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Participation Costs and the Sensitivity of Fund Flows to Past Performance

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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. By incorporating participation costs into a model in which investors learn about managers' ability from past returns, we show that mutual funds with lower participation costs have a higher flow sensitivity to medium performance and a lower flow sensitivity to high performance than their higher-cost peers. Using various fund characteristics as proxies for the reduction in participation costs, we provide empirical evidence supporting the model's implications for the asymmetric flow-performance relationship.

MANY RESEARCHERS DOCUMENT AN asymmetric relationship between mutual fund flows and past performance: Funds with superior recent performance enjoy disproportionately large new money inflows, while funds with poor performance suffer smaller outflows.[1] Moreover, fund characteristics such as age, volatility of past performance, affiliation with a large or "star"-producing fund complex, and marketing expenditures affect both the level of fund flows and the sensitivity of flows to past performance.[2] In this paper, we develop a rational model to explain simultaneously the asymmetric response of fund flows to past performance and

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[1] See, for example, 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 (2005) for the effect of marketing and advertising expenses; Sirri and Tufano (1998) and Huang, Wei, and Yan (2004) for the importance of performance volatility; and Sirri and Tufano (1998), Massa (2003), Khorana and Servaes (2004), and Nanda, Wang, and Zheng (2004b) for the significance of the affiliation with large or star-producing fund families.

the impact of various fund characteristics on the flow-performance relationship. We then conduct an empirical analysis to test the model predictions.

Our model relies on two main assumptions regarding investor behavior. First, investors learn about unobservable managerial ability from realized fund performance. This assumption, common to most existing models of mutual fund flows, implies that fund flows chase after past performance due to investors' Bayesian updating process. Second, investors face participation costs when investing in mutual funds. We show that participation costs can lead to different flow responses at different performance levels and can cause cross-sectional variations in the flow-performance relationship.

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 Capon, Fitzsimons, and Prince (1996) and Goetzmann and Peles (1997) demonstrate.[3] We examine two types of participation costs in this paper. The first type of cost is related to the *information cost* of collecting and analyzing information about a new fund before investing in it.[4] We model the information cost as a fixed cost faced by new investors. Although investors can freely observe past performance of all funds, they have varied degrees of familiarity with different funds. To make an informed choice, investors can either *actively* seek out the relevant information about the fund or *passively* accumulate knowledge as it comes to them through advertising or broker recommendations. These two types of information gathering are complementary to each other: The more funds expend in resources to lower information barriers, the less investors have to bear the active cost. The second type of cost is related to the *transaction cost* of purchasing or redeeming fund shares. We model the transaction cost as a proportional cost that applies to both existing and new investors.

Participation costs affect fund flows through three channels. First, for a given fund, there are cross-sectional differences in participation costs due to investors' various levels of financial sophistication. Because past performance has to exceed a threshold value for an individual investor to realize a utility gain from investigating and potentially investing in the fund, better past performance attracts investors with higher costs to overcome their participation barriers. Hence, fund flows are increasingly more sensitive to higher past performance. We use the term *participation effect* to account for this differential participation of new investors. Second, for an individual investor, the cost of active information collection limits the number of funds he investigates.

[3] According to the Investment Company Institute data, the number of stock mutual funds in the United States increased from 399 in January 1984 to 4,601 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 (2004)).

[4] The type of information we are concerned about may be regarded as "soft" information. It is related to the familiarity of an investor with a fund, and is crucial for investors in making their allocation decisions as it helps narrow the variance of their expectation of future fund returns. In contrast, the cost of acquiring "hard" information, such as funds' past performance, is minimal given the vast amount of financial data publicly available.

Since past performance provides a signal of managerial ability, the investor considers both the ranking of past performance and his participation costs in each fund when deciding which funds to learn more about. The higher his participation costs, the fewer funds he investigates, and the more likely he concentrates his investment in a few funds with superior past performance. We denote this reliance on relative performance the *individual winner-picking effect*. Third, transaction costs make it more costly for investors to trade in mutual funds. As a result, investors do not purchase (sell) funds unless their past performance is sufficiently good (bad). This *no-trading effect* makes flows less sensitive to medium levels of performance for higher transaction-costs funds.

Our theory suggests that funds with different participation costs should have different sensitivities of flows to past performance. First, the participation effect is driven by the differential costs of individual investors, and the range of these costs varies across funds. For example, the high profile of the Fidelity Magellan Fund lowers its information barrier so that most investors can overcome their participation hurdles even if the fund has only mediocre performance; therefore, its participation effect is stronger in the medium performance range. In contrast, a small no-name fund's information barrier is very high, especially for unsophisticated investors; a superior past performance is required before these investors will find it worthwhile to learn more about the fund, and thus the participation effect for this fund is more significant in the high performance range.

Second, the individual winner-picking effect is more pronounced for funds with higher participation costs, since investors will only investigate and eventually invest in a few funds with superior performance within this group. For lower-cost funds, investors can afford to study more of them and may discover good investments even if the recent performance of these funds has not been stellar. Therefore, their flows are more sensitive to medium performance. Finally, proportional transaction costs reduce trade in funds with medium performance and in turn the flow sensitivity. This no-trading effect is stronger for funds with larger transaction costs.

We carry out an empirical analysis to test these predictions. Although the information costs for individual investors are not directly observable, we can proxy for them using various fund characteristics that relate to fund visibility. Specifically, we use marketing expenses and the affiliation with fund families that have produced "star" funds to proxy for the variation in investors' information costs across funds, as these variables relate to the level of visibility that funds enjoy. We also use the parent family size, measured by either the value of assets under management or the diversity of fund categories offered, to capture participation costs related to the economy of scale in distribution and services that helps reduce participation barriers. Given that the overall level of information costs has declined over time due to the maturing of the mutual fund industry, we examine different time periods to investigate the effect of the change in the overall cost level. Finally, to isolate 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 various proxies, we find that participation costs contribute significantly to the previously documented nonlinear flow-performance relationship. Specifically, in the medium performance range, funds with lower participation costs have higher flow sensitivities than their higher-cost counterparts, while in the high performance range, this relationship may be reversed. This finding demonstrates the significant effect of participation costs on investors' choice of mutual funds and is consistent with the predictions of our model.

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 carry this intuition further by constructing a rational model to examine how participation costs affect investors' allocation decisions among funds. Our model delineates the effect of investor participation across different performance ranges and illustrates how participation costs affect the flow-performance relationship in a structural framework. Our empirical analysis provides supporting evidence for this theoretical insight.

Several previous theoretical studies examine the asymmetric flow-performance relationship. Berk and Green (2004) assume a perfectly competitive capital market in which the return to an actively managed fund decreases with its portfolio size. Using variable cost functions for managers, they show that a convex relationship between new investments and past performance exists even in the absence of performance persistence. Lynch and Musto (2003) argue that investment companies can exercise an option to abandon poorly performing strategies and/or fire bad managers. Since poor returns are not likely to be informative about future performance, investors will respond less strongly to bad performance, leading to the convexity in the flow-performance relationship.

Our model departs from these studies by recognizing the frictions investors encounter in allocating their wealth among actively managed mutual funds. We propose a new mechanism for explaining the documented nonlinear flow-performance relationship and its cross-sectional variation. The impact of participation costs on the flow-performance relationship underscores the idea that funds without superior performance can still attract new investors by reducing their participation barriers through non–performance-related means. Moreover, our model provides a fresh perspective on the flow-performance relationship by emphasizing the role of new investors to a mutual fund. This is particularly relevant given the tremendous growth of the mutual fund industry over the past two decades.

The rest of the paper is organized as follows: In Section I we present our theoretical model and outline its empirical implications. The data and the empirical methodology are described in Section II. We discuss our empirical results in Section III, and Section IV concludes. Appendix A contains proofs for the model and Appendix B presents the simulation procedure.

I. The Model

A. Model Setup

We consider a partial equilibrium model with a finite horizon of three dates, $t = 0, 1, 2$. Investors allocate wealth between a risk-free bond and an array of actively managed mutual funds. The return on the risk-free bond is normalized to $r_f = 0$ each period, and mutual fund i produces a risky return of r_{it} at time $t = 1, 2$ according to the process

$$r_{it} = \alpha_i + \epsilon_{it}. \tag{1}$$

The term α_i, which represents the unobservable ability of the manager of fund i to deliver positive excess returns, is assumed to be constant over time for each fund and independently and identically distributed (i.i.d.) across funds; ϵ_{it}, which represents the idiosyncratic noise in the return of fund i, is i.i.d. both over time and across funds with a normal distribution, that is,

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

The return r_{it} should be interpreted as the fund return in excess of a benchmark. Therefore, the assumption that both α_i and ϵ_{it} are i.i.d. across funds should be reasonable. This modeling technique, following both Berk and Green (2004) and Lynch and Musto (2003), allows us to abstract away the common component in fund returns and thereby focus on the differential ability across fund managers.[5]

For each fund i, there are two types of investors, each with a different information set regarding the distribution of α_i. *Existing investors*, indexed by e, invest in fund i at time 0 and have a prior belief that managerial ability α_i is also normally distributed,

$$\alpha_i \sim N\big(\alpha_{i0}, \sigma_0^2\big). \tag{3}$$

At time 1, the existing investors observe the first-period return (r_{i1}) of fund i, and then use Bayesian updating to derive the following posterior distribution regarding managerial ability:

$$\alpha_i \,|\, r_{i1} \sim N\big(\alpha_{i1}, \sigma_1^2\big), \tag{4}$$

where

$$\alpha_{i1} = \alpha_{i0} + \frac{\sigma_0^2}{\sigma_0^2 + \sigma_\epsilon^2}\,(r_{i1} - \alpha_{i0}), \quad \sigma_1^2 = \frac{\sigma_0^2 \sigma_\epsilon^2}{\sigma_0^2 + \sigma_\epsilon^2}. \tag{5}$$

[5] As Lynch and Musto (2003) argue, investors may use index funds or index futures contracts to hedge out their market exposure and isolate the return component attributable to the manager's ability.

New investors, indexed by n, initially have coarser information about fund i than existing investors. Specifically, although both types of investors believe that the ability α_i is normally distributed, existing investors know with certainty the expected ability level α_{i0} while new investors know only that α_{i0} is drawn from a normal distribution,

$$\alpha_{i0} \sim N(\mu_0, \sigma_\mu^2). \tag{6}$$

New investors can improve their information set by paying participation costs, however. For simplicity, we assume that once new investors have incurred a fixed participation cost, they acquire all the relevant information that existing investors have and, in particular, they know α_{i0} for certain.

It is conceivable that the participation cost will vary both across investors and across funds. We assume that it takes the form $c_{ki} = \delta_k \bar{c}_i$ for investor k and fund i, where $\delta_k \sim$ Unif[0, 1] captures the level of financial sophistication across new investors,[6] and $\bar{c}_i$ reflects the variation across funds in the difficulty with which investors narrow down the uninformative prior for α_{i0}. Since the uninformative prior is assumed to be identical across funds, the overall cost of narrowing down a prior should be similar across all funds. However, this overall cost can be shared by individual investors through active information acquisition, and by the mutual fund through the improvement of its visibility and the reduction of other information barriers for investors. Given the complementarity between the costs borne by the mutual fund and those incurred by investors, the participation cost $\bar{c}_i$, which measures the maximum cost incurred by investors for active information acquisition, is lower for funds with a higher level of visibility and familiarity.

