Participation Costs and the Sensitivity of Fund Flows to Past Performance*

Jennifer Huang†
University of Texas at Austin

Kelsey D. Wei‡
Binghamton University - SUNY

Hong Yan§
University of Texas at Austin

September 20, 2004
First draft: March 14, 2004

Abstract

We present a simple rational model to highlight the effect of investors' participation costs on the response of mutual fund flows to past fund performance, and provide supporting empirical evidence for the model's implications for the asymmetric flow-performance relationship. By incorporating participation costs, which include both search and transaction costs, into a model in which investors learn about managers' ability from past returns, we show that fund flows are increasingly more sensitive to good performance, as better performance allows more new investors to overcome the hurdle of investing in the fund. Using various fund characteristics as proxies for participation costs, we demonstrate that, for funds with low participation costs, it does not require top-tier performance to attract potential investors. The overall flow-performance relationship of these funds is thus less convex than that of their higher-cost peers.

*We thank Jonathan Berk, Keith Brown, Alexei Goriaev, Lubos Pastor, Lukasz Pomorski, Mark Seasholes, Clemens Sialm, Laura Starks, Sheridan Titman, Tong Yao, and Lu Zheng for insightful suggestions, and presentation participants at CKGSB, Texas and the 2004 European Finance Association meeting for useful comments. The usual disclaimers apply. The latest version may be found at http://www.mccombs.utexas.edu/faculty/hong.yan/research/HWY_PC.pdf.

†Department of Finance, McCombs School of Business, University of Texas at Austin, Austin, Texas 78712-1179. Email: jennifer.huang@mccombs.utexas.edu.

‡School of Management, Binghamton University - SUNY, Binghamton, NY 13902-6000. Email: dwei@binghamton.edu.

§Department of Finance, McCombs School of Business, University of Texas at Austin, Austin, Texas 78712-1179. Email: hong.yan@mccombs.utexas.edu.

Participation Costs and the Sensitivity of Fund Flows to Past Performance

ABSTRACT

We present a simple rational model to highlight the effect of investors' participation costs on the response of mutual fund flows to past fund performance, and provide supporting empirical evidence for the model's implications for the asymmetric flow-performance relationship. By incorporating participation costs, which include both search and transaction costs, into a model in which investors learn about managers' ability from past returns, we show that fund flows are increasingly more sensitive to good performance, as better performance allows more new investors to overcome the hurdle of investing in the fund. Using various fund characteristics as proxies for participation costs, we demonstrate that, for funds with low participation costs, it does not require top-tier performance to attract potential investors. The overall flow-performance relationship of these funds is thus less convex than that of their higher-cost peers.

There has been an explosive growth in mutual fund offerings in the last two decades with more investors allocating their wealth, through various channels, to actively managed mutual funds. According to Investment Company Institute data, the number of stock mutual funds in the United States has increased from 399 in January 1984 to 4601 in December 2003. Meanwhile, in 2001, 52% of households held assets in mutual funds, up from a mere 6% in 1980 (see, e.g., Hortaçsu and Syverson (2003)). With the vast universe of fund offerings available, investors, especially new and unsophisticated ones, face a daunting task: namely, choosing an appropriate set of funds to invest in.

Many researchers have documented that investors chase after funds with superior recent performance. They put a disproportionately large amount of new money into these funds, although they withdraw less quickly from funds with poor performance.[1] Moreover, recent evidence shows that non-performance-related fund characteristics, such as fund age, volatility of past performance, affiliation with a large or "star"-producing fund complex, and fund's marketing expenditure, affect both the level of fund flows and the sensitivity of flows to past performance.[2]

In this paper, we develop a simple rational model to highlight the effect of new investors' participation costs on the asymmetric response of fund flows to past performance. Specifically, the model predicts that reducing a fund's participation costs for new investors both raises the level of inflows and reduces the overall convexity in the flow-performance relationship. Our empirical analysis of the flow-performance sensitivity confirms these predictions.

The consideration of participation costs is plausible given the naivety of average investors and the dizzying array of funds from which they can choose, as demonstrated in Capon, Fitzsimons and Prince (1996) and Goetzmann and Peles (1997). We examine

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

[2]See, for example, Chevalier and Ellison (1997) for the impact of fund age; Sirri and Tufano (1998), Jain and Wu (2000), and Gallaher, Kaniel and Starks (2004) for the effect of marketing and advertising expenses; Sirri and Tufano (2000) and Huang, Wei and Yan (2004) for the importance of performance volatility; and Sirri and Tufano (1998), Khorana and Servaes (2004), Massa (2003), and Nanda, Wang and Zheng (2004a) for the significance of the affiliation with large or "star"-producing fund families.

explicitly two types of participation costs in this paper. The first type is termed "search costs," and is related to the cost of identifying and collecting information before investing in a new fund. We model the search cost as a fixed up-front cost faced by new investors. For instance, Sirri and Tufano (1996), Jain and Wu (2000), and Gallaher, Kaniel and Starks (2004) demonstrate that funds can promote fund growth by improving investor recognition – effectively lowering search costs for new investors – through increasing their marketing and advertising expenses. The second type of costs is related to "transaction costs," such as loads, which are incurred when an investor allocates new money to a fund or switches from another fund family. We model the transaction cost as a proportional cost that applies to both old and new investors.

Our model relies on two main assumptions regarding investors' behavior. First, investors learn about unobservable managerial ability from the realized past fund performance. Second, investors face participation costs associated with identifying, investigating, and investing in a new fund. The first assumption is common to most learning models and implies that fund flows chase after past performance due to investors' Baysian updating process. Our second assumption is the driving force behind the increasing sensitivity of flows to superior performance. Specifically, we show that, because of participation costs, a fund's past performance has to exceed a threshold value for investors to realize a utility gain from investing in the fund. Therefore, an improvement in fund performance leads to an inflow of new investment due not only to the updated belief in higher managerial ability, but also to the fact that more new investors are able to overcome their participation barriers. With a continuum of participation costs among new investors, we demonstrate that the net flow into a fund becomes a continuous and mostly convex function of its past performance.

Our theory suggests that funds with different participation costs should have different sensitivities of flows to past performance. For example, as the flagship fund for Fidelity, the Magellan Fund is well known to most investors given its frequent media coverage. Its affiliation with Fidelity also provides investors with easy access to a wide range of funds and services. We can view it as having low search and transaction costs for investors. As a result, most potential investors would have overcome their participation barriers to invest in the fund at a reasonable level of performance. Hence the flow sensitivity to this range of performance will be higher than that of its peers. As the fund performance improves further, however, few additional new investors are there to be drawn to the fund, and its fund inflow will therefore not be as sensitive to its performance as that of its peers. On the other hand, take an example of a small no-name fund that is not affiliated with a large fund family. Its ex-ante high participation costs for new investors make new money into the fund particularly sensitive to its good performance, because investors won't become aware of the fund unless it achieves a more outstanding performance record. Therefore, we predict that, cross-sectionally, the overall flow-performance relationship is less convex for funds with lower participation costs, and the result is driven mainly by the increased sensitivity of flows to medium levels of performance.

The simple intuition derived from our model produces a rich set of empirical implications that we examine with data. To test the effect of participation costs on the asymmetric response of flows to past performance, we employ various proxies for participation costs based upon fund characteristics. Specifically, we use marketing expenses and the affiliation with fund families that have produced "star" funds to proxy for the variation in investors' search costs across funds. And we use parent family size, measured by the value of assets under management and by the number of funds, as well as the diversity of fund categories offered by the affiliated family, to capture participation costs related to transaction costs and the economy of scale in distribution and product offerings. To separate the effect of transaction costs, we compare flows to different share classes of the same fund, because they are associated with the same underlying portfolios and differ mainly in their transaction costs.

Using these varied proxies, we find that participation costs contribute significantly to the previously documented convex flow-performance relationship. Specifically, at the medium performance range, a reduction in participation costs results in an increase in the flow sensitivity, while at the high performance range, a reduction in participation costs either does not significantly affect the flow-performance sensitivity or even decreases it. Combining the results in both performance ranges, we conclude that the overall convexity of the flow-performance relationship is significantly smaller among funds that are associated with smaller participation costs.

Our paper is closely related to that of Sirri and Tufano (1998). They conjecture that reducing search costs should lead to an increased sensitivity of fund flows to past performance. Our main contribution is to construct a rational model that explains the impact of search and transaction costs on the flow-performance relationship. While our model prediction generally supports their intuition that funds with lower search costs enjoy greater investor awareness and hence stronger flow-performance sensitivity, we are able to delineate the effect of "investor participation" across different performance ranges. Lower-cost funds start attracting new investors at the medium performance range, and may exhaust the potential investor pool before they achieve top-tier performance. On the other hand, high-cost funds can only attract a substantial number of new investors at high performance levels. As a result, in the high performance range, lower-participation-cost funds may have a smaller flow-performance sensitivity relative to their higher-cost counterparts. Our empirical analysis provides supporting evidence for this new insight.

There have been several previous theoretical studies that have examined the asymmetric flow-performance relationship. Berk and Green (2004) assume a perfectly competitive capital market in which there is a decreasing return to scale in active management. Using variable cost functions for managers, they show that a convex relationship of new investments and past performance exists even in the absence of performance persistency. Lynch and Musto (2003) argue that investment companies can exercise an option to abandon bad performing strategies and/or fire bad managers. Under this scenario, since poor past returns are not likely to be informative about future performance, investors will respond less strongly to poor performance.

Our model departs from these studies by recognizing the frictions investors encounter in allocating their wealth among actively managed mutual funds, and thus proposes a new mechanism for explaining the documented convex flow-performance relationship. It implies that mutual funds can enhance the sensitivity of flow to their moderately good performance by reducing investors' participation costs. Our study complements the emerging literature on the importance of marketing and product differentiation for attracting flows,[3] and provides support for the mutual fund industry's practice of working to increase investor awareness while at the same time competing over fees, services, and other non-performance-related features. Our results suggest that funds with medium levels of performance, in particular, generally have the most to gain from these efforts in reducing investors' participation costs.

The rest of the paper is organized as follows: In Section 1 we present our theoretical model. The data and the empirical methodology are described in Section 2. Our empirical results are discussed in Section 3. Section 4 concludes. The appendix contains proofs for the model.

1 The Model

In this section, we set up a model with two main features: (i) investors learn about a fund manager's ability through past performance, and (ii) they incur participation costs when investing in the mutual fund. We use the model to highlight the effect of participation costs on the asymmetric flow response to past performance and to derive new empirical implications for the flow-performance relationship.

1.1 Model Setup

We consider a partial equilibrium model in a finite horizon economy with three dates, $t = 0, 1, 2$. Investors allocate wealth between a risk-free bond and an actively managed mutual fund. The return on the risk-free bond is normalized to $r_f = 0$ each period, and

[3] In addition to Sirri and Tufano (1998) and Jain and Wu (2000), more recent papers on that issue include Barber, Odean and Zheng (2002), Del Guercio and Tkac (2002b), Gallaher, Kaniel and Starks (2004), Hortaçsu and Syverson (2003), Khorana and Servas (2004) and Massa (2003).

the mutual fund gives a risky return of r_t at time $t = 1, 2$, determined by the process

$$r_t = \alpha + \epsilon_t \tag{1}$$

where ϵ_t is the idiosyncratic noise in the fund return, and is distributed normally and i.i.d. (independently and identically distributed) over time, i.e.,

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

The term α represents the unobservable ability of the manager to deliver positive excess returns, and is assumed to be constant over time and independent of the fund size.

