How Does Reputation Affect Subsequent Mutual Fund Flows?

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Abstract

This paper offers a novel evidence that the link between recent mutual fund performance and subsequent fund flows is largely shaped by a fund's reputation as measured by its long-term performance. Both the sensitivity and level of fund flows increase in reputation. In particular, for a fund with a low level of reputation, flows are weakly responsive to recent performance. In short, *return chasing* is limited only to funds with strong reputation. Some of the earlier models (Berk & Green; 2004, and Lynch & Musto; 2003) derive equilibrium fund flows which are independent of reputation. In light of this, I explain the dependence of fund flows on priors using the presence of *Inattentive Investors* who are otherwise rational. Model generates implication about performance persistence which is confirmed in the data. I conduct a small calibration exercise to estimate degree of inattention across funds with different reputation. Additionally, I conduct two experiments using the data on manager replacement and fee structure to validate model mechanism of inattentive investors.

JEL classification: G10, G11, G23.
Keywords: Mutual fund flows, Reputation, Bayesian Learning, Inattention.

1 Introduction

In this chapter, I study the importance of a mutual fund's long-term performance or *reputation* for determining mutual fund flows.[1] Previous studies have mainly focused on relationship between recent performance and subsequent fund flows. This relationship is usually termed as *flow-schedule*. But very little is known about how reputation measured in terms of long-term performance affects fund flows in general and *flow-schedule* in specific. This is the focus of the present paper.

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[1]Fund flows are capital inflows and outflows from a mutual fund and are usually measured as a fraction of assets under management.

The consensus view in the literature is that mutual fund flows exhibit a pattern of *return chasing*: capital moves in and out of a mutual fund as a reaction to its recent performance. [[18] ; [9]]. To the contrary, I present a novel evidence that *return chasing* is prominent only for funds with a sufficiently high level of reputation. For funds with a low level of reputation, flows are weakly responsive to recent performance. In short, the responsiveness of fund flows to recent performance is largely shaped by a fund's reputation and *return chasing* is not ubiquitous. These results present a new perspective to understand mutual fund flows. My paper underscores the importance of reputation (in terms of historical performance) in determination of fund flows.

The Main empirical experiment in the paper is as follows. I study how the link between time $t+1$ fund flows and time t performance depends upon the history of performance (reputation) up to time $t-1$. The idea is that long-term performance up to $t-1$ serves as a prior or an reputation index of manager's ability and time t performance serves as a signal. The objective is to understand how much of the time $t+1$ flows can be attributed to each of the following three sources: recent performance at time t, reputation at time $t-1$ which is computed using the history of performance up to $t-1$ and the interaction between the two. For terminology, let total flows explained by these three factors be called *fund flows due to performance*. My analysis yields five main results:

1. **Presence of *return chasing* without interaction terms:** Without considering interaction terms between recent performance and reputation, my regression estimates strongly support the hypothesis of *return chasing* of [13] and [18]. For example, a fund within the top quantile of recent performance experiences roughly 22%-24% more asset growth due to fund flows as compared to a fund within bottom quantile of recent performance. This result remains valid even after controlling for the stand-alone effect of reputation as in [9].

2. ***Interaction effect* cuts the importance of *return chasing effect*:** The quantitative importance of the pure *return chasing effect* is substantially reduced once the regression includes interaction terms between reputation and recent performance. For example, a fund with a 10^{th} percentile reputation index experiences only 12%-13% asset growth due to flows after a jump from the bottom to the top quantile of recent performance. In the regression without interaction terms, similar jump results in almost twice as large additional capital inflows. This implies that flows attributable to a pure *return chasing effect* are reduced by more than half after inclusion of interaction terms.

3. ***Dominance of Interaction Effect:*** In the regression estimate, interaction term between reputation and every quantile of recent performance is statistically significant and economically large. For example, the coefficient on interaction between reputation and top quantile of recent performance is around 21% to 26%. This magnitude is more than twice as large as coefficient on the top quantile of recent performance. For example, a fund with 90^{th} percentile reputation index experiences 29% to 33% asset growth due to flows after a jump from the bottom quantile to the top quantile of recent performance. A similar jump for a fund with 10^{th} percentile reputation index results in mere 12% to 13% asset growth. The difference is attributable to an *interaction effect*

which makes it a dominant source of flows for high reputation funds. This way, my estimation finds an entirely novel source of fund flows.

4. **Flows are sensitive for high reputation funds:** Interaction terms rise monotonically over the quantiles of recent performance. This implies that gap between fund flows accruing to high and low reputation funds increase with quantiles of recent performance. In other words, flow-schedule is more sensitive for high reputation funds. Because all the interaction terms are significant, it implies in particular that flow-schedule for high reputation fund is sensitive even at the lower end of the recent performance. This is not the case for low reputation funds. For example, a jump from the bottom to the next quantile of recent performance brings additional flows to the tune of 0.40% to 0.60% for a fund with 10^{th} percentile of reputation. On the other hand, a similar jump brings 4% to 5.5% additional flows for a fund with 90^{th} percentile of reputation. This is in line with [4]. But what is novel is that high reputation funds have more sensitive right end of flow-schedule.

5. **Stand-alone *reputation effect*:** Fifth, the independent effect of reputation on the level of fund flows is strongly positive; a fund experiences asset growth to the tune of 7% to 8% for having a greater reputation, independent of recent performance. This implies that reputation raises the level of fund flows. This result is consistent with some earlier regression models including those of [9]. This effect may possibly capture the impact of better promotions in the following year after a winning year for mutual fund.

[2] rationalizes return chasing behavior for mutual funds. They present a theory of mutual fund flows with two features. First, capital movement is a result of new information in the form of recent performance. Second, Gaussian learning implies that an update to investor beliefs about managerial ability is a function of new information, completely independent of prior information (reputation). These two features together imply that fund flows are independent of reputation in that model. But my evidence suggests that reputation matters for fund flows.

To this end, I construct an equilibrium model with heterogeneous investors. Model is in spirit of [2] with one modification: some investors are only occasionally attentive. My model has a mutual fund managed by a manager with unknown and unobservable skill. The manager incurs costs to manage assets, and costs per dollar are increasing in the total assets he manages. That is, there are decreasing returns to scale. There are two type of investors: *Always Attentive* (AA) and *Occasionally Attentive* (OA). Conditional on paying attention, investors are otherwise rational. That is, they process all the information efficiently to which they pay attention and make optimal investment choices based on this information: they invest in a fund until its expected returns are non-negative. Decreasing returns to scale implies that capital inflow drives down expected net returns and vice versa. It is assumed that *outside* investors have infinite capital at their disposal. Note that expected net returns, fund size and investor composition are all endogenous to the model.

This setup has some interesting implications. First, expected net returns for any fund are always non-positive. If a fund has positive expected net returns, enough capital always flows into the fund as outside investors have deep pockets. Capital inflows drive the expected net returns to zero. On the contrary, for a fund with negative expected net returns, capital outflows are limited to the extent investors are inattentive. This raises the possibility that funds with high proportion of inattentive investors remain over-sized in the equilibrium relative to its competitive size[2] and offers negative expected net return in the equilibrium. As such the model replaces the *zero expected net return* condition central to [2] with *non-positive expected net return* condition. Second, OA-type investors are dominant stake holders in poorly performing funds in the equilibrium. To see this, consider a fund that offers negative expected net return. Then all the AA-type investors liquidate their holdings until expected net returns reach to zero. But OA-type investors may not liquidate their holdings as they are inattentive by construction. In equilibrium, this leads to poorly performing funds being mainly owned by OA-type investors. Third, fund flows are less sensitive for poorly performing funds over an entire range of recent performance. Because OA-type investors are the majority of investors in poorly performing funds, these funds experience limited capital outflows after bad performance. On the other hand, even if such a fund performs well so as to offer a positive net expected return, the required capital inflows to exhaust positive opportunity are small given that it is already over-sized. This explains the lack of sensitivity of flows for poorly performing funds. Fourth, investor composition becomes more heterogeneous across high and low reputation funds as the horizon over which reputation is measured increases. This implies that the interaction effects between reputation and recent performance should become more significant and dominant as the horizon for reputation measurement increases. It must be mentioned at this stage that my model explains how reputation interacts with recent performance in shaping flows. But it is not a model to understand independent effect of the fund reputation.

I employ two indirect tests to confirm the model mechanism that reputation matters for fund flows due to investor inattention. The first test uses managerial replacement data. If a fund experiences a managerial replacement, some of the otherwise inattentive investors would become attentive as managerial replacement generates lot of *soft information* in the form of media reports, personal communication from the fund to investors, etc. This implies that effective heterogeneity in investor attentiveness across high and low reputation funds is diminished after replacement of fund manager. The data exactly supports this hypothesis. Interaction terms between reputation and recent performance are almost insignificant after the replacement. Second test exploits structure of fees. Investors of a fund charging a higher front load are usually more attentive as they have paid costs upfront and hence care more about performance. If this is true, then for funds with higher front loads and costs, the investor population is in general more attentive, irrespective of past performance. This implies that interaction effects between reputation and recent performance should diminish for such funds. Again the data confirm the hypothesis.

2 Literature Review

The literature on estimation of responsiveness of mutual fund flows to fund performance is vast. [13], using annual frequency, documented that fund flows chase recent winners. [9], and [18] further documented the presence of convexity in fund flow sensitivity: fund flows

[2]size where expected net returns are zero

are non-responsive at the lower range of performance but highly sensitive at the higher range of recent performance. The main difference between my paper and these papers is that my regression estimate recognizes the important role of historic performance in shaping fund flow sensitivity to recent performance. [9] use historic performance as a control, and fail to consider interactions. The reason to control for reputation is that funds might be promoted by fund families in terms of advertisement budgets etc. which can elevate the level of flows to these funds. But what I show is that reputation not only alters the level of *flow-schedule* but also influences the shape of the *flow-schedule*.

Some earlier papers recognized the importance of other fund characteristics in determining the level and sensitivity of fund flows: fund age reduces flow sensitivity [9]. Volatility of performance damps learning and flow responsiveness [12]. Young and small funds, also referred to as *hot funds*, have a steeper flow schedule as compared to old and large funds, referred to as *cold funds* [19]. Funds within families having a *star performer* experience greater level of fund flows [17]. Most of these papers consider the impact of other fund characteristics on flow sensitivity. I show that my results are valid across size and age groups even after controlling for family effects. I document the impact of reputation as a fund characteristic in determining flow sensitivity and level. To that end, my paper brings out a new and relevant classification of mutual funds.

[4] document that repeat loser funds have lower sensitivity at a lower range of recent performance. Though this paper considers the impact of lagged performance in an interactive manner, my paper adds further value to the literature. First, I characterize the dependence of flow-schedule on reputation completely, not only at the lower range of recent performance. Second, [4] use one year of historic performance. I show that dependence of flow-schedule on historic performance increase with a longer history period considered to compute reputation. Third, [4] document that repeat winning funds do not have a substantially different flow-schedule as compared to first-time winners. I document that repeat winners exhibit more a steeper flow-schedule and also attract higher level of flows.

Importance of mutual fund reputation has been explored other contexts. For example, [14],[10], and [15] among others document that the risk of fund managers getting fired is inversely related to the historic fund performance. A quick look at my sample present the same evidence. There are 664 episodes of managerial replacements. 200 of those or roughly 30% belong to bottom quintile of reputation and only 12% of the replaced managers belong to top quintile of reputation.[3] Hence reputation has a clear bearing on the employment incentives. But the other component that drives the incentives is the compensation which depends on the asset size a manager manages. Fund flows alter the fund size and shape the level and volatility of compensation for the manager. But as suggested earlier, there has been a very little exploration as to how fund flows are influenced by the fund reputation. This paper aims to fill this gap.

There is a large literature on the *return chasing effect.* Outside the domain of mutual funds, return chasing is rationalized by [6], among others, who explain positive contemporaneous correlation between net flows and foreign equity returns, and [1], in whose analysis

[3] If the performance did not have any bearing on the firing probability, then these numbers should have been close to 20%. Hence, these give an indication of the inverse relationship between performance and firing probability. But some of the replacements could be due to voluntary retirement or promotions, which complicate the analysis to some extent.

within-country investor heterogeneity generates return chasing in foreign markets by American investors on an average. Within the domain of mutual funds, [2] show that investors chase positive expected return opportunities, which is rational. But return chasing, together with decreasing returns to scale, leads to zero net returns on an average. Competitive capital provision with Gaussian learning makes capital flows in that model independent of reputation. I augment the [2] framework with the presence of inattentive investors to break the independence of flows on reputation to match observed data. [16] also consider a model with return chasing and managerial replacement to explain fund flow convexity. But their model counter-factually predicts return persistence for better funds.

[7] presents the evidence of lack of performance persistence for mutual funds. Though [5] find some persistence at monthly frequency, overall there has been a scarce evidence on persistence at medium to long-term performance. I show that low reputation predicts poor performance. This is true in my model as well as the data.

Some papers generate inattention as an optimal response when information acquisition is costly, for example [11]. My paper takes an agnostic view about why some investors are inattentive.[4]

3 Data and Empirical Methodology

3.1 Data

Data for my paper comes from CRSP Survivor Bias Free Mutual Fund Database, covering a period from 1983 to 2014 at annual frequency.[5] Sample selection is in line with earlier literature.[6] I focus on US domestic open-ended equity funds. I exclude sector, index and specialty funds. Because names or styles may not reflect the true nature of fund, I also exclude funds whose mean equity holdings are less than 70%. I exclude any funds where size is smaller than 15 million USD and also any fund whose age is 3 years or less. Many funds offer multiple share classes to represent various categories of investors or types of distribution used to market the fund. Following earlier literature, I aggregate all the share classes belonging to one fund. The size of the fund is sum of sizes of all the share classes, and fund age is age of the oldest share class. Other variables like turnover, expense ratio, returns etc. are computed on size-weighted average basis.[7]

3.2 Variables

The main variable of interest is fund flows. In line with more recent literature [[2]; [12]], I define fund flows as percentage growth in assets under management (AUM) due to capital

[4]Though the model in the paper assumes inattention exogenously, there is a potential mechanism that can generate inattention optimally. If information acquisition is costly, portfolio re-balancing may not be optimal for investors with low wealth. These are precisely the investors who are invested with losing funds. This can create a rational inertia.