The investors' costs correspond to any active information collection costs that may help investors form an opinion about a particular fund. These may include the cost of studying the fund prospectus, determining its Morningstar rating, understanding its investment strategies, and seeking advice from friends and financial advisors. This type of information is of the "soft" variety that helps investors narrow the variance of their expectations. Although the costs of these individual activities may not be significantly different across funds, the amount of work that investors need to do before they can comfortably form an opinion varies across funds. For example, given the high profile of the Fidelity Magellan fund, investors need little additional information before they feel comfortable investing in the fund. On the other hand, investors are generally much more skeptical about a no-name fund, in which case they may require a lot more additional information before they decide whether it is a good investment. We note, however, that arriving at an informed expectation (reduction in σ_μ) is different from forming a favorable opinion (higher α_{i0}). Therefore, investors will not automatically choose more familiar funds.

[6] This distributional assumption is made for tractability. Other continuous distributions can also be used without qualitatively affecting our results.

The population mass is normalized to one for existing investors and λ_i for new investors. All investors are assumed to have constant absolute risk aversion (CARA) utility over their terminal wealth W_{j2} at date $t = 2$:

$$E\left[-e^{-\gamma W_{j2}}\right], \quad j = e, n.$$

They have the same risk aversion coefficient γ and the same initial wealth W_0 at time 0. Each investor is endowed with a stake X_{i0} in fund i at time 0, where $X_{i0} > 0$ for an existing investor in fund i and $X_{i0} = 0$ for a new investor to the fund. At time 1, investors optimally allocate their wealth between the risk-free asset and the mutual funds to maximize their terminal utility. Since our study focuses on open-end mutual funds, we assume that investors are not allowed to sell funds short.

In the following subsections, we first discuss the results from a setting in which investors have no portfolio constraints, that is, they can freely borrow to finance their purchases in as many funds as they wish. Then we introduce portfolio constraints in a reduced-form specification to examine the role of participation costs in the presence of competition for flows among funds.

B. The Benchmark Case: No Portfolio Constraints

Each investor has two decisions to make at $t = 1$. First, after observing the first-period returns of all funds, he decides for each fund i that he does not own whether or not to pay the participation cost c_{ki} to acquire full information about α_{i0}. Second, for all the funds he owns or for which he chooses to pay the cost, he decides if and how much he will allocate to each one. If he chooses not to pay the cost for a new fund, he makes no investment in it.

We solve for the optimal decisions backwards by first deriving the optimal portfolio allocation given the participating decision, and then solving for the participation decision itself. The following lemma indicates that the allocation to fund i is identical between the existing and new investors.

LEMMA 1: *At time $t = 1$, the optimal holdings of both existing investors and participating new investors in fund i are*

$$X^e_{i1} = X^n_{i1} \equiv X_{i1}(r_{i1}) = \begin{cases} \dfrac{\alpha_{i0}}{\gamma\left(2\sigma_0^2 + \sigma_\epsilon^2\right)} + \dfrac{\sigma_0^2}{\gamma\sigma_\epsilon^2\left(2\sigma_0^2 + \sigma_\epsilon^2\right)} r_{i1}, & r_{i1} \geq \underline{r_i} \\ 0, & \textit{otherwise}, \end{cases} \tag{7}$$

where $\underline{r_i} = -\alpha_{i0}\sigma_\epsilon^2/\sigma_0^2$.

The allocation to fund i depends only on the information related to fund i, that is, it is independent of other funds. This independence result and the fact that holdings are linear and increasing in past performance are common to CARA-normal models with learning about managerial ability; see, for example, 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. If $r_{i1} < \underline{r}_i$, the unconstrained optimal holding is negative, so the short-sale constraint bounds the holdings from below at zero. Because all participating new investors share the same information set as existing investors, they have identical holdings when there are no additional frictions.

After deriving the optimal individual allocation for participating new investors, we compute their certainty-equivalent wealth gain from investing in new funds and solve for the optimal participation decision, whereby new investors choose to participate if and only if doing so leads to a net gain in their expected utility.

LEMMA 2: *The certainty-equivalent wealth gain from investing in fund i is*

$$g(r_{i1}) \equiv -\frac{1}{\gamma}\ln\left(\frac{1-\operatorname{erf}(B)}{2} + \frac{1+\operatorname{erf}\left(\frac{B}{A}\right)}{2A}e^{-\left(1-\frac{1}{A^2}\right)B^2}\right), \tag{8}$$

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

$$A \equiv \sqrt{1+\frac{\sigma_\epsilon^2\sigma_\mu^2}{\left(\sigma_\epsilon^2+\sigma_0^2\right)\left(\sigma_\epsilon^2+2\sigma_0^2\right)}}, \quad B \equiv \frac{\sigma_\epsilon^2\mu_0+\sigma_0^2 r_{i1}}{\sqrt{2}\sigma_\epsilon^2\sigma_\mu}. \tag{9}$$

A new investor k chooses to pay the cost c_{ki} to investigate fund i if and only if the cost is lower than the certainty-equivalent wealth gain, $c_{ki} \leq g(r_{i1})$.

The certainty-equivalent wealth gain $g(r_{i1})$ is a function of the uninformative prior μ_0. It does not depend on existing investors' knowledge of α_{i0}, because new investors do not have that information before they incur the cost. The gain is monotonically increasing in r_{i1} and is independent of other funds. Hence, investors base their participation decision in each fund only on its own past performance.

COROLLARY 1: *For a new investor with participation cost c_{ki} for fund i, there exists a unique cutoff return level $\hat{r}(c_{ki})$ such that the investor chooses to participate if and only if the first-period return of the fund $r_{i1} \geq \hat{r}(c_{ki})$, where $\hat{r}(c_{ki})$ is the solution of r_{i1} for $g(r_{i1}) = c_{ki}$. Moreover, the cutoff return $\hat{r}(c_{ki})$ increases with the cost level c_{ki}.*

Our model recognizes the sunk nature of information costs, that is, new investors may choose not to invest in a fund after expending resources to investigate it. This situation can arise, for example, if a fund has a good realized return, r_{i1}, but a low ex ante expected ability level, α_{i0}, such that $\hat{r}(c_{ki}) < r_{i1} < \underline{r}_i(\alpha_{i0})$. Without knowing α_{i0} a priori, new investors would optimally decide that it is worthwhile to pay the cost to study the fund, only to find out later that the fund manager was just lucky.

To facilitate discussion of empirical implications, we define the flow, f_i, as the new money invested in the fund from time 0 to time 1. We express f_i in terms of a fraction of the initial asset in the fund, X_{i0}. 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: *The net flow into fund i on date 1 is given by*

$$f_i(r_{i1}) = \frac{X^e_{i1} - X_{i0}(1 + r_{i1})}{X_{i0}} + \lambda_i \min\left[1, \frac{g(r_{i1})}{\bar{c}_i}\right] \frac{X^n_{i1}}{X_{i0}}, \tag{10}$$

where X^e_{i1} *and* X^n_{i1} *are given in equation (7), and* $g(r_{i1})$ *is the certainty-equivalent wealth gain in equation (8).*

The first term of equation (10) describes the new money flow from existing investors, whereas the second term corresponds to the flow from participating new investors. Past performance has two effects on the current-period fund flows. The first is the *learning effect*, in which both existing investors and participating new investors allocate more wealth to the fund given a higher realized return, r_{i1}, since their allocations, (X^e_{i1}, X^n_{i1}), are increasing in r_{i1}. The second effect is the *participation effect*, in which higher past returns attract more new investors into the fund. This is because better past performance implies a higher certainty-equivalent wealth gain ($g(r_{i1})$) for new investors and enables investors with higher costs to overcome their participation hurdles.

In Figure 1, we plot fund flows in equation (10) as a function of past performance. Given the independence of flows across funds, we can interpret the comparative static analysis in this figure as the cross-sectional flow-performance relationship for funds with similar characteristics but different past performance. When costs are low (solid line, $\bar{c} = 0.1$), the fund flow is an increasing and convex function of the past performance in the low-to-medium performance range (approximately $r_{i1} < 0.25$ in the figure), and it becomes linear in the high performance range ($r_{i1} > 0.25$).[7] For these funds, even high-cost (δ high) investors have low levels of costs ($\delta\bar{c}$ low). Medium performance is sufficient to attract most investors to these funds. Hence, fund flows respond more strongly to past performance and the participation effect is more pronounced in the medium performance range. On the other hand, if these funds achieve high levels of performance, all potential new investors participate in the funds. Beyond the saturation point (around $r_{i1} \sim 0.25$), the participation effect dissipates and the fund flow is a linear function of performance as it is driven only by the learning effect.

For high-cost funds (dot-dashed and dashed lines), however, a large fraction of potential investors face high levels of information costs. So, while low-cost investors (with low δ) may participate in the low-to-medium performance ranges, the rest are only drawn to the funds at high levels of performance. As a result,

[7] In the very low performance range ($r_{i1} < -0.07$), the flow should be constant at -100%, yet the plotted line appears to be decreasing in performance. This feature is an artifact of the definition of the fund flow, as equation (10) reduces to $f = -(1 + r_1)$ when $X_1 = 0$. See also Berk and Green (2004) for further discussion.

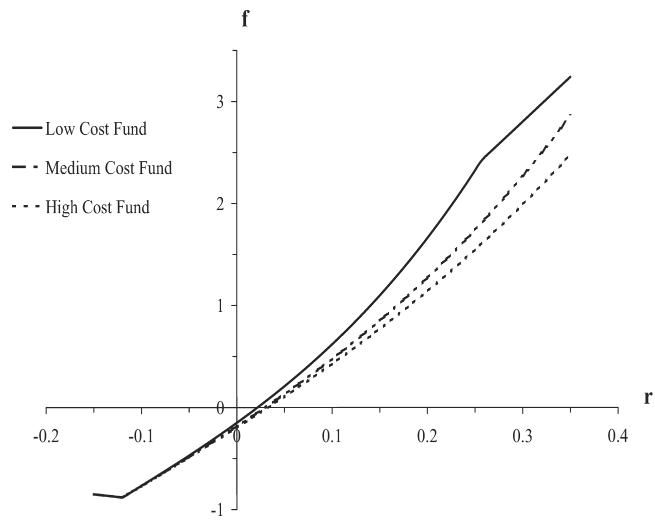

Figure 1. Theoretical flow-performance relationship for different levels of information costs. The solid line corresponds to a low information cost, where the maximum cost is $\bar{c} = 0.1$, and the other two lines correspond to higher information costs, where the dot-dashed line has maximum cost $\bar{c} = 0.2$ and the dashed line has $\bar{c} = 0.3$. Other parameters are $\gamma = 1$, $\lambda = 0.5$, $\sigma_\epsilon = 16\%$, $\alpha_{i0} = 3\%$, $\sigma_0 = 8\%$, $\mu_0 = 3\%$, and $\sigma_\mu = 3\%$, where γ is the risk aversion of the CARA investor, and λ is the relative population weight of new investors. Fund return is $r_{it} = \alpha_i + \epsilon_{it}$, where $\alpha_i \sim N(\alpha_{i0}, \sigma_0^2)$ is the prior about the managerial ability and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ is the i.i.d. noise over time and across funds. While the existing investors know the expected ability α_{i0} for sure, the new investors only have an uninformative prior about it, $\alpha_{i0} \sim N(\mu_0, \sigma_\mu^2)$.

these funds have a flatter flow response to past medium performance than do their lower-cost peers (solid line), while the response is steeper in the range of superior performance, as demonstrated in the figure.[8]

For these high-cost funds, the saturation point may not be reached at any realistic performance level. A comparison between the two high-cost funds implies that, in the empirically relevant performance range, the lower-cost fund of the two will always have higher flow sensitivities to performance than the higher-cost fund. Combined with the behavior of the low-cost fund (solid line), this observation illustrates that whether higher-costs funds have higher (solid vs. dashed lines) or lower (dot-dashed vs. dashed lines) sensitivities in the empirically feasible high-performance range is an empirical question to be answered by the data.

