Sharpe ratio $SR_{max}(Z)$ is a time-varying function of Z. The expected upper bound is computed as $(1/T)\Sigma_t \{\sigma(\varepsilon_p)\, SR_{max}(Z_t)\}$. If the fund residual is conditionally heteroskedastic, then its volatility, $\sigma(\varepsilon_p | Z)$, varies over time with Z and the expected bound is $E\{\sigma(\varepsilon_p | Z_t)\, SR_{max}(Z_t)\}$, allowing for a covariance between the two terms. We pursue this calculation in Table 5. Funds are assumed to have linear conditional betas, following Ferson and Schadt (1996). In Panel A we model the conditional heteroskedasticity of the funds and the benchmarks using a regression for the absolute residuals, following Davidian and Carroll (1987). In Panel B we model the heteroskedasticity using a GARCH model (the equations are in the table header). The results of these two models roughly bracket those in Table 4, leading to similar conclusions. The GARCH models tend to produce slightly larger upper bounds, while the Davidian-Carroll approach produces slightly smaller upper bounds than in Table 4.

7.4 *The Upper Bound: Summary*

To summarize, the issue of investor heterogeneity can be of comparable importance in practice as the issues of the benchmark choice and the problem of statistical imprecision in alpha estimates. Each of these issues has received a great deal of attention in the literature on performance measurement, but investor heterogeneity has hardly begun to be explored.

One interesting question regarding the upper bound is whether there are any mutual funds whose traditional alphas are so large that we expect all investors to agree that they are positive (or negative). This question can be addressed using our upper bound in a simulation approach that accounts for the number of correlated funds examined to find large traditional alphas. Kosowski, Timmermann, Wermers and White (2006) use a simulation approach and find that the largest traditional alphas are statistically significant. However, Fama and French (2010) criticize their simulation approach and find insignificant alphas for net returns, in both the positive and negative tails. If the largest traditional alphas are insignificantly different from zero, it follows that they will not be significantly larger than our bounds. There are unlikely to be many funds where all investors agree that the alpha is positive (or negative). Thus, investor heterogeneity is likely to be important in the evaluation of almost all mutual funds.

7.5 The Lower Bound

The lower bound on the impact of investor heterogeneity in Equation (10) is the upper bound multiplied by the correlation, $\rho_{\varepsilon m}$. Of course, the correlation is unobservable. If it is zero, then the lower bound is zero and heterogeneity across investors may not matter. If it is 0.10 for a particular fund, then the impact of heterogeneity on alpha is at least 10% of the size of the bounds discussed above. The correlation is likely to be small when $\sigma(\varepsilon_p)$ is small, as the common factors are likely to capture most of the correlation of the fund's return with the investors' marginal rate of substitution in such cases. But we saw above that $\sigma(\varepsilon_p)$ is substantial for many funds using traditional factors. And there is reason to think that the correlation will not be zero. For example, we know that the correlations of consumption growth rates are small across individuals and countries, suggesting heterogeneity in the marginal rates of substitution. This has been interpreted as imperfect risk sharing, because in complete markets individuals' marginal rates of substitution are perfectly dependent and there can be no disagreement in our model about a fund manager's expected alpha. Asset market returns are more highly correlated across countries than is consumption, and the common factors in returns are important, but it is hard to believe that investors face complete markets in practice. It is difficult, for example, to trade claims on human capital. Many forms of borrowing are restricted, and uncertain tax liabilities may be difficult to hedge with passive assets. The question of the lower bound is whether some funds' residual returns are correlated with aspects of investors' utility that are not captured by the common factors. This can in principle by addressed by looking at data on individual investors. While it is beyond the scope of this study to fully investigate the correlation of funds' residual returns with individual investors' marginal utilities, we offer suggestive evidence in the next section.

7.6 *Cross-sectional Implications*

The bounds in (9) and (10) provide an interesting perspective on some recent studies of the cross section of mutual fund performance. Recent studies find that mutual funds that depart further from benchmark weights or that have low R-squares in return regressions against common factor benchmarks have larger traditional alphas.[15] These are high residual volatility funds, for which the traditional alphas are likely to be unreliable indictors of investment attractiveness. When investors disagree more about the true alpha, there should be less coordination of their responses to the traditional alpha. Thus, we predict that funds with greater investor disagreement should, other things equal, exhibit a more muted flow response to their past performance.

The effects of investor heterogeneity differs across funds, according to our model, in

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[15] See for example, Brand, Brown and Gallagher (2005), Cremers and Patajisto (2009), Kacperczyk, Sialm and Zheng (2005) and Amihud and Goyenko (2010).

proportion to the product $|\rho_{\epsilon m}\,\sigma(\varepsilon_p)|$. We estimate $\sigma(\varepsilon_p)$ above, but $\rho_{\epsilon m}$ is more challenging. We construct a proxy for the cross-fund variation in $\rho_{\epsilon m}$ following Da and Yun (2010), who find that electricity consumption works better than nondurables plus services consumption expenditures in consumption-based asset pricing models. We use annual electricity consumption growth, measured for the 50 states and the District of Columbia during 1984-2008.[16] We take the cross-state variation in the time-series correlations between a fund's annual residual return, ε_p, and state electricity consumption growths, G, as a proxy for the variation in $\rho_{\epsilon m}$ across "clients." Specifically, we construct two alternative measures of disagreement about a given fund's performance:

$$\begin{aligned} \text{DISAGREE1}_p &= \sigma(\varepsilon_p)\,\sigma_G[\,|\rho(\varepsilon_p,G)|\,], \text{ and} \\ \text{DISAGREE2}_p &= \sigma(\varepsilon_p)\,\sigma_G[\,|\rho(\varepsilon_p,G)/\rho(r_{j^*},G)|\,], \end{aligned} \tag{11}$$

Where $\sigma_G[.]$ denotes the cross-sectional standard deviation across the electricity consumption growths for the 51 "states." The second measure, DISAGREE2_p, is motivated by the second line of equation (9), which shows that the ratio $\rho_{\epsilon m}/\rho_{mrj^*}$ determines the extent of disagreement. The correlation in the denominator, $\rho(r_{j^*},G)$, between the maximum Sharpe ratio portfolio return and the electricity consumption growth, varies across the benchmark models, changing the relative importance of $\sigma(\varepsilon_p)$ and $\rho(\varepsilon_p,G)$ in the measure of disagreement.

Our conjecture is that funds for which there is greater disagreement across investors should experience a muted flow response to a given performance, as measured by traditional alphas.[17] To investigate this, we embed the measures of disagreement in

[16] We are grateful to Zhi Da and Hayong Yun for allowing us to use their data.

[17] In this experiment we use annual disagreement measures, so we restrict to the subset of funds for which return data for the 1984-2008 period is available.

standard "flow-performance" regressions of mutual fund flows on their recent traditional performance measures and control variables. Mutual fund flows are measured in the usual way as:

$$Flow_{p,t} = [TNA_{p,t} - TNA_{p,t-1}(1+R_{pt})]/\ TNA_{p,t-1}, \tag{12}$$

where TNA is the total net assets of the fund and R_{pt} is the reported return. Fund flows are measured quarterly and disagreement is measured annually.

The flow-performance regressions follow Sirri and Tufano (1998), Chevalier and Ellison (1997) and Huang, Wei and Yan (2007). These are panel regressions of the flow on lagged performance measures and control variables. The lagged control variables follow previous studies and include fund age (the natural logarithm of the number of months since fund inception), size (the natural logarithm of TNA), the expense ratio plus one-seventh of any front-end load charges, the lagged fund flow, the traditional performance measure at several lags, the lagged fund total return volatility, and multiplicative terms in lagged fund age and lagged performance. The regressions include both time and fund fixed effects. Following these earlier studies, the performance measures and the total return volatility are estimated from the 36 months prior to quarter t.

Our interest is the coefficients on the lagged performance, and how they vary with investor disagreement. We use two approaches, a parametric and a "nonparametric" approach. In the first approach the lagged performance enters linearly and as the squared performance, assuming a quadratic relation. We include interaction terms with a measure of disagreement, and our conjecture is that the interaction terms should carry negative coefficients. The results are presented in tables 6 and 7 for two traditional performance measures, the CAPM alpha and the Fama-French three-factor alpha, respectively.

There are four panels each in tables 6 and 7, reflecting the two disagreement measures and two alternative assumptions about the variation in disagreement over time. One assumption is that the disagreement for each fund is fixed over time. The alternative assumption allows for time-varying disagreement, where we use rolling estimation over the past 36 months up to but not including data for the current quarter. The tables show that the coefficients on the control variables are similar to what previous studies find. The coefficients on the interaction terms between lagged performance and disagreement are negative in each of the four panels, and statistically significant in all but one case. The effects of disagreement have larger t-ratios in the linear terms than in the quadratic terms, with t-ratios in the linear terms exceeding 8.3 in absolute value in each of the eight examples. The results for the quadratic terms are somewhat stronger when using the Fama-French alphas in Table 7, but still weaker than the linear terms. Thus, higher levels of disagreement about alpha are associated with lower levels of fund flows for a given performance measure.

We repeat the experiment in Table 6 using conditional alphas following Ferson and Schadt (1996). The t-ratios on the interaction terms between alpha and disagreement range from -5.13 to -6.20. The coefficients on the interactions with the quadratic terms are insignificant. Thus, disagreement about alpha is associated with a lower level of flow response to a given performance, when measured by the conditional alpha.

Our second, nonparametric approach replaces the quadratic functional form assumption with dummy variables for the ranked levels of performance. The performance measures for the funds are ranked and each fund is assigned values for two dummy variables indicating the performance rank. PM_H is equal to 1.0 if the fund's performance falls in the top third, PH_M is equal to 1.0 if it falls in the middle third, and the bottom third is the reference. In the A and B panels of tables 8 and 9, these performance ranks are interacted with the measures of disagreement. The tables show stronger negative effects of disagreement on flow response to performance in the PM_H group, using either the CAPM alphas in Table 8, or the Fama-French alphas in Table 9.

In the C and D panels of tables 8 and 9, we assign dummy variables to the ranks in which a fund's measure of disagreement lies and retain the quadratic functional form in performance. Here we find negative interaction coefficients in most of the cases, and strongly significant for the high-disagreement funds. The coefficients allow a graphical representation of the flow-performance relation for the low, medium and high-disagreement groups, as shown in Figure 1. Here the fitted values of the fund flows include the control variables and are fitted with a cubic spline. The graph illustrates the economic magnitudes of the differences in flow between the high, medium and low-disagreement funds. For example, a lagged performance one standard error above the cross-sectional mean CAPM alpha is associated with an increase in expected fund flow of 0.20% for the high-disagreement group, compared to 0.89% for the low-disagreement group. Thus, investor heterogeneity leading to disagreement about alpha has an economically significant relation to fund flows.

One potential issue with the cross-sectional analysis is the influence of estimation error on the results. If the variation in the disagreement measures across funds is driven by variation in the funds' residual volatilities, the regression results could be driven by the volatilities, which are highly correlated with estimation error in the funds' alphas. In this case, the effect we measure in the panel regressions could reflect estimation uncertainty and not the disagreement effect that we have in mind. Funds with high estimation uncertainty in alpha could also experience a muted flow response to a given alpha estimate. To address this concern we conduct a number of experiments.