[5]Results at quarterly frequency are available on request

[6]See data appendix for further details.

[7]Following [12], results are validated with share class level data. This allows conditioning the results on fee schedules and investor type which is important for the present paper.

flows.[8] In particular,

$$FLOW_{it} = \frac{AUM_{it} - [AUM_{it-1} \times (1 + r_{it})]}{AUM_{it-1} \times (1 + r_{it})}, \tag{1}$$

where AUM_{it} denotes assets under management at the end of time t and r_{it} is the net return earned by the fund at the end of time t. There are potential outliers due to small funds growing exponentially. I winsorize the data at 1% from both the tails.[9]

The second main variable of interest is the fund performance. I measure fund performance using two methods: Raw fund returns as well as CAPM-Alpha. For each method, funds are ranked within their investment style following [18] or [19]. Though some recent papers use four-factor model of [7] to measure fund performance [3] show that CAPM-Alpha better fits the revealed preferences of investors as compared to four-factor alpha. Use of raw returns as a measure is not new. [9] use excess returns as a performance measure without considering any risk adjustment. [18] consider raw returns instead. In this case, ranks are computed within each investment style which ensures that the raw return is compared for similar funds.

The next issue is to compute a measure of recent performance and a measure of reputation. At any year-end, recent performance is computed using data for the recent period, which is the year currently ending, and reputation index is computed using a window of five years immediately before that recent period. For example, at the end of 2008, 2008 becomes the recent period, and 2003-2007 becomes the reputation window. The recent raw return denoted by r_{it}^{st} is the annual raw return of a fund over the recent period and the reputation index using raw returns denoted by r_{it}^{lt} is computed using aggregate raw return over the reputation window. To compute performance using CAPM-Alpha, the following regression is estimated over a k year window leading up to time t on monthly basis:

$$r_{i\tau} - RF_{\tau} = \alpha_{it,k} + \beta_{it,k} \times (r_{m,\tau} - RF_{\tau}) + \varepsilon_{i\tau} \tag{2}$$

$k = 1$ to compute recent CAPM-Alpha, and $k = 5$ to compute reputation according to CAPM-Alpha. $\alpha_{it,k}$ denotes the α over the window of length k years ending at time t. RF_{τ} is the risk free rate during month τ. $R_{m,\tau}$ is the market return during month τ.

After computing a performance measure, each fund is ranked within it investment category and is assigned a reputation rank and recent performance rank based upon its recent performance and reputation respectively. These ranks are normalized to fall between 0 (lowest) and 1 (highest). I denote normalized reputation rank by repute_{it} and recent performance normalized rank by Perf_{it}.

I compute recent period risk using the recent period's monthly return observation. A measure of long-term risk is volatility of returns over reputation window. Other variables used are log of fund age, fund size, expense ratio, and turnover ratio. Following [18], I add one-seventh of the front-load and end-load to each year's management fees to compute the expense ratio. I also control for overall flows accruing to each investment style to which the fund belongs.

[8] Previous literature used AUM_{it-1} as a base in the formula for flows. If a fund loses all the assets, then this traditional definition would measure a $FLOW_{it}$ different than -100%, which is clearly incorrect.

[9] Results are robust to winsorization.

3.3 Summary Statistics

Basic summary statistics are presented in table 1. Funds are sorted in to bottom quintile (Low), top quintile (Top) and middle three quintiles (Med), according to their year-end reputation rank. The table also provides overall statistics for entire sample.

The first two columns exhibit the spread in performance across various reputation quintiles. The mean spread between the *low* and *top* reputation group is sizable in terms of both excess returns (8.4% annually) and CAPM-Alpha (7.9% annually). This shows that sorting based on long-term performance is a meaningful exercise. Next consider size. Both the mean and median sizes of funds increase with reputation quintile. The mean and median size of the *low* reputation group is three times smaller than that of *top* reputation group. This difference in size is not a result of the age of funds in various categories or other fund characteristics. Mean and median age across groups are very similar. In particular, expense ratio, front load structure, turnover ratio and volatility of returns are all very similar across reputation quantiles. This makes it easier to estimate regression models, as most of the control variables need not be interacted with reputation quintile.

3.4 Empirical Methodology

The objective is to understand how reputation affects the link between recent performance and fund flows. For example, we want to analyze the link between performance of 2009 and flows of year 2010, conditional on long-term performance up to and including 2008. To control for non-linearities in fund flows, as documented by [18], [9], and [12], I divide the funds into quintiles according to their recent time t performance given by Perf_{it}. Let Q_{jt} be the dummy variable indicating that a fund lies in j^{th} quantile when sorted on the basis of Perf_{it}. I run following regression.

$$FLOW_{it+1} = a + \sum_{j=2}^{J} \phi_j Q_{jit} + \sum_{j=2}^{J} \psi_j \left(Q_{jit} \times repute_{it-1}\right) + \gamma \times repute_{it-1} + CONTROL_{it} + \varepsilon_{it+1}, \tag{3}$$

$CONTROL_{it}$ denotes other control variables like age and size. Note two important points about this regression. First, there are three periods. It's a regression of time $t+1$ flows on time t recent performance and reputation index, capturing long-term performance up to and including time $t-1$. Second, because the model has an intercept we lose the coefficient ϕ_1 on the first quintile of recent performance. Because the equation identifies the independent effect of $repute_{it-1}$ through γ, we lose ψ_1 too on the first quintile of recent performance in interaction terms. Given this structure, we can interpret each of the coefficients as follows: For $j = 2, 3, 4, 5$, ϕ_j captures the incremental $FLOW_{it}$ to j^{th} quintile over first quantile Q_1. Similarly, ψ_j captures the incremental interaction effect for j^{th} quantile over and above that of the interaction effect on first quantile.[10]

[10] There is another way to express this regression. By omitting the intercept and merging the independent effect of reputation, we can run following regression:

$$FLOW_{it+1} = \sum_{j=1}^{J} \phi_j Q_{jt} + \sum_{j=1}^{J} \psi_j \left(Q_{jt} \times repute_{it-1}\right) + CONTROL_{it} + \varepsilon_{it+1},$$

4 Empirical Evidence

4.1 Main Results

Results are reported in the table 2 and table 3. The table 2 uses the raw returns measure, while the Table 3 uses CAPM-Alpha. In each table, the first model considers only recent performance, the second model controls for reputation, and the third model includes interaction terms between the reputation and recent performance quintiles. I discuss the results in a series of hypothesis. All the hypotheses are formally tested and presented in table 10.

Hypothesis 1 ***(Unconditional Return Chasing)***
Fund flows are positively related to recent performance in a model without interaction effects. Formally, $\psi_j - \psi_1 > \psi_{j-1} - \psi_1$ *for* $j = 2, 3, 4, 5$.

Consider the first model of table **??** and table **??**. First note that the coefficients on Q_{jt} are positive and statistically significant for all $j = 2, 3, 4, 5$. This means that a jump from the bottom quintile to any higher quintile leads to additional flows. Second, coefficients rise monotonically as we move up the recent performance quintiles, which means that improving recent performance leads to additional flows. For example, as compared to a fund within the bottom quintile of recent performance, funds within second, third, fourth and fifth quantiles of recent performance get 3.4%, 8.4%, 12.4% and 24.1% more flows annually. Results are similar for the CAPM measure. This result is consistent with the earlier findings of [13] and [18] and others that fund flows are positively linked to recent performance.

Hypothesis 2 ***(Return Chasing is valid even after controlling for reputation)***
Hypothesis 1 is valid even after controlling for reputation.

A good past performance can result in fund being promoted by the fund family in terms of advertisement budgets or preference in distribution channels. This can lead to higher level of flows accruing to more reputed funds for any given level of recent fund performance. [9] control for the historic performance and find a positive coefficient on the same. To understand the stand-alone effect of reputation, I include the reputation variable $repute_{t-1}$ in the second model within each table. We see that the relationship between recent performance and fund flows is almost unchanged. We also see a statistically significant and economically large coefficient on $repute_{t-1}$: 20% for raw returns and 17.7% for CAPM. This magnitude is comparable to being a top performer during the recent period. This suggests that high performance in the past elevates the level of flows for the current period considerably.

But the main focus of the paper is to understand not the stand alone effect of the reputation but the way it interacts with recent performance. In third model for each measure, I include the interaction between $repute_{t-1}$, which is a normalized reputation rank, and each of the quintiles of recent performance. Including interaction effects unmasks heterogeneity across the funds in terms of the link between recent performance and flows.

In this case, each coefficient (ψ_j) and (ϕ_j) capture the level of FLOW rather than difference between j^{th} and the first quintile.

Hypothesis 3 ***(Interactions reduce the strength of return chasing effect)***
The magnitude of additional fund flows attributable to better recent performance is reduced by more than half after inclusion of the interaction effect. Additionally, stand-alone effect of reputation diminishes.

Consider the last columns within each table. We see that, after considering the interaction effects, coefficients on recent performance quintiles are reduced by more than half for all the quantiles: the $Q_{2t} - Q_{1t}$ coefficient loses it significance, while $Q_{5t} - Q1t$ coefficient stands reduced from 22%-24% to a mere 10%. This indicates that a fund with a lower level of reputation cannot hope to achieve flow growth by performing well during recent period. The bottom line is that fund flows attributable purely to a better recent performance are far smaller once we include the reputation interactions. In other words, the quantitative importance of the *return chasing effect* identified by previous papers is greatly reduced. Similarly, the coefficient on reputation is cut by more than half under both the measures.

The next result shows that lost coefficients on stand-alone variables are all transferred to interaction effect.

Hypothesis 4 ***(Significance of Interaction Terms)***
All the interaction terms between recent performance and reputation are statistically significant. Formally, $(Q_j - Q_1|repute = high) > (Q_j - Q_1|repute = low)$ *for any* $j = 2, 3, 4, 5$. *Moreover, the magnitude of interaction is large.*

The fact that all the interaction terms are significant implies that an same level of improvement in recent performance leads to higher additional flows for high reputation funds. For example, a jump from the first to second quintile of recent performance leads to 1.7%-1.9% additional flows for a fund with 10^{th} percentile reputation rank ($repute_{t-1} = 0.10$) but leads to 5.5%-6.5% additional asset growth due to flows for a 90^{th} percentile reputed fund ($repute_{t-1} = 0.90$). Moreover, the coefficients on interaction terms are quantitatively large compared to coefficients on recent performance quintiles. For example, for a fund with a 90^{th} percentile reputation rank ($repute_{t-1} = 0.90$), a jump from bottom to top quintile of recent performance leads to 29%-33% additional asset growth due to flows. Out of which 19%-23% or more than two-thirds is attributable to *interaction effect*. This implies that *interaction effect* is far more important than *return chasing effect* for a high reputation fund.

Hypothesis 5 ***(Sensitivity of high vs low reputation funds)***
Interaction terms between recent performance and reputation increase monotonically as we move to higher quantiles of recent performance. Formally, $(Q_j - Q_{j-1}|repute = high) > (Q_j - Q_{j-1}|repute = low)$ *for any* $j = 2, 3, 4, 5$.

Interaction terms represent the difference in the level of fund flows between high and low reputation funds at each quintile of recent performance. The fact that interaction terms rise monotonically suggests that the gap between flow-schedules for high and low reputation funds grows as we move to the higher quintiles of recent performance, Or that sensitivity of the flow-schedule increases in fund reputation. Also because interaction terms rise monotonically over each quintile, fund flows are more sensitive for reputed funds over the whole range of recent performance. [4] document lack of flow sensitivity at the left end of the flow-schedule for repeat losers. But my results indicate that a low reputation fund has less sensitive flow-schedule even at the right end.

As explained earlier, the economic magnitude of interactions is substantially larger than the *return chasing effect*. This implies that differences in sensitivity are substantial too.

To understand overall results together, consider a concrete example. Consider a *best fund* with $repute_{t-1} = 0.90$ and $Q_{5t} = 1$ and a *worst fund* with $repute_{t-1} = 0.10$ and $Q_{1t} = 1$. Assume that, apart from performance, these funds are identical. Then on average a *best fund* experiences additional asset growth of 40.80% due to fund flows as compared to a *worst fund* according to raw return rankings. Out of this 40.80% additional asset growth, 10.7% of the gain or roughly one-fourth is attributable purely to improvement in recent performance from the bottom to top quintile. This is the *return chasing effect*. 6.6% or roughly one-seventh of the asset growth is attributable to the pure *reputation effect*. But all of the remaining 23.50% increase, which amounts to roughly 60% of additional growth, is attributable to the *interaction effect*: A joint effect of improvement in recent performance and an improvement in reputation. This is the main result in the paper. The fund flow-schedule for a high reputation fund is not only more sensitive as compared to a low reputation fund, but that extra sensitivity explains most of the flows accruing to reputed funds. These results identify an entirely new and until now unknown factor that drives mutual funds: interaction between reputation and recent performance. To better visualize the results, I plot the fund flow schedules for the bottom and the top reputation quintile fund against recent performance in figure 1.

In summary, flows are not very sensitive to recent performance for funds with low reputation. Sensitivity increases with reputation, and for high reputation funds, the *interaction effect* becomes the dominant explanation of fund flows due to performance, and not the *return chasing effect*.

