Volatility of Performance, Investor Learning, and the Flow-Performance Sensitivity*

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Abstract

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Abstract

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Keywords: Bayesian learning, mutual fund flows, flow-performance relationship.

JEL Classification: G10, G11, G20, G23.

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 based on a fraction of 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) investigate as well the risk-shifting behavior of fund managers.

While 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 reaction 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, because it can affect the equilibrium incentive for fund managers to engage in risk-shifting strategies. We address this question in the paper.

Our findings imply that investors recognize and respond to risk levels 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 investor reaction when modeling the risk-taking incentives of mutual fund managers.

The fact that performance volatility does affect the flow-performance relationship is consistent with the investor learning hypothesis. We show that in the Bayesian learning framework, investor's posterior expectations about funds' future performance are determined by their prior expectations about managerial ability and observed past performance. Specifically, the learning hypothesis implies 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 prior uncertainty and the variance of the signal. Holding the prior uncertainty constant, more volatile performance provides a noisier signal and hence carries less weight in investors' posterior expectations. As a result, investors' allocation into the fund is less sensitive to the past performance if it is volatile.

Therefore, we also contribute to the literature by providing supporting evidence for investor rationality when understanding 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 chase 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)). Although we can not rule out investor irrationality, our evidence that volatility dampens the flow-performance sensitivity is strongly supportive of the investor learning hypothesis.

Another prediction of the investor learning hypothesis is that, for funds with which investors have more uncertain priors, investors rely more on the past performance in forming their posterior expectations. Hence, we should observe weaker flow-performance sensitivity among funds where investors have less prior uncertainty. We should also expect the effect of volatility on the flow-performance sensitivity to be reduced 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.

Existing studies, such as Sirri and Tufano (1998) and Huang, Wei, and Yan (2005), have demonstrated the important impact of information costs on the flow-performance relationship. Information costs refer to the effort and the resources investors have to expend in order to obtain better, or more precise, information about a particular fund. Because information costs affect the prior uncertainty of investors, we investigate how the presence of information costs influences the impact of performance volatility on the flow-performance sensitivity. We argue that since incurring information costs helps investors narrow the variance of their prior expectations, for funds with lower information barriers, more investors will be able to obtain accurate priors about the future prospects of these funds. Therefore, we expect the dampening effect of performance volatility on the flow-performance sensitivity to be weaker for these funds, because investors rely less on getting precise signals from their past performance in order to make investment decisions.

Following Sirri and Tufano (1998) and Huang, Wei, and Yan (2005), we use various fund characteristics to proxy for information costs. We show that if a fund is affiliated with a large or a "star" producing family, or if it has expended significant resources in marketing and distributing its products, its flow-performance sensitivity is less affected by performance volatility. These findings are consistent with the notion that learning process of investors is affected by information costs.

Our evidence on the effect of performance volatility suggests that investors' weaker response to volatile performance may counteract fund managers' incentives for taking excessive risk. To further explore how the dampening effect of volatility on the flow-performance sensitivity may create disincentives for excessive risk-taking, we examine the possible differential effects of volatility across different performance ranges. We find that while performance volatility reduces the flow-performance sensitivity in all performance ranges, its dampening effect is particularly strong for funds with superior performance.

Therefore, the payoff to achieving high performance by gambling is not as large as that in the absence of the volatility effect. This implies that volatility can potentially "flatten" the convex flow-performance relationship and hence mitigate, albeit not eliminate, managerial risk-taking incentives.

Given the mitigating effect of volatility, the question of the optimal choice of portfolio volatility by managers naturally arises. While this question should be addressed in a general equilibrium framework that takes into account the actions of both managers and investors, an issue that is beyond the scope of this paper, we shed some light on the question by examining the determinants of performance volatility. We show that older funds, growth funds and funds with higher turnover ratio all tend to have more volatile performance. On the other hand, funds that have greater total assets or are associated with a large complex tend to have less volatile performance.

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 empirical tests of the learning hypothesis, and Section 5 discusses the effect of performance volatility in the presence of information costs. Section 6 explores the potential effect of performance volatility on the managerial risk-taking incentives and Section 7 characterizes the cross-sectional determinants of performance volatility. We conclude in Section 8.

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

$$\epsilon_i \sim N(0, \sigma_{i\epsilon}^2). \tag{1}$$

The return r_i should be interpreted as the fund return in excess of a benchmark. 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}. They form a posterior expectation, $\hat{\alpha}_i$, after observing r_i following the Bayes rule:

$$\hat{\alpha}_i = \alpha_i | r_i \sim N(\mu_i, \Sigma_i), \tag{2}$$

where

$$\mu_i = \frac{\sigma_{i\epsilon}^2}{\sigma_{i0}^2 + \sigma_{i\epsilon}^2}\alpha_{i0} + \frac{\sigma_{i0}^2}{\sigma_{i0}^2 + \sigma_{i\epsilon}^2} r_i, \tag{3}$$

and

$$\Sigma_i = \frac{\sigma_{i0}^2 \sigma_{i\epsilon}^2}{\sigma_{i0}^2 + \sigma_{i\epsilon}^2}. \tag{4}$$

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 variance of the signal, $\sigma_{i\epsilon}^2$.

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).[1] 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 periods with three dates in the model. On date 1, investors optimally allocate into the mutual fund based on their prior. Given the objective function with the absolute risk aversion parameter, γ, it is straightforward that the allocation in a mutual fund is

$$X_1 = \frac{\alpha_0}{\gamma\left(\sigma_0^2 + \sigma_\epsilon^2\right)}.$$

On date 2, based on the posterior expectation, $\hat{\alpha}_i$, investors' optimal allocation is

$$X_2 = \frac{\mu}{\gamma\left(\Sigma + \sigma_\epsilon^2\right)} = \frac{\sigma_0^2 r + \sigma_\epsilon^2 \alpha_0}{\gamma \sigma_\epsilon^2 (2\sigma_0^2 + \sigma_\epsilon^2)}.$$

