Investment Decisions under Ambiguity: Evidence from Mutual Fund Investor Behavior

Abstract

This study provides novel evidence on the role of ambiguity aversion in determining the response of mutual fund investors to historical fund performance information. We present a model of ambiguity averse investors who receive multiple performance-based signals of uncertain precision about manager skill. A key implication of the model is that when investors receive multiple signals of uncertain quality, they place a greater weight on the worst signal. We find strong empirical support for this prediction in the data. Fund flows display significantly higher sensitivity to the worst performance measure even after controlling for performance volatility and a host of other relevant explanatory variables. This effect is particularly pronounced in the case of retail funds in contrast to institutional funds. Our results suggest that fund investor behavior is best characterized as reflecting both Bayesian learning and ambiguity aversion.

Keywords: Ambiguity aversion, Mutual fund performance, Investor behavior, Bayesian learning, Flow-performance sensitivity

" When the individual is plunged into a fast and irregularly changing situation or a novelty-loaded context ... his predictive accuracy plummets. He can no longer make the reasonably correct assessments on which rational behavior is dependent." (Alvin Toffler in *Future Shock*, pp. 350)

I. Introduction

The technological advances of recent decades and the resulting reduction in the cost of information have made *information overload*, a term popularized by futurist Alvin Toffler, a reality. Investors today operate in a world with increasing complexity requiring them to process large amounts of information while making decisions. However, information quality can often be difficult to judge for investors. As argued by Epstein and Schneider (2008), when faced by information signals of unknown quality, investors treat the signals as being ambiguous. In this situation, investors do not update their beliefs in Bayesian fashion. Instead, they act as if they have multiple likelihoods in mind. There is considerable experimental evidence documenting that investors are ambiguity averse (e.g., Bossaerts, Ghirardato, Guarnaschelli and Zame (2010), Ahn, Choi, Gale, and Kariv (2011)). Understanding how information ambiguity impacts investor choices is clearly important. In this study we provide novel evidence on this issue by examining the response of mutual fund investors to historical fund performance information.

Mutual funds offer an appealing setting in which to study the role of ambiguity on investor decisions for a number of reasons. First, mutual funds represent a very substantial component of U.S. household portfolios. Second, the well-documented phenomenon of performance-chasing by fund investors suggests a natural link between performance-related information and the investment/divestment decisions of investors. Third, funds typically make available performance statistics including relative rankings measured at various horizons (e.g., 1-year, 3-year, 5-year, and since-inception) which serve as multiple signals to investors about fund manager skill. Each of the multiple signals reflects the performance of a particular fund relative to the available pool of funds, albeit over different time horizons. In this sense, the signals are comparable and studying the response of investors to various signals allows for a natural test of decision making under ambiguity in a non-experimental setting.

Our study extends the extant literature by examining the impact of ambiguity about manager skill on investor decisions. We adopt the standard distinction made in the literature between risk and uncertainty following Knight (1921). Knight considered risky events as those that could be described by known probability distributions versus uncertain events for which the probability distributions were not known. As famously demonstrated by Ellsberg (1961), individuals are averse to the ambiguity that characterizes decisions under conditions of uncertainty. It is reasonable to believe that individual investors are faced with considerable ambiguity when it comes to their fund investment decision. Investors face a dizzying array of choices when choosing a mutual fund. For example, according to the 2012 Investment Company Fact Book, there were more than 4,500 U.S. equity mutual funds in existence at the end of 2011. Investors are also subjected to a barrage of performance statistics on the funds. While these performance data provide signals of the fund managers′ skill, the investors clearly face a great deal of uncertainty about the quality of the signals. Past performance is at best a noisy signal of managerial skill. How do ambiguity averse investors interpret and respond to such signals? The goal of this study is to provide some answers to this question as a way to further our understanding of mutual fund investor behavior.

We present a simple model of ambiguity averse investors who receive multiple performance-based signals of uncertain precision about manager skill or fund alpha. The model relies on the framework of Epstein and Schneider (2008), Klibanoff, Marinacci and Mukerji (2005), and Ju and Miao (2012). Investors in the model are risk-neutral yet averse to the ambiguity regarding manager skill or alpha. Given the uncertainty about the quality of multiple signals, investors do not update their beliefs in standard Bayesian fashion but rather they behave as if they have multiple conditional distributions in mind for the future fund performance. Intuitively, ambiguity averse investors prefer to make a fund choice that is more robust across the multiple distributions. A key implication of the model is that when investors receive multiple signals of uncertain quality, they place a greater weight on the worst signal. In practical terms this implies that ambiguity averse investors are more sensitive to the worst-case scenario when evaluating funds. We find strong empirical support for this prediction in the data. Specifically, we examine the sensitivity of fund flows to past performance measured over multiple time horizons: 1 year, 3 years, and 5 years. We find that fund flows display significantly higher sensitivity to the worst performance measure even after controlling for performance volatility and a host of other relevant explanatory variables. This effect is particularly pronounced in the case of retail funds whose investors are likely to face a higher degree of uncertainty regarding the quality of performance-related signals they observe, compared to the institutional fund investors.

We use a number of fund characteristics as proxies for the degree of ambiguity about fund performance/manager skill. These include the fund′s investment strategy shifts, return volatility, fund flow volatility, family size, and marketing effort/expenditure. We consistently find that in cases with higher degree of ambiguity as captured by our proxy measures, fund flows display significantly higher sensitivity to the worst performance measure.

We next examine the implications of the potential differences in the ambiguity-aversion of retail and institutional investors. The latter are typically viewed as being relatively sophisticated investors with a better understanding of the fund industry and who are therefore better able to interpret performance-related signals. Consequently, such investors face less ambiguity and may update their beliefs after observing the signals in a manner consistent with Bayesian rules. In a recent paper Huang, Wei, and Yan (2012) show that investor fund flow sensitivity to past performance is decreasing with fund return volatility. An increase in fund return volatility implies that past performance is a less precise signal of skill or ability and hence investors rationally moderate their response to the signal. High volatility is naturally associated with a high degree of uncertainty. Traditionally, uncertainty has been viewed as being the result of low signal precision. However, for ambiguity averse agents, high volatility could also imply a high degree of ambiguity surrounding the signal. Hence, as we show later, the impact of volatility on the flow-performance sensitivity is likely to reflect both the impact of signal precision as well as the ambiguity aversion of the investors.

In contrast to institutional investors, the retail investors are generally thought of as being less sophisticated. They have access to the same past performance related signals, but view these as being ambiguous. Our results suggest that ambiguity aversion plays a role in the behavior of both groups of investors to a varying degree. Consistent with Bayesian updating, investor flow sensitivity to past performance declines with increasing fund return volatility. The dampening effect of return volatility on flow-performance sensitivity is more pronounced for institutional investors, which is consistent with the notion of such investors being more sophisticated.

Interestingly, however, increasing performance volatility can in fact also lead to an increase in flow sensitivity to the worst performance signal for both groups of investors, although the increase is more pronounced for retail investors. This suggests that investor behavior is best characterized as reflecting both Bayesian updating and ambiguity-aversion with the two groups of investors displaying interesting differences in their response behavior. Institutional investors appear to behave in a manner more consistent with Bayesian updating whereas ambiguity aversion appears to play a relatively bigger role in the fund investment decisions of retail investors.

Our study makes a number of contributions to the mutual fund literature and more generally to the evolving literature on the role of ambiguity in asset pricing. One, to our knowledge, it is the first study that explores the impact of ambiguity on fund investor decisions. Two, the paper complements recent findings on how fund investors respond to information about past fund performance. Three, the paper extends recent results in the literature on the impact of uncertainty in addition to risk, on expected asset returns. For example, when investors receive information of uncertain quality, theoretical models imply that aversion to ambiguity not only induces ambiguity premia and skewness in returns (Epstein and Schneider (2008)), but also results in non-participation (Easley and O′Hara (2009), portfolio inertia and excess volatility (Illeditsch (2011)). However, there is limited empirical evidence in the literature on ambiguity-aversion behavior in asset markets. A recent exception is the study by Anderson, Ghysels, and Juergens (2009), which provides empirical evidence of an uncertainty-return tradeoff in equity markets.

The rest of the paper is organized as follows. Section II reviews the literature on ambiguity aversion. Section III presents our model of ambiguity averse fund investors and derives testable implications. The data and empirical methodology are described in Section IV while Section V presents the main empirical results. Section VI presents the results of tests contrasting the response of Bayesian fund investors with that of ambiguity averse investors. Section VII presents the results of robustness tests and concluding remarks are presented in Section VIII.

II. Ambiguity Aversion

The distinction between risk and uncertainty was highlighted by Knight (1921) who defined uncertain events as those for which the probability distribution of outcomes is unknown.[1] The work of Daniel Ellsberg (1961) famously provided evidence of individual aver-

[1] According to Knight (1921), "The practical difference between risk and uncertainty, is that in the former the distribution of the outcome in a group of instances is known (either through calculation a priori or from statistics of past experiences), while in the case of uncertainty this is not true, the reason being that it is impossible to form a group of instances, because the situation dealt with is in a high degree unique." (p. 103).

sion to ambiguity or uncertainty (in contrast to risk). Subsequently, a large theoretical literature has evolved to formally develop models that accommodate ambiguity averse behavior and its implications. For example, Gilboa and Schmeidler (1989) propose an axiomatic framework of ambiguity aversion. They construct an atemporal model in which preferences are represented by max-min expected utility over multiple possible distributions. Epstein and Schneider (2003) provide axiomatic foundation for intertemporal multiple-priors utility in discrete time. Chen and Epstein (2002) extend the model to continuous time.

This ambiguity aversion framework has subsequently been applied to explain some of the well known phenomena in asset markets. For example, Leippold, Trojani and Vanini (2007) incorporate both learning and ambiguity in a Lucas exchange economy. The model is able to match the observed equity premium, the interest rate and the stock return volatility, under empirically plausible parameter values. Epstein and Schneider (2008) study ambiguity averse investor behavior when processing information of uncertain quality. They find that aversion to ambiguity induces ambiguity premia and skewness in returns. Easley and O′Hara (2009) find that ambiguity aversion on the part of some traders can lead to non-participation in asset markets. Illeditsch (2011) finds that when investors receive a signal with unknown precision, ambiguity aversion causes portfolio inertia and excess volatility. In an experimental setting, Bossaerts, Ghirardato, Guarnaschelli and Zame (2010) find that investors hold heterogeneous attitudes toward ambiguity across the population. Moreover, they show that there is a wide range of prices for which a sufficiently ambiguity averse investor will avoid an ambiguous portfolio. In contrast to the experimental studies, there is limited empirical evidence regarding the ambiguity averse behavior of investors. An exception is the study by Anderson, Ghysels, and Juergens (2009) that provides empirical evidence of an uncertainty-return tradeoff in equity markets.

Our paper contributes to the ambiguity literature in two aspects. First, we extend the extant theoretical framework to a multiple signals setting. We provide an answer to the question of how ambiguity aversion impacts investor decisions when facing multiple signals with unknown quality. Second, we provide empirical evidence based on the behavior of mutual fund investors that is consistent with the model′s implications. To our knowledge ours is the first attempt at using an ambiguity aversion framework to study the response of fund investors to fund performance based signals.

III. The Model and Its Empirical Implications

In this section, we build a model to analyze the important features of the flow-performance sensitivity for an ambiguity-averse mutual fund investor and derive testable empirical predictions.

A. The Model

Assume there is a population of investors, each with 1 unit of capital to invest with a fund. The investor decides on whether to fully invest her unit of capital with a particular fund. Her decision is based on her opportunity cost of capital, denoted hereafter by k, which is assumed to differ across the investors. The investors, indexed by k, are otherwise assumed to be identical. We assume that k has the support in $[0, \infty)$,with cumulative distribution function denoted by $F(k)$.

The fund′s return, R, is governed by

$$R = \mu + \alpha + \epsilon, \tag{1}$$

where α denotes the fund manager′s skill, μ is the market risk premium given the fund′s risk profile, and $\epsilon \sim N\left(0, \sigma_\epsilon^2\right)$ represents the noisy component of the fund′s return. The risk-free rate is normalized to zero. We note that the managerial skill, α, is not directly observable by the investor. The investor is assumed to have knowledge about the distribution of skill in the population of the fund managers, i.e., investor knows a priori: $\alpha \sim N\left(\mu_\alpha, \sigma_\alpha^2\right)$. The investor, at the time of making investing decision, observes two signals, $s_{1,2}$, about managerial ability α, $s_i = (\alpha - \mu_\alpha) + \eta_i$, with

$$(2) \qquad \begin{pmatrix} \eta_1 \\ \eta_2 \end{pmatrix} \sim N\left(0, \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{pmatrix}\right).$$ [2]

We define the signal-to-noise ratio by $H_i = \sigma_\alpha^2/\sigma_i^2$, which captures the precision of the signal. Through the standard Bayesian updating, we have the posterior distribution of α, after observing the two signals, as

$$(3) \qquad N\left(\mu_\alpha + a^T s, \sigma_\alpha^2/H\right) \equiv N\left(\mu_p, \sigma_p^2\right),$$

where

$$a = \begin{bmatrix} H_1/H \\ H_2/H \end{bmatrix},$$

and $H = 1 + H_1 + H_2$.