In the first set of experiments we modify the two disagreement measures by setting the residual volatilities to equal 1.0, so the measures reflect only the cross-state variation in the electricity correlations for a given fund. These results are summarized in Table 10 for the CAPM and FF3-factors alphas, both in unconditional and in conditional form following Ferson and Schadt (1996). In the unconditional CAPM the t-ratios on the interaction terms are negative and larger than four in absolute value using the first measure and negative but only significant on the quadratic term using the second modified measure of disagreement. Stronger results with negative t-ratios are found using the unconditional FF3 alphas. The conditional FF3 model produces similar results, but those for the conditional CAPM are weaker, and in one case for this model an interaction term between flow and disagreement receives a significant positive sign. Overall, however, the results strongly support our conclusion that high disagreement funds have a muted flow response to a given traditional alpha.

In the second set of experiments we orthogonalize the disagreement measures to estimation uncertainty in alpha. We run cross-sectional regressions, across funds, of the disagreement measures on the White (1980) standard errors of the alphas estimated from time series regressions, and construct the orthogonalized disagreement measures as the intercept plus the residuals from the cross-sectional regression. We repeat the flow performance regressions using the orthogonalized disagreement measures in Table 11. There are eight cases, with four measures of alpha and the two disagreement measures. The coefficients on the interaction between disagreement and lagged performance are negative in five cases, with t-ratios between -1.86 and -5.12. The three positive coefficients have smaller t-ratios, but the largest is 2.27. The coefficients on the interaction between the orthogonalized disagreement and squared performance are negative in all but one case, with five of the t-ratios between -3.45 and -4.91. The single positive coefficient is not significant. These results show that the attenuating effect of disagreement on the flow response to fund performance is not driven by estimation uncertainty in the funds' alphas.

In summary, the relation of fund flows to recent performance measures varies significantly with the extent to which investors are likely to disagree with the performance measure. Funds with greater disagreement due to investor heterogeneity experience a weaker relation of their flows to past measured performance. We conclude that the effects of investor heterogeneity are of economic and statistical significance.

8. Conclusions

The ambiguities in the interpretation of alpha that plagued the early literature are largely resolved when alpha is defined relative to the client's preferences, and proper performance evaluation is inherently client specific. In evaluating managed portfolios, one size does not fit all. This paper evaluates the effects of investor heterogeneity on investment performance measurement and finds that heterogeneity is both statistically and economically significant. This has important implications for the existing literature, for practical investment evaluation and for future research.

The traditional alphas used in much of the existing literature can be interpreted as signals to buy or sell in special circumstances. This occurs in our model when the traditional factors completely capture the covariance of a fund's return with the client's marginal utility. Our upper bound for the difference between a client's alpha and the traditional measures is comparable in magnitude to various measures of the ambiguity in the traditional alphas. In particular, disagreement with the traditional alphas can be similar in magnitude to the sensitivity of alpha to the choice of benchmark (e.g., Roll, 1978). Disagreement effects can be similar in magnitude to the estimation errors in traditional alphas. We find that funds for which investors are more likely to disagree with traditional alphas display a muted flow response to performance measured by traditional alphas. This is a separate effect from uncertainty about the true value of the traditional alpha.

While our analysis indicates that investor heterogeneity is economically significant, it likely understates the case. We use iterated expectations to integrate out clients' different information sets. We do not consider taxes or transaction costs. These are additional sources of potential disagreement about alpha across investors.

The implications of our results for the practical evaluation of investments are important. One client is likely to view the performance of a given fund differently from another client. If the client's life situation is idiosyncratic, he is likely to view the performance of a fund as idiosyncratically different.

Our results suggest an important avenue for new research on investment performance evaluation. If the client-specific nature of alpha is important, then studies should develop client-specific measures, or more realistically, clientele-specific measures of fund performance.

Appendix

Proof of Proposition 1:

The first order condition for an optimal response that maximizes the lifetime utility implies:

$$- u_c(C_t-\Delta) + E\{\beta J_w(W(\Delta)) [R_{pt+1} + (W_t-C_t) (\partial x(\Delta)/\partial\Delta)'R] \mid Z_t\} = 0. \qquad \text{(A.1)}$$

Assuming regular utility functions, we can use the mean value theorem to represent

$$u_c(C_t-\Delta) = u_c(C_t) - u_{cc}^* \Delta \text{ and} \qquad \text{(A.2)}$$
$$J_w(W(\Delta)) = J_w(W_{t+1}) + J_{ww}^* [W(\Delta)-W_{t+1}],$$

where * indicates that the functions are evaluated at points in the intervals $(C_t-\Delta,C_t)$ and $(W(\Delta),W_{t+1})$ respectively. Substituting (A.2) into (A.1) yields:

$$u_c(C_t) -u_{cc}^*\Delta=E\{\beta [J_w(W_t)+J_{ww}^* (W(\Delta)-W_{t+1})] [R_{p,t+1} + (W_t-C_t)(\partial x(\Delta)/\partial\Delta)'R]\}. \qquad \text{(A.3)}$$

Substituting in $(W(\Delta)-W_{t+1}) = \Delta R_p + (W_t-C_t)[x(\Delta)-x]'R$, where $x(\Delta)$ is the new optimal portfolio weight vector for the N base assets, normalized to sum to 1.0, and x is the old optimal weight vector, and using the first order condition $E\{\beta J_w(W_t) R\}=\underline{1}u_c(C)$ and the fact that $x(\Delta)'\underline{1}=1$ implies $(\partial x(\Delta)/\partial\Delta)'\underline{1}=0$, and using the definition of α_p, (A.3) reduces to:

$$u_c(C_t) - u_{cc}^*\Delta = (1+\alpha_p)u_c(C_t) + \Delta Q, \qquad \text{(A.4)}$$
$$Q = E\{\beta J_{ww}^* [R_{pt+1} + (W_t-C_t) (\partial x(\Delta)/\partial\Delta)'R] [R_{pt+1} + (W_t-C_t) (x(\Delta)-x)/\Delta)'R].$$

Solving for the optimal Δ we have:

$$\Delta = \alpha_p \{u_c / (-u_{cc}^* - Q)\}, \tag{A.5}$$

and the conditions of the theorem guarantee that Q<0, which establishes the result. QED.

Proof of Proposition 2:

When J(.) is quadratic in wealth, then J_w is a linear function and using the first order conditions again we have $E\{\beta\, [aJ_w(W^I) + (1\text{-}a)J_w(W^u)]\, [R_p - R_u] \,|\, \Omega\} = E\{\beta(1\text{-}a)J_w(W^u)\, [R_p - R_u] \,|\, \Omega\} = (1\text{-}a)u_c\, \alpha_p > 0$, implying that alpha is positive. QED.

Review of the Second Fundamental Question

The second Fundamental Question is whether an informed manager will generate a positive alpha. Mayers and Rice (1979) argued for an affirmative answer. They assumed complete markets, quadratic utility and the CAPM. They also assumed that the manager either has no information about the market return (i.e., no timing information) and that either the expected conditional beta is the unconditional beta (generally not true) or that the agent's optimal consumption is unaffected by the information. Dybvig and Ingersoll (1982) showed that you can't marry complete markets with quadratic utility because it leads to negative state prices, and Verrechia (1980) gave a counterexample with quadratic utility to the more general proposition that the informed earn higher returns than the uninformed expect, based on the Mayers and Rice set up. Dybvig and Ross (1985a) generalized the Mayers and Rice result to avoid the complete markets assumption (their Theorem 2) but assumed that the manager has no information about the mean or variance of the uninformed client's portfolio.

Connor and Korajczyk (1986) work in an APT setting, assuming that the idiosyncratic components of returns, ϵ_i, are pure risk in the sense of Rothschild and Stiglitz (that is, $E(\varepsilon_i)=0=E(\varepsilon_i|f)$, where f are the common factors). They also assume that the informed manager gets a signal about only one asset return. They shown that alpha, defined as the summed covariance of the manager's optimal portfolio weights with idiosyncratic returns, will be positive. They also show that under constant absolute risk aversion (their Theorem 4) that this alpha divided by its standard error orders informed managers' information sets in terms of managers' expected utility. This may be the best positive answer to the second Fundamental Question in the current literature.

Grinblatt and Titman (1989) also get close to a general positive answer to the question of whether an informed manager will generate a positive alpha. They use a single period model under the assumption of normality, and thus, mean variance preferences.[18] They consider alpha measured relative to a benchmark that is mean variance efficient given the uninformed client's information. Sadly, they find that alpha can be negative for an informed manager, even assuming that the manager has nonincreasing Rubinstein (1976) risk aversion. Grinblatt and Titman also introduce a positive period weighting measure. The positive period weighting measure is a set of scalars $\{w_t\}$ that are strictly positive, sum to 1.0 and are bounded in the sample size T: $|\text{plim}(Tw_t)|<\infty$. The alpha for a portfolio with excess return r_t is defined as $\text{Plim}(\Sigma_t\, w_t r_t)$. A positive period weighting measure produces a zero alpha for a portfolio r_{Et} that is mean variance efficient conditioned on the uninformed client's information set: $\text{Plim}(\Sigma_t\, w_t r_{Et}) = 0$. Grinblatt and Titman show that alphas relative to this measure will be positive if the informed manager has constant Rubinstein risk aversion (their Proposition A1) or has no

[18] They do allow for nontraded human capital, and thus a hedging demand related to human capital. The informed agent's optimal portfolio in their set up is conditional multifactor minimum variance efficient (Ferson, Siegel and Xu, 2006) given the client's information. With the additional assumption of normality, that will also be the case in the model developed here.

timing information, or has selectivity information that is independent of both the benchmark and the weighting measure and optimally increases beta when receiving a positive timing signal about the efficient portfolio (their Proposition 2).

It seems that the conditions under which a manager with superior information will generate a positive alpha are fairly special, and there are examples where it won't be true. Dybvig and Ross (1985a) and Grinblatt and Titman (1989) show that a manager that is a positive market timer can generate a negative alpha. Dybvig and Ross (1985a) and Hansen and Richard (1987) show that a manager's portfolio can be mean variance efficient given the manager's knowledge, but appear inefficient to the uninformed client. In general, the answer from the previous literature to the second Fundamental Question is negative.

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Table 1

Summary Statistics

The table reports summary statistics for actively managed mutual funds and benchmark returns. The data are from January of 1984 through December of 2008. We exclude from our analysis using unconditional (conditional) models funds with less than 12 (48) monthly returns. The benchmark assets include a stock market portfolio (market), the Fama French three factors (FF 3 Factors), six equal-weighted portfolios of index mutual funds grouped according to their benchmarks (Index MFs), their equal-weighted average (EW Idx), a set of ETFs (ETFs), and an equal-weighted portfolio of ETFs (EW ETFs). Index MFs are classified into six categories based on their target benchmarks as indicated below. ETFs reflect eight asset classes: SPY (large cap), MDY (mid cap), IJR (small cap), QQQQ (Technology), EWJ (Japan), EFA (MSCI non-US), XLE (Energy), IYR (Mortgage/Real Estimate). Mean is the sample mean, Std Dev is the sample standard deviation, Min is the sample minimum, Max is the sample maximum, AR1 is the first order sample autocorrelation, and SR is the sample Sharpe ratio. All statistics are computed on excess returns. The excess returns are measured net of the one month return on a three-month Treasury bill. The columns for the actively managed mutual funds are sorted separately on each statistic shown. Monthly percentage figures are reported in the first four columns.

