Volatility of Performance and Mutual Fund Flows

Jennifer Huang, Kelsey D. Wei, and Hong Yan*

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Abstract

We investigate the impact of fund volatility on the sensitivity of flows to past performance. We find that flows respond less strongly to volatile past performance, and that this dampening effect of volatility is more significant for younger funds. These findings are consistent with the hypothesis that at least some investors are sophisticated enough to recognize the risk level of funds and to adjust their learning and investments accordingly. As the dampening effect of performance volatility is driven mainly by sophisticated investors, we further support our hypothesis by demonstrating the variation in the volatility dampening effect across load/no-load funds and star/non-star funds which attract different mixes of sophisticated/unsophisticated investors. Our results shed light on the behavior of mutual fund investors and have significant implications for the equilibrium incentive for fund managers to engage in risk-shifting strategies.

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*Huang is at the McCombs School of Business, the University of Texas at Austin (email: `jennifer.huang@mccombs.utexas.edu`). Wei is at the School of Management, the University of Texas at Dallas (email: `kelsey.wei@utdallas.edu`). Yan is at the Moore School of Business, University of South Carolina (email: `yanh@moore.sc.edu`). We thank Keith Brown, Jay Hartzel, Laura Starks, Sheridan Titman, Roberto Wessels and seminar participants at the University of Texas at Austin and the University of Texas at Dallas. All remaining errors are our own.

1 Introduction

Flows into actively managed mutual funds have been used to represent the dynamic demand from investors for the services provided by these funds. Extant research has established that past performance strongly influences flows. Recent literature, e.g., Chevalier and Ellison (1997), Ippolito (1992), and Sirri and Tufano (1998), has found that this flow-performance relationship is asymmetric and convex. Namely, flows respond strongly to prior superior performance, but they are much less sensitive to past poor performance.

Since most mutual fund management fees are proportional to the assets under management, the convex relationship between flow and performance implies an option-like payoff structure for managers. As argued by Starks (1987), Grinblatt and Titman (1989), and Carpenter (2000), this implicit compensation scheme may create incentives for managers to take more risky positions. It may also induce the type of tournament behavior investigated by Brown, Harlow, and Starks (1996) who find that funds that have bad performances by mid-year tend to increase their risk profiles in the remainder of the year. Chevalier and Ellison (1997), Busse (2001), and Chen and Pennacchi (2002) study as well the risk-shifting behavior of fund managers.

While much of the literature has focused on the incentives for managers to manipulate fund risk levels given the convex flow-performance relationship, relatively less effort has been devoted to understanding the response of investors that determines fund flows in the first place. In particular, to the extent that the volatility of performance is easily measurable, do investors recognize and account for it in interpreting past performance and allocating their wealth among funds? The answer to this question is important, as it sheds lights on the sophistication level of individual investors—which has direct policy implications—and can affect the equilibrium incentive for fund managers to engage in risk-shifting strategies.

To address this question, we set up a model of optimal mutual fund allocation in a Bayesian learning framework. Investors update their expectations about funds' future performance based on their prior expectations about managerial ability and observed past performance. Similar to the literature, we find that investors' posterior expectation of the fund's future excess performance is a weighted average of both their prior expectation and the observed performance with the weights determined by the uncertainty of the prior and the variance of the signal.[1] Our main departure from the literature is to study the behavior of investors with different sophistication levels. On the one hand, if they are sophisticated enough to recognize the risk level of mutual funds and to form their expectations through Bayesian updating, their allocation into a fund should be less sensitive to its past performance when the performance is more volatile. The reason is that, holding the prior uncertainty constant, more volatile performance provides a noisier signal and hence carries less weight in investors' posterior expectations. On the other hand, if investors are less sophisticated and assume an identical risk level for all funds, the sensitivity of their fund allocations to past performance should be independent of its true volatility level.

Using the CRSP mutual fund data, we find that at least some investors recognize and respond to the risk level of fund performance when allocating their wealth among funds. In particular, when we regress fund flows on past performance and its interaction with performance volatility, the interaction term is significantly negative. Hence, the volatility of performance dampens the sensitivity of flows to past performance. This result points to the importance of considering investors' response when modeling the risk-taking incentives of mutual fund managers.

Another prediction of the investor learning hypothesis is that, for funds of which investors have more uncertain priors, investors rely more on the past performance in forming their posterior expectations. Hence, we should observe stronger flow-performance sensitivity among funds where investors have more uncertainty in their priors. Moreover, we should expect the dampening effect of volatility on the flow-performance sensitivity to be strengthened among these funds. Because investors usually have better information about funds with longer track records, i.e., older funds, we can use fund age to proxy for the prior uncertainty about a fund. Using a sample of funds during the period of 1989-1994, Chevalier and Ellison (1997) show that younger funds have a stronger sensitivity of flows to performance than older funds. We confirm this result for our sample period of 1993-2004. More importantly, we demonstrate that the dampening effect of performance volatility is stronger for younger funds, providing more supporting evidence for the investor learning hypothesis.

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[1] See, for example, Lynch and Musto (2003), Berk and Green (2004), and Huang, Wei, and Yan (2005).

We further test our hypothesis by examining the difference in the effect of performance volatility between funds with different clienteles—load vs. no-load funds and star vs. non-star funds. Load funds tend to be distributed by brokers or financial advisors, who may provide financial advices to their clients. It is thus reasonable to conjecture that flows into load funds are more likely to come from sophisticated investors. In contrast, the high profile of a "star" fund will likely attract more attention from unsophisticated investors who pour money into the star fund irrespective of the volatility of past performance. Consistent with our hypothesis, we find that the volatility dampening effect is significantly stronger for load funds than for no-load funds. Similarly, we find that the dampening effect of performance volatility is significantly reduced for the star funds. These results are supportive of our hypothesis that at least some investors are sophisticated enough to recognize the risk level of funds, to properly update their belief, and to rationally allocate their wealth.