What differentiates our model from the standard Bayesian model is that we assume the investor is ambiguous about the signal precision. To capture the investor′s attitude about this ambiguity, we adapt the framework in Klibanoff, Marinacci and Mukerji (2005). We model investors as being risk neutral but ambiguity averse. Specifically, the investor′s utility is

$$(4) \qquad U(c) = E_\theta\left[-\exp\left(-\frac{1}{\gamma}E_\pi(c)\right)\right],$$

where c is the investment payoff on a state space S, π is a probability measure on S. The parameter θ is the investor′s subjective prior over Δ, the set of possible probabilities π over S, and therefore measures the subjective relevance of a particular probability, π as the "right" probability. The size of Δ captures the degree of ambiguity. To capture such uncertainty

[2] There may be some potential interest in analyzing the ambiguity of the signal correlation. But it is turned off here by assuming the noise terms in two signals are uncorrelated.

faced by the investor, we assume that the probability measure θ in the definition of her utility function, is such that H_1 and H_2 are i.i.d. with a 50% probability of being equal to either h or l, with $h > l$. In this context, the degree of ambiguity faced by the investor is directly related to the difference between h and l. In the limiting case, as this differences converges to zero, we have the standard Bayesian learning framework.

From the above assumption, we have that $E_\pi(c) = \mu + \mu_\alpha + a^T s$. Investor k, by investing with the fund, achieves the following utility:

$$U(c) = -\frac{1}{4}e^{\frac{-(\mu+\mu_\alpha)}{\gamma}}\left[e^{\frac{-h(s_1+s_2)}{\gamma(1+2h)}} + e^{\frac{-l(s_1+s_2)}{\gamma(1+2l)}} + e^{\frac{-(hs_1+ls_2)}{\gamma(1+h+l)}} + e^{\frac{-(ls_1+hs_2)}{\gamma(1+h+l)}}\right].$$

The investor will invest with the fund if and only if the above utility is above her reservation level of utility, $-e^{-k/\gamma}$. We note the following propositions regarding fund flows.

Proposition 1 *The amount of capital under the management of the fund is $F(k^\star)$, where*

$$k^\star = \mu + \mu_\alpha - \frac{\gamma}{4}\log\left[e^{\frac{-h(s_1+s_2)}{\gamma(1+2h)}} + e^{\frac{-l(s_1+s_2)}{\gamma(1+2l)}} + e^{\frac{-(hs_1+ls_2)}{\gamma(1+h+l)}} + e^{\frac{-(ls_1+hs_2)}{\gamma(1+h+l)}}\right]. \tag{5}$$

Flow-performance sensitivity is captured by $dF(k^\star)/ds_i$, with

$$\begin{aligned}\frac{dF(k^\star)}{ds_i} =& \frac{1}{4}F'e^{\frac{(k^\star-\mu-\mu_\alpha)}{\gamma}}\left[\frac{h}{1+2h}e^{-\frac{h(s_1+s_2)}{\gamma(1+2h)}} + \frac{l}{1+2l}e^{-\frac{l(s_1+s_2)}{\gamma(1+2l)}}\right.\\ &\left. + \frac{l}{1+h+l}\left(e^{-\frac{(hs_1+ls_2)}{\gamma(1+h+l)}} + e^{-\frac{(ls_1+hs_2)}{\gamma(1+h+l)}}\right) + \frac{h-l}{1+h+l}e^{-\frac{(h-l)s_i+l(s_1+s_2)}{\gamma(1+h+l)}}\right].\end{aligned} \tag{6}$$

Proof: Let $U(c) = -e^{-k^\star/\gamma}$ and solve for $k^\star$ to get Equation (5). Then taking the derivative of $F(k^\star)$ with respect to s_1 and s_2 respectively, yields Equation (6).

This leads to the following proposition regarding the fund flow-performance sensitivity.

Proposition 2 *The flow-performance sensitivity is higher for the signal with relatively lower realized value:*

$$\frac{dF(k^\star)}{ds_1} > \frac{dF(k^\star)}{ds_2} \tag{7}$$

if and only if $s_1 < s_2$, *i.e., the signal,* s_1, *conveys bad news, while the signal,* s_2, *conveys good news.*[3]

Proof: As a consequence of Proposition 1, we have

$$\frac{dF(k^\star)}{ds_1} - \frac{dF(k^\star)}{ds_2} = \frac{1}{4} F' e^{\frac{(k^\star - \mu - \mu_\alpha)}{\gamma}} \left(\frac{h-l}{1+h+l} \right) \left[e^{\frac{-(hs_1 + ls_2)}{\gamma(1+h+l)}} - e^{\frac{-(ls_1 + hs_2)}{\gamma(1+h+l)}} \right]. \tag{8}$$

When $h > l$, we have $hs_1 + ls_2 < ls_1 + hs_2$, thus the above expression is always positive.

Thus, the model implies that ambiguity averse investors′ fund flow is more responsive to the worst signal. In other words, in the population of ambiguity averse investors, we expect to observe heightened flow sensitivity towards the signal that conveys bad news.

Denote $(h - l)/2$ by δ. The higher the parameter value for δ, the wider the gap between the two possible parameter values for the signal precision, and therefore the higher the ambiguity the investor faces. As a shorthand, we denote $e^{\delta(s_2 - s_1)/\gamma(1+h+l)}$ by X. Clearly, $X > 1$ if $s_1 < s_2$. We have the following corollary.

Corollary 1 *The extra sensitivity to the worse signal is higher when the level of ambiguity is higher, keeping the average precision of the signal constant (i.e.,* $(h + l)/2$ *is fixed). That is:*

$$\frac{d}{d\delta} \left(\frac{dF}{ds_1} - \frac{dF}{ds_2} \right) > 0 \tag{9}$$

if $s_1 < s_2$.

[3]Remark: In the model, the shape of the flow-performance relation (i.e., whether or not it is convex) depends on the specification of the cumulative distribution function $F(k)$. On one hand, this implies that the model is unable to explain why the flow-performance relation has a specific functional form, because such a relation is driven by direct assumption. On the other hand, the model is flexible enough to allow for such a relation. Our point is that our key result, namely, that the flow-performance sensitivity is higher for the signal with relatively lower realized value, is logically consistent and potentially complementary to the convexity in the flow-performance relation.

Proof: In fact, taking the derivative of Equation (8) with respect to δ yields:

$$\frac{d}{d\delta}\left(\frac{dF}{ds_1}-\frac{dF}{ds_2}\right)=\frac{1}{2(1+h+l)X}F'e^{\left[\frac{k^\star-\mu-\mu_\alpha}{\gamma}-\frac{(h+l)(s_1+s_2)}{2(1+h+l)\gamma}\right]}\left[\left(X^2-1\right)+\delta\frac{s_2-s_1}{1+h+l}\left(X^2+1\right)\right]$$
$$>0.$$

B. Bayesian Benchmark

The standard case where there is no ambiguity and thus the investor is Bayesian can be viewed as a special case in our model when the precision H is known to the investor. Specifically, consider the case when $h=l$. By plugging this into Equation (5), we have

$$k^\star=\mu+\mu_\alpha+\frac{H}{1+2H}(s_1+s_2). \tag{10}$$

The flow-performance sensitivity is captured by $dF(k^\star)/ds_i$, with

$$\frac{dF(k^\star)}{ds_1}=\frac{dF(k^\star)}{ds_2}=F'\left(\frac{H}{1+2H}\right), \tag{11}$$

independent of whether $s_1<s_2$. Thus, for Bayesian investors, the flow-performance sensitivity depends only on signal precision H, and is independent of the level of the signal realization.

Unlike an ambiguity averse investor, a Bayesian investor has the same flow sensitivity to the two signals regardless of which one is the better signal. This implies we would not expect to observe additional flow sensitivity to the poor signal in the population of Bayesian investors.

C. Distinction with Other Behavioral Biases

In the behavioral finance literature, a number of alternatives have been suggested as departures from the traditional rational agent (Savage utility) paradigm. Examples include loss-averse preferences as well as behavioral biases such as overconfidence.[4] It is worth noting

[4]Bailey, Kumar, and Ng (2011) provide evidence of the impact of behavioral biases including overconfidence, on the decisions of mutual fund investors.

that the hypothesis developed in Proposition 2 is uniquely attributable to the existence of ambiguity aversion on the part of investors. In particular, neither loss aversion, nor overconfidence will lead to a differential sensitivity of investor fund flows to the lower realization signal in the absence of ambiguity aversion. To illustrate this, we next formally examine the implications of loss aversion and overconfidence respectively, on the behavior of investors who face multiple noisy signals. For this analysis we abstract from the effect of ambiguity aversion by imposing the restriction that the two signals have equal precision, i.e., $H_1 = H_2 = H$.

First, consider the case of loss-averse utility preferences. The case with habit formation utility follows in similar fashion. Assume, as in Kahneman and Tversky (1979), the investor displays loss aversion in her utility function but she is not ambiguous about the signal precision. Thus, given the posterior distribution of α, we assume the utility function takes the following form:

$$U(c) = E_\pi\left(\alpha \mathbb{1}[0,\infty)\right) + \lambda E_\pi\left(\alpha \mathbb{1}[0,\infty)\right), \tag{12}$$

where $\lambda > 1$. Writing the above equation in explicit form, we have:

$$\begin{aligned} U(c) = & \int_0^\infty \frac{\alpha}{\sqrt{2\pi\sigma_p^2}} e^{\frac{-(x-\mu_P)^2}{2\sigma_p^2}} d\alpha + \lambda \int_{-\infty}^0 \frac{\alpha}{\sqrt{2\pi\sigma_p^2}} e^{\frac{-(x-\mu_P)^2}{2\sigma_p^2}} d\alpha \\ = & \frac{\sigma_p(1-\lambda)}{\sqrt{2\pi}} e^{\frac{-\mu_p^2}{2\sigma_p^2}}, \end{aligned} \tag{13}$$

where α_p and μ_p are given in Equation (3) with $H_1 = H_2 \equiv H$. Thus, the flow-performance sensitivity under the assumption of loss aversion is:

$$\frac{dF(k^\star)}{ds_1} = \frac{dF(k^\star)}{ds_2} = \frac{(\lambda-1)H\mu_p^2}{\sigma_p(1+2H)\sqrt{2\pi}} F' e^{\frac{-\mu_p^2}{2\sigma_p^2}}, \tag{14}$$

which is independent of whether or not $s_1 < s_2$.

Second, we note that overconfidence cannot by itself result in the asymmetric sensitivity to signals with different realizations. Overconfidence is the belief on the part of the investor that a certain signal is more precise than it actually is. For example, suppose that an overconfident investor receives a signal, s_1, from a private channel, while another signal, s_2, is publicly available. She is confident that her private signal, s_1, is always more reliable than the public signal, s_2. As a result, when making investment decisions, the investor allocates additional capital to the fund whenever s_1 is sufficiently positive, and conversely she withdraws money from the fund whenever the signal, s_1, is negative. The public signal, s_2, on the other hand, regardless of its realization, will have a lesser influence on the investor′s fund investment decisions. Simply put, under the assumption of overconfidence, regardless of whether $s_2 > s_1$, or $s_2 \leq s_1$, we always have:

$$\frac{dF(k^\star)}{ds_1} > \frac{dF(k^\star)}{ds_2}. \tag{15}$$

Obviously under this setting of overconfidence, we cannot arrive at Proposition 2.

D. Empirical Predictions

In order to develop testable hypotheses, it is important to first clarify why the mutual fund industry provides a perfect setting to test our model. First, mutual funds represent a significant proportion of the U.S. household assets.[5] These investors span all age, income groups, and wealth levels and are thus representative of the population of individual investors whose investment decisions may be influenced by an aversion to ambiguity. Another favorable feature about the mutual fund industry is that it has separate share classes for individual investors and institutional investors, which allows us to study the behavioral differences between the two types of investors.

Second, the mutual fund flow-performance relationship has been well documented in the literature. Previous studies (e.g., Ippolito (1992), Gruber (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998)) show that mutual fund investors make investment or redemption decisions relying on past fund performance. This relationship allows us to directly

[5] As reported in 2011, 44% of all U.S. households, owned mutual funds. Source: 2012 Investment Company Institute Fact Book.

observe the investors′ response to performance related information. Third, mutual funds make their past performance statistics widely available to investors. Such statistics include the performance figures for each share class over the previous 1 year, 3 years, 5 years, as well as the entire period since inception. However, the degree to which past performance is informative of fund manager skill is unknown to investors. Also, these performance data have different realizations since a fund′s performance may fluctuate overtime. Thus, these performance statistics over different time horizons serve as multiple comparable signals with unknown quality and different realizations from which investors learn about fund manager skill. Fourth, the comprehensive data on fund flows and past performance make it possible for us to study investors′ response to multiple signals under ambiguity aversion in a non-experimental setting.