	Mean	Std Dev	Min	Max	AR1	SR
FF 3 Factors						
Market	0.457	4.468	-22.977	12.386	0.098	0.102
SMB	0.027	3.273	-16.850	21.990	-0.031	0.008
HML	0.353	3.075	-12.370	13.870	0.114	0.115
Index MFs						
S&P 500	0.476	4.218	-16.852	16.468	-0.030	0.113
S&P MidCap	0.540	4.762	-21.724	11.538	0.084	0.113
SmallCap	0.387	4.976	-19.706	9.252	0.019	0.078
Russell	0.444	4.668	-20.436	10.058	0.089	0.095
MSCI	0.566	4.482	-19.263	11.532	0.100	0.126
Others	0.394	4.465	-19.204	10.977	0.058	0.088
EW Idx	0.467	4.269	-18.254	13.234	0.020	0.109
ETFs						
EFA	0.165	4.893	-20.871	10.073	0.358	0.034
EWJ	-0.384	5.982	-16.835	20.742	0.126	-0.064
IJR	0.263	5.369	-19.798	10.783	0.115	0.049
IYR	0.441	6.076	-31.352	14.251	0.097	0.073
MDY	0.545	5.126	-21.584	12.181	0.146	0.106
QQQQ	-0.375	8.825	-26.599	23.046	0.105	-0.043
SPY	0.297	4.152	-16.555	9.211	0.087	0.072
XLE	0.678	6.491	-18.836	16.552	-0.040	0.105
EW ETFs	0.386	4.472	-20.014	12.029	0.130	0.086

	Mean	Std Dev	Min	Max	AR1	SR
Active MFs – with at least 12 observations						
Bottom 1%	-3.491	1.908	-35.609	3.124	-0.308	-1.830
Bottom 10%	-1.353	3.250	-24.947	4.980	-0.058	-0.416
Bottom 25%	-0.461	4.109	-21.187	6.920	0.031	-0.112
Median	0.034	4.956	-17.707	9.553	0.102	0.007
Top 25%	0.378	6.080	-13.665	13.323	0.173	0.062
Top 10%	0.663	7.738	-9.191	20.237	0.242	0.086
Top 1%	1.671	12.412	-3.629	37.454	0.361	0.135
Mean	-0.169	5.323	-17.529	11.416	0.094	-0.032
Active MFs – with at least 48 observations						
Bottom 1%	-0.962	2.117	-36.096	4.165	-0.145	-0.454
Bottom 10%	-0.388	3.382	-25.250	6.567	-0.006	-0.115
Bottom 25%	-0.114	4.108	-21.655	8.503	0.050	-0.028
Median	0.161	4.858	-18.233	10.660	0.105	0.033
Top 25%	0.416	5.804	-14.954	14.876	0.164	0.072
Top 10%	0.640	7.421	-11.472	22.508	0.226	0.086
Top 1%	1.236	11.082	-5.525	39.133	0.316	0.112
Mean	0.148	5.176	-18.469	12.996	0.106	0.029

Table 2

Mutual Funds' Traditional Alphas and Residual Volatilities

This table summarizes the cross-sectional distribution of alpha estimates, their standard errors, and the volatility of the idiosyncratic residuals for actively managed mutual funds. Mkt is the market portfolio, FF3 denotes the three Fama-French factors, Idx MFs are the six equal-weighted portfolios of index mutual funds, EW Idx MFs is their equal-weighted portfolio, ETFs are a set of eight ETFs, and EW ETFs is their equal-weighted portfolio. The symbols r_p and r_j denote the fund excess returns and the vector of benchmark excess returns, respectively. Z denotes the public information variables – the lagged one-month Treasury Bill, the lagged dividend yield, the lagged term spread, and the lagged default spread. All figures are in monthly percentage units. The sample period is January, 1984 through December, 2008. Panel A shows unconditional results using the following regression:

$$r_p = a_p + B_p' r_j + \varepsilon_p,$$

and Panel B shows conditional results following Ferson and Schadt (1996) using the regression:

$$r_p = a_{0p} + B_{0p}' r_j + B_p'(r_j \otimes Z) + \varepsilon_p.$$

Alpha is the intercept, a_p, or a_{0p}. Std is the White (1980) standard error of the alpha and $\sigma(\varepsilon_p)$ is the standard deviation of the fund residual. The unconditional (conditional) specification uses only actively managed mutual funds with at least 12 (48) monthly returns. Each column of statistics is sorted separately on that statistic.

Panel A: UNCONDITIONAL MODELS

Benchmark:	**Mkt**				**FF3**		
Fractile	Alpha	std	$\sigma(\varepsilon_p)$	Fractile	alpha	std	$\sigma(\varepsilon_p)$
Bottom 1%	-1.699	0.062	0.492	Bottom 1%	-1.674	0.057	0.422
Bottom 10%	-0.549	0.110	0.896	Bottom 10%	-0.522	0.096	0.751
Bottom 25%	-0.256	0.164	1.362	Bottom 25%	-0.271	0.135	1.087
Median	-0.043	0.248	2.118	Median	-0.090	0.209	1.697
Top 25%	0.180	0.378	3.042	Top 25%	0.087	0.321	2.492
Top 10%	0.480	0.608	4.457	Top 10%	0.371	0.523	3.564
Top 1%	1.642	1.388	8.162	Top 1%	1.492	1.238	7.146
Mean	-0.035	0.322	2.455	Mean	-0.086	0.276	2.001

Benchmark	6 Idx MF				EW Idx MFs		
Fractile	Alpha	Std	$\sigma(\varepsilon_p)$	Fractile	alpha	std	$\sigma(\varepsilon_p)$
Bottom 1%	-1.720	0.042	0.300	Bottom 1%	-1.714	0.066	0.574
Bottom 10%	-0.572	0.097	0.649	Bottom 10%	-0.548	0.115	0.983
Bottom 25%	-0.279	0.139	0.990	Bottom 25%	-0.226	0.165	1.416
Median	-0.069	0.212	1.601	Median	-0.004	0.248	2.164
Top 25%	0.124	0.330	2.404	Top 25%	0.222	0.388	3.096
Top 10%	0.379	0.544	3.456	Top 10%	0.535	0.630	4.640
Top 1%	1.379	1.366	6.556	Top 1%	1.716	1.441	8.407
Mean	-0.076	0.284	1.892	Mean	-0.003	0.330	2.541

Benchmark:	8 ETFs				EW ETFs		
Fractile	Alpha	Std	$\sigma(\varepsilon_p)$	Fractile	alpha	std	$\sigma(\varepsilon_p)$
Bottom 1%	-3.310	0.000	0.000	Bottom 1%	-1.888	0.091	0.693
Bottom 10%	-0.582	0.073	0.490	Bottom 10%	-0.776	0.153	1.233
Bottom 25%	-0.304	0.108	0.745	Bottom 25%	-0.454	0.198	1.671
Median	-0.117	0.161	1.076	Median	-0.206	0.269	2.271
Top 25%	0.047	0.242	1.587	Top 25%	0.025	0.400	3.152
Top 10%	0.281	0.380	2.342	Top 10%	0.284	0.628	4.577
Top 1%	2.384	0.997	7.847	Top 1%	1.338	1.464	8.279
Mean	-0.173	0.209	1.473	Mean	-0.229	0.349	2.655

Panel B: CONDITIONAL MODELS

Benchmark:	Mkt				FF3		
Fractile	Alpha	std	$\sigma(\varepsilon_p)$	Fractile	alpha	std	$\sigma(\varepsilon_p)$
Bottom 1%	-0.952	0.060	0.487	Bottom 1%	-0.969	0.051	0.377
Bottom 10%	-0.410	0.104	0.948	Bottom 10%	-0.418	0.083	0.697
Bottom 25%	-0.208	0.148	1.396	Bottom 25%	-0.247	0.117	1.009
Median	-0.036	0.222	2.093	Median	-0.094	0.177	1.543
Top 25%	0.162	0.316	2.968	Top 25%	0.077	0.254	2.218
Top 10%	0.432	0.462	4.226	Top 10%	0.322	0.373	3.053
Top 1%	1.185	0.928	7.413	Top 1%	0.926	0.764	6.303
Mean	-0.007	0.262	2.398	Mean	-0.072	0.211	1.792

Benchmark:		6Idx MFs				EW Idx MFs	
Fractile	Alpha	std	$\sigma(\varepsilon_p)$	Fractile	alpha	std	$\sigma(\varepsilon_p)$
Bottom 1%	-1.373	0.043	0.226	Bottom 1%	-0.974	0.060	0.551
Bottom 10%	-0.468	0.089	0.521	Bottom 10%	-0.383	0.104	0.998
Bottom 25%	-0.229	0.125	0.796	Bottom 25%	-0.172	0.149	1.416
Median	-0.034	0.189	1.276	Median	0.008	0.220	2.104
Top 25%	0.141	0.277	1.914	Top 25%	0.211	0.317	3.026
Top 10%	0.375	0.423	2.706	Top 10%	0.482	0.476	4.457
Top 1%	1.234	0.919	5.301	Top 1%	1.261	0.973	7.605
Mean	-0.041	0.234	1.512	Mean	0.033	0.266	2.464

Benchmark:		8 ETFs				EW ETFs	
Fractile	Alpha	std	$\sigma(\varepsilon_p)$	Fractile	alpha	std	$\sigma(\varepsilon_p)$
Bottom 1%	-1.192	0.000	0.000	Bottom 1%	-1.253	0.082	0.736
Bottom 10%	-0.416	0.076	0.313	Bottom 10%	-0.608	0.147	1.327
Bottom 25%	-0.215	0.105	0.485	Bottom 25%	-0.377	0.184	1.754
Median	-0.060	0.145	0.709	Median	-0.162	0.235	2.292
Top 25%	0.110	0.212	1.032	Top 25%	0.034	0.326	3.120
Top 10%	0.328	0.301	1.429	Top 10%	0.243	0.471	4.380
Top 1%	1.183	0.693	2.868	Top 1%	0.823	0.921	7.663
Mean	-0.044	0.178	0.831	Mean	-0.171	0.283	2.641

Panel C: Range of Mutual Funds' Traditional Alphas Across Six Benchmark Models:

Fractile	**Unconditional**	**Conditional**
Bottom 1%	0.119	0.086
Bottom 10%	0.240	0.211
Bottom 25%	0.323	0.307
Median	0.433	0.434
Top 25%	0.658	0.616
Top 10%	1.062	0.911
Top 1%	5.375	2.052
Mean	0.690	0.548

Table 3

Bounds on the Effects of Investor Heterogeneity in Unconditional Models

This table summarizes the distribution of the upper bounds on the effects of heterogeneity on alphas using different benchmark assets. Mkt is the market portfolio, FF3 is the three Fama French three factors, Idx MFs are the six equal-weighted indexes of index mutual funds, EW Idx MFs is their equal-weighted portfolio, ETFs are a set of eight ETFs, and EW ETFs is their equal-weighted portfolio. The symbols r_p and r_i denote the fund excess returns and the vector of benchmark excess returns, respectively. The form of the regression for actively managed mutual funds is:

$$r_p = a_p + B_p' r_j + \varepsilon_p$$

SR_{max} is the maximum unconditional Sharpe ratio, adjusted for finite sample bias following Ferson and Siegel (2003). The upper bounds are calculated as the product $\sigma(\varepsilon_p)\, SR_{max.}$, where $\sigma(\varepsilon_p)$ is the unconditional standard deviation of ε_p. The figures are in monthly percentage units.