Our findings contribute to the literature by providing a new perspective on investor sophistication level and its impact on the positive association between fund flows and past performance. While some recent papers, such as Berk and Green (2004), Huang, Wei, and Yan (2005), and Lynch and Musto (2003), make the explicit assumption that investors learn about the managerial ability from past performance, thereby demonstrating that flows respond positively to past performance due to rational Bayesian updating, other papers attribute this phenomenon to investor irrationality in that they blindly go after past winners even if there is only weak evidence of performance persistence (see, e.g., Gruber (1996)). Even though the presence of both types of investors contributes to the positive flow-performance relationship, our evidence on the dampening effect of performance volatility isolates the impact of the sophisticated investors on the dynamics of fund flows and hence validates the investor learning hypothesis among these sophisticated investors. The differential impact of performance volatility on load funds vs. no-load funds and on star funds vs. non-star funds signifies the importance of clienteles of these funds. This has significant implications for understanding the managerial incentives for risk-shifting.

The rest of the paper is organized as follows: In the next section, we use a simple learning model to establish testable implications for the effect of volatility on the flow-performance relationship. The data and the empirical methodology are described in Section 3. Section 4 presents the empirical tests of the learning hypothesis, and Section 5 discusses the impact of investor sophistication on the effect of performance volatility. Section 6 concludes.

2 Investor Learning and the Sensitivity of Fund Flows to Past Performance

Mutual fund flows reflect the allocation decisions by investors. In the absence of search and transaction frictions, rational investors' optimal allocations among funds should be based on their posterior expectations of future fund returns that are determined by both their priors of the unobservable managerial ability and observations of funds' past performance. This is a common and crucial assumption in the models for explaining the observed positive flow-performance relationship, such as Berk and Green (2004), Huang, Wei, and Yan (2005) and Lynch and Musto (2003), although its empirical validity has not yet been systematically tested. Moreover, this framework provides a natural setting to evaluate the effect of performance volatility on the flow-performance sensitivity. In this section, we use a simple model to highlight the investor learning hypothesis and to derive relevant testable empirical implications.

We consider a setting in which investors allocate without friction between a risk-free asset and an array of actively managed mutual funds. The return on the risk-free asset is assumed to be zero without loss of generality. The observable return on mutual fund i is assumed to be described by $r_i = \alpha_i + \epsilon_i$, where α_i represents the unobservable ability of the manager of fund i to deliver positive excess return and is taken to be constant over time and independent across funds. Although investors do not observe α_i, they have a prior about it that is normally distributed with a mean of α_{i0} and a variance of σ_{i0}, i.e.,

$$\alpha_i \sim N(\alpha_{i0}, \sigma_{i0}^2). \tag{1}$$

The idiosyncratic noise ϵ_i in the return of fund i is independently distributed over time and across funds with a normal distribution, i.e.,

$$\epsilon_i \sim N(0, \sigma_{i\epsilon}^2). \tag{2}$$

The return r_i should be interpreted as the fund return in excess of a benchmark.

There are two different types of investors in the model: a fraction q of investors are *sophisticated*, indexed by s, who understand that funds can choose their risk level, and they observe the true risk level $\sigma_{i\epsilon}$ of funds; the rest of investors (fraction $1-q$) are *naive*, indexed by n, who assume that all funds have the same risk level $\sigma_{i\epsilon} = \bar{\sigma}$.[2] All investors use Bayesian rule to update their prior about funds based on the first period return. Their posterior expectation, $\hat{\alpha}_i$, after observing r_i is:

$$\hat{\alpha}_{ij} = \alpha_i | r_i \sim N(\mu_{ij}, \Sigma_{ij}), \quad j = s, n \tag{3}$$

where

$$\mu_{is} = \frac{\sigma_{i\epsilon}^2}{\sigma_{i0}^2 + \sigma_{i\epsilon}^2}\,\alpha_{i0} + \frac{\sigma_{i0}^2}{\sigma_{i0}^2 + \sigma_{i\epsilon}^2}\,r_i, \qquad \Sigma_{is} = \frac{\sigma_{i0}^2 \sigma_{i\epsilon}^2}{\sigma_{i0}^2 + \sigma_{i\epsilon}^2} \tag{4a}$$

$$\mu_{in} = \frac{\bar{\sigma}^2}{\sigma_{i0}^2 + \bar{\sigma}^2}\,\alpha_{i0} + \frac{\sigma_{i0}^2}{\sigma_{i0}^2 + \bar{\sigma}^2}\,r_i, \qquad \Sigma_{in} = \frac{\sigma_{i0}^2 \bar{\sigma}^2}{\sigma_{i0}^2 + \bar{\sigma}^2}. \tag{4b}$$

This basic setting captures the essence of investors' information structure in the models for the flow-performance relationship in the literature discussed before. It demonstrates that the posterior expectation, μ_i, is a weighted average of both the prior mean, α_{i0}, and the observed signal, r_i, with the weights determined by both the prior uncertainty, σ_{i0}^2, and the perceived variance of the signal, $\sigma_{i\epsilon}^2$ and $\bar{\sigma}^2$, for the sophisticated and the naive investors, respectively.

To characterize investors' allocation problem, we assume that investors' objective function is depicted by a constant absolute risk aversion (CARA) utility over the accumulated wealth in the next period, following Lynch and Musto (2003) and Huang, Wei, and Yan (2005). Given the distributional assumptions of investor priors and fund returns and of the CARA utility for investors, the allocation into each fund will be independent of those into other funds. Therefore, for notational simplicity, we can drop the subscript i without causing confusion.

There are two dates, $t = 0, 1$ in the model. On date 0, investors start with initial holding X_0. And on date 1, after observing the first period return r_1, all investors update their prior

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[2] Even our naive investors are capable of Bayesian updating and portfolio optimization. The only difference between them and the sophisticated investors is the knowledge of the risk level of a specific fund. This assumption allows us to put some structure on the modelling of naive investors, and to sharpen our prediction regarding the link between investors sophistication level and the impact of fund volatility.

and choose their investments. In particular, investors' optimal allocation is

$$X_j = \frac{\mu_j}{\gamma\left(\Sigma_j + \sigma_\epsilon^2\right)}, \quad j = s, n.$$

Plugging the posterior in (4), we have the optimal allocations for the sophisticated and the naive investors:

$$X_s = \begin{cases} \frac{\sigma_0^2}{\gamma\sigma_\epsilon^2(2\sigma_0^2+\sigma_\epsilon^2)}\, r + \frac{\sigma_\epsilon^2}{\gamma\sigma_\epsilon^2(2\sigma_0^2+\sigma_\epsilon^2)}\, \alpha_0, & \text{if } r > r_s; \\ 0 & \text{otherwise} \end{cases} \tag{5a}$$

$$X_n = \begin{cases} \frac{\sigma_0^2}{\gamma\bar{\sigma}^2(2\sigma_0^2+\bar{\sigma}^2)}\, r + \frac{\bar{\sigma}^2}{\gamma\bar{\sigma}^2(2\sigma_0^2+\bar{\sigma}^2)}\, \alpha_0, & \text{if } r > r_n; \\ 0 & \text{otherwise.} \end{cases} \tag{5b}$$

where $r_s = -\alpha_0 \frac{\sigma_\epsilon^2}{\sigma_0^2}$ and $r_n = -\alpha_0 \frac{\bar{\sigma}^2}{\sigma_0^2}$.

