Inattentive Investors and Mutual Fund-Flows

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Abstract

Gruber (1996) drew attention to performance-chasing behavior exhibited by mutual fund investors. In this paper, I uncover a large heterogeneity in fund flow-performance sensitivity (fps) between and within mutual funds after conditioning the results on the prior performance of the fund . I explain this dependence of *fps* on fund's prior performance using the existence of *inattentive* investors as hypothesized by Christoffersen and Musto (2002). Further I present various tests to pin down this mechanism by conditioning the results on type of funds, or investment styles, market states which are more likely to attract inattentive investors. I present a novel evidence that funds with poor past performance are more likely to increase fees given their low *fps*. I further show that this fee increase does not lead to additional fund outflows as it should within rational expectations model.

JEL classification: G10, G11, G23.
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1 Introduction

Large body of literature documents the evidence that mutual fund flows exhibit a pattern of *return-chasing*: capital moves in and out of the fund in response to it's recent performance. In other words, flow-performance sensitivity (*fps* for short) is positive.[1] Berk and Green (2004) rationalizes such return-chasing in a model where recent performance is a signal about the managerial ability and investors optimally allocate more (less) capital to the funds with positive (negative) expected net returns. In the set-up of Berk and Green (2004), any new information is immediately acted upon by the investors by providing required capital

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[1]For example see Ippolito (1992), Gruber (1996), Chevalier and Ellison (1997), and Sirri and Tufano (1998)

and fund size is *marked-to-ability* to reflect the fund managers ability. In this set-up, past performance has no bearing on how investors react to recent or current fund performance.[2]

Yet in the data I uncover a substantial heterogeneity in estimated *fps* when conditioned upon the fund's past performance (performance prior to the current performance period). In particular, I find that fund's *fps* is increasing in level of past performance. That is a fund with a better past performance faces a more elastic fund flow schedule: any positive (negative) net return surprise is associated with larger capital inflows (outflows). I show that this excess sensitivity is economically large. I further show that such excess sensitivity is present over the entire range of recent performance indicating that both the inflows and outflows have higher sensitivity. This result is economically important for several reasons. First, if we are ready to assume that the dependence of *fps* on prior performance is not a result of the distribution of the information structure that the investor receives (Gaussian vs Binomial signals about managerial ability), then the result is a reflection upon the competitive capital provisioning assumption of Berk and Green (2004) model. Second, this result is also interesting from behavioral perspective. A typical behavioral view represented by *confirmation bias* suggests that investors put more reliance on the signals that corroborates their priors. That is we would expect investors to react sluggishly by not withdrawing their capital from a fund with a recent poor performance but a high prior performance. But the evidence suggests exactly the opposite: A fund with good prior performance would experience a higher marginal capital outflows per unit of reduction in net returns.

Then what explains the result? I interpret the results as the evidence for the presence of less that fully attentive or *inattentive* investors. The idea is similar to one proposed by Christoffersen and Musto (2002). I build an equilibrium model similar to Berk and Green (2004) augmented to include inattentive investors. In Berk and Green's model, investors learn about managerial ability through fund returns and provide capital competitively. They invest additional capital in a fund with positive net expected return. *Decreasing returns to scale* at the fund level implies that this additional capital lowers the expected net return. The process of investing continues till the time expected net return hits zero mark at which point there is no incentive for any investor to invest or withdraw. Similar process ensures that a fund with a negative expected net return faces capital outflows till the time expected net return reaches zero mark. Hence in their model, all the funds have zero expected net returns and fund size reflects that manager's estimated ability.

The presence of inattentive investors changes the equilibrium in some important ways. In particular it implies that after a recent poor performance, attentive investors leave the fund and the proportion of inattentive investors within the fund increases. That is fund's performance history determines the composition of investors within the fund. Two results follow. First, a higher fraction of inattentive investors leads to sluggish capital outflows in

[2] In Berk and Green (2004) model, the priors and the signals about the managerial ability are assumed to be Gaussian. One property of Bayesian learning with Gaussian shocks is that the quantum of update or change in the estimate of the unknown parameter is independent of the current estimated level of the parameter. This property along with competitive capital provisioning implies that *fps* in unaffected by the past performance. With other shock structure like Binomial, it is possible to induce an interaction of *fps* on past performance because the magnitude of update is dependent upon the current estimated level. I abstain from any mechanism that is specific to the structure of the shock and concentrate on the other economic forces that link *fps* to past performance.

future. The *outflow fps* stands reduced. Second, if the fund is already composed of large fraction of inattentive investors, then a poor performance may not lead to adequate capital outflow. This would keep the fund size above it's rational expectation equilibrium level implying a negative expected net return. Third, if a poor performance fund thus remains over-sized relative to it's ability, then even a good performance will lead to moderate inflows as the gap between new *marked-to-ability* size of the fund and the current size is lower than what it would be under rational expectations equilibrium. Hence a simple model is able to explain the observed relation between the prior performance and the *fps*. At the same time it generates additional prediction that the funds with sufficient poor performance over time are over-sized and hence would generate negative net returns on an average. This corroborates with the evidence in Carhart (1997).

Though not modeled here, I propose and confirm an interesting hypothesis that exhibits a strategic behavior in part of the fund management: Funds with poor track record are more likely to increase the fund fees. This is because such funds are least likely to experience further capital outflows. Hence increasing the fee gives fund companies an easy way to generate additional revenue. I confirm in the data that such increases in the fee does not lead to additional capital outflows for funds with poor performance record, though fee increases lead to capital outflows for funds with good track record.

To test the *inattention hypothesis*, I carry out some experiments. I show that *fps* depends more strongly upon the prior performance for funds with simple investment styles like funds that focus on large cap stock or funds with blend value-growth orientation. In the second test, I show that the link between *fps* and prior performance breaks after a managerial replacement. Presumably, manager change generates a lot of media coverage as well as communication from fund house to the investors. Such event can lead to increase in the attentiveness within the fund and investors adjust the fund size swiftly which breaks the dependence of *fps* on the prior performance. Third test focuses on broad market conditions. Good market returns attract less sophisticated investors as suggested by Glode et al. (2009). I confirm that *fps* depends more heavily on the prior performance after good market returns.

2 Literature Review

The literature on estimation of responsiveness of mutual fund flows to fund performance is vast. Ippolito (1992), using annual frequency, documented that fund flows chase recent winners. Chevalier and Ellison (1997), and Sirri and Tufano (1998) further documented the presence of convexity in fund flow sensitivity: fund flows are non-responsive at the lower range of performance but highly sensitive at the higher range of recent performance. The main difference with these papers lies in the fact that I focus not on *fps* as these papers did but on how the *fps* depends upon the prior performance. Chevalier and Ellison (1997) uses prior performance as a control, but fail to consider how it interacts with the *fps*. One reason that earlier literature control for performance prior to the recent performance is that fund families might promote better performing funds and higher promotion can lead to elevated fund flows unrelated to the current performance. But what I show is that not only the level but the shape of entire *fps* depends upon the prior performance.