Benchmark:	**Mkt**	**FF3**	**Idx MFs**	**EW Idx MFs**	**ETFs**	**EW ETFs**
Bottom 1%	0.050	0.078	0.061	0.060	0.000	0.060
Bottom 10%	0.092	0.138	0.132	0.103	0.143	0.106
Bottom 25%	0.139	0.201	0.201	0.152	0.217	0.144
Median	0.216	0.313	0.324	0.233	0.314	0.196
Top 25%	0.311	0.460	0.487	0.337	0.463	0.272
Top 10%	0.455	0.657	0.700	0.510	0.683	0.395
Top 1%	0.834	1.318	1.329	0.942	2.288	0.714
Mean	0.251	0.369	0.383	0.276	0.429	0.229
SR_{max}	10.2	18.4	20.3	10.9	29.2	8.6

Table 4

Bounds on the Effects of Investor Heterogeneity on Alphas using Conditional Models with Homoskedasticity and Linear Conditional Means

This table summarizes cross-sectional distributions of the upper bounds on the effects of investor heterogeneity on alphas using alternative benchmark assets. Mkt is the market portfolio, FF3 is the three Fama French factors, Idx MFs are the six equal-weighted indexes of index mutual funds, EW Idx MFs is their equal-weighted portfolio, ETFs are a set of eight ETFs, and EW ETFs is their equal-weighted portfolio. The symbols r_p and r_j denote the fund excess returns and the vector of benchmark excess returns, respectively. Z denotes the public information variables – the lagged one-month Treasury Bill, the lagged dividend yield, the lagged term spread, and the lagged default spread. The regressions for the active funds are:

$$r_p = a_{0p} + B_{0p}' r_j + B_{1p}' Z + e_p$$

Avg SR_{max} is the average of time-varying conditional maximum Sharpe ratios after finite sample bias correction, based on the fitted conditional mean excess returns of the benchmarks and their residual covariances in regressions of the benchmark returns on the lagged Zs and a constant only. The sample residual covariance matrix is the expected conditional covariance matrix, on the assumption that the conditional covariance matrix is constant over time. The bounds are calculated as $\sigma(e_p)\, SR_{max.}$ where $\sigma(e_p)$ is the standard deviation of e_p. Avg SR_{max} is in decimals and the other numbers are in monthly percentage units.

Benchmark:	**Mkt**	**FF3**	**Idx MFs**	**EW Idx MFs**	**ETFs**	**EW ETFs**
Bottom 1%	0.098	0.159	0.239	0.092	0.228	0.105
Bottom 10%	0.184	0.280	0.484	0.166	0.398	0.186
Bottom 25%	0.273	0.399	0.709	0.236	0.531	0.246
Median	0.412	0.607	1.069	0.353	0.724	0.326
Top 25%	0.579	0.861	1.561	0.503	1.022	0.444
Top 10%	0.813	1.177	2.156	0.738	1.401	0.625
Top 1%	1.423	2.370	4.083	1.287	2.911	1.095
Mean	0.466	0.693	1.245	0.411	0.859	0.375
Avg. SRmax	0.189	0.344	0.636	0.162	0.655	0.140

Table 5

Bounds on the Effects of Investor Heterogeneity on Alphas using Conditional Models with Heteroskedasticity

This table reports the cross-sectional distribution of estimates of the upper bounds on the effects of investor heterogeneity on alphas for various benchmark assets. Mkt is the market portfolio, FF3 is the Fama French three factors, Idx MFs are the six equal-weighted indexes of index mutual funds, EW Idx MFs is their equal-weighted portfolio, ETFs are a set of eight ETFs, and EW ETFs is their equal-weighted portfolio. The symbols r_p and r_j denote the fund excess returns and the vector of benchmark excess returns, respectively. Z denotes the lagged public information variables – the lagged one-month Treasury Bill, the lagged dividend yield, the lagged term spread, and the lagged default spread. The econometric model for the mutual fund returns in panel A has linear conditional means and conditional heteroskedasticity:

$$r_{p,t} = a_{0p} + \beta_{0\,p}'Z + \beta_p'(r_j \otimes Z) + \varepsilon_{p,t}$$

$$\text{sqrt}(\pi/2)\,|\varepsilon_{p,t}| = a_{1p} + \beta_{1p}'Z + e_{p,t}$$

For panel B the GARCH(1,1) model is used:

$$r_{p,t} = \theta_{0\,p} + \Gamma_{0\,p}'Z + \Gamma_p'(r_j \otimes Z) + u_{p,t}\,,\quad u_{p,t} \sim N(0,h_{p,t})$$

$$h_{p,t+1} = \theta_{1p} + \lambda\, u^2_{p,t} + \varphi h_{p,t}$$

The conditional means and variances of the benchmark excess returns are estimated using similar models, except the conditional means of the benchmark returns are assumed to be linear in the lagged variables, Z. In Panel A the conditional volatility, $\sigma(\varepsilon_p|Z)$ is computed as $a_{1p} + \beta_{1p}'Z$. In the second model it is the fitted value of h_{pt}. Avg. SRmax is the average of the conditional maximum Sharpe ratios, $SR_{max}(Z)$, after adjustment for finite sample bias following Ferson and Siegel (2003). The conditional Sharpe ratios assume that the benchmark returns have linear conditional means, that their conditional standard deviations are the fitted values above, and that their conditional correlations are the sample correlations of the residuals from their regressions on the lagged Zs. The bounds are calculated as the sample mean of $\{\sigma(\varepsilon_p|Z) \text{ x } SR_{max.}(Z)\}$. Avg. SRmax is reported in decimals and other numbers are in percentages.

Panel A:

Benchmark:	Mkt	FF3	Idx MFs	EW Idx MFs	ETFs	EW ETFs
Bottom 1%	0.069	0.126	0.196	0.062	0.137	0.101
Bottom 10%	0.138	0.240	0.386	0.112	0.276	0.178
Bottom 25%	0.211	0.352	0.563	0.161	0.398	0.225
Median	0.311	0.529	0.868	0.237	0.563	0.281
Top 25%	0.448	0.752	1.282	0.332	0.812	0.361
Top 10%	0.635	1.036	1.768	0.464	1.115	0.480
Top 1%	1.246	2.172	3.456	0.894	2.202	0.875
Mean	0.364	0.613	1.022	0.271	0.664	0.314
Avg. SRmax	0.234	0.447	0.686	0.162	0.762	0.140

Panel B:

Benchmark:	Mkt	FF3	Idx MFs	EW Idx MFs	ETFs	EW ETFs
Bottom 1%	0.070	0.167	0.313	0.055	0.129	0.111
Bottom 10%	0.135	0.308	0.677	0.102	0.440	0.195
Bottom 25%	0.201	0.435	1.062	0.146	0.685	0.249
Median	0.297	0.647	1.669	0.211	1.156	0.312
Top 25%	0.414	0.908	2.570	0.290	2.190	0.414
Top 10%	0.580	1.262	3.907	0.408	4.329	0.557
Top 1%	1.054	2.695	9.724	0.765	12.451	0.985
Mean	0.337	0.751	2.171	0.240	2.008	0.353
Avg. SRmax	0.187	0.404	1.017	0.136	0.995	0.148

Table 6

Quarterly Panel Flow-performance Regressions Using CAPM Alphas

The panel regressions are for January, 1984 through December, 2008. The net flow is defined as the quarter-to-quarter growth in total net assets (TNA) in excess of fund returns. The performance measure ($PM_{p,t}$) is the unconditional alpha from the CAPM. Two measures of disagreement about alpha are used:

$$DISAGREE1_p = \sigma(\varepsilon_p)\,\sigma_G[\,|\rho(\varepsilon_p,G)|\,], \text{ and}$$

$$DISAGREE2_p = \sigma(\varepsilon_p)\,\sigma_G[\,|\rho(\varepsilon_p,G)/\rho(r_{j^*},G)|\,],$$

where $\rho(\varepsilon_p,G)$ is the time-series correlation between a fund's residual return and a state's electricity consumption growth and $\sigma_G[.]$ denotes the cross-sectional standard deviation across the electricity consumption growths for the 50 states and the District of Columbia.
The symbol r_{j^*} **d**enotes the maximum correlation portfolio in a given set of benchmark returns, in this case the Sharpe ratio of the market proxy. The control variables include the lagged age (the natural logarithm of months since inception (AGE_{t-1}), the lagged size (the natural logarithm of TNA, $SIZE_{t-1}$), the expense ratio plus one-seventh of the front-end load ($EXPENSE_{t-1}$), the lagged net flow, the lagged performance measure (PM_{t-1}), the lagged fund total return volatility ($TVOL_{t-1}$), cross terms and other lags as shown. Panels A and B assume that DISAGREE is time-varying and uses the rolling standard deviations of fund residuals over the previous 36 months at each quarter t. Panel C and D assumes that DISAGREE is constant over the sample period.

Panel A: Rolling $DISAGREE1_p$

	Coeff	Std	T-value
Intercept	0.08	0.06	1.49
PM_{t-1}	0.80	2.41	0.33
PM_{t-1}x$DISAGREE1_{t-1}$	-186.98	20.99	-8.91
PM_{t-1}^2	54.65	174.34	0.31
PM_{t-1}^2x$DISAGREE1_{t-1}$	-3654.13	1358.63	-2.69
PM_t	4.75	0.40	11.78
PM_{t-2}	0.80	0.54	1.47
PM_{t-3}	-0.82	0.41	-2.02
PM_{t-1}xAGE_{t-1}	-0.11	0.40	-0.27
PM_{t-1}^2xAGE_{t-1}	-2.23	29.47	-0.08
AGE_{t-1}	-0.01	0.02	-0.69
$SIZE_{t-1}$	-0.02	0.00	-8.33
$EXPENSE_{t-1}$	0.96	0.44	2.19
$FLOW_{t-1}$	0.15	0.01	15.77
$TVOL_{t-1}$	-0.21	0.11	-1.97

Panel B: Rolling DISAGREE2$_p$

	Coeff	Std	T-value
Intercept	0.08	0.06	1.46
PM_{t-1}	1.12	2.42	0.46
$PM_{t-1}xDISAGREE2_{t-1}$	-176.34	21.32	-8.27
PM_{t-1}^2	60.49	174.90	0.35
$PM_{t-1}^2xDISAGREE2_{t-1}$	-2699.56	1397.74	-1.93
PM_t	4.75	0.40	11.77
PM_{t-2}	0.80	0.54	1.47
PM_{t-3}	-0.82	0.41	-2.01
$PM_{t-1}xAGE_{t-1}$	-0.19	0.40	-0.47
$PM_{t-1}^2xAGE_{t-1}$	-6.09	29.51	-0.21
AGE_{t-1}	-0.01	0.02	-0.67
$SIZE_{t-1}$	-0.02	0.00	-8.29
$EXPENSE_{t-1}$	0.95	0.44	2.16
$FLOW_{t-1}$	0.15	0.01	15.77
$TVOL_{t-1}$	-0.19	0.11	-1.82

Panel C: constant DISAGREE1$_p$

	Coeff	Std	T-value
Intercept	0.08	0.06	1.51
PM_{t-1}	1.73	2.41	0.72
$PM_{t-1}xDISAGREE2_{t-1}$	-210.79	22.03	-9.57
PM_{t-1}^2	82.88	176.04	0.47
$PM_{t-1}^2xDISAGREE2_{t-1}$	-2829.09	1471.12	-1.92
PM_t	4.82	0.40	11.94
PM_{t-2}	0.73	0.54	1.34
PM_{t-3}	-0.80	0.41	-1.97
$PM_{t-1}xAGE_{t-1}$	-0.25	0.39	-0.64
$PM_{t-1}^2xAGE_{t-1}$	-11.58	29.28	-0.40
AGE_{t-1}	-0.01	0.02	-0.72
$SIZE_{t-1}$	-0.01	0.00	-8.25
$EXPENSE_{t-1}$	0.95	0.44	2.18
$FLOW_{t-1}$	0.15	0.01	15.72
$TVOL_{t-1}$	-0.27	0.11	-2.54