Let X_0 be the total amount invested in the fund at time 0. We define the flow into the fund driven by type $j = s, n$ investors on date 1 as the amount of their new investments going into the fund from date 0 to date 1 and measure it as a fraction of X_0, i.e,

$$F_s = \frac{X_s - X_0 * (1+r)}{X_0}, \qquad F_n = \frac{X_n - X_0 * (1+r)}{X_0}. \tag{6}$$

Hence, in the unconstrained region ($X_j > 0$), the flows from both the sophisticated and the naive investors are linearly related to the past performance. For easy exposition, we introduce a measure for the sensitivity of the flow to performance, which is defined as

$$S_s = \frac{\sigma_0^2}{\gamma\sigma_\epsilon^2(2\sigma_0^2+\sigma_\epsilon^2)X_0}\,\mathbf{1}_{\{r>r_s\}} - 1, \qquad S_n = \frac{\sigma_0^2}{\gamma\bar{\sigma}^2(2\sigma_0^2+\bar{\sigma}^2)X_0}\,\mathbf{1}_{\{r>r_n\}} - 1. \tag{7}$$

We assume the parameters are such that

$$\frac{\sigma_0^2}{\gamma\sigma_\epsilon^2(2\sigma_0^2+\sigma_\epsilon^2)\, X_0} > 1$$

for any σ_ϵ (including $\bar{\sigma}$). Hence, the flow always responds positively to past performance. In our setting, the positive flow-performance sensitivity is a consequence of investors rationally learning from past performance to update their expectations and optimally making their fund allocations.

The sensitivity S_j is dependent on the perceived variance of past performance. In particular, the sophisticated investors recognize the true volatility σ_ϵ^2 for each fund while the naive investors assume all funds have the same risk level $\bar{\sigma}$ and hence are unaware of σ_ϵ^2. The following result characterizes this difference between investors.

Result 1 *The sensitivity of flows to past performance is decreasing in fund volatility for sophisticated investors and independent of fund volatility for naive investors, i.e.,*

$$\frac{\partial S_s}{\partial \sigma_\epsilon^2} < 0; \quad \textit{and} \quad \frac{\partial S_n}{\partial \sigma_\epsilon^2} = 0. \tag{8}$$

On the other hand, in our setting, both the sophisticated and the naive investors have the same prior about managerial ability, σ_0^2, and their flow sensitivities are affected similarly by the prior.

Result 2 *The sensitivity of flows to past performance is increasing in σ_0^2 for both the sophisticated and the naive investors, i.e.,*

$$\frac{\partial S_s}{\partial \sigma_0^2} > 0; \quad \textit{and} \quad \frac{\partial S_n}{\partial \sigma_0^2} > 0. \tag{9}$$

The total investments to a fund can be calculated as a weighted average of investments by the two groups of investors, so are the flow into the fund and the resulting flow-performance sensitivity. In particular, we define $X_1 = q\, X_s + (1-q)\, X_n$, $F = q\, F_s + (1-q)\, F_n$, and $S = q\, S_s + (1-q)\, S_n$, where q is the fraction of sophisticated investors. Combining Results 1 and 2, we see that, the overall flow sensitivity always depends on the prior precision, and it also depends on the variance of the observed performance σ_ϵ^2 as long as there are some sophisticated investors (i.e., $q > 0$). The following result characterizes this dependence.

Result 3 *The fund flow is more responsive to past performance when the prior about managerial ability is noisier (higher σ_0^2); as long as there are some sophisticated investors ($q > 0$), the fund flow is less responsive to past performance when the performance is more volatile.*

The intuition of this result is straightforward in a Bayesian learning context. The observed performance is less informative if it is volatile. Investors will then respond less strongly to noisy past performance, as its weight in forming investors' posterior expectations will be smaller. Because in the model σ_ϵ^2 corresponds to the variance of the excess fund return, we arrive at a testable hypothesis as follows.

Hypothesis 1 *If some investors recognize the risk level of funds, the sensitivity of flows to past performance is weaker for funds with more volatile excess performance.*

On the other hand, if the prior about managerial ability is diffuse and noninformative, then investors will put more weight on the observed performance in forming their posterior expectations and allocating their money. Hence, the sensitivity of flows to performance will be greater. One natural proxy for the prior uncertain is the age of a fund, as funds with a longer track record would allow investors to form an informative prior of managerial ability.[3] Therefore, we have the following hypothesis:

Hypothesis 2 *All else equal, the sensitivity of flows to past performance is stronger for younger funds than for older funds.*

Although both the prior uncertainty and the volatility of past performance affect the flow-performance sensitivity, their roles are complementary to each other. This is because if investors are fairly certain about the managerial ability due to a long track record, their expectation will be less sensitive to the recent performance of the fund, and hence to its volatility. Therefore, we can establish the following result on the interaction effect of σ_0^2 and σ_ϵ^2 on the flow-performance sensitivity.

Result 4 *If $q > 0$, the cross derivative of the flow sensitivity to σ_0^2 and σ_ϵ^2 is negative, i.e.,*

$$\frac{\partial^2 S}{\partial \sigma_0^2 \partial \sigma_\epsilon^2} < 0. \tag{10}$$

Because $\frac{\partial S}{\partial \sigma_\epsilon^2} < 0$, this result means that the effect of σ_ϵ^2 on the flow sensitivity is more negative for larger σ_0^2. This translates into the following hypothesis:

Hypothesis 3 *If some investors recognize the risk level of funds, the dampening effect of performance volatility on the sensitivity of flows to past performance is stronger for younger funds than for older funds.*

From Result 1 and the definition of total sensitivity (S), it is clear that the dampening effect of performance volatility (σ_ϵ) on the flow-performance sensitivity is increasing in the fraction of sophisticated investors, q. In fact, the dampening effect of performance volatility is solely driven by the presence of sophisticated investors. This leads us to obtain the following testable hypothesis:

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[3] We are not distinguishing the tenure of a manager and the age of a fund here, implicitly assuming that funds switch managers infrequently.