In this subsection, we develop several testable hypotheses from the model concerning the impact of ambiguity aversion on mutual fund investor flow-performance sensitivity. We have the following hypotheses:

Hypothesis 1 *When a fund′s past performance is measured over multiple time horizons, fund flows display additional sensitivity to the minimum performance measure in the presence of ambiguity averse investors.*

According to Proposition 2, given signals with unknown quality, ambiguity averse investors′ fund flow response is more sensitive to the worst signal, i.e., the signal with the worst realization. In the mutual fund industry, fund investors are routinely provided with performance statistics measured over past 1 year, 3 years, and 5 years, from which they try to learn about fund manager skill. Proposition 2 says that ambiguity averse investors′ fund flows will display additional sensitivity towards the worst signal, i.e., the minimum performance over multiple time horizons in this setting.

Hypothesis 2 *Individual investors show stronger ambiguity aversion than institutional investors, as measured by a higher marginal sensitivity to the minimum performance measure.*

The above hypothesis reflects the notion that individual (retail) investors are less sophisticated compared to institutional investors. As a result, they may be less confident about how much the past performance is indicative about fund manager skill. They may therefore be subject to greater ambiguity in terms of interpreting such information. On the other hand, institutional investors, who are believed to be much more sophisticated, may hold more confident beliefs about the precision of signals when they look at past performance measures. As a result, we expect to see stronger ambiguity aversion in the sample of retail investors compared to institutional investors.

Hypothesis 3 *Funds that change their investment strategy more frequently are characterized by a higher degree of ambiguity. Investor fund flows in such funds will display a higher marginal sensitivity to the minimum performance measure.*

Fund investment strategy changes can be viewed as a proxy for a funds ambiguity level. If a fund constantly switches its investment strategy, e.g., from a passive diversification strategy to active factor timing or stock selection, investors may find it hard to evaluate its relative performance and to form a concrete expectation of future return. Thus, the more aggressively and/or frequently a fund changes its strategy, the more ambiguous it is from investors′ perspective.

Hypothesis 4 *Funds with more volatile cash flows are characterized by a higher degree of ambiguity. Investor fund flows in such funds will display a higher marginal sensitivity to the minimum performance measure.*

Fund inflows reflect a general positive view among investors about the fund′s future prospects and outflows are indicative of a negative view about the fund. Thus, flow volatility can be viewed as a proxy for the degree of variability or uncertainty of investor opinion with respect to the fund′s prospects. In this sense, highly volatile investor fund flows imply greater uncertainty about the fund′s future performance. Hence, funds with more volatile flows may appear to be more ambiguous to investors.

Hypothesis 5 *Funds that belong to a smaller family appear more ambiguous to investors. Investor fund flows to such funds will display a higher marginal sensitivity to the minimum performance measure.*

Since the 1990s, there has been a sharp increase in multiple share classes that belong to the same fund family. If a fund belongs to a family with a large asset base, it is more recognizable and enjoys the reputation built up by the entire fund family. On the other hand, if a fund belongs to a small and little known family, investors may be more conservative when making their investment decisions. It may also be harder for them to rely on past performance of such funds in drawing inference about manager skill. In other words, funds belonging to smaller families may appear more ambiguous to investors.

Hypothesis 6 *Funds with greater marketing expenditures are less ambiguous to investors. Investor fund flows to such funds will display a lower marginal sensitivity to the minimum performance measure.*

We hypothesize that funds that spend more on marketing are less ambiguous to investors since investors are likely to be more familiar with funds that advertise more.[6]. In most advertisement, funds advocate their superior past performance and service through magazines, TV programs, etc., as studied in Jain and Wu (2000). A higher visibility (due to increased advertising) may lead to a greater degree of confidence among investors regarding

[6]Marketing related expenses including 12b-1 fees have been employed as empirical proxies for investor search and participation costs in studies by Sirri and Tufano (1998) and Huang, Wei, and Yan (2007).

the quality of past performance as signals for manager skill. In other words, funds with higher advertising related expenditures may be less ambiguous to investors in general.

IV. Data and Methodology

A. Data

We use data from the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database, which includes information on the funds′ total net assets, returns and characteristics. We focus on actively managed U.S. equity mutual funds, thus, we also exclude index funds and funds that are closed to new investors. To be consistent with prior studies, we exclude sector funds, international funds, bond funds, and balanced funds from our analysis. We classify funds into five categories based on their objective codes:[7] aggressive growth, growth, growth and income, income and others. We also classify funds into retail shares or institutional shares.

We primarily study the period from January 1993 through December 2011, since the CRSP database does not report 12b-1 fees until 1992 and institutional funds begin to mushroom in the 1990s. However, as a robustness check we confirm that our results are qualitatively unchanged when we extend the sample to the period: January 1985 through December 2011. We examine fund flows and other characteristics at the quarterly frequency. Consistent with prior studies, we define quarterly net flow into a fund as

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}}, \tag{16}$$

[7]We categorize funds according to the following criteria. First, funds with Lipper objective codes G, LCGE, MCGE, MLGE, SCGE, with Wiesenberger objective codes G, G-S, S-G, GRO, LTG, SCG, or with Strategic Insight objective codes GRO, SCG are classified as growth funds. Second, funds with Wiesenberger objective code AGG or with Strategic Insight objective code AGG are classified as aggressive growth. Third, funds with Lipper objective code GI, with Wiesenberger objective codes G-I-S, G-S-I, I-G, I-G-S, GCI, G-I, I-S-G, S-G-I, S-I-G, GRI, or with Strategic Insight objective code GRI are classified as growth and income funds. Fourth, funds with Lipper objective codes EI, EIEI, I, with Wiesenberger objective codes I, I-S, IEQ, ING, or with Strategic Insight objective codes ING are classified as income funds. Fifth, all the other actively managed equity funds in our sample are classified as others.

where $R_{i,t}$ denotes fund i's return during quarter t, and $TNA_{i,t}$ is the fund′s total net asset value at the end of quarter t. Thus, our definition of flows reflects the percentage growth of the fund′s assets in quarter t. To prevent the potential impact of extreme values of flows resulting from the errors associated with mutual fund mergers and splits in CRSP mutual fund database, we filter out the top and bottom 1% tails of the net flow data. To further guard against this issue, we delete records of funds from our analysis before their total net asset value first hits the $3 million mark.

Table 1 reports the summary statistics of mutual funds characteristics. We note that since we are interested in studying the fund flow behavior of retail as well as institutional investors we treat each fund share class as an individual fund, consistent with the practice in the CRSP database. In 1993, there are 707 distinct fund share classes in our sample and 63 of them are open only to institutional investors. In 2011, the number of funds in our sample grows to 4,242 with 785 institutional funds. In total, our sample includes 7,020 distinct fund share classes and 216,366 fund share class-quarters. In an average quarter, the sample includes 2,847 funds with average total net assets (TNA) of $678.06 million and an average net flow of 1.51%. Following Sirri and Tufano (1998) we measure total expense as the expense ratio plus one-seventh of the front-end load. The 12b-1 fees are the part of fund expenses that cover distribution expenses and sometimes shareholder service expenses. Distribution expenses include marketing, advertising and compensation paid for brokers who sell the funds. As may be seen from Table 1, the 12b-1 fees for retail funds are 0.57%, which is nearly three times of that for institutional funds.

B. Empirical Methodology

We formally analyze the relationship between fund flows and performance measured over multiple time horizons when controlling for other factors. We estimate the following model using 76 quarters of fund-level data over the period 1993 to 2011 to test our baseline hypothesis:

$$(17) \qquad Flow_{i,t} = a + b_1 Perf\_1yr_{i,t} + b_2 Perf\_3yr_{i,t} + b_3 Perf\_5yr_{i,t} + cMin\_Rank_{i,t} + Controls + \epsilon_{i,t}.$$

Following Sirri and Tufano (1998), the variables $Perf\_1yr$, $Perf\_3yr$, and $Perf\_5yr$ represent fractional performance ranks ranging from 0 to 1 based on fund i's performance during past 12 months, 36 months, and 60 months, respectively. The variable Min_Rank is defined as:

$$(18) \qquad Min\_Rank_{i,t} = Min\left(Perf\_1yr_{i,t}, Perf\_3yr_{i,t}, Perf\_5yr_{i,t}\right).$$

Thus, the coefficient c in Equation (17) captures the additional flow sensitivity to performance measured over the particular horizon during which the fund had the worst performance ranking. This coefficient is the focus of our tests. As we discuss below, this additional sensitivity is significant in both economic and statistical sense in the population of retail investors.

Since it is unclear which measure of performance a typical investor would focus on when evaluating funds, we consider two alternative measures. The first measure is the average monthly raw return measured over a specified time horizon, i.e., 12 months, 36 months or 60 months. The second measure is the fund′s risk-adjusted performance using the Carhart (1997) four-factor model. In order to estimate the four factor model, we first calculate fund i's factor loadings in quarter t by regressing the past 60 months′ excess returns on the four factors:

$$(19) \quad R_{i,\tau} - R_{f,\tau} = \alpha_i + \beta_i^{MKT} MKT_\tau + \beta_i^{SMB} SMB_\tau + \beta_i^{HML} HML_\tau + +\beta_i^{UMD} UMD_\tau + \epsilon_{i,\tau},$$

where $R_{i,\tau}$ is the return for fund i and $R_{f,\tau}$ is the one-month T-bill rate in month τ. The market factor, MKT_τ, represents the monthly excess market return. The factors SMB_τ, HML_τ, and UMD_τ represent the monthly returns on the size, value, and momentum factor mimicking portfolios, respectively. We obtain the factor returns from Ken French′s website. We then calculate the fund′s risk adjusted alpha each month using the monthly fund excess returns and the factor loadings estimated as above. We compute the average of these monthly alphas over distinct horizons of 12 months, 36 months, or 60 months, respectively.

To obtain fractional performance ranks ($Perf\_1yr$, $Perf\_3yr$, and $Perf\_5yr$) ranging from 0 to 1, we apply different approaches to ranking funds based on the two performance measures. In the case of the raw return measure, we rank funds every quarter within fund objective categories based on their average raw returns over each of the three lagged time horizons. For rankings based on the 4-factor alphas, we rank all funds each quarter according to their average risk adjusted returns over each of the three time horizons considered.

The control variables employed in Equation (17) include a number of fund characteristics that have been shown to affect fund flows. In particular, we control for the logarithm of one plus fund age, previous quarter′s flow, fund size as measured by the natural logarithm of fund total net asset in the previous quarter, volatility of monthly raw returns during the prior 12 months, and the lagged total expense ratio. Finally, following Sirri and Tufano (1998) we also include the category flow, defined as the percentage quarterly net asset growth of the fund′s objective category.

We estimate the model in Equation (17) by conducting a cross-sectional linear regression each quarter and reporting the time-series means and the related Newey-West t-statistics of the coefficients following Fama and Macbeth (1973). We follow this approach for all of the analysis throughout the paper.

V. Empirical Results

A. Ambiguity Aversion

In this subsection, we test Hypotheses 1 and 2 by studying investor ambiguity aversion behavior within subsamples of retail funds and institutional funds respectively. Our model implies that in the presence of ambiguity averse investors, fund flows will display additional sensitivity to a fund′s minimum performance ranking. This marginal sensitivity is in addition to the general response of flows to past performance measures.

To test this implication, we estimate the baseline model in Equation (17) for retail funds and institutional funds separately. According to Hypothesis 2, we expect to see a significant coefficient, c, for the variable Min_Rank for the subsample of retail funds only. The results are reported in Table 2. Columns 1 and 2 report results using raw return as the performance measure and Columns 3 and 4 report results using the Carhart (1997) alpha as the performance measure.

Consistent with Hypothesis 2, we find that the coefficient for Min_Rank is significantly positive for retail funds. This effect is robust across both measure of performance, both at 1% significant levels. However, for institutional funds, the coefficient is positive but insignificant. Focusing on the results for retail funds in Column 1 where the performance is measured in terms raw returns, the coefficient for the Min_Rank variable is 0.048. The coefficient for performance measured over the 1-year horizon is 0.05, and this is the performance horizon that has the largest affect on fund flows. This implies that for retail funds, a 1% increase in the fund′s 1-year performance rank will result in a 0.05% increase in fund flows. However, if the 1-year performance rank happens to be the worst among the three horizons, a 1% increase in the fund′s (1-year) ranking results in an inflow equal to $(0.048 + 0.05)1\% = 0.098\%$ of the fund′s assets. Thus, a 1% improvement in the worst performance rank results in a doubling of the fund flows enjoyed by the fund relative to the normal increase in flows from general performance improvement. The economic magnitude is quite significant given the average flow in the retail sample is 1.32%. In Column 3 when performance is measured using Carhart (1997) 4-factor alpha, we observe a similar coefficient for the Min_Rank. As seen from the results presented in Columns 2 and 4 of Table 2, in the case of institutional funds, even though the coefficients for Min_Rank are positive, they are not statistically significant and are much smaller in magnitude than their retail counterparts.