Panel D: constant DISAGREE2$_p$

	Coeff	Std	T-value
Intercept	0.08	0.06	1.47
PM_{t-1}	1.96	2.43	0.81
PM_{t-1}xDISAGREE2$_{t-1}$	-202.24	22.58	-8.96
PM_{t-1}^2	68.52	177.10	0.39
PM_{t-1}^2xDISAGREE2$_{t-1}$	-1871.63	1549.95	-1.21
PM_t	4.82	0.40	11.93
PM_{t-2}	0.73	0.54	1.34
PM_{t-3}	-0.80	0.41	-1.96
PM_{t-1}xAGE_{t-1}	-0.31	0.40	-0.78
PM_{t-1}^2xAGE_{t-1}	-11.81	29.37	-0.40
AGE_{t-1}	-0.01	0.02	-0.68
$SIZE_{t-1}$	-0.01	0.00	-8.23
$EXPENSE_{t-1}$	0.95	0.44	2.18
$FLOW_{t-1}$	0.15	0.01	15.73
$TVOL_{t-1}$	-0.25	0.11	-2.34

Table 7

Quarterly Panel Flow-performance Regressions using Three-factor Alphas

The performance measure ($PM_{p,t}$) is the alpha from the Fama-French factors:

$$r_{p,t} = \alpha_{p,FF3} + \beta_{mkt} r_{mkt,t} + \beta_{smb} r_{smb,t} + \beta_{hml} r_{hml,t} + \zeta_{p,t}$$

where all the $r_{,t}$ are excess returns. The panel regressions are for January, 1984 through December, 2008. The net flow is defined as the quarter-to-quarter growth in total net assets (TNA) in excess of fund returns. The performance measure ($PM_{p,t}$) is the unconditional alpha from the CAPM. Two measures of disagreement about alpha are used:

$$DISAGREE1_p = \sigma(\varepsilon_p)\, \sigma_G[\,|\rho(\varepsilon_p,G)|\,], \text{ and}$$

$$DISAGREE2_p = \sigma(\varepsilon_p)\, \sigma_G[\,|\rho(\varepsilon_p,G)/\rho(r_{j^*},G)|\,],$$

where $\rho(\varepsilon_p,G)$ is the time-series correlation between a fund's residual return and a state's electricity consumption growth and σ_G[.] denotes the cross-sectional standard deviation across the electricity consumption growths for the 50 states and the District of Columbia.
The symbol r_{j^*} **d**enotes the maximum correlation portfolio in a given set of benchmark returns, in this case the Sharpe ratio of the market proxy. The control variables include the lagged age (the natural logarithm of months since inception (AGE_{t-1}), the lagged size (the natural logarithm of TNA, $SIZE_{t-1}$), the expense ratio plus one-seventh of the front-end load ($EXPENSE_{t-1}$), the lagged net flow, the lagged performance measure (PM_{t-1}), the lagged fund total return volatility ($TVOL_{t-1}$), cross terms and other lags as shown. Panels A and B assume that DISAGREE is time-varying and uses the rolling standard deviations of fund residuals over the previous 36 months at each quarter t. Panel C and D assumes that DISAGREE is constant over the sample period.

Panel A: Rolling $DISAGREE1_p$

	Coeff	Std	T-value
Intercept	0.04	0.06	0.77
PM_{t-1}	1.07	3.01	0.35
PM_{t-1}x$DISAGREE_{t-1}$	-262.34	30.70	-8.55
PM_{t-1}^2	-18.09	207.82	-0.09
PM_{t-1}^2x$DISAGREE_{t-1}$	-6279.68	1865.95	-3.37
PM_t	4.77	0.47	10.09
PM_{t-2}	1.32	0.66	2.01
PM_{t-3}	-0.53	0.48	-1.11
PM_{t-1}xAGE_{t-1}	-0.17	0.50	-0.35
PM_{t-1}^2xAGE_{t-1}	15.23	35.58	0.43
AGE_{t-1}	0.00	0.02	-0.07
$SIZE_{t-1}$	-0.01	0.00	-7.65

$EXPENSE_{t-1}$	1.24	0.44	2.82
$FLOW_{t-1}$	0.15	0.01	16.01
$TVOL_{t-1}$	-0.26	0.11	-2.45

Panel B: Rollng DISAGREE2$_p$

	Coeff	Std	T-value
Intercept	0.04	0.06	0.75
PM_{t-1}	1.55	3.01	0.51
PM_{t-1}x$DISAGREE_{t-1}$	-267.64	31.93	-8.38
PM_{t-1}^2	-3.35	207.71	-0.02
PM_{t-1}^2x$DISAGREE_{t-1}$	-5937.93	1944.43	-3.05
PM_t	4.78	0.47	10.09
PM_{t-2}	1.32	0.66	2.01
PM_{t-3}	-0.52	0.48	-1.09
PM_{t-1}xAGE_{t-1}	-0.25	0.50	-0.50
PM_{t-1}^2xAGE_{t-1}	11.79	35.52	0.33
AGE_{t-1}	0.00	0.02	-0.05
$SIZE_{t-1}$	-0.01	0.00	-7.66
$EXPENSE_{t-1}$	1.22	0.44	2.77
$FLOW_{t-1}$	0.15	0.01	15.98
$TVOL_{t-1}$	-0.24	0.11	-2.24

Panel C: constant DISAGREE1$_p$

	Coeff	Std	T-value
Intercept	0.04	0.06	0.75
PM_{t-1}	3.37	3.03	1.11
PM_{t-1}x$DISAGREE_{t-1}$	-285.23	32.07	-8.90
PM_{t-1}^2	77.85	210.51	0.37
PM_{t-1}^2x$DISAGREE_{t-1}$	-4688.70	2028.06	-2.31
PM_t	4.82	0.47	10.19
PM_{t-2}	1.28	0.66	1.95
PM_{t-3}	-0.64	0.48	-1.34
PM_{t-1}xAGE_{t-1}	-0.52	0.50	-1.05
PM_{t-1}^2xAGE_{t-1}	-7.68	34.99	-0.22
AGE_{t-1}	0.00	0.02	-0.02
$SIZE_{t-1}$	-0.01	0.00	-7.60
$EXPENSE_{t-1}$	1.24	0.44	2.83
$FLOW_{t-1}$	0.15	0.01	16.01
$TVOL_{t-1}$	-0.31	0.11	-2.91

Panel D: constant DISAGREE2$_p$

	Coeff	Std	T-value
Intercept	0.04	0.06	0.72
PM_{t-1}	3.84	3.04	1.26
PM_{t-1}x$DISAGREE_{t-1}$	-298.86	34.15	-8.75
PM_{t-1}^2	77.27	211.18	0.37
PM_{t-1}^2x$DISAGREE_{t-1}$	-4503.22	2174.06	-2.07

PM_t	4.82	0.47	10.19
PM_{t-2}	1.28	0.66	1.95
PM_{t-3}	-0.64	0.48	-1.33
$PM_{t-1}xAGE_{t-1}$	-0.58	0.50	-1.17
$PM_{t-1}^2xAGE_{t-1}$	-8.24	35.01	-0.24
AGE_{t-1}	0.00	0.02	0.01
$SIZE_{t-1}$	-0.01	0.00	-7.62
$EXPENSE_{t-1}$	1.23	0.44	2.81
$FLOW_{t-1}$	0.15	0.01	16.00
$TVOL_{t-1}$	-0.30	0.11	-2.76

Table 8

Quarterly Nonparametric Panel Flow-performance Regressions Using CAPM Alphas

The panel regressions are for January, 1984 through December, 2008. The net flow is defined as the quarter-to-quarter growth in total net assets (TNA) in excess of fund returns. The performance measure ($PM_{p,t}$) is the unconditional alpha from the CAPM. Two measures of disagreement about alpha are used:

$$DISAGREE1_p = \sigma(\varepsilon_p)\, \sigma_G[\,|\rho(\varepsilon_p,G)|\,], \text{ and}$$

$$DISAGREE2_p = \sigma(\varepsilon_p)\, \sigma_G[\,|\rho(\varepsilon_p,G)/\rho(r_{j^*},G)|\,],$$

where $\rho(\varepsilon_p,G)$ is the time-series correlation between a fund's residual return and a state's electricity consumption growth and σ_G[.] denotes the cross-sectional standard deviation across the electricity consumption growths for the 50 states and the District of Columbia.
The symbol r_{j^*} denotes the maximum correlation portfolio in a given set of benchmark returns, in this case the Sharpe ratio of the market proxy. The control variables include the lagged age (the natural logarithm of months since inception (AGE_{t-1}), the lagged size (the natural logarithm of TNA, $SIZE_{t-1}$), the expense ratio plus one-seventh of the front-end load ($EXPENSE_{t-1}$), the lagged net flow, the lagged performance measure (PM_{t-1}), the lagged fund total return volatility ($TVOL_{t-1}$), cross terms and other lags as shown.

Panel A and B use dummies for the ranked performance measures. At each quarter t, the funds' performance measures are ranked and funds are classified into high (H), medium (M), and low (L) performance groups. For example, $PM_{H,p,t-1}$ **refers to a dummy indicating that the fund is in the H group.** The panel regression is:

$$\begin{aligned}FLOW_{p,t} = {} & a + \beta_1 * PM_{H,p,t-1} + \beta_2 * PM_{M,p,t-1} + \beta_3 * PM_{H,p,t-1} xDISAGREE_{p,t-1} + \beta_4 * PM_{M,p,t-1} xDISAGREE_{p,t-1} \\ & + \beta_5 * PM_{p,t} + \beta_6 * PM_{p,t-2} + \beta_7 * PM_{p,t-3} + \beta_8 * PM_{p,t-1} xAGE_{p,t-1} + \beta_9 * PM^2_{p,t-1} xAGE_{p,t-1} \\ & + \beta_{10} * AGE_{t-1} + \beta_{11} * SIZE_{p,t-1} + \beta_{12} * EXPENSE_{p,t-1} + \beta_{13} * VOL_{p,t-1} + \beta_{14} * FLOW_{p,t-1} + u_{i,t-1}\end{aligned}$$

Panel C and D use dummies for the ranked measures of disagreement. For example, $DISAGREE_{H,p,t-1}$ **is equal to 1.0 if the fund's disagreement measure falls into the top third at quarter t-1.** The panel regression is:

$$\begin{aligned}FLOW_{p,t} = {} & a + \beta_1 * PM_{p,t-1} + \beta_2 * PM^2_{p,t-1} + \beta_3 * PM_{p,t-1} xDISAGREE_{H,p,t-1} + \beta_4 * PM^2_{p,t-1} xDISAGREE_{H,p,t-1} \\ & + \beta_5 * PM_{p,t-1} xDISAGREE_{M,p,t-1} + \beta_6 * PM^2_{p,t-1} xDISAGREE_{M,p,t-1} + \beta_7 * PM_{p,t} + \beta_8 * PM_{p,t-2} + \beta_9 * PM_{p,t-3} \\ & + \beta_{10} * PM_{p,t-1} xAGE_{p,t-1} + \beta_{11} * PM^2_{p,t-1} xAGE_{p,t-1} + \beta_{12} * AGE_{t-1} + \beta_{13} * SIZE_{p,t-1} + \beta_{14} * EXPENSE_{p,t-1} \\ & + \beta_{15} * VOL_{p,t-1} + \beta_{16} * FLOW_{p,t-1} + u_{i,t-1}\end{aligned}$$