[8] The critical level of performance at which all potential investors will participate is much higher for these funds. 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 numerically solve a case in which the participation cost is normally distributed and reach similar conclusions.

C. With Portfolio Constraints

In our benchmark model there is no interaction among funds. Individual investors rely solely on the *absolute* performance of each fund when they allocate wealth across funds. Interestingly, even in this setting, we show that the predicted flow-performance relationship is consistent with the "winner-take-all" phenomenon in which winner funds have much higher flow sensitivity to performance than loser funds.

In reality, investors face various constraints that may lead to the consideration of funds' *relative* performance in wealth allocation. For instance, given the minimum investment levels required by most mutual funds and the existence of reasonable fixed costs for keeping track of their portfolios, investors are likely to concentrate their investment in a few funds with superior past performance. It is sensible to conjecture that this individual-level winner-picking behavior will lead to a more convex overall flow-performance relationship. What is less obvious, however, is whether the previously predicted impact of participation costs on the flow-performance relationship carries through in this case. To answer this question, we explicitly incorporate this individual winner-picking behavior into the existing model and reexamine the impact of participation costs.

To focus on the combined effect of participation costs and the winner-picking behavior on fund flows, we take a reduced-form approach to capture the reliance on relative fund performance in wealth allocation. Specifically, instead of trying to distinguish among different frictions that may lead to winner-picking by individual investors, we directly impose the portfolio constraint that each investor can invest in at most one new fund at time 1. Since the investor is still allowed to investigate as many funds as he chooses, this constraint naturally leads to the winner-picking behavior.

With the portfolio constraint, an investor takes a sequential approach in making participation and investment decisions, that is, he chooses whether to invest in the best fund that provides the highest utility gain among the ones that he has studied so far, or to incur additional costs to investigate another fund in the hope of identifying a better one. The following lemma establishes the criteria for such a decision based on the certainty-equivalent wealth gain.

LEMMA 3: *Assume that an investor can invest in at most one new fund at time 1. Let $\hat{\alpha}_1$ be the maximum posterior ability for all the funds that he has studied so far and $\mathcal{I}$ be the remaining set of funds available to him. Then,*

(i) The certainty-equivalent gain of studying a new fund with past performance r_{i1} is

$$G(r_{i1}, \hat{\alpha}_1) \equiv -\frac{(A^2-1)B_1^2}{\gamma} - \frac{1}{\gamma} \ln\left(\Phi_1 e^{-(A^2-1)B_1^2} + \Phi_2 e^{-(A^2-1)\frac{B^2}{A^2}}\right), \tag{11}$$

where A and B are as defined in Lemma 2,

$$B_1 \equiv \frac{(\sigma_\epsilon^2 + \sigma_0^2)\hat{\alpha}_1}{\sqrt{2}\sigma_\epsilon^2\sigma_\mu}, \quad \Phi_1 \equiv \frac{1 - \text{erf}(B - B_1)}{2}, \; \textit{and } \Phi_2 \equiv \frac{1 + \text{erf}\left(\dfrac{B}{A} - AB_1\right)}{2A}.$$

Moreover, $G(r_{i1}, \hat{\alpha}_1)$ is increasing in r_{i1} and is decreasing in $\hat{\alpha}_1$.

(ii) Investor k with cost level c_{ki} chooses to investigate a new fund $i_{\max}$ if and only if

$$\max_{i \in \mathcal{I}} G(r_{i1}, \hat{\alpha}_1) - c_{ki} > 0 \quad \textit{and} \quad i_{\max} \equiv \arg\max_{i \in \mathcal{I}} G(r_{i1}, \hat{\alpha}_1) - c_{ki},$$

and he invests in the fund with ability level $\hat{\alpha}_1$ when he stops investigating.

In general, an investor trades off the gain and the cost of investigating another fund in order to maximize his net utility gain. Given the portfolio constraints, whether or not an investor decides to investigate a fund depends not only on the fund's past performance (r_{i1}) and his participation costs (c_{ki}), but also on the performance of other funds. In particular, the certainty-equivalent wealth gain $G(r_{i1}, \hat{\alpha}_1)$ is decreasing in $\hat{\alpha}_1$, indicating that an investor is less inclined to investigate more funds if he has identified one with high posterior ability. Similar to the unconstrained case, $G(r_{i1}, \hat{\alpha}_1)$ is increasing in r_{i1}. Among mutual funds with the same level of participation costs, an investor always starts with the one with the highest rank of past performance.

To understand the impact of participation costs on fund flows in the presence of portfolio constraints, we consider the case in which all funds have the same participation cost $\bar{c}$. If $\bar{c} = 0$, all investors optimally choose to investigate all available funds. With homogeneous expectations, they all choose to invest in the same fund. It is important to point out that the best fund may not be the one with the highest past performance. Rather, it is the one with the highest posterior managerial ability, which also depends on the prior α_{i0}. If $\bar{c} > 0$, for an investor with a very low individual cost (δ_k close to zero), the decision is similar to that in the zero-cost case. Specifically, he studies all funds and invests in the best fund with the highest posterior ability. On the other hand, an investor with a high level of individual costs (large δ_k) would optimally investigate funds with higher past returns first. He is likely to stop investigating more funds once he has identified a reasonably good one, potentially missing the best fund, which may not have a stellar recent performance. Contrasting these two cases, we conclude that flows to mutual funds with higher participation costs are more concentrated in funds with superior performance relative to their lower-cost counterparts.

This setting also implies that flows are likely to be concentrated in just a few funds. In reality, however, a large number of mutual funds receive inflows. This discrepancy may be accounted for by realizing that there are a lot of investor heterogeneities that we have not considered in the model. Most investors settle on a subset of funds in which they will potentially invest in a rather arbitrary way. For example, they may heed the recommendations of friends or brokers, or may simply be constrained by the limited offerings in their 401(K) plans. To

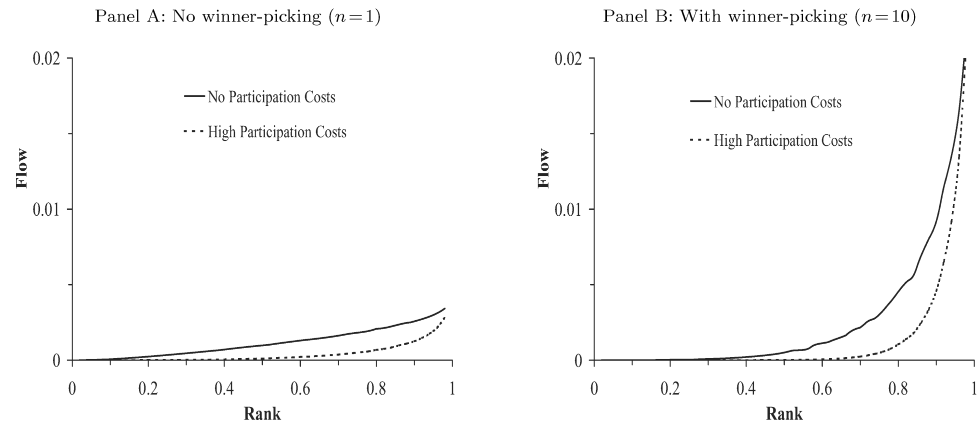

Figure 2. Theoretical flow-performance relationship for different levels of information costs, under portfolio constraints. We report only the flow from new investors. Panel A (B) reports fund flows in the absence (presence) of individual winner-picking by assuming that investors have access to a randomly selected subset of $n = 1 (n = 10)$ fund(s). The solid line in each panel corresponds to no participation costs ($\bar{c} = 0$), and the dashed line to high participation costs ($\bar{c} = 0.2$). Other parameters are $\gamma = 1, \sigma_\epsilon = 16\%, \alpha_{i0} = 3\%, \sigma_0 = 8\%, \mu_0 = 3\%$, and $\sigma_\mu = 3\%$, where γ is the risk aversion of the CARA investor. Fund return is $r_{it} = \alpha_i + \epsilon_{it}$, where $\alpha_i \sim N(\alpha_{i0}, \sigma_0^2)$ is the prior about the managerial ability and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ is the i.i.d. noise over time and across funds. While the existing investors know the expected ability α_{i0} for sure, the new investors only have an uninformative prior about it, $\alpha_{i0} \sim N(\mu_0, \sigma_\mu^2)$.

account for these heterogeneities, we assume that each individual investor has access to only a random subset of n mutual funds. They are either unaware of or, for exogenous reasons, unwilling to invest in other funds. We further assume that the investment opportunity sets are independent across investors, and that the probability of a fund being included in an investment opportunity set is independent of its past performance.[9]

While a closed-form solution is not attainable, we can obtain the flow-performance relationship using numerical simulations, which we describe in Appendix B. The results are illustrated in Figure 2. Since fund flows for existing investors are not affected by participation costs and are exactly the same as those in the unconstrained case, we plot only the flows for new investors to focus on the impact of participation costs. To be consistent with our empirical tests later, we use the relative performance rank in percentiles.

In Panel A, we plot fund flows for the case of each investor having only one randomly selected fund in his opportunity set. There is no winner-picking at the individual level, and the resulting fund flows are driven by the gradual participation of new investors identified in the unconstrained case. Our previous result on the participation effect is confirmed by comparing the dashed

[9] Although a fund's past superior performance generally helps improve its visibility, our assumption is conservative in that it biases against finding the result that high-cost funds have higher flow-performance sensitivity in the high performance range.

(high-cost funds) and the solid lines (zero-cost funds). In Panel B, there is individual winner-picking since each investor is restricted to investing in only 1 fund out of the 10 randomly selected funds in his opportunity set ($n = 10$). The graph clearly demonstrates that investment from new investors in funds with lower participation costs is more sensitive to past performance in the medium performance range and that this relationship is reversed in the high performance range.

Comparing the solid lines (or the dashed lines) across Panels A and B, we observe that, for a given level of participation costs, the individual winner-picking effect leads to a more convex flow-performance relationship. Moreover, the contrast between the solid and the dashed lines in Panel B indicates that the participation and the individual winner-picking effects reinforce each other and produce the same prediction regarding the impact of participation costs on fund flows.

D. Transaction Costs

In addition to a fixed information cost for investing in a new fund, both existing and new investors may also face a proportional transaction cost for purchasing (or redeeming) shares of a mutual fund, corresponding to front (or back)-end loads. For simplicity, we consider fund flows in the absence of portfolio constraints in this part.