The flow into the fund on date 2 is defined as the amount of new investment going into the fund from date 1 to date 2 and measured as a fraction of the assets invested in the fund on date 1, i.e.,

$$F = \frac{X_2 - X_1 * (1+r)}{X_1} \tag{5}$$

$$= \left[\frac{\sigma_0^2(\sigma_0^2 + \sigma_\epsilon^2)}{\sigma_\epsilon^2(2\sigma_0^2 + \sigma_\epsilon^2)\alpha_0} - 1\right] r - \frac{\sigma_0^2}{2\sigma_0^2 + \sigma_\epsilon^2}. \tag{6}$$

Hence, in the simple setting considered here, the flow into the fund is linearly related to the past performance. Flows will respond positively to past performance if the prior expectation is not so high as to set up a disappointment, that is if

$$\alpha_0 < \frac{\sigma_0^2(\sigma_0^2 + \sigma_\epsilon^2)}{\sigma_\epsilon^2(2\sigma_0^2 + \sigma_\epsilon^2)}. \tag{7}$$

In our setting, the positive flow-performance sensitivity is a consequence of investors rationally learning from past performance to update their expectations and optimally

[1] In this sense, the model presented here is of a myopic nature for expositional simplicity. An intertemporal version of the model involves more complicated formulation while delivering the same intuition.

making their fund allocations. If we measure the sensitivity of the flow to performance by the slope in equation (6),

$$S = \frac{\sigma_0^2(\sigma_0^2 + \sigma_\epsilon^2)}{\sigma_\epsilon^2(2\sigma_0^2 + \sigma_\epsilon^2)\alpha_0} - 1 \tag{8}$$

then S is dependent upon the uncertainty in the prior about managerial ability, σ_0^2, and the variance of the observed performance, r, which is represented by σ_ϵ^2. The following result characterizes this dependence.

Result 1 *All else equal, the sensitivity of flows to past performance is increasing in σ_0^2, and decreasing in σ_ϵ^2, i.e.,*

$$\frac{\partial S}{\partial \sigma_0^2} > 0; \quad \textit{and} \quad \frac{\partial S}{\partial \sigma_\epsilon^2} < 0. \tag{9}$$

The intuition of this result is straightforward in a Bayesian learning context. On the one 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.[2] This leads to the following testable hypothesis:

Hypothesis 1 *All else equal, the sensitivity of flows to past performance is stronger for younger funds than for older funds.*

On the other hand, the observed performance is less informative if it's volatile. Investors will then respond less strongly to noisy past performance, as its weight in forming investors' posterior expectations will be smaller. Since in the model σ_ϵ^2 corresponds to the variance of the excess fund return, the testable hypothesis based on this result is then:

Hypothesis 2 *All else equal, the sensitivity of flows to past performance is weaker for funds with more volatile excess performance.*

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

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 2

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

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 *All else equal, the dampening effect of performance volatility on the sensitivity of flows to past performance is stronger for younger funds than for older funds.*

These hypotheses highlight the effect of performance volatility on mutual fund flows in the context of investor learning that leads to the positive relationship between fund flows and past performance. 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 investment objectives and management company names of funds starting from 1993. We exclude index funds from our analysis because we are interested in investors' learning aoubt 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.[3] 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 others. We also extract from this database information about fund characteristics such as expense ratio, load, fund age, fund size and fund family affiliation.

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:

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

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,[4] we filter out the top and bottom 2.5% of the flow data to minimize the impact of outliers.

We measure volatility of excess performance in both the short-run (12 months) and the long-run (36 months). We first obtain the excess performance through the Carhart (1997) four-factor model in the following regression:

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

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

[3]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'.

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

French (1993) three factors and the momentum factor, respectively.[5] When measuring the short-run performance, we first estimate the factor-loadings of each fund under the assumption 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 performance volatility in the past 12 months.

Since fund characteristics may change overtime due to various reasons, we also employ a rolling regression that allows for time-varying factor loadings. Specifically, for each quarter t, we estimate the above four-factor models using a fund's monthly returns in the past 36 months. The alpha obtained in the rolling regression is matched with the fund flow in quarter t. Correspondingly, we define the long-run volatility of past performance as the standard deviation of the risk-adjusted performance during the previous 36-month period.

Over our sample period, the number of actively managed equity funds has grown steadily from 923 funds in 1993 to 4607 funds in 2004. Since 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 compensation schemes, in Table I we report the quarterly average of the cross-sectional mean and median of the end of quarter fund size, fund age, total expenses, flows, and Carhart four-factor adjusted returns in the past 12 months. In addition, since our main focus is on the effect of performance volatility on investors' learning process, we report descriptive statistics for the volatility of raw performance and risk-adjusted performance in the past 12 months. Table I also shows the 25th and 75th percentiles of these fund characteristics. There seem to be considerable cross-sectional dispersions in fund flows, fund performance, and fund risk measures.

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

3.2 Empirical Methodology

Our focus in this paper is on the effect of performance volatility on the flow-performance sensitivity. We follow the Fama and MacBeth (1973) methodology to examine the cross-sectional determinants of fund flows. Specifically, for each quarter we run cross-sectional regressions 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 t-statistics are calculated using Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors to account for the auto-correlations in flows and other explanatory variables.

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.[6] To capture this nonlinear flow-performance relationship, we follow Sirri and Tufano (1998) to conduct a piecewise linear regression. Each quarter, fractional performance ranks ranging from 0 to 1 are assigned to funds according to their Carhart four-factor-adjusted returns during the past 12 or 36 months. The factional rank for funds in the bottom performance quintile (Low) is defined as $Min(Rank_{t-1}, 0.2)$. Funds in the three medium performance quintiles (Mid) are grouped together and receive ranks that are defined as $Min(0.6, Rank_{t-1} - Low)$. The rank for the top performance quintile (High) is defined as $Rank_{t-1} - Mid - Low$. Each quarter, flows are regressed on performance ranks in the low, medium, and high performance ranges along with other variables.