There are two types of investors with information sets that differ regarding the distribution of α. The first type is called "existing" investors, indexed by $i = e$, who invest in the fund at time 0, and have a prior belief that the managerial ability α is also normally distributed,

$$\alpha \sim N(\alpha_0, \sigma_0^2). \tag{3}$$

At time 1, after observing the first-period return (r_1) of the fund, they use Baysian updating to derive the following posterior distribution regarding the managerial ability,

$$\alpha | r_1 \sim N(\alpha_1, \sigma_1^2), \quad \text{where} \quad \alpha_1 = \alpha_0 + \frac{\sigma_0^2}{\sigma_0^2 + \sigma_\epsilon^2} (r_1 - \alpha_0), \quad \sigma_1^2 = \frac{\sigma_0^2 \sigma_\epsilon^2}{\sigma_0^2 + \sigma_\epsilon^2}. \tag{4}$$

The second type is called "new" investors, indexed by $i = n$, who are not familiar with the mutual fund at time 0. Their lack of information is modeled as a diffused prior regarding the distribution of the managerial ability. Specifically, while both types of investors believe that the ability α is normally distributed, existing investors know with certainty the expected ability level α_0 and new investors know only that the distribution of α_0 is also normal,

$$\alpha_0 \sim N(\mu_0, \sigma_\mu^2). \tag{5}$$

One can view the distribution of α_0 as the prior that new investors hold for any mutual fund they are unfamiliar with. New investors have to incur a fixed participation cost c to narrow down their diffused prior. For ease of exposition, we assume that, once the cost is paid, they will learn exactly the same information as existing investors, i.e., they will also know α_0 with certainty.

The participation cost, c, that new investors incur in this setting is related to the search cost discussed in the literature. Intuitively, it would seem that the search cost reflects the cost of active information collection by investors, such as the cost of studying the fund prospectus or learning about its Morningstar ratings. It is conceivable that, for the same fund, different investors face different levels of search costs depending on their varying levels of financial sophistication. Although search costs are just one type of participation costs, we will use both terms interchangeably in an appropriate context. We assume that the cost is uniformly distributed among new investors,

$$c \sim \text{Unif}[0, \bar{c}]. \tag{6}$$

In reality, many investors also gain information about a fund in a passive way. For instance, they may hear about it in the news, see it in a TV commercial, or receive recommendations for it from their brokers. The more likely it is that they will be exposed to a fund, the lower the participation costs they will incur. Hence, for the same investor, this type of cost can vary across different funds. For instance, as a fund expends more on advertising or brokerage commissions, its visibility to investors increases and its search costs are effectively reduced. Similarly, if a fund belongs to a large fund family, it may be easier for investors in other funds belonging to the family to collect information about its fund managers. We capture this cross-sectional difference in search costs for different funds by a single parameter $\bar{c}$ in equation (6). Funds having lower participation costs are modeled as having a lower $\bar{c}$.

The second type of participation cost we consider is the transaction cost. To be consistent with the prevailing industry practice, we assume that there is a proportional transaction cost ρ_+ (or ρ_-) for purchasing (or redeeming) shares of a mutual fund, corresponding to front (or back)-end loads or other types of transaction costs. These transaction costs apply to new transactions for both existing and new investors.[4]

[4] A recent paper by Sigurdsson (2004) also examines the effect of proportional transaction costs.

Since our study focuses on open-end mutual funds, we assume that investors are not allowed to sell the fund short at any time. For simplicity, however, we allow investors to borrow freely in both periods.

All investors are assumed to have constant absolute risk aversion (CARA) utility over their terminal wealth W_{i2} at date $t = 2$:

$$E\left[-e^{-\gamma W_{i2}}\right]$$

where $i = e, n$. They have the same risk aversion coefficient γ and the same initial wealth W_0 at time 0. The population mass is normalized to 1 for existing investors, and λ for new investors.

Existing investors optimally allocate their wealth between the risk-free asset and the mutual fund both at time 0 and time 1 to maximize their terminal utility. For tractability, we assume that the uncertainty about the prior (σ_μ^2) is high enough that new investors never invest in the fund without first paying the search cost, c, to narrow down their prior.[5] As a result, new investors only enter the market at time 1 when they make their participation decision (whether to pay c) and the asset allocation decision (after they choose to participate) to maximize terminal utility.[6]

1.2 Optimal Allocations for Existing Investors

We first solve for the optimal allocation between the risk-free asset and the mutual fund for existing investors at time 1. After updating their prior beliefs regarding the manager's ability using equation (4), existing investors choose the optimal allocation to maximize their terminal utility.

With the CARA preference and zero risk-free rate, it is easy to show that an investor

[5] Allowing new investors to invest without paying the participation costs will not change the intuition behind our results, but it will make the expression more unnecessarily complicated.

[6] We may also interpret existing investors as the ones who have very low participation costs and who hence have already paid the cost at time 0, while new investors are the ones who have higher hurdles and who have decided to delay the decision. They may choose to enter at time 1 either if the fund return is so high that it justifies studying it more carefully, or if the fund has spent a lot of resources to effectively reduce search costs for investors.

optimally allocates $X_1 = \frac{\alpha_1}{\gamma(\sigma_1^2+\sigma_\epsilon^2)}$ dollars into the mutual fund if there are neither transaction costs nor the short-sale constraint. Imposing transaction costs and the short-sale constraint and incorporating expressions for α_1 and σ_1 in (4), we have the following result:

Lemma 1 *Let X_0 be the dollar holding of the mutual fund for an existing investor at time 0, r_1 be the first period return of the fund, and ρ_+ (or ρ_-) be the proportional transaction cost for purchasing (or redeeming) one dollar of the mutual fund at time* 1. *At time $t = 1$, the existing investor allocates X_{e1} dollars to the mutual fund, where*

$$X_{e1}(X_0, r_1) = \begin{cases} \frac{1}{\gamma(2\sigma_0^2+\sigma_\epsilon^2)}(\alpha_0 - \rho_+) + \frac{\sigma_0^2}{\gamma\sigma_\epsilon^2(2\sigma_0^2+\sigma_\epsilon^2)}(r_1 - \rho_+), & r_1 \geq k_p(X_0) \\ X_0(1+r_1), & k_s(X_0) \leq r_1 < k_p(X_0) \\ \frac{1}{\gamma(2\sigma_0^2+\sigma_\epsilon^2)}(\alpha_0 + \rho_-) + \frac{\sigma_0^2}{\gamma\sigma_\epsilon^2(2\sigma_0^2+\sigma_\epsilon^2)}(r_1 + \rho_-), & k_0 \leq r_1 < k_s(X_0) \\ 0 & r_1 < k_0 \end{cases} . \tag{7}$$

where $k_p(X_0)$, $k_s(X_0)$, and k_0 are defined in the appendix.

The desired holding of the mutual fund is piecewise linear in the first period realized return r_1. The result that the holding is linear and increasing with past performance is common to CARA-normal models with learning about managerial ability, such as Berk and Green (2004) and Lynch and Musto (2003). Investors increase their holdings of the fund because a higher realized return leads to a higher posterior expected ability of the fund manager.

The piecewise feature of the result is a direct outcome of proportional transaction costs, similar to solutions obtained in Constantinides and Magill (1976) and Davis and Norman (1990). When $r_1 > k_p(X_0)$, the past performance is good enough that investors choose to purchase additional shares of the fund. Proportional transaction costs effectively reduce the posterior expected return in equation (4) by ρ_+ for the next period. Similarly, when $r_1 < k_s(X_0)$, the past performance is bad enough that investors choose to sell some of their existing holdings. Since investors save the transaction cost ρ_- on each dollar they do not sell, their holding level is determined as if the expected posterior return were increased by ρ_-. There is a range of past performance in which investors do not trade and the dollar holdings change only due to the realized return on existing positions. Finally, holdings have a lower bound of zero since investors are not allowed to sell short the fund.

We need to determine the time 0 allocation X_0 for existing investors based on their prior belief about the manager's ability. Since the time 1 optimal allocation X_{e1} is a complicated function of X_0 (through the definition of $k_p(X_0)$ and $k_s(X_0)$) due to transaction costs and the short-sale constraint, it is hard to obtain a closed-form solution for X_0. We solve it numerically at time 0. For our purposes here, however, the exact level of X_0 does not affect our main results. Hence we do not discuss it in detail.

1.3 Optimal Allocations for New Investors

New investors have two decisions to make at time 1. First, after observing the first period return r_1, they decide whether or not to pay the participation cost to become informed of the expected ability level α_0. If they choose to participate by paying c, they will then solve for optimal holdings of the mutual fund to maximize their expected utility. If, instead, they choose not to pay the cost, they will invest only in the risk-free asset.

We solve the two decisions through backward induction by first solving for the optimal allocation to mutual funds and computing the corresponding expected utility level after investors have made their participation decisions. Then we solve for the optimal participation decision whereby new investors choose to participate only if doing so will lead to a utility gain.

Once new investors have paid the participation cost c, their optimal allocation to the mutual fund is straightforward. Since the information set of participating new investors is identical to that of existing investors, and there is no wealth effect for CARA investors, the optimal allocation should be the same as that for an existing investor with an initial holding $X_0 = 0$. Applying the result in Lemma 1, we have the following time 1 allocation for participating new investors.

Lemma 2 *At time $t = 1$, if a new investor chooses to participate in the mutual fund, he optimally allocates X_{n1} dollars to the mutual fund, where*

$$X_{n1}(r_1) = X_{e1}(0, r_1) = \begin{cases} \frac{1}{\gamma(2\sigma_0^2+\sigma_\epsilon^2)}(\alpha_0 - \rho_+) + \frac{\sigma_0^2}{\gamma\sigma_\epsilon^2(2\sigma_0^2+\sigma_\epsilon^2)}(r_1 - \rho_+), & r_1 \geq k_p(0) \\ 0 & o.w. \end{cases} . \quad (8)$$

Given the optimal asset allocation (8) once investors participate in the mutual fund, we can compare the expected utilities when they choose to participate and when they do not, and derive their optimal participation decision.

Lemma 3 *A new investor with a participation cost of c chooses to participate if and only if his participation cost is below a threshold level, or*

$$c \leq \widehat{c}(r_1) \equiv -\frac{1}{\gamma} \ln \left(\frac{1 - \Phi(B)}{2} + \frac{1 + \Phi\left(\frac{B}{A}\right)}{2A} e^{-\left(1-\frac{1}{A^2}\right)B^2} \right) \quad (9)$$

where $\Phi(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt$ is the error function, and

$$A \equiv \sqrt{1 + \frac{\sigma_\epsilon^2 \sigma_\mu^2}{(\sigma_\epsilon^2 + \sigma_0^2)(\sigma_\epsilon^2 + 2\sigma_0^2)}}, \qquad B \equiv \frac{\sigma_\epsilon^2(\mu_0 - \rho_+) + \sigma_0^2(r_1 - \rho_+)}{\sqrt{2}\ \sigma_\epsilon^2 \sigma_\mu}.$$

Investors base their participation decision on their diffused prior about the ability level of the manager. Hence the threshold level $\widehat{c}(r_1)$ is a function of the uninformative prior, μ_0 and σ_μ. It does not depend on existing investors' knowledge of α_0, since new investors do not have that information before they pay their participation costs. It is easy to verify that $\widehat{c}(r_1)$ is monotonically increasing in r_1. The following corollary describes the participation decision of a given investor as a function of r_1.