LEMMA 4: *Let ρ_+ (or ρ_-) be the proportional transaction cost for purchasing (or redeeming) shares of the mutual fund. At time $t = 1$, the existing investor allocates X_{i1}^e dollars to the mutual fund, where*

$$X_{i1}^e(X_{i0}, r_{i1}) = \begin{cases} \dfrac{1}{\gamma(2\sigma_0^2+\sigma_\epsilon^2)}(\alpha_{i0}-\rho_+) + \dfrac{\sigma_0^2}{\gamma\sigma_\epsilon^2(2\sigma_0^2+\sigma_\epsilon^2)}(r_{i1}-\rho_+), & \text{if } r_{i1} \geq \bar{r}_{i+} \\ X_{i0}(1+r_{i1}), & \text{if } \bar{r}_{i-} \leq r_{i1} < \bar{r}_{i+} \\ \dfrac{1}{\gamma(2\sigma_0^2+\sigma_\epsilon^2)}(\alpha_{i0}+\rho_-) + \dfrac{\sigma_0^2}{\gamma\sigma_\epsilon^2(2\sigma_0^2+\sigma_\epsilon^2)}(r_{i1}+\rho_-), & \text{if } \underline{r_i} \leq r_{i1} < \bar{r}_{i-} \\ 0, & \text{otherwise}, \end{cases} \tag{12}$$

and $\bar{r}_{i+}, \bar{r}_{i-}$, and $\underline{r_i}$ are defined in Appendix A. The dollar holding for participating new investors is $X_{i1}^n(r_{i1}) = X_{i1}^e(0, r_{i1})$.

The desired holding of the mutual fund is piecewise linear in past performance r_{i1}. When $r_{i1} > \bar{r}_{i+}$, the past performance is sufficiently good that investors choose to purchase additional shares of the fund. Proportional transaction costs effectively reduce the posterior expected return in equation (5) by ρ_+ for the next period. In contrast, when $r_{i1} < \bar{r}_{i-}$, the past performance is so bad 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_-. Between

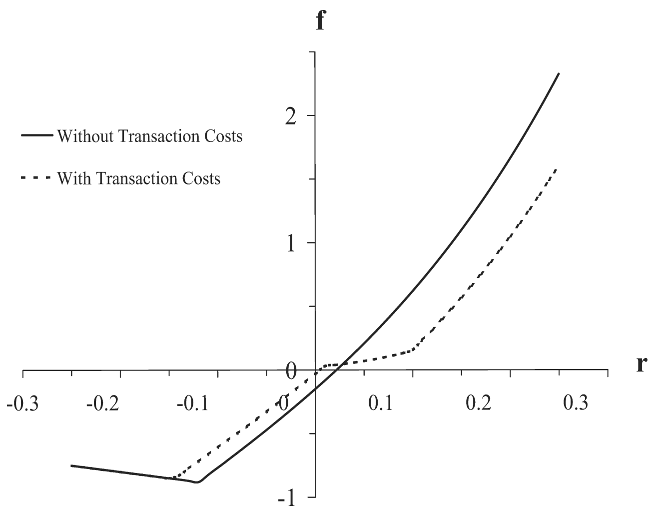

Figure 3. Theoretical flow-performance relationship for different levels of transaction costs. The solid line corresponds to zero transaction costs when $\rho_+ = \rho_- = 0$, and the dotted line corresponds to positive transaction costs when $\rho_+ = 1\%$ and $\rho_- = 0.5\%$. Other parameters are $\bar{c} = 0.1, \gamma = 1, \lambda = 0.5, \sigma_\epsilon = 16\%$, $\alpha_{i0} = 3\%, \sigma_0 = 8\%, \mu_0 = 3\%$, and $\sigma_\mu = 3\%$, where $\bar{c}$ is the maximum participation cost, γ is the risk aversion of the CARA investor, and λ is the relative population weight of new investors. Fund return is $r_{it} = \alpha_i + \epsilon_{it}$, where $\alpha_i \sim N(\alpha_{i0}, \sigma_0^2)$ is the prior about the managerial ability and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ is the i.i.d. noise over time and across funds. While the existing investors know the expected ability α_{i0} for sure, the new investors only have an uninformative prior about it, $\alpha_{i0} \sim N(\mu_0, \sigma_\mu^2)$.

the two cutoff return levels is a no-trade region where the past performance is not sufficient to induce new purchases but still high enough to discourage redemptions. Investors do not trade and the dollar holdings change only due to the realized return on existing positions. Holdings have a lower bound of zero since investors are not allowed to sell short the fund. Finally, since a participating new investor has the same information as an existing investor, the holding of the former is the same as that of the latter with zero initial holding of the fund.

Figure 3 plots the flow-performance relationship in equation (10) with the optimal holdings X_{i1}^n and X_{i1}^e given in Lemma 4. Comparing the cases with (the dotted line) or without (the solid line) transaction costs, we observe that fund flows are less sensitive to medium performance for funds with higher transaction costs. The driving force for this result is the presence of the no-trade region. Although the mechanisms are entirely different, the predicted impact of proportional transaction costs on the flow-performance relationship is similar to that of information costs in the medium performance range.

E. Empirical Implications

Our theory highlights the effect of participation costs on the flow-performance relationship. While in the model the participation cost refers mainly to individual investors' cost of actively seeking out information about funds, it is complemented by the cost borne by funds to increase their visibility and reduce information barriers for investors. The more a fund expends resources in this effort, the less cost an investor needs to incur in actively collecting information. This leads to cross-sectional implications of our model that may be tested using fund characteristics that proxy for differences in visibility and information barriers across funds. For expositional convenience, we describe funds with high information barriers or low visibility as having high information costs.

In our model, we outline three channels through which participation costs can influence fund flows, namely, the participation and individual winner-picking effects due to information costs, and the no-trade effect due to transaction costs. All three effects lead to a stronger response of flows to performance in the medium performance range for funds with lower participation costs. In the high performance range, although the individual winner-picking effect predicts a stronger response of flows to performance for funds with higher participation costs, the implication of the participation effect may depend on the overall level of participation costs among the funds, as we discussed earlier in connection with Figure 1. Finally, the effect of transaction costs alone does not predict a difference in the high performance range.

Therefore, our main empirical prediction is that, in the medium performance range, both information costs and transaction costs will lead lower-cost funds to have a higher flow sensitivity to performance than their higher-cost counterparts. In the high performance range, information costs may cause this relationship to reverse.[10] In the following sections, we identify different proxies for both information costs and transaction costs and empirically verify this prediction.

II. Data and Empirical Methodology

A. Data

Our main data source is the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database, from 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. 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 data set mainly consists of

[10] Participation costs also have an effect on the level of fund flows, as Figure 1 illustrates. This is consistent with the earlier empirical evidence in Sirri and Tufano (1998), Jain and Wu (2000), Massa (2003), and Nanda et al. (2004b). In this paper, we focus instead on the implications of our model for the sensitivity of flows to past performance.

actively managed equity funds in the following investment objective categories: aggressive growth, growth, and growth and income.

Our sample period spans the years from 1981 to 2001, when complete information about fund managers and investment objectives is available.[11] 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, age, and total net assets, we extract these data from the CRSP mutual fund database.

Using quarterly total net asset values from CRSP, we define the quarterly net flow into a fund as

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

where $R_{i,t}$ is the return of fund i during quarter t, and $TNA_{i,t}$ is fund i's total net asset value at the end of quarter t. Hence, our definition of the 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 Elton, Gruber, and Blake (2001) indicate, there exists a large number of errors associated with mutual fund mergers and splits in the CRSP mutual fund database, which leads to extreme values of flows. To prevent a potential impact from these outliers, we filter out the top and bottom 2.5% tails of the net flow data.

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 3,265 funds in 2001 for our empirical analysis.[12] During our sample period, the average number of funds managed by each fund family has increased from about 4 in 1981 to 14 in 2001. At the same time, the average age of funds has 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,[13] 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%.

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

[12] 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 flows, listing each share class separately does not lead to the double-counting problem. Nonetheless, we have also conducted all analysis at the fund level by combining multiple share classes of the same fund. Our results regarding the effect of information costs are not affected by the treatment of share classes.

[13] 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 7 years.

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, four-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 (%)	Four-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

B. Empirical Methodology

To examine the flow-performance sensitivity, in each quarter we run cross-sectional regressions to estimate the sensitivity of flows to performance, controlling for other factors that could potentially affect the level of flows. We report the means and t-statistics from the time series of coefficient estimates following Fama and MacBeth (1973).[14] Because we relate quarterly flows 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 autocorrelated. To account for this problem, we calculate the Fama–MacBeth t-statistics using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors.

[14] We also repeat all analysis using unbalanced panel regressions with time effects and panel-corrected standard errors that adjust for autocorrelations for each fund and heteroskedasticity across funds. The results are not materially different from those reported later in this paper.

We use two measures of fund performance. The first measure is the ranking of funds' preceding 12-month returns within their respective investment objective categories. The second measure is the ranked risk-adjusted returns in the preceding 36 months according to the four-factor model of Carhart (1997):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{MOM} MOM_t + \varepsilon_{i,t}, \tag{13}$$

where $R_{i,t}$ and $R_{f,t}$ are the return for fund i and the 1-month T-bill rate in month t, respectively, and MKT_t, SMB_t, HML_t, and MOM_t are the month-t returns of the three Fama and French (1993) factors and the momentum factor.[15] To ensure the accuracy of estimation, we include only funds that exist for at least 20 months during the estimation period.

Previous studies document that other non–performance-related variables also affect flows and their sensitivity to performance. Therefore, we include as control variables the total risk of a fund measured by the standard deviation of returns over the performance estimation period, fund age measured by the natural logarithm of $(1 + age)$ and its interaction with performance, fund size measured by the natural logarithm of fund TNA in the previous quarter, and the lagged total fee ratio. Finally, we include the aggregate flow into each fund category in quarter t to control for other unobserved factors, such as sentiment shifts, that can potentially influence 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 rank all funds according to their past relative performance within their respective investment objective categories or their Carhart four-factor alphas, and assign them a continuous rank ranging from zero (worst) to one (best), with the rankings corresponding to their performance percentiles. Funds are then classified into low, medium, and high performance groups. Funds ranked in the lowest (highest) performance quintile are in the low (high) group. The medium group includes funds with performance ranked in the middle three quintiles. To examine the impact of participation costs on the flow-performance sensitivity at different performance levels, we interact performance rank with a proxy for lower participation costs ($LPC_{i,t-1}$) in the following regression:

$$\begin{aligned} Flow_{i,t} = a &+ b_1 * Low_{i,t-1} + \beta_1 * Low_{i,t-1} \times LPC_{i,t-1} \\ &+ b_2 * Mid_{i,t-1} + \beta_2 * Mid_{i,t-1} \times LPC_{i,t-1} \\ &+ b_3 * High_{i,t-1} + \beta_3 * High_{i,t-1} \times LPC_{i,t-1} \\ &+ Controls + \varepsilon_{i,t}, \end{aligned} \tag{14}$$

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

where $Low_{i,t-1}$ represents the performance rank in the lowest quintile, $Mid_{i,t-1}$ represents the performance rank in quintiles 2–4, and $High_{i,t-1}$ represents the performance rank in the highest quintile.[16]

III. Empirical Results

Our theory highlights investors' participation costs as an important determinant of the asymmetric flow-performance relationship. In this section, we empirically test this prediction using several proxies for variations in funds' participation costs.