4.2 Robustness And Generality of Evidence

1. **Change in market share as an alternative dependent variable** The evidence above is robust to alternative measurements of capital flows. Instead of using fund flows as a dependent variable, [19] propose *change in market share*. An excellent property of this measure is that the market share changes over all the funds sum to zero for any given period. The authors show that this measure is less prone to a possible spurious convex link between recent performance and fund flows. I run the same regression as in equation 3 using *change in market share* as a dependent variable instead of fund flows. Formally, change in market share is defined as

$$\Delta Mkt_{it+1} = \frac{AUM_{it+1}}{\sum_i AUM_{it+1}} - \frac{AUM_{it} \times (1 + r_{it+1})}{\sum_i AUM_{it} \times (1 + r_{it+1})},$$

   The results are presented in table 4. All the main results carry over to this new dependent variable. Column 1 of each panel, where I regress ΔMkt_{t+1} without considering interaction effect, suggests a strong positive *return chasing effect*. But once we include the *interaction effect* (column 2 of each panel), two observations can be made. First, coefficients on the recent performance quintile $Q_{jt} - Q_{1t}$ become negative, which means that a low reputation fund loses market share with better recent performance. This is possibly indicative of liquidation out of low reputation funds following at least partial recovery of losses. That is, the *return chasing effect* is negative with this measure. Second, coefficients on interaction terms are all positive. Together with the negative return chasing effect, this suggests that only high reputation funds can capture market share with better recent performance performance. Third, coefficients on interaction terms are monotonically increasing, suggesting that the market capture line is more sensitive for high reputation funds. These results speak even more strongly about the importance of the *interaction effect* for capturing market share or investor's capital. [19] identify hot and cold funds. Hot funds that are small and young have a sensitive flow schedule while cold funds that are large and old have less a sensitive flow schedule. Similar in spirit to Spiegel and Zhang, I identify high reputation funds with sensitive flow schedule and low reputation funds with less a sensitive flow schedule. But high reputation funds are not young and small compared to low reputation funds. On the contrary, a fund belonging to top reputation quintile, is roughly three times larger as compared to a fund belonging to the bottom reputation quintile. On the other hand, age profile is invariant across reputation quintiles as shown in summary table 1. In conclusion, I identify another grouping of funds that has vast heterogeneity in terms of flow sensitivity.

2. **Results across age and size categories:** The empirical evidence in [9] among others and the theoretical model of [2] show that small and young funds have more sensitive flows. Though mean age across high and low reputation funds is almost the same (12 years over all the quantiles of reputation), mean size of high reputation fund (fund within top quintile of reputation rank) is almost three times larger than that of low reputation fund (fund within bottom quintile of reputation rank). If anything, the results of [9] suggest that high reputation funds should have lower flow sensitivity as they are larger. This means that the higher sensitivity of high reputation funds is a pretty strong result. To show that reputation factor is a genuine separate effect not subsumed by age and size, I re-run the regression across the age and size bins. The results are presented in table 5 with CAPM-Alpha and raw-returns measure. A fund with below median age is *young*, while a fund below median size is *small*. In the first and the third column, the control dummy refers to fund being *young* and *small*, respectively. There are three observations.

   First, except column 2, in all the other models, being young and being small increases fund flow sensitivity. This can be seen from the statistical significance of $(Q_{5t} - Q_{1t}) \times$ *Control Dummy* coefficient. [9], [18] , [2] and others have discussed these effects. But this effect is true for a fund of any reputation index. Second, all interaction terms are still statistically and economically significant over all quintiles of recent performance. Third, none of the three-way interaction terms between the reputation, the recent performance dummy, and the control dummy are significant, suggesting that interaction terms are valid across all the age and size bins: young and old as well as small and large. Hence, the *interaction effect* identified in this paper is a genuine distinct effect that is not explained by size or age effects.

3. **Longer period to measure short-term performance** One possible argument

against the existence of the *interaction effect* is that it possibly just captures the fact that the evaluation period used to compute recent performance is longer than a year. Even then, all the coefficients should have been split over the recent performance and the stand-alone *reputation effect*. The interaction terms would still be zero. As a robustness check, I re-run the regression model with following changes. I measure recent performance using two-year window instead of one year. I measure reputation using the immediately preceding four year window. I drop one year from reputation window to have matching time frame with earlier regression estimates. Results are presented in table 7. All the results are valid even with longer evaluation period to compute recent performance.

First, without interactions, (columns 1-2 and 4-5), the link between flows and recent performance is strong even with two-year horizon to measure the recent performance. Second, after considering the interactions, pure *return chasing effect* completely vanishes. In particular, the results suggest that improving recent performance has no bearing on flows for low reputation funds. Third, all the interaction terms (except the first interaction term for raw returns) are significant and explain the dominant fraction of flows due to performance. Interaction terms are monotonically increasing, which means results about sensitivity also carry over.

What this test reveals is that, even if investors use a longer period to evaluate fund performance, the importance of interactions is not reduced. That is, this test suggests that *interaction effect* is a separate effect and can't be explained by merely longer horizon.

5 Model

The model modifies [2] framework to include non-attentive investors. Presence of heterogeneous investors is the main mechanism that generates heterogeneity in the fund flow schedule for funds with different reputations.

5.1 Set-Up

The model has two types of investors with a total unit mass of which μ fraction are *always attentive* (AA) and $1-\mu$ fraction are *occasionally attentive* (OA). OA type investors are attentive with probability of $\delta < 1$ every period. All investors are risk-neutral. Investors are assumed to have infinitely deep pockets. A mutual fund is managed by a manager with unobservable and unknown skill α, and it generates gross return as follows;

$$R_t = \alpha + \varepsilon_t, \tag{4}$$

Investors learn about α by observing R_t. But noise ε_t hinders learning about α from observing R_t. Noise has following structure;

$$\varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right), \tag{5}$$

Let $\phi_t = E_t(\alpha)$ be the estimated ability of the manager, given time t information, which includes time t performance and the entire history of performance. The fund manager charges a fixed fee f per dollar managed from investors and has a choice of managing money actively or passively. Active management generates gross return of R_t on each dollar actively managed. Passive management generates zero gross return. With these assumptions, α can be interpreted as excess return over the benchmark. Denote by q_t the total money a fund has at the end of time t after all the capital adjustments are complete for time t. This is the total money it manages during $t+1$. Denote by h_t the fraction of money that is actively manages during time $t+1$.[11] The fund incurs the cost of active management. This cost is a function of actively managed assets and is denoted by $C(x)$ for managing x dollars actively. To be specific, I assume that $C(x) = \eta x^2$, with $\eta > 0$. With this set-up, the investor's net return per dollar invested is given by

$$r_t = (h_{t-1} R_t) - f - \eta \left[\frac{(h_{t-1} \times q_{t-1})^2}{q_{t-1}} \right], \tag{6}$$

Note that r_t is generated from investing q_{t-1}. So the cost of management is computed on q_{t-1}. This completes the basic description of the model. h_t is the policy variable of a manager. In a rational equilibrium, h_t, q_t and r_t are endogenously determined given the learning technology.

5.2 Solution Under Competitive Benchmark ($\delta = 1$)

When $\delta = 1$, all the investors are attentive. An assumption of competitive capital supply with investor risk neutrality implies the following equilibrium condition;

$$E_t(r_{t+1}) = 0, \tag{7}$$

If $E_t(r_{t+1}) > 0$, then deep pocket investors invest more capital in the fund. Capital inflows raise per dollar management cost, bringing expected net returns down. Capital inflows continue until $E_t(r_{t+1}) = 0$. Capital outflows on the other hand reduce cost of management per dollar and pushes the expected returns higher. If $E_t(r_{t+1}) < 0$, then outflows continue until drop in per dollar cost is enough to restore zero expected net return condition. Under rational expectations equilibrium, this condition determines equilibrium fund size.

First I solve for manager's policy h_t. The manager's objective is to maximize revenues from the fee. Assuming a fixed fee per dollar f, maximizing fee revenue is equivalent to maximizing fund size. In equilibrium, fund size is determined using equilibrium condition in equation 7. Formally, manager solves

$$\max_{h_t \geq 0} \{ f \times q_t \}, \tag{8}$$

subject to equilibrium condition 7 namely,

$$E_t(r_{t+1} | h_t) = 0.$$

The solution is characterized in the following lemma.

[11] In a later section, it will be shown that $h(.)$ policy is a function of ϕ

Lemma 1 (Optimal Policy) *Manager's optimal policy is given by*

$$h_t \equiv h(\phi_t) = \frac{2f}{\phi_t}, \tag{9}$$

Substituting the optimal policy given in equation 9 into equilibrium condition given in equation 7 we get equilibrium fund size;

$$q_t \equiv q(\phi_t) = \frac{\phi_t^2}{4\eta f}. \tag{10}$$

This expression ties q_t with ϕ_t directly. Given the solution of q_t in terms of ϕ_t, fund flows are easily computed using equation 1. To compute q_{t+1}, we need to know how investors update skill from ϕ_t to ϕ_{t+1}. Let $\alpha \sim N(\phi_t, \sigma_t^2)$ be the prior at the end of time t. Investors observes r_{t+1} and back out R_{t+1}, given h_t, q_t and other parameters. This is used to update $\phi_{t+1} = E_{t+1}(\alpha)$, according to Bayesian learning.

Lemma 2 (Belief Update) *Investors update the beliefs as*

$$\phi_{t+1} = \phi_t + \left(\frac{r_{t+1}}{h_t}\right)\left(\frac{\sigma_t^2}{\sigma_t^2 + \sigma_\varepsilon^2}\right). \tag{11}$$

This update formula has an intuitive structure. Because for every fund expected net $E_t(r_{t+1})$ is zero in equilibrium, belief is updated only with a surprise return; that is, when $r_{t+1} \neq 0$. Additionally, the magnitude of update is scaled for active share. Note that the variance of beliefs can be updated as follows

$$\sigma_{t+1}^2 = \left(\frac{1}{\sigma_t^2} + \frac{1}{\sigma_\varepsilon^2}\right)^{-1},$$

5.3 Solution With Inattentive Customers ($\delta < 1$)

When $\delta < 1$, some investors are not always attentive. This means that they do not update beliefs with every new piece of information, so capital flows may not reflect new information completely. This implies that fund size and history of performance are disconnected. Investor composition is also affected by history of performance. In this section, I solve the model with inattentive investors and explore other implications of this mechanism in detail.

Initial Investor Composition: The economy is populated with a unit mass of deep pocket investors of which μ fraction are *always attentive* (AA) and $1-\mu$ fraction are *occasionally attentive* (OA) with attention probability of $\delta < 1$. The continuum of investors implies that at any point in time $(1-\mu)\times\delta$ fraction of OA-type investors are attentive. If required capital to any fund is contributed by every attentive investor equally, then every μ unit of capital from AA-type investors is matched by $(1-\mu)\delta$ units from OA-type investors. This implies that, initially at $t = 0$, each fund's fraction of assets owned by AA-type investors denoted by λ_0 is given by

$$\lambda_0 = \frac{\mu}{\mu + (1-\mu)\delta}. \tag{12}$$

In general, λ_t denotes fraction of fund assets owned by AA type investors at the end of time t after all the capital adjustment for that period. With $\delta < 1$, we have $\lambda_0 > \mu$.

Competitive Inflows and Limited Outflows Capital inflows are competitive even with inattentive customers. This follows because all the investors are assumed to have infinitely deep pockets. With at least one attentive investor in the economy, it is assured that, if there is any fund with positive expected net returns, then capital flows into the fund until the increase in per dollar management costs wipes out the positive expected net return. But with inattentive investors, capital outflows may not be competitive. In spite of negative expected net returns, the fund might not have enough attentive capital to flow out of it to bring the expected net returns back to zero. To formalize this, let $\widehat{q}_t = q_{t-1}(1 + r_t)$ be the size of the fund after realizing r_t but before any capital adjustments. Then total *attentive capital* at time t within a fund is given by

$$z_t = [\lambda_{t-1} + (1 - \lambda_{t-1})\,\delta]\,\widehat{q}_t. \tag{13}$$

To see this, note that all the AA-type investors are attentive whose fraction of ownership is λ_{t-1}. Additionally, out of OA-type investors, the δ fraction are attentive. This means that the fraction of attentive capital is given by $[\lambda_{t-1} + (1 - \lambda_{t-1})\,\delta]$.

Capital Flows and Equilibrium Fund Size At time t after realizing r_t but before capital adjustments, a fund is characterized by the vector of following state variables: $\Omega_t = (\lambda_{t-1}, \phi_t, \widehat{q}_t)$. Let h_t be an active share policy that determines the active share of a fund's capital for time $t+1$. Given this policy and Ω_t, competitive fund size denoted by $q_t(\Omega_t, h_t)$ or q_t^* for short satisfies the zero expected net returns condition.

$$E_t\left[r_{t+1} | \Omega_t, h_t, q_t(\Omega_t, h_t)\right] = 0 \tag{14}$$

Denote by $e(\Omega_t, h_t) \equiv e_t^*$ the competitive capital flows needed at t given Ω_t and h_t to make fund size equal to new competitive size q_t^*. That is,

$$e(\Omega_t, h_t) \equiv e_t^* = q_t^* - q_{t-1}(1 + r_t). \tag{15}$$

Denote actual capital flows at the end of period t by e_t, which can be characterized using following cases:

- **Expected net returns are positive and $e_t^* > 0$:**
  With deep pocket outside investors, it is assured that whenever $e_t^* > 0$, then $e_t = e_t^*$. This also ensures that $q_t = q_t^*$ and $E_t(r_{t+1}) = 0$.