Some earlier papers recognized the importance of other fund characteristics in determining the level and sensitivity of fund flows: fund age reduces flow sensitivity (Chevalier and Ellison (1997)), volatility of performance damps learning and flow responsiveness (Huang et al. (2012)), young and small funds, also referred to as *hot funds*, have a steeper *fps* as compared to old and large funds, referred to as *cold funds* (Spiegel and Zhang (2013)), funds within families having a *star performer* experience greater level of fund flows (Nanda et al. (2004)) to mention some of such effects. I uncover a new factor affecting the *fps* namely the historic performance.

Berk and Tonks (2007) document that repeat loser funds have lower sensitivity at a lower range of recent performance. Extending their result I show that such excess *fps* carries even at the higher end of the recent performance. I provide an equilibrium explanation for differential *fps* over the entire range of recent peformance.

There is a large literature on the *return chasing effect*. Outside the domain of mutual funds, return chasing is rationalized by Brennan and Cao (1997), among others, who explain positive contemporaneous correlation between net flows and foreign equity returns, and Albuquerque et al. (2007), in whose analysis within-country investor heterogeneity generates return chasing in foreign markets by American investors on an average. Within the domain of mutual funds, apart from Berk and Green (2004), Lynch (2003) 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.

My paper is also related to the literature on pricing within money management industry. Gil-Bazo and Ruiz-Verdu (2009) provides the evidence that funds with worse before fee performance charge higher fees. Instead of looking at the level of fees, I look at the changes in the level of fees and provide a novel evidence that funds with poor track record are more likely to increase the fees given the short term benefits of higher revenue due to lower *fps*. If such changes in fees are not reversed in the near future, then my hypothesis also extends to the level of fees that higher level of fees are associated with worse before fee performance because only funds with poor track record (possibly reflecting lower ability) increase the fee in the first place. Hence two hypothesis about level of fees as proposed by Gil-Bazo and Ruiz-Verdu (2009) and fee change hypothesis proposed in this paper can be consistent with each other. I additionally provide the evidence that fee changes do not lead to additional capital withdrawals (beyond demanded by the recent performance) which in some sense confirms that the strategy to raise the fees is a *smart* strategy. My model has implications for performance persistence. Carhart (1997) presents the evidence of lack of performance persistence for mutual funds except for the funds with poor lagged performance. This is consistent with my model. Though Bollen and Busse (2005) find some persistence at monthly frequency, overall there has been a scarce evidence on persistence at medium to long-term performance.

Some papers generate inattention as an optimal response when information acquisition is costly, for example Huang (2007). My paper takes an agnostic view about why some investors are inattentive.[3]

[3]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 in losing funds. This can create a rational inertia.

3 Data and Empirical Methodology

3.1 Data

Paper utilizes the CRSP Survivor Bias Free Mutual Fund Database, covering a period from 1999 to 2014 at annual frequency. Return data for the fund is available at daily frequency which is used to estimate the annual fund performance. I focus on US domestic open-ended equity oriented mutual funds. I exclude the sectoral funds, specialty funds (leveraged or market-neutral), passive funds, and funds with restrictions on liquidation. Because the stated investment styles may not reflect the true investment style, I also condition that funds in sample have average equity allocation of minimum of 70%. I exclude funds with assets below 15 Mn $ and also funds with age less than 3 years. Many funds offer different share classes representing different load and expense ratio structure. Because each type of share class can attract different type of investors, I perform all the analysis at the share class level. This is crucial as potentially some of the differential in *fps* could be due to differential clientele of each share class and we want to disentangle this effect while estimating the impact of prior fund performance on *fps*. Because decreasing returns operate at the fund level, I aggregate assets at fund level instead of share class level. Fund assets are computed as the value weighted mean of assets across all the share classes belonging to that fund. Fund age is the age of the oldest share class of that fund. Other variables like turn over, expense ratios, loads, etc. are share-class level variables.

3.2 Variables

The main variable of interest is fund -flow which is computed following Huang et al. (2012) and most of the other literature. In particular flows are expressed as a fraction of assets under management q_{it} as follows.

$$flow_{it} = \frac{q_{it} - (q_{it-1} \times r_{it})}{q_{it-1} \times r_{it}} \tag{1}$$

where q_{it} indicates assets under management with fund i at time t. The variable is winsorized at 1% level from both the tails due to potential outliers given the small denominator as well as data entry errors. The second variable of interest is the recent or current fund performance. I use the daily share-class return data to estimate the fund performance at the share class level. CRSP provides daily return on net basis which gives return after deducting fees and expenses and I denote it by r_{it}. I require at least 200 days of return data be available for estimating the model for a given share class for year t. Then For for any year t, I estimate a four-factor model at daily frequency

$$r_{it\tau} = \alpha_{it}^{net} + \beta_{it}^{rm} rm_{t\tau} + \beta_{it}^{smb} smb_{t\tau} + \beta_{it}^{hml} hml_{t\tau} + \beta_{it}^{mom} mom_{t\tau} + \epsilon_{it\tau} \tag{2}$$

where τ indicates the day of year t. α_{it} measures the *net alpha* for share class i during year t. The gross alpha is given by

$$\alpha_{it}^{gross} = \alpha_{it}^{net} + expense_{it} \tag{3}$$

In regressions, this gross alpha is denoted by *Perf (t-1)*. There are several comments in order. First, note that all the factor betas are estimated for each year separately. This implies that the estimation is valid even if factor betas change over time. Earlier literature uses monthly data to estimate the factor betas. This implies that current α is based upon the assumption of constant factor betas for a window which goes back well beyond the performance period. Second, use of the daily data increases power of estimation as evidenced by Bollen and Busse (2005). Third, alternative measures of performance exists. Sirri and Tufano (1998) or Spiegel and Zhang (2013) ranks the funds within the investment style based on the raw fund return. Berk and Van Binsbergen (2014) show that CAPM-Alpha better fits the revealed preferences of investors as compared to four-factor alpha. In the robustness tests, I show that main results of the model are valid for alternative definitions of performance.

To compute the long-term fund performance at the end of year t, I average the four-factor alpha over past five years including year t. I denote this variable by *LT Perf (t)*. For current or long-term performance, I also compute the normalized rank by sorting the funds based on *Perf (t)* or *LT Perf (t)* and denote the variable by *Rank Perf (t)* and *Rank LT Perf (t)* respectively.

Some other variables used in the regression analysis are log of fund assets (*Log Assets*), log of fund age in years (*Log Age*), fund turnover ratio (*turnover*) (expressed in %), fund return volatility computed as the standard deviation of daily returns for year t (*Perf Volatility*), market returns which is measured as the annual returns on the value-weighted CRSP US stock market index.