We note that the coefficients on the other control variables included in Equation (17) are consistent with previous findings in literature. The positive and significant coefficients for all three performance measures in Columns 1 through 4 conform to the performance chasing behavior as documented in Chevalier and Ellison (1997), and Sirri and Tufano (1998), among others. Sirri and Tufano (1998) also document the negative impact of volatility on flows. The positive coefficient on $PreviousQuarterlyFlow$ confirms the persistence in fund flows. Similarly, the negative coefficients for $TotalExpense$ in Columns 1 through 4 are consistent with previous studies by Barber, Odean and Zheng (2005) and Sirri and Tufano (1998), among others.

After controlling for above factors, the significant coefficients for Min_Rank in Columns 1 and 3 indicate that minimum performance ranks have an important explanatory power for fund flows. The inclusion of the Min_Rank variable substantially increases the R-square values in models describing the flow-performance relationship, suggesting the importance of the variable in the context of studies of the flow-performance relationship. In sum, Table 2 provides evidence for ambiguity aversion behavior among retail funds investors as shown by the significant positive coefficient for minimum performance, which is consistent with Hypotheses 1 and 2.

B. Strategy Changes as a Proxy for Fund Ambiguity

Hypothesis 3 states that fund strategy changes could be viewed as a proxy for a fund′s ambiguity level. Investors are likely to face a higher degree of ambiguity with regard to a fund that switches its investment strategy too aggressively/frequently. We adopt two ways to measure a fund′s strategy shifts. The first measure is the fund′s average absolute change in its factor loadings, while the second measure is the fund′s R-square computed from a time series regression using the entire history of fund returns.

The first proxy is motivated by Lynch and Musto (2003). Each quarter t, we compute a fund′s factor loadings with respect to the four Carhart (1997) model factors over two non-overlapping 30-month periods, namely, the prior 1-30 and 31-60 month periods. We then compute the average absolute change in the factor loadings from the initial 30-month period to the most recent 30-month period as

$$LDEL_{i,t} = \frac{1}{4}\sum_{f} |\beta^{f}_{i,t,1-30} - \beta^{f}_{i,t,31-60}|, \tag{20}$$

for $f = MKT, HML, SML$ and UMD. A higher loading-change indicates a more aggressive shift in the fund′s strategy.

The second proxy is the fund′s R-square from a time series regression of the fund′s monthly returns on the four Carhart (1997) factors. A low R-square value implies that the four-factor model is a poor performance attribution model for the fund. A potential reason could be that the factor loadings of the fund are not constant over the sample period implying frequent shifts in the factor exposures or the investment style. Such shifts would make it harder for investors to interpret past performance related signals and contribute to an enhanced level of ambiguity in interpreting such signals. Each quarter, we divide the sample of funds into three groups, Low, Mid and $High$ based on their $LDEL$ or R-square values. We then we apply the baseline model described in Equation (17) to each group and report the time-series average of the coefficients. The results are reported in Table 3.

Performance in this table is measured by raw return (Column 1-3) or Carhart (1997) 4-factor model alpha (Column 4-6). Panel A of Table 3 reports results when strategy changes are measured using the average absolute change in factor loadings ($LDEL$). As shown in Column 1, for the group of funds with low loading-change, an indication of less aggressive strategy shifts, the additional flow sensitivity to minimum performance is only 0.11 and it is statistically insignificant. However, for funds which shift their strategies more aggressively, as shown in Column 3, the marginal sensitivity to minimum performance is nearly six times higher at 0.61 which is significant at the 1% level. Columns 4-6 report similar results when performance is measured using the Carhart (1997) 4-factor alpha.

Panel B of the table presents results using a fund′s four-factor model R-square values as a proxy for the fund′s ambiguity. Flows of funds with low R-square values show additional sensitivity to minimum performance rank 0.056, significant at 1%, as shown in Column 1. In Column 3, however, flows of funds with high R-square values, an indication of relatively stable investment strategy, have marginal sensitivity to minimum performance of only 0.14 which is statistically insignificant. Columns 4-6 report results when performance is measured using the Carhart (1997) 4-factor alpha. We note that in this case, the additional sensitivity on minimum performance is similar for funds with low and high R-square values. A potential reason could be that investor fund flows are particularly responsive to the raw return performance of the fund, rather than to the 4-factor model alphas. If so, the results for the case where performance is measured using raw returns should offer more insight into this issue.

In conclusion, the results in Table 3 show that funds that change investment strategy more aggressively/frequently are more ambiguous to investors, as evidenced by the greater marginal sensitivity of investor fund flows to the minimum performance measure.

C. Flow Volatility as a Proxy for Fund Ambiguity

Hypothesis 4 states that the flow volatility could be used as a proxy for a fund′s ambiguity level. That is, a fund′s flow volatility increases the fund′s ambiguity level from the investor′s perspective. Note that fund flows are the consequence of investors′ asset allocation decisions. A net inflow is an indication of an overall positive view of the fund while a net outflow represents an overall negative view. Thus, flow volatility is a direct measure of the uncertainty about the funds′ future performance from the perspective of an average investor. In this sense, flow volatility is a direct measure of the fund′s ambiguity level. We expect to observe stronger ambiguity aversion behavior among investors of funds with more volatile past flows. We measure flow volatility ($Flow\_Vol$) as the standard deviation of a fund′s previous 12 quarters′ fund flows.

To test this hypothesis, we estimate the following regression model:

$$
\begin{aligned}
(21) \qquad Flow_{i,t} =& a + b_{11} Low\_Flowvol_{i,t} \times Perf\_1yr_{i,t} + b_{12} Mid\_Flowvol_{i,t} \times Perf\_1yr_{i,t} \\
&+ b_{13} High\_Flowvol_{i,t} \times Perf\_1yr_{i,t} + b_{21} Low\_Flowvol_{i,t} \times Perf\_3yr_{i,t} \\
&+ b_{22} Mid\_Flowvol_{i,t} \times Perf\_3yr_{i,t} + b_{23} High\_Flowvol_{i,t} \times Perf\_3yr_{i,t} \\
&+ b_{31} Low\_Flowvol_{i,t} \times Perf\_5yr_{i,t} + b_{32} Mid\_Flowvol_{i,t} \times Perf\_5yr_{i,t} \\
&+ b_{33} High\_Flowvol_{i,t} \times Perf\_5yr_{i,t} + c_1 Low\_Flowvol_{i,t} \times Min\_Rank_{i,t} \\
&+ c_2 Mid\_Flowvol_{i,t} \times Min\_Rank_{i,t} + c_3 High\_Flowvol_{i,t} \times Min\_Rank_{i,t} \\
&+ Flow\_Vol_{i,t} + Controls + \epsilon_{i,t},
\end{aligned}
$$

where $Low\_Flowvol_{i,t}$ is a dummy variable that equals one if the fund i's flow volatility falls into the bottom tercile in quarter t, $Mid\_Flowvol_{i,t}$ is a dummy variable that equals one if it belongs to the medium tercile, and $High\_Flowvol_{i,t}$ is a dummy variable that equals one if the flow volatility is ranked in the top tercile. Each quarter we conduct a cross-sectional regression of flows on the interaction of the three dummy variables with $Perf\_1yr$, $Perf\_3yr$, $Perf\_5yr$ and Min_Rank, respectively, together with the set of control variables and report the time-series mean and Newey-West t-statistics of the coefficients. The control variables are the same as those in (17). The coefficients on the interaction terms capture the differential flow sensitivity to a certain performance horizon or to the minimum performance for funds with low, medium or high flow volatility. For example, the coefficient of $High\_Flowvol \times Min\_Rank$, i.e., c_3, captures the additional sensitivity to the Min_Rank for funds with high flow volatility. Given Hypothesis 4, we expect a large and positive coefficient for $High\_Flowvol \times Min\_Rank$, and a small coefficient for $Low\_Flowvol \times Min\_Rank$.

Table 4 presents the flow-performance results based on flow volatility as a proxy for fund ambiguity level. Columns 1 and 2 report results using raw return and Carhart (1997) alpha as performance measures, respectively. As expected, in Column 1, the coefficients for the three interaction terms $Low\_Flowvol \times Min\_Rank$, $Mid\_Flowvol \times Min\_Rank$ and $High\_Flowvol \times Min\_Rank$ increase monotonically from -0.002 (statistically insignificant) to 0.11 (significant at 1% level). This increase in the magnitude of the coefficients across the three interaction terms is statistically significant in an unreported test. In Column 2 of Table 4, where fund performance is measured using the Carhart (1997) alpha, we observe a similar increase in the value of the coefficients across the three flow volatility terciles.

In conclusion, the results in Table 4 are consistent with Hypothesis 4 that funds with more volatile flow are more ambiguous to investors.

D. Family Size as a Proxy for Fund Ambiguity

Hypothesis 5 states that family size can also be used as a proxy for a fund′s ambiguity level. In this subsection, we use the sum of total net assets for each fund share class in the same family as a measure of family size. We then test whether a larger family size is associated with a reduction in the marginal flow sensitivity to a fund′s minimum performance measure.

To test this hypothesis, we estimate the following model:

$$
\begin{aligned}
(22) \quad Flow_{i,t} =& a + b_{11} Low\_FamSize_{i,t} \times Perf\_1yr_{i,t} + b_{12} Mid\_FamSize_{i,t} \times Perf\_1yr_{i,t} \\
&+ b_{13} High\_FamSize_{i,t} \times Perf\_1yr_{i,t} + b_{21} Low\_FamSize_{i,t} \times Perf\_3yr_{i,t} \\
&+ b_{22} Mid\_FamSize_{i,t} \times Perf\_3yr_{i,t} + b_{23} High\_FamSize_{i,t} \times Perf\_3yr_{i,t} \\
&+ b_{31} Low\_FamSize_{i,t} \times Perf\_5yr_{i,t} + b_{32} Mid\_FamSize_{i,t} \times Perf\_5yr_{i,t} \\
&+ b_{33} High\_FamSize_{i,t} \times Perf\_5yr_{i,t} + c_1 Low\_FamSize_{i,t} \times Min\_Rank_{i,t} \\
&+ c_2 Mid\_FamSize_{i,t} \times Min\_Rank_{i,t} + c_3 High\_FamSize_{i,t} \times Min\_Rank_{i,t} \\
&+ D\_FamilySize_{i,t} + Controls + \epsilon_{i,t},
\end{aligned}
$$

where $Low\_FamSize_{i,t}$ is a dummy variable that equals 1 if fund i belongs to a fund family whose size falls into the bottom tercile in quarter t, $Mid\_FamSize_{i,t}$ is a dummy variable that equals 1 if family size belongs to the medium tercile and $High\_FamSize_{i,t}$ is a dummy variable that equals one if the family size is in the top tercile. The variable $D\_FamilySize_{i,t}$ is a dummy variable that equals 1 if the fund family size is above the median value for that quarter. We regress quarterly flows on the interaction of the three dummy variables with $Perf\_1yr$, $Perf\_3yr$, $Perf\_5yr$ and Min_Rank, respectively. The coefficients on the interaction terms represent the differential flow sensitivity to a certain performance horizon or to the minimum performance rank for funds that belong to a small-sized family, medium-sized family or large-sized family, respectively. For example, the coefficient c_1 for the variable $Low\_FamSize \times Min\_Rank$ in Equation (22) captures the additional flow sensitivity to the minimum performance rank for funds in a small family. Given Hypothesis 5, we expect a large and positive coefficient for $Low\_FamSize \times Min\_Rank$, but a small coefficient for $High\_FamSize \times Min\_Rank$.

Table 5 presents results using fund family size as a proxy for the fund′s ambiguity level. Columns 1 and 2 report results using raw returns and the Carhart (1997) alpha as performance measures, respectively. Consistent with our expectation, in Column 1, the coefficients for the three interaction terms $Low\_FamSize \times Min\_Rank$, $Mid\_FamSize \times Min\_Rank$ and $High\_FamSize \times Min\_Rank$ decrease monotonically from 0.073 (significant at the 1% level) to 0.014 (statistically insignificant). This means that the flow sensitivity to minimum performance rank for funds in a large family is five times that for funds belonging to a small family. In Column 2, when performance is measured in terms of the Carhart (1997) alpha, the coefficients for $Low\_FamSize \times Min\_Rank$ and $High\_FamSize \times Min\_Rank$ are 0.069 and 0.031 respectively, both significant at the 1% level.

As seen from the estimated coefficients for the variable, $D\_FamilySize$, family size has a positive and significant impact on fund flows, consistent with the findings of Sirri and Tufano (1998). This suggests that funds belong to bigger families experience a faster growth in assets. As noted by Gallaher, Kaniel, and Starks (2005), strategic decisions regarding advertising, and distribution channels are made at the fund family level. Funds that belong to a large family have more resources in terms of both management and reputation, allowing them to grow at a faster rate. In conclusion, the results in Table 5 are consistent with Hypothesis 5 that funds belonging to smaller families appear more ambiguous to investors.