- **Expected net returns are negative and $e_t^* < 0$:**
  Whenever $e_t^* < 0$, then $e_t \leq e_t^*$. This holds because a fund may not have enough attentive capital to support the required competitive outflows. There are two cases to consider depending upon how much attentive capital (z_t) a fund has.

  - $e_t^* < 0$ and $z_t \geq |e_t^*|$
    In this case, the fund has enough attentive capital to support required competitive outflows. This again means that $q_t = q_t^*$. It also means that $E_t(r_{t+1}) = 0$ for such a fund.

- $e_t^* < 0$ and $z_t < |e_t^*|$
  In this case, required outflows are more than available attentive capital, and only part of required capital outflows actually materialize. In particular, actual capital flows satisfy $e_t = -z_t$. This implies that $q_t > q_t^*$ or a fund being over-sized relative to its competitive benchmark given Ω_t and h_t. As r_{t+1} is decreasing in q_t given other state variables and parameters, $E_t(r_{t+1}|q_t, \Omega_t, h_t) < 0$ in this case. Also note that, in this case, capital outflows equal z_t and this magnitude is independent of h_t. This observation will be useful while characterizing manager's policy.

Dynamics of Investor Composition Next I describe how investor composition changes after capital flows. Note that λ_{t-1} fraction of fund assets q_{t-1} are owned by AA investors at the end of period $t-1$. Because fund returns accrue to all the investors in proportion to their fund ownership, λ_{t-1} is also the fraction of $\widehat{q}_t$ (assets after realization of r_t but before any capital adjustment) owned by AA investor. I characterize the dynamics of investor composition for fund inflows and outflows separately.

Lemma 3 *Suppose* $\lambda_{t-1} > 0$. *If* $e_t^* < 0$, *then* $\lambda_t < \lambda_{t-1}$.

Proof. First consider the easy case where $e_t^* < 0$ and $z_t < |e_t^*|$. That is, total attentive capital is not enough to achieve competitive capital outflows. In this case, all of the attentive capital shifts out. In particular, all of the AA-type investors shift out of the fund. Any remaining fund owners are necessarily OA-type investors. This follows from the observation that $E_t(r_{t+1}|q_t = \widehat{q}_t - z_t, \Omega_t, h_t) < 0$ and no AA-type investor would invest in a negative expected net return opportunity. So we have that $\lambda_{t-1} > \lambda_t = 0$.
Now consider the other case, where $e_t^* < 0$ and $z_t > |e_t^*|$. Now required capital outflows will be achieved. AA-type and OA-type investors contribute to required outflows in the proportion of their respective shares of attentive capital. The AA-type investor's share of attentive capital is given by $\frac{\lambda_{t-1}}{\lambda_{t-1}+(1-\lambda_{t-1})\delta} > \lambda_{t-1}$. Inequality follows because $\lambda_{t-1} + (1-\lambda_{t-1})\delta < 1$. This implies that AA-type investors contribute to capital outflows proportionately more as compared to their ownership. This immediately implies that $\lambda_t < \lambda_{t-1}$. ■

Now consider the case of capital inflows. Next lemma shows that any inflow of capital raises the ownership share of AA-type investors.

Lemma 4 $\lambda_t \geq \lambda_{t-1}$ *whenever* $e_t^* > 0$

Proof. First I show that λ_0 serves as an upper limit of λ_{t-1}. Consider $t = 1$. If $e_1^* > 0$, then AA-type contributes λ_0 fraction of it which is same as their existing share of ownership given by λ_0. Hence $\lambda_1 = \lambda_0$. If $e_t^* < 0$, then as shown in above lemma, $\lambda_1 < \lambda_0$. Hence $\lambda_1 \leq \lambda_0$. If $e_2^* > 0$, then λ_2 is a weighted average of λ_1 and λ_0 and as $\lambda_1 < \lambda_0$, it follows that $\lambda_2 < \lambda_0$. On the other hand if $e_2 < 0$, then $\lambda_2 < \lambda_1 \leq \lambda_0$. In either case, $\lambda_2 \leq \lambda_0$. Continuing in this fashion recursively, it follows that $\lambda_{t-1} \leq \lambda_0$.
Proceeding for one more period, λ_t is a weighted average of λ_{t-1} and λ_0. If $\lambda_{t-1} \leq \lambda_0$, then $\lambda_{t-1} \leq \lambda_t \leq \lambda_0$. ■

In summary, because AA-type investors are always more proactive and contribute to both inflows and outflows more than proportionately as compared to their existing ownership in a fund, any inflows push up their ownership fraction and outflows reduce it. This formalizes the link the between investor composition and performance history. In particular, a corollary can be stated;

Corollary 1 *Consider two funds: fund 1 and 2. If* $\phi_{0,1} = \phi_{0,2}$ *and further that* $r_{\tau,1} - E_{\tau-1,1}(r_{\tau,1}) > r_{\tau,2} - E_{\tau-1,2}(r_{\tau,2})$ $\forall \tau = 1, 2, ..t$*, then* $\lambda_{t,1} > \lambda_{t,2}$

Manager's Policy The manager's objective is same as before: maximize fee revenue. But now with inattentive investors, the size constraint or expected net return constraint is distorted. In particular, $q_t \geq q_t^*$. But such a distortion is independent of h_t. This follows because, whenever $z_t < |e_t^*|$, fund outflows equal z_t, and this magnitude is independent of h_t. h_t plays a role only in deciding required capital flows e_t^* but not the actual capital flows. This leads to the following characterization of optimal policy.

Lemma 5 (Manager's Policy With Inattention) *Manager's optimal policy* h_t^* *is equivalent to competitive benchmark:* $h(\phi_t) = \frac{2f}{\phi_t}$

Learning Similar to the competitive case, realization of r_t leads to an update in the estimated α for the manager. With inattentive investors, it is possible that $E_t(r_{t+1}) \neq 0$. In this case, the update formula is given by equation 20.

$$\phi_t = \phi_{t-1} + \left(\frac{r_t - E_{t-1}(r_t)}{h_{t-1}}\right)\left(\frac{\sigma_{t-1}^2}{\sigma_{t-1}^2 + \sigma_\varepsilon^2}\right)$$

The formula is derived in proof to lemma 2. There are several observations to make.

First note that, through $E_{t-1}(r_t)$, learning depends upon level of reputation ϕ_{t-1}. It is more likely that lower ϕ_{t-1} funds are over-sized and for such funds $E_{t-1}(r_t) < 0$. This is not the case under the competitive equilibrium where for each fund $E_{t-1}(r_t) = 0$. Second, learning technology has an implicit trade-off for over-sized funds. With the presence of inattentive investors, it is possible to have $E_{t-1}(r_t) < 0$. For such funds, ϕ_t is larger as compared to a competitively sized fund for which $E_{t-1}(r_t) = 0$ for any given level of r_t and ϕ_{t-1}. This effect works to increase the new competitive size q_t^*. But because these funds are over-sized, required capital adjustment to achieve a competitive fund size commensurate with ϕ_t is smaller in the first place. But note that these two effects are linked. Size increases the magnitude of surprise $r_t - E_{t-1}(r_t)$, thereby boosting required flows, but size also cuts the gap between new competitive size and current size, requiring less flows. Hence, magnitude of these two opposing effects is tightly linked. Next I derive the expression for fund flows analytically, which makes this trade-off explicit.

Fund Flows Consider a fund characterized by $\Omega_t = (\phi_t, \lambda_t, q_{t-1}(1 + r_t))$. Fund assets q_{t-1} can be expressed as $q_{t-1} = q_{t-1}^* \times (1 + \psi_{t-1})$, where q_{t-1}^* is the competitive fund size such that $E_{t-1}(r_t|\phi_{t-1}, h_{t-1}, q_{t-1}^*) = 0$ and ψ_{t-1} is the extent of fund size distortion at the end of time $t - 1$. Note that in the model $\psi_t \geq 0$. I derive an expression for expected net return first. This will be useful in the calibration exercise too.

Lemma 6 (Size Distortion and Expected Net Return) *For a fund with size given by $q_t = q_t^*(1+\psi_t)$, expected net return is given by*

$$E_t\left(r_{t+1}\right) = -\eta h_t^2 q_t^* \psi_t. \tag{16}$$

With this expression, we can derive an expression for equilibrium fund flows. There are two cases. Given Ω_t, r_t is such that the fund achieves new optimum size q_t^*. In that case dollar flows are given by $q_t^* - q_{t-1} \times (1 + r_{t+1})$. Otherwise, in the case where enough capital cannot flow out, dollar flows equals $-z_t$. In the following lemma, I characterize the flows in the terms of observables.

Lemma 7 (Equilibrium Fund Flows) *For a fund characterized by Ω_t, and ψ_{t-1}, equilibrium flows are given by*

$$FF_t = \begin{cases} \frac{1}{(1+\psi_{t-1})(1+r_t)}\left[1+\omega_{t-1}\left(\frac{r_t}{2f}+\frac{\psi_{t-1}}{2}\right)\right]^2 - 1 & \textit{If } z_t > |e_t^*| \\ -\frac{z_t}{q_{t-1}(1+r_t)} & \textit{otherwise} \end{cases} \tag{17}$$

There are few points worth stressing. First, by substituting $\psi_{t-1} = 0$, we get an expression for capital flows for an optimally sized fund. Second, ψ_{t-1} is implicitly a function of the performance history. For poor history funds, ψ_{t-1} is likely to be positive. Hence FF_t is history dependent. Third, the trade-off coming from $\psi_{t-1} > 0$ is apparent now: the first effect scales down the entire expression for fund flows by a factor of $1 + \psi_{t-1}$. This represents the fact that fund is already over-sized and in percentage terms requires less flows. Second effect boosts the skill update and is seen through $\frac{\psi_{t-1}}{2}$ inside the brackets, which increase the flows.

The comparison between fund flows between a competitively sized fund and an over-sized fund crucially depends upon parameter values, especially ω_{t-1} and the size-distortion parameter ψ_{t-1}. I calibrate these parameters in the next section and compare the fund schedules.

6 Performance Persistence, Size Distortion and Calibration

[7], and [4] document persistence in performance for recent poor performers. The model in this paper explains why this is the case: Poorly performing funds are over-sized and hence produce negative expected returns net of fees and expenses. In particular, the *zero expected net return* prediction of [2] is replaced by a *non-positive expected net returns* prediction in my model. I test this prediction formally in this section using a methodology similar to [7].

At the end of each year, I sort the funds according to four-factor alpha (reputation) computed using a five-year window. Then I form 10 equally weighted portfolios each representing a decile of reputation. I compute the performance of each decile portfolio for each of the months in the following year where portfolio weights are rescaled to account for only surviving funds. I repeat the process for each year-end. This generates a sequence of monthly portfolio returns for each decile portfolio. Then I estimate a four-factor regression model for each decile portfolio separately. Results are presented in table 11.

D1 (D10) represents the bottom (top) decile portfolio. The results strongly support the main prediction of the model, namely that of *non-positive expected net returns*. Bottom four decile portfolios from D1 through D4 exhibit strong negative four-factor alpha, indicating persistence in poor performance while the remaining decile portfolios from D5 through D10 exhibit close to a zero four-factor alpha. This is exactly what the model predicts: High reputation funds are optimally sized and produce zero net returns on average. But low reputation funds are over-sized and produce negative net returns on average.

Interestingly, the magnitude of negative returns among low reputation funds presents a direct way to estimate size distortion. Under the null of the model, expected net returns are given by

$$E_t\left(r_{t+1}\right) = -\eta h_t^2 q_t^* \psi_t,$$

where ψ_t gives the percentage of size distortion or extent of fund excess size above optimal size q_t^*. Substituting q_t^* and h_t from the model equilibrium, we get $E_t\left(r_{t+1}\right) = -f\psi_t$. Mean annual expense ratio for a fund including amortizing for front- and back-end load is around 1.76%. This is a bit higher than the estimate used by [8] or [2], who use numbers in the range of 1.20% to 1.50% per annum. This is because I also include exit loads in amortization. From table 11, a point estimate of monthly alpha for a bottom decile fund is -0.137% or on an annual basis -1.64%. Feeding these numbers into the expression above, we get -1.64% = -1.76% $\times$ ψ_t which gives $\psi_t = 0.93$ or 93%. This is a point estimate for size distortion: an average bottom decile fund is 93% over-sized relative to its optimal size which ensures zero expected net returns. A similar procedure gives size distortion for funds within other reputation deciles. In particular for highest reputation decile, size distortion is close to zero.

Next I carry estimate other parameters. The purpose of the calibration exercise is to find an empirically plausible range of parameters that lead to the model-implied fund flows being close to observed fund flows for funds with different reputations. Some model parameters can be directly estimated, and others are estimated using moment fitting exercise.

I estimate ω_t and $\lambda + (1-\lambda)\delta$ jointly by fitting the model implied flow schedule with observed flow schedule. It should be stressed that independent identification of λ and δ is not possible in this model. I call $\lambda + (1-\lambda)\delta$ the *attentiveness index* for a fund. To estimate ω_t, we need two inputs: σ_ε, which indicates fund return volatility, and σ_t, which captures belief uncertainty about the mean level of α or managerial skill. Summary statistics in table 1 show that fund return volatility is almost invariant across reputation deciles. Uncertainty in beliefs about α can be measured using cross-sectional dispersion of alpha. Again, such cross-sectional dispersion in performance is not very different across various reputation deciles. Given this, I estimate a common ω_t across low and high reputation deciles but a separate *attentiveness index* given by $\lambda + (1-\lambda)\delta$ for low and high reputation deciles. In total, I fit three parameters by minimizing the squared difference between observed and model-implied fund flows. To this end, I use five data points for the low reputation decile and five data points for the top reputation decile. Each point represents a quintile of recent performance and gives data on recent performance and fund flows. Then I minimize the mean squared error computed from the difference between model-implied and observed flows. Estimated parameters are $\omega_t = 0.068$, attentiveness index for high reputation funds is

$\lambda_{high}+(1-\lambda_{high})\delta_{high} = 0.490$ and that for low reputation funds is $\lambda_{low}+(1-\lambda_{low})\delta_{low} = 0.201$. The estimated value for ω_t looks reasonable.[2] use a value of $\omega_t = 0.0955$. Using a similar procedure as in [2],[12] a direct estimate of ω_t in my sample is around 0.18, which generates an attentiveness index of 0.20 for low reputation funds and 0.42 for high reputation funds. This puts credence on the estimated value for an attentiveness index for mutual funds of different reputation. This is the first paper to estimate the extent of investor inattention in the context of mutual funds. Parameters suggests that half of the capital is attentive for funds with high reputation and only 20% of the capital is attentive for funds with low reputation.