3.3 Summary Statistics

Table 1 presents the evolution of number of share classes (which is highly correlated with number of funds) over the sample period. Two trends are worth noting. First, institutional share class was a minor segment in 2000 compared to retail funds (323 institutional classes against 1134 retail classes). But by 2014, both the type of classes are almost comparable standing at 1588 and 1697 classes respectively. Second, after the crises of 2008, the number of retail classes are on a steady decrease from 1900 in 2008 to 1697, but institutional classes are on the rise unabated. Table 2 presents main variables decomposed into pre and post crises periods. First major trend is that the right tail of fund -flow distribution has been curtailed post financial crises. The interquartile range in the pre-crises period was -14% to 8% for retail classes which stands at -14% to -4% during post-crises period. Similar trend is observed for institutional classes. This means that time effects are important for the sample period under consideration. Second, for institutional classes entry and exit loads are substantially lower as compared to retail classes. Third, there is a dramatic improvement in the gross and net performance measures of the fund from pre-crises to post-crises period. Fourth, the median fund size has increased by at least 30% from 344 Mn \$ to 452 Mn \$ from pre to post crises period for retail funds and by 50% from 443 Mn \$ to 678 Mn \$ for institutional funds. Because the focus of the paper is on the impact of long-term performance on *fps*, in Table 3 I summarize main variables by sorting funds by their lagged long-term performance (*LT Perf*). Funds within top quantile (top 20%) of LT Perf are 3 times bigger in median size as compared to the funds within bottom quantile (bottom 20%). Second, the flows as a fraction of assets are significantly higher in level terms for funds within top quantile (top 20%) of LT Perf. The difference in median flows is 16% of assets between these two groups.

4 Impact of Long-Term Performance on Flow-Performance Sensitivity (*fps*)

4.1 Results

In a well functioning capital markets purported by Berk and Green (2004) characterized by competitive capital provision and efficient learning, capital moves swiftly in and out of a mutual fund to reflect the manager's ability. Leaving aside the cases where update to the manager's ability is prior-dependent due to a particular distribution of signals about manager's quality, such a well functioning capital markets imply that *fps* is independent of any performance beyond the most recent performance.[4] To the contrary, I present the evidence in this section that *fps* is highly dependent upon the past performance prior to the recent performance period.

Table 4 presents the main result. In panel A, I regress fund flows given by $flow_{it}$ on the recent performance given by *Perf (t-1)* and control for other factors such as age, size, turnover, risk profile of the fund, time effects and investment-style fixed effects. Panel A confirms the *return-chasing* pattern consistent with the earlier literature: a 1% point increase in *Perf (t-1)* leads to 1.54 % points increase in fund flows. Next I turn the focus to the long-term performance prior to the recent performance. Note that *fps* is a link between flows at time t and performance at time $t-1$. To asses how prior performance affect the *fps* we need to look at the performance for the period $t-2$ and prior. This is given by *LT Perf (t-2)*. In Panel C, I control for the *LT Perf (t-2)* as in Chevalier and Ellison (1997). The coefficient on *LT Perf (t-2)* is highly positive indicating that a fund with highest rank according to long-term performance just prior to the recent performance period attracts 23.71% additional fund flows compared to the fund with the worst long-term performance rank. This could be due to higher promotion efforts by the fund house. Note that these additional flows are independent of the current performance and not the focus of the current paper. To asses how *fps* depends upon the prior performance, I interact the *LT Perf (t-2)* with recent performance *Perf (t-1)* in Panel D. The results change dramatically compared to Panel A or C. First, the coefficient on *Perf (t-1)* is cut to half compared to the pure *return-chasing* model in Panel A or C. Second and the focus of this table, the coefficient on the interaction of the recent and the prior performance is 1.29 and statistically highly significant. The coefficient on the interaction term has the interpretation of the additional *fps* for a fund with highest LT Perf (t-2) rank. This implies that a fund with a top rank of

[4] In the appendix I present a small example with binomial signals about manager's ability which generate interaction between the quantum of update to manager's estimated ability and the prior about the ability. It is hard to believe that an observed pattern about *fps* is a result specific to some distribution of the information in the economy. Hence I abstain from such mechanism to explain the dependence of *fps* on prior performance and focus instead on the other economic mechanisms.

prior performance has an estimated *fps* of 0.87 + 1.29 = 2.16.[5] That is about 60% of the *fps* is explained by the prior performance. This result has an important bearing in that it uncovers a new and economically large driver of the *fps* and suggests that prior performance acts like a leverage for the recent performance in driving the flows.

To get a sense of economic mechanism behind the result, it is important to understand if the pattern of inflows or the pattern of outflows or both are driving the differences in *fps*. This is because outflows reflects the behavior of the fund owners or *inside money* while inflows reflects the characteristics of the entire economy or the *outside money*. To this end, I repeat the exercise of Table 4 in Table 5 but I estimate the *fps* separately for inflows and outflows. Panel A is a pure return-chasing model while Panel B interacts the fps with prior performance. Panel A exhibits the convexity of the *fps* which is consistent with Chevalier and Ellison (1997) and Sirri and Tufano (1998). *fps for inflows* is 0.67 while *fps for outflows* is 0.32, less than half of that for inflows. Panel B brings out the nature of dependence of *fps* on prior performance. The coefficient on the interaction term is positive for both inflow model (first column of Panel B) and outflow model (second column of Panel B). This evidence is very important as it indicates that the *fps* for good prior performance funds is large for both inflows and outflows. This evidence would guide us in detecting the economic mechanism behind the result.

In summary, the main empirical evidence in this section suggests thet

1. *fps* or sensitivity of flows to the recent performance depends upon the prior performance

2. Funds with high prior performance have almost twice steeper *fps*. About 60% of the *fps* magnitude is explained by prior performance. Stand-alone or pure return-chasing pattern fades in importance once we conditon results on prior performance.

3. The differential *fps* is valid for both inflows and outflows.

4.2 Robustness

I conduct two robustness tests.

- **Performance Measurement:** Literature has used various methods to measure fund performance: Relative performance rank using raw returns (Sirri and Tufano (1998)), CAPM-Alpha (Berk and Van Binsbergen (2014)), four-factor alpha (Carhart (1997)). I show that my results are valid with alternative definitions. Table 6 shows that all the main results hold valid even with raw-returns as the basis for ranking the funds: *returns-chasing* becomes weaker for low LT Perf funds.

[5]The total fps is computed as

$$\frac{\partial flow_{it}}{\partial Perf_{it-1}}|_{\text{Rank LT Perf}(t-2)=1} = 2.16 \tag{4}$$

while

$$\frac{\partial flow_{it}}{\partial Perf_{it-1}}|_{\text{Rank LT Perf}(t-2)=0} = 0.87 \tag{5}$$

- **fps with size bins:** Rational theory of Berk-Green as well as the evidence from Chevalier and Ellison (1997) suggests that larger funds grow slower in percentage terms. Summary statistics also suggests that long-term well performing funds are much larger in the size compared to funds with poor prior performance. One needs to be sure that the results presented are not merely picking up the size-effect. To this end, I re-run the regressions on funds with different size bins. Table 7 presents the results. As one can see, *return-chasing* as well as interaction effect is present for smaller and larger funds. It is true that for larger funds the interaction effect is lower than that for smaller funds, but still it is significant and large. This mitigates the concerns that the result is driven by size differences between funds with high and low prior performance.

5 Selecting the Mechanism

5.1 Inattentive Investors

The evidence we have from the last section presents an interesting puzzle. First, it rejects the idea of rational and competitive capital provisioning under some assumptions on the structure of the information. Second, if anything, behavioral view would have predicted a lower *outflow fps* for a fund with high prior performance. This is because investors would be unwilling to update the beliefs contrary to their prior beliefs. But results show higher *inflow fps* and higher *outflow fps* for such funds. I propose a simple mechanism to explain the evidence. In particular, I hypothesize the presence of some investors who are less than fully attentive or as I lable them *Occaisionally attentive* (OA for short). Christoffersen and Musto (2002) also alluded to the presence of inattentive or less responsive investors within the mutual fund industry. The logic of the model is rather simple. Funds with losing track record are predominantly owned by OA investors as *Always Attentive* (AA) investors must have already left the fund. This implies a reduced *outflow fps* compared to a fund composed more of AA investors. Because capital moves out of the funds with losing track-record rather sluggishly due to the presence of OA investors, these funds stay over-sized or above their *market-to-ability* rational equilibrium size. Hence the capital adjustment required even after a good recent performance to mark the fund to it's new ability is lower because. This implies a lower *inflow fps*. Model additionally generates a prediction for funds with losing track record: Because they are over-sized relative to their ability, the expected net returns for such fund must be negative.