Corollary 1 *For a new investor with participation cost c, there exists a unique cutoff return level $\widehat{r}(c)$ such that he chooses to participate if and only if the first-period return of the fund is high enough, or $r_1 \geq \widehat{r}(c)$, where $\widehat{r}(c)$ is the solution of r_1 for $\widehat{c}(r_1) = c$. Moreover, the cutoff return $\widehat{r}(c)$ increases with the cost level c.*

New investors choose to participate if and only if the first-period return is good enough, because a higher realized return indicates a higher expected managerial ability, and investors expect to benefit more from investing in the fund. It is important to recognize that $k_p(0)$ may be higher than $\widehat{r}(c)$, and, as a result, new investors do not always choose to invest in the mutual fund *after* paying the participation cost. Specifically, when $\widehat{r}(c) < r_1 < k_p(0)$, they pay the cost and then choose not to invest. This outcome is consistent with individual optimization, since $k_p(0)$ is a function of α_0 and is not known to new investors before they pay the cost. It is possible that a fund has a good realized return r_1, but a rather low ex-ante expected ability level α_0. Without knowing the α_0, new investors may decide that it is worthwhile to pay the cost to study the fund, only to find out that the fund manager is just lucky. Therefore, our model demonstrates the effect of participation despite the sunk nature of search costs.

1.4 Flows into the Mutual Fund at Time 1

The dollar flow F into the fund at time 1 is defined as the new money invested in the fund from time 0 to time 1. Specifically, at time 1 existing investors change their dollar holdings of the mutual fund from $X_0(1+r_1)$ to X_{e1}, and new investors change their holdings from 0 to X_{n1}. To facilitate discussion of empirical implications, we define flow as a fraction of the initial asset in the fund,

$$f \equiv \frac{F}{X_0}. \tag{10}$$

The following proposition combines the previous results regarding participation and optimal allocation decisions to characterize the net flow into the fund at time 1.

Proposition 1 *Assuming the participation cost for new investors is uniformly distributed over the support of $[0, \overline{c}]$, the net flow into the fund on date 1 is given by*

$$f(r_1) = \frac{X_{e1} - X_0(1+r_1)}{X_0} + \lambda \min\left[1, \frac{\widehat{c}(r_1)}{\overline{c}}\right] \frac{X_{n1}}{X_0}, \tag{11}$$

where X_{e1} and X_{n1} are the time 1 holdings for existing and new investors expressed in equations (7) and (8), respectively, and $\widehat{c}(r_1)$ is the threshold cost level in equation (9).

The interpretation of Proposition 1 is straightforward. The first term of equation (11) describes the new money flow from existing investors, whereas the second term corresponds to the money flow from participating new investors. Observing the first-period return r_1, all new investors with participation costs lower than $\widehat{c}(r_1)$ choose to participate. The term within the min$[\cdot]$ operator describes the fraction of new investors who choose to participate.

Proposition 1 shows that past performance has two effects on the current-period mutual fund flow. First, both X_{e1} and X_{n1} are increasing functions of r_1: that is, both existing investors and participating new investors allocate more wealth to the fund given a higher realized return. This effect is due to investors' learning from past performance, as a higher realized return indicates greater managerial ability. Second, $\widehat{c}(r_1)$ is an increasing function of r_1: that is, a better past performance attracts more new investors into the fund. This effect is driven by the interaction between learning and participation costs. The fixed participation cost acts as an investment barrier. As a result of learning, new investors expect a higher-quality fund given the fund's better past performance. Since investors enjoy a larger utility gain from investing in a higher-quality fund, they are more likely to overcome their participation hurdle after seeing a higher past performance.[7]

Figure 1 plots the flow-performance relationship under different search costs ($\overline{c}$). To simplify the discussion, we ignore the proportional transaction cost by setting $\rho_+ = \rho_- = 0$ in this graph. The fund flow is shown to be an increasing and convex function of past performance.[8] The solid and dotted lines correspond to fund flows when $\overline{c}$ is low and high, respectively. Proposition 1 shows that, when new investors face smaller participation costs, more of them start to participate at a lower realized return. Therefore, in the

[7]The interaction between learning and participation costs may explain the lack of significant empirical evidence for a similar relationship between aggregate fund flow and market return (see, e.g., Warther (1995)). It is reasonable to assume that there is not much learning about managerial ability at the aggregate level. As a result, investors' participation may be insensitive to market performance. A full understanding of such an aggregate relationship requires a dynamic equilibrium approach, which is beyond the scope of our framework.

[8]In the very low performance range, the flow appears to be decreasing in performance. This decreasing result is an artifact of the definition of the fund flow, as equation (11) reduces to $f = -(1 + r_1)$ when $X_{e1} = X_{n1} = 0$. This is also discussed in Berk and Green (2004).

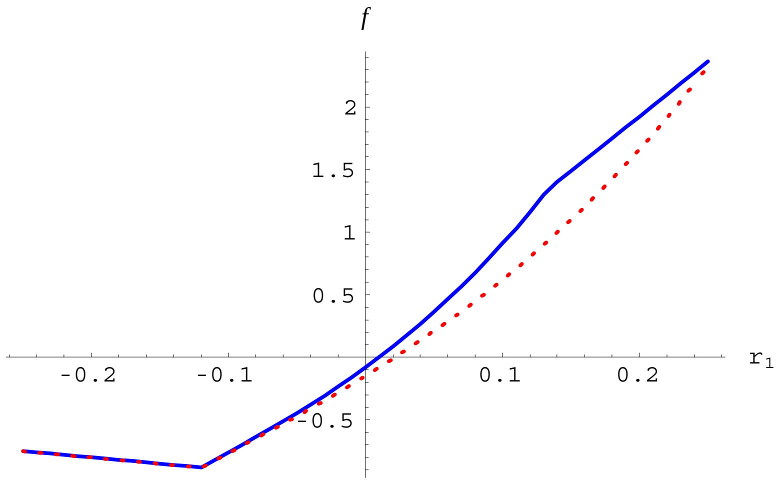

Figure 1: Illustration of flow-performance relationship for different levels of search costs. The solid line corresponds to a low search cost when $\bar{c} = 0.05$, and the dotted line corresponds to a high search cost of $\bar{c} = 0.1$ where the search costs for all new investors are uniformly distributed over $[0, \bar{c}]$. Other parameters are $\rho_+ = \rho_- = 0$, $\mu_0 = 0.03, \sigma_\mu = 3\%, \alpha_0 = 0.03, \sigma_0 = 8\%, \sigma_\epsilon = 16\%, \gamma = 1$, and $\lambda = 0.5$.

medium performance range (that is, for returns below $r_1 = 0.12$ in the figure), the flow-performance relationship is steeper when participation costs are lower (the solid line). On the other hand, it is easier for the lower-cost fund to reach a point at which all potential new investors have already participated, and a further increase in r_1 does not attract additional new investors.[9] For example, when $r_1 > 0.12$, the flow-performance relationship depicted by the solid line becomes linear, as is predicted by the learning effect alone. The higher-cost fund would reach this point at a higher performance level. Hence, for past performance higher than 0.12, the higher-cost fund has a more sensitive flow-performance relationship. If we define the overall convexity of the flow-performance relationship as the increase in flow-performance sensitivity when performance improves, then the graph demonstrates that the lower-cost fund has an overall less convex flow-

[9]In reality, it may be the case that the distribution of participation costs has an infinite support, and funds never totally exhaust the pool of potential investors. However, the intuition that funds with different participation costs have different intensities in attracting new investors is robust. We have numerically solved a case in which the participation cost is normally distributed and reached similar conclusions.

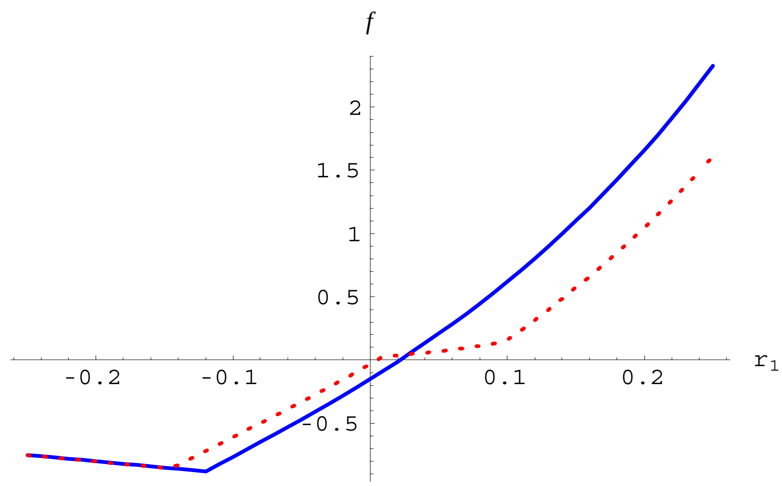

Figure 2: Illustration of flow-performance relationship for different levels of transaction costs. The solid line corresponds to zero transaction costs when $\rho_+ = \rho_- = 0$, and the dotted line corresponds to positive transaction costs $\rho_+ = 1\%$ and $\rho_- = .05\%$. Other parameters are $\bar{c} = 0.1$, $\mu_0 = 0.03, \sigma_\mu = 3\%, \alpha_0 = 0.03, \sigma_0 = 8\%, \sigma_\epsilon = 16\%, \gamma = 1$, and $\lambda = 0.5$.

performance relationship.

Figure 2 illustrates the flow-performance relationship under different transaction costs (ρ_+ and ρ_-). Transaction costs have a direct and an indirect effect on fund flows. The direct effect is that, for a participating investor, a cost ρ_+ on new purchases makes it less attractive to purchase the fund, and a cost ρ_- on sales makes it more attractive to hold on to the fund. Hence, we expect the level of the flow to be lower at the higher performance and higher at the lower performance. The indirect effect is the reduced willingness to participate for new investors. Since the proportional transaction cost effectively reduces the expected return on the fund, a higher hurdle rate on past performance is required for a new investor to overcome his participation costs. Comparing the solid and the dashed lines, we observe that fund flows are less sensitive to performance in the medium performance range for funds with higher transaction costs, leading to a more convex overall flow-performance relationship.

1.5 Discussion

Because our model deals with a single mutual fund and with investors' decision problems over a single period, it seems that the comparative statics, as illustrated in Figures 1 and 2, depict the relationship between flow and past performance for one fund. The existing empirical literature, however, documents the flow-performance relationship mainly in the cross-section after controlling for some fund characteristics.

In order to make a connection between our model and the empirical literature, we need to extend the model to a setting with multiple mutual funds. The extension is straightforward under the CARA-normal setting in which our model is built, with a few additional assumptions. First, investors can both long and short a passive market index fund (through futures contracts, for example) to hedge out their market exposure. Second, managerial ability, which is measured by the excess returns of a mutual fund over a market index, is independent across different funds.[10] Given these assumptions and the absence of the wealth effect due to the CARA preference, there is no interaction between different funds for individual participation and allocation decisions. Thus, the single-fund solution can be extended directly to the multiple-fund setting.

In our model, we also introduce transaction costs and impose a short-sale constraint on the fund. As long as investors are allowed to borrow and the returns on different funds are independent of each other, the short-sale constraints on individual funds do not affect the generalization of our results into the multiple-fund setting, as unrestricted borrowing allows investors to buy a fund without having to sell short another fund to raise money. If, however, borrowing is restricted, then there will be interactions between different mutual funds. This may lead to additional mechanisms that can also affect the flow-performance relationship.[11] In this paper we mainly focus on the role of participation costs in a more

[10] Berk and Green (2004) and Lynch and Musto (2003) also make these assumptions with a similar modeling device.

[11] When the borrowing constraint binds, investors may allocate to different funds based on their relative levels of performance rather than their absolute levels of performance. They will be less likely to purchase new funds due to lack of funding and more likely to sell existing funds if they need to raise money to buy a better performing fund. These constraints will likely raise the hurdle for investing in a new fund. However, we expect that, qualitatively, the cross-sectional difference in the effect of participation costs

stylized setting.