Panel A:

	Coeff	Std	T-value
Intercept	0.07	0.06	1.30
$PM_{H,t-1}$	0.03	0.00	7.76
$PM_{M,t-1}$	0.01	0.00	3.56
$PM_{H,t-1}xDISAGREE1_{t-1}$	-1.59	0.72	-2.19
$PM_{M,t-1}xDISAGREE1_{t-1}$	-1.45	0.87	-1.66
PM_{t}	4.57	0.40	11.41
PM_{t-2}	0.68	0.54	1.26
PM_{t-3}	-0.98	0.41	-2.40
$PM_{t-1}xAGE_{t-1}$	-0.45	0.10	-4.61
$PM_{t-1}^{2}xAGE_{t-1}$	-3.71	1.61	-2.30
AGE_{t-1}	-0.01	0.02	-0.77
$SIZE_{t-1}$	-0.01	0.00	-8.16
$EXPENSE_{t-1}$	0.92	0.44	2.11
$FLOW_{t-1}$	0.15	0.01	15.93
$TVOL_{t-1}$	-0.12	0.11	-1.08

Panel B:

	Coeff	Std	T-value
Intercept	0.07	0.06	1.30
$PM_{H,t-1}$	0.03	0.00	7.62
$PM_{M,t-1}$	0.01	0.00	3.55
$PM_{H,t-1}xDISAGREE2_{t-1}$	-1.28	0.72	-1.78
$PM_{M,t-1}xDISAGREE2_{t-1}$	-1.42	0.90	-1.58
PM_{t}	4.55	0.40	11.37
PM_{t-2}	0.68	0.54	1.25
PM_{t-3}	-0.99	0.41	-2.41
$PM_{t-1}xAGE_{t-1}$	-0.46	0.10	-4.73
$PM_{t-1}^{2}xAGE_{t-1}$	-3.78	1.61	-2.34
AGE_{t-1}	-0.01	0.02	-0.75
$SIZE_{t-1}$	-0.01	0.00	-8.14
$EXPENSE_{t-1}$	0.93	0.44	2.12
$FLOW_{t-1}$	0.15	0.01	15.95
$TVOL_{t-1}$	-0.13	0.11	-1.16

Panel C:

	Coeff	Std	T-value
Intercept	0.09	0.06	1.59
PM_{t-1}	2.80	2.62	1.07
PM_{t-1}^{2}	307.80	209.07	1.47
$PM_{t-1}xDISAGREE1_{H,t-1}$	-2.75	0.68	-4.06
$PM_{t-1}xDISAGREE1_{M,t-1}$	-1.11	0.73	-1.53
$PM_{t-1}^{2}xDISAGREE1_{H,t-1}$	-11.31	112.28	-0.10
$PM_{t-1}^{2}xDISAGREE1_{M,t-1}$	-36.40	114.35	-0.32
PM_{t}	4.67	0.40	11.56
PM_{t-2}	0.77	0.54	1.41

PM_{t-3}	-0.98	0.41	-2.40
$PM_{t-1}xAGE_{t-1}$	-0.40	0.40	-1.00
$PM_{t-1}^2xAGE_{t-1}$	-53.54	28.88	-1.85
AGE_{t-1}	-0.01	0.02	-0.85
$SIZE_{t-1}$	-0.01	0.00	-8.12
$EXPENSE_{t-1}$	1.00	0.44	2.27
$FLOW_{t-1}$	0.15	0.01	16.14
$TVOL_{t-1}$	-0.12	0.11	-1.10

Panel D:

	Coeff	Std	T-value
Intercept	0.09	0.06	1.57
PM_{t-1}	2.47	2.55	0.97
PM_{t-1}^2	331.15	201.32	1.64
$PM_{t-1}xDISAGREE2_{H,t-1}$	-2.89	0.66	-4.39
$PM_{t-1}xDISAGREE2_{M,t-1}$	-1.06	0.71	-1.50
$PM_{t-1}^2xDISAGREE2_{H,t-1}$	-30.68	101.04	-0.30
$PM_{t-1}^2xDISAGREE2_{M,t-1}$	-70.84	103.93	-0.68
PM_t	4.69	0.40	11.61
PM_{t-2}	0.77	0.54	1.41
PM_{t-3}	-0.96	0.41	-2.34
$PM_{t-1}xAGE_{t-1}$	-0.34	0.40	-0.84
$PM_{t-1}^2xAGE_{t-1}$	-54.32	28.82	-1.88
AGE_{t-1}	-0.01	0.02	-0.83
$SIZE_{t-1}$	-0.01	0.00	-8.14
$EXPENSE_{t-1}$	1.02	0.44	2.32
$FLOW_{t-1}$	0.15	0.01	16.03
$TVOL_{t-1}$	-0.12	0.11	-1.08

Table 9

Quarterly Nonparametric Panel Flow-performance Regressions Using Three-factor Alphas

The panel regressions are for January, 1984 through December, 2008. The net flow is defined as the quarter-to-quarter growth in total net assets (TNA) in excess of fund returns. The performance measure ($PM_{p,t}$) is the unconditional alpha from the Fama-French three-factor model. Two measures of disagreement about alpha are used:

$$DISAGREE1_p = \sigma(\varepsilon_p)\, \sigma_G[\,|\rho(\varepsilon_p,G)|\,], \text{ and}$$

$$DISAGREE2_p = \sigma(\varepsilon_p)\, \sigma_G[\,|\rho(\varepsilon_p,G)/\rho(r_{j^*},G)|\,],$$

where $\rho(\varepsilon_p,G)$ is the time-series correlation between a fund's residual return and a state's electricity consumption growth and σ_G[.] denotes the cross-sectional standard deviation across the electricity consumption growths for the 50 states and the District of Columbia.
The symbol r_{j^*} **d**enotes the maximum correlation portfolio in a given set of benchmark returns, in this case the Sharpe ratio of the market proxy. The control variables include the lagged age (the natural logarithm of months since inception (AGE_{t-1}), the lagged size (the natural logarithm of TNA, $SIZE_{t-1}$), the expense ratio plus one-seventh of the front-end load ($EXPENSE_{t-1}$), the lagged net flow, the lagged performance measure (PM_{t-1}), the lagged fund total return volatility ($TVOL_{t-1}$), cross terms and other lags as shown.

Panel A and B use dummies for the ranked performance measures. At each quarter t, the funds' performance measures are ranked and funds are classified into high (H), medium (M), and low (L) performance groups. For example, $PM_{H,p,t-1}$ **refers to a dummy indicating that the fund is in the H group.** The panel regression is:

$$FLOW_{p,t} = a + \beta_1 * PM_{H,p,t-1} + \beta_2 * PM_{M,p,t-1} + \beta_3 * PM_{H,p,t-1} xDISAGREE_{p,t-1} + \beta_4 * PM_{M,p,t-1} xDISAGREE_{p,t-1}$$
$$+ \beta_5 * PM_{p,t} + \beta_6 * PM_{p,t-2} + \beta_7 * PM_{p,t-3} + \beta_8 * PM_{p,t-1} xAGE_{p,t-1} + \beta_9 * PM^2_{p,t-1} xAGE_{p,t-1}$$
$$+ \beta_{10} * AGE_{t-1} + \beta_{11} * SIZE_{p,t-1} + \beta_{12} * EXPENSE_{p,t-1} + \beta_{13} * VOL_{p,t-1} + \beta_{14} * FLOW_{p,t-1} + u_{i,t-1}$$

Panel C and D use dummies for the ranked measures of disagreement. For example, $DISAGREE_{H,p,t-1}$ **is equal to 1.0 if the fund's disagreement measure falls into the top third at quarter t-1.** The panel regression is:

$$FLOW_{p,t} = a + \beta_1 * PM_{p,t-1} + \beta_2 * PM^2_{p,t-1} + \beta_3 * PM_{p,t-1} xDISAGREE_{H,p,t-1} + \beta_4 * PM^2_{p,t-1} xDISAGREE_{H,p,t-1}$$
$$+ \beta_5 * PM_{p,t-1} xDISAGREE_{M,p,t-1} + \beta_6 * PM^2_{p,t-1} xDISAGREE_{M,p,t-1} + \beta_7 * PM_{p,t} + \beta_8 * PM_{p,t-2} + \beta_9 * PM_{p,t-3}$$
$$+ \beta_{10} * PM_{p,t-1} xAGE_{p,t-1} + \beta_{11} * PM^2_{p,t-1} xAGE_{p,t-1} + \beta_{12} * AGE_{t-1} + \beta_{13} * SIZE_{p,t-1} + \beta_{14} * EXPENSE_{p,t-1}$$
$$+ \beta_{15} * VOL_{p,t-1} + \beta_{16} * FLOW_{p,t-1} + u_{i,t-1}$$

Panel A:

	Coeff	Std	T-value
Intercept	0.04	0.06	0.79
$PM_{H,t-1}$	0.03	0.00	6.76
$PM_{M,t-1}$	0.01	0.00	2.57
$PM_{H,t-1}xDISAGREE1_{t-1}$	-1.59	0.72	-2.22
$PM_{M,t-1}xDISAGREE1_{t-1}$	-1.09	1.03	-1.06
PM_{t}	4.72	0.47	10.08
PM_{t-2}	1.29	0.65	1.97
PM_{t-3}	-0.60	0.48	-1.25
$PM_{t-1}xAGE_{t-1}$	-0.54	0.12	-4.51
$PM_{t-1}^{2}xAGE_{t-1}$	-0.92	1.98	-0.47
AGE_{t-1}	0.00	0.02	-0.27
$SIZE_{t-1}$	-0.01	0.00	-7.61
$EXPENSE_{t-1}$	1.20	0.44	2.72
$FLOW_{t-1}$	0.15	0.01	16.25
$TVOL_{t-1}$	-0.18	0.11	-1.70

Panel B:

	Coeff	Std	T-value
Intercept	0.05	0.06	0.80
$PM_{H,t-1}$	0.03	0.00	6.75
$PM_{M,t-1}$	0.01	0.00	2.81
$PM_{H,t-1}xDISAGREE2_{t-1}$	-1.59	0.74	-2.13
$PM_{M,t-1}xDISAGREE2_{t-1}$	-1.47	1.05	-1.40
PM_{t}	4.72	0.47	10.08
PM_{t-2}	1.29	0.65	1.97
PM_{t-3}	-0.60	0.48	-1.25
$PM_{t-1}xAGE_{t-1}$	-0.54	0.12	-4.55
$PM_{t-1}^{2}xAGE_{t-1}$	-0.98	1.98	-0.50
AGE_{t-1}	0.00	0.02	-0.27
$SIZE_{t-1}$	-0.01	0.00	-7.61
$EXPENSE_{t-1}$	1.19	0.44	2.71
$FLOW_{t-1}$	0.15	0.01	16.25
$TVOL_{t-1}$	-0.17	0.11	-1.58

Panel C:

	Coeff	Std	T-value
Intercept	0.05	0.06	0.95
PM_{t-1}	5.11	3.25	1.58
PM_{t-1}^{2}	371.28	250.03	1.48
$PM_{t-1}xDISAGREE1_{H,t-1}$	-3.13	0.79	-3.97
$PM_{t-1}xDISAGREE1_{M,t-1}$	-0.90	0.83	-1.08
$PM_{t-1}^{2}xDISAGREE1_{H,t-1}$	-1.62	134.88	-0.01
$PM_{t-1}^{2}xDISAGREE1_{M,t-1}$	-64.52	138.03	-0.47
PM_{t}	4.76	0.47	10.03