Hypothesis 4 *The magnitude of the dampening effect of performance volatility on the sensitivity of flows to past performance is larger for funds with a higher fraction of sophisticated investors.*

These hypotheses highlight the effect of performance volatility on mutual fund flows in the context of investor learning. In the following sections, we test these implications empirically, focusing specifically on the effect of performance volatility.

3 Data and Empirical Methodology

3.1 Data

We measure mutual fund flows and returns using information from the Center for Research in Security Prices (CRSP) mutual fund database. We focus on the period between 1993 and 2004 since CRSP reports consistent classifications of fund investment objectives starting from 1993. We exclude index funds from our analysis because we are only interested in investors' learning about the managerial ability of actively managed funds. To make sure that volatilities of fund returns in our sample are comparable to each other, we also exclude sector funds, international funds, bond funds and balanced funds.[4] Essentially, our data mainly consist of actively managed equity funds that fall into the following investment objective categories: aggressive growth, growth, growth and income, and income funds. We also extract from this database information about fund characteristics such as expense ratio, load, fund age, and fund size.

Quarterly net flows into a fund are defined as the percentage of beginning-of-quarter total net asset value with an adjustment for increase in fund total net asset due to mergers:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t}) - Merger_{i,t}}{TNA_{i,t-1}} \tag{11}$$

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[4] Specifically, we select funds that meet the following criteria according to their fund types. First, we include funds that are classified as aggressive growth, growth and income, long-term growth according to their ICDI objectives. If a fund has an ICDI objective of total return but is classified as a flexible, growth or income growth fund according to its Strategic Insight fund objective, it is also included. Since ICDI objectives are only available after 1993, we also include funds with the following Strategic Insight's fund objectives: 'AGG', 'GRI', 'GRO', 'ING' and 'SCG'. Finally, for funds that have neither ICDI objectives nor Strategic Insight's objectives, we include those with Weisenberger fund types of 'AAL', 'AGG', 'G', 'G-I', 'G-I-S', 'G-S', 'G-S-I', 'GCI', 'GRI', 'GRO', 'I-G', 'I-G-S', 'I-S', 'I-S-G', 'MCG', 'SCG' or 'TR'.

where $R_{i,t}$ is the return of fund i during quarter t, $TNA_{i,t}$ is fund i's total net asset at the end of quarter t, and $Merger_{i,t}$ stands for changes in fund i's TNA due to merging of other funds into fund i. Hence flows reflect the percentage growth of a fund that is due to new investments. By adopting this definition of fund flows, we assume implicitly that new money comes in at the end of each quarter since we have no information regarding the timing of new investment. Since previous literature has documented errors in CRSP mutual fund database regarding the exact timing of fund mergers,[5] we filter out the top and bottom 1% of the flow data to exclude outliers.

Since it is not clear whether average investors focus on raw performance or risk-adjusted performance when allocating their investments across funds, we measure performance and performance volatility in both ways. When measuring the risk-adjusted performance, we employ the Carhart (1997) four-factor model:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{MOM} MOM_t + \varepsilon_{i,t}, \quad (12)$$

where $R_{i,t}$ and $R_{f,t}$ are the return for fund i and the one-month T-bill rate in month t, respectively. MKT_t, SMB_t, HML_t, and MOM_t are month t returns of the Fama and French (1993) three factors and the momentum factor, respectively.[6] Specifically, we first estimate the factor-loadings of each fund assuming that they remain constant for the entire sample period. The excess performance for each fund is then the difference between the realized return and the predicted return from the four-factor model. We match quarter t's flow of each fund with its average excess performance and the corresponding volatility of the excess performance in the past 12 months. Similarly, we use the average of monthly fund returns and the standard deviation of returns in the past 12 months to measure raw performance and performance volatility.

Over our sample period, the number of actively managed domestic equity funds has grown steadily from 856 funds in 1993 to 4256 funds in 2004. Our sample spans a period of time during which the mutual fund industry has gone through tremendous changes in terms of fund size, number of investment styles, distributional channels, and management

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[5] See, for instance, Elton, Gruber, and Blake (2001).

[6] All of these factor returns are obtained through Ken French's website. We thank Ken French for making the data available to the public.

compensation schemes. In Table 1, we report the averages of the cross-sectional means and medians, measured at the end of each quarter, of fund size, fund age, total expenses, net fund flows, and raw fund returns as well as Carhart four-factor-adjusted returns over the preceding 12 months. We also report descriptive statistics for the volatility of raw performance and risk-adjusted performance in the preceding 12 months. In addition, Table 1 shows the standard deviation, 25th and 75th percentiles of these fund characteristics. There are considerable cross-sectional dispersions in fund flows, fund performance, and fund risk measures.

3.2 Empirical Methodology

To capture the flow-performance relationship, we follow the Fama and MacBeth (1973) methodology to examine the cross-sectional determinants of fund flows. Specifically, for each quarter we run a cross-sectional regression to estimate the sensitivity of flows to past performance in the presence of other control variables. We then report means and t-statistics from the time series of coefficient estimates. The effect of potential auto-correlations in flows and other explanatory variables is accounted for through using Newey and West (1987) autocorrelation- and heteroskedasticity-consistent standard errors from which we calculate $t-$statistics.

Previous literature has documented that new investments react to past performance in an asymmetric way, namely, the sensitivity of flows to performance is higher for funds with superior performance.[7] To capture this nonlinear flow-performance relationship, we follow Sirri and Tufano (1998) to conduct a piecewise linear regression. Each quarter, fractional performance ranks ($Rank_{i,t}$) ranging from 0 to 1 are assigned to funds according to their Carhart four-factor-adjusted returns during the past 12 months. The factional rank at time t for fund i in the bottom performance quintile ($Low_{i,t}$) is defined as $Min(Rank_{i,t}, 0.2)$, in the three medium performance quintiles ($Mid_{i,t}$) as $Min(0.6, Rank_{i,t} - Low_{i,t})$, and in the top performance quintile ($High_{i,t}$) as $Rank_{i,t} - Mid_{i,t} - Low_{i,t}$. Each quarter, flows are regressed on performance ranks in the low, medium, and high performance ranges along with other variables.