With these caveats, we interpret our comparative statics in Figures 1 and 2 as cross-sectional results to derive the empirical implications of our model for the asymmetric flow-performance relationship.

As demonstrated in Figure 1, the sensitivity of flow to past performance is increasing in the performance itself if past returns are below a threshold level, $\widehat{r}(\overline{c})$. This is because the flow response to past performance is caused not only by the learning effect, but also by the participation of new investors that increases with performance. Therefore, our model predicts that at intermediate levels of performance, i.e., levels just below funds' respective thresholds, the sensitivity of flow to performance is larger for funds with lower participation costs.

If $\overline{c}$ is small, then it does not require a very large return on the fund, $\widehat{r}(\overline{c})$, to attract all potential new investors to the fund. When performance exceeds this threshold, all investors will have invested in the fund. Then the flow response comes only from the learning effect and becomes linear in performance with a smaller slope than that in the performance range just below the threshold. This drop in slope creates a local concavity in the flow-performance relationship. Empirically, we may not be able to see this change quite so dramatically, but we expect to observe the difference in the overall convexity of the relationship. As the onset of this change occurs at lower performance levels for funds with smaller participation costs, the overall convexity of the flow-performance relationship will be reduced for these funds.

In addition, Figure 1 indicates that at any given level of performance, the flow into a fund with low participation costs is always higher than that into a fund with high participation costs. Thus, lower participation costs will lead to higher levels of flow. While this effect on the level of fund flows is not our focus here, this prediction is consistent with the empirical evidence in Sirri and Tufano (1998), Jain and Wu (2000), and Gallaher, Kaniel and Starks (2004). Moreover, this result suggests that funds with

on fund flows will persist even in this setting.

medium levels of performance, rather than the best performers, may have the most to gain in terms of fund flows from decreasing participation costs (via marketing, etc.).

Figure 2 demonstrates that transaction costs affect flows mostly in the medium performance range. The larger the transaction cost, the more likely it is that investors will choose not to trade, making the fund flow less sensitive to performance. Therefore, all else being equal, funds with lower transaction costs will have higher levels of flows and higher flow sensitivity in a reasonable performance range.

In summary, these results lead to the following empirical hypothesis that we test later with a number of proxies for participation costs: Across different mutual funds, lower participation costs for new investors lead to less convex flow-performance relationships. In particular, this reduction in convexity is manifested in the increased slope of the flow-performance relationship over the intermediate performance range.

2 Data and Empirical Methodology

2.1 Data

Our main data source is the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database in which we obtain information about fund net asset value, return and characteristics. Since CRSP does not provide consistent fund investment objectives and fund family names for the years prior to 1992, we classify funds into different types and identify their family affiliation based upon the CDA-Spectrum mutual fund data from Thomson Financial, Inc.[12] Because we focus on flows into actively managed funds, we exclude index funds from our sample. To facilitate comparison with the prior literature, we also exclude sector funds, international funds, bond funds and balanced funds from our study. Consequently, our dataset mainly consists of actively managed equity funds in three CDA investment objective categories: aggressive growth, growth, and growth and income.

Our sample period spans the years 1981 to 2001 when complete information about

[12] The matching of the two databases is done using the MFLINK data file provided by WRDS.

fund managers and investment objectives is available.[13] Since CRSP does not report end-of-month total net asset values until after 1991, we examine fund flows at the quarterly level for our entire sample period. To control for fund growth that is driven by fund characteristics such as total expense ratios, fund age, and size of a fund measured by its total net assets, we extract these data from the CRSP mutual fund database. The characteristics applied in the current quarter's flow estimation are measured in the previous period.

Using quarterly total net asset values from CRSP, we define quarterly net flow into a fund as the percentage of beginning-of-quarter total net asset value:

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

where $R_{i,t}$ is the return of fund i during quarter t, and $TNA_{i,t}$ is fund i's total net asset at the end of quarter t. Hence, our definition of fund flow reflects the percentage growth of a fund that is due to new investments. By adopting this definition, we are assuming that new money comes in at the end of each quarter since we have no information regarding the timing of new investment. As indicated in Elton, Gruber and Blake (2001), there exists a large number of errors associated with mutual fund mergers and splits in the CRSP mutual fund database. This leads to extreme values of flow. To prevent a potential impact from these outliers, we filter out the top and bottom 2.5% tails of the net flow data.[14]

Table I shows the number of funds included in this study at the end of each year. Over time, the number of actively managed funds has grown tremendously. We utilize 217 funds in 1981 and 3265 funds in 2001 for our empirical analysis.[15] During our sample

[13] Although the CRSP-CDA merged dataset begins in 1980, our empirical analysis begins in 1981 because lagged information is required to calculate fund flow, performance and other variables.

[14] We have also tried winsorizing the flow data instead of filtering out the outliers. Our results are not affected by this alternative method of data treatment.

[15] During the 1990s, mutual funds started to offer different share classes that represent claims to the same underlying portfolios but with different fee structures. As noted in the CRSP mutual fund manual, CRSP treats each share class as a stand-alone fund and assigns it a separate fund identification number. Since our main purpose is to study fund flow, listing each share class separately does not lead to the double-counting problem. In addition, given that different share classes of the same fund may be

period, the average number of funds managed by each fund family had increased from about 4 in 1981 to 14 in 2001. At the same time, the average age of funds had decreased due to the mushrooming of new funds in recent boom markets. The total fees, defined as the total expense ratio plus one-seventh of the up-front load,[16] have remained rather stable. Table I also reports that the cross-sectionally averaged year-end quarterly fund flow has varied between -4.03% and 4.41%. Volatility of fund returns, measured as the standard deviation of monthly returns in the 12-month period prior to each quarter, has fluctuated between the mid-1990 low of 2.63% and the post-1987 high of 8.29%.

2.2 Empirical Methodology

To examine the flow-performance sensitivity, in each quarter we run cross-sectional regressions to estimate the sensitivity of flow to performance, controlling for other factors that could potentially affect the level of flow. We report the means and t-statistics from the time series of coefficient estimates following Fama and MacBeth (1973).[17] Because we relate quarterly flow to past performance measured over the preceding 12 or 36 months, the cross-sectional flow-performance sensitivity estimated in each quarter is likely to be auto-correlated. To alleviate this problem, we calculate the t-statistics for the Fama-MacBeth coefficients using the Newey-West (1987) autocorrelation and heteroskedasticity consistent standard errors.

Since it is unclear which measure of performance influences investors the most, we measure performance in alternative ways. Previous studies, such as Brown, Harlow

associated with differential participation costs, it seems more appropriate to consider each share class as a stand alone fund. Nontheless, we have also conducted all analyses at the fund level by combining multiple share classes of the same fund. Our results are not affected by the treatment of share classes.

[16]Sirri and Tufano (1998) estimate that the TNA-weighted redemption rate of equity funds was 14% in 1990. This implies an average holding period of seven years.

[17]We have also repeated all analyses using unbalanced panel regressions with time effects and panel corrected standard errors that adjust for autocorrelations within each panel and heteroskedasticity across panels. The results are not materially different from those reported later in this paper. Panel regressions, however, constrain the flow-performance sensitivity, making it constant over time. Since participation costs on average are decreasing over recent years as the mutual fund industry has experienced tremendous changes in terms of reducing investment barriers and enhancing services, we expect the flow-performance relationship to be changing over time. Therefore, we focus on the results based on the Fama-MacBeth regressions.

and Starks (1996), Sirri and Tufano (1998), and Boudoukh, Richardson, Stanton and Whitelaw (2003), as well as rankings in business publications, suggest that when performance of a fund is evaluated, it is often compared with its peers that have similar investment objectives, reflecting the tournament nature of the money management business. Therefore, our first measure of performance is the rankings of funds' preceding 12-month returns within their respective categories. In addition, we also measure fund performance on a risk-adjusted basis. Specifically, our second measure of performance is the ranked risk-adjusted returns in the preceding 36 months according to the following four-factor model:

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

where $R_{i,t}$ and $R_{rf,t}$ 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-French three factors and the momentum factor.[18] To ensure the accuracy of estimation, we include only funds that exist for at least 20 months during the estimation period.

Holding performance constant, investors should be more averse to funds with greater risk. Since it is not obvious whether investors care more about systematic or unsystematic risk of fund portfolios, we include, as a control variable, the total risk of a fund as measured by standard deviation of returns over the performance estimation period. Chevalier and Ellison (1997), Bergstresser and Poterba (2002) and Boudoukh, Richardson, Stanton and Whitelaw (2003) have documented the effect of fund age on flow and flow-performance sensitivity. Hence, we control for fund age by including logged value of $(1 + age)$ and its interaction with performance in the flow regression. To incorporate the scaling effect of fund size on percentage fund growth, we include logged fund TNA in quarter $t-1$ when estimating the flow regression in quarter t. Moreover, since mutual funds deduct operating expenses from fund value, investors' realized return on funds with the same pre-expense performance is lower if they are charged with higher fees. Therefore, we also include total fees as a control. Finally, we include the aggregate

[18] All of these factor returns are obtained through Ken French's website.

flow into each fund category at quarter t to control for other unobserved factors, such as sentiment shifts, that can potentially affect fund flows.

Because our main interest is in the asymmetric flow-performance relationship, we estimate flows using a piecewise linear regression that allows for different flow-performance sensitivities at different levels of performance. Each quarter we first rank all funds according to their past performance measured with or without risk adjustment. If performance is measured as raw returns in the past 12 months, we rank funds according to their relative performance among funds with similar investment objectives. We assign them a continuous rank ranging from 0 (worst) to 1 (best), with the rankings corresponding to their performance percentiles. Funds are then classified into low, medium and high performance groups, i.e., funds ranked in the lowest (highest) performance quintile are in the low (high) group, and the medium group includes funds with performance ranked in the middle three quintiles. Each quarter, we conduct a piecewise linear regression of flows on the ranked performance, allowing for separate coefficients for different performance groups. To examine the impact of participation costs on flow-performance sensitivity at different performance levels, we interact ranked performance with a proxy of participation costs by running the following regression:

$$\begin{aligned} Flow_{i,t} &= a + b_1 * Low_{i,t-1} + \beta_1 * Low_{i,t-1} \times PC_{i,t-1} \\ &\quad + b_2 * Mid_{i,t-1} + \beta_2 * Mid_{i,t-1} \times PC_{i,t-1} \\ &\quad + b_3 * High_{i,t-1} + \beta_3 * High_{i,t-1} \times PC_{i,t-1} \\ &\quad + Controls + \varepsilon_{i,t}, \end{aligned} \tag{13}$$

where $Low_{i,t-1}$ represents the ranked performance in the lowest quintile, $Mid_{i,t-1}$ the ranked performance in quintiles 2 to 4, and $High_{i,t-1}$ the ranked performance in the highest quintile.[19] $PC_{i,t-1}$ represents a proxy for participation costs.

[19]Specifically, the factional rank for fund i is defined as: $Low_{i,t-1} = Min(Rank_{i,t-1}, 0.2)$, $Mid_{i,t-1} = Min(0.6, Rank_{i,t-1} - Low_{i,t-1})$, and $High_{i,t-1} = Rank_{i,t-1} - Low_{i,t-1} - Mid_{i,t-1}$, where $Rank_{i,t-1}$ is fund i's performance percentile.

3 Empirical Results

Our model highlights investors' participation costs as an important determinant of the asymmetric flow-performance relationship. Specifically, we predict that funds with smaller participation costs have a significantly stronger response of flows to moderately good performance, but not necessarily to extremely good performance. In this section, we empirically test this prediction using several proxies for participation costs, including marketing expenses, affiliation with a "star"-producing family, family size and diversity of fund offerings. In addition, we also compare the difference between the flow-performance relationship of A shares and C shares among funds with multiple share classes.