Our main hypotheses concern the effect of performance volatility on the sensitivity of flows to past performance. This is tested by including an interaction term between performance volatility and performance itself in the regression. We also include an interaction term between fund age, as measured by the logarithm of $age + 1$, and performance to account for the effect of prior uncertainty. In addition, equation (6) indicates that both performance volatility and fund age may affect the level of flows beyond the flow-performance sensitivity. So we include in our regression performance volatility and fund

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

age as stand alone explanatory variables. Moreover, since Barber, Odean, and Zheng (2004) have documented the differential effects of various annual charges and loads on flows, we separately control the operating and distribution expenses of funds as of the previous year end. Distribution expenses are measured by 12b-1 fees plus one-seventh of the front-end load in the prior year. To control for the effect of scaling on the percentage growth of a fund due to the large variation in fund size, we include logged fund TNA in quarter $t-1$ when estimating the flow regression in quarter t. Lastly, 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 flow 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 Empirical Results

4.1 Volatility of Performance and the Flow Sensitivity to Past Performance

According to the investor learning hypothesis, the sensitivity of flows to past performance should be increasing with investors' prior uncertainty about a fund and decreasing with the noisiness of the observed past performance. Since at any given time, investors' prior confidence in their knowledge about a fund is closely related to the cumulative amount of available information up to that time, it is reasonable to assume that investors have more precise priors about funds that have existed for a long period of time with an established track record. Therefore, we expect flows to be less sensitive to past performance of older funds. This implication of the investor learning hypothesis is consistent with Chevalier and Ellison (1997), who show that younger funds not only in general attract more new money, but also have stronger flow-performance sensitivity. In this paper our focus is on how the noisiness of signal observed from past performance affects the flow-performance sensitivity. Using performance volatility as the measure of the noisiness of signal, we should expect that large performance volatility reduces the sensitivity of flows to past performance.

Table II reports results of the Fama-MacBeth regression of flows on past performance and the interaction term between performance and its volatility, controlling for the aggregate flow into a fund's investment objective category, fund age, fund size, distribution expenses and operating expenses. To verify the effect of fund age on the flow-performance relationship after controlling for volatility, we also interact the logarithmic value of $(age + 1)$ with performance ranks.

Our result shows a strongly positive flow-performance relationship that also exhibits convexity, illustrated by a significantly greater coefficient on high performance than on low or medium performance, consistent with the existing literature. This implies that although flows chase past good performance, investors pull out much more slowly from funds with poor past performance. More interestingly, however, flows react less sensitively to volatile performance, as reflected by the negative coefficient for the interaction term between performance and volatility. The effect of volatility is also economically significant. Specifically, if the volatility of performance in the past 12 months increases by 1%, it will reduce the sensitivity of flow to performance by more than 10% for funds with average performance. This effect is robust whether we measure the volatility in the short run (12 months) or in the long run (36 months), although the magnitude is slightly stronger if the volatility of performance is measured over the last 36 months. Volatility itself has a positive coefficient, although it is not statistically significant. 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.

Consistent with the prediction of the learning model, 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 reply 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, while flows increase with distribution expenses, they are negatively or insignificantly affected by operating expenses. This is consistent with findings in recent studies (see, for example, Jain and Wu (2000), Sirri and Tufano (1998) and Huang, Wei, and Yan (2005)) that advertising and marketing can lower investors' search costs and therefore help funds attract more flows. On the other hand, although higher operating expenses 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 (2004). In addition, funds often use operating expenses to pay for distribution or marketing as well. Therefore, it is not surprising that flows are sometimes insensitive to operating expenses.

4.2 Fund Age and the Effect of Performance Volatility

The learning hypothesis also suggests that the effects of investors' prior and the signal in past performance are complementary to each other. That is, investors place more weight on either the prior or the signal, whichever that is more precise. As shown in the previous section, 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, the volatility of recent performance should have a significantly diminished effect on the flow-performance sensitivity for older funds.

In Table III, we examine the joint effect of performance volatility and fund age. Specifically, we augment the analysis in Table II by including an interaction term between performance ranks, volatility and age. We find a significant positive coefficient for this interaction term. Since performance volatility reduces the response of flows to past performance, a positive sign on this interaction term demonstrates that the effect of volatility on the sensitivity of flows to prior performance may be strongest for young funds and diminishes with older 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 countervailing effect of fund age on performance volatility is slightly stronger if the volatility of performance is measured during the past 12 months than if it is measured during the past 36 months. In addition, after controlling for the interaction between volatility and fund age, the dampening effect of volatility on the flow-performance sensitivity becomes more salient. This may be due to the possibility that older funds tend to have more volatile performance, as we explore in more details in Section 7.

5 Information Costs and the Effect of Performance Volatility

So far, our discussion of investors' learning of managerial ability has assumed that investors can invest in funds without any friction. Sirri and Tufano (1997) and Huang, Wei and Yan (2005) point out that when investors choose from the vast universe of mutual funds, they often face various investment barriers due to costly search in the mutual fund market. In this section, we examine how investor uncertainty affects the flow-performance sensitivity in the presence of information costs, which are the investors' costs of obtaining information to form an informed opinion about a particular fund.

For an investor who is new to an unfamiliar fund, her prior about the managerial ability can be very uninformative. Expending efforts to gather information about the fund, i.e., incurring the information cost, can help her narrow the variance of her prior expectation. In this sense, incurring information costs allows an investor to obtain a more informed prior and therefor rely less on getting a precise signal from past performance in order to make investment decisions. However, investors have to decide if the cost of information collection can be more than compensated by the potential benefit of investing in the fund. The expected benefit of incurring information costs depends on investors' posterior expectation of the future return of the fund, which in turn is determined by the level and noisiness of the observed performance. If information costs are low, then more investors will be able to obtain accurate information about the fund, and hence require less precise signal from its past performance to decide on their investments. The impact of performance volatility on the posterior expectation will then be mitigated. Therefore, we should expect that the effect of volatility of performance on the flow-performance sensitivity is weaker when information costs are smaller.

In reality, information costs may be related to the effort of studying the fund prospectus, of finding out about its Morningstar rating and understanding its investment strategies, or of seeking advice from friends and financial advisors. Although individuals' information costs may depend on their own traits, such as their education or experience, which are difficult to measure, it is conceivable that the same investor may face different information barriers when studying different funds. For example, given the high profile of the Fidelity Magellan fund, investors may need little additional information before they feel they have a fairly accurate prior about the fund. On the other hand, for a no-name fund, and investors generally are more skeptical about their performance and may require a lot more additional information, i.e., incur higher information costs, before they can decide whether it is a good investment. This illustrates that individual-level and fund-level information costs are complementary to each other. Therefore, we expect the effect of performance volatility on the flow-performance sensitivity to vary across funds.