A. The Effects of Information Costs

Since funds' marketing efforts can potentially lower investors' information costs, we use marketing expenses as one proxy for the reduction in fund-level participation costs. Due to data limitations, we follow Sirri and Tufano (1998) and measure marketing expenses using a fund's total fee ratio, defined as the annual expense ratio plus one-seventh of the up-front load fees. Although this measure includes components other than marketing expenses, Sirri and Tufano point out that funds spend close to half of their expenses on marketing. Therefore, it is reasonable to conjecture that funds with higher total fees spend more on advertising and distribution efforts on average.[17]

Del Guercio and Tkac (2002b), Khorana and Servaes (2004), and Nanda et al. (2004b) 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 increased fund flows. Since investors who are attracted to a star fund can potentially become aware of other offerings of the family, the information costs for those star-affiliated funds may be reduced. Therefore, we use a fund's affiliation with a family that has produced star funds as a second proxy for the reduced participation costs.[18]

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 large and established families such as Fidelity or Vanguard (see Capon et al. (1996) and Goetzmann and Peles (1997)). Affiliated funds are also able 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. Therefore, our third and fourth proxies capture the effect of family affiliation, which leads to reduction of information barriers and the economy of scale in services provided. Specifically, the third proxy is family size,

[16] Specifically, the fractional 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. We also form three groups consisting of an equal number of funds based on their performance ranking and find similar results.

[17] We also use the 12b-1 fees plus one-seventh of front-end loads as an alternative measure of marketing expenses.

[18] Details of the identification of a star fund are discussed later.

measured by the total net assets under management in the affiliated family, which reflects the brand recognition and resources of the family; the fourth proxy is the number of fund categories offered by the affiliated family, which measures the breadth of offerings.

To get an overview of the impact of participation costs, we first compare the flow-performance relationship for funds with different levels of participation costs. In each quarter of our sample period, we separate all funds into two groups according to their respective levels of the aforementioned characteristics. For the star-affiliation measure, the groups are defined as whether or not the fund is affiliated with a family that has produced other star funds. For all other measures, we use the median level of the particular characteristic as the break point for the two groups. Within each group, we rank fund returns into 10 bins based on their Carhart four-factor alphas estimated from equation (13). We average the flows for all funds in each performance bin to obtain a flow-performance relationship. The results are presented in Figure 4.

The first impression one obtains from the figure is that, for all four proxies, funds with low participation costs (solid lines) attract more flows than funds with high participation costs across the entire performance spectrum. This effect of participation costs on the level of flows is consistent with both our model prediction and earlier empirical evidence, as documented in Sirri and Tufano (1998), Jain and Wu (2000), Del Guercio and Tkac (2002b), Massa (2003), and Nanda et al. (2004b). The only exception is that the non–star-affiliated funds do not seem to attract lower flows when they achieve superior past performance than do the star-affiliated funds. This is mainly because funds achieving this level of performance are more likely to be stars than star-affiliated, and hence attract more inflows by themselves.

Close inspection of Figure 4 reveals that, in Panel A, funds with high-marketing expenses have a stronger flow-performance sensitivity in the medium performance range than do their low-marketing-expenses counterparts, while in the high performance ranges, the slope for the low-marketing-expenses funds is higher. Similar patterns obtain in all other panels as well.

Although the flow-performance relationships presented in Figure 4 are consistent with our predictions, we need to interpret these observations with caution, as we have not controlled for other fund characteristics that also have effects on fund flows. To provide more rigorous statistical evidence for our predictions, we carry out regression analyses in the following subsections using the four proxies discussed above. Specifically, after controlling for other characteristics known to affect fund flows, we expect to find a positive coefficient β_2 and a negative coefficient β_3 in the regression (14).

A.1. Marketing Expenses

Using the total fee ratios in place of $LPC_{i,t-1}$ in regression (14), we study the effect of marketing expenses on flow sensitivity to performance in a multivariate regression analysis. The results are presented in Table II. Consistent

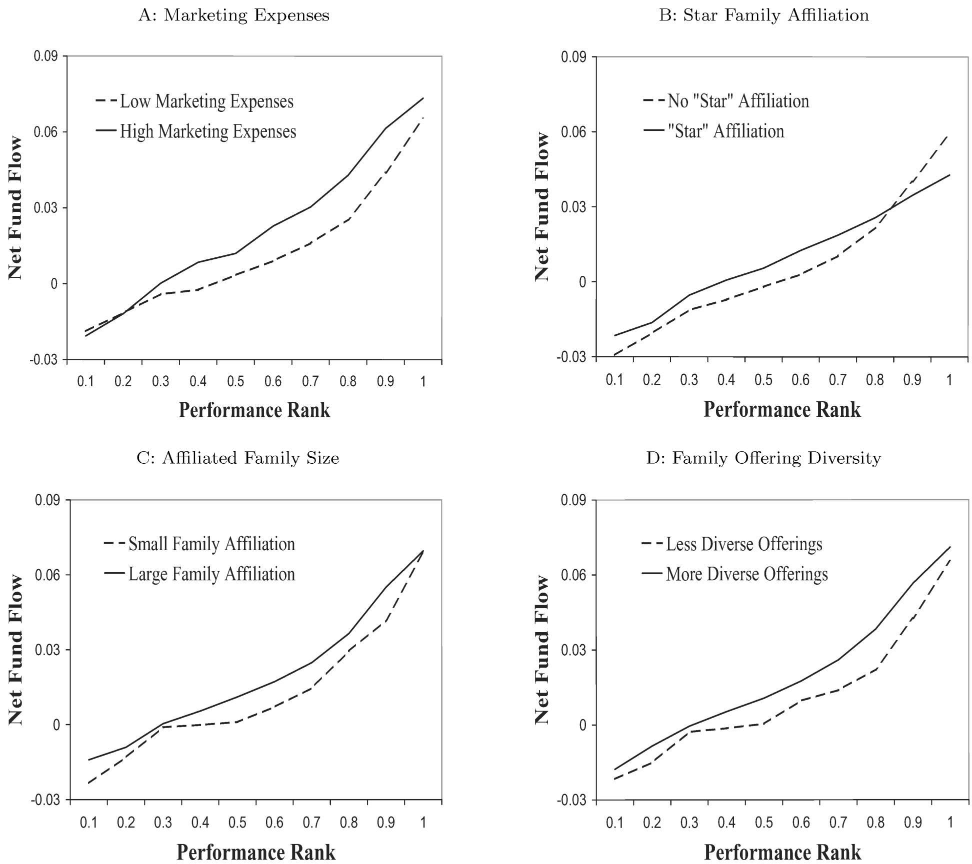

Figure 4. The flow-performance relationship for different levels of information costs proxied by fund characteristics during 1981–2001. Panel A reports the result for marketing expenses, measured by the total fee ratio. Panel B reports the result for the affiliation with a star-producing family. Panel C reports the result for the affiliated-family size, measured by the total net assets under management within the fund family. Panel D reports the result for the diversity of the affiliated-family offering, measured by the number of fund categories offered by the fund family.

with the model prediction, the coefficient for the interaction term between performance and the total fee ratio is significantly positive in the medium performance range and significantly negative in the high performance range. In particular, if we focus on the first column, where the ranking of raw returns is used as a measure of performance, the result shows that a 1% increase in the total fee ratio will increase the sensitivity of flows to the mid-range performance from 0.104 to 0.122, an 18% increase, while reducing flow sensitivity to the top-quintile performance from 0.428 to 0.380, an 11% decrease. This leads to an overall less convex flow-performance relationship for funds that have high marketing expenditures. Moreover, this result is robust if we use

Table II

The 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 zero to one 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 four-factor model alphas during the past 36 months. The fractional rank for funds in the bottom performance quintile (Low) is defined as Min ($Rank_{t-1}$, 0.2). Funds in the three medium performance quintiles (Mid) are grouped together and receive ranks that are defined as Min (0.6, $Rank_{t-1}$ − Low). The rank for the top performance quintile (High) is defined as $Rank_{t-1}$ − Mid − Low. Each quarter a piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance rankings over the low, medium, and high performance ranges, their interaction terms with total fees, or distribution expenses (measured as 12b-1 fees plus one-seventh front-end loads). The control variables include aggregate flow into the fund objective category, volatility of monthly returns during the performance measurement period, the logarithm of one plus fund age and its interaction with performance, the logarithm of fund size as proxied by lagged total net asset value, and lagged total fees (or lagged distribution expenses). Time-series average coefficients and the Fama–MacBeth *t*-statistics (in parentheses) calculated with Newey–West robust standard errors are reported. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Marketing Expense Proxy	Expense Ratio + 1/7 Front-End Loads		12b-1 Fees + 1/7 Front-End Loads	
Performance Measured by	Raw Return	Four-Factor Alpha	Raw Return	Four-Factor Alpha
Intercept	0.015*	0.020**	0.008	0.012
	(1.78)	(2.54)	(1.09)	(1.51)
Category Flow	0.671***	0.362***	0.652***	0.327***
	(7.57)	(5.05)	(7.58)	(3.76)
Low	0.117***	0.064**	0.009***	0.057***
	(3.32)	(2.44)	(4.39)	(3.26)
Low ∗ Marketing Expense	1.645	1.434	9.583***	8.468***
	(0.98)	(1.22)	(3.78)	(3.99)
Mid	0.104***	0.064***	0.123***	0.072***
	(9.52)	(6.12)	(14.17)	(9.75)
Mid ∗ Marketing Expense	1.802***	1.023***	1.747**	1.136**
	(3.79)	(2.70)	(2.48)	(2.09)
High	0.428***	0.291***	0.380***	0.227***
	(10.06)	(8.87)	(13..90)	(10.20)
High ∗ Marketing Expense	−4.810**	−5.256***	−5.536*	−5.273**
	(−2.26)	(−3.05)	(−1.96)	(−2.05)
Volatility	−0.271***	−0.164*	−0.257***	−0.156*
	(−3.15)	(−1.90)	(−3.02)	(−1.77)
Age	−0.011***	−0.012***	−0.010***	−0.012***
	(−6.93)	(−9.33)	(−7.21)	(−9.83)
Age ∗ Performance	−0.022***	−0.006***	−0.022***	−0.005***
	(−9.76)	(−2.97)	(−9.97)	(−2.72)
Size	−0.002***	−0.001**	−0.001	0.000
	(−3.70)	(−2.44)	(−1.59)	(−0.33)
Expense Ratio			0.141	0.353**
			(0.93)	(2.50)
Distribution Expenses			−1.965***	−1.667***
			(−5.30)	(−4.80)
Total Fees	−0.723***	−0.345*		
	(−3.14)	(−1.91)		

a performance ranking based on risk-adjusted returns measured by the four-factor alphas (Carhart 1997), as shown in the second column of Table II.

The effects of other determinants of flows shown in Table II are consistent with those demonstrated in previous studies. For example, we find a negative relationship between fund flows and the standard deviation. This finding holds for regressions with both performance measures, although the effect of risk on fund flows is weaker when performance is measured using the four-factor alphas. Consistent with the results of Chevalier and Ellison (1997), we find that both the level of flows and the sensitivity of flows to past performance are lower for older funds. In addition to the interaction between total fees and performance, we control for the total expense ratio itself in the regression. As the table shows, after controlling for the effect of the expense ratio on reducing information costs, a higher expense ratio lowers the level of fund flows.

Barber, Odean, and Zheng (2005) document that flows are more sensitive to 12b-1 fees than other components of the costs incurred by fund investors. Therefore, we use distribution expenses, which is the sum of the 12b-1 fees plus one-seventh of the front-end loads, as an alternative measure of marketing expenses.[19] The results, also presented in Table II, are qualitatively similar to the ones using total fee ratios.

In summary, funds with greater marketing and distribution efforts enjoy greater investor recognition and a lower performance threshold for attracting new investors. A moderate level of performance is sufficient to attract most investors into these funds, leading to higher flow sensitivity in the medium performance range. On the other hand, funds with lower marketing expenses will start to attract more new investors only as performance improves further, and flows become more sensitive to performance only in the superior performance range.