3.1 Marketing Expenses

Investors' choices of mutual funds are complicated by the costly search process. Since funds that engage in significant marketing efforts can potentially lower investors' search costs, we use marketing expenses as one proxy for the reduction in participation costs. Due to data limitation, we follow Sirri and Tufano (1998) and measure the marketing expenses using a fund's total fee ratio, defined as annual expense ratio plus one-seventh of the up-front load fees. Although this measure includes components other than marketing expenses, it is a reasonable proxy for our purpose as long as funds with higher total fees spend more on advertising and distribution efforts on average.[20]

Given that our model predicts asymmetric flow-performance sensitivity at different performance levels due to participation costs, we conduct a piecewise linear regression, as specified in (13), that allows for different sensitivities of flows to different performance rankings. In this regression, for each of the three performance groups, we interact perfor-

[20]Sirri and Tufano (1998) point out that funds spend more than half of their expenses on marketing, and Sirri and Tufano (1993) provide estimates for components of the total expenses, such as security selection, marketing and administrative costs. We have also used the 12b-1 fees plus one-seventh of front-end loads as an alternative measure of marketing expenses and found similar results. But given that 12b-1 fees were not explicitly recognized until 1992 and many funds that don't charge front-end loads actually have their marketing expenses embedded in the total expense ratio, we focus on the current measure used by Sirri and Tufano (1998).

mance rankings with total fee ratios to capture the effect of marketing expenses on flow sensitivity to performance. We present in Table II two sets of results using alternative measures of performance.

To measure performance, the first set of results, uses the ranking of returns in the preceding 12 months among funds with similar investment objectives. Consistent with the model prediction, the interaction term between performance and total fee ratio is significantly positive over the medium performance range and significantly negative over the high performance range. Specifically, the result shows that a one-percent increase in expense ratio will increase the sensitivity of flows to the mid-range performance (quintiles 2 to 4) from 0.104 to 0.122, an 18% increase, while reducing the flow sensitivity to the top-quintile performance from 0.428 to 0.380, a 11% decrease. This leads to an overall less-convex flow-performance relationship for funds that have high marketing expenditures.

In the second column of Table II, we use risk-adjusted returns based upon the four-factor model to measure performance, to confirm the results showing that increasing marketing expenses leads to stronger sensitivity of flows to mid-range performances and weaker sensitivity to top-tier performances.

Table II also shows a negative relationship between fund flow and standard deviation. This finding holds for regressions with both performance measures, although the effect of risk on fund flows is much weaker when performance is measured on a risk-adjusted basis. Consistent with Chevalier and Ellison (1996), we find that both the level of flow and the sensitivity of flow to past performance are lower for older funds. In addition to the interaction between total fees and performance, we have controlled for the total expense ratio itself in the regression. As shown in the table, after controlling for the effect of expense ratio on reducing search costs, higher expense ratio lowers the level of fund flow.

In summary, funds with greater marketing and distribution efforts enjoy better investor recognition and a lower performance threshold for attracting new investors. As indicated in Table II, for a moderate level of performance, funds with higher marketing expenses have a higher sensitivity of flows to performance since their incremental performance attracts more new investors. If funds achieving superior performance spend heavily on marketing, then most potential investors would have already overcome their participation barriers to invest in these funds, and an incremental performance would attract few additional investors. On the other hand, funds with lower marketing expenses continue to attract new investors as performance improves. As a result, flows may be less sensitive to performance for funds with higher marketing expenses in the superior performance range because of the absence of new investors' participation. This is indicated by the significantly negative interaction term between total fees and top-tier performance. Therefore, higher marketing expensea lead to an overall less-convex flow-performance relationship.

Using a similar methodology, Sirri and Tufano (1998) document that only the interaction term between marketing expenses and top-tier performance is significantly positive. Although this seemingly contradicts our results, the difference may be attributable to the difference in sample periods. Our dataset spans the years 1981 to 2001, while Sirri and Tufano (1998) examine data from 1971 to 1990. In an unreported subperiod analysis, we find that the difference is attributable to the fact that fund returns were relatively low in the 1970s. Measures that help reduce participation costs, such as family affiliation and product innovation and differentiation, did not become popular until the 1990s; participation costs were, in general, very high in the 1970s. According to our model, when participation costs are high, funds may not be able to attract all potential investors at any reasonable performance level. Therefore, it is possible that, in the 1970s, even the funds categorized as having lower participation costs had a high absolute level of participation costs and they continued to attract new investors at very high (relative) levels of performance. As a result, the empirical finding of Sirri and Tufano (1998) is consistent with our model prediction, since funds in that period would generally not reach the saturation performance level as illustrated in Figure 1. On the other hand, the time period in our dataset coincides with dramatic reductions in search and transaction costs; therefore, we are able to capture a different facet of the model implications.

3.2 "Star" Family Affiliation

Del Guercio and Tkac (2002b), Khorana and Servas (2004), and Nanda, Wang and Zheng (2004a) provide evidence indicating that the presence of a "star" fund can have a positive "spillover" effect, whereby other funds in the same family also enjoy higher fund flows. Based on this evidence, we use a fund's affiliation with a family that has produced "star" funds as a proxy for reduced participation costs. Intuitively, we believe that investors who are attracted to the star fund can potentially become aware of other offerings of the family, and the search costs for those "star"-affiliated funds may be reduced. Before we analyze the impact of "star" family membership on the flow-performance sensitivity, we need to specify how a "star" status is determined by the historical performance of funds. Similar to Nanda, Wang and Zheng (2004a), we use two different procedures to define "star" funds: by ranking funds according to their risk-adjusted performance that mimics the Morningstar ratings, or by ranking funds according to their four-factor-adjusted returns.

Because unsophisticated investors may only be aware of "star" funds featured in various rating services, Morningstar 5-star ratings, that heuristically adjust for risk with respect to an appropriate benchmark, can bring funds that earn the designation elevated visibility. Del Guercio and Tkac (2002b) show that Morningstar ratings can significantly affect fund flows. An upgrade or downgrade by Morningstar is usually followed by abnormal cash flows, in addition to those induced by performance changes.

According to this procedure,[21] in each period a fund is assigned a three-year score based upon the difference between a load-adjusted return and a risk measure during the past three years. Within each fund category, funds are then ranked according to their three-year scores relative to their peers. Funds that are ranked in the top 10% of each

[21] Details of the procedure that mimics the Morningstar ratings system may be found in the appendix of Nanda, Wang and Zheng (2004a). They find that 88% of the five-star funds determined by this mimicking procedure overlap with five-star funds from the Morningstar publications for a randomly picked date in May 1995.

category are assigned 5-star ratings. Similarly, Morningstar also provides five-year and ten-year star ratings and computes the overall rating as a weighted average of ratings over different horizons. Although the overall star rating is widely cited among business publications, it overlaps considerably with the three-year rating among young funds and for many other funds in certain years, as pointed out in Sharpe (1997). In this study, we focus on the three-year Morningstar ratings to make the analysis comparable to the alternative star definition. Specifically, within each fund investment objective category, we rank all funds according to their Morningstar risk-adjusted performance score in the prior 36 months. Funds that are ranked in the top 10% of each category are considered "star" funds. Their parent companies are hence designated as "star" families.

Table III presents the analysis based on this star-identifying scheme. The second column reports the piecewise linear regression analysis measuring fund performance as the ranking of returns in the preceding 12 months among funds with similar investment objectives. In this analysis, we proxy for participation costs with a dummy variable that is equal to 1 if a fund is affiliated with a "star" family but not a "star" itself, and 0 otherwise. To control for the effect of the publicity surrounding the star status, we also include a dummy variable indicating star funds.

As shown in Table III, the interaction term between mid-range performance and the "star" family affiliation dummy is significantly positive, indicating that being in a "star" family helps a fund attract more potential investors by raising their awareness of the fund and its performance, even if the fund itself may not be a "star." Meanwhile, the interaction term for the high performance range is not significant, implying that being in a "star" family is not beneficial to a fund with stellar performance as it may already have had all potential investors participating in it. Based on point estimates, being affiliated with a "star" family changes the flow sensitivity to different levels of performance from (0.16, 0.11, 0.24) to (0.13, 0.13, 0.21), for (low, medium, high) performance ranges. Our piecewise linear regression analysis using risk-adjusted performance yields results consistent with this, as reported in the third column of Table III.

Table III also shows that, while the "star" family affiliation is not significant once its effect on the flow sensitivity is accounted for, the "star" dummy itself is significantly positive. This is also an indication that our star rating scheme captures well the name recognition and media attention received by funds with outstanding performance.

In contrast with Table II, in which they negatively affect fund flow, the effect of total fees becomes positive in Table III, albeit insignificant or only marginally significant. This may be understood by recognizing, as demonstrated earlier, that total fees are also associated with greater marketing efforts, which help promote fund growth. When the interaction terms between performance and total fees are absent, the effect of total fees is ambiguous. This finding is also consistent with evidence reported in Barber, Odean and Zheng (2002).

To verify the robustness of the impact of the "star"-family affiliation on flows, we use an alternative method of identifying "star" funds. For this procedure, we rank all funds at the beginning of each quarter according to their four-factor adjusted performance, estimated using returns in the proceeding 36 months. Funds that are ranked above the 90th percentile are defined as "star" funds.

Using this classification, we again find similar patterns in the impact of "star" family affiliation on the flow-performance relationship, as reported in Table IV. While "star" affiliation significantly increases the flow sensitivity to mid-range performances, it doesn't materially affect the flow response to both the top and the bottom tier performances. Among the control variables, the only notable difference in comparison with Table III is that being a "star" fund itself does not increase fund inflow when performance is measured by alphas from the four-factor model. This is possibly due to the fact that the star designation using four-factor alphas does not capture the effect of publicity as well as the Morningstar type of rankings, the latter of which are more accessible to average investors.

Our results extend the previous findings on the spillover effect of "star" funds on other funds in the same family by identifying the source of the positive externality.

Specifically, we show that other funds benefit mainly from an improved sensitivity of flows to moderately good performance.

3.3 Fund Family Size

A fund's affiliation with a large family can proxy for lower participation costs due to brand recognition, since it is easier for new investors to pay attention to established brands such as Fidelity or Vanguard.[22] It also enables the fund to tap into the investor base of the whole family by increasing investors' recognition of the fund and reducing the transaction costs associated with switching from one fund to another. Massa (2003) shows that in recent years the mutual fund industry has employed strategies that target investor heterogeneity. For instance, most fund families allow investors to switch among their own funds at no cost. Additionally, most fund families introduce "break points", dollar levels reached in transactions with the family at which investors qualify for discounts on the up-front sales charges on their subsequent share purchases (see, e.g., Reid and Rea (2003)). Therefore, if a fund is affiliated with a large fund family, it is a lot easier to attract potential investors due to the economy of scale in services provided and reduction in transaction costs. This conclusion is also suggested by the evidence in Khorana and Servaes (2004).

In this subsection, we examine the effect of affiliation with large fund families. We measure family size in two different ways. First, we use the amount of assets under the management of a fund complex at the beginning of each quarter, similar to Sirri and Tufano (1998). Second, we simply count the number of equity funds in a fund's affiliated family at the beginning of each quarter.[23] These two measures are designed to capture both the depth and the breadth of family affiliation.

Table V presents the results when family size is measured by the logged value of total assets managed by an affiliated family. Sirri and Tufano (1998) posit that, with this measure, funds affiliated with larger families will receive greater inflows and the flow-

[22] See Capon, Fitzsimons and Prince (1996) and Goetzmann and Peles (1997).