Following Huang, Wei and Yan (2005), we use fund characteristics to proxy for fund level information costs. Massa (2003) argues that if a fund is affiliated with a large fund family or with a family that offers an array of different types of funds, it is a lot easier to attract potential investors because of the economy of scale in services provided and the associated informational externality that helps reduce the average information costs. This argument is supported by Huang, Wei and Yan (2005) who find that funds that belong to large complexes are able to attract more new investors even when their performance is mediocre. Hence, we use the size of a fund's affiliated family, measured by the logarithm of the total net asset value managed by the parent complex in the previous quarter, as a proxy for information costs.

Table IV investigates how affiliation with families of various sizes affects the effect of performance volatility on the sensitivity of flows to past performance. Specifically, we examine the interaction among the three variables: complex size, performance volatility and performance itself. The result shows a significantly positive coefficient for this interaction term when performance is measured in the prior 12 months. This indicates that when a fund belongs to a large family, investors seems to care less about the volatility of past performance in making their investment decisions. This is consistent with the notion that with lower information costs, more investors are able to reach informative priors about the fund, and hence their posterior expectations are less sensitive to the realized returns and the noisiness associated with them. Similar results are also observed when volatility is measured over a longer period of past 36 months, although the effect of family affiliation is a bit weaker.

In addition, even after we control for family size, we still find the interaction term between fund age and performance to be significantly negative, and the interaction term between age, performance and volatility to remain significantly positive. This implies that the effect of information costs are complimentary to the effect of age. This is consistent with the notion that although incurring information costs helps reduce prior uncertainty, information costs themselves do not measure the level of prior uncertainty. Also consistent with existing findings on the effect of family affiliation, Table IV shows that controlling for performance, size and other characteristics, funds belonging to larger complexes attract significantly more flows.

Another potential benefit of family affiliation is the spillover effect in flows within a large family that has produced super stars, as reported in Del Guercio and Tkac (2002), Khorana and Servaes (2004) and Nanda, Wang, and Zheng (2004). Intuitively, investors who are attracted to a star fund can potentially become aware of the other offerings of the same family. As a result, the presence of a "star" fund can help increase the overall flow to the entire family. Hence, we should expect the dampening effect of volatility on the flow-performance sensitivity to be weaker among funds that belong to a "star"-producing family because of their lower information costs.

To determine the "star" status of a fund, we follow Nanda, Wang, and Zheng (2004) to mimic the Morningstar rankings by calculating the risk-adjusted performance score of funds. Specifically, at the beginning of each quarter, we rank funds according to the difference between a load-adjusted return and a risk measure during the past 3 years.[7] Funds that are ranked above the 90th percentile are defined as "star" funds. If a fund is affiliated with a family that has produced at least one "star" fund, but is not a "star" itself, it is considered as being affiliated with a "star" family. As reported in Nanda, Wang and Zheng (2004), "star" funds designated this way overlap significantly with those identified in the popular Morningstar star ranking that average investors may be more familiar with. In addition, although the most popular Morningstar ranking is the weighted average of the ratings for performance in the past three, five and ten years, as pointed out by Sharpe (1997), the three-year ratings are highly correlated with the overall ratings. Therefore, we believe that our measure of "star" affiliation should be a reasonable proxy for the reduction in information costs for investors.

In Table V, in addition to the interaction term between performance and performance volatility and that between fund age, performance and its volatility, we include an interaction term between the "star" family membership dummy, performance and volatility in the estimation of fund flows. Consistent with our prediction, we find that, for both short-run and long-run performances, investors are less sensitive to performance volatility if the fund is from a "star" producing family. In other words, investors seem to have

[7] Details of the procedure that mimics the Morningstar ratings system may be found in the appendix of Nanda, Wang, and Zheng (2004).

strong confidence in funds in families that have produced proven records or enjoyed high investor recognition.

Finally, Sirri and Tufano (1997) and Huang, Wei and Yan (2005) document that lowering search costs can induce more fund flows and increase the sensitivity of flows to past good performance. We expect funds that expend more resources in marketing and advertising to have greater investor recognition and consequently lower investment costs for new investors. Similarly, investors in funds that are sold by brokers are more likely to believe the pitches by the brokers, and thus are less sensitive to the volatility of past performance. Therefore, we may use a fund's marketing and distributional expenses as another proxy for its information costs. We measure these marketing expenses by 12b-1 fees plus one-seventh of the front-end load in percentage. The result with this proxy is presented in Table VI where we interact a fund's marketing expenses with its performance and performance volatility. Consistent with the effect of family size and "star" family affiliation, we find this interaction term to be significantly positive, suggesting that greater marketing efforts weaken the negative impact of performance volatility on the flow-performance sensitivity. In an unreported analysis, we also separate funds into load versus no-load funds to capture the effect of brokers. The result is very similar to those reported in Table VI.

6 Implications for Managerial Risk-taking Incentives

The convex flow-performance relationship documented in the literature has spawned a hot debate about its implications on managerial incentives to take risk. The rationale for risk taking is that if a fund has highly volatile performance, it is likely to have more dispersed performance, and hence a larger expected fund flow given the convexity of the flow-performance relationship. Our results, however, have demonstrated that investors discount past performance when observing high performance volatility. So far, we have shown this reduction in the flow-performance sensitivity across all performance ranges, i.e., the "tilting" effect of volatility on the flow-performance sensitivity. Because it is the asymmetric response of flows to performance that drives the managerial risk-taking incentives, we investigate in this section whether the effect of performance volatility is symmetric across low and high performances.[8] For example, if a fund delivers "star" performance, will investors be more or less willing to overlook its performance volatility than if the performance was extremely poor?

To examine if the effect of volatility affects the flow-performance sensitivity differently in different performance ranges, we replace the interaction term between volatility and performance in the previous regressions with three interaction terms that interact volatility separately with performance in the lowest decile, in the highest decile, and in the rest of performance ranges. We focus on the top and the bottom deciles of performance to highlight the effect of high volatility. The results for performance measured in the preceding twelve or thirty six months are presented in Table VII.