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[7] See, for example, Ippolito (1992), Gruber (1996), Chevalier and Ellison (1997), and Sirri and Tufano (1998).

Our main hypotheses concern the effect of performance volatility on the sensitivity of flows to past performance. This effect is tested through an interaction term between performance volatility and performance itself in the regression. Our theoretical discussion also indicates that the flow-performance sensitivity is affected by prior uncertainty. Because for older funds, investors' prior uncertainty is less due to funds' long track records, investors rely less on these funds' recent performance to make an investment decision. Therefore, we expect older funds to have weaker flow-performance sensitivity. Since fund age is a discrete variable and often clusters, we use a dummy variable that takes the value of 1 for older funds whose age is above the sample median during the current period and 0 for all others. The interaction term between the old-fund dummy and fund performance is hence included in the regression to capture the effect of prior uncertainty. In addition, we also include in our regression performance volatility and fund-age dummy as stand alone explanatory variables. To measure the effect of expenses on fund flows, we calculate total expenses as the sum of one-seventh of the front-end load and the expense ratio. To control for the effect of scaling on the percentage growth of a fund due to the large variation in fund sizes, we include logged fund TNA in quarter $t-1$ when estimating the flow regression in quarter t. Finally, to control for possible effects of sentiment and style shifts, we include the aggregate flow into each fund's investment objective category in quarter $t-1$ in our estimations.

Therefore, for each quarter t between 1993 and 2004, we analyze the relation between flows and performance through the following piecewise linear regression:

$$\begin{aligned} Flow_{i,t} &= a + b_1 * Low_{i,t-1} + b_2 * Mid_{i,t-1} \\ &\quad + b_3 * High_{i,t-1} + c * PERF_{i,t-1} * Vol_{i,t-1} \\ &\quad + Controls_{i,t-1} + \varepsilon_{i,t}, \end{aligned}$$

where $Flow_{i,t}$ is the percentage growth of fund assets that is due to new money. $Low_{i,t-1}$, $Mid_{i,t-1}$, and $High_{i,t-1}$ represent performance rank in quintile 1, quintiles 2 through 4, and quintile 5, respectively. $PERF_{i,t-1} * Vol_{i,t-1}$ is the interaction between fund i's performance rank and the standard deviation of past performance in the proceeding 12 or 36 months of quarter t. $Controls$ refer to all other explanatory variables we have discussed above.

4 Volatility of Performance and the Flow Sensitivity to Past Performance

Based on our theoretical discussion, the investor learning hypothesis implies that the sensitivity of flows to past performance should be increasing with investors' prior uncertainty about a fund manager's ability and decreasing with the noisiness of the observed past performance. Specifically, as stated in Hypothesis 1, using performance volatility as the measure of the noisiness of signals, we should expect that large performance volatility reduces the sensitivity of flows to past performance. Moreover, according to Hypothesis 2, we expect flows to be less sensitive to past performance of older funds as the fund age is used to proxy for the prior uncertainty. This second hypothesis is consistent with the evidence in Chevalier and Ellison (1997).

To test these hypotheses, we perform the Fama-MacBeth-type regression of flows on past performance ranking, measured in three performance ranges, and the interaction terms between performance and its volatility and between performance and the age dummy. We also control for aggregate flows into a fund's investment objective category, fund age, fund size, distribution expenses and operating expenses. The results are presented in Table 2.

Our results from the cross-sectional regression show a strongly positive flow-performance relationship that also exhibits convexity, illustrated by a significantly greater flow sensitivity to high performance rankings than to low or medium performance rankings, consistent with the existing literature. More interestingly, confirming our hypothesis, flows respond less sensitively to volatile performance, as reflected by the negative coefficient for the interaction term between performance and volatility. The dampening effect of volatility on the flow-performance sensitivity is also economically significant. Specifically, if the volatility of monthly risk-adjusted performance in the previous 12 months increases by 1%, it will reduce the sensitivity of flows to performance by more than 10% for funds with average performance. This effect is robust whether we use the risk-adjusted performance or the raw performance, as demonstrated in the table. Performance volatility itself has a muted effect on flows. This is probably due to the offsetting effects of several factors. On the one hand, Dybvig, Farnsworth, and Carpenter (2003) argue that volatility is part of an optimal incentive contract when both manager's information and effort are unobservable so that active managers can be differentiated from "closet indexers". On the other hand, high volatility may discourage investments from risk averse investors, as implied in Sirri and Tufano (1998).

Consistent with the prediction of Hypothesis 2, the interaction term between performance and fund age is significantly negative, indicating that a longer track record helps investors acquire a more precise prior about the fund's ability to deliver excess performance, so that they rely less on the fund's past performance to make their investment decisions. Also, younger funds tend to attract more flows in addition to having a stronger flow-performance sensitivity. This result is consistent with the findings in Chevalier and Ellison (1997) and adds more weight in supporting the investor learning hypothesis.

The coefficients on other control variables conform to earlier findings in the literature. We find that flows into individual mutual funds are highly correlated with the aggregate flow into funds with the same investment objectives, and decrease in fund size. Interestingly, flows are not significantly affected by the total expense ratio. This is consistent with findings in recent studies that advertising and marketing can lower investors' search costs and therefore help funds attract more flows.[8] On the other hand, although higher expense ratios reduce investors' net returns, it is often easily masked by the volatility in net returns reported by mutual funds, as argued in Barber, Odean, and Zheng (2005). Therefore, it is not surprising that flows are sometimes insensitive to the total expense ratio.

Hypothesis 3 suggests that the effects of investors' prior uncertainty and the noisiness of the signal in past performance are complementary to each other. That is, investors place more weight on either the prior or the signal, whichever is more precise, when they form their posterior expectations. As shown in the previous subsection, investors discount past performance when its volatility is high because volatility of past performance hinders investors' ability to learn the true type of fund managers. However, for funds with long track records, information about their ability to deliver excess performance should be widely available and fairly accurate. According to the learning hypothesis, for these funds, the dampening effect of performance volatility on the flow-performance sensitivity should be diminished.

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[8] See, for example, Jain and Wu (2000), Sirri and Tufano (1998) and Huang, Wei, and Yan (2005).