Using these parameter estimates, I plot fund flow schedules implied by the model for high and low reputation funds. For these estimated parameter values, the model reproduces the empirical fact that flow schedule is more sensitive for high reputation funds. In particular, the boosting effect in learning coming from $E_t(r_{t+1})$ being negative is dominated by the effect that fund is already over-sized and requires less capital adjustment, which results in the model generating the desired flow schedule as in the data. The results are presented in figure 2.

7 Three Thought Experiments

In this section, I carry out three experiments to validate model mechanism. The model predicts that high and low reputation funds differ in terms of the type of investors who own them. This heterogeneity explains heterogeneous fund flow patterns across these funds. Statistically, this mechanism implies that fund flows are determined by interaction of reputation and recent performance. Experiments in this section directly test the implications that arise from the conjectured behavior of inattentive investors under some situations.

1. **Managerial Replacement and Impact of Reputation** One test of the proposed mechanism (namely the presence of inattentive investors) is to identify events that would draw attention of otherwise inattentive investors and then to compare the results for the subsample of data with such events. Managerial replacement presents such a natural experiment. Media reports, communication from the fund to investors and other soft information can grab the attention of at least some of the otherwise non-attentive investors. Once these investors pay attention, they react to all the information that has accumulated since they last followed the fund's performance. This re-balancing from non-attentive investors breaks or weakens the link between investor composition and historic performance. With such re-balancing, we should see reduced

[12] First parameter to estimate is σ_ε which is the volatility of R_t conditional on α. In the model, α denotes managerial ability. In the data, both raw fund returns and factor model explain the fund flow patterns or serve as potential measures of managerial ability. I use raw fund returns as a measure of ability to estimate ω_t. Calculations are similar with CAPM-α or 4-factor α. [2] use empirical fund return volatility to match signal volatility σ_ε. Mean annual volatility of fund excess returns is around 17.37% in the sample. Second parameter to estimate is σ_t which indicates uncertainty in beliefs about mean level of α or ability. I use cross-sectional dispersion in raw returns computed using 5-yearly window to estimate it. Using this measure, σ_t is 8.62% within whole sample. Using these numbers, $\omega_t = \frac{\sigma_t^2}{\sigma_t^2+\sigma_\varepsilon^2}$ =0.18. Using excess returns, CAPM-α and 4-factor α, ω_t is around 0.36, 0.30 and 0.32 respectively using similar computation.

importance of interaction terms as the overall level of attentiveness among the investors increases following the replacement episode. In other words, effective heterogeneity across funds with different reputation reduces after the replacement episode and this should cut the influence of reputation in determining the shape of flow-schedule. To test this conjecture, I construct the following hypothesis:

Hypothesis 6 *If there is a managerial replacement during t, then interaction between time t performance ($Perf_{it}$) and reputation up to $t-1$ ($repute_{it-1}$) is weaker while explaining fund flows during $t+1$.*

To analyze flows during $t+1$, I divide the sample into two subsamples: One subsample with funds that experience a manager replacement either at time $t+1$ or t and the other consisting of funds with no replacement during either $t+1$ or t. The reason to include $t+1$ is that with a yearly horizon, replacements occurring during the early part of $t+1$ can influence the flows during $t+1$. I run the following regression model on the two subsamples separately.

$$FLOW_{it+1} = a+b_1 Perf_{it}+b_2\left(Perf_{it} \times repute_{it-1}\right)+b_3 \times repute_{it-1}+CONTROL_{it}+\varepsilon_{it+1} \tag{18}$$

As the focus is on understanding the impact of managerial replacement on interaction terms rather than on the non-linear nature of fund flow-schedule, I use normalized rank variables: namely Perf_t and $repute_{t-1}$ instead of analyzing interaction within each quintile. Results are presented in table 8. Panel A uses raw returns, and panel B uses CAPM-α to rank the funds. First model within each panel uses the subsample with replacement and the second model uses the subsample without replacement. Data precisely support the conjecture. Interaction between recent performance and reputation lose their significance within the subsample with managerial replacement during the previous period.

First note that, in both the subsamples, the link between flows and recent performance is similar: Perf_t has a strongly positive coefficient in both the samples. This is important as we are assured that other characteristics of the regression estimates are not significantly different during two subsamples, which would make comparison very difficult. Now consider the interaction effect. As expected, the significance of interaction effects is much weaker within the sample with manager replacement. According to the CAPM model, interaction is not significant even at the a 10% level of significance. For the raw returns model, interaction effect is reduced by a third in magnitude, and it is significant only at around 10% level of significance. These results lend support to the idea that lack of attentive investors within low reputation funds causes lack of sensitivity in flow schedule for such funds during non-replacement periods. But managerial replacement increases the average attentiveness within the investor population. This means that even low reputation funds have sensitive flow schedule after managerial replacement.

2. **Fee Structure and Impact of Reputation** Investors paying higher fees or loads will in general be more attentive. If this is true, then reputation-recent performance

interactions should not be as important with funds with lower loads or fees. To this end, I sort the funds into quintiles based on front loads. Front load is a one-time expense and is more visible in nature. I re-run the regression in equation 18 separately on the subsample of funds within the top and bottom quintile sorted on front load. The reason for considering top and bottom quintiles is that middle quintiles of front load have very little variation. The results are presented in table 9. There are two results. First, coefficient on expense ratio is negative for low front load funds and positive for high front-load funds.[13] Second, as conjectured, interaction terms are weaker or insignificant for funds with high front loads.

3. **Interaction Effects With Shorter Reputation Window** As the model suggests, longer sequence of poor (good) performance generates more heterogeneity across high and low reputation funds in terms of type of investors who own them. A simple way to test this prediction is to re-run the regression model in equation 3 with shorter reputation window, say three years or one year and then to compare the strength of the interaction effects. According to the model, it should diminish. To this end, I re-run the regression model using one year of reputation window preceding that of recent performance instead of five-year window used earlier. Results are presented in table 6.

   As can be seen, interaction terms are substantially smaller as compared to the interaction terms with the longer reputation window. This is true for both Flow_{it+1} and ΔMkt_{it+1}. For example, none of the interaction terms on second quintile are significant. These were statistically and economically significant with the longer reputation window. Even for the top quintile, there is substantial reduction in the strength of coefficients. These results indicate that interaction effects strengthen with reputation horizon, reflecting the fact that a longer horizon allows investor composition to be more heterogeneous across reputed and non-reputed funds.

8 Conclusion

This paper presents a novel fact that mutual fund flow sensitivity to recent performance is weak for funds with low reputation. Additionally, for higher reputation funds, the bulk of the flows are attributable to the interactions between recent performance and prior reputation. I rationalize this heterogeneity in flow sensitivity using the presence of the inattentive investors. These investors fail to shift out of poorly performing funds thereby concentrating in poorly performing funds. This simple mechanism has many important implications. First, investor attentiveness and with it the flow sensitivity both increases in the fund's historical performance. Second, not enough capital flows out of a fund with poor reputation if required as most investors are inattentive which implies that poor reputation funds are above the competitive size. Decreasing returns to scale together with the second implication results in negative expected returns for poor reputation funds.

[13] One possible reason for this sign switch is that, when investors are on the lookout for cheaper funds, they tend to choose the cheapest funds. But when they are on the lookout for thematic investments and are ready to pay extra fees or loads, then they may chase high fee funds with a possibly erroneous belief that high loads imply higher expected net returns.

I calibrate the model and find that roughly half of the capital is attentive within high reputation funds but only 20% within low reputation funds. I also estimate that low reputation funds are on an average twice their competitive size. This paper is the first to my knowledge to quantify the attentiveness parameter using an equilibrium model. I also conduct three experiments to test the model mechanism. I find that reputation has less bearing on flow sensitivity for funds experiencing managerial replacements, and for the funds with high front loads.

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A Proofs

Proof of lemma 1
Consider equilibrium condition given in equation 7. Substituting r_{t+1} from equation 6 and taking expectation on both the sides we get

$$h_t\phi_t - f - \eta h_t^2 q_t = 0$$

and solving for q_t we get

$$q_t = \frac{(h_t \times \phi_t) - f}{\eta h_t^2}$$

Substituting this expression for q_t in revenue maximization problem for the manager, we get

$$\mathcal{L} = f \times \left[\frac{h_t \times \phi_t - f}{\eta h_t^2}\right]$$

Taking first order conditions, we get

$$-\frac{f\phi_t}{\eta h_t^2} + \frac{2f^2}{\eta h_t^3} = 0$$

and solving for h_t, we get

$$h_t = \frac{2f}{\phi_t}$$

Given fixed f, it can be seen that optimal h_t is only dependent upon ϕ_t. Hence I denote it by $h(\phi_t)$. This is non-negative as far as fixed fee is non-negative and $\phi_t > 0$.

Proof of lemma 2

Using Bayesian Formula

$$\phi_{t+1} = \phi_t + (R_{t+1} - \phi_t)\left(\frac{\sigma_t^2}{\sigma_t^2 + \sigma_\varepsilon^2}\right)$$

Consider definition of net returns

$$r_{t+1} = h_t R_{t+1} - f - \eta h_t^2 q_t$$

Taking expectations,

$$E_t(r_{t+1}) = h_t\phi_t - f - \eta h_t^2 q_t$$

Backing out R_{t+1} from net return equation and backing out ϕ_t from expected net return equation, we get following for $R_{t+1} - \phi_t$

$$R_{t+1} - \phi_t = \frac{r_{t+1}}{h_t} + \frac{f}{h_t} + \eta h_t q_t - \left(\frac{E_t(r_{t+1})}{h_t} + \frac{f}{h_t} + \eta h_t q_t\right) = \frac{r_{t+1} - E_t(r_{t+1})}{h_t} \tag{19}$$

Substituting in Bayesian formula, we get

$$\phi_{t+1} = \phi_t + \left(\frac{r_{t+1} - E_t(r_{t+1})}{h_t}\right)\left(\frac{\sigma_t^2}{\sigma_t^2 + \sigma_\varepsilon^2}\right) \tag{20}$$

In competitive equilibrium, $E_t(r_{t+1}) = 0$. Which leads to update formula.

Proof of lemma 5

As f is fixed, revenue is maximized by maximizing q_t. Note that

$$\underline{q} \equiv \widehat{q}_t - z_t$$

is the lower bound on fund size at time t as there is no more attentive capital left to flow out. Let $H_t(\Omega_t) = \left\{h_t \geq 0 | q_t = q_t^* > \underline{q}\right\}$ be the set of $h_t \geq 0$ for which optimal size is greater than lower bound. If $H_t = \emptyset$, then any $h_t \geq 0$ generates same revenue and any $h_t \geq 0$ is optimal. Suppose $H_t \neq \emptyset$. Then any policy $h_t \in H_t$ is better than $h_t \notin H_t$. Further $h_t^* = \frac{2f}{\phi_t} \in H_t$. If not, then $\exists h_t^{'} \in H_t$ such that $f \times q_t(\Omega_t, h_t^{'}) > f \times q_t(\Omega_t, h_t^*)$ which contradicts that h_t^* is optimal within competitive set up with $\delta = 1$. As $h_t^* \in H_t$, using lemma 1, we know that h_t^* is the optimal policy even in this case.