E. The Role of Advertising

In previous subsections we examined the impact of proxies for a fund′s ambiguity level on the behavior of investors. The results suggest that investors′ marginal sensitivity to a fund′s historical minimum performance is increasing in the perceived ambiguity of a fund. Of course, the additional flow-performance sensitivity can be costly from a fund′s standpoint. We now focus on the possible ways a fund may be able to reduce its ambiguity level from the perspective of fund investors. According to Hypothesis 6 a fund′s marketing effort can help reduce investors′ ambiguity towards the fund when making decisions. In our empirical test of this hypothesis, we measure marketing effort using the amount of 12b-1 fees charged by a fund.

In order to test the above hypothesis, we estimate the following regression model in the subsample of retail funds:

$$
\begin{aligned}
(23) \qquad Flow_{i,t} =& a + b_{11} Low\_Exp_{i,t} \times Perf\_1yr_{i,t} + b_{12} Mid\_Exp_{i,t} \times Perf\_1yr_{i,t} \\
&+ b_{13} High\_Exp_{i,t} \times Perf\_1yr_{i,t} + b_{21} Low\_Exp_{i,t} \times Perf\_3yr_{i,t} \\
&+ b_{22} Mid\_Exp_{i,t} \times Perf\_3yr_{i,t} + b_{23} High\_Exp_{i,t} \times Perf\_3yr_{i,t} \\
&+ b_{31} Low\_Exp_{i,t} \times Perf\_5yr_{i,t} + b_{32} Mid\_Exp_{i,t} \times Perf\_5yr_{i,t} \\
&+ b_{33} High\_Exp_{i,t} \times Perf\_5yr_{i,t} + c_1 Low\_Exp_{i,t} \times Min\_Rank_{i,t} \\
&+ c_2 Mid\_Exp_{i,t} \times Min\_Rank_{i,t} + c_3 High\_Exp_{i,t} \times Min\_Rank_{i,t} \\
&+ Expense_{i,t} + Controls + \epsilon_{i,t}.
\end{aligned}
$$

To emphasize the particular role of advertising in reducing fund ambiguity, we also study the effect of the expense ratio and non-12b-1 expenses, defined as expense ratio minus 12b-1 fees, using the same model. In Equation (23), $Low\_Exp_{i,t}$ is a dummy variable that equals 1 if the fund i's corresponding type of fees (12b-1, non 12b-1 or expense ratio) falls in the bottom tercile in quarter t, $Mid\_Exp_{i,t}$ is a dummy variable that equals 1 if it belongs to the medium tercile, and $High\_Exp_{i,t}$ is a dummy variable that equals 1 if the fund is in the top tercile in terms of the expenses. The variable $Expense_{i,t}$ is the 12b-1, non-12b-1 or expense ratio depending on which type of fees is under investigation.

We regress quarterly flows on the interaction of the three dummy variables with $Perf\_1yr$, $Perf\_3yr$, $Perf\_5yr$ and Min_Rank, respectively, for all three types of fees. For example, when we study the effect of 12b-1 fees, the coefficients on the interaction terms represent the marginal flow sensitivity to a certain performance horizon or to the minimum performance rank for funds with the low, medium or high 12b-1 fees, respectively. According to Hypothesis 6, when focusing on 12b-1 fees, we expect a large and positive coefficient for $Low\_Exp \times Min\_Rank$, which captures the additional flow sensitivity to the minimum performance rank for funds with low 12b-1 fees.

Table 6 reports results based on the above test. Columns 1 and 2 of the table report results of the effect of 12b-1 fees on the flow-performance relationship when performance is measured using raw returns or the Carhart (1997) alpha, respectively. In Column 1, the coefficient for $Low\_Exp \times Min\_Rank$ is 0.058, and is significant at 1% level. The coefficient for $High\_Exp \times Min\_Rank$, however, is only 0.021 and it is insignificant. This suggests that moving from the bottom tercile of 12b-1 expenditures funds to the top tercile, investors′ flow sensitivity to the minimum performance rank is reduced by 63.7%. Column 2 reports similar results when performance is measured using the Carhart (1997) alphas. Columns 3 and 4 present results for the non-12b-1 expenditures for both measures of performance. In Columns 3 and 4, the three coefficients of interest display, surprisingly, an increasing pattern, suggesting that the higher the non-12b-1 fees charged by funds, the more ambiguous they appear to their investors. Columns 5 and 6 present results for the expense ratio and we observe similar patterns as for the non-12b1 fees. We conjecture that this set of results may be attributed to the fact that high expense ratio funds attract relatively less sophisticated investors, since the sophisticated investors should have learned to avoid high expense funds. Thus we observe stronger ambiguity aversion among the investors with high expense ratios or non-12b-1 fees.

In conclusion, we find evidence that 12b-1 fees that are spent on marketing and advertising do help reduce the ambiguity of funds from the investors′ perspective.

VI. Contrast between the Response of Ambiguity Averse Investors and Bayesian Investors

Finally, we develop a test to distinguish ambiguity averse investor behavior from the Bayesian learning benchmark. Following earlier discussion, we argue that a fund′s performance volatility is another proxy for the fund′s ambiguity level in addition to the flow volatility and family size. The more volatile the fund′s past performance, the harder it is for investors to learn about the fund′s future performance. Thus, a fund with a higher degree of performance volatility is more ambiguous from an investor′s perspective. Accordingly, we expect to observe greater marginal flow sensitivity to the minimum performance rank for such funds.

In a recent study, Huang, Yan and Wei (2007) hypothesize that the volatility of funds′ past performance should have a dampening effect on flow performance sensitivity if investors update their beliefs in a Bayesian manner. As we note below, the two seemingly contradictory hypotheses can in fact be reconciled.

We want to first document the two effects by performing two separate tests. We apply the following model to test our baseline hypothesis of ambiguity aversion:

$$
\begin{aligned}
(24) \qquad Flow_{i,t} =& a + b_1 Min_{i,t} \times Perf\_3yr_{i,t} + e_1 Low\_3yr_{i,t} + e_2 Mid\_3yr_{i,t} + e_3 High\_3yr \\
& + Controls + \epsilon_{i,t}.
\end{aligned}
$$

For the purpose of comparison, we adopt similar measures and time periods as in Huang, Yan and Wei (2012). For example, in this subsection, we expand our sample to include both retail and institutional funds. Also, we focus on a fund′s previous 3 years performance ($Perf\_3yr$), defined as a fund′s performance measured by its raw return rankings within its objective category over the past 36 months. We define the following fractional performance rankings over the low, medium and high performance ranges[8]. The fractional rank for funds in the bottom performance quintile (Low_3yr) is Min($Perf\_3yr$,0.2), in the three medium quintiles (Mid_3yr) is $Min(0.6, Perf\_3yr - Low\_3yr)$, and in the top quintiles ($High\_3yr$) is $Perf\_3yr - Mid\_3yr - Low\_3yr$. We also include the identical set of control variables as in our baseline model specified in Equation (17).

In the above specification, the variable $Min_{i,t}$ is a dummy variable that equals 1 if fund

[8]See, for example, Huang, Yan and Wei (2007) and Sirri and Tufano (1998).

i's 3-year performance happens to be the worst among 1-year, 3-year and 5-year performance measures in quarter t. The coefficient b_1 for the interaction term $Min \times Perf\_3yr$ captures the additional sensitivity to the 3-year performance, if it happens to be the worst among the three performance measures. Thus, the coefficient b_1 captures the ambiguity aversion effect. We expect b_1 to be positive and significant. The results are presented in Column 1 of Table 7. The coefficient b_1 is estimated to be 0.053 which is highly significant in both statistical and economic terms. It is worth noting that we do observe the convexity in the flow-performance relationship reflected in the respective coefficients for the performance ranges (Low_3yr, Mid_3yr and $High\_3yr$). In particular, the coefficient for the high performance range (0.407) is nearly 6 times the coefficient for the low performance range (0.070) suggesting a convex flow-performance relationship.

Next, we replicate the Huang, Yan and Wei (2012) results using the following test:

$$\begin{aligned} Flow_{i,t} =& a + cVol_{i,t} \times Perf\_3yr_{i,t} + e_1 Low\_3yr_{i,t} + e_2 Mid\_3yr_{i,t} + e_3 High\_3yr_{i,t} \\ &+ Controls + \epsilon_{i,t}. \end{aligned} \tag{25}$$

The variable $Vol_{i,t}$ is the fund i's previous 36 months$'$ raw return volatility in quarter t. If the dampening effect of performance volatility on the flow-performance relationship exists, we expect to see a significant negative coefficient for the interaction term, $Vol \times Perf\_3yr$. As shown in Column 2 of Table 7, this coefficient is estimated to be -0.777, which is significant at 1% level. All of the other coefficients are also qualitatively similar to the values reported by Huang, Yan and Wei (2012).

Finally, it is of interest to show that ambiguity aversion and the dampening effect of performance volatility could co-exist. We distinguish our ambiguity aversion phenomenon using the following model:

$$(26) \qquad Flow_{i,t} = a + b_2 Min_{i,t} \times Vol_{i,t} \times Perf\_3yr_{i,t} + cVol_{i,t} \times Perf_3yr_{i,t} + Low\_3yr_{i,t} + e_2 Mid\_3yr_{i,t} + e_3 High\_3yr_{i,t} + fVol_{i,t} + Controls + \epsilon_{i,t}.$$

Here b_2 captures the effect of performance volatility on 3-year performance if it happens to be the minimum performance rank and c captures the impact of performance volatility on the 3-year performance, on average. Under ambiguity aversion, we expect b_2 to be positive and significant, since past performance volatility is expected to increase the fund′s ambiguity level. However, if investors are Bayesian learners as modeled in Huang, Yan and Wei (2012), we also expect to observe a negative value for the coefficient c, since high signal noise should dampen flow sensitivity, in general.

The results from estimation (26) are reported in Column 3 of Table 7. We find that the coefficient b_2 has a value equal to 1.143 while the coefficient c equals -0.906, and both coefficients are significant at 1% level. In economic terms, a 1 unit increase in performance volatility will **decrease** sensitivity to performance by $0.906 \times 1 = 0.906$, on average. However, it will **increase** sensitivity to the minimum performance rank by $(1.143 - 0.906) \times 1 = 0.237$. Here we observe clearly that the presence of ambiguity aversion leads to a net increase in the overall flow-performance sensitivity despite the dampening effect of performance volatility.

These findings show that the dampening effect and ambiguity aversion are not contradictory to each other and may actually co-exist. This is intuitive, since it is reasonable to conjecture that there are two distinct types of fund investors. The first type is the sophisticated investors who have a better understanding of the performance generating mechanism in the mutual fund industry. Upon observing past fund performance, these investors face less ambiguity and are able to update their beliefs in a manner similar to Bayesian rules. The other type of investors is less sophisticated. They have access to the same past performance information, but cannot update their beliefs about the fund manager′s skill in a Bayesian fashion. They display aversion to ambiguity, as shown by the positive and significant coefficient on the minimum performance rank variable.

We further examine the above intuition by including a dummy variable $Inst_i$, which equals 1 if a fund is only open to institutional investors. We develop the following test to separate the two types of fund investors with different level of sophistication:

$$\begin{aligned} Flow_{i,t} =& a + b_2 Min_{i,t} \times Vol_{i,t} \times Perf\_3yr_{i,t} + d_1 Inst_i \times Vol_{i,t} \times Min_{i,t} \times Perf\_3yr_{i,t} \\ &+ cVol_{i,t} \times Perf_3 yr_{i,t} + d_2 Inst_i \times Vol_{i,t} \times Perf\_3yr_{i,t} + d_3 Inst_i + e_1 Low\_3yr_{i,t} \\ &+ e_2 Mid\_3yr_{i,t} + e_3 High\_3yr_{i,t} + Controls + \epsilon_{i,t}. \end{aligned}$$

We expect to observe a stronger volatility dampening effect in institutional fund flows and a weaker ambiguity aversion effect. Similar to Equation (26), the coefficient, b_2, captures ambiguity aversion and the coefficient, c captures the dampening effect. The coefficient d_1 captures the marginal ambiguity aversion for the institutional investors and d_2 captures the marginal volatility dampening effect for institutional investors. We expect d_1 to be negative and d_2 to be positive. The results of this test are presented in Column 4 of Table 7. As expected, the coefficient d_1 is estimated to be -0.237 (significant at 10% level) and d_2 equals -0.405 (significant at 1% level). This implies that a 1 unit increase in volatility will **decrease** flow sensitivity to performance by $0.885 + 0.405 = 1.29$ for institutional investors. However, it will **decrease** sensitivity by only $1.29-(1.181-0.237) = 0.346$ if the performance measure is the minimum among 1-year, 3-year and 5-year performance ranks. Thus, for institutional funds, regardless of whether the 3-year performance is the minimum performance or not, there is a volatility dampening effect which dominates the impact of ambiguity aversion. This is consistent with our intuition that for sophisticated investors, we should see a stronger dampening effect of performance volatility on flow-performance sensitivity.

In order to more closely match the results of Huang, Wei and Yan (2012) we repeat our tests using an identical sample period: 1983-2006. We find qualitatively similar results and report them in Columns 5-8 in Table 7. In conclusion, we find that in a population with a larger fraction of naive investors, ambiguity aversion behavior dominates the dampening effect of performance volatility on the flow-performance relation. Conversely, in a population with a greater fraction of sophisticated investors, the volatility dampening effect dominates ambiguity aversion.