5.2 Alternative Mechanisms

In the next section, I tests some implications that naturally flow from *inattention hypothesis*. This adds credence to the mechanism proposed in the paper. Having said this, it is difficult to pin down any mechanism in a more direct manner. Hence, I discuss some alternative mechanisms which may seem to explain this evidence.

Confirmation Bias: In Rabin and Schrag (1999), investors exhibit a learning mechanism whereby they are reluctant to update the beliefs when the new information is not consistent with the prior beliefs they hold. Can such *confirmation bias* explain the evidence at hand? With such bias, investors will react more strongly to positive (negative) news for funds with high (low) prior performance and sluggishly to negative (positive) news for funds with high (low) prior performance. But then we would have observed weakening of *outflow fps* and steepening of *inflow fps* as the prior performance increase. This contradicts the observed pattern that even *outflow fps* becomes steeper with rising prior performance. Hence confirmation bias might explain higher *inflow fps*, but fails to explain higher *outflow fps* for such funds.

***Loss Aversion*:** Loss aversion presents an interesting alternative. Investors stick with the losing funds because they are unwilling to realize or *book the paper loss.* This behavior would explain low *outflow fps* for losing funds. Additionally, when a losing fund performs better, many of the loss averse investors now book the loss as the quantum of the loss has decreased. Hence a good performance from a losing fund generates heterogeneous responses from *inside* and *outside* investors. While inside investors liquidate their stake, outside investors invest in such a fund. Hence compared to the winning funds, losing funds will face a less steep *inflow fps* as well. Hence, loss aversion is a viable alternative to explain the evidence of heterogeneous *fps.*

5.3 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;

$$R_t = \alpha + \varepsilon_t, \tag{6}$$

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

$$\varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right), \tag{7}$$

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 $t+1$.[6] 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.

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

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

$$r_t = (h_{t-1}R_t) - f - \eta \left[\frac{(h_{t-1} \times q_{t-1})^2}{q_{t-1}} \right], \tag{8}$$

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.

5.4 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;

$$E_t(r_{t+1}) = 0, \tag{9}$$

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 9. Formally, manager solves

$$\max_{h_t \geq 0} \left\{ f \times q_t \right\}, \tag{10}$$

subject to equilibrium condition 9 namely,

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

The solution is characterized in the following lemma.

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

$$h_t \equiv h(\phi_t) = \frac{2f}{\phi_t}, \tag{11}$$

Substituting the optimal policy given in equation 11 into equilibrium condition given in equation 9 we get equilibrium fund size;

$$q_t \equiv q(\phi_t) = \frac{\phi_t^2}{4\eta f}. \tag{12}$$

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 **??**. 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*

$$\phi_{t+1} = \phi_t + \left(\frac{r_{t+1}}{h_t}\right)\left(\frac{\sigma_t^2}{\sigma_t^2 + \sigma_\varepsilon^2}\right). \tag{13}$$

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

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

5.5 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

$$\lambda_0 = \frac{\mu}{\mu + (1-\mu)\delta}. \tag{14}$$

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

$$z_t = [\lambda_{t-1} + (1-\lambda_{t-1})\,\delta]\,\widehat{q}_t. \tag{15}$$

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.

$$E_t\left[r_{t+1}|\Omega_t, h_t, q_t(\Omega_t, h_t)\right] = 0 \tag{16}$$

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,

$$e(\Omega_t, h_t) \equiv e_t^* = q_t^* - q_{t-1}(1+r_t). \tag{17}$$

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 21.

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

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*

$$E_t\left(r_{t+1}\right) = -\eta h_t^2 q_t^* \psi_t. \tag{18}$$

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*

$$FF_t = \begin{cases} \frac{1}{(1+\psi_{t-1})(1+r_t)} \left[1 + \omega_{t-1}\left(\frac{r_t}{2f} + \frac{\psi_{t-1}}{2}\right)\right]^2 - 1 & \text{If } z_t > |e_t^*| \\ -\frac{z_t}{q_{t-1}(1+r_t)} & \text{otherwise} \end{cases} \tag{19}$$

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 Indirect Tests to Validate the Mechanism

Though it is very difficult to give a direct test of presence of inattentive investors, I present a three indirect tests or experiments that give some credence to the mechanism of inattention.

1. **Investment-Style and Impact of prior performance on *fps*:** Inattentive investors by construction are also more likely to be naive or less sophisticated. Hence it is more likely that these investors own the funds with less complicated or more common investment-styles. To the extent this hypothesis is true, the initial composition of such fund will be highly skewed toward inattentive investors as compared to funds employing more complicated styles. This initial skew in the investor type exacerbates even further once funds with simple styles perform poorly. This implies that capital will adjust more sluggishly for these funds. In empirical terms, prior performance which proxies the inattention within the fund should have a stronger influence on the *fps* for funds employing simple investment styles. Hence we have following hypothesis

   Hypothesis 1 *Funds with simple or less complicated investment-styles attract more of naive investors and this exacerbates the influence of prior performance on fps.*

   To this end, I construct a mornigstar-type style box where each fund is classified on two dimensions: value orientation o and capitalization orientation of the fund. In particular, a fund can have value orientation, growth orientation or blend of two. For the capitalization dimension, fund can have small-cap, mid-cap, large cap or core (blend) orientation. This generates 12 distinct fund investment styles. I categorize funds with either growth-value blend orientation or large-cap orientation as having *simple* styles.

Table 8 presents the results. In the table the variable *Simple Style* is a dummy for the style mentioned at the top of each panel. For example, for Panel A, Style takes value 1 if a fund has either large-cap orientation or blend value orientation or both. I consider how the influence of prior performance on *fps* varies with style by including the interaction of *simple style* with interaction of prior and recent performance. The result confirms the hypothesis. First, funds with *complex styles* exhibit *return-chasing* as well as steeper *fps* for funds with higher prior performance. This is seen from the positive coefficients on *Perf (t-1)* and *Perf(t-1)*× *LT Perf(t-2)*. But more importantly, for the funds with *simple styles*, the three-way interaction term *Simple Style*×*Perf(t-1)*× *LT Perf(t-2)* is positive, significant and economically large. The positive coefficient on the three-way interaction term indicates that for funds with *simple styles*, *fps* is even more steeper for funds with good prior record. This is exactly what hypothesis predicted: impact of inattention captured through the steeper *fps* is more pronounced for funds with *simple styles*