[23] We count all share classes of the same fund as one fund to avoid artificially inflating fund numbers.

performance relationship will be stronger for larger complexes. We confirm that funds affiliated with larger families do tend to receive higher levels of inflows, ceteris parabus. Moreover, our results reveal a more specific mechanism by which parent complex size affects the flow-performance relationship: that is, affiliation with large families makes it easier for funds to attract new investors with moderately good performance. This may also lead to a reduction in the sensitivity of flow to extremely good performance.[24]

We obtain similar results when we use the logged value of fund count in an affiliated family to measure family size, as reported in Table VI. Specifically, over the medium performance range, the sensitivity increases with fund count in the affiliated family, while the sensitivity declines with fund count over the top performance range. The combined evidence from Tables V and VI is consistent with the notion that affiliation with a large fund family helps reduce participation costs, and hence lessens the asymmetry in the response of flow to performance.

In addition to the interaction terms, we include the logarithm of fund count as a control variable as well. The significantly positive coefficient on logged fund count indicates that if a family has a large number of fund offerings, it has a direct effect on the level of fund flows for affiliated funds. This is consistent with the evidence provided by Khorana and Servaes (2004) and Massa (2003), showing that increasing fund offerings is a strategy families use as a marketing device to target investor heterogeneity and increase market shares. Our result implies that this effect also trickles down to the individual fund level.

[24]When performance is ranked by raw returns within each fund category, parent family size also weakens the flow sensitivity of low performance. This observation holds for both mearsures of family size. Our model is ambiguous regarding this effect, as search costs make it marginally positive and transaction costs render it marginally negative. We argue that this effect may be attributable to reasons outside the framework of the model. For instance, the weaker sensitivity for funds affiliated with large families may indicate that investors give these brand-name funds more benefit of the doubt before they pull their money out. We note that this observation occurs only when proxies are based on family-level characteristics rather than fund-level characteristics, which seems to support the above conjecture.

3.4 Diversity of Family Offerings

Khorana and Servaes (2004) provide evidence to show that families with more diverse fund offerings tend to have higher inflows. While diversity of offerings may be correlated with family size, it captures the effort by fund families to accommodate investors' desire to diversify within the same family. As shown in Elton, Gruber and Busse (2004), among funds that offer an essentially homogeneous product (an S&P 500 index fund), those that are part of a family offering a variety of other types of funds attract significantly more cash flows. Therefore, being affiliated with a family with more diverse offerings can lead to a larger pool of potential investors. To examine the effect of this specific type of reduction in participation costs for investors, we use the number of CDA investment objectives offered by the parent complex to measure the diversity of product offerings.[25] Because of the clustering nature of such a measure, we employ a binary dummy that takes 1 if the measure is above the median among all families and 0 otherwise.

The results are reported in Table VII. On average, funds in families that offer more than the median number of fund types see their flow sensitivity to mid-range performances increase by about 10%, from 0.123 to 0.136, when the performance is measured by the rank of returns (by about 25%, from 0.072 to 0.089, when the performance is measured on a risk-adjusted basis). The sensitivity of flow to top-tier performances tends to be lower for these funds. This is consistent with the intuition that diversity of offerings helps reduce participation costs in a multitude of ways. Interestingly, once its effect on flow sensitivity is accounted for, diversity of family offerings does not have a significant effect on fund-level inflows, although it may still have a statistically significant effect for the family's market share, as indicated in Khorana and Servaes (2004).

[25] When constructing this measure, we examine all types of funds managed by a fund family rather than restricting ourselves only to a sample of equity funds.

3.5 Funds with Multiple Share Classes

The proxies for participation costs we have discussed so far either pertain to search costs or embody both search and transaction costs for investors. To separate out the effect of transaction costs on the asymmetry of flow-performance relationship, in this subsection we examine a subsample of funds that offer multiple share classes.

By construction, different share classes of the same fund are associated with the same underlying portfolio. They only differ in terms of distribution strategies and the means by which investors pay for advice and service. This sample of funds provides an ideal setup for our study, because different share classes of the same fund serve as control samples for each other in terms of other fund-level factors that can also affect flow. While Nanda, Wang and Zheng (2004b) have considered how the existence of multiple share classes affects the level and volatility of fund flow as well as fund performance, our focus is on the effect of transaction costs on flow-performance sensitivity.

Among these different share classes, class A shares generally charge a front-end load and a 12b-1 fee of 25 to 35 basis points. Class B shares do not use front-end loads to pay for brokers' distributional services. Rather, they compensate brokers through a combination of a back-end load starting from 5% in the first year and an annual 12b-1 fee of about 100 basis points. The back-end load is triggered on redemption and usually decreases by 1% each year the shares are held. In addition, after six to eight years, B shares can be converted to A shares that carry lower 12b-1 fees. Like B shares, C shares do not charge front-end loads and their distribution costs are paid through a back-end load and an annual 12b-1 fee of about 100 basis points. However, the back-end load is usually set at 1% in the first year and is not charged for redemption after that. Therefore, class C shares are considered most attractive by investors who prefer flexibility in switching across different fund families with a relatively short investment horizon.

Intuitively, it would seem that different share classes of the same fund differ largely in their transaction costs because the performance of the underlying fund portfolio is the same. Comparing flow-performance relationships across different share classes would seem to be an ideal test for our hypothesis regarding transaction costs. Because class B shares feature a contingent deferred sales load that has an ambiguous impact on investors depending on their investment horizons and mainly affects fund outflow due to bad performance, we limit our comparison to flows into class A and class C shares because our main focus is on the response of flow to good performance.[26]

When identifying the two share classes, we mainly rely on checking fund names, though we supplement this with information on loads and 12b-1 fees. To create a sample with a perfect control of performance, we include only funds that offer both A and C classes. Since most funds did not introduce multiple share classes until the early 1990s, we focus on the post-1993 period.

In Table VIII, we include in the flow estimation the interaction terms between a dummy indicating C shares and performance rankings at low, medium and high ranges. We expect that, compared with flows into A shares, flows into C shares should be more responsive to moderately good performance because of the lower transaction costs for investors in buying C shares. Indeed, Table VIII shows that the interaction term between the C-share dummy and performance is significantly positive in medium performance ranges. It is either insignificant or significantly negative in the high performance range depending on alternative performance ranking measures. Based on point estimates, the flow sensitivity in the medium performance range varies from 0.186 for A shares to 0.255 for C shares, when performance is measured by the rank of fund returns within respective objective categories. When performance is measured by four-factor adjusted returns, the change is from 0.112 for A shares to 0.155 for C shares. Therefore, the lower transaction costs for C shares lead to a less convex flow-performance relationship.

[26]In addition to classes A, B and C, in recent years many funds have also created share classes targeted to specific investor groups, such as institutional share classes and retirement and 529 plan classes. Since investors in these classes may have very different investment objectives, in this study we do not consider these other classes.

4 Concluding Remarks

We have presented a simple rational model to highlight the effect of new investors' participation costs on the flow-performance relationship. We show that participation costs are instrumental for the convex relationship between flow and performance. Specifically, as performance improves, more new investors are able to overcome their participation costs to invest in the fund, and flows are increasingly more sensitive to performance. Moreover, different levels of participation costs affect flows differently in different performance ranges. For example, at medium levels of performance, funds with low participation costs may attract more investors and enjoy a more sensitive flow-performance relationship. On the other hand, when funds achieve top-tier performance, they may have fewer potential investors left to attract and their fund flows may be less sensitive to performance relative to their higher-cost peers.

With several proxies for participation costs, our systematic empirical analysis confirms model predictions and demonstrates that funds with lower participation costs tend to have enhanced sensitivity of flow to medium-range performance, and a less convex overall flow response to performance.

The impact of participation costs on the flow-performance relationship illustrates the idea that funds without superior performance can still attract new investors by reducing their participation costs through marketing and product differentiation. Also, these medium performers generally have the most to gain from marketing and advertising expenses in terms of expected fund flows. Moreover, our model provides a new perspective on the flow-performance relationship by emphasizing the role of new investors to mutual funds. This is particularly relevant given the tremendous growth of the mutual fund industry over the past two decades.

Finally, our results have important implications for the literature regarding fund managers' risk-taking incentives. Specifically, because fund managers' compensation is often contracted as a fraction of assets under management, the asymmetric sensitivity of flows to performance yields an implicit call-option-like payoff for fund managers, and may thus induce excessive risk-taking.[27] Our paper complements this literature by highlighting the effect of participation costs on convexity. In future research, we plan to examine explicitly the variation in managers' risk-taking incentives across funds with different levels of participation costs.

[27]The theoretical arguments are found in Carpenter (2000), Dybvig, Farnsworth and Carpenter (2003), Grinblatt and Titman (1989), Ross (2003) and Starks (1987). The empirical literature includes Brown, Harlow and Starks (1996), Busse (2001), Chen and Pennacchi (2002), Chevalier and Ellison (1997), Del Guercio and Tkac (2002a) and Golec and Starks (2002).

5 Appendix

5.1 Proof of Lemma 1

We derive the optimal holding depending on the first-period return. First, if the return is high enough that investors purchase new shares, it is easy to show that the optimal holding is

$$X_{1+} = \frac{\alpha_1 - \rho_+}{\gamma(\sigma_1^2 + \sigma_\epsilon^2)}.$$

Similarly, if the return is low enough that investors sell shares, then

$$X_{1-} = \frac{\alpha_1 + \rho_-}{\gamma(\sigma_1^2 + \sigma_\epsilon^2)}.$$

Plugging in the definitions of α_1 and σ_1 from equation (4), and checking the boundary condition such that investors are in the purchasing regime when $X_{1+} > X_0$ and in the selling regime when $X_{1-} < X_0$, we obtain the results in the lemma, where

$$\begin{aligned}
k_p(X_0) &\equiv \frac{\rho_+(\sigma_0^2 + \sigma_\epsilon^2)}{\sigma_0^2 - \gamma X_0 \sigma_\epsilon^2 (2\sigma_0^2 + \sigma_\epsilon^2)} - \frac{\sigma_\epsilon^2(\alpha_0 - \gamma X_0(2\sigma_0^2 + \sigma_\epsilon^2))}{\sigma_0^2 - \gamma X_0 \sigma_\epsilon^2 (2\sigma_0^2 + \sigma_\epsilon^2)}, \\
k_s(X_0) &\equiv -\frac{\rho_-(\sigma_0^2 + \sigma_\epsilon^2)}{\sigma_0^2 - \gamma X_0 \sigma_\epsilon^2 (2\sigma_0^2 + \sigma_\epsilon^2)} - \frac{\sigma_\epsilon^2(\alpha_0 - \gamma X_0(2\sigma_0^2 + \sigma_\epsilon^2))}{\sigma_0^2 - \gamma X_0 \sigma_\epsilon^2 (2\sigma_0^2 + \sigma_\epsilon^2)}, \\
k_0 &\equiv -\frac{\rho_-(\sigma_0^2 + \sigma_\epsilon^2)}{\sigma_0^2} - \frac{\alpha_0 \sigma_\epsilon^2}{\sigma_0^2}.
\end{aligned}$$

Note that when $X_{1+} < X_0$ and $X_{1-} > X_0$, the investor neither purchases nor sells shares. His dollar holding is simply $X_0(1 + r_1)$, which is equal to the original holding increased by the first-period return.