Proof of lemma 6
Using definition of net returns and taking expectations we have

$$E_t\left(r_{t+1}\right) = \phi_t h_t - f - \eta h_t^2 q_t$$

Using $q_t = q_t^*(1+\psi_t)$ we get

$$\begin{aligned} E_t\left(r_{t+1}\right) &= \phi_t h_t - f - \eta h_t^2 q_t^* \left(1+\psi_t\right) \\ &= \phi_t h_t - f - \eta h_t^2 q_t^* + \eta h_t^2 q_t^* \psi_t \end{aligned}$$

By definition of competitive equilibrium size, q_t^* is such that expected net return is zero. That is

$$\phi_t h_t - f - \eta h_t^2 q_t^* = 0$$

This gives us

$$E_t\left(r_{t+1}\right) = -\eta h_t^2 q_t^* \psi_t \tag{21}$$

Proof of lemma 7
Define fund flows as Define Fund flows (FF_t) by

$$FF_t = \frac{q_t}{q_{t-1}(1+r_t)} - 1 \tag{22}$$

This definition is identical to one tested in empirical section. Now consider a fund with Ω_t, h_{t-1} and ψ_{t-1}. Suppose r_t is such that q_t^* can be achieved as $z_t > |e_t^*|$. In that case $q_t = q_t^*$. Using equation 10, we have

$$q_t^* = \frac{\phi_t^2}{4\eta f}$$

. Substituting q_t^* and q_t^* and using $q_{t-1} = q_{t-1}^*(1+\psi_{t-1})$, and denoting $\frac{\sigma_{t-1}^2}{\sigma_{t-1}^2+\sigma_\varepsilon^2} = \omega_{t-1}$, we get

$$FF_t = \frac{\phi_t^2}{\phi_{t-1}^2(1+\psi_{t-1})(1+r_t)} - 1$$

Now substituting the expression for ϕ_t in terms of ϕ_{t-1} using Bayesian Update we get

$$FF_t = \frac{\left(\phi_{t-1} + \frac{\omega_{t-1}(r_t - E_{t-1}(r_t))}{h_{t-1}}\right)^2}{\phi_{t-1}^2(1+\psi_{t-1})} - 1$$

Finally substituting for h_{t-1} from equation 9 and $E_{t-1}(r_t)$ from equation 21, and simplifying we get

$$FF_t = \frac{\left(\phi_{t-1} + \frac{\omega_{t-1}\left(r_t + \eta h_{t-1}^2 q_{t-1}^* \psi_{t-1}\right)}{h_{t-1}}\right)^2}{\phi_{t-1}^2(1+\psi_{t-1})(1+r_t)} - 1$$

Simplifying above expression we get FF_t in case where $q_t = q_t^*$

$$FF_t = \frac{1}{(1+\psi_{t-1})(1+r_t)} \left[1 + \omega_{t-1}\left(\frac{r_t}{2f} + \frac{\psi_{t-1}}{2}\right)\right]^2 - 1 \tag{23}$$

In the other case where $e_t^* < 0$ and $z_t < |e_t^*|$, capital outflows equal z_t. In that case percentage capital flows are given by

$$FF_t = -\frac{z_t}{q_{t-1}(1+r_t)} \tag{24}$$

Table 2: Historical Raw Performance and Fund Flows

Table presents estimation of the equation 3 with $FLOW_{it}$ as the dependent variable defined in the equation 1. $Q_{jit} = 1$ if recent performance at time t denoted by Perf_{it} lies in the j^{th} quintile. $repute_{it-1}$ denotes the normalized reputation index computed using a five-year window ending at the year $t-1$. Panel A uses raw return measure to sort the funds. Control variables include half yearly performance during $t+1$ (Perf-Half_{t+1}), logarithm of the fund size, logarithm of fund age plus one, turnover, expense ratio, risk, which is computed using monthly return data for the period t, and category flow for time $t+1$, which is the asset weighted growth of the investment category to which a fund belongs. All the specifications have time fixed effects. Standard errors are clustered at the fund level to control for serial correlation within each panel. Standard errors are in parenthesis and *, ** and *** denote significance of coefficient at 10%, 5% and 1% level respectively. All the models have an intercept. Q_1 is the base group and hence effects of Q_j are incremental over Q_1. Similarly interactions effects for $Q_j \times repute$ are incremental over $Q_1 \times repute$.

Table 2: Historical Raw Performance and Fund Flows

	Panel A: Raw Returns		
$Q_{2t} - Q_{1t}$	0.034***	0.037***	0.013
	(0.006)	(0.006)	(0.011)
$Q_{3t} - Q_{1t}$	0.084***	0.090***	0.032***
	(0.007)	(0.007)	(0.012)
$Q_{4t} - Q_{1t}$	0.124***	0.130***	0.050***
	(0.007)	(0.007)	(0.014)
$Q_{5t} - Q_{1t}$	0.241***	0.246***	0.107***
	(0.010)	(0.010)	(0.018)
$repute_{t-1}$		0.202***	0.083***
		(0.013)	(0.015)
$repute_{t-1} \times (Q_{2t} - Q_{1t})$			0.043**
			(0.019)
$repute_{t-1} \times (Q_{3t} - Q_{1t})$			0.108***
			(0.021)
$repute_{t-1} \times (Q_{4t} - Q_{1t})$			0.149***
			(0.026)
$repute_{t-1} \times (Q_{5t} - Q_{1t})$			0.261***
			(0.033)
Perf-Half(t+1)	0.201***	0.202***	0.201***
	(0.011)	(0.011)	(0.011)
Risk (t)	-0.892***	-0.922***	-0.887***
	(0.251)	(0.250)	(0.251)

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Table 2 – **Continued from previous page**

	Panel A: Raw Returns		
Size (t)	-0.006***	-0.017***	-0.017***
	(0.002)	(0.002)	(0.002)
Expense Ratio (t)	-0.183	0.062	-0.016
	(0.686)	(0.702)	(0.696)
Age (t)	-0.041***	-0.022***	-0.022***
	(0.006)	(0.005)	(0.005)
Category Flow (t+1)	0.234***	0.226***	0.218***
	(0.066)	(0.065)	(0.064)
Intercept	0.056	-0.067*	-0.008
	(0.037)	(0.035)	(0.035)
N	11879	11879	11879
Adj. R-sq	0.176	0.208	0.215

Table 1: Summary Statistics

Table reports the summary statistics for important variables. Funds are sorted as Low (bottom 20 %), Medium (Middle 60%) or Top (top 20%) according to their reputation rank based on raw return measure. Statistics are over the entire sample from 1981 to 2014.

Reputation	**Excess Ret**^{LT}	α^{LT}	**Exp Ratio**	**Front Load**	**Turn over**	σ^{LT}	**Size Mn$**	**Age Years**
Low								
Mean	-0.042	-0.038	0.013	0.038	0.886	0.186	670.933	17.268
Median	-0.041	-0.037	0.013	0.041	0.700	0.176	122.750	12.000
Med								
Mean	-0.003	-0.001	0.012	0.038	0.715	0.172	1329.879	17.335
Median	-0.007	-0.004	0.012	0.043	0.550	0.167	208.500	12.000
Top								
Mean	0.042	0.041	0.012	0.035	0.702	0.175	2019.931	16.014
Median	0.031	0.032	0.012	0.038	0.520	0.170	351.650	11.000
Full Sample								
Mean	0.000	0.002	0.012	0.037	0.743	0.175	1368.062	17.027
Median	-0.005	-0.002	0.012	0.042	0.570	0.169	211.475	12.000

Table 3: Historical CAPM-Alpha and Fund Flows

Table presents estimation of the equation 3 with $FLOW_{it}$ as the dependent variable defined in the equation 1. $Q_{jit} = 1$ if recent performance at time t denoted by Perf_{it} lies in the j^{th} quintile. $repute_{it-1}$ denotes the normalized reputation index computed using a five-year window ending at the year $t-1$. Panel uses CAPM-Alpha to sort the funds. Control variables include half yearly performance during $t+1$ (Perf-Half_{t+1}), logarithm of the fund size, logarithm of fund age plus one, turnover, expense ratio, risk, which is computed using monthly return data for the period t, and category flow for time $t+1$, which is the asset weighted growth of the investment category to which a fund belongs. All the specifications have time fixed effects. Standard errors are clustered at the fund level to control for serial correlation within each panel. Standard errors are in parenthesis and *, ** and *** denote significance of coefficient at 10%, 5% and 1% level respectively. All the models have an intercept. Q_1 is the base group and hence effects of Q_j are incremental over Q_1. Similarly interactions effects for $Q_j \times repute$ are incremental over $Q_1 \times repute$.

Table 3: Historical CAPM-Alpha and Fund Flows

	Panel A: Raw Returns		
$Q_{2t} - Q_{1t}$	0.041***	0.045***	0.012
	(0.006)	(0.006)	(0.011)
$Q_{3t} - Q_{1t}$	0.087***	0.091***	0.038***
	(0.007)	(0.007)	(0.013)
$Q_{4t} - Q_{1t}$	0.134***	0.137***	0.061***
	(0.008)	(0.008)	(0.014)
$Q_{5t} - Q_{1t}$	0.226***	0.225***	0.109***
	(0.010)	(0.010)	(0.019)
$repute_{t-1}$		0.177***	0.069***
		(0.013)	(0.015)
$repute_{t-1} \times (Q_{2t} - Q_{1t})$			0.061***
			(0.020)
$repute_{t-1} \times (Q_{3t} - Q_{1t})$			0.102***
			(0.023)
$repute_{t-1} \times (Q_{5t} - Q_{1t})$			0.143***
			(0.026)
$repute_{t-1} \times (Q_{5t} - Q_{1t})$			0.216***
			(0.033)
Perf-Half(t+1)	0.198***	0.202***	0.202***
	(0.011)	(0.011)	(0.011)
Risk (t)	-0.590**	-0.467*	-0.440*

Continued on next page

Table 3 – **Continued from previous page**

	Panel A: Raw Returns		
	(0.250)	(0.251)	(0.252)
Size (t)	-0.006***	-0.016***	-0.016***
	(0.002)	(0.002)	(0.002)
Expense Ratio (t)	-0.013	0.278	0.237
	(0.696)	(0.709)	(0.708)
Age (t)	-0.042***	-0.025***	-0.025***
	(0.006)	(0.006)	(0.006)
Category Flow (t+1)	0.233***	0.227***	0.222***
	(0.066)	(0.065)	(0.065)
Intercept	0.042	-0.076**	-0.024
	(0.036)	(0.035)	(0.035)
N	11879	11879	11879
Adj. R-sq	0.164	0.189	0.193

Table 4: Reputation and Market Share

Table presents estimation of the following regression equation

$$\Delta Mkt_{it+1} = a + \sum_{j=2}^{J} \phi_j Q_{jit} + \sum_{j=2}^{J} \psi_j \left(Q_{jit} \times repute_{it-1}\right) + (\gamma \times repute_{it-1}) + CONTROL_{it} + \varepsilon_{it+1}$$

Dependent variable is defined as

$$\Delta Mkt_{it+1} = \frac{q_{it+1}}{\sum_i q_{it+1}} - \frac{q_{it} \times (1 + r_{it+1})}{\sum_i q_{it} \times (1 + r_{it+1})}$$

$Q_{jit} = 1$ if recent performance at time t denoted by Perf$_t$ lies in the j^{th} quintile. $repute_{it-1}$ denotes the normalized reputation index computed using a five-year window ending at the year $t-1$. Panel A and B uses raw return measure and CAPM-Alpha to sort the funds. Control variables include half yearly performance during $t+1$ (Perf-Half$_{t+1}$), logarithm of the fund size, logarithm of fund age plus one, turnover, expense ratio, risk, which is computed using monthly return data for the period t, and category flow for time $t+1$, which is the asset weighted growth of the investment category to which a fund belongs. All the specifications have time fixed effects. Standard errors are clustered at the fund level to control for serial correlation within each panel. Standard errors are in parenthesis and *, ** and *** denote significance of coefficient at 10%, 5% and 1% level respectively. All the models have an intercept. Q_1 is the base group and hence effects of Q_j are incremental over Q_1. Similarly interactions effects for $Q_j \times repute$ are incremental over $Q_1 \times repute$.

Table 4: Reputation and Market Share

	Panel A: Raw Returns		**Panel B: CAPM-Alpha**	
$Q_{2t} - Q_{1t}$	0.042	-0.125***	0.061**	-0.085*
	(0.026)	(0.046)	(0.026)	(0.044)
$Q_{3t} - Q_{1t}$	0.107***	-0.186**	0.131***	-0.130*
	(0.032)	(0.079)	(0.036)	(0.071)
$Q_{4t} - Q_{1t}$	0.258***	-0.158***	0.276***	-0.110**
	(0.033)	(0.051)	(0.035)	(0.053)
$Q_{5t} - Q_{1t}$	0.510***	-0.167**	0.490***	-0.149**
	(0.046)	(0.070)	(0.047)	(0.069)
$repute_{t-1}$		-0.048		-0.023
		(0.060)		(0.066)
$repute_{t-1} \times (Q_{2t} - Q_{1t})$		0.326***		0.297***
		(0.098)		(0.088)
$repute_{t-1} \times (Q_{3t} - Q_{1t})$		0.577***		0.517***
		(0.169)		(0.166)

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Table 4 – **Continued from previous page**

	Panel A: Raw Returns		**Panel B: CAPM Alpha**	
$repute_{t-1} \times (Q_{4t} - Q_{1t})$		0.811***		0.753***
		(0.124)		(0.121)
$repute_{t-1} \times (Q_{5t} - Q_{1t})$		1.309***		1.195***
		(0.186)		(0.186)
Perf-Half(t+1)	0.761***	0.760***	0.706***	0.717***
	(0.068)	(0.067)	(0.068)	(0.068)
Risk(t)	-2.239*	-2.212*	-1.182	-0.587
	(1.242)	(1.235)	(1.263)	(1.284)
Size(t)	0.004	-0.031***	0.003	-0.029**
	(0.012)	(0.012)	(0.012)	(0.011)
Expense Ratio(t)	0.274	0.499	0.559	1.210
	(3.332)	(3.276)	(3.387)	(3.372)
Age(t)	-0.101***	-0.049*	-0.103***	-0.054**
	(0.029)	(0.026)	(0.029)	(0.026)
Category Flow(t+1)	-0.579*	-0.655**	-0.588**	-0.651**
	(0.298)	(0.298)	(0.297)	(0.300)
Intercept	-0.189	-0.217	-0.220	-0.305
	(0.240)	(0.223)	(0.231)	(0.221)
N	11715	11715	11715	11715
Adj R^2	0.062	0.088	0.055	0.077

Table 5: Reputation and of Fund Flows Across Age and Size Bins

Table presents estimation of the following regression equation

$$\begin{aligned} FLOW_{it+1} &= a + \sum_{j=2}^{J} \phi_j Q_{jit} + \sum_{j=2}^{J} \eta_j (Q_{jit} \times \text{control dummy}) \\ &+ \sum_{j=2}^{J} \psi_j \left(Q_{jit} \times repute_{it-1}\right) + \sum_{j=2}^{J} \zeta_j \left(Q_{jit} \times repute_{it-1} \times \text{control dummy}\right) \\ &+ (\gamma_1 \times repute_{it-1}) + (\gamma_2 \times repute_{it-1} \times \text{control dummy}) + Controls_{it} + \varepsilon_{it+1} \end{aligned}$$

Dependent variable is defined as

$$FLOW_{it} = \frac{AUM_{it} - AUM_{it-1} \times (1 + R_{it})}{AUM_{it-1} \times (1 + R_{it})}$$

$Q_{jit} = 1$ if recent performance at time t denoted by Perf_t lies in the j^{th} quintile. $repute_{it-1}$ denotes the normalized reputation index computed using a five-year window ending at the year $t-1$. A fund is young (small) at time t, if at the end of t, fund age (size) is below median age (size) within same investment objective. Control dummy indicates fund being young (small).