2. **Market returns and Impact of prior performance on *fps*:** Good stock market years are more likely to attract naive or unsophisticated investors who are more likely to be not so active with their portfolio decisions Glode et al. (2009). If this is true, then we would expect the average inattention to fall after the periods of good market returns. This should widen the difference between the *fps* for funds with good prior performance and funds with poor prior performance after the good market returns. That is for a fund with good prior track record, the *fps* would be relatively more steep after a good market returns. Hence we have following hypothesis

   Hypothesis 2 *Good market returns attract more capital from unsophisticated investors which leads to built up of inattentive capital. Hence*

   - *fps will be lower after good market returns for all the funds*
   - *Additionally, the difference between fps for funds with good LT Perf and bad LT Perf widens after a period of good market returns.*

   To test the hypothesis, I construct a following experiment. Suppose at time $t-2$ market return turns out to be high. This will attract relatively more naive investors during period $t-1$ after observing the stock returns. This should lead to differential *fps* for period t as investors attend differentially to the performance at time $t-1$. Table 10 present the results. Note that the coefficient on the interaction term is positive only when lagged market returns are high enough. Flows following down market are more smart or sophisticated and hence the capital adjustments are swift in the periods following down markets. Note that the coefficient on *Perf (t-1)* is also significantly higher for the sample following poor lagged market returns again indicating that average attentiveness is higher.

3. **Managerial Replacements and Impact of prior performance on *fps*:** Managerial replacement is yet another event which affects the average attention level in the

industry. A managerial replacement leads to lot of media attention as well as communication from mutual fund to the investors. Replacement is an infrequent event and is more likely to attract the attention of otherwise inattentive investors. According to this hypothesis, if there is a managerial change in recent period, then average attention level of the investors is higher than otherwise which leads to swift capital adjustments after the realization of fund performance. That is irrespective of the prior performance, the *fps* will be steeper and the influence of the prior performance on the *fps* stands reduced.

Hypothesis 3 *Managerial replacements generate a lot of communication and media attention, thereby increasing the investor attention. Hence*

- *fps is higher after managerial changes for all the funds.*
- *Additionally, the importance of prior performance for fps reduces as the past performance does not reflect investor attention any more.*

To this end, I estimate *fps* for two subsamples: Funds which had managerial replacements during the performance period *(t-1)* and the other sample of funds for which no replacement took place. Also for replacement to be a significant event, I only consider replacement of single-manager funds. If one of the manager is replaced out of a team of managers, investors may not find it an economically important event. Table 9 present the results. The results confirm the hypothesis. For a sample of funds with managerial change at time *t-1*, the *fps* is a lot steeper compared to the other sample of funds with no replacement (slope is 2.16 for sample with replacement as against 0.86 for sample without manager replacement). More importantly, the interaction of prior performance and the recent performance loses the significance after managerial replacement. But the interaction coefficient is still large and significant if there is no replacement. This confirms the hypothesis that average attention level rises post managerial replacement and hence prior performance has a weaker bearing on the *fps*.

These tests though indirect in nature, provide some comfort as they confirm the logical implications that follow from *inattention hypothesis*.

7 Prior Performance, Fee Changes and Subsequent Fund Flows

Shifting the focus on the strategic behavior of the mutual funds, in this section I link the evidence on the heterogeneity in *fps* to the pricing of the fund. To run ahead and give the snapshot of the results, I find that funds with poor long-term performance are more likely to increase fund fee. I also find that such fee changes do not have any effects on fund flows for the funds with lower *fps*.

Prior performance and Fee Changes: In Christoffersen and Musto (2002), authors suggests that mutual funds' fees are set taking into account the elasticity of the money flows or the *fps* and funds facing less elastic flows charge higher fees. In particular authors establish that investors who stick with the fund which has lost 50% or more of it's capital over a particular period pay 10 basis points higher fees on average. In this section, I propose and establish an alternative hypothesis which I believe is more consistent with the rational expectations framework. In particular, I propose that instead of the *level of fees* one should study the link between *changes in the fees* and prior performance. If pricing of mutual fund really reflects the elasticity of flows to performance or *fps*, then we should observe changes in fees corresponding to changes in *fps*. Hence I focus on changes in fees. Christoffersen and Musto (2002) looks at fee changes after mergers of the fund and finds fee changes to reflect the new *fps* which combines the *fps* of merged funds. There is no logic as to why funds would change the fees only after merger but not otherwise. Hence I look for fee changes at fund level even outside merger events.

Table 11 presents the basic evidence. Expense ratio proxies fund fees in the CRSP data set. I split annual fee changes into five quantiles. Table clearly shows that fee reductions are associated with higher long-term gross performance and vice versa. Q1 of fee change corresponds to average long-term gross alpha of 0.42% while the same number for Q5 of fee changes is -0.16%. Last column of the table shows that it is rather difficult to see a clear link between the level of fees and gross performance or with fee changes. This indicates that *fee changes* is a better test of pricing of mutual funds. To link the fee changes to prior performance, I estimate a multivariate logit model of fee changes on lagged prior performance while controlling for other variables like age, size, turnover, style and year fixed effects etc. The estimated relationship is depicted in figure 2. Though model's overall explanation power is low, it brings out a clear link between fee changes and prior performance. Graph shows the predicted probabilities for each bin or quantile of fee change as a function of lagged long-term performance. The green line indicates that as the lagged performance improves from -10% to +10% (improvement from 10^{th} percentile to 90^{th} percentile), the probability of a large fee increase (a fee change that lies in the top 25% of the fee change distribution) reduces from almost 0.35 to meager 0.10. Similarly, as the prior performance improves, the predicted probability of large fee decline increases from 0.10 to almost 0.40. Hence the result of the logit model clearly indicates that poor (high) performing funds are more likely to increase (decrease) the fees. This is a stronger results compared to earlier literature.

Fund flows after a fee change: Next obvious question to ask is if this strategic fee change by the mutual fund is *smart*. We gage this by looking at the flows that can be attributable to the fee changes. Table 12 conducts this test. LOW, MED and TOP fee change represents bottom 25%, middle 50% and top 25% of the fee change distribution respectively. In Panel A, I regress a flows on dummies reflecting quantum of fee change apart from the recent performance *Perf (t-1)* and other control variables. It shows that a large fee increase leads to 5.82% reduction in asset size of the fund due to capital outflow. This would indicate that investors account for such fee changes and adjust the fund size accordingly. But Panel B shows that after accounting for the prior performance, a pattern more consistent with the *inattention hypothesis* emerge. In particular, the coefficient on fee changes dummies are now not significant. Hence, for a fund with very low long-term performance rank, fee increase do not lead to any associated capital outflows. This also confirms that the strategic fee setting by the funds is *smart*. The coefficient on the interaction of TOP fee change dummy with prior performance is significantly positive on the other hand indicating that fee increase if carried out for a fund with high prior performance or high *fps* will lead to large capital outflows. The evidence on mutual fund flows after the fee changes is a novel one and this is the first paper to my knowledge establishing this result.