5.2 Proof of Lemma 3

Given their current wealth level W_{n1}, and after paying a fixed participation cost c to learn about the true expected ability α_0, the participating new investors have a value function that can be expressed as

$$E\left[-e^{-\gamma W_{n2}} | \alpha_0, c\right] = \begin{cases} -e^{-\gamma(W_{n1}-c) - \frac{\left(\sigma_\epsilon^2(\alpha_0 - \rho_+) + \sigma_0^2(r_1 - \rho_+)\right)^2}{2\sigma_\epsilon^2(\sigma_\epsilon^2 + \sigma_0^2)(\sigma_\epsilon^2 + 2\sigma_0^2)}}, & r_1 \geq k_p(0) \\ -e^{-\gamma(W_{n1}-c)} & o.w. \end{cases}$$

Averaging over their prior regarding the distribution of $\alpha_0 \sim N(\mu_0, \sigma_\mu^2)$, the expected utility after paying the participation cost is

$$J^P \equiv E\left[-e^{-\gamma W_{n2}}|c\right] = -e^{-\gamma(W_{n1}-c)}\left(\frac{1-\Phi(B)}{2} + \frac{1+\Phi\left(\frac{B}{A}\right)}{2A}\, e^{-\left(1-\frac{1}{A^2}\right)B^2}\right),$$

where $\Phi(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}dt$ is the error function, and

$$A \equiv \sqrt{1 + \frac{\sigma_\epsilon^2 \sigma_\mu^2}{(\sigma_\epsilon^2 + \sigma_0^2)(\sigma_\epsilon^2 + 2\sigma_0^2)}}, \qquad B \equiv \frac{\sigma_\epsilon^2(\mu_0 - \rho_+) + \sigma_0^2(r_1 - \rho_+)}{\sqrt{2}\ \sigma_\epsilon^2 \sigma_\mu}. \tag{14}$$

If they choose not to participate, their value function is simply $J^{NP} = -e^{-\gamma W_{n1}}$ since they will hold only the risk-free asset returning $r_f = 0$. Hence, new investors choose to participate if and only if $J^P \geq J^{NP}$. The threshold cost level $\widehat{c}(r_1)$ in Lemma 3 solves $J^P = J^{NP}$.

5.3 Proof of Propositions 1

The proposition follows directly from Lemmas 1-3 and the definition of fund flows. Lemma 3 shows that all new investors with $c < \widehat{c}(r_1)$ choose to participate. Hence the fraction of new investors who participate is simply $\min\left[1, \frac{\widehat{c}(r_1)}{\bar{c}}\right]$.

References

[1] Barber, B.M., T. Odean, and L. Zheng, 2002, Out of Sight, Out of Mind: The Effects of Expenses on Mutual Fund Flows, forthcoming in *Journal of Business.*

[2] Bergstresser, D., and J. Poterba, 2002, Do After-Tax Returns Affect Mutual Fund Inflows? *Journal of Financial Economics*, 63, 381-414.

[3] Berk, J.B., and R.C. Green, 2004, Mutual Fund Flows and Performance in Rational Markets, forthcoming in *Journal of Political Economy.*

[4] Boudoukh, J., M. Richardson, R. Stanton and R.F. Whitelaw, 2003, Valuing Mutual Fund Companies, *working paper.*

[5] Brown, K.C., W.V. Harlow and L.T. Starks, 1996, Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry, *Journal of Finance,* 51, 85-110.

[6] Busse, J., 2001, Another Look at Mutual Fund Tournaments, *Journal of Financial and Quantitative Analysis,* 36, 53-73.

[7] Capon, N., G.J. Fitzsimons, and R.A. Prince, 1996, An Individual Level Analysis of the Mutual Fund Investment Decisions, *Journal of Financial Services Research*, 10, 59-82.

[8] Carpenter, J.N., 2000, Does Option Compensation Increase Managerial Risk Appetite? *Journal of Finance,* 55, 2311-2331.

[9] Chen, H.-L., and G.G. Pennacchi, 2002, Does Prior Performance Affect A Mutual Fund's Choice of Risk? Theory and Further Empirical Evidence, *working paper.*

[10] Chevalier, J., and G. Ellison, 1997, Risk Taking by Mutual Funds as a Response to Incentives, *Journal of Political Economy,* 105, 1167-1200.

[11] Constantinides, G.M., and M.J.P. Magill, 1976, Portfolio Selection with Transactions Costs, *Journal of Economic Theory*, 13, 245-263.

[12] Davis, M. H. A., and A.R. Norman, 1990, Portfolio Selection with Transaction Costs, *Mathematics of Operations Research*, 15, 676-713.

[13] Del Guercio, D., and P.A. Tkac, 2002a, The Determinants of the Flow of Funds of Managed Portfolios: Mutual Funds vs. Pension Funds, *Journal of Financial and Quantitative Analysis*, 37, 523-557.

[14] Del Guercio, D., and P.A. Tkac, 2002b, Star Power: The Effect of Morningstar Ratings on Mutual Fund Flows, *working paper.*

[15] Dybvig, P.H., H.K. Farnsworth and J.N. Carpenter, 2003, Portfolio Performance and Agency, *working paper.*

[16] Elton, E.J., M.J. Gruber, and C.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.

[17] Elton, E.J., M.J. Gruber, and J.A. Busse, 2004, Are Investors Rational? Choices among Index Funds, *Journal of Finance*, 59, 261-288.

[18] Gallaher, S., R. Kaniel, and L. Starks, 2004, Mutual Funds and Advertising, *working paper.*

[19] Goetzmann, W.N., and N. Peles, 1997, Cognitive Dissonance and Mutual Fund Investors, *Journal of Financial Research*, 20, 145-158.

[20] Golec, J., and L. Starks, 2002, Performance Fee Contract Change and Mutual Fund Risk, *Journal of Financial Economics*, forthcoming.

[21] Grinblatt, M., and S. Titman, 1989, Adverse Risk Incentives and the Design of Performance-based Contracts, *Management Science,* 35, 807-822.

[22] Gruber, M.J., 1996, Another Puzzle: The Growth in Actively Managed Mutual Funds, *Journal of Finance,* 51, 783-810.

[23] Hortaçsu, A., and C. Syverson, 2004, Product Differentiation, Search Costs, and Competition in the Mutual Fund Industry: A Case Study of S&P 500 Index Funds, *Quarterly Journal of Economics*, 119, 403-456.

[24] Huang, J., K.D. Wei, and H. Yan, 2004, Volatility of Performance and Mutual Fund Flows, *working paper.*

[25] Ippolito, R.A., 1992, Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual Fund Industry, *Journal of Law and Economics*, 35, 45-70.

[26] Jain, P.C., and J.S. Wu, 2000, Truth in Mutual Fund Advertising: Evidence on Future Performance and Fund Flows, *Journal of Finance*, 55, 937-958.

[27] Khorana, A., and H. Servaes, 2004, Conflicts of Interest and Competition in the Mutual Fund Industry, *working paper.*

[28] Lynch, A., and D. Musto, 2003, How Investors Interpret Past Fund Returns, *Journal of Finance*, 58, 2033-2058.

[29] Massa, M., 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.

[30] Nanda, V., Z. Wang and L. Zheng, 2004a, Family Values and the Star Phenomenon: Strategies of Mutual Fund Families, *Review of Financial Studies*, 17, 667-698.

[31] Nanda, V., Z. Wang and L. Zheng, 2004b, The ABCs of Mutual Funds: A Natural Experiment on Fund Flows and Performance, *working paper.*

[32] Newey, W.K., and Kenneth D.W., 1987, A Simple, Positive Semi-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica,* 55, 703-708.

[33] Reid, B.K., and J.D. Rea, 2003, Mutual Fund Distribution Channels and Distribution Costs, *Perspectives* (Investment Company Institute), 9(3).

[34] Ross, S.A., 2004, Compensation, Incentives, and the Duality of Risk Aversion and Riskiness, *Journal of Finance*, 207-225.

[35] Sharpe, W., 1997, Morningstar's Performance Measures, *working paper.*

[36] Sigurdsson, K., 2004, The Effect of New Money Inflows on the Flow-Performance Relationship in the U.S. Mutual Fund Industry, *working paper.*

[37] Sirri, E.R., and P. Tufano, 1993, Competition and Change in the Mutual Fund Industry, in Samuel Hayes III, ed., *Financial Services: Perspectives and Challenges* (Harvard Business School Press, Boston, MA).

[38] Sirri, E.R., and P. Tufano, 1998, Costly Search and Mutual Fund Flows, *Journal of Finance,* 53, 1589-1622.

[39] Starks, L.T., 1987, Performance Incentive Fees: An Agency Theoretic Approach, *Journal of Financial and Quantitative Analysis*, 22, 17-32.

[40] Warther, V.A., 1995, Aggregate Mutual Fund Flows and Security Returns, *Journal of Financial Economics*, 39, 209-235.

Table I
Summary Statistics

This table reports summary statistics of our full sample from 1981 to 2001. At the end of each year, we calculate the cross-sectional mean value of the following fund characteristics: total net asset value, fund age, total fees, average number of funds per family (we count multiple share classes of the same fund only once), average quarterly flow per fund, 4-factor model adjusted return (alpha), and standard deviation of monthly fund returns in the 12 months prior to each quarter (volatility).

	N	TNA (in millions)	Age	Total Fees	Number of Funds per Family	Quarterly Flow	4-Factor Alpha	Volatility
1981	217	148.93	21.05	1.68%	3.84	-0.36%	-0.05%	4.89%
1982	231	157.08	21.24	1.60%	3.82	0.10%	0.06%	4.76%
1983	239	242.53	21.36	1.65%	3.86	0.72%	-0.02%	4.50%
1984	262	236.73	21.12	1.56%	4.43	-1.59%	-0.02%	4.78%
1985	287	277.60	20.10	1.59%	5.11	1.11%	-0.06%	3.73%
1986	329	331.92	20.12	1.58%	5.56	0.20%	-0.05%	5.02%
1987	404	445.30	18.23	1.48%	7.26	-4.03%	0.02%	4.29%
1988	466	326.37	17.36	1.49%	9.21	-3.58%	0.07%	8.29%
1989	515	372.61	16.65	1.67%	10.28	-0.23%	0.09%	3.21%
1990	544	305.81	16.36	1.70%	9.72	0.93%	0.07%	5.13%
1991	604	406.56	15.82	1.74%	9.61	3.47%	-0.01%	4.20%
1992	718	450.79	14.05	1.40%	9.20	4.27%	0.01%	4.33%
1993	891	533.47	12.29	1.66%	9.29	2.51%	0.04%	2.65%
1994	1339	415.63	9.22	1.61%	12.59	0.69%	-0.04%	3.11%
1995	1793	452.10	7.84	1.62%	14.58	4.00%	-0.07%	2.63%
1996	2131	539.68	7.59	1.71%	12.05	3.88%	-0.10%	3.46%
1997	2629	615.88	6.95	1.73%	14.38	4.41%	-0.09%	4.45%
1998	3213	540.31	6.64	1.72%	14.80	1.07%	-0.19%	6.38%
1999	3434	662.38	7.12	1.71%	10.61	0.60%	-0.19%	4.75%
2000	3446	805.06	7.67	1.72%	14.43	1.65%	0.14%	6.91%
2001	3265	578.60	8.63	1.68%	14.16	1.49%	0.11%	6.53%

Table II
Effect of Marketing Expenses on the Flow-Performance Relationship

This table examines the effect of marketing expenses on the sensitivity of flow to past performance. Each quarter, fractional performance ranks ranging from 0 to 1 are assigned to funds according to their returns in the past 12 months relative to other funds with similar investment objectives, or according to their 4-factor model alphas during the past 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 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 ranks over the low, medium and high performance ranges, their interaction terms with the total fee ratios. The control variables include aggregate flow into the fund objective category, volatility of monthly returns during the performance measurement period, the logged value of 1 plus fund age and its interaction with performance, logged value of fund size as proxied by the previous year's total net asset value, and 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 10%, 5% and 1% levels, respectively.