PM_{t-2}	1.26	0.66	1.92
PM_{t-3}	-0.60	0.48	-1.25
$PM_{t-1}xAGE_{t-1}$	-0.82	0.50	-1.62
$PM_{t-1}^{2}xAGE_{t-1}$	-62.50	34.39	-1.82
AGE_{t-1}	0.00	0.02	-0.26
$SIZE_{t-1}$	-0.01	0.00	-7.54
$EXPENSE_{t-1}$	1.16	0.44	2.64
$FLOW_{t-1}$	0.15	0.01	16.17
$TVOL_{t-1}$	-0.21	0.11	-1.97

Panel D:

	Coeff	Std	T-value
Intercept	0.05	0.06	0.92
PM_{t-1}	5.62	3.21	1.75
PM_{t-1}^{2}	237.57	243.57	0.98
$PM_{t-1}xDISAGREE2_{H,t-1}$	-3.48	0.78	-4.49
$PM_{t-1}xDISAGREE2_{M,t-1}$	-1.24	0.82	-1.51
$PM_{t-1}^{2}xDISAGREE2_{H,t-1}$	109.47	121.14	0.90
$PM_{t-1}^{2}xDISAGREE2_{M,t-1}$	7.26	125.36	0.06
PM_{t}	4.78	0.47	10.08
PM_{t-2}	1.30	0.66	1.98
PM_{t-3}	-0.59	0.48	-1.22
$PM_{t-1}xAGE_{t-1}$	-0.85	0.50	-1.70
$PM_{t-1}^{2}xAGE_{t-1}$	-58.33	34.43	-1.69
AGE_{t-1}	0.00	0.02	-0.22
$SIZE_{t-1}$	-0.01	0.00	-7.61
$EXPENSE_{t-1}$	1.16	0.44	2.65
$FLOW_{t-1}$	0.15	0.01	16.09
$TVOL_{t-1}$	-0.22	0.11	-2.04

Table 10

Quarterly Panel Flow-performance Regression with the Correlation Component of the DISAGREE measures

The panel regressions are for January, 1984 through December, 2008. Two measures of disagreement about alpha are used:

$$\text{DISAGREE1}_p = \sigma_G[\,|\rho(\varepsilon_p,G)|\,], \text{ and}$$
$$\text{DISAGREE2}_p = \sigma_G[\,|\rho(\varepsilon_p,G)/\rho(r_{j^*},G)|\,],$$

where $\rho(\varepsilon_p,G)$ is the time-series correlation between a fund's residual return and a state's electricity consumption growth and $\sigma_G[.]$ denotes the cross-sectional standard deviation across the electricity consumption growths for the 50 states and the District of Columbia. The symbol r_{j^*} denotes the maximum correlation portfolio in a given set of benchmark returns, for the CAPM the market proxy excess return. The control variables include the lagged age (the natural logarithm of months since inception (AGE_{t-1}), the lagged size (the natural logarithm of TNA, $SIZE_{t-1}$), the expense ratio plus one-seventh of the front-end load ($EXPENSE_{t-1}$), the lagged net flow, the lagged performance measure (PM_{t-1}), the lagged fund total return volatility ($TVOL_{t-1}$), cross terms and other lags as shown. Panel A and B use the unconditional alpha from the CAPM as the performance measure ($PM_{p,t}$). Panel C and D use the alpha from the Fama-French factors. Panels E-H use the Ferson and Schadt (1996) conditional alphas. Panels E and F use conditional CAPM alphas and panels G and H use conditional Fama-French factor alphas. The public information variables include the lagged one-month Treasury Bill, the lagged dividend yield, the lagged term spread, and the lagged default spread.

Panel A: DISAGREE1_p with Unconditional CAPM alphas

	Coeff	Std	T-value
PM_{t-1}	0.08	0.06	1.36
$PM_{t-1}xDISAGREE_{t-1}$	3.61	2.71	1.33
PM_{t-1}^2	-18.30	4.48	-4.08
$PM_{t-1}^2xDISAGREE_{t-1}$	742.56	192.04	3.87
PM_t	-1107.88	241.15	-4.59
PM_{t-2}	4.63	0.40	11.47
PM_{t-3}	0.75	0.54	1.38
$PM_{t-1}xAGE_{t-1}$	-1.00	0.41	-2.44
$PM_{t-1}^2xAGE_{t-1}$	-0.31	0.40	-0.77
AGE_{t-1}	-91.07	29.64	-3.07
$SIZE_{t-1}$	-0.01	0.02	-0.68
$EXPENSE_{t-1}$	-0.01	0.00	-7.83
$FLOW_{t-1}$	1.08	0.44	2.46
$TVOL_{t-1}$	0.15	0.01	16.27
	-0.31	0.11	-2.82

Panel B: DISAGREE2$_p$ with Unconditional CAPM alpha

	Coeff	Std	T-value
PM_{t-1}	0.08	0.06	1.44
PM_{t-1}x$DISAGREE_{t-1}$	-0.89	2.68	-0.33
PM_{t-1}^2	-3.01	4.05	-0.74
PM_{t-1}^2x$DISAGREE_{t-1}$	599.72	195.82	3.06
PM_t	-588.90	241.73	-2.44
PM_{t-2}	4.62	0.40	11.42
PM_{t-3}	0.76	0.54	1.40
PM_{t-1}xAGE_{t-1}	-1.01	0.41	-2.46
PM_{t-1}^2xAGE_{t-1}	-0.05	0.40	-0.12
AGE_{t-1}	-84.82	30.04	-2.82
$SIZE_{t-1}$	-0.01	0.02	-0.80
$EXPENSE_{t-1}$	-0.01	0.00	-7.84
$FLOW_{t-1}$	1.11	0.44	2.53
$TVOL_{t-1}$	0.15	0.01	16.31
	-0.19	0.11	-1.76

Panel C: DISAGREE1$_p$ with Unconditional Fama-French alphas

	Coeff	Std	T-value
PM_{t-1}	0.04	0.06	0.68
PM_{t-1}x$DISAGREE_{t-1}$	4.61	3.33	1.39
PM_{t-1}^2	-26.18	5.20	-5.04
PM_{t-1}^2x$DISAGREE_{t-1}$	763.23	231.61	3.30
PM_t	-1482.12	320.73	-4.62
PM_{t-2}	4.72	0.47	9.96
PM_{t-3}	1.37	0.66	2.09
PM_{t-1}xAGE_{t-1}	-0.81	0.48	-1.68
PM_{t-1}^2xAGE_{t-1}	-0.35	0.50	-0.70
AGE_{t-1}	-82.72	35.69	-2.32
$SIZE_{t-1}$	0.00	0.02	0.00
$EXPENSE_{t-1}$	-0.01	0.00	-7.51
$FLOW_{t-1}$	1.28	0.44	2.91
$TVOL_{t-1}$	0.16	0.01	16.51
	-0.38	0.11	-3.48

Panel D: DISAGREE2$_p$ with Unconditional Fama-French alphas

	Coeff	Std	T-value
PM_{t-1}	0.04	0.06	0.65
PM_{t-1}x$DISAGREE_{t-1}$	1.96	3.34	0.59
PM_{t-1}^2	-15.12	5.25	-2.88
PM_{t-1}^2x$DISAGREE_{t-1}$	860.28	239.91	3.59
PM_t	-1407.05	355.14	-3.96
PM_{t-2}	4.75	0.47	10.01
PM_{t-3}	1.39	0.66	2.11

$PM_{t-1}xAGE_{t-1}$	-0.76	0.48	-1.57
$PM_{t-1}^2xAGE_{t-1}$	-0.23	0.50	-0.47
AGE_{t-1}	-101.32	36.16	-2.80
$SIZE_{t-1}$	0.00	0.02	0.03
$EXPENSE_{t-1}$	-0.01	0.00	-7.65
$FLOW_{t-1}$	1.27	0.44	2.90
$TVOL_{t-1}$	0.16	0.01	16.55
	-0.30	0.11	-2.82

Panel E: $DISAGREE1_p$ with Conditional CAPM alphas

	Coeff	Std	T-value
PM_{t-1}	0.08	0.06	1.47
$PM_{t-1}xDISAGREE_{t-1}$	0.06	2.43	0.02
PM_{t-1}^2	-4.14	4.08	-1.02
$PM_{t-1}^2xDISAGREE_{t-1}$	303.01	129.62	2.34
PM_t	110.00	155.54	0.71
PM_{t-2}	3.09	0.35	8.88
PM_{t-3}	-0.74	0.48	-1.53
$PM_{t-1}xAGE_{t-1}$	-0.59	0.35	-1.67
$PM_{t-1}^2xAGE_{t-1}$	0.17	0.36	0.48
AGE_{t-1}	-59.03	19.76	-2.99
$SIZE_{t-1}$	-0.01	0.02	-0.80
$EXPENSE_{t-1}$	-0.01	0.00	-7.73
$FLOW_{t-1}$	0.86	0.44	1.96
$TVOL_{t-1}$	0.16	0.01	16.35
	-0.25	0.11	-2.25

Panel F: $DISAGREE2_p$ with Conditional CAPM alphas

	Coeff	Std	T-value
PM_{t-1}	0.09	0.06	1.58
$PM_{t-1}xDISAGREE_{t-1}$	-3.95	2.44	-1.62
PM_{t-1}^2	8.95	3.99	2.24
$PM_{t-1}^2xDISAGREE_{t-1}$	389.48	135.00	2.88
PM_t	-121.77	169.76	-0.72
PM_{t-2}	3.06	0.35	8.78
PM_{t-3}	-0.73	0.48	-1.51
$PM_{t-1}xAGE_{t-1}$	-0.64	0.35	-1.82
$PM_{t-1}^2xAGE_{t-1}$	0.44	0.36	1.23
AGE_{t-1}	-66.26	20.25	-3.27
$SIZE_{t-1}$	-0.01	0.02	-0.92
$EXPENSE_{t-1}$	-0.01	0.00	-7.80
$FLOW_{t-1}$	0.88	0.44	2.02
$TVOL_{t-1}$	0.16	0.01	16.43
	-0.21	0.11	-1.90

Panel G: DISAGREE1$_p$ with Conditional Fama-French alphas

	Coeff	Std	T-value
PM_{t-1}	0.05	0.06	0.89
$PM_{t-1}xDISAGREE_{t-1}$	3.94	2.72	1.45
PM_{t-1}^2	-20.00	3.78	-5.29
$PM_{t-1}^2xDISAGREE_{t-1}$	298.32	165.08	1.81
PM_t	-973.98	210.06	-4.64
PM_{t-2}	2.35	0.33	7.17
PM_{t-3}	0.87	0.43	2.04
$PM_{t-1}xAGE_{t-1}$	0.08	0.32	0.23
$PM_{t-1}^2xAGE_{t-1}$	-0.23	0.41	-0.57
AGE_{t-1}	-18.00	25.30	-0.71
$SIZE_{t-1}$	-0.01	0.02	-0.39
$EXPENSE_{t-1}$	-0.01	0.00	-6.90
$FLOW_{t-1}$	1.27	0.44	2.90
$TVOL_{t-1}$	0.17	0.01	17.70
	-0.29	0.10	-2.75