8 Conclusion

The paper presents a novel evidence that the elasticity of fund-flows to recent performance or *fps* is increasing in prior performance. I propose *inattention mechanism*: inattentive investors stay invested with low performance funds, there by reducing the *outflow fps* of such funds. Additionally, because such funds are above their equilibrium size, even after a good performance, the required capital inflow to achieve the equilibrium size is low. Hence low performance funds also face low *inflow fps*. I present the tests to validate the mechanism. In particular I show that the impact of prior performance on *fps* (which proxies the attention within the fund) reduces after managerial replacements. Such influence is also highest for fund employing simple portfolio strategies. Good market returns also attract lot of naive investors and I show that prior performance affect *fps* significantly more in the periods following good market returns. I also link the fee changes to the elasticity of the funds. I find that fund with low *fps* or funds with poor prior performance are more likely to increase the fees. Further I show that this strategy is smart in the sense that such fee increase does not lead to fund flows from the funds where *fps* is low.

The paper adds significant body of evidence to the literature. The fact that prior performance affect not only outflow fps but inflow fps too is a novel one. The evidence on fee changes extends the analysis presented in Gil-Bazo and Ruiz-Verdu (2009) or Christoffersen and Musto (2002).

A Tables

Table 1: Evolution of Mutual Funds Over Time

The table presents annual number of share classes from 2000 to 2014. Each fund can have multiple share classes, and some share classes are dedicated for institutional investors. The table gives the decomposition of the total number in to retail vs institutional classes.

Year	Number of Share Classes	
	Retail	Institutional
2000	1134	323
2001	1346	417
2002	1509	486
2003	1677	637
2004	1803	766
2005	1780	839
2006	1824	913
2007	1757	993
2008	1900	1238
2009	1861	1263
2010	1819	1301
2011	1713	1351
2012	1610	1367
2013	1624	1446
2014	1697	1588

Table 2: Summary Statistics

Panel A: Pre Financial Crises Period (1999-2008)

	Institutional Share Class					Retail Share Class				
	Mean	Q25	Median	Q75	Std. dev	Mean	Q25	Median	Q75	Std. dev
Assets (Mn $)	3586.535	137.45	443.85	1312.3	14000	1823.093	116.8	344.6	1134.2	7398.806
Age (Years)	15.527	6	10	16	16.37	16.2	7	10	18	15.642
Expense Ratio (%)	1.041	0.83	1.01	1.24	0.33	1.564	1.19	1.5	1.98	0.517
Front Loads (%)	0.472	0	0	0	1.519	2.558	0	1	5.75	2.961
End Loads (%)	0.935	0	1	2	0.971	1.509	0	1	2	1.573
Gross Alpha (%)	-0.498	-3.045	-0.063	2.524	6.216	-0.403	-3.39	-0.013	2.89	7.087
Net Alpha (%)	-1.54	-4.05	-1.086	1.506	6.238	-1.968	-5.005	-1.56	1.379	7.126
Gross Fund Ret (%)	-1.019	-19.104	7.656	14.54	23.561	0.55	-14.766	7.657	15.173	22.464
Net Fund Ret (%)	-2.059	-19.981	6.631	13.472	23.568	-1.033	-16.315	6.109	13.65	22.462
Market Ret (%)	-1.514	-20.613	6.854	11.913	21.015	-0.352	-9.622	6.398	11.913	19.761
Flow (%)	-0.1	-14.704	-3.874	10.455	20.577	-1.171	-14.719	-5.45	8.044	19.974

Panel B: Post Financial Crises Period (2009-2014)

	Institutional Share Class					Retail Share Class				
	Mean	Q25	Median	Q75	Std. dev	Mean	Q25	Median	Q75	Std. dev
Assets (Mn $)	4130.416	187.65	678.15	1956.7	1.40E+04	2296.973	134.3	452.1	1462.7	8918.006
Age (Years)	18.351	9	13	20	16.61	18.406	9	14	21	15.221
Expense Ratio (%)	1.025	0.8	0.99	1.25	0.348	1.457	1.13	1.36	1.87	0.485
Front Loads (%)	0.434	0	0	0	1.512	2.528	0	0	5.75	2.891
End Loads (%)	1.155	0	2	2	0.938	1.176	0	1	2	1.198
Gross Alpha (%)	0.107	-2.244	0.008	2.35	4.363	0.189	-2.309	0.068	2.505	4.474
Net Alpha (%)	-0.917	-3.275	-0.958	1.334	4.362	-1.267	-3.73	-1.354	1.049	4.481
Gross Fund Ret (%)	18.421	10.601	16.537	28.482	11.922	18.663	10.736	16.924	28.587	12.064
Net Fund Ret (%)	17.392	9.597	15.547	27.472	11.906	17.209	9.285	15.484	27.186	12.044
Market Ret (%)	17.931	11.8	16.057	28.615	9.392	18.147	11.8	17.821	28.615	9.4
Flow (%)	-1.869	-13.949	-5.594	5.389	19.554	-2.75	-14.302	-6.41	4.261	18.937

Table 3: Summary Statistics of Funds Sorted on Lagged Long-Term Performance

	Long-Term Performance Bottom Quantile					Long-Term Performance Top Quantile				
	Mean	P25	P50	P75	SD	Mean	P25	P50	P75	SD
Assets (Mn $)	1114.075	101.5	266.1	774.7	6212.603	2625.441	318.8	898.5	2316.4	5719.927
Age (Years)	18.378	11	14	20	13.79	19.035	11	15	21	14.244
Expense Ratio (%)	1.385	1.05	1.29	1.73	0.47	1.337	0.99	1.25	1.67	0.456
Front Loads (%)	2.131	0	0	5.5	2.846	2.122	0	0	5.5	2.812
End Loads (%)	1.275	0	1	2	1.359	1.284	0	1	2	1.206
Gross Alpha (%)	0.135	-2.525	-0.009	2.798	4.746	-0.059	-2.486	0.194	2.82	4.711
Net Alpha (%)	-1.25	-3.905	-1.378	1.468	4.76	-1.397	-3.793	-1.126	1.521	4.736
Gross Fund Ret (%)	12.726	7.111	13.565	21.613	17.232	10.877	5.963	13.677	21.004	18.926
Net Fund Ret (%)	11.341	5.774	12.203	20.153	17.247	9.528	4.623	12.454	19.665	18.941
Flow (%)	-2.497	-18.628	-4.831	10.418	31.566	19.98	-4.52	12.893	37.399	42.909

Table 4: Flow Performance Sensitivity: Linear Specification

The table presents the regression estimates of fund flow(%) on to the measure of performance. Performance is gross Four-Factor Alpha estimated using daily returns. *Perf (t)* indicates the gross annual alpha for year *t* while *H1 Perf* indicates the gross alpha for the first-half of the year. *Rank LT Perf (t)* indicates normalized rank of Long-Term Performance measured over past 3 years including *t* that lies between 0 and 1. Other control variables are daily fund return volatility(*Perf Volatility*), market returns (*Market Perf*), log size (logassets), log of age measured in years (logage), annual expense ratio, fund turnover, and a dummy for if a share class is an institutional class. All the models have time and investment-style fixed effects and standard errors are clustered at the share class level. Panel A uses the entire sample, while Panel B-D restrict the sample to the funds for which *LT Perf (t-2)* variable is available during time *t*. *, ** and *** indicates significance at 10%, 5% and 1% respectively.