A.2. "Star" Family Affiliation

As a prominent gauge of fund quality followed by many investors, Morningstar five-star ratings can bring the designated funds 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. Following Nanda et al. (2004b), we use a procedure to mimic the Morningstar ratings by ranking funds according to their risk-adjusted performance.

According to this procedure,[20] in each period a fund is assigned a score based upon the difference between a load-adjusted return and a risk measure during

[19] The 12b-1 fees were not explicitly recognized until 1992. Our results are robust to using either the post-1992 sample period or the entire sample period with the 12b-1 fees in the pre-1992 period set to be zero. The results presented here are from the entire sample period. We also use 12b-1 fees only as a proxy for the post-1992 period and find consistent results.

[20] Details of the procedure that mimics the Morningstar ratings system may be found in the appendix of Nanda et al. (2004b). They find that 88% of the five-star funds determined by this mimicking procedure overlap five-star funds from the Morningstar publications for a randomly selected date in May 1995.

the past 3 years. Within each fund category, funds are then ranked according to their 3-year scores relative to their peers. Funds that are ranked in the top 10% of each category are assigned five-star ratings. Morningstar also provides 5-year and 10-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 in business publications, it is highly correlated with the 3-year ratings, as Sharpe (1997) points out. Therefore, we focus on the 3-year ratings to designate star funds. Their parent companies are hence designated as star families.

Table III presents an analysis based on this star-identifying scheme. We proxy for participation costs with a dummy variable that is equal to one if a fund is affiliated with a star family but is not a star itself, and zero otherwise. To control for the effect of the publicity surrounding star status, we also include a dummy variable indicating star funds.

As Table III shows, 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, even if the fund itself is not a star. Meanwhile, the interaction term for the high performance range is not significant. This shows that being affiliated with a star-producing family does not help a fund that has already achieved superior performance. This can be seen in that the star dummy itself is significantly positive, which is also an indication that our star rating scheme well captures the name recognition and media attention received by funds with outstanding performance. 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.

A.3. Affiliation with Large Families

In this subsection, we examine the effect of affiliation with large fund families to account for the economy of scale in raising fund visibility, providing services, and reducing investment barriers. We measure the effect of family affiliation in two different ways. The first measure is the logarithm of total net assets under management for the fund complex at the beginning of each quarter. The second measure is the number of fund categories offered by the affiliated family.

Sirri and Tufano (1998) posit that funds affiliated with larger families will receive greater inflows, and that the flow-performance relationship will be stronger for larger complexes. Our results in Table IV reveal a more specific mechanism by which parent complex size affects the flow-performance relationship: Affiliation with a large family makes it easier for funds with moderately good performance to attract new investors, resulting in a higher flow sensitivity to medium performance. This affiliation also leads to a reduction in the sensitivity of flows to superior performance.

Another benefit of being affiliated with a large family is that investors can obtain access to a wide range of products. Accordingly, we use the number of fund types available to measure the breadth of offerings by the family. While this

Table III

The Effect of Affiliation with a Star Family on the Flow-Performance Relationship

This table examines the effect of affiliation with a star-producing family 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 one for funds that are affiliated with star families but are not stars themselves, and zero otherwise. A piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance rankings over the low, medium, and high performance ranges, a dummy variable indicating star family affiliation, and 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, the logarithm of one plus fund age and its interaction with performance, the logarithm of lagged fund size, and lagged total fee ratio. Time-series average coefficients and the Fama–MacBeth t-statistics (in parentheses) calculated with Newey–West robust standard errors are reported. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Performance Measured by	Raw Return	Four-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 ∗ Star Affiliation	−0.030	0.008
	(−0.82)	(0.09)
Mid	0.113***	0.084***
	(14.61)	(11.86)
Mid ∗ Star Affiliation	0.020***	0.018***
	(3.21)	(3.15)
High	0.242***	0.127***
	(14.74)	(7.70)
High ∗ Star Affiliation	−0.031	−0.012
	(−0.67)	(−0.41)
Star Affiliation	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)

measure may be correlated with family size, it captures the effort by fund families to accommodate investors' desire to diversify within the same family, as well as to target investor heterogeneity and increase market share. Elton, Gruber, and Busse (2004) find that, among funds that offer an essentially homogeneous

Table IV

The Effects of Family Size on the Flow-Performance Relationship

This table examines the effect of family size, as measured by total assets or total number of investment categories 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 rankings over the low, medium, and high performance ranges, a measure of the size of 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, the logarithm of one plus fund age and its interaction with performance, the logarithm of lagged fund size, and lagged total fee ratio. Time-series average coefficients and the Fama–MacBeth t-statistics (in parentheses) calculated with Newey–West robust standard errors are reported. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Family Size Proxy	Log [Family Assets]		Diversity Dummy	
Performance Measured by	Raw Return	Four-Factor Alpha	Raw Return	Four-Factor Alpha
Intercept	−0.020**	−0.001	0.002	0.009
	(−2.32)	(−0.07)	(0.24)	(1.27)
Category Flow	0.605***	0.272***	0.667***	0.358***
	(6.76)	(3.35)	(7.79)	(5.09)
Low	0.240***	0.121***	0.161***	0.103***
	(6.23)	(4.27)	(8.76)	(5.78)
Low ∗ Family Size	−0.013*	−0.005	−0.011	−0.017
	(−1.91)	(−0.93)	(−0.43)	(−0.79)
Mid	0.105***	0.056***	0.123***	0.072***
	(9.41)	(5.85)	(14.11)	(10.27)
Mid ∗ Family Size	0.004***	0.004***	0.013**	0.017***
	(3.94)	(3.49)	(2.13)	(3.63)
High	0.394***	0.368***	0.380***	0.265***
	(9.01)	(8.28)	(15.47)	(12.76)
High ∗ Family Size	−0.006	−0.023***	−0.054*	−0.083***
	(−0.85)	(−3.54)	(−1.80)	(−3.69)
Family Size	0.004***	0.002**	0.004	0.004
	(3.33)	(2.63)	(0.96)	(1.12)
Volatility	−0.260***	−0.108	−0.295***	−0.166*
	(−2.97)	(−1.21)	(−3.35)	(−1.93)
Age	−0.009***	−0.011***	−0.010***	−0.011***
	(−5.63)	(−9.06)	(−6.68)	(−8.80)
Age ∗ Performance	−0.025***	−0.006***	−0.023***	−0.007***
	(−10.68)	(−3.07)	(−10.11)	(−3.53)
Size	−0.003***	−0.003***	−0.002***	−0.001***
	(−5.47)	(−4.66)	(−4.30)	(−2.91)
Total Fees	−0.063	0.039	−0.076	0.043
	(−0.74)	(0.56)	(−0.86)	(0.60)

product (an S&P 500 index fund), those that are part of a family that offers a variety of other types of funds attract significantly more cash flows. To examine the effect of this type of reduction in participation costs for investors, we use the number of CDA investment objectives offered by the parent family as our second measure of family affiliation.[21] Because of the clustering nature of such a

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

measure, we employ a binary dummy that takes the value of one if the measure is above the median among all families, and zero otherwise.

These results are also reported in Table IV. On average, funds in families with diverse offerings see their flow sensitivities to mid-range performance increase by about 10%, from 0.123 to 0.136, when the performance is measured by the rank of returns (or by about 25%, from 0.072 to 0.089, when the performance is measured on a risk-adjusted basis). The sensitivity of flows to top-tier performance tends to be lower for these funds. This is consistent with the hypothesis that diversity of offerings helps reduce participation costs.

A.4. The Combination of Various Proxies

The analysis so far focuses on individual variables that proxy for different aspects of information costs. It is possible that some of these variables may be correlated with each other and hence affect our interpretation of their respective effects. In Table V, we report the time-series averages of the cross-sectional correlation coefficients of these proxies, flow, and performance. The table shows that larger fund families tend to charge lower fees, produce more star funds, and offer a wider range of funds. It is, therefore, useful to examine the joint effect of these variables in a multiproxy regression analysis. The results of this analysis are presented in Table VI, where, due to space limitations, we only report the slope coefficients for different levels of performance, measured by the Carhart four-factor alpha, and their interaction terms with proxies for participation costs.

Table V

Correlation Matrix among Proxies for Information Costs

This table presents the correlation matrix among proxies for information costs, flow, and performance. “Performance” is measured as the Carhart four-factor alphas during the previous 36 months; “Total Fees” is the expense ratio plus one-seventh front-end loads; “Distribution Expenses” is measured as 12b-1 fees plus one-seventh front-end loads; “Star Affiliation” is a dummy variable that is one if the fund is affiliated with a star-producing family, where a star fund is designated by mimicking the Morningstar classification; “Family Assets” measures the logarithm of total net assets managed by the affiliated family; and “Diversity” is a dummy variable that is one if the number of different fund categories offered by the affiliated family is larger than the medium number for all families, and zero otherwise. The correlations reported are time-series averages of the Pearson correlations calculated each quarter.

	Performance	Flow	Total Fees	Distribution Expenses	Star Affiliation	Family Assets	Diversity
Performance	1.00						
Flow	0.22	1.00					
Total Fees	−0.12	0.00	1.00				
Distribution Expenses	−0.01	−0.01	0.59	1.00			
Star Affiliation	−0.01	0.00	−0.04	0.06	1.00		
Family Assets	0.15	0.05	−0.17	0.17	0.39	1.00	
Diversity	0.03	0.01	0.01	0.21	0.28	0.59	1.00

Table VI

The Joint Effect of Proxies for Information Costs on the Flow-Performance Relationship

This table examines the combined effect of all proxies for lower information costs, as measured by total fee ratio, star family dummy, logarithm of total net assets managed by the affiliated family, and the diversity of its fund offerings dummy. Each quarter a piecewise linear regression is performed by regressing flows on funds' fractional performance rankings over the low, medium, and high performance ranges, proxies of information costs, and their interaction terms. The control variables include aggregate flow into the fund objective category, volatility of performance, the logarithm of one plus fund age and its interaction with performance, the logarithm of lagged fund size, and lagged total fee ratio. To save space, only the time-series average coefficients on performance rankings and their interaction terms with proxies of information costs and their corresponding Fama–MacBeth t-statistics (in parentheses) calculated with Newey–West robust standard errors are reported. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Proxy for Lower Information Costs	(1)	(2)	(3)	(4)
Low	0.135***	0.150***	0.135***	0.138***
	(5.66)	(3.13)	(4.82)	(2.83)
Low ∗ Total Fees	−0.756	−0.859	−0.732	−0.723
	(−0.69)	(−0.75)	(−0.64)	(−0.60)
Low ∗ Star Affiliation	0.048	0.033	0.045	0.020
	(0.41)	(0.30)	(0.37)	(0.19)
Low ∗ Family Assets		0.000		0.001
		(−0.03)		(0.07)
Low ∗ Diversity			0.005	0.011
			(0.22)	(0.43)
Mid	0.059***	0.045***	0.055***	0.047***
	(5.51)	(3.81)	(5.07)	(3.76)
Mid ∗ Total Fees	1.261***	1.259***	1.188***	1.225***
	(3.54)	(3.52)	(3.35)	(3.46)
Mid ∗ Star Affiliation	0.017***	0.013*	0.013**	0.014**
	(2.84)	(1.93)	(2.17)	(2.06)
Mid ∗ Family Assets		0.003**		0.002
		(2.07)		(1.23)
Mid ∗ Diversity			0.011**	0.006
			(2.62)	(1.12)
High	0.197***	0.336***	0.241***	0.300***
	(4.97)	(5.93)	(5.97)	(4.81)
High ∗ Total Fees	−4.883**	−4.840**	−4.001**	−3.860*
	(−2.51)	(−2.49)	(−2.00)	(−1.99)
High ∗ Star Affiliation	0.014	0.051	0.045	0.052
	(0.41)	(1.48)	(1.28)	(1.49)
High ∗ Family Assets		−0.019***		−0.009
		(−2.77)		(−0.91)
High ∗ Diversity			−0.094***	−0.062*
			(−4.41)	(−1.95)

Column 1 of Table VI reports the results with both marketing expenses and star family affiliation. The patterns that we observe with these variables individually in Tables II and III are preserved. This is not surprising, given the low correlation between these two variables. In particular, the interaction terms between medium performance and these two variables are both very significant, implying that these two variables capture complementary ways of reducing a fund's information barriers to investors, one through spotlighting the fund itself and the other through the spillover effect from the attention paid to a star fund in the same family.