Panel A and B uses raw return measure and CAPM-Alpha to sort the funds. Control variables include half yearly performance during $t+1$ (Perf-Half_{t+1}), logarithm of the fund size, logarithm of fund age plus one, turnover, expense ratio, risk, which is computed using monthly return data for the period t, and category flow for time $t+1$, which is the asset weighted growth of the investment category to which a fund belongs. All the specifications have time fixed effects. Standard errors are clustered at the fund level to control for serial correlation within each panel. Standard errors are in parenthesis and *, ** and *** denote significance of coefficient at 10%, 5% and 1% level respectively. All the models have an intercept. Q_1 is the base group and hence effects of Q_j are incremental over Q_1. Similarly interactions effects for $Q_j \times repute$ are incremental over $Q_1 \times repute$.

Table 5: Reputation and of Fund Flows Across Age and Size Bins

	Panel A: Returns		**Panel B: Alpha**	
Ctrl Dummy	**Young=1**	**Small=1**	**Young=1**	**Small=1**
$Q_{2t} - Q_{1t}$	0.012	0.032**	0.011	0.013
	(0.012)	(0.016)	(0.013)	(0.013)
$Q_{3t} - Q_{1t}$	0.025*	0.043**	0.028**	0.039**
	(0.014)	(0.018)	(0.014)	(0.019)
$Q_{4t} - Q_{1t}$	0.050***	0.044***	0.039***	0.059***
	(0.014)	(0.017)	(0.014)	(0.017)

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Table 5 – **Continued from previous page**

	Panel A: Returns		**Panel B: Alpha**	
Ctrl Dummy	**Young=1**	**Small=1**	**Young=1**	**Small=1**
$Q_{5t} - Q_{1t}$	0.066***	0.075***	0.064***	0.080***
	(0.018)	(0.021)	(0.019)	(0.022)
$(Q_{2t} - Q_{1t})\times$Ctrl Dum	0.001	-0.033	0.003	0.003
	(0.025)	(0.022)	(0.024)	(0.024)
$(Q_{3t} - Q_{1t})\times$Ctrl Dum	0.018	-0.026	0.028	0.028
	(0.027)	(0.024)	(0.032)	(0.032)
$(Q_{4t} - Q_{1t})\times$Ctrl Dum	-0.002	-0.004	0.043	0.043
	(0.029)	(0.029)	(0.033)	(0.033)
$(Q_{5t} - Q_{1t})\times$Ctrl Dum	0.116***	0.047	0.128***	0.128***
	(0.039)	(0.033)	(0.041)	(0.041)
$repute_{t-1}$	0.087***	0.090***	0.071***	0.066***
	(0.019)	(0.020)	(0.018)	(0.018)
$repute_{t-1} \times (Q_{2t} - Q_{1t})$	0.055**	0.018	0.054**	0.062***
	(0.022)	(0.026)	(0.023)	(0.024)
$repute_{t-1} \times (Q_{3t} - Q_{1t})$	0.116***	0.075***	0.096***	0.105***
	(0.025)	(0.028)	(0.025)	(0.030)
$repute_{t-1} \times (Q_{4t} - Q_{1t})$	0.115***	0.129***	0.132***	0.123***
	(0.026)	(0.028)	(0.025)	(0.027)
$repute_{t-1} \times (Q_{5t} - Q_{1t})$	0.268***	0.272***	0.236***	0.230***
	(0.035)	(0.038)	(0.036)	(0.035)
$repute_{t-1} \times (Q_{2t} - Q_{1t})\times$Ctrl Dum	-0.028	0.038	0.014	0.014
	(0.042)	(0.042)	(0.042)	(0.042)
$repute_{t-1} \times (Q_{3t} - Q_{1t})\times$Ctrl Dum	-0.022	0.083*	0.017	0.017
	(0.046)	(0.045)	(0.053)	(0.053)
$repute_{t-1} \times (Q_{4t} - Q_{1t})\times$Ctrl Dum	0.083	0.088	0.031	0.031
	(0.054)	(0.061)	(0.055)	(0.055)
$repute_{t-1} \times (Q_{5t} - Q_{1t})\times$Ctrl Dum	-0.028	0.042	-0.067	-0.067
	(0.068)	(0.065)	(0.067)	(0.067)
Ctrl Dum	-0.010	-0.001	-0.026	-0.010
	(0.019)	(0.017)	(0.019)	(0.018)
Ctrl Dum $\times repute_{t-1}$	-0.006	-0.035	-0.001	-0.001
	(0.031)	(0.030)	(0.030)	(0.030)
Perf-Half(t+1)	0.204***	0.205***	0.204***	0.205***
	(0.011)	(0.011)	(0.011)	(0.011)
Risk(t)	-0.916***	-0.925***	-0.356	-0.365
	(0.254)	(0.252)	(0.253)	(0.253)
Size(t)	-0.017***	-0.016***	-0.016***	-0.016***
	(0.002)	(0.003)	(0.002)	(0.003)
Expense Ratio(t)	-0.113	-0.098	0.126	0.113
	(0.705)	(0.699)	(0.722)	(0.718)

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Table 5 – **Continued from previous page**

	Panel A: Returns		**Panel B: Alpha**	
Ctrl Dummy	**Young=1**	**Small=1**	**Young=1**	**Small=1**
Age(t)	-0.013*	-0.022***	-0.017**	-0.025***
	(0.007)	(0.005)	(0.007)	(0.006)
Category Flow(t+1)	0.355***	0.355***	0.358***	0.357***
	(0.055)	(0.055)	(0.056)	(0.057)
Intercept	-0.039	-0.024	-0.052	-0.034
	(0.039)	(0.038)	(0.038)	(0.037)
N	11780	11780	11780	11780
Adj R^2	0.228	0.225	0.203	0.201

Table 6: Short Horizon of Reputation and Fund Flows

Table presents estimation of the following regression equation

$$\Delta Mkt_{it+1} = a + \sum_{j=2}^{J} \phi_j Q_{jit} + \sum_{j=2}^{J} \psi_j \left(Q_{jit} \times repute_{it-1}\right) + (\gamma \times repute_{it-1}) + CONTROL_{it} + \varepsilon_{it+1}$$

Dependent variable is $FLOW_{it}$ for the purpose of panel A and ΔMkt_{it} for panel B. $repute_{it-1}$ is computed using one-year window instead of five years as earlier.

$Q_{jit} = 1$ if recent performance at time t denoted by Perf_t lies in the j^{th} quintile. Panel A and B uses raw return measure and CAPM-Alpha to sort the funds. Control variables include half yearly performance during $t+1$ (Perf-Half_{t+1}), logarithm of the fund size, logarithm of fund age plus one, turnover, expense ratio, risk, which is computed using monthly return data for the period t, and category flow for time $t+1$, which is the asset weighted growth of the investment category to which a fund belongs. All the specifications have time fixed effects. Standard errors are clustered at the fund level to control for serial correlation within each panel. Standard errors are in parenthesis and *, ** and *** denote significance of coefficient at 10%, 5% and 1% level respectively. All the models have an intercept. Q_1 is the base group and hence effects of Q_j are incremental over Q_1. Similarly interactions effects for $Q_j \times repute$ are incremental over $Q_1 \times repute$.

Table 6: Short Horizon of Reputation and Fund Flows

	Panel A: Flow$_{t+1}$		**Panel B: ΔMkt_{t+1}**	
	Raw	**Alpha**	**Raw**	**Alpha**
$Q_{2t} - Q_{1t}$	0.024**	0.046***	0.001	0.047
	(0.011)	(0.012)	(0.046)	(0.050)
$Q_{3t} - Q_{1t}$	0.050***	0.066***	-0.077	-0.026
	(0.013)	(0.014)	(0.070)	(0.064)
$Q_{4t} - Q_{1t}$	0.061***	0.077***	0.021	0.112**
	(0.014)	(0.013)	(0.050)	(0.054)
$Q_{5t} - Q_{1t}$	0.123***	0.150***	0.059	0.101
	(0.015)	(0.016)	(0.061)	(0.062)
$repute_{t-1}$	0.100***	0.117***	0.108**	0.143***
	(0.014)	(0.015)	(0.049)	(0.052)
$repute_{t-1} \times (Q_{2t} - Q_{1t})$	0.018	-0.012	0.083	0.027
	(0.020)	(0.021)	(0.090)	(0.086)
$repute_{t-1} \times (Q_{3t} - Q_{1t})$	0.063***	0.045*	0.358**	0.308**
	(0.022)	(0.025)	(0.150)	(0.137)
$repute_{t-1} \times (Q_{4t} - Q_{1t})$	0.115***	0.095***	0.459***	0.314***
	(0.026)	(0.026)	(0.106)	(0.105)
$repute_{t-1} \times (Q_{5t} - Q_{1t})$	0.218***	0.129***	0.872***	0.722***
	(0.029)	(0.029)	(0.151)	(0.139)

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Table 6 – **Continued from previous page**

	Panel A: FLOW$_{t+1}$		**Panel B: ΔMkt_{t+1}**	
	Raw	**Alpha**	**Raw**	**Alpha**
Perf-Half(t+1)	0.199***	0.195***	0.767***	0.715***
	(0.011)	(0.011)	(0.066)	(0.066)
Risk(t)	-0.976***	-0.609**	-1.984	-0.931
	(0.250)	(0.250)	(1.245)	(1.278)
Size(t)	-0.010***	-0.009***	-0.007	-0.007
	(0.002)	(0.002)	(0.012)	(0.012)
Exp Ratio(t)	-0.009	0.197	0.904	1.405
	(0.691)	(0.713)	(3.302)	(3.398)
Age(t)	-0.035***	-0.037***	-0.098***	-0.102***
	(0.005)	(0.006)	(0.028)	(0.029)
Cat Flow(t+1)	0.365***	0.362***	-0.532*	-0.543*
	(0.052)	(0.055)	(0.301)	(0.299)
Intercept	-0.012	-0.035	-0.234	-0.283
	(0.035)	(0.035)	(0.237)	(0.229)
N	11780	11780	11780	11780
Adj. R^2	0.221	0.198	0.081	0.070

Table 7: Impact of Reputation With Longer Horizon for Recent Performance

Table presents estimation of the following regression equation

$$FLOW_{it+1} = a + \sum_{j=2}^{J} \phi_j Q_{jit} + \sum_{j=2}^{J} \psi_j \left(Q_{jit} \times repute_{it-1} \right) + \left(\gamma \times repute_{it-1} \right) + CONTROL_{it} + \varepsilon_{it+1}$$

Dependent variable is defined as

$$FLOW_{it} = \frac{AUM_{it} - AUM_{it-1} \times (1 + R_{it})}{AUM_{it-1} \times (1 + R_{it})}$$

Perf_{it} is computed using two-year window ending at t and $repute_{it-1}$ is computed using a four-year window ending at the year $t-1$. $Q_{jit} = 1$ if recent performance at time t denoted by Perf_t lies in the j^{th} quintile. Panel A and B uses raw return measure and CAPM-Alpha to sort the funds. Control variables include half yearly performance during $t+1$ (Perf-Half_{t+1}), logarithm of the fund size, logarithm of fund age plus one, turnover, expense ratio, risk, which is computed using monthly return data for the period t, and category flow for time $t+1$, which is the asset weighted growth of the investment category to which a fund belongs. All the specifications have time fixed effects. Standard errors are clustered at the fund level to control for serial correlation within each panel. Standard errors are in parenthesis and *, ** and *** denote significance of coefficient at 10%, 5% and 1% level respectively. All the models have an intercept. Q_1 is the base group and hence effects of Q_j are incremental over Q_1. Similarly interactions effects for $Q_j \times repute$ are incremental over $Q_1 \times repute$.