In Table 6, we examine the joint effect of performance volatility and fund age. Specifically, we augment the analysis in Table 2 by including a triple-interaction term between performance ranks, volatility and the fund age dummy. In addition, we include the interaction term between volatility and the fund age dummy. While younger funds are still found to attract more flows and have a stronger flow-performance sensitivity, the regression coefficient on the triple-interaction term between performance, volatility and the age dummy is significantly positive. Since performance volatility reduces the response of flows to past performance, a positive sign on this interaction term indicates that the effect of volatility on the sensitivity of flows to prior performance is strongest for young funds and diminishes with old funds. In other words, if a fund has a long history of past performance, investors will be less concerned about its volatile performance than if it is a new fund that does not have much of a track record. This is consistent with the complementary roles that an uncertain prior and a noisy signal have on investors' investment decisions. This finding is robust whether we measure performance on a risk-adjusted basis or on the raw basis, as demonstrated in the table.

5 Investor Sophistication and the Dampening Effect of Performance Volatility

The evidence presented above is consistent with the investor learning hypothesis. As we argued in Section 2, the dampening effect of performance volatility on the flow-performance sensitivity is driven by the presence of sophisticated investors who rationally update their posterior expectations based on their priors and observed signals in past performance. There are, however, many investors who are not sophisticated, as indicated in Capon, Fitzsimons, and Prince (1996) and Goetzmann and Peles (1997). Their lack of sophistication may be represented by either their inability to estimate the volatility of performance or their irrational behavior of blindly following the past winners. Although the presence of unsophisticated investors contributes to the positive and convex flow-performance relationship, it weakens the dampening effect of performance volatility on the sensitivity of flows to past performance. Therefore, as indicated in Hypothesis 4, we should expect that funds attracting more sophisticated investors should exhibit stronger effect of performance volatility. In this section, we test this hypothesis by examining the difference in the effect of performance volatility between load funds and no-load funds, and between star funds and non-star funds.

Load funds tend to be distributed by brokers or financial advisors, who may provide advices to their clients (see, e.g., Christoffersen, Evans, and Musto (2005)). Assuming that these financial professionals are more sophisticated than average mutual fund investors and that they provide honest advices to their clients, we argue that flows into load funds are more informed, i.e., with a higher portion coming from sophisticated investors or their advisors. In our examination of the differential effect of performance volatility on load and no-load funds, we define load funds as those with either a front-end load, or a back-end load or a 12b-1 fee that is higher than 25 basis points a year. We assign a load dummy of 1 to these load funds, and a dummy of zero to the remaining no-load funds.

Table 4 reports the results obtained from the cross-sectional regressions that examine the differential effects of performance volatility in load and no-load funds. It shows that for no-load funds, the volatility dampening effect is substantially reduced compared to the magnitude in Tables 2 and 6. However, for load funds, the dampening effect of performance volatility strengthens significantly, ranging from approximately 60% to 120% higher in magnitude than the effect for no-load funds. This result is robust both for the risk-adjusted performance measure, in Panel A, and for the raw performance measure, in Panel B. These results are consistent with the notion that the dampening effect is driven by the sophisticated investors.

There are some additional points about load funds that are worth noting. First, the regression results in Table 4 show that loads reduce the level of fund flows, consistent with the evidence in the prior literature (Barber, Odean, and Zheng (2005)). They also indicate that the negative relation between the total expense ratio is driven by the role of loads. Second, all else equal, the flow-performance sensitivity is stronger for load funds than no-load funds.

The next proxy we use for the fraction of sophisticated investors is the "star" status of a fund. When a fund achieves a superior performance and becomes a star fund at one time, it receives much media attentional and attracts many unsophisticated investors. Then our hypothesis implies that for these star funds, the dampening effect of performance volatility should diminish. We test this hypothesis in Table 5, where we define star funds as those funds whose performance in the previous 12 months ranks among the top 5% each quarter.

We first examine the dampening effect of volatility in different performance ranges. The results for the risk-adjusted performance measure, presented in the first two columns in panel A, indicates that the volatility dampening effect is most significant in the middle performance range, and it is almost non-existent in the high performance range. This result may appear surprising at the first glance, but it is in fact consistent with our argument. This is because sophisticated investors weigh both recent performance and historical record when the make their decision, therefore they tend to congregate in funds that provide consistent, albeit not necessarily stellar, performance. While for funds with recent good performance, they attract more unsophisticated investors, so that the flow-performance sensitivity is very high, irrespective of the volatility of the past performance.

This interpretation is bolstered when we further separate good-performing funds into star funds, those that rank among the top 5% in each quarter, and the remaining funds in the top quintile. For those star funds, the effect of volatility is in fact *increasing* the flow-performance sensitivity. This implies that the funds that achieve the star performance through very volatile returns have the highest flow-performance sensitivity. These are exactly the type of funds that will attract unsophisticated investors, but shunned by sophisticated investors. In contrast, for the remaining non-star funds in the next top 20% funds, the dampening effect of performance volatility is the strongest of all. This is consistent with the notion that sophisticated investors can identify these good and persistent performers while unsophisticated investors flee to the flash, and usually short-lived, stars. This pattern holds when we use raw returns to measure performance, albeit the magnitude is somewhat reduced.

In summary, the results in Tables 4 and 5 present cross-sectional evidence that is supportive of the investor learning hypothesis despite the presence of unsophisticated investors, because the dampening effect of performance volatility on the flow-performance sensitivity is mainly driven by sophisticated investors.

6 Concluding Remarks

There is a growing literature on the widely-documented asymmetric response of flows to the past performance of actively managed funds and the associated implication for incentives for fund managers to take excessive risk. In this paper, we investigate how investors would respond to performance achieved with different levels of risk, as reflected in the effect of performance volatility. We find that investors respond less strongly to volatile performance, and this dampening effect of performance volatility is more significant for young funds. We show that our result is consistent with the hypothesis of investors learning from past performance to form their posterior expectations of managerial ability. To the best of our knowledge, our study represents the first systematic empirical examination of the investor learning hypothesis frequently assumed in theoretical models for explaining the behavior of fund flows.