When we add an additional variable, family assets, to column 2 of our regression model, we observe that the variable total fees maintains its own effect as expected. The individual effects of star affiliation and family size are also statistically significant, although their magnitudes are weakened somewhat due to the positive correlation between them. The same pattern persists when we replace the family assets variable with the diversity of offerings variable, as shown in column 3. Because of the relatively high correlation between these two variables, their joint presence in the regression diminishes their statistical significance, as demonstrated in column 4, although both have the correct sign. Overall, these results are consistent with our earlier findings with individual proxies.

B. The Effect of Time-Varying Information Costs

Another way to examine the effect of participation costs is to compare the flow-performance relationship over time. It can be argued that the overall level of participation costs for investors has declined over time, due either to the effort of mutual funds to reduce information barriers in the face of increasing competition by educating investors and raising their own visibility, or to the increasingly easy access to financial information provided by technological advances. Therefore, we should expect a different shape of the flow-performance relationship in the 1980s versus the 1990s. The results of such an analysis, illustrated in Table VII, show that in the 1990s, flows become significantly more sensitive in the low and medium performance ranges than they were in the 1980s, while there is no notable difference in the sensitivity of flows to high performance levels across these two periods. This finding is in accordance with our expectation that fund flows should be more responsive to performance in the medium performance range when the general level of participation costs is lower (as in the 1990s) than when the general cost level is high (as in the 1980s), leading to an overall less convex flow-performance relationship.

This difference across time periods may also explain the discrepancy between our results and those of Sirri and Tufano (1998). Using data from 1971 to 1990, they assert that only the interaction term between marketing expenses and top-tier performance is significantly positive. As we illustrate in the discussion following Figure 1, if both the higher- and lower-cost groups of funds all have high absolute levels of costs (which was likely true in the 1970s), the higher-cost funds will have lower flow sensitivities in the high performance range, resembling the comparison between the dot-dashed and dashed lines in Figure 1. Therefore, the empirical finding of Sirri and Tufano (1998) is in fact consistent with our model prediction. On the other hand, in our sample period, especially in the 1990s, lower-cost funds such as the Fidelity Magellan Fund may have

Table VII

The Flow-Performance Sensitivity over Time

This table compares the sensitivity of flow to past performance in the two subperiods: 1981–1989 and 1990–2001. Each quarter a piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance rankings over the low, medium, and high performance ranges, aggregate flow into the fund objective category, volatility of performance, the logarithm of one plus fund age and its interaction with performance, the logarithm of lagged fund size, and lagged total fees. Time-series average coefficients and the Fama–MacBeth t-statistics (in parentheses) calculated with Newey–West robust standard errors are reported. The differences of the coefficients on the low, medium, and high performance rankings between the two subperiods and their corresponding F-test statistics are presented in the last column. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Sub-Period	1981–1989	1990–2001	Difference
Intercept	0.028**	0.018**	
	(2.30)	(2.16)	
Category Flow	0.420**	0.219**	
	(2.40)	(2.53)	
Low	0.037	0.118***	−0.080***
	(1.60)	(8.20)	(8.63)
Mid	0.058***	0.093***	−0.035**
	(4.73)	(12.10)	(5.69)
High	0.220***	0.255***	−0.036
	(5.47)	(11.04)	(0.60)
Volatility	−0.455***	−0.191	
	(−3.67)	(−1.65)	
Age	−0.007***	−0.018***	
	(−3.66)	(−14.11)	
Age ∗ Performance	−0.006	−0.002	
	(−1.64)	(−1.24)	
Size	−0.0005	−0.002***	
	(−0.77)	(−4.63)	
Total Fees	0.055	0.083	
	(0.49)	(0.83)	

had very low absolute levels of costs. Therefore, our empirical results likely correspond to the comparison between the solid and dot-dashed lines in the figure.

C. The Effect of Transaction Costs

Although the proxies for participation costs that we have discussed so far pertain mainly to information costs for investors, loads and family affiliation are also related to transaction costs. In order to investigate the separate effect of transaction costs on the asymmetry of the 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 services. 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 flows. While Nanda et al. (2004a) consider how the existence of multiple share classes affects the level and volatility of fund flows as well as fund performance, our focus is on the effect of transaction costs on the flow-performance sensitivity.

Among these different share classes, class A shares generally charge a front-end load. Class B shares charge a back-end load that is triggered on redemption and usually decreases by 1% each year. In addition, after 6 to 8 years, B shares can be converted to A shares that carry lower 12b-1 fees. Like B shares, C shares charge a back-end load of 1%, but only for the first year (see Reid and Rea 2003). 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.

Class B shares feature a contingent deferred sales load whose impact on investors depends on their investment horizons. Moreover, back-end loads should affect fund flows mostly in the low performance range. Since our main focus is on the response of flows to high performance, we limit our comparison to respective flows into class A and class C shares.[22] 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 order to have sufficient observations for each year.

In Table VIII, we include in the flow estimation the interaction terms between a dummy indicating C shares and performance rankings in low, medium, and high ranges. We expect that, compared with flows into A shares, flows into C shares should be more responsive to medium 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. 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 an enhanced flow sensitivity to the medium level of performance.

[22] 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.

Table VIII
Comparing the Flow-Performance Sensitivity between Different Share Classes

This table presents 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 these funds, a piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance rankings 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, the logarithm of one plus fund age and its interaction with performance, the logarithm of lagged fund size, and lagged total fees. Time-series average coefficients and the Fama–MacBeth *t*-statistics (in parentheses) calculated with Newey–West robust standard errors are reported. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Performance Measured by	Raw Return	Four-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)

IV. Concluding Remarks

We present a simple rational model that highlights the effect of new investors' participation costs on the flow-performance relationship. Given fund-level participation barriers, more new investors are able to overcome their participation costs to invest in a fund only as its performance improves. Hence, flows are increasingly more sensitive to performance. Moreover, different levels of participation costs across funds affect flows in various performance ranges differently. For example, at medium levels of performance, funds with low participation costs may attract more investors and enjoy a more sensitive flow-performance relationship than their high-cost peers. High-participation-cost funds, on the other hand, have a more sensitive flow response to their performance than their low-cost counterparts in the high performance range. We show that this result is robust even with portfolio constraints that lead investors to exhibit winner-picking behavior. Using fund characteristics as proxies for participation costs, our empirical analysis supports the model predictions.

The results add to our understanding of the behavior of investors when investing in mutual funds and show that the asymmetric response of fund flows to past performance is consistent with individual optimization. Our findings also have important implications for the literature regarding fund managers' risk-taking incentives, because, given mutual funds' compensation structure, the asymmetric sensitivity of flows to performance yields an implicit call-option-like payoff for fund managers.[23] Our paper suggests a new vantage point for examining this issue by highlighting the effect of participation costs on the flow-performance relationship.

Appendix A: Proofs

Proof of Lemmas 1 and 4: Let $\mathcal{P}$ be the set of funds that an investor chooses to participate in and X_{i0} be his initial holdings. The investor maximizes the following utility function at time $t = 1$:

$$J_{\mathcal{P}} \equiv \max_{\{X_{i1}\geq 0, i\in\mathcal{P}\}} \mathrm{E}\left[-e^{-\gamma W_2}\right] \tag{A1}$$

$$\text{s.t.} \quad W_2(X_{i0}, X_{i1}) = W_1 + \sum_{i\in\mathcal{P}} [X_{i1} r_{i2} - (X_{i1} - (1 + r_{i1})X_{i0})\rho_i(X_{i1})],$$

where

$$r_{i2} = \alpha_{i1} + \epsilon_{i2}, \quad \rho_i(X_{i1}) = \begin{cases} \rho_+, & \text{if } X_{i1} > (1 + r_{i1})X_{i0}; \\ 0, & \text{if } X_{i1} = (1 + r_{i1})X_{i0}; \\ -\rho_-, & \text{if } X_{i1} < (1 + r_{i1})X_{i0}. \end{cases}$$

Solving the first-order conditions yields the optimal holding X_{i1} in fund i:

$$X_{i1}(r_{i1}) = \begin{cases} X_{i1,+}(r_{i1}) \equiv \dfrac{\alpha_{i1}(r_{i1}) - \rho_+}{\gamma\left(\sigma_1^2 + \sigma_\epsilon^2\right)}, & \text{if } X_{i1} > (1 + r_{i1})X_{i0}; \\ (1 + r_{i1})X_{i0}, & \text{if } X_{i1} = (1 + r_{i1})X_{i0}; \\ X_{i1,-}(r_{i1}) \equiv \dfrac{\alpha_{i1}(r_{i1}) + \rho_-}{\gamma\left(\sigma_1^2 + \sigma_\epsilon^2\right)}, & \text{if } X_{i1} < (1 + r_{i1})X_{i0}. \end{cases}$$

[23] The theoretical papers on managers' incentives include Carpenter (2000), Dybvig, Farnsworth, and Carpenter (2003), Grinblatt and Titman (1989), Ross (2004), 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 (2004).

Let $\bar{r}_{i+}, \bar{r}_{i-}$, and $\underline{r_i}$ solve the boundary conditions

$$\begin{cases} X_{i1,+}(\bar{r}_{i+}) = (1+\bar{r}_{i+})X_{i0}, \\ X_{i1,-}(\bar{r}_{i-}) = (1+\bar{r}_{i-})X_{i0}, \\ X_{i1,-}(\underline{r_i}) = 0. \end{cases}$$

The first two boundary conditions separate the purchasing, no trade, and redemption regions in the return space. The last condition is the short-selling constraint. Plugging in the definitions of $\alpha_{i1}(r_{i1})$ and σ_1 from equation (5), we can derive the optimal holding in Lemma 4 with the following bounds that separate all the cases:

$$\begin{aligned} \overline{r}_{i+} &\equiv \frac{\rho_+\left(\sigma_0^2+\sigma_\epsilon^2\right)}{\sigma_0^2-\gamma X_{i0}\sigma_\epsilon^2\left(2\sigma_0^2+\sigma_\epsilon^2\right)} - \frac{\sigma_\epsilon^2\left(\alpha_{i0}-\gamma X_{i0}\left(2\sigma_0^2+\sigma_\epsilon^2\right)\right)}{\sigma_0^2-\gamma X_{i0}\sigma_\epsilon^2\left(2\sigma_0^2+\sigma_\epsilon^2\right)}, \\ \overline{r}_{i-} &\equiv -\frac{\rho_-\left(\sigma_0^2+\sigma_\epsilon^2\right)}{\sigma_0^2-\gamma X_{i0}\sigma_\epsilon^2\left(2\sigma_0^2+\sigma_\epsilon^2\right)} - \frac{\sigma_\epsilon^2\left(\alpha_{i0}-\gamma X_{i0}\left(2\sigma_0^2+\sigma_\epsilon^2\right)\right)}{\sigma_0^2-\gamma X_{i0}\sigma_\epsilon^2\left(2\sigma_0^2+\sigma_\epsilon^2\right)}, \\ \underline{r_i} &\equiv -\frac{\rho_-\left(\sigma_0^2+\sigma_\epsilon^2\right)}{\sigma_0^2} - \frac{\alpha_{i0}\sigma_\epsilon^2}{\sigma_0^2}. \end{aligned}$$

Since a new investor in a fund has an initial holding of $X_{i0} = 0$, and his information set is identical to that of an existing investor, the optimal holding for a new investor is a simple application of the general result. This concludes the proof for Lemma 4.