Panel H: DISAGREE2$_p$ with Conditional Fama-French alphas

	Coeff	Std	T-value
PM_{t-1}	0.05	0.06	0.90
$PM_{t-1}xDISAGREE_{t-1}$	1.38	2.73	0.51
PM_{t-1}^2	-13.00	4.14	-3.14
$PM_{t-1}^2xDISAGREE_{t-1}$	441.74	167.79	2.63
PM_t	-1220.09	230.05	-5.30
PM_{t-2}	2.26	0.33	6.89
PM_{t-3}	0.83	0.43	1.93
$PM_{t-1}xAGE_{t-1}$	0.03	0.32	0.11
$PM_{t-1}^2xAGE_{t-1}$	-0.03	0.40	-0.06
AGE_{t-1}	-37.04	25.50	-1.45
$SIZE_{t-1}$	-0.01	0.02	-0.37
$EXPENSE_{t-1}$	-0.01	0.00	-7.18
$FLOW_{t-1}$	1.31	0.44	2.97
$TVOL_{t-1}$	0.17	0.01	17.85
	-0.24	0.10	-2.29

Table 11

Quarterly Flow-performance Regressions with Orthogonalized Disagreement Measures

The panel regressions are for January, 1984 through December, 2008. We first run cross-sectional regressions of the disagreement measures on the White standard errors of mutual fund alphas from their time series regressions, and construct the orthogonalized disagreement measures as the intercept plus residuals from the cross-sectional regression. Two measures of disagreement about alpha are used:

$$DISAGREE1_p = \sigma(\varepsilon_p)\,\sigma_G[\,|\,\rho(\varepsilon_p,G)\,|\,], \text{ and}$$

$$DISAGREE2_p = \sigma(\varepsilon_p)\,\sigma_G[\,|\,\rho(\varepsilon_p,G)/\rho(r_{j^*},G)\,|\,],$$

where $\rho(\varepsilon_p,G)$ is the time-series correlation between a fund's residual return and a state's electricity consumption growth and $\sigma_G[.]$ denotes the cross-sectional standard deviation across the electricity consumption growths for the 50 states and the District of Columbia. The symbol r_{j^*} denotes the maximum correlation portfolio in a given set of benchmark returns, which for the CAPM is the market proxy excess return. The control variables include the lagged age (the natural logarithm of months since inception (AGE_{t-1}), the lagged size (the natural logarithm of TNA, $SIZE_{t-1}$), the expense ratio plus one-seventh of the front-end load ($EXPENSE_{t-1}$), the lagged net flow, lagged performance measures (PM_{t-j}), the lagged fund total return volatility ($TVOL_{t-1}$), cross terms and other lags as shown. Panels A and B use the unconditional alpha from the CAPM as the performance measure (PM_{t-1}). Panels C and D use the alpha from the Fama-French factors. Panels E-H use the Ferson and Schadt (1996) conditional alphas. Panels E and F use conditional CAPM alphas and panels G and H use conditional Fama-French factor alphas. The public information variables include the lagged one-month Treasury Bill, the lagged dividend yield, the lagged term spread, and the lagged default spread.

Panel A: $DISAGREE1_p$ with Unconditional CAPM alphas

	Coeff	Std	T-value
Intercept	0.07	0.06	1.28
PM_{t-1}	1.41	2.67	0.53
$PM_{t-1}xDISAGREE1_{t-1}$	-11.69	4.20	-2.79
PM_{t-1}^2	722.60	191.38	3.78
$PM_{t-1}^2xDISAGREE1_{t-1}$	-1006.54	223.43	-4.51
PM_t	4.62	0.40	11.44
PM_{t-2}	0.75	0.54	1.38
PM_{t-3}	-1.02	0.41	-2.49
$PM_{t-1}xAGE_{t-1}$	-0.17	0.40	-0.42
$PM_{t-1}^2xAGE_{t-1}$	-93.36	29.91	-3.12
AGE_{t-1}	-0.01	0.02	-0.61
$SIZE_{t-1}$	-0.01	0.00	-7.77
$EXPENSE_{t-1}$	1.09	0.44	2.49

$FLOW_{t-1}$	0.15	0.01	16.29
$TVOL_{t-1}$	-0.28	0.11	-2.55

Panel B: DISAGREE2$_p$ with Unconditional CAPM alpha

	Coeff	Std	T-value
Intercept	0.08	0.06	1.51
PM_{t-1}	-2.61	2.74	-0.95
$PM_{t-1}xDISAGREE1_{t-1}$	2.02	4.19	0.48
PM_{t-1}^2	750.47	202.08	3.71
$PM_{t-1}^2xDISAGREE1_{t-1}$	-828.58	240.22	-3.45
PM_t	4.61	0.40	11.41
PM_{t-2}	0.76	0.54	1.40
PM_{t-3}	-1.02	0.41	-2.50
$PM_{t-1}xAGE_{t-1}$	0.09	0.41	0.23
$PM_{t-1}^2xAGE_{t-1}$	-104.79	30.95	-3.39
AGE_{t-1}	-0.01	0.02	-0.85
$SIZE_{t-1}$	-0.01	0.00	-7.90
$EXPENSE_{t-1}$	1.08	0.44	2.47
$FLOW_{t-1}$	0.15	0.01	16.32
$TVOL_{t-1}$	-0.17	0.11	-1.57

Panel C: DISAGREE1$_p$ with Unconditional Fama-French alphas

	Coeff	Std	T-value
Intercept	0.04	0.06	0.71
PM_{t-1}	3.55	3.32	1.07
$PM_{t-1}xDISAGREE1_{t-1}$	-23.04	5.43	-4.24
PM_{t-1}^2	823.55	230.27	3.58
$PM_{t-1}^2xDISAGREE1_{t-1}$	-1576.33	326.91	-4.82
PM_t	4.73	0.47	9.97
PM_{t-2}	1.39	0.66	2.11
PM_{t-3}	-0.81	0.48	-1.67
$PM_{t-1}xAGE_{t-1}$	-0.30	0.50	-0.60
$PM_{t-1}^2xAGE_{t-1}$	-92.92	35.69	-2.60
AGE_{t-1}	0.00	0.02	-0.03
$SIZE_{t-1}$	-0.01	0.00	-7.54
$EXPENSE_{t-1}$	1.27	0.44	2.89
$FLOW_{t-1}$	0.16	0.01	16.55
$TVOL_{t-1}$	-0.36	0.11	-3.35

Panel D: DISAGREE2$_p$ with Unconditional Fama-French alphas

	Coeff	Std	T-value
Intercept	0.04	0.06	0.72
PM_{t-1}	0.51	3.32	0.15
$PM_{t-1}xDISAGREE1_{t-1}$	-9.98	5.38	-1.86

PM_{t-1}^2	896.27	236.91	3.78
$PM_{t-1}^2xDISAGREE1_{t-1}$	-1459.51	355.14	-4.11
PM_t	4.76	0.47	10.04
PM_{t-2}	1.40	0.66	2.12
PM_{t-3}	-0.74	0.48	-1.54
$PM_{t-1}xAGE_{t-1}$	-0.17	0.50	-0.34
$PM_{t-1}^2xAGE_{t-1}$	-109.27	36.13	-3.02
AGE_{t-1}	0.00	0.02	-0.03
$SIZE_{t-1}$	-0.01	0.00	-7.68
$EXPENSE_{t-1}$	1.26	0.44	2.87
$FLOW_{t-1}$	0.16	0.01	16.56
$TVOL_{t-1}$	-0.28	0.11	-2.63

Panel E: $DISAGREE1_p$ with Conditional CAPM alphas

	Coeff	Std	T-value
Intercept	0.08	0.06	1.50
PM_{t-1}	-1.25	2.36	-0.53
$PM_{t-1}xDISAGREE1_{t-1}$	0.23	3.85	0.06
PM_{t-1}^2	307.05	130.32	2.36
$PM_{t-1}^2xDISAGREE1_{t-1}$	89.68	150.35	0.60
PM_t	3.08	0.35	8.83
PM_{t-2}	-0.74	0.48	-1.53
PM_{t-3}	-0.61	0.35	-1.72
$PM_{t-1}xAGE_{t-1}$	0.25	0.36	0.72
$PM_{t-1}^2xAGE_{t-1}$	-58.97	20.00	-2.95
AGE_{t-1}	-0.01	0.02	-0.84
$SIZE_{t-1}$	-0.01	0.00	-7.74
$EXPENSE_{t-1}$	0.86	0.44	1.95
$FLOW_{t-1}$	0.16	0.01	16.38
$TVOL_{t-1}$	-0.22	0.11	-1.99

Panel F: $DISAGREE2_p$ with Conditional CAPM alphas

	Coeff	Std	T-value
Intercept	0.09	0.06	1.65
PM_{t-1}	-3.99	2.44	-1.64
$PM_{t-1}xDISAGREE1_{t-1}$	8.63	3.80	2.27
PM_{t-1}^2	336.23	138.20	2.43
$PM_{t-1}^2xDISAGREE1_{t-1}$	-14.33	162.89	-0.09
PM_t	3.07	0.35	8.83
PM_{t-2}	-0.73	0.48	-1.52
PM_{t-3}	-0.63	0.35	-1.77
$PM_{t-1}xAGE_{t-1}$	0.46	0.36	1.27
$PM_{t-1}^2xAGE_{t-1}$	-60.80	20.80	-2.92
AGE_{t-1}	-0.02	0.02	-0.98
$SIZE_{t-1}$	-0.01	0.00	-7.80

$EXPENSE_{t-1}$	0.84	0.44	1.92
$FLOW_{t-1}$	0.16	0.01	16.41
$TVOL_{t-1}$	-0.20	0.11	-1.85

Panel G: $DISAGREE1_p$ with Conditional Fama-French alphas

	Coeff	Std	T-value
Intercept	0.06	0.06	1.01
PM_{t-1}	2.42	2.70	0.90
$PM_{t-1}xDISAGREE1_{t-1}$	-16.86	4.17	-4.04
PM_{t-1}^2	326.99	159.53	2.05
$PM_{t-1}^2xDISAGREE1_{t-1}$	-1051.38	205.21	-5.12
PM_t	2.32	0.33	7.08
PM_{t-2}	0.87	0.43	2.04
PM_{t-3}	0.06	0.32	0.18
$PM_{t-1}xAGE_{t-1}$	-0.12	0.40	-0.30
$PM_{t-1}^2xAGE_{t-1}$	-24.28	25.04	-0.97
AGE_{t-1}	-0.01	0.02	-0.51
$SIZE_{t-1}$	-0.01	0.00	-6.97
$EXPENSE_{t-1}$	1.32	0.44	2.99
$FLOW_{t-1}$	0.17	0.01	17.81
$TVOL_{t-1}$	-0.29	0.10	-2.77

Panel H: $DISAGREE2_p$ with Conditional Fama-French alphas

	Coeff	Std	T-value
Intercept	0.05	0.06	0.94
PM_{t-1}	0.68	2.72	0.25
$PM_{t-1}xDISAGREE1_{t-1}$	-10.76	4.40	-2.45
PM_{t-1}^2	364.66	161.61	2.26
$PM_{t-1}^2xDISAGREE1_{t-1}$	-1084.03	220.66	-4.91
PM_t	2.27	0.33	6.94
PM_{t-2}	0.85	0.43	1.99
PM_{t-3}	0.03	0.32	0.10
$PM_{t-1}xAGE_{t-1}$	-0.01	0.40	-0.02
$PM_{t-1}^2xAGE_{t-1}$	-31.44	25.17	-1.25
AGE_{t-1}	-0.01	0.02	-0.42
$SIZE_{t-1}$	-0.01	0.00	-7.18
$EXPENSE_{t-1}$	1.29	0.44	2.94
$FLOW_{t-1}$	0.17	0.01	17.85
$TVOL_{t-1}$	-0.25	0.10	-2.39

Figure 1: Fund Flow-performance of High/Medium/Low Disagreement Funds