Dep Var →	Panel A $flow_{it}$ %	Panel B $flow_{it}$ %	Panel C $flow_{it}$ %	Panel D $flow_{it}$ %
H1 Perf (t)	1.232***	1.344***	1.363***	1.366***
	(0.023)	(0.037)	(0.036)	(0.036)
Perf (t-1)	1.543***	1.419***	1.539***	0.871***
	(0.038)	(0.057)	(0.058)	(0.092)
Rank LT Perf (t-2)			23.719***	23.494***
			(1.107)	(1.093)
Rank LT Perf (t-2)* Perf (t-1)				1.299***
				(0.180)
Market Perf (t-1)	-2.175***	-21.615***	-19.436***	-19.537***
	(0.792)	(1.170)	(1.110)	(1.111)
Perf Volatility (t-1)	-0.778***	-0.982***	-0.728***	-0.710***
	(0.059)	(0.131)	(0.124)	(0.124)
Expense Ratio (t)	-2.028***	-1.671**	-1.992***	-1.941***
	(0.507)	(0.690)	(0.669)	(0.666)
Log Assets (t-1)	-1.074***	-0.842***	-1.786***	-1.780***
	(0.132)	(0.177)	(0.180)	(0.179)
Log Age (t-1)	-6.408***	-1.827***	-0.705	-0.693
	(0.330)	(0.499)	(0.472)	(0.471)
Turnover (t-1)	-0.134	-1.374***	0.148	-0.044
	(0.334)	(0.473)	(0.475)	(0.472)
Institutional Class	-0.086	-1.096	-0.902	-0.881
	(0.503)	(0.685)	(0.663)	(0.661)
Intercept	133.800***	684.027***	604.597***	607.517***
	(22.772)	(37.185)	(35.153)	(35.211)
N	43767	17231	17231	17231
adj. R-sq	0.357	0.357	0.386	0.388

Table 5: Impact of Prior Performance on outflow *fps* and Inflow *fps*

The table exhibits the regression of $flow_{it}$ on measure of fund performance separately for inflows and outflows. Panel A estimates an unconditional model without considering the interactions with prior performance while Panel B considers the interaction. All the models have time and investment-style fixed effects and standard errors are clustered at the share class level. *, ** and *** indicates significance at 10%, 5% and 1% respectively.

	Panel A		Panel B	
Model Restriction →	$flow_{it} > 0$	$flow_{it} < 0$	$flow_{it} > 0$	$flow_{it} < 0$
H1 Perf (t)	0.562***	0.317***	0.686***	0.287***
	(0.022)	(0.012)	(0.033)	(0.025)
Perf (t-1)	0.674***	0.328***	0.536***	0.298***
	(0.031)	(0.017)	(0.079)	(0.060)
Rank LT Perf (t-2)			13.998***	2.043***
			(0.802)	(0.495)
Rank LT Perf (t-2)* Perf (t-1)			0.418***	0.275***
			(0.139)	(0.105)
Market Perf (t-1)	-0.739	0.290	-9.585***	-3.395***
	(0.564)	(0.348)	(0.798)	(0.631)
Perf Volatility (t-1)	-0.384***	-0.350***	-0.234***	-0.165**
	(0.055)	(0.027)	(0.086)	(0.068)
Expense Ratio (t)	-0.763**	-0.579***	-1.248**	-0.371
	(0.385)	(0.214)	(0.522)	(0.327)
Log Assets (t-1)	0.182*	0.114*	-0.278**	-0.118
	(0.102)	(0.063)	(0.138)	(0.097)
Log Age (t-1)	-5.373***	0.270*	-3.195***	2.130***
	(0.274)	(0.138)	(0.425)	(0.259)
Turnover (t-1)	-0.092	-0.481***	0.180	-0.339
	(0.261)	(0.147)	(0.352)	(0.234)
Institutional Class	0.792**	-0.600***	0.489	-1.140***
	(0.374)	(0.216)	(0.511)	(0.334)
Intercept	68.218***	-7.273	308.925***	87.867***
	(16.278)	(9.972)	(25.156)	(19.891)
N	22022	17377	9001	6792
adj. R-sq	0.152	0.391	0.211	0.403

Table 6: Estimated *fps* with Raw Returns

The table presents the regression estimates of fund flow(%) on to the measure of performance. Performance variable is normalized rank of funds based upon their raw returns(*Rank Perf (t)*). *H1 Perf* indicates the raw returns for the first-half of the year. *Rank LT Perf (t)* indicates normalized rank of Long-Term Performance measured over past 3 years including t that lies between 0 and 1 using fund raw returns. Other control variables are daily fund return volatility(*Perf Volatility*), market returns (*Market Perf*), log size (logassets), log of age measured in years (logage), annual expense ratio, fund turnover, and a dummy for if a share class is an institutional class. All the models have time and investment-style fixed effects and standard errors are clustered at the share class level. *, ** and *** indicates significance at 10%, 5% and 1% respectively.

	Panel A	Panel B	Panel C
Dep Var →	Flow %	Flow %	Flow %
H1 Perf (t)	1.168***	1.298***	1.302***
	(0.022)	(0.036)	(0.036)
Rank Perf (t-1)	22.492***	21.748***	13.181***
	(0.648)	(0.897)	(1.693)
Rank LT Perf (t-2)		20.718***	12.594***
		(1.157)	(1.740)
Rank LT Perf (t-2)* Rank Perf (t-1)			15.940***
			(3.020)
Market Perf (t-1)	-3.616***	-24.938***	-25.203***
	(0.810)	(1.151)	(1.153)
Perf Volatility (t-1)	-0.740***	-1.261***	-1.258***
	(0.061)	(0.128)	(0.128)
Expense Ratio (t)	-2.178***	-2.165***	-2.166***
	(0.515)	(0.676)	(0.674)
Log Assets (t-1)	-1.060***	-1.558***	-1.558***
	(0.133)	(0.183)	(0.183)
Log Age (t-1)	-6.507***	-0.912*	-0.882*
	(0.335)	(0.493)	(0.492)
Turnover (t-1)	-0.900**	-1.460***	-1.419***
	(0.353)	(0.463)	(0.462)
Institutional Class	-0.197	-0.894	-0.907
	(0.513)	(0.671)	(0.670)
Intercept	167.926***	774.471***	786.410***
	(23.303)	(36.461)	(36.567)
N	43767	17231	17231
adj. R-sq	0.348	0.372	0.374

Table 7: Impact of Prior Performance on *fps* With Varying Fund Size

The table exhibits the regression of $flow_{it}$ on measure of fund performance separately for small funds and large funds (below and above median size for a given year). Panel A estimates an unconditional model without considering the interactions with prior performance while Panel B considers the interaction. All the models have time and investment-style fixed effects and standard errors are clustered at the share class level. *, ** and *** indicates significance at 10%, 5% and 1% respectively.