Lemma 1 is a special case of Lemma 4 in which $\rho_+ = \rho_- = 0$. In particular, the top three cases collapse to one case since $\overline{r}_{i+} = \overline{r}_{i-}$, $X_{i1,+} = X_{i1,-}$. The condition for the short-selling constraint reduces to $\underline{r_i} = -\frac{\alpha_{i0}\sigma_\epsilon^2}{\sigma_0^2}$. Q.E.D.

Proof of Lemma 2: We solve for the optimal participation in two steps: (i) We start with no participation in any fund and consider the sequential participation decision one fund at a time, and (ii) we show that the participation decision for each fund is independent of the rest of the funds and hence the sequential solution is equivalent to the optimal solution.

Let $\mathcal{P}$ be the set of all funds that the investor has chosen to participate in, and $J_{\mathcal{P}}$ be the value function in equation (A1). Consider the decision to participate in a new fund $j \notin \mathcal{P}$. If the investor chooses to pay the cost c_{kj} to learn the posterior ability α_{j1}, his value function conditional on α_{j1} can be written as

$$\begin{aligned} J_{\mathcal{P}\cup\{j\}}|_{\alpha_{j1}} &= \max_{\{X_{i1}\geq 0, i\in\mathcal{P}\cup\{j\}\}} \mathrm{E}\left[-e^{-\gamma W_2}|_{\alpha_{j1}}\right] \\ &\equiv \left(\max_{\{X_{i1}\geq 0, i\in\mathcal{P}\}} \mathrm{E}\left[-e^{-\gamma W_2}\right]\right) \times \left(\max_{X_{j1}\geq 0} \mathrm{E}\left[e^{-\gamma\left[-c_{kj}+X_{j1}r_{j2}\right]}|_{\alpha_{j1}}\right]\right) \\ &= J_{\mathcal{P}} \times e^{-\gamma(\hat{g}(\alpha_{j1})-c_{kj})}, \end{aligned}$$

where $\hat{g}(\alpha_{j1})$ is the certainty-equivalent wealth gain for investing in fund j,

$$\hat{g}(\alpha_{j1}) = \begin{cases} \dfrac{\alpha_{j1}^2}{2\gamma\left(\sigma_1^2 + \sigma_\epsilon^2\right)}, & \text{if } \alpha_{j1} > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{A2}$$

Substituting in the definition of α_{j1} and σ_1 from equation (5) and integrating over the prior regarding the distribution of α_{j0}, we obtain the expected utility

$$J_{\mathcal{P}\cup\{j\}} = J_{\mathcal{P}} \times e^{-\gamma\left(g(r_{j1}) - c_{kj}\right)},$$

where $g(\cdot)$ is defined in equation (8). Investors choose to participate in fund j if and only if $J_{\mathcal{P}\cup\{j\}} > J_{\mathcal{P}}$, which is achieved if and only if $g(r_{j1}) > c_{kj}$ (since $J_{\mathcal{P}} < 0$). Clearly, the participation decision for fund j is independent of all other funds, completing the proof. Q.E.D.

Proof of Proposition 1: The proposition follows directly from Lemmas 1 and 2 and the definition of fund flows. Corollary 1 shows that all new investors with $c_{ki} < g(r_{i1})$ choose to participate. Hence the fraction of new investors who participate is simply $\min[1, \frac{g(r_{i1})}{\bar{c}}]$. Q.E.D.

Proof of Lemma 3: If an investor participates in only one fund with posterior ability α_{i1}, then the certainty-equivalent gain from investing in the fund is given by (A2). Since $\hat{g}(\alpha_{i1})$ increases in α_{i1}, investors optimally invest in the fund with the highest α_{i1} within their information set.

Assume that the investor has investigated some funds and the best fund has a posterior ability level $\hat{\alpha}_1$. If he decides to stop investigating, he can invest in this fund and obtain certainty-equivalent wealth gain $\hat{g}(\hat{\alpha}_1)$. If he chooses to investigate another fund with past return r_{i1}, then his certainty-equivalent wealth gain, conditional on his updated information α_{i1}, can be expressed as

$$G^p(\alpha_{i1}, \hat{\alpha}_1) = \begin{cases} \hat{g}(\alpha_{i1}), & \text{if } \alpha_{i1} > \hat{\alpha}_1 \\ \hat{g}(\hat{\alpha}_1), & \text{otherwise.} \end{cases}$$

Therefore, the expected wealth gain from paying the cost c_{ki} can be calculated by integrating $G^p(\alpha_{i1}, \hat{\alpha}_1)$ over the distribution of α_{i0}:

$$\begin{aligned} G(r_{i1}, \hat{\alpha}_1) &= \int_{\{\alpha_{i0}\}} G^p(\alpha_{i1}(\alpha_{i0}), \hat{\alpha}_1) f(\alpha_{i0})\, d\alpha_{i0} \\ &= \int_{\{\alpha_{i1}(\alpha_{i0}) > \max\{0, \hat{\alpha}_1\}\}} \frac{\alpha_{i1}^2(\alpha_{i0})}{2\gamma\left(\sigma_1^2 + \sigma_\epsilon^2\right)} f(\alpha_{i0})\, d\alpha_{i0} \\ &\quad + \int_{\{\alpha_{i1}(\alpha_{i0}) \le \hat{\alpha}_1, \hat{\alpha}_1 > 0\}} \frac{\hat{\alpha}_1^2}{2\gamma\left(\sigma_1^2 + \sigma_\epsilon^2\right)} f(\alpha_{i0})\, d\alpha_{i0}, \end{aligned}$$

where α_{i1} and σ_1 are defined in equation (5). Simplifying the expression for $G(r_{i1}, \hat{\alpha}_1)$ yields the results in Lemma 3.

Appendix B: The Simulation Procedure

The following is the simulation procedure to derive fund flows when each investor has access to a random subset of n funds. For simplicity, we assume that all the N funds in the universe have identical maximum cost level $\bar{c}_i = \bar{c}$.

Step 1: For N funds, simulate (i) prior ability level, $\alpha_{i0} \sim N(\mu, \sigma_\mu^2)$, and (ii) true ability level, $\alpha_i \sim N(\alpha_{i0}, \sigma_0^2)$.

Step 2: Simulate the past return through $r_{i1} = \alpha_i + \epsilon_{i1}$ for each fund i and then rank all the funds by their past returns. Index the rank by $i = 1, \ldots, N$; that is, fund 1 has the highest past return, and fund N the lowest. Let F_i be the dollar flow of new investors to fund i and initialize it to zero.

Step 3: Apply equation (5) to calculate the posterior ability level of all funds, α_{i1}.

Step 4: Randomly select a subset of n funds out of the total N funds. Let $s_1 < s_2 < \cdots < s_n$ be the overall index of these n funds (which correspond to their return ranks in Step 2). Then fund s_1 has the highest past return among the n funds in the subset, and investors optimally follow the sequence of $s_1, \ldots, s_n$ in choosing funds to investigate. Use set $\mathcal{S} = \{s_1, \ldots, s_n\}$ to denote this subset of funds.

Step 5: Assume there is a continuum of investors (with total population mass normalized to one), with different individual costs $\delta_k \in$ Unif[0, 1], who observe the same subset of funds. Calculate the fraction β_{s_j} of those investors who choose to invest in fund s_j, $j = 1, \ldots, n$.

- Step 5a: Initialize $\beta_{s_j} = 0$ for all j. Let $\alpha_{s_j 1}$ be the posterior ability of fund $s_j, j = 1, \ldots, n$, calculated in Step 3.
- Step 5b: Let m_j be the index of the fund with the maximum posterior ability among funds $\{s_1, \ldots, s_j\}$. That is, $m_j = m_{j-1}$ if $\alpha_{m_{j-1}1} > \alpha_{s_j 1}$ and $m_j = s_j$ otherwise. Clearly, $m_1 = s_1$. We also set $m_0 = 0$, since $G(r_{i1}, 0) = g(r_{i1})$, that is, for an investor who has not studied any fund, the utility gain from studying a new fund is the same as that for an investor whose best fund has ability $\hat{\alpha}_1 = 0$. Thus, investors who have investigated j funds within the subset would optimally invest in fund m_j. Moreover, only funds with $m_j = s_j$ could potentially receive inflows.
- Step 5c: Find the largest $s_j \in \mathcal{S}$ such that $m_j = s_j$. This is the best fund within the set $\mathcal{S}$. Use index $j^* = j$ to denote the j-index of this fund. Since m_{j^*-1} is the best fund for any investor who has not investigated fund m_{j^*}, an investor would optimally choose to investigate fund m_{j^*} if and only if his cost is lower than the expected utility gain, or $\delta_k \bar{c} < G(r_{m_{j^*}}, \alpha_{m_{j^*-1}1})$ (where $G(\cdot)$ is defined in Lemma 3. Once having investigated this fund, investors would only invest in funds $s_j \geq m_{j^*}$ since m_{j^*} is better than any fund $s_j < m_{j^*}$. Given the uniform distribution of δ_k, we can update the fraction of investors who invest in fund m_{j^*} as follows:

$$\beta_{m_{j^*}} = \frac{\min\left\{G\left(r_{m_{j^*}}, \alpha_{m_{j^*-1}1}\right), \bar{c}\right\}}{\bar{c}} - \left(\sum_{j=j^*+1}^{n} \beta_{s_j}\right).$$

The second term in the expression represents the fraction of investors investing in funds better than j^*.

– Step 5d: If $j^* = 1$, go to Step 6. Otherwise, reset $\mathcal{S} = \{s_1, \ldots, s_{j^*-1}\}$ and repeat Step 5c.

Step 6: Update the fund flows from new investors:

$$F_{s_j} = F_{s_j} + \beta_{s_j} X^n_{s_j 1}, \quad j = 1, \ldots, n,$$

where $X^n_{s_j 1}$ is defined in equation (7) for fund s_j as a function of $\alpha_{s_j 0}$ and $r_{s_j 1}$.

Step 7: Repeat Steps 4–6 for desired number of simulations, say 1,000 times, to yield realistic flows for a given fund return realization.

Step 8: Repeat Steps 2–7 for desired number of simulations, say 100 times, to yield flow-performance rank relationship for different return realizations. Average fund flows for the same performance rank over different simulations.

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