VII. Robustness

In previous tests we investigated the asymmetric sensitivity of fund flows to performance measured over 1-, 3-, and 5-year horizons caused by investor ambiguity aversion. In particular, we find that the more ambiguous a fund appears to its investors, the greater the flow-performance sensitivity to the minimum performance over the three time horizons. Of course, investors have access to additional information beyond the above three measures of performance. Other information available to investors includes the performance of the fund since inception and the Morningstar fund ratings.[9] In fact, previous studies show that investor flows do respond to Morningstar ratings. A natural question is whether the additional sensitivity to minimum performance documented in our tests is simply due to the omission of long term performance measures and/or Morningstar ratings. To address this concern we reexamine the baseline model in Equation (17) while controlling for the funds′ performance since inception and the Morningstar fund ratings.

We measure a fund′s performance since its inception in the same manner as its 1, 3 and 5 years performance. We rank funds based on their average monthly raw returns since inception within their objective category. The resulting ranking is a number between 0 and 1.

[9] See, e.g., Del Guercio and Tkac (2002b).

The Morningstar rating is another important signal of fund manager skill and it is sometimes featured in fund advertisements. According to Sharpe (1997), Morningstar ranks funds within four asset classes before 1996 and within smaller categories thereafter. We replicate the latter rating scheme because it covers most of our sample period. Since we do not have access to the criteria that Morningstar uses to classify funds into style categories, we continue to employ the classifications used for our primary tests. Morningstar rates all funds based on their 3-, 5- and 10-year return and risk, respectively and then a weighted overall rating is determined. We follow the procedure described in Nanda et al. (2004b) to replicate the funds′ Morningstar fund ratings.

Our robustness tests are based on the following specification:

$$\begin{aligned}(27)\qquad Flow_{i,t} =& a + b_1 Perf\_1yr_{i,t} + b_2 Perf\_3yr_{i,t} + b_3 Perf\_5yr_{i,t} + b_4 Perf\_Incep_{i,t} + \\ & b_5 MorningstarRating_{i,t} + cMin\_Rank_{i,t} + Controls + \epsilon_{i,t},\end{aligned}$$

The $MorningstarRating$ represents fund i's rating based on the Morningstar fund rating scheme in quarter t. The variable $Perf\_incep_{i,t}$ captures a fund i's performance since inception in quarter t.

Table 8 presents results of the robustness tests. We note that the coefficient of Min_Rank is consistently positive and significant for the sample of retail funds when we control for performance since inception and/or Morningstar rating, while it is insignificant for the institutional sample. Moreover, the coefficient of Per_Incep is negative and insignificant in all cases except in one case for retail funds (Column 5). However, the coefficient for $MorningstarRating$ is consistently positive and significant. For example, based on results in Column 5, if a retail fund′s Morningstar rating increases by 1 star, there is a corresponding increase of 1.3% in terms of fund flows. By contrast, for an institutional fund, a 1 star increase in the Morningstar rating is associated with a fund flow increase of only 0.5%, based on the results in Column 6. These results suggest that the Morningstar rating is an important signal for retail investors when making investment decisions. On the other hand, institutional investors seem to rely to a much lesser extent on this rating.

One of the most well-known findings in mutual fund literature is the convex relationship between investor flows and past fund performance. Previous studies (e.g. Sirri and Tufano (1998), Chevalier and Ellision (1997)) find that investor flows respond strongly to good past performance while being less sensitive to bad performance. In this paper we do not aim to provide an explanation for the convex relationship, but we do want to show that our baseline result is robust after controlling for the convex flow-performance relationship. Table 9 presents results regarding this test. As in the baseline model in Equation (17), we regress quarterly flow on past performance measured over 1-, 3-, and 5-year. We adopt fractional ranks for each of the 1-, 3-, and 5-year performance (same as Low_3yr, Mid_3yr and $High\_3yr$ defined in Equation (24)) to capture the convexity in flow-performance relationship. The results presented in Table 9 confirm that the additional sensitivity to the minimum performance measure remains positive and significant in the retail fund sample even after controlling for the convexity of the flow-performance relationship.

In conclusion, the results of the robustness tests confirm that mutual fund flows display an additional sensitivity to the minimum performance rank even after controlling for performance since inception, the funds′ Morningstar star ratings, and convexity in the flow-performance relation.

VIII. Concluding Remarks

This paper presents a model of an ambiguity averse mutual fund investor who faces multiple signals about the performance of the fund. The model implies that an ambiguity averse investor, in attempting to learn about manager skill, always puts additional weight on the worst signal. We empirically test the key implications of the model by using a fund′s past performance measured over multiple time horizons, as multiple signals about manager skill observed by investors.

Our study provides novel evidence on the role of ambiguity aversion in determining the response of mutual fund investors to historical fund performance information. We find that consistent with our model, fund flows display heightened sensitivity to the minimum performance measure. Further, we observe this ambiguity averse behavior only among retail fund investors. By contrast, fund flows in institutional funds appear to be more consistent with standard Bayesian learning behavior. We also find that funds with more volatile past flows and funds belonging to smaller fund families appear more ambiguous to investors while advertising expenditure appears to reduce the degree of ambiguity perceived by investors. Furthermore, we distinguish between the effect of increased performance volatility on ambiguity averse investors and on investors whose behavior is more consistent with Bayesian learning. We find that fund volatility increases ambiguity averse investors′ response to the minimum performance measure while it dampens the Bayesian investors′ sensitivity to past performance in general. Taken together, these results suggest that fund investor behavior is best characterized as reflecting both Bayesian learning and ambiguity aversion.

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Table 1: Summary Statistics of the Equity Mutual Fund Sample

This table reports the time-series averages of quarterly cross-sectional averages of fund characteristics for the period 1993-2011. TNA is the total net assets. Flow is the percentage change in TNA. Expense Ratio is the total quarterly management and administrative expenses divided by average TNA. Total Expense is estimated as expense ratio plus 1/7 of maximum front-end load. 12-b1 Fees are fees paid by the fund out of fund assets to cover marketing expenses, distribution expenses and sometimes shareholder service expenses. The 12-b1 fees are only available since 1992. Raw Return is the average monthly raw return during the prior 12 months and volatility is the corresponding standard deviation. The statistics are reported for all funds (i.e., share classes), and for share classes open only to retail investors and share classes available only to institutional investors.

	Share Classes		
	All Funds	Retail Shares	Institutional Shares
Total Fund Number	7,020	5,781	1,239
Average Fund Number	2,847	2,359	466
Flow (in % per quarter)	1.51	1.32	2.33
Age (in years)	11.60	12.07	8.67
TNA (in millions)	678.06	739.36	330.49
Expense Ratio (in %)	1.41	1.49	0.96
Total Expense (in %)	1.61	1.73	0.99
12b-1 Fee (in %)	0.56	0.57	0.20
Raw Return (in % per month)	0.73	0.72	0.79
Vol. of Raw Return (in % per month)	4.60	4.59	4.66

Table 2: Ambiguity Aversion of Retail and Institutional Investors

This table examines the ambiguity aversion behavior of both retail and institutional investors during period 1993-2011. The sample is divided into retail shares and institutional shares. Each quarter, funds are assigned ranks between zero and one according to their performance during the past 12 months (Perf_1yr), 36 months (Perf_3yr) and 60 months (Perf_5yr) respectively. Performance is measured by the average monthly raw returns or the Carhart (1997) four-factor alphas. Funds are ranked based on raw returns within the funds objective category while ranks based on alphas are computed across all funds in the sample. Min_Rank is defined as the minimum performance rank among three periods. A linear regression model is estimated by regressing quarterly flows on funds three performance ranks (Perf_1yr, Perf_3yr and Perf_5yr) and the minimum rank (Min_Rank). The control variables include fund age, defined as log (1+age), quarterly flow in previous quarter, logarithm of lagged fund TNA, volatility of monthly raw return in prior 12 months, lagged total expense, and aggregate flow into the fund objective category. Time-series averages of coefficients and the Newey-West t-statistics (in parentheses) are reported. The symbols *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Performance Measured by	Raw Return		4-Factor Alpha	
	Retail	Institutional	Retail	Institutional
Perf_1yr	0.050***	0.055***	0.036***	0.045***
	(8.33)	(3.55)	(7.11)	(5.23)
Perf_3yr	0.039***	0.035**	0.049***	0.067***
	(6.78)	(2.41)	(10.55)	(5.78)
Perf_5yr	0.011***	0.042***	-0.015**	0.012
	(2.64)	(3.16)	(-2.50)	(1.12)
Min_Rank	0.048***	0.017	0.057***	0.010
	(7.02)	(0.89)	(7.74)	(0.85)
Age	-0.017***	-0.027***	-0.010***	-0.018***
	(-9.79)	(-6.94)	(-10.41)	(-4.80)
Previous Quarter Flow	0.177***	0.137***	0.209***	0.167***
	(7.52)	(5.71)	(8.25)	(5.08)
Size	-0.004***	-0.011***	-0.004***	-0.010***
	(-6.77)	(-7.42)	(-8.45)	(-6.49)
Volatility	-0.394***	-0.622***	0.322**	0.293***
	(-3.98)	(-2.89)	(2.08)	(1.31)
Total Expense	-0.434***	-1.912***	-0.278**	-1.947***
	(-2.72)	(-3.42)	(-2.10)	(-2.85)
Category Flow	0.288***	0.060	0.208***	0.028
	(3.46)	(0.38)	(3.52)	(0.20)
Intercept	0.020***	0.089***	-0.011	0.040***
	(3.06)	(5.69)	(-1.50)	(3.49)

Table 3: Strategy Changes as a Proxy for Fund Ambiguity Level

This table presents results of tests that use fund strategy changes as a proxy for a funds ambiguity level. The sample includes only the retail funds. Each quarter, the sample is divided into three groups, Low, Mid and High based on proxy of strategy changes. Panel A reports results when strategy changes are measured by Loading Change, which is the average absolute change in risk loadings of Carhart (1997) 4-factor model between prior 1-30 and 31-60 months. In Panel B, the proxy is the funds R square over its lifetime from the 4-factor model of Carhart (1997). A linear regression is performed in each group by regressing quarterly flows on funds three performance ranks (Perf_1yr, Perf_3yr and Perf_5yr) and the minimum rank (Min_Rank). Performance is measured by the average monthly raw returns or the Carhart (1997) 4-factor alphas. The control variables include fund age, defined as log (1+age), quarterly flow in previous quarter, logarithm of lagged fund TNA, volatility of monthly raw return in prior 12 months, lagged total expense, and aggregate flow into the fund objective category. Time-series averages of coefficients and the Newey-West t-statistics (in parentheses) are reported. The symbols *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Panel A: Strategy Changes Proxy by Loading Change

Performance Measured by	Raw Return			4-Factor Alpha		
	Low	Mid	High	Low	Mid	High
Perf_1yr	0.053***	0.046***	0.045***	0.038***	0.031***	0.035***
	(5.91)	(6.89)	(7.27)	(5.01)	(4.43)	(5.92)
Perf_3yr	0.038***	0.030***	0.036***	0.053***	0.046***	0.039***
	(6.50)	(4.55)	(4.58)	(5.79)	(7.30)	(4.25)
Perf_5yr	0.032***	0.015**	0.008	-0.005	-0.020**	-0.012**
	(6.31)	(2.55)	(1.33)	(-0.73)	(-2.06)	(-2.33)
Min_Rank	0.011	0.044***	0.061***	0.033***	0.053***	0.061***
	(1.13)	(4.03)	(6.12)	(3.04)	(4.56)	(4.67)
Age	-0.014***	-0.016***	-0.015***	-0.007***	-0.009***	-0.011***
	(-6.88)	(-8.44)	(-9.84)	(-6.86)	(-5.89)	(-6.19)
Previous Quarter Flow	0.189***	0.260***	0.253***	0.217***	0.291***	0.279***
	(7.64)	(9.19)	(9.70)	(8.31)	(8.62)	(9.03)
Size	-0.004***	-0.005***	-0.006***	-0.004***	-0.004***	-0.005***
	(-6.14)	(-8.05)	(-4.99)	(-5.28)	(-5.80)	(-4.78)
Volatility	-0.378***	-0.368***	-0.370***	0.628**	0.253	0.140
	(-3.07)	(-2.73)	(-3.45)	(2.49)	(1.02)	(1.08)
Total Expense	-1.085***	-0.869***	-0.092	-0.462	-0.576**	-0.174
	(-3.36)	(-3.49)	(-0.58)	(-1.61)	(-2.44)	(-1.34)
Category Flow	0.364***	0.130	0.225	0.131	0.036	0.323**
	(3.71)	(1.41)	(1.60)	(1.58)	(0.43)	(2.35)
Intercept	0.023**	0.027***	0.016*	-0.026*	-0.000	0.002
	(2.13)	(3.16)	(1.87)	(-1.91)	(-0.03)	(0.20)