Consistent with the results discussed earlier, Table VII shows that performance volatility significantly reduces the sensitivity of flows to past performance in all performance ranges. However, the effect is much stronger for funds whose performance is among the top 10%, with the point estimate of the coefficient for the high performance range more than six times larger than those for both the low and the middle performance ranges. This difference is also statistically significant as indicated by t-statistics for tests of the differences in these coefficients. There is no discernible difference, however, between the interaction terms of volatility with the low and the medium performance ranges. This result implies a "flattening" effect of performance volatility on the flow-performance relationship. That is, performance volatility reduces the convexity of the flow-performance relationship. In this sense, the effect of volatility mitigates the incentive for managers to take excessive risk because taking more risk reduces the benefit of achieving superior performance.[9]

[8]This empirical examination is outside of the direct implications of the learning hypothesis discussed in Section 2. A full theoretical modelling would involve a more general equilibrium setup, which is left for future research. Here we explore empirically the impact of performance volatility on the convexity of the flow-performance relationship and assess its role in managerial incentives.

[9]We note that the effect of performance volatility on managerial incentives is different from the tournament effect discussed in the literature, because we are concerned about the *level* of volatility measured contemporaneously with performance, not the *change* in volatility next period conditional on the current performance.

7 Determinants of Performance Volatility

Table I shows that there are significant variations in performance volatility across funds. Given our earlier finding that volatility has differential effects on the flow-performance sensitivity depending on fund characteristics, it is possible that mutual funds strategically choose the optimal level of volatility. On the one hand, funds may benefit from volatile performance given that they will be well rewarded for good performance but not equally punished for poor performance, as suggested by the convex flow-performance relationship. On the other hand, flows may respond much less sensitively to past good performance if it is volatile. While fully characterizing this optimal choice of volatility level requires a general equilibrium framework considering actions of both managers and investors, which is beyond the scope of this paper, we shed some light on the issue by examining the determinants of fund volatility in this section.

Since we have demonstrated earlier that volatility has less impact on the flow-performance sensitivity of funds that have established track records, we anticipate older funds to be able to afford to have higher volatility which allows them to outperform their peers from time to time and hence to maintain high levels of inflows. Similarly, funds that have made significant efforts in selling their products or funds that are affiliated with a large complex or with a "star" producing fund family may worry less about their performance volatility because their lower information costs tend to reduce the impact of volatility on their flow-performance sensitivity. In fact, the evidence in Nanda, Wang, and Zheng (2004) and Gaspar, Massa, and Matos (2006) suggests that the "star" creating strategy by the family usually involves volatile performance. However, Huang, Wei, and Yan (2005) show that these funds also tend to have a less convex flow-performance relationship, and hence may not benefit much from taking more risk. Therefore, the net effect of information costs on volatility is not immediately clear.

We also examine the effect of funds' turnover ratios. A higher turnover ratio should indicate more active fund management and potentially higher performance volatility. In addition, we include a dummy variable indicating funds that have an investment objective of aggressive growth or growth because managers in these funds may adopt riskier strategies commensurate with their investment styles. Although we have controlled for systematic risk when we measure performance volatility on a risk-adjusted basis, small funds may hold more of the small-cap stocks that have larger idiosyncratic risk, as illustrated in Chen, Hong, Huang, and Kubik (2004). So we expect volatility to be decreasing with fund size. Finally, we control for extreme performance by including dummy variables that indicating funds whose performances are in the top or bottom 10% of the sample according to their Carhart 4-factor adjusted returns during the year. Holding everything else equal, the extreme outcomes of these funds are more likely to be the result of volatile performance.

In Table VIII, we regress the volatility of the risk-adjusted return on aforementioned fund characteristics year by year and report the time-series average coefficients and the Fama-Macbeth t-statistics. As expected, we find that funds that are ranked among the top or bottom 10% have significantly higher performance volatility. In addition, growth funds and funds with higher turnover ratio also seem to involve riskier strategies and take on more idiosyncratic risk. Moreover, performance volatility appears to be increasing with fund age, consistent with the earlier finding that investors care less about the volatility of older funds. Interestingly, while "star" family affiliation leads to lower performance volatility in model 1, its effect becomes insignificant once we control for the size of the affiliated family complex. This is probably because a fund is more likely to belong to a "star" producing family if it is affiliated with a large family which can employ diverse star creating strategies. So the explanatory power of "star" affiliation in model 1 may actually come from that of complex size. Similarly, since large family complexes usually expend more on advertising and marketing on dollar amount, we do not find distribution expenses to significantly affect performance volatility once we control for complex size. On the other hand, complex size has a strong negative effect on performance volatility, suggesting that funds affiliated with large families benefit less from taking more risk, consistent with flatter flow-performance relationships for these funds documented in Huang, Wei, and Yan (2005). Finally, consistent with the observation in Chen, Hong, Huang, and Kubik (2004) that small size funds tend to hold more small-cap stocks, small funds seem to have larger risk-adjusted performance volatility.

8 Concluding Remarks

The widely-documented asymmetric response of flows to the past performance of actively managed funds has been argued to generate 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 on the sensitivity of mutual fund flows to past performance. We find that investors respond less strongly to volatile performance, but volatility's dampening effect on the flow-performance sensitivity is lessened for older funds and for funds with lower investment barriers. 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 demonstrate that performance volatility has a particularly strong effect in the top performance range, and thus tends to reduce the convexity of the flow-performance relationship. This has an important implication for the much-debated managerial risk-taking incentives. Our results illustrate that because volatility of performance impedes the learning process of investors, funds employing more risky strategies can face a more "flattened" flow-performance relationship. Hence, managerial risk-taking incentives should be mitigated, albeit not eliminated. This implication also suggests an optimal level of volatility different funds may choose. Although we try to explore the determinants of fund-level performance volatility, 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.

References

Barber, Brad M., Terrance Odean, and Lu Zheng, 2004, Out of sight, out of mind: The effects of expenses on mutual fund flows, *Journal of Business* forthcoming.