Table 7: Impact of Reputation With Longer Horizon for Recent Performance

	Panel A: Returns			Panel B: Alpha		
$Q_{2t} - Q_{1t}$	0.019**	0.008	0.005	0.039***	0.029***	0.001
	(0.008)	(0.008)	(0.015)	(0.008)	(0.008)	(0.014)
$Q_{3t} - Q_{1t}$	0.060***	0.042***	0.021	0.058***	0.041***	0.017
	(0.009)	(0.009)	(0.016)	(0.008)	(0.008)	(0.017)
$Q_{4t} - Q_{1t}$	0.101***	0.074***	0.024	0.123***	0.097***	0.035*
	(0.009)	(0.009)	(0.018)	(0.010)	(0.010)	(0.018)
$Q_{5t} - Q_{1t}$	0.217***	0.177***	0.048*	0.212***	0.173***	0.034
	(0.013)	(0.013)	(0.028)	(0.013)	(0.013)	(0.028)
$repute_{t-2}$		0.158***	0.066***		0.156***	0.040*
		(0.014)	(0.022)		(0.014)	(0.022)
$repute_{t-2} \times (Q_{2t} - Q_{1t})$			0.022			0.079***
			(0.029)			(0.027)
$repute_{t-2} \times (Q_{3t} - Q_{1t})$			0.063**			0.076**
			(0.030)			(0.030)
$repute_{t-2} \times (Q_{4t} - Q_{1t})$			0.117***			0.144***
			(0.031)			(0.031)
$repute_{t-2} \times (Q_{5t} - Q_{1t})$			0.230***			0.257***
			(0.043)			(0.044)
Perf-Half(t+1)	0.280***	0.283***	0.283***	0.270***	0.277***	0.277***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Risk(t)	-0.497*	-0.579*	-0.576*	0.089	0.061	0.104
	(0.297)	(0.300)	(0.298)	(0.308)	(0.308)	(0.306)
Size(t)	-0.008***	-0.014***	-0.015***	-0.008***	-0.014***	-0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Exp Ratio(t)	-1.367*	-1.089	-1.136	-1.170	-0.891	-0.927
	(0.714)	(0.727)	(0.723)	(0.725)	(0.736)	(0.735)
Age(t)	-0.042***	-0.031***	-0.030***	-0.042***	-0.032***	-0.031***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)
Cat Flow(t+1)	0.108***	0.105***	0.105***	0.108***	0.104***	0.104***
	(0.026)	(0.026)	(0.025)	(0.026)	(0.026)	(0.025)
Intercept	0.035	-0.035	-0.005	0.002	-0.074**	-0.037
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.037)
N	9384	9384	9384	9384	9384	9384
Adj. R^2	0.329	0.343	0.347	0.326	0.339	0.344

Table 8: Reputation and Managerial Replacements

Table presents estimation of the following regression equation

$$FLOW_{it+1} = a + \phi Perf_{it} + \psi \left(Perf_{it} \times repute_{it-1} \right) + \gamma repute_{it-1} + CONTROL_{it} + \varepsilon_{it+1}$$

Perf_t and $repute_{it-1}$ denote the normalized ranks for recent performance and reputation index (computed using five-year window ending at year $t-1$) respectively . First two columns use raw returns and next two use CAPM-Alpha to rank the funds within each investment style. First and third columns report regression for the subsample where there was a managerial replacement during time $t-1$. Second and fourth columns report regression for the subsample where there was no managerial replacement during $t-1$. Control variables include half yearly performance during $t+1$ ($\mathrm{Perf\text{-}half}_{t+1}$) ,log fund size, log(age+1), turnover, expense ratio, risk, which is computed using monthly data of recent period and category flow which is the asset weighted growth of fund's investment category during $t+1$. All specifications have time fixed effects. Standard errors are clustered at the fund level to control for serial correlation within each panel. Standard errors are in parenthesis and *, ** and *** denote significance of coefficient at 10%, 5% and 1% level respectively.

Table 8: Reputation and Managerial Replacements

	Panel A: Raw Returns		**Panel B: CAPM-Alpha**	
Replacement	**Yes**	**No**	**Yes**	**No**
Perf_t	0.135**	0.123***	0.169***	0.146***
	-0.052	-0.029	-0.061	-0.033
$repute_{t-1}$	0.007	0.034	-0.013	-0.036
	-0.046	-0.024	-0.047	-0.023
$\mathrm{Perf}_t \times repute_{t-1}$	0.196*	0.313***	0.104	0.280***
	-0.102	-0.05	-0.099	-0.052
Perf-Half(t+1)	0.191***	0.194***	0.198***	0.197***
	-0.033	-0.014	-0.035	-0.014
Risk(t)	-0.172	-0.261**	-0.232*	-0.029
	-0.149	-0.107	-0.136	-0.11
Size(t)	-0.012*	-0.014***	-0.011	-0.013***
	-0.007	-0.003	-0.007	-0.003
Expense Ratio(t)	-1.09	-0.542	-0.895	-0.348
	-1.7	-0.836	-1.638	-0.837
Age(t)	0	-0.028***	-0.003	-0.030***
	-0.015	-0.007	-0.016	-0.007
Category Flow(t+1)	0.181***	0.069***	0.181***	0.072***
	-0.058	-0.022	-0.057	-0.023
Intercept	-0.123	0.008	-0.084	-0.009
	-0.087	-0.043	-0.088	-0.045
N	1136	7014	1136	7014
Adj R^2	0.158	0.21	0.152	0.208

Table 9: Impact of Reputation With Various Fee Structures

Table presents estimation of the following regression equation

$$FLOW_{it+1} = a + \phi Perf_{it} + \psi\left(Perf_{it} \times repute_{it-1}\right) + \gamma repute_{it-1} + CONTROL_{it} + \varepsilon_{it+1}$$

Perf_t and $repute_{it-1}$ denote normalized ranks for recent performance and reputation index (computed using five-year window ending at year $t-1$) respectively . First two columns use raw returns and next two use CAPM-Alpha to rank the funds within each investment style. The first and third columns report regression for the subsample of funds with low front loads (bottom quintile of front loads) and the second and fourth columns report regression for the subsample of funds with high front loads (top quintile of front loads). Control variables include half yearly performance during $t+1$ (Perf-half_{t+1}) ,log fund size, log(age+1), turnover, expense ratio, risk which is computed using monthly data of recent period and category flow which is the asset weighted growth of fund's investment category during $t+1$. All specifications have time fixed effects. Standard errors are clustered at the fund level to control for serial correlation within each panel. Standard errors are in parenthesis and *, ** and *** denote significance of coefficient at 10%, 5% and 1% level respectively.

Table 9: Impact of Reputation With Various Fee Structures

	Panel A: Raw Returns		**Panel B: CAPM-Alpha**	
Front Load	**Low**	**High**	**Low**	**High**
Perf_t	0.171***	0.153***	0.167***	0.166***
	(0.042)	(0.039)	(0.049)	(0.039)
$repute_{t-1}$	0.054	0.096***	0.058	0.098***
	(0.036)	(0.035)	(0.037)	(0.032)
$\text{Perf}_t \times\ repute_{t-1}$	0.268***	0.140**	0.222***	0.102
	(0.071)	(0.066)	(0.081)	(0.067)
Perf-Half(t+1)	0.221***	0.123***	0.220***	0.131***
	(0.021)	(0.020)	(0.022)	(0.021)
Risk(t)	-1.053*	-1.473***	-0.814	-0.984**
	(0.557)	(0.453)	(0.495)	(0.450)
Size(t)	-0.028***	-0.016***	-0.026***	-0.016***
	(0.005)	(0.004)	(0.004)	(0.004)
Expense Ratio(t)	-6.730***	3.680*	-6.927***	3.764*
	(1.804)	(1.937)	(1.821)	(1.937)
Age(t)	-0.018	-0.016	-0.022	-0.013
	(0.015)	(0.010)	(0.014)	(0.010)
Category Flow(t+1)	0.437***	0.119***	0.484***	0.117***
	(0.096)	(0.043)	(0.100)	(0.042)
Intercept	0.106	-0.057	0.108	-0.092
	(0.085)	(0.066)	(0.085)	(0.066)
N	2581	2785	2581	2785
Adj R^2	0.239	0.169	0.223	0.164

Table 10: Hypothesis Testing For Main Results

This table presents the hypothesis tests for the main results in table **??**. Two hypothesis are tested. For $j = 2, 3, 4, 5$

$$H_0 : Q_j = Q_{j-1}$$

and second hypothesis is about monotonically increasing interactions

$$H_0 : repute \times Q_j = repute \times Q_{j-1}$$

Both the hypothesis are tested with two-sided alternative. F-values are reported for each test and p-value is reported in bracket below F-value.

Table 10: Hypothesis Testing: Return Chasing and Interaction Effects

	Panel A Model Without Interaction Effects		**Panel B Model With Interaction Effects**	
	CAPM	**Raw Returns**	**CAPM**	**Raw Returns**
Return Chasing Effect				
$Q_{2t} - Q_{1t}$	42.24	33.19	1.33	2.01
	(0)	(0)	(0.24)	(0.156)
$Q_{3t} - Q_{2t}$	56.09	70.66	3.35	2.1
	(0)	(0)	(0.06)	(0.147)
$Q_{4t} - Q_{3t}$	34.42	30.79	2.13	1.44
	(0)	(0)	(0.14)	(0.23)
$Q_{5t} - Q_{4t}$	87.79	138.26	5.45	8.83
	(0)	(0)	(0.019)	(0.003)
Interaction Effect				
$repute_{t-1} \times (Q_{2t} - Q_{1t})$			8.69	4.23
			(0.003)	(0.039)
$repute_{t-1} \times (Q_{3t} - Q_{2t})$			4.01	11.64
			(0.045)	(0)
$repute_{t-1} \times (Q_{4t} - Q_{3t})$			2.16	2.61
			(0.141)	(0.106)
$repute_{t-1} \times (Q_{5t} - Q_{4t})$			4.93	10.17
			(0.026)	(0.001)

Table 11 Reputation and Performance Persistence

At the end of each year, funds are sorted based on their four-factor alpha reputation computed using five-year window. Ten equally weighted portfolios are formed to represent each decile of the reputation. For each portfolio, monthly returns are computed for each month in the following year with weights rescaled to account for any fund disappearance. This process is repeated for each year which generates a series of 420 monthly return observations for each decile portfolio. Table presents regression estimates of the four-factor model ran separately for each decile portfolio. Market, SMB, HML and Momentum, represents factor betas for each portfolio and Alpha is the four-factor Alpha. CRSP value-weighted index is used as a proxy for market returns. Rest of the factor data comes from Ken French's website. t-stats are in parenthesis.

Table 11: Reputation and Performance Persistence

Reputation Decile	**Market Beta**	**SMB Beta**	**HML Beta**	**Momentum Beta**	**4-factor Alpha**	**Adj R^2**
D1	1.00426***	0.16568***	-0.02126	0.00836	-0.00137***	0.968
	(0.01232)	(0.01845)	(0.02147)	(0.01435)	(0.00045)	
D2	1.00323***	0.17559***	-0.00004	0.02108	-0.00138***	0.976
	(0.00988)	(0.01873)	(0.01886)	(0.01535)	(0.00039)	
D3	1.01012***	0.14140***	0.02330	0.01872	-0.00118***	0.976
	(0.01136)	(0.01883)	(0.02081)	(0.01400)	(0.00040)	
D4	0.98307***	0.13459***	0.03731**	0.00185	-0.00060*	0.978
	(0.01017)	(0.01757)	(0.01775)	(0.01180)	(0.00035)	
D5	0.97228***	0.13435***	0.02788	0.00757	-0.00059	0.975
	(0.01108)	(0.02109)	(0.01739)	(0.01116)	(0.00037)	
D6	0.96283***	0.08781***	0.00442	-0.00417	-0.00039	0.972
	(0.01688)	(0.02009)	(0.01763)	(0.01291)	(0.00045)	
D7	0.96463***	0.13536***	0.01433	0.00991	-0.00022	0.974
	(0.01140)	(0.01836)	(0.02146)	(0.01302)	(0.00040)	
D8	0.97028***	0.16909***	-0.01974	0.01421	-0.00048	0.977
	(0.01387)	(0.01493)	(0.01666)	(0.01190)	(0.00041)	
D9	0.94807***	0.17254***	-0.02423	-0.00728	0.00023	0.972
	(0.01533)	(0.01826)	(0.02095)	(0.01340)	(0.00044)	
D10	0.98846***	0.20101***	-0.00393	-0.01694	-0.00018	0.969
	(0.01092)	(0.02160)	(0.01902)	(0.01344)	(0.00044)	

Figure 1: Reputation and Fund Flow Schedule

The figure plots fund flow schedule for funds with top and bottom reputation quantile, keeping all the other explanatory variables at their respective mean levels. Fund flows are expressed in percentage terms. X-axis denotes the recent performance quantile. The shaded area is the 95% confidence interval around the point estimate which is depicted by the line connected by dots

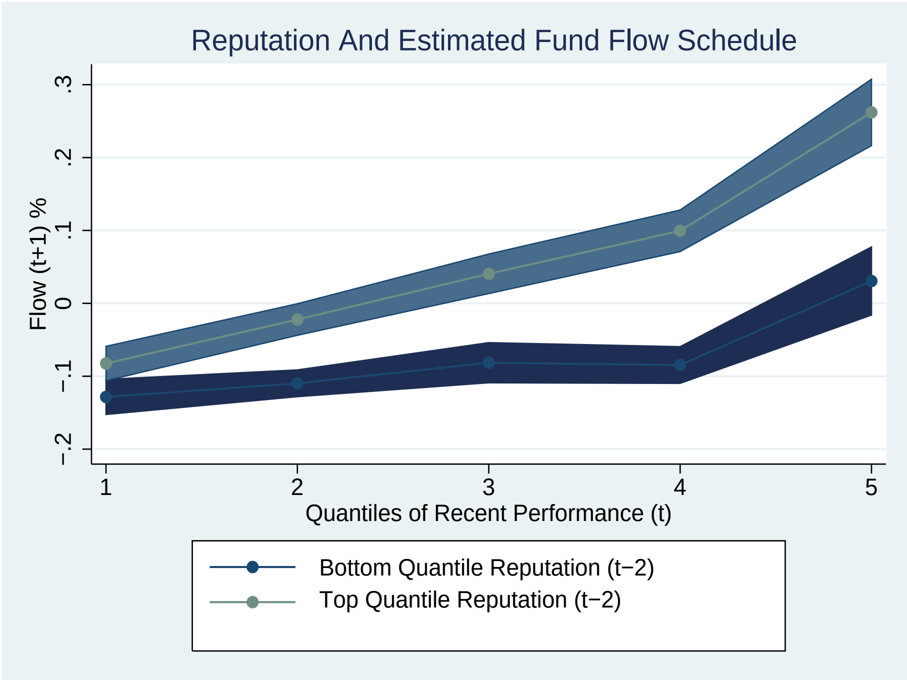

Figure 2: Model Implied Fund Flows

This figure plots the model implies fund flow schedules. Graph is produced with following parameters: $\lambda_{high} = 0.96$, $\lambda_{low} = 0$, $f = 1.5\%$, $\psi_{low} = .50$, $\psi_{high} = 0$