Table 3 Continued

Panel B: Panel B: Strategy Changes Proxy by R Square

Performance Measured by	Raw Return			4-Factor Alpha		
	Low	Mid	High	Low	Mid	High
Perf_1yr	0.046***	0.058***	0.046***	0.032***	0.049***	0.020**
	(10.39)	(6.53)	(6.37)	(5.54)	(6.08)	(2.29)
Perf_3yr	0.031***	0.037***	0.034***	0.034***	0.051***	0.056***
	(3.76)	(6.28)	(6.76)	(4.19)	(8.46)	(4.79)
Perf_5yr	0.005	0.020***	0.026***	-0.014**	-0.009	-0.021**
	(0.96)	(3.61)	(5.01)	(-2.51)	(-1.53)	(-2.37)
Min_Rank	0.056***	0.028***	0.014	0.063***	0.027**	0.054***
	(6.01)	(3.04)	(1.63)	(5.52)	(2.62)	(3.97)
Age	-0.013***	-0.019***	-0.014***	-0.007***	-0.013***	-0.007***
	(-6.93)	(-11.25)	(-5.63)	(-5.07)	(-7.76)	(-5.22)
Previous Quarter Flow	0.274***	0.228***	0.199***	0.298***	0.286***	0.201***
	(11.00)	(8.30)	(7.75)	(11.83)	(8.47)	(9.72)
Size	-0.005***	-0.004***	-0.003***	-0.005***	-0.004***	-0.004***
	(-5.17)	(-6.73)	(-4.70)	(-5.85)	(-6.03)	(-5.73)
Volatility	-0.409***	-0.388***	-0.398***	0.188	0.446**	0.674*
	(-3.64)	(-3.41)	(-2.93)	(1.44)	(2.18)	(1.93)
Total Expense	-0.169	-0.900***	-0.676**	-0.151	-0.493*	-0.568*
	(-1.31)	(-3.15)	(-2.62)	(-1.30)	(-1.73)	(-1.85)
Category Flow	0.291**	0.150*	0.398***	0.207*	0.083	0.160
	(2.22)	(1.89)	(5.28)	(1.67)	(1.11)	(1.35)
Intercept	0.013*	0.034***	0.024**	-0.009	-0.003	-0.012
	(1.86)	(3.51)	(2.18)	(-0.97)	(-0.33)	(-0.70)

Table 4: Flow Volatility as a Proxy for Fund Ambiguity Level

This table presents results of tests that use flow volatility as a proxy for a funds ambiguity level. The sample includes only the retail funds. Flow_Vol is the standard deviation of quarterly flows over prior 12 quarters. Each quarter, a dummy variable Low_Flowvol equals one if the flow volatility falls in the bottom tercile, a dummy variable Mid_Flowvol eqauls one if the flow volatility belongs to the medium tercile and a dummy variable High_Flowvol equals one if the flow volatility is in the top tercile. A linear regression is performed by regressing quarterly flows on funds three performance ranks (Perf_1yr, Perf_3yr and Perf_5yr) and the minimum rank (Min_Rank) interacted with the three dummy variables. The control variables include fund age, defined as log (1+age), quarterly flow in previous quarter, logarithm of lagged fund TNA, volatility of monthly raw return in prior 12 months, lagged total expense, and aggregate flow into the fund objective category. Time-series averages of coefficients and the Newey-West t-statistics (in parentheses) are reported. The symbols *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Performance Measured by	Raw Return	4-Factor Alpha
Low_Flowvol×Perf_1yr	0.046***	0.033***
	(9.94)	(6.84)
Mid_Flowvol×Perf_1yr	0.050***	0.044***
	(7.35)	(6.35)
High_Flowvol×Perf_1yr	0.072***	0.045***
	(6.78)	(4.50)
Low_Flowvol×Perf_3yr	0.026***	0.028***
	(5.63)	(5.60)
Mid_Flowvol×Perf_3yr	0.038***	0.052***
	(6.04)	(8.53)
High_Flowvol×Perf_3yr	0.049***	0.067***
	(4.70)	(6.36)
Low_Flowvol×Perf_5yr	0.036***	0.016***
	(9.65)	(2.56)
Mid_Flowvol×Perf_5yr	0.008	-0.022***
	(1.59)	(-2.90)
High_Flowvol×Perf_5yr	-0.035***	-0.064***
	(-4.06)	(-7.07)
Low_Flowvol×Min_Rank	-0.002	0.007
	(-0.54)	(1.08)
Mid_Flowvol×Min_Rank	0.041***	0.043***
	(5.10)	(4.31)
High_Flowvol×Min_Rank	0.110***	0.122***
	(8.12)	(7.41)
Flow_Vol	0.060***	0.034***
	(6.36)	(3.11)
Age	-0.008***	-0.004***
	(-6.20)	(-3.43)
Previous Quarter Flow	0.158***	0.192***
	(7.11)	(7.74)

Table 4 Continued		
Performance Measured by	Raw Return	4-Factor Alpha
Size	-0.003***	-0.003***
	(-5.08)	(-6.44)
Volatility	-0.527***	0.135
	(-5.08)	(0.92)
Total Expense	-0.292**	-0.187
	(-2.05)	(-1.58)
Category Flow	0.281***	0.201***
	(3.89)	(3.39)
Intercept	-0.006	-0.026***
	(-1.12)	(-3.48)

Table 5: Fund Family Size as a Proxy for Fund Ambiguity Level

This table presents results of tests using family size as a proxy for a funds ambiguity level. The sample includes only retail funds. Family size is total net asset of all fund share classes that belong to the same fund family. Each quarter, a dummy variable Low_FamSize equals one if fund *i* belongs to a family whose size falls into the bottom tercile, a dummy variable Mid_FamSize equals one if family size belongs to the medium tercile, and a dummy variable High_FamSize equals one if the family size is in the top tercile. D_FamliySize is a dummy variable that equals one if family size is above the median value for that quarter. A linear regression is performed by regressing quarterly flows on funds three performance ranks (Perf_1yr, Perf_3yr and Perf_5yr) and the minimum rank (Min_Rank) interacted with the three dummy variables. The control variables include fund age, defined as log (1+age), quarterly flow in previous quarter, logarithm of lagged fund TNA, volatility of monthly raw return in prior 12 months, lagged total expense, and aggregate flow into the fund objective category. Time-series averages of coefficients and the Newey-West t-statistics (in parentheses) are reported. The symbols *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Performance Measured by	Raw Return	4-Factor Alpha
Low_Famsize×Perf_1yr	0.043***	0.030***
	(8.53)	(4.55)
Mid_Famsize×Perf_1yr	0.045***	0.037***
	(8.54)	(7.67)
High_Famsize×Perf_1yr	0.066***	0.049***
	(5.10)	(5.35)
Low_Famsize×Perf_3yr	0.027***	0.042***
	(4.44)	(5.52)
Mid_Famsize×Perf_3yr	0.036***	0.054***
	(3.87)	(6.26)
High_Famsize×Perf_3yr	0.048***	0.049***
	(5.77)	(7.28)
Low_Famsize×Perf_5yr	-0.005	-0.028***
	(-0.86)	(-3.61)
Mid_Famsize×Perf_5yr	0.009	-0.020***
	(1.49)	(-3.58)
High_Famsize×Perf_5yr	0.031***	0.013*
	(5.97)	(1.72)
Low_Famsize×Min_Rank	0.073***	0.069***
	(6.68)	(5.07)
Mid_Famsize×Min_Rank	0.061***	0.061***
	(6.52)	(4.88)
High_Famsize×Min_Rank	0.014	0.031***
	(1.26)	(3.28)
D_FamilySize	0.009***	0.011***
	(4.20)	(4.59)
Age	-0.015***	-0.009***
	(-8.21)	(-8.16)

Table 5 Continued		
Performance Measured by	Raw Return	4-Factor Alpha
Previous Quarter Flow	0.173***	0.205***
	(7.68)	(8.40)
Size	-0.009***	-0.010***
	(-6.10)	(-8.50)
Volatility	-0.396***	0.303*
	(-3.97)	(1.99)
Total Expense	-0.541***	-0.407***
	(-3.67)	(-3.26)
Category Flow	0.285***	0.210***
	(3.44)	(3.54)
Intercept	0.037***	0.009
	(5.18)	(0.98)

Table 6: Impact of Fund Advertising on Funds Ambiguity

This table examines the impact of various types of fund expenses on funds ambiguity. The sample includes only retail funds during 1993-2011. Expense Ratio is the total quarterly management and administrative expenses divided by average TNA. 12b-1 fees are the part of total management and administrative expenses that cover distribution expenses and sometimes shareholder services. The non-12b-1 fees are the expense ratio less 12b-1 fees. The 12b-1 fees are only available in CRSP database after 1992. Each quarter, a dummy variable Low_Exp equals one if the fund is corresponding type of fees falls into the bottom tercile, a dummy variable Mid_Exp equals one if it belongs to the medium tercile, and a dummy variable High_Exp equals one if it is in the top tercile. Expense is 12b-1 fees, non-12b-1 fees or Expense Ratio. A linear regression is performed by regressing quarterly flows on the funds three performance ranks (Perf_1yr, Perf_3yr and Perf_5yr) and the minimum rank (Min_Rank) interacted with the three dummy variables for each of the three expense types. Performance is measured by the average monthly raw returns or the Carhart (1997) four-factor alphas (Alpha). The control variables include fund age, defined as log (1+age), quarterly flow in previous quarter, logarithm of lagged fund TNA, volatility of monthly raw return in prior 12 months, and aggregate flow into the fund objective category. Time-series average coefficients and the Newey-West t-statistics (in parentheses) are reported. The symbols *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	12b-1		Non-12b-1		Expense Ratio	
Performance Measure by	Raw Return	Alpha	Raw Return	Alpha	Raw Return	Alpha
Low_Exp×Perf_1yr	0.045***	0.020**	0.063***	0.042***	0.067***	0.051***
	(4.97)	(2.20)	(6.03)	(6.82)	(7.53)	(8.52)
Mid_Exp×Perf_1yr	0.038***	0.028***	0.048***	0.036***	0.044***	0.030***
	(4.70)	(4.64)	(6.32)	(6.08)	(7.81)	(5.33)
High_Exp×Perf_1yr	0.064***	0.049***	0.043***	0.030***	0.040***	0.031***
	(5.94)	(5.52)	(8.25)	(4.03)	(5.78)	(3.57)
Low_Exp×Perf_3yr	0.030***	0.048***	0.047***	0.045***	0.034***	0.041***
	(3.78)	(7.42)	(6.50)	(7.27)	(4.81)	(6.15)
Mid_Exp×Perf_3yr	0.052***	0.032***	0.027***	0.045***	0.042***	0.049***
	(5.87)	(4.80)	(4.12)	(6.97)	(5.82)	(8.22)
High_Exp×Perf_3yr	0.056***	0.076***	0.042***	0.052***	0.039***	0.051***
	(4.46)	(6.03)	(4.92)	(7.77)	(4.59)	(6.37)
Low_Exp×Perf_5yr	0.012	-0.005	0.032***	0.013*	0.043***	0.018**
	(1.55)	(-0.55)	(6.17)	(1.93)	(8.45)	(2.44)
Mid_Exp×Perf_5yr	0.006	-0.014*	0.015***	-0.017**	0.009	-0.024***
	(0.71)	(-1.83)	(2.84)	(-2.23)	(1.35)	(-2.99)

Table 6 Continued

	12b-1		Non-12b-1		Expense Ratio	
Performance Measure by	Raw Return	Alpha	Raw Return	Alpha	Raw Return	Alpha
High_Exp×Perf_5yr	0.003	-0.023*	-0.009	-0.034***	-0.020***	-0.036***
	(0.57)	(-1.95)	(-1.21)	(-5.14)	(-3.37)	(-4.32)
Low_Exp×Min_Rank	0.058***	0.069***	0.005	0.020***	0.007	0.013*
	(4.67)	(4.56)	(0.49)	(3.15)	(0.83)	(1.80)
Mid_Exp×Min_Rank	0.048***	0.081***	0.060***	0.058***	0.065***	0.078***
	(3.27)	(5.96)	(6.93)	(6.02)	(7.10)	(7.23)
High_Exp×Min_Rank	0.021	0.024	0.084***	0.092***	0.078***	0.074***
	(1.40)	(1.22)	(6.41)	(5.64)	(6.27)	(4.20)
Expense	-3.587***	-2.599***	0.144	-0.202	-0.258*	-0.445***
	(-6.75)	(-4.74)	(0.98)	(-1.23)	(-1.84)	(-2.72)
Age	-0.023***	-0.014***	-0.018***	-0.010***	-0.018***	-0.012***
	(-8.73)	(-8.04)	(-8.98)	(-10.74)	(-9.10)	(-10.28)
Previous Quarter Flow	0.209***	0.215***	0.176***	0.209***	0.174***	0.207***
	(6.91)	(7.19)	(7.58)	(8.26)	(7.42)	(8.14)
Size	-0.004***	-0.004***	-0.004***	-0.004***	-0.006***	-0.005***
	(-6.67)	(-5.30)	(-5.88)	(-9.89)	(-11.92)	(-10.60)
Volatility	-0.542***	0.129	-0.437***	0.303*	-0.354***	0.355**
	(-5.23)	(0.79)	(-4.05)	(1.92)	(-3.71)	(2.25)
Category Flow	0.216**	0.163***	0.297***	0.207***	0.270***	0.186***
	(2.57)	(3.07)	(3.66)	(3.13)	(3.10)	(2.96)
Intercept	0.051***	0.012	0.013*	-0.014*	0.021***	-0.005
	(6.03)	(1.30)	(1.88)	(-1.71)	(3.26)	(-0.60)