In addition, we argue theoretically that the volatility dampening effect is present despite the presence of unsophisticated investors who may not pay attention to performance volatility. The empirical validation of this argument comes from the cross-sectional variation in the volatility dampening effect in load/no-load funds and in star/no-star funds. The volatility dampening effect is significantly weakened in no-load funds and all but disappears in recent-"star" funds because these funds tend to attract more unsophisticated investors. In contrast, sophisticated investors, either by their own virtue or through their financial advisors, may populate load funds and funds with good and consistent performance rather than flashy and volatile stars, and their presence in these funds help strengthen significantly the dampening effect of volatility on the flow-performance sensitivity.

Our work illustrates the importance of understanding investment decisions of individual investors in the study of dynamics of mutual fund flows. While both sophisticated and unsophisticated investors contribute to the positive and convex flow-performance relationship, we show that it is the decision-making process of sophisticated investors that drives the dampening effect of performance volatility on the sensitivity of fund flows to past performance. This finding has implications for the issue of managerial incentives for taking excess risk given the convex flow-performance relationship as one has to consider the endogenous response of investors to such risk-shifting behavior. Fully characterizing this optimal choice of volatility level, however, requires a general equilibrium framework that takes into account the actions of both managers and investors. This is an important and challenging task that we leave for future research.

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Table 1: **Summary Statistics**

This table reports summary statistics of our full sample from 1993 to 2004. At the end of each quarter, we calculate the cross-sectional mean, median, standard deviation, and the interquartile range of the following fund characteristics: total net asset value, fund age, total fees, quarterly flow, average monthly raw returns and Carhart-four-factor-adjusted returns, and their corresponding standard deviations in the prior 12 months. The time-series averages of these variables are reported.

	Mean	Median	Stdev	25%	75%
TNA (in millions)	543.5	73.3	2376.9	18.0	281.6
Fund Age	8.3	4.3	11.5	2.1	9.2
Total Expense	1.68%	1.73%	0.81%	1.14%	2.09%
Quarterly Flow	3.92%	0.50%	14.89%	-3.46%	7.19%
Raw Return	0.87%	0.83%	0.96%	0.30%	1.42%
Four-Factor Alpha	-0.13%	-0.12%	0.65%	-0.47%	0.22%
Stdev of Raw Return	4.63%	4.23%	1.61%	3.59%	5.36%
Stdev of Alpha	1.70%	1.51%	0.96%	1.07%	2.10%

Table 2: **The Dampening Effect of Performance Volatility**

This table examines the effect of volatility on dampening the sensitivity of mutual fund flows to past performance. Each quarter, fractional performance ranks ranging from zero to one are assigned to funds according to their raw returns or according to their Carhart-four-factor alphas in the prior 12 months. The factional rank at time t for fund i in the bottom performance quintile ($Low_{i,t}$) is defined as $Min(Rank_{i,t}, 0.2)$, in the three medium performance quintiles ($Mid_{i,t}$) as $Min(0.6, Rank_{i,t} - Low_{i,t})$, and in the top performance quintile ($High_{i,t}$) as $Rank_{i,t} - Mid_{i,t} - Low_{i,t}$. Each quarter a piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance rankings over the low, medium, and high performance ranges, volatility of monthly returns during the performance measurement period, and their interaction terms. The control variables include aggregate flow into the fund objective category, a dummy variable that takes the value of one if the fund age is older than that of the median fund and its interaction with performance, the logarithm of lagged fund size, and lagged total expense. Time-series average coefficients and the Fama-MacBeth t-statistics calculated with Newey-West robust standard errors are reported. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

Performance Measured by	Four-Factor Alpha		Raw Return	
	Estimate	t-Value	Estimate	t-Value
Intercept	−0.003	−0.38	−0.011	−0.86
Category Flow	0.612***	4.42	0.330	1.00
Low	0.265***	11.94	0.324***	12.86
Mid	0.142***	12.19	0.223***	10.25
High	0.526***	14.03	0.726***	13.24
Volatility	0.188	0.82	−0.034	−0.14
Volatility * Performance	−1.346***	−3.76	−1.663***	−5.48
Age	−0.033***	−8.20	−0.028***	−7.47
Age * Performance	−0.044***	−8.10	−0.051***	−9.64
Size	−0.007***	−11.61	−0.007***	−11.06
Total Expense	0.125	1.04	0.131	1.11

Table 3: **Fund Age and the Volatility Dampening Effect**

This table examines the effect of fund age on both the flow-performance sensitivity and the volatility dampening effect. Each quarter, fractional performance ranks ranging from zero to one are assigned to funds according to their raw returns or their four-factor alphas during the past 12 months. The factional rank at time t for fund i in the bottom performance quintile ($Low_{i,t}$) is defined as $Min(Rank_{i,t}, 0.2)$, in the three medium performance quintiles ($Mid_{i,t}$) as $Min(0.6, Rank_{i,t} - Low_{i,t})$, and in the top performance quintile ($High_{i,t}$) as $Rank_{i,t} - Mid_{i,t} - Low_{i,t}$. Each quarter a piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance rankings over the low, medium, and high performance ranges, volatility of monthly returns during the performance measurement period, its interaction term with performance rankings, and the interaction term between volatility, performance rankings and the older fund dummy. The control variables include aggregate flow into the fund objective category, the older fund dummy and its interaction terms with performance rankings and performance volatility, respectively, the logarithm of lagged fund size, and lagged total fee ratio. Time-series average coefficients and the Fama-MacBeth t-statistics (in parentheses) calculated with Newey-West robust standard errors are reported. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

Performance Measured by	Four-Factor Alpha		Raw Return	
	Estimate	t-Value	Estimate	t-Value
Intercept	−0.007	−0.81	−0.016	−1.06
Category Flow	0.625***	4.44	0.333	0.97
Low	0.279***	11.74	0.349***	12.38
Mid	0.157***	10.85	0.252***	10.58
High	0.546***	14.04	0.760***	13.59
Volatility	0.385	1.20	−0.026	−0.08
Volatility * Performance	−2.166***	−4.15	−2.230***	−5.66
Age	−0.025***	−5.09	−0.016	−1.53
Age * Performance	−0.071***	−7.18	−0.104***	−6.45
Age * Volatility	−0.288	−1.21	0.023	0.11
Age * Volatility * Performance	1.359***	2.93	0.985**	2.64
Size	−0.007***	−11.69	−0.007***	−10.87
Total Expense	0.114	0.93	0.123	1.02