Berk, J. B., and R. C. Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269–1295.

Brown, Keith C., W. V. Harlow, and Laura T. Starks, 1996, Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry, *Journal of Finance* 51, 85–110.

Busse, Jeffrey A., 2001, Another look at mutual fund tournaments, *Journal of Financial and Quantitative Analysis* 36, 53–73.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Carpenter, Jennifer N., 2000, Does option compensation increase managerial risk appetite?, *Journal of Finance* 55, 2311–2331.

Chen, Hsiu-lang, and George G. Pennacchi, 2002, Does prior performance affect a mutual fund's choice of risk? theory and further empirical evidence, Working Paper, University of Illinois at Urbana-Champaign.

Chen, Joe, Harrison Hong, Ming Huang, and Jeffrey Kubik, 2004, Does fund size erode mutual fund performance? the role of liquidity and organization, *American Economic Reviewy* 95, 1276–1302.

Chevalier, Judith A., and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167–1200.

Del Guercio, Diane, and Paula A. Tkac, 2002, Star power: The effect of morningstar ratings on mutual fund flows, Working Paper, University of Oregon.

Dybvig, Philip H., Heber K. Farnsworth, and Jennifer N. Carpenter, 2003, Portfolio performance and agency, Working Paper, New York University.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 2001, A first look at the accuracy of crsp mutual fund database and a comparison of the crsp and morningstar mutual fund database, *Journal of Finance* 56, 2415–2430.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Gaspar, Osé-Miguel, Massimo Massa, and Pedro Matos, 2006, Favoritism in mutual fund families? evidence on strategic cross-fund subsidization, *Journal of Finance* 61, 73–104.

Grinblatt, Mark, and Sheridan Titman, 1989, Adverse risk incentives and the design of performance-based contracts, *Management Science* 35, 807–822.

Gruber, Martin J., 1996, Another puzzle: The growth in actively managed mutual funds, *Journal of Finance* 51, 783–810.

Huang, Jennifer, Kelsey D. Wei, and Hong Yan, 2005, Participation costs and the sensitivity of fund flows to past performance, *Journal of Finance* forthcoming.

Ippolito, Richard A., 1992, Consumer reaction to measures of poor quality: Evidence from the mutual fund industry, *Journal of Law and Economics* 35, 45–70.

Jain, Prem C., and Joanna S. Wu, 2000, Truth in mutual fund advertising: Evidence on future performance and fund flows, *Journal of Finance* 55, 937–958.

Khorana, Ajay, and Henri Servaes, 2004, Conflicts of interest and competition in the mutual fund industry, Working Paper, London Business School.

Lynch, Anthony W., and David K. Musto, 2003, How investors interpret past fund returns, *Journal of Finance* 58, 2033–2058.

Massa, Massimo, 2003, How do family strategies affect fund performance? when performance-maximization is not the only game in town, *Journal of Financial Economics* 67, 249–304.

Nanda, Vikram, Zhi Wang, and Lu Zheng, 2004, Family values and the star phenomenon: Strategies of mutual fund families, *Review of Financial Studies* 17, 667–698.

Newey, Whitekey K., and Kenneth D. West, 1987, A simple, positive semi-definite heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Sharpe, William, 1997, Morningstar's performance measures, Working Paper, Stanford University.

Sirri, Erik R., and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589–1622.

Starks, Laura T., 1987, Performance incentive fees: An agency theoretic approach, *Journal of Financial and Quantitative Analysis* 22, 17–32.

Table I

Summary Statistics of Fund Characteristics

This table reports summary statistics of fund characteristics for the full sample from 1993-2004. Each quarter, we calculate the cross-sectional mean, median, the 25^{th} and 75^{th} percentiles 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 past 12 months. The time-series averages of these descriptive statistics are reported.

	Mean	Median	25^{th}	75^{th}
TNA (Million $)	479.22	65.63	15.12	251.79
Age (year)	7.70	3.81	1.73	8.17
Total Fees	1.70%	1.76%	1.17%	2.11%
Quarterly Flow	4.24%	0.79%	-3.21%	7.90%
Raw Return	0.86%	0.82%	0.28%	1.42%
4-Factor Alpha	-0.13%	-0.12%	-0.47%	0.22%
Volatility of Raw Return	4.63%	4.24%	3.58%	5.39%
Volatility of Alpha	1.70%	1.51%	1.06%	2.11%

Table II

The Effects of Fund Age and Performance Volatility on the Flow-Performance Sensitivity

This table reports the effects of fund age and performance volatility on the flow-performance volatility. Each quarter, fractional performance ranks ranging from 0 to 1 are assigned to funds to their 4-factor model adjusted returns during the past 12 or 36 months. The factional rank for funds in the bottom performance quintile (Low) is defined as Min ($Rank_{t-1}$, 0.2). Funds in the three medium performance quintiles (Mid) are grouped together and receive ranks that are defined as Min (0.6, $Rank_{t-1}$ – Low). The rank for the top performance quintile (High) is defined as $Rank_{t-1}$ – Mid – Low. 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, as well as on the standard deviation of risk-adjusted returns during the period performance is measured and its interaction with performance ranks. The control variables include aggregate flows into the corresponding fund objective category, the logarithmic value of one plus fund age and its interaction with performance, the logarithmic value of the lagged total net asset value, lagged distribution expenses and operating expenses. Time-series averaged coefficients and the Fama-MacBeth t-statistics (in parentheses) calculated with Newey-West robust standard errors are reported. *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

	12 months	36 months
Intercept	0.0152*	0.0059
	(1.89)	(0.73)
Objective Flows	0.3745***	0.3428***
	(3.49)	(4.15)
Low	0.2592***	0.1780***
	(11.97)	(10.68)
Mid	0.1511***	0.1135***
	(14.07)	(11.69)
High	0.4633***	0.3618***
	(16.21)	(17.80)
Volatility	0.3283*	0.2636
	(1.80)	(1.67)
Volatility*Performance	-1.6164***	-1.9682***
	(-5.52)	(-4.98)
Fund Age	-0.0271***	-0.0197***
	(-13.46)	(-13.05)
Fund Age*Performance	-0.0209***	-0.0043**
	(-9.90)	(-2.53)
Fund Size	-0.0036***	-0.0026***
	(-7.64)	(-5.07)
Distribution Exp	1.7102***	1.0657***
	(4.55)	(3.41)
Operating Exp	-0.1182	-0.1733
	(-0.75)	(-1.54)
R^2	0.192	0.151

Table III
Fund Age and the Effect of Performance Volatility

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 during the past 12 or 36 months, the standard deviation of their performance during the corresponding period and its interaction term with performance, and the interaction term between volatility, performance rank and the logarithmic value of 1 plus fund age. The control variables include aggregate flow into the fund objective category, the logarithmic value of 1 plus fund age and its interaction with performance, the logarithmic value of the lagged total net asset value of the fund, lagged distribution expenses and operating expenses. 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 10%, 5%, and 1% levels, respectively.