Performance measured by	*Raw Return*	*4-Factor Alpha*
Intercept	0.015*	0.020**
	(1.78)	(2.54)
Category Flow	0.671***	0.362***
	(7.57)	(5.05)
Low	0.117***	0.064**
	(3.32)	(2.44)
Low*Total Fees	1.645	1.434
	(0.98)	(1.22)
Mid	0.104***	0.064***
	(9.52)	(6.12)
Mid* Total Fees	1.802***	1.023***
	(3.79)	(2.70)
High	0.428***	0.291***
	(10.06)	(8.87)
High* Total Fees	-4.810**	-5.256***
	(-2.26)	(-3.05)
Volatility	-0.271***	-0.164*
	(-3.15)	(-1.90)
Age	-0.011***	-0.012***
	(-6.93)	(-9.33)
Age*Performance	-0.022***	-0.006***
	(-9.76)	(-2.97)
Size	-0.002***	-0.001**
	(-3.70)	(-2.44)
Total Fees	-0.723***	-0.345*
	(-3.14)	(-1.91)

Table III
Effect of Affiliation with a "Star" Family: Mimicking Morningstar

This table examines the effect of affiliation with "star"-producing families on the sensitivity of flow to past performance. Each quarter, funds are ranked according to their performance during the past 36 months by a procedure that mimics the Morningstar rating system. A dummy variable is assigned 1 for funds that are 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 ranks over the low, medium and high performance ranges, a dummy variable indicating "star" family affiliation, their interaction terms. The control variables include a dummy variable indicating funds' own "star" status, aggregate flow into the fund objective category, volatility of monthly returns during the performance measurement period, logged value of 1 plus fund age and its interaction with performance, logged value of fund size as proxied by the previous year's total net asset value, and 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 10%, 5% and 1% levels, respectively.

Performance measured by	*Raw Return*	*4-Factor Alpha*
Intercept	-0.035***	-0.020***
	(-6.58)	(-3.40)
Category Flow	0.567***	0.331***
	(7.99)	(5.32)
Low	0.160***	0.126***
	(11.32)	(9.50)
Low*Morningstar	-0.030	0.008
	(-0.82)	(0.09)
Mid	0.113***	0.084***
	(14.61)	(11.86)
Mid*Morningstar	0.020***	0.018***
	(3.21)	(3.15)
High	0.242***	0.127***
	(14.74)	(7.70)
High*Morningstar	-0.031	-0.012
	(-0.67)	(-0.41)
Star Affiliated	0.006	-0.001
	(0.97)	(-0.06)
Star	0.038***	0.040***
	(15.49)	(14.58)
Volatility	-0.158**	-0.031
	(-2.31)	(-0.41)
Age	-0.002	-0.005***
	(-1.46)	(-4.08)
Age*Performance	-0.022***	-0.013***
	(-10.48)	(-6.16)
Size	0.000	0.000
	(-0.07)	(-1.08)
Total Fees	0.030	0.132*
	(0.42)	(1.94)

Table IV
Effect of Affiliation with a "Star" Family: Four-Factor Alpha

This table examines the effect of affiliation with "star"-producing families on the sensitivity of flow to past performance. Each quarter, funds are ranked according to their four-factor model adjusted returns during the past 36 months. A dummy variable is assigned 1 for funds that are 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 ranks over the low, medium and high performance ranges, a dummy variable indicating "star" family affiliation, their interaction terms. The control variables include a dummy variable indicating funds' own "star" status, aggregate flow into the fund objective category, volatility of monthly returns during the performance measurement period, logged value of 1 plus fund age and its interaction with performance, logged value of fund size as proxied by the previous year's total net asset value, and 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 10%, 5% and 1% levels, respectively.

Performance measured by	*Raw Return*	*4-Factor Alpha*
Intercept	-0.016***	0.009
	(-2.97)	(1.37)
Category Flow	0.620***	0.344***
	(7.44)	(5.55)
Low	0.166***	0.111***
	(11.17)	(8.07)
Low*4-Factor Star	-0.054	-0.055*
	(-1.34)	(-1.78)
Mid	0.122***	0.074***
	(15.23)	(10.11)
Mid*4-Factor Star	0.013**	0.016***
	(1.99)	(3.31)
High	0.291***	0.255***
	(15.26)	(8.62)
High*4-Factor Star	0.000	-0.020
	(0.01)	(-0.33)
Star Affiliated	0.010	0.009
	(1.39)	(1.44)
Star	0.028***	-0.005
	(10.41)	(-1.28)
Volatility	-0.326***	-0.168*
	(-4.33)	(-1.95)
Age	-0.005***	-0.012***
	(-3.92)	(-9.46)
Age*Performance	-0.022***	-0.006***
	(-10.07)	(-3.11)
Size	-0.001*	-0.001**
	(-1.97)	(-2.62)
Total Fees	-0.039	0.050
	(-0.51)	(0.70)

Table V
Effect of Family Size (Total Assets) on the Flow-Performance Relationship

This table examines the effect of family size, as measured by total assets under the management of the fund family, on the sensitivity of flow to past performance. Each quarter a piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance ranks over the low, medium and high performance ranges, logged value of the total assets managed by their parent families, and their interaction terms. The control variables include aggregate flow into the fund objective category, volatility of monthly returns during the performance measurement period, logged value of 1 plus fund age and its interaction with performance, logged value of fund size as proxied by the previous year's total net asset value, and 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 10%, 5% and 1% levels, respectively.

Performance measured by	*Raw Return*	*4-Factor Alpha*
Intercept	-0.020**	-0.001
	(-2.32)	(-0.07)
Category Flow	0.605***	0.272***
	(6.76)	(3.35)
Low	0.240***	0.121***
	(6.23)	(4.27)
Low*log(Complex Size)	-0.013*	-0.005
	(-1.91)	(-0.93)
Mid	0.105***	0.056***
	(9.41)	(5.85)
Mid* log(Complex Size)	0.004***	0.004***
	(3.94)	(3.49)
High	0.394***	0.368***
	(9.01)	(8.28)
High* log(Complex Size)	-0.006	-0.023***
	(-0.85)	(-3.54)
log(Complex Size)	0.004***	0.002**
	(3.33)	(2.63)
Volatility	-0.260***	-0.108
	(-2.97)	(-1.21)
Age	-0.009***	-0.011***
	(-5.63)	(-9.06)
Age*Performance	-0.025***	-0.006***
	(-10.68)	(-3.07)
Size	-0.003***	-0.003***
	(-5.47)	(-4.66)
Total Fees	-0.063	0.039
	(-0.74)	(0.56)

Table VI
Effect of Family Size (Number of Funds) on the Flow-Performance Relationship

This table examines the effect of family size, as measured by the total number of funds under management by a fund family, on the sensitivity of flow to past performance. Each quarter a piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance ranks over the low, medium and high performance ranges, logged value of the total number of funds within their parent family, and their interaction terms. The control variables include aggregate flow into the fund objective category, volatility of monthly returns during the performance measurement period, logged value of 1 plus fund age and its interaction with performance, logged value of fund size as proxied by the previous year's total net asset value, and 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 10%, 5% and 1% levels, respectively.

Performance measured by	*Raw Return*	*4-Factor Alpha*
Intercept	-0.010	0.004
	(-1.38)	(0.62)
Category Flow	0.663***	0.346***
	(7.52)	(5.15)
Low	0.208***	0.110***
	(9.55)	(5.74)
Low*log(Number of Funds)	-0.034**	-0.014
	(-2.39)	(-1.18)
Mid	0.124***	0.077***
	(13.48)	(10.62)
Mid* log(Number of Funds)	0.006**	0.004*
	(2.05)	(1.80)
High	0.396***	0.311***
	(15.71)	(13.27)
High* log(Number of Funds)	-0.030*	-0.060***
	(-1.83)	(-4.79)
log(Number of Funds)	0.007***	0.004*
	(2.85)	(1.97)
Volatility	-0.285***	-0.151*
	(-3.31)	(-1.77)
Age	-0.010***	-0.011***
	(-6.22)	(-8.94)
Age*Performance	-0.024***	-0.008***
	(-10.74)	(-3.73)
Size	-0.002***	-0.001**
	(-3.84)	(-2.51)
Total Fees	-0.071	0.044
	(-0.82)	(0.63)

Table VII
Effect of Diversity of Fund Offerings on the Flow-Performance Relationship

This table examines the effect of family diversity, as measured by the total number of fund types offered by the fund family, on the sensitivity of flow to past performance. Each quarter a piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance ranks over the low, medium and high performance ranges, a dummy variable indicating affiliation with a parent family that offers above median number of fund types, and their interaction terms. The control variables include aggregate flow into the fund objective category, volatility of monthly returns during the performance measurement period, logged value of 1 plus fund age and its interaction with performance, logged value of fund size as proxied by the previous year's total net asset value, and 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 10%, 5% and 1% levels, respectively.

Performance measured by	*Raw Return*	*4-Factor Alpha*
Intercept	0.002	0.009
	(0.24)	(1.27)
Category Flow	0.667***	0.358***
	(7.79)	(5.09)
Low	0.161***	0.103***
	(8.76)	(5.78)
Low* Diversity Dummy	-0.011	-0.017
	(-0.43)	(-0.79)
Mid	0.123***	0.072***
	(14.11)	(10.27)
Mid* Diversity Dummy	0.013**	0.017***
	(2.13)	(3.63)
High	0.380***	0.265***
	(15.47)	(12.76)
High* Diversity Dummy	-0.054*	-0.083***
	(-1.80)	(-3.69)
Diversity Dummy	0.004	0.004
	(0.96)	(1.12)
Volatility	-0.295***	-0.166*
	(-3.35)	(-1.93)
Age	-0.010***	-0.011***
	(-6.68)	(-8.80)
Age*Performance	-0.023***	-0.007***
	(-10.11)	(-3.53)
Size	-0.002***	-0.001***
	(-4.30)	(-2.91)
Total Fees	-0.076	0.043
	(-0.86)	(0.60)

Table VIII
Difference in the Flow-Performance Sensitivity between Share Classes

This table presents the results on the difference in the flow-performance sensitivity between A shares and C shares of the same fund. Each quarter during 1994 to 2001, we identify funds that offer both A and C shares. Among A and C shares, respectively, a piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance ranks over the low, medium and high performance ranges, a dummy variable indicating C shares, and their interaction terms. The control variables include aggregate flow into the fund objective category, volatility of monthly returns during the performance measurement period, logged value of 1 plus fund age and its interaction with performance, logged value of fund size as proxied by the previous year's total net asset value, and 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 10%, 5% and 1% levels, respectively.

Performance measured by	*Raw Return*	*4-Factor Alpha*
Intercept	0.007	0.008
	(0.60)	(0.55)
Category Flow	0.977***	0.337
	(2.93)	(1.62)
Low	0.219***	0.123***
	(6.88)	(3.88)
Low*C Class Dummy	-0.061	0.007
	(-1.22)	(0.12)
Mid	0.186***	0.112***
	(10.06)	(8.92)
Mid*C Class Dummy	0.069***	0.043**
	(4.76)	(2.30)
High	0.419***	0.311***
	(7.84)	(6.51)
High*C Class Dummy	0.081	-0.167*
	(0.70)	(-2.01)
C Class Dummy	0.010	0.004
	(1.12)	(0.37)
Volatility	-0.259	0.081
	(-1.54)	(0.40)
Age	-0.014***	-0.013***
	(-4.28)	(-5.37)
Age*Performance	-0.031***	-0.006
	(-5.69)	(-1.69)
Size	-0.006***	-0.006***
	(-6.21)	(-4.39)
Total Fees	-0.187	-0.011
	(-0.90)	(-0.04)