Table 4: **The Volatility Dampening Effect for Load vs No-Load Funds**

This table examines the volatility dampening effect among load and non-load funds. Panels A and B report the results where performance is measured based upon raw returns and four-factor alphas, respectively. A piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance rankings over the low, medium, and high performance ranges, volatility of monthly returns during the performance measurement period, its interaction term with performance rankings, and the interaction term between volatility, performance rankings and the load fund dummy. The control variables include a dummy variable indicating load funds and its interaction terms with performance rankings and performance volatility, the interaction term between the older fund dummy, performance rankings and performance volatility; aggregate flow into the fund objective category, volatility of monthly returns during the performance measurement period, the logarithm of one plus fund age and its interaction with performance, the logarithm of lagged fund size, and lagged total fees or lagged total expense ratio. Time-series average coefficients and the Fama-MacBeth t-statistics (in parentheses) calculated with Newey-West robust standard errors are reported. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Performance Measured by Carhart Four-Factor Alpha

	Estimate	t-Value	Estimate	t-Value
Intercept	0.008	0.89	0.009	0.90
Category Flow	0.632***	4.47	0.625***	4.47
Low	0.237***	9.03	0.243***	10.60
Mid	0.117***	7.44	0.127***	10.49
High	0.514***	12.15	0.530***	13.40
Volatility	−0.014	−0.04	0.340	1.08
Volatility * Performance	−1.239*	−1.91	−1.614***	−3.39
Load * Performance	0.067***	4.41	0.050***	6.60
Load * Volatility	0.659*	1.91	0.229	1.44
Load * Volatility * Performance	−1.532**	−2.14	−0.941***	−2.85
Age	−0.028***	−5.54	−0.029***	−5.34
Age * Performance	−0.068***	−6.62	−0.066***	−7.29
Age * Volatility	−0.170	−0.61	−0.036	−0.16
Age * Volatility * Performance	1.343**	2.48	1.153**	2.67
Size	−0.007***	−10.92	−0.007***	−11.39
Load	−0.017**	−2.04		
Expense Ratio	−0.161	−1.32		
Total Expense			−0.766***	−5.35

Panel B: Performance Measured by Raw Return

	Estimate	t-Value	Estimate	t-Value
Intercept	0.002	0.13	0.000	0.00
Category Flow	0.330	0.96	0.330	0.97
Low	0.290***	9.74	0.295***	10.74
Mid	0.197***	9.54	0.212***	10.43
High	0.724***	13.43	0.743***	13.66
Volatility	−0.176	−0.54	0.064	0.20
Volatility * Performance	−1.725***	−4.25	−1.996***	−5.02
Load * Performance	0.094***	4.96	0.072***	5.51
Load * Volatility	0.208	1.15	−0.071	−0.65
Load * Volatility * Performance	−0.903***	−2.83	−0.517***	−2.83
Age	−0.021*	−1.91	−0.019*	−1.70
Age * Performance	−0.096***	−5.79	−0.097***	−6.04
Age * Volatility	0.131	0.55	0.122	0.53
Age * Volatility * Performance	0.844**	2.11	0.824**	2.22
Size	−0.007***	−10.43	−0.008***	−10.58
Load	−0.020**	−2.59		
Expense Ratio	−0.133	−1.03		
Total Expense			−0.678***	−5.39

Table 5: **The Volatility Dampening Effect for Star vs Non-Star Funds**

This table examines the volatility dampening effect for star vs non-star funds. Each quarter, funds are ranked according to their raw returns or their Carhart four-factor alphas in the prior 12 months. Funds that are ranked among the top 5% are considered as "star" funds. Panels A and B report results where performance is measured based upon raw returns and four-factor alphas, respectively. A piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance rankings over the low, medium, and high performance ranges (in Column 1), and their intercation terms with performance volatility. In column 2, we further split the top 5% performers from the high performance group. The control variables include performance volatility, the older fund dummy and its interaction terms with performance rankings and performance volatility, respectively; the interaction term between the older fund dummy, performance ranking and performance volatility; aggregate flows into the fund objective category, the logarithm of lagged fund size, and lagged total fees. Time-series average coefficients and the Fama-MacBeth t-statistics (in parentheses) calculated with Newey-West robust standard errors are reported. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Performance Measured by Carhart Four-Factor Alpha

	Estimate	t-Value	Estimate	t-Value
Intercept	−0.010	−0.83	−0.010	−0.85
Category Flow	0.611***	4.49	0.603***	4.39
Low	0.289***	7.32	0.295***	7.28
Mid	0.163***	10.61	0.157***	9.95
High	0.523***	8.40	0.611***	9.93
Star			1.259***	3.16
Volatility	0.470	1.29	0.544	1.45
Low * Volatility	−2.421	−1.59	−3.397**	−2.18
Mid * Volatility	−2.533***	−4.25	−1.733**	−2.58
High * Volatility	−0.762	−0.26	−13.854***	−5.08
Star * Volatility			26.052*	1.78
Age	−0.024***	−4.33	−0.023***	−4.00
Age * Performance	−0.075***	−7.49	−0.079***	−7.60
Age * Volatility	−0.332	−1.33	−0.413	−1.54
Age * Volatility * Performance	1.547***	3.46	1.822***	3.63
Size	−0.007***	−11.75	−0.007***	−11.75
Total Expense	0.117	0.92	0.121	0.95

Panel B: Performance Measured by Raw Return

	Estimate	t-Value	Estimate	t-Value
Intercept	−0.024	−1.59	−0.023	−1.58
Category Flow	0.316	0.91	0.309	0.90
Low	0.425***	8.06	0.433***	7.88
Mid	0.261***	9.63	0.246***	9.87
High	0.607***	5.18	0.786***	6.29
Star			1.261*	1.87
Volatility	0.196	0.69	0.217	0.78
Low * Volatility	−4.435***	−3.10	−4.924***	−3.39
Mid * Volatility	−2.222***	−5.09	−1.688***	−4.10
High * Volatility	0.271	0.11	−6.352***	−2.85
Star * Volatility			6.036	0.47
Age	−0.019*	−1.72	−0.020*	−1.81
Age * Performance	−0.104***	−6.11	−0.104***	−6.25
Age * Volatility	0.121	0.52	0.114	0.50
Age * Volatility * Performance	0.920**	2.30	0.971**	2.47
Size	−0.007***	−10.90	−0.007***	−10.90
Total Expense	0.106	0.88	0.109	0.90