	12 months	36 months
Intercept	0.0138*	0.0061
	(1.73)	(0.76)
Objective Flows	0.3802***	0.3422***
	(3.54)	(4.16)
Low	0.2762***	0.1858***
	(13.34)	(9.57)
Mid	0.1673***	0.1221***
	(14.84)	(9.38)
High	0.4853***	0.3713***
	(18.42)	(16.76)
Volatility	0.3561*	0.2542
	(1.92)	(1.55)
Volatility*Performance	-2.5073***	-2.4093***
	(-7.99)	(-3.69)
Volatility*Performance	0.4424***	0.3313**
*Fund Age	(4.03)	(2.09)
Fund Age	-0.0265***	-0.0193***
	(-12.85)	(-13.05)
Fund Age*Performance	-0.0293***	-0.0103***
	(-9.03)	(-3.37)
Fund Size	-0.0036***	-0.0026***
	(-7.62)	(-5.14)
Distribution Exp	1.7243***	1.0722***
	(4.58)	(3.44)
Operating Exp	-0.1430	-0.2034*
	(-0.88)	(-1.77)
R^2	0.193	0.152

Table IV

Family Size and the Effect of Performance Volatility

This table examines the effect of family size, as measured by the logarithm of total assets under the management of the fund family, on the dampening effect of volatility on flow-performance sensitivity. 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 over the previous 12 or 36 months, the standard deviation of their performance during the corresponding period and its interaction term with performance, and the interaction term between volatility, performance and the size of their parent families. The control variables include aggregate flow into the fund objective category, the logarithm of lagged family size, the logarithm of 1 plus fund age and its interaction terms with performance alone, and with volatility and performance, the logarithmic value of the lagged total net asset value, lagged distribution expenses and operating expenses. 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 10%, 5%, and 1% levels, respectively.

	12 months	36 months
Intercept	-0.0044 (-0.51)	-0.0141 (-1.44)
Objective Flows	0.3367*** (3.16)	0.3073*** (3.67)
Low	0.2738*** (13.08)	0.1926*** (9.89)
Mid	0.1642*** (14.00)	0.1250*** (9.41)
High	0.4797*** (17.90)	0.3745*** (16.62)
Volatility	0.3066* (1.68)	0.2726* (1.68)
Volatility*Performance	-3.5187*** (-9.30)	-3.0839*** (-4.66)
Volatility*Performance *Family Size	0.1446*** (3.36)	0.0595* (1.79)
Volatility*Performance *Fund Age	0.5608*** (4.39)	0.4714*** (2.71)
Fund Age	-0.0240*** (-12.66)	-0.0173*** (-10.88)
Fund Age*Performance	-0.0310*** (-9.28)	-0.0122*** (-3.76)
Family Size	0.0025*** (4.58)	0.0026*** (4.98)
Fund Size	-0.0055*** (-8.71)	-0.0044*** (-8.62)
Distribution Exp	1.1612*** (3.32)	0.6382** (2.23)
Operating Exp	0.2060 (1.06)	0.0708 (0.53)
R^2	0.200	0.157

Table V

“Star” Family Affiliation and the Effect of Performance Volatility

This table examines the effect of affiliation with a “star”-producing family on the dampening effect of volatility on flow-performance sensitivity. Each quarter, funds are ranked according to their risk-adjusted performance in the past 36 months. Those ranked above the 90^{th} percentile are considered as “star” funds. A “star” family affiliation dummy variable is assigned the value of 1 for funds that affiliated with “star” families but are not stars themselves, and 0 otherwise. A piecewise linear regression is performed by regressing quarterly flows on funds’ fractional performance rankings over the low, medium, and high performance ranges over the previous 12 or 36 months, the standard deviation of their performance during the corresponding period and its interaction term with performance, and the interaction term between volatility, performance and a dummy variable indicating “star” family affiliation. The control variables include aggregate flow into the fund objective category, the “star” family affiliation dummy, the logarithm of 1 plus fund age and its interaction terms with performance alone, and with volatility and performance, the logarithm of lagged fund size, and the 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 10%, 5%, and 1% levels, respectively.

	12 months	36 months
Intercept	-0.0298*** (-3.80)	-0.0172** (-2.16)
Objective Flows	0.3515*** (4.72)	0.3604*** (4.60)
Low	0.2040*** (12.89)	0.1846*** (10.26)
Mid	0.1183*** (15.09)	0.1070*** (9.41)
High	0.2557*** (14.73)	0.2207*** (9.17)
Volatility	0.2431* (1.87)	0.091 (0.51)
Volatility*Performance	-1.3102*** (-4.33)	-1.4647** (-2.61)
Volatility*Performance *Star Family	0.7020*** (3.04)	0.7980*** (4.00)
Star Family Affiliation	0.0011 (0.80)	0.0008 (0.67)
Star	0.0545*** (15.63)	0.0484*** (12.73)
Volatility*Performance *Fund Age	0.1429 (1.26)	0.1414 (0.81)
Fund Age	-0.0077*** (-5.67)	-0.0087*** (-6.37)
Fund Age*Performance	-0.0199*** (-10.65)	-0.0151*** (-4.96)
Fund Size	-0.0010** (-2.66)	-0.0021*** (-5.46)
Distribution Exp	0.7019*** (3.04)	0.7824*** (3.29)
Operating Exp	-0.3944*** (-3.27)	-0.2889** (-2.25)
R^2	0.186	0.172

Table VI
Distribution Expenses and the Effect of Performance Volatility

This table examines the effect of distribution expenses, as measured by the 12b-1 fees plus one-seventh of the front-end load in percentage, on the dampening effect of volatility on flow-performance sensitivity. 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 over the previous 12 or 36 months, the standard deviation of their performance during the corresponding period and its interaction term with performance, and the interaction term between volatility, performance and distribution expenses. The control variables include aggregate flow into the fund objective category, the family size, the logarithm of 1 plus fund age and its interaction terms with performance alone, and with volatility and performance, the logarithm of lagged fund size, distribution expenses and operating expenses. 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 10%, 5%, and 1% levels, respectively.