Table 7: Contrast between the Response of Ambiguity Averse Investors and Bayesian Investors

This table examines the differences in the response of ambiguity averse investors and Bayesian investors during the periods: 1983-2006 and 1993-2011. The sample includes all retail and institutional funds. Perf_3yr is a fractional rank ranging from 0 to 1 reflecting a funds ranking within an objective category based on the average monthly raw returns over prior 36 months. The performance of a fund in the bottom quintile (Low_3yr) is defined as Min(Perf_3yr, 0.2), in the three medium quintiles (Mid_3yr) is defined as Min(0.6, Perf_3yr-Low_3yr), and in the top quintiles (High_3yr) is defined as Perf_3yr-Low_3yr-Mid_3yr. Vol is the standard deviation of raw returns over prior 36 months. The dummy variable Min equals one if the 3-year performance rank is the minimum among the performance ranks during the 1-year, 3-year and 5-year ranking periods. A dummy variable Inst equals one if the fund is open only to institutional investor. Each quarter, a linear regression is performed by regressing quarterly flows on funds Perf_3yr and its interaction with Min, Vol, and Inst. The control variables include fund age, defined as log (1+age), quarterly flow in previous quarter, logarithm of lagged fund TNA, lagged total expense, and aggregate flow into the fund objective category. Time-series averages of coefficients and the Newey-West t-statistics (in parentheses) are reported. The symbols *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	Panel A: 1993-2011				Panel B: 1983-2006			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Min×Perf_3yr	0.053***	.	.	.	0.052***	.	.	.
	(13.50)	.	.	.	(9.05)	.	.	.
Min×Vol×Perf_3yr	.	.	1.143***	1.181***	.	.	1.110***	1.151***
	.	.	(8.91)	(8.67)	.	.	(7.48)	(7.61)
Vol×Perf_3yr	.	-0.777***	-0.906***	-0.885***	.	-0.575**	-0.686***	-0.683**
	.	(-2.32)	(-2.98)	(-2.87)	.	(-2.06)	(-2.65)	(-2.60)
Inst×Min×Vol×Perf_3yr	.	.	.	-0.237	.	.	.	-0.441**
	.	.	.	(-1.60)	.	.	.	(-2.30)
Inst×Vol×Perf_3yr	.	.	.	-0.405**	.	.	.	-0.312
	.	.	.	(-2.26)	.	.	.	(-1.65)
Inst	.	.	.	0.005	.	.	.	-0.004
	.	.	.	(1.50)	.	.	.	(-0.90)
Low_3yr	0.070***	0.147***	0.128***	0.126***	0.057***	0.120***	0.098***	0.097***
	(3.61)	(6.60)	(5.70)	(5.63)	(2.36)	(4.30)	(3.50)	(3.37)
Mid_3yr	0.091***	0.134***	0.137***	0.139***	0.075***	0.104***	0.107***	0.109***
	(18.28)	(8.25)	(9.06)	(9.39)	(11.55)	(8.64)	(9.58)	(9.83)

Table 7 Continued

	Panel A: 1993-2011				Panel B: 1983-2006			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High_3yr	0.407***	0.428***	0.467***	0.469***	0.358***	0.364***	0.398***	0.402***
	(17.29)	(12.44)	(15.06)	(15.55)	(11.76)	(11.49)	(12.89)	(12.82)
Age	-0.020***	-0.022***	-0.020***	-0.021***	-0.014***	-0.016***	-0.015***	-0.015***
	(-10.01)	(-10.74)	(-10.28)	(-11.11)	(-6.94)	(-7.47)	(-7.21)	(-7.46)
Previous Quarter Flow	0.127***	0.129***	0.127***	0.126***	0.170***	0.174***	0.170***	0.169***
	(6.14)	(6.07)	(6.11)	(6.12)	(6.38)	(6.53)	(6.31)	(6.26)
Size	-0.005***	-0.005***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(-8.43)	(-8.28)	(-8.67)	(-8.39)	(-11.93)	(-11.55)	(-12.09)	(-12.03)
Vol	-0.668***	-0.204	-0.272	-0.274*	-0.450***	-0.187	-0.232*	-0.206
	(-4.31)	(-1.24)	(-1.65)	(-1.72)	(-3.30)	(-1.41)	(-1.72)	(-1.56)
Total Expense	-0.619***	-0.661***	-0.643***	-0.694***	-0.287**	-0.320**	-0.303**	-0.436***
	(-2.89)	(-3.13)	(-3.02)	(-3.81)	(-2.29)	(-2.55)	(-2.43)	(-3.49)
Category Flow	0.197**	0.189**	0.203**	0.216**	0.424***	0.407***	0.415***	0.418***
	(2.33)	(2.20)	(2.41)	(2.61)	(9.91)	(9.33)	(9.88)	(10.04)
Intercept	0.064***	0.042***	0.042***	0.044***	0.051***	0.042***	0.040***	0.044***
	(5.96)	(5.15)	(5.32)	(5.20)	(4.17)	(3.38)	(3.33)	(3.52)

Table 8: Robustness Test Controlling for Morningstar Rating and/or Performance since Inception

This table reexamines the baseline model that studies ambiguity aversion behavior of both retail and institutional investors when controlling for performance since inception and/or the Morningstar star rating during the period 1993-2011. The sample includes all retail and institutional shares. Each quarter, funds are assigned ranks between zero and one within their objective category according to their performance during past 12 months (Perf_1yr), 36 months (Perf_3yr), 60 months (Perf_5yr) and since inception (Perf_Incep), respectively. Performance is measured by the ranking within category of the average monthly raw returns. Morningstar overall rating (Morningstar Rating) is a weighted average of a funds 3, 5 and 10 years category star rating ranging from 1 to 5 (See Nanda et al. (2004b) for details). Min_Rank is defined as the minimum performance rank among 1-year, 3-year and 5-year performance ranks. A linear regression is performed by regressing quarterly flows on funds three performance ranks and the minimum rank. The control variables include fund age, defined as log (1+age), quarterly flow in previous quarter, logarithm of lagged fund TNA, volatility of monthly raw return in prior 12 months, lagged total expense, and aggregate flow into the fund objective category. Time-series averages of coefficients and the Newey-West t-statistics (in parentheses) are reported. The symbols *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	Retail	Institutional	Retail	Institutional	Retail	Institutional
Perf_1yr	0.050***	0.063***	0.052***	0.068***	0.052***	0.068***
	(10.13)	(3.48)	(9.68)	(3.47)	(9.82)	(3.44)
Perf_3yr	0.032***	0.023	0.014*	0.014	0.014**	0.012
	(4.68)	(1.16)	(1.95)	(0.65)	(2.06)	(0.51)
Perf_5yr	0.017***	0.049**	-0.01	0.026	-0.009	0.036**
	(3.05)	(2.47)	(-1.53)	(1.66)	(-1.45)	(2.04)
Perf_Incep	-0.001	-0.013	.	.	-0.007	-0.016
	(-0.16)	(-1.24)	.	.	(-1.29)	(-1.54)
Morningstar Rating	.	.	0.016***	0.007*	0.017***	0.008**
	.	.	(9.05)	(1.87)	(8.92)	(2.02)
Min_Rank	0.054***	0.019	0.045***	0.012	0.045***	0.012
	(7.68)	(0.93)	(6.38)	(0.50)	(6.37)	(0.52)
Age	-0.007***	-0.021***	-0.008***	-0.020***	-0.006***	-0.021***
	(-6.67)	(-4.31)	(-9.01)	(-5.11)	(-5.37)	(-4.34)
Previous Quarter Flow	0.199***	0.161***	0.197***	0.161***	0.196***	0.161***
	(8.35)	(5.09)	(8.48)	(5.03)	(8.45)	(5.03)
Size	-0.006***	-0.011***	-0.007***	-0.011***	-0.007***	-0.011***
	(-8.37)	(-6.68)	(-9.56)	(-6.72)	(-8.77)	(-6.70)

Table 8 Continued

	Retail	institutional	Retail	institutional	Retail	institutional
Volatility	-0.300***	-0.431*	0.001	-0.369*	0.055	-0.350
	(-4.06)	(-1.97)	(0.01)	(-1.69)	(0.75)	(-1.53)
Total Expense	-0.230*	-2.001***	-0.186	-1.955***	-0.195	-1.970***
	(-1.72)	(-3.03)	(-1.44)	(-2.99)	(-1.49)	(-3.01)
Category Flow	0.411***	0.318**	0.389***	0.279*	0.412***	0.313**
	(6.90)	(2.17)	(6.05)	(1.77)	(6.30)	(2.00)
Intercept	-0.006	0.066***	-0.034***	0.050***	-0.042***	0.053***
	(-1.35)	(4.11)	(-6.92)	(2.96)	(-7.30)	(3.14)

Table 9: Robustness Test Controlling for Flow-Performance Convex Relationship

This table reexamines the baseline model that studies ambiguity aversion behavior of both retail and institutional investors when controlling for the convexity in flow-performance relationship during the period 1993-2011. The sample includes all retail and institutional shares. Each quarter, we adopt fractional ranks for funds performance measured over past 1-, 3-, and 5-year horizon. For example, the 1-year performance of a fund in the bottom quintile (Low_1yr) is defined as Min(Perf_1yr, 0.2), in the three medium quintiles (Mid_1yr) is defined as Min(0.6, Perf_1yr-Low_1yr), and in the top quintiles (High_1yr) is defined as Perf_1yr-Low_1yr-Mid_1yr. Performance is measured by the ranking within category of the average monthly raw returns. Min_Rank is defined as the minimum performance rank among 1-year, 3-year and 5-year performance ranks. A linear regression is performed by regressing quarterly flows on funds fractional performance ranks and the minimum rank. The control variables include fund age, defined as log (1+age), quarterly flow in previous quarter, logarithm of lagged fund TNA, volatility of monthly raw return in prior 12 months, lagged total expense, and aggregate flow into the fund objective category. Time-series averages of coefficients and the Newey-West t-statistics (in parentheses) are reported. The symbols *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Performance Measured by	Raw Return		4-Factor Alpha	
	Retail	Institutional	Retail	Institutional
Low_1yr	0.070***	0.091**	0.076***	0.038
	(4.27)	(2.57)	(4.04)	(1.03)
Mid_1yr	0.029***	0.052***	0.018***	0.043***
	(4.81)	(2.98)	(3.96)	(2.97)
High_1yr	0.241***	0.101**	0.200***	0.098**
	(10.47)	(2.50)	(10.36)	(2.20)
Low_3yr	0.042***	0.028	0.029**	0.147**
	(2.80)	(0.49)	(2.23)	(2.07)
Mid_3yr	0.026***	0.027*	0.036***	0.056***
	(4.26)	(1.77)	(7.35)	(4.89)
High_3yr	0.184***	0.139**	0.207***	0.215***
	(6.17)	(2.56)	(7.72)	(2.87)
Low_5yr	-0.033*	-0.190***	-0.015	-0.094
	(-1.82)	(-3.62)	(-0.81)	(-1.34)
Mid_5yr	0.013***	0.052***	-0.015*	0.011
	(2.87)	(3.38)	(-1.92)	(0.81)
High_5yr	0.056**	0.118***	0.009	0.059
	(2.34)	(2.69)	(0.33)	(1.01)
Min_Rank	0.036***	0.005	0.041***	-0.006
	(4.85)	(0.24)	(6.20)	(-0.34)
Age	-0.018***	-0.027***	-0.010***	-0.017***
	(-9.59)	(-7.32)	(-10.30)	(-4.16)
Previous Quarter Flow	0.172***	0.137***	0.203***	0.162***
	(7.57)	(5.94)	(8.38)	(5.06)

Table 9 Continued

Performance Measured by	Raw Return		4-Factor Alpha	
	Retail	Institutional	Retail	Institutional
Size	-0.004***	-0.010***	-0.004***	-0.009***
	(-6.92)	(-7.40)	(-8.24)	(-5.98)
Volatility	-0.573***	-0.693***	0.106	0.012
	(-5.47)	(-3.06)	(0.71)	(0.05)
Total Expense	-0.509***	-2.031***	-0.351**	-2.172***
	(-3.14)	(-3.79)	(-2.54)	(-2.93)
Category Flow	0.295***	0.130	0.219***	0.083
	(3.45)	(0.77)	(3.17)	(0.54)
Intercept	0.038***	0.125***	0.001	0.058***
	(5.18)	(7.68)	(0.15)	(4.36)