	12 months	36 months
Intercept	0.0175***	0.0079
	(2.31)	(1.00)
Objective Flows	0.3798***	0.3424***
	(3.55)	(4.15)
Low	0.2740***	0.1842***
	(13.31)	(9.56)
Mid	0.1660***	0.1214***
	(14.91)	(9.32)
High	0.4875***	0.3721***
	(15.84)	(16.85)
Volatility	0.3360*	0.2408
	(1.81)	(1.47)
Volatility*Performance	-2.7799***	-2.5614***
	(-9.05)	(-3.93)
Volatility*Performance	0.4766**	34.5007**
* Distribution Exp	(2.58)	(2.11)
Volatility*Performance	0.4765***	0.3509**
*Fund Age	(4.22)	(2.16)
Fund Age	-0.0268***	-0.0195***
	(-13.08)	(-12.80)
Fund Age*Performance	-0.0293***	-0.0103***
	(-9.08)	(-3.39)
Fund Size	-0.0036***	-0.0026***
	(-8.72)	(-5.14)
Distribution Exp	0.0129***	0.0082***
	(3.53)	(2.78)
Operating Exp	-0.1458	-0.2031*
	(-1.14)	(-1.77)
R^2	0.194	0.153

Table VII

The Effect of Volatility Across Different Performance Ranges

Each quarter a piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance rankings over the low decile, medium, and highest decile performance ranges during the past 12 or 36 months, the standard deviation of their performance during the corresponding period and its interaction terms with low, medium and high performances, and the interaction term between volatility, performance rank and the logarithmic value of 1 plus fund age. The control variables include aggregate flow into the fund objective category, the logarithmic value of 1 plus fund age and its interaction with performance, the logarithmic value of the lagged total net asset value, lagged distribution expenses and operating expenses. Time-series average coefficients and the Fama-MacBeth t-statistics (in parentheses) calculated with Newey-West robust standard errors are reported. t-statistics for the differences in coefficients for the interaction terms between volatility and the low, medium and high performance rankings calculated using the Newey-West robust standard errors are also reported at the bottom of the table. *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

	12 months	36 months
Intercept	0.0313***	0.0209***
	(3.62)	(2.81)
Objective Flows	0.3789***	0.3085***
	(3.47)	(3.23)
Lowest 10%	0.1698***	0.1159***
	(12.60)	(8.90)
Mid	0.1797***	0.1283***
	(15.92)	(10.77)
Highest 10%	1.1461***	0.9282***
	(9.84)	(8.39)
Volatility	0.2513	-0.2219
	(1.19)	(-0.84)
Lowest 10%*Volatility	-2.0556***	-1.0981*
	(-4.74)	(-1.74)
Mid*Volatility	-2.0954***	-1.6132***
	(-6.63)	(-2.77)
Highest 10%*Volatility	-14.5717***	-21.2051***
	(-3.31)	(-3.90)
Volatility*Performance *Fund Age	0.4519***	0.5400***
	(3.72)	(4.43)
Fund Age	-0.0265***	-0.0192***
	(-12.83)	(-13.08)
Fund Age*Performance	-0.0295***	-0.0137***
	(-8.89)	(-5.70)
Fund Size	-0.0036***	-0.0026***
	(-7.65)	(-4.94)
Distribution Exp	1.7208***	1.0938***
	(4.60)	(3.50)
Operating Exp	-0.1565	-0.2331**
	(-0.96)	(-2.12)
R^2	0.194	0.153
	t-stat	t-stat
High*Vol – Low*Vol	-2.44**	-2.87***
High*Vol – Mid*Vol	-2.41**	-2.79***
Mid*Vol – Low*Vol	-0.22	-2.24**

Table VIII
Determinants of Performance Volatility

Each year, we regress the standard deviation of the Carhart 4-factor adjusted monthly returns on the logarithmic value of 1 plus fund age, the logarithmic value of family size, a binary variable that takes the value of one for funds that are affiliated with a "star" producing family and zero otherwise, lagged distribution expenses, the logarithmic value of the total net asset value of the fund, a binary variable that takes the value of one for aggressive growth and growth funds, turnover ratio, and two binary variables that take the value of 1 for funds that are ranked in the top or bottom 10%, respectively, according to their average Carhart 4-factor adjusted returns during the year. Time-series average coefficients and the Fama-MacBeth t-statistics (in parentheses) are reported. *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3
Intercept	0.0107***	0.0144***	1.4457***
	(21.18)	(14.12)	(13.68)
Age	0.1044***	0.0695***	0.0695***
	(4.30)	(3.18)	(3.18)
Complex		-0.0609***	-0.0629***
		(-7.47)	(-6.73)
Star Affiliation	-0.0737***		0.0228
	(-6.35)		(1.43)
Distribution Exp	-3.3128**	1.4772	1.5105
	(-2.44)	(1.11)	(1.20)
Size	-0.0468***	-0.0170***	-0.0166***
	(-8.18)	(-4.11)	(-4.07)
Growth	0.5368***	0.5333***	0.5333***
	(8.65)	(8.77)	(8.81)
Turnover	0.1812***	0.1821***	0.1818***
	(6.71)	(6.86)	(6.91)
Bottom 10%	0.6326***	0.6237***	0.6235***
	(6.37)	(6.21)	(6.19)
Top 10%	0.7256***	0.7423***	0.7554***
	(7.68)	(7.40)	(7.38)
R^2	0.246	0.260	0.260