	Panel A		Panel B	
Size Restriction →	Small	Large	Small	Large
H1 Perf (t)	1.005***	1.119***	1.031***	1.136***
	(0.044)	(0.034)	(0.043)	(0.034)
Perf (t-1)	1.019***	1.155***	0.365***	0.948***
	(0.066)	(0.049)	(0.104)	(0.083)
Rank LT Perf (t-2)			11.415***	19.179***
			(1.099)	(0.924)
Rank LT Perf (t-2)* Perf (t-1)			1.553***	0.607***
			(0.205)	(0.148)
Market Perf (t-1)	-15.247***	-17.328***	-14.714***	-15.207***
	(1.209)	(0.975)	(1.162)	(0.940)
Perf Volatility (t-1)	-0.644***	-0.686***	-0.568***	-0.402***
	(0.137)	(0.106)	(0.132)	(0.105)
Expense Ratio (t)	-0.223	-2.139***	-0.219	-2.359***
	(0.786)	(0.634)	(0.771)	(0.607)
Log Assets (t-1)	-0.420	0.473**	-1.309***	-0.061
	(0.416)	(0.231)	(0.421)	(0.209)
Log Age (t-1)	-1.379**	-1.387***	-0.987	-0.582
	(0.645)	(0.503)	(0.636)	(0.455)
Turnover (t-1)	-0.233	-2.956***	0.142	-1.707***
	(0.417)	(0.558)	(0.415)	(0.518)
Institutional Class	-1.357*	-0.825	-1.314*	-0.611
	(0.768)	(0.626)	(0.757)	(0.600)
Intercept	477.845***	539.039***	458.697***	461.315***
	(37.898)	(31.143)	(36.339)	(30.052)
N	6056	9737	6056	9737
adj. R-sq	0.376	0.433	0.396	0.471

Table 8: Effect of Styles on Flow-Performance Sensitivity

Table presents impact of complex vs simple fund-styles on flow-performance sensitivity (fps). *Style* variable is a dummy for the fund investment style mentioned for each panel at the top. For panel A, *style* = 1 if fund's investment style is either *large-cap* or value orientation is *blend* and similar interpretation applies for Panel B and C. Other variables are as defined in table 4. The regressions are run with time fixed effects, but not with style fixed effects and all the errors are clustered at the share class level. *, ** and *** indicates significance at 10%, 5% and 1% respectively.

	Panel A	Panel B	Panel C
Simple Style →	Large Cap or Value-Blend	Large Cap	Value-Blend
Dep Var →	Flow %	Flow %	Flow %
H1 Perf (t)	1.313***	1.326***	1.312***
	(0.036)	(0.036)	(0.036)
Perf (t-1)	0.939***	0.928***	1.016***
	(0.125)	(0.107)	(0.109)
Rank LT Perf (t-2)	21.239***	22.201***	21.459***
	(1.729)	(1.297)	(1.352)
Perf (t-1)*Rank LT Perf (t-2)	0.608**	0.985***	0.718***
	(0.256)	(0.211)	(0.216)
Simple Style	-0.749	1.013	-0.270
	(1.100)	(1.126)	(1.033)
Simple Style*Perf (t-1)	-0.217	-0.289	-0.534***
	(0.171)	(0.191)	(0.206)
Simple Style*Rank LT Perf (t-2)	0.634	-0.748	0.423
	(2.024)	(2.055)	(1.938)
Simple Style*Perf (t-1)*Rank LT Perf (t-2)	1.247***	1.024***	1.556***
	(0.345)	(0.379)	(0.383)
Market Perf (t-1)	-0.701***	-0.709***	-0.695***
	(0.061)	(0.062)	(0.061)
Perf Volatility (t-1)	-0.954***	-0.920***	-0.930***
	(0.109)	(0.113)	(0.106)
Expense Ratio (t)	-1.688***	-1.614***	-1.688***
	(0.621)	(0.618)	(0.623)
Log Assets (t-1)	-1.640***	-1.646***	-1.641***
	(0.179)	(0.179)	(0.180)
Log Age (t-1)	-0.504	-0.593	-0.490
	(0.450)	(0.456)	(0.453)
Turnover (t-1)	0.082	0.165	0.149
	(0.475)	(0.470)	(0.471)
Intercept	28.661***	27.424***	27.768***
	(3.166)	(3.063)	(3.042)
N	17231	17231	17231
adj. R-sq	0.384	0.384	0.384

Table 9: Manager Change and Flow-Performance Sensitivity

Table presents a linear fps estimation similar to table 4 but conditioning on whether fund replaced it's manager during the performance period. Panel A (B) exhibits the results when fund replaced (did not replaced) it's manager during the performance period (t-1). Other variables are as defined in table 4. All the models have time and investment-style fixed effects and standard errors are clustered at the share class level. *, ** and *** indicates significance at 10%, 5% and 1% respectively.

	Manager Change	
Model Restriction →	Change (t-1)	No Change (t-1)
Dep Var →	Flow %	Flow %
H1 Perf (t)	1.282***	1.368***
	(0.282)	(0.036)
Perf (t-1)	2.187***	0.865***
	(0.540)	(0.094)
Rank LT Perf (t-2)	4.011	23.965***
	(5.657)	(1.097)
Rank LT Perf (t-2)* Perf (t-1)	0.189	1.319***
	(1.017)	(0.183)
Market Perf (t-1)	-0.728	-19.697***
	(6.135)	(1.122)
Perf Volatility (t-1)	1.658**	-0.734***
	(0.760)	(0.126)
Expense Ratio (t)	-0.059	-1.587***
	(3.102)	(0.613)
Log Assets (t-1)	-6.126***	-1.740***
	(1.593)	(0.179)
Log Age (t-1)	-5.639	-0.565
	(3.798)	(0.475)
Turnover (t-1)	-4.096	0.084
	(3.101)	(0.467)
Intercept	46.761	611.074***
	(186.740)	(35.619)
N	310	16921
adj. R-sq	0.416	0.390

Table 10: Lagged Market Returns and flow-Performance Sensitivity

Table presents a linear fps estimation similar to table 4 but conditioning on the lagged market returns. Panel A (B) exhibits the results for poorest (highest) 25% lagged market returns. Other variables are as defined in table 4. All the models have time and investment-style fixed effects and standard errors are clustered at the share class level. *, ** and *** indicates significance at 10%, 5% and 1% respectively.

	Market Return State (t-2)	
Model Restriction →	Panel A: Top 25%	Panel B: Bottom 25%
Dep Var →	Flow %	Flow %
H1 Perf (t)	0.778***	1.519***
	(0.067)	(0.182)
Perf (t-1)	0.812***	1.283***
	(0.225)	(0.285)
Rank LT Perf (t-2)	24.444***	26.934***
	(1.920)	(2.743)
Rank LT Perf (t-2)* Perf (t-1)	2.102***	0.329
	(0.430)	(0.444)
Perf Volatility (t-1)	-0.200*	-0.379**
	(0.111)	(0.180)
Expense Ratio (t)	-2.458**	1.862
	(1.027)	(1.632)
Log Assets (t-1)	-2.376***	-1.735***
	(0.321)	(0.496)
Log Age (t-1)	-0.691	-0.436
	(0.760)	(1.310)
Turnover (t-1)	-2.969***	2.034*
	(0.903)	(1.132)
Intercept	11.331***	34.924***
	(4.281)	(7.054)
N	4952	1916
adj. R-sq	0.150	0.159

Table 11: Long-Term Performance and Fee Changes

Table presents the Long-Term performance of the funds sorted on change in the expense ratio. Change in fee is given by Fee Change (t) = expense ratio(t) - expense ratio (t-1). Q1 indicates bottom 20 % and Q5 indicates top 20%. All the numbers are mean numbers.

Quantile of Fee Change	Fee Change (t)	Gross LT Perf (t-1)	Net LT Perf (t-1)	Expense (t) Ratio (t)
Unit	Basis Points	%	%	%
Q1	-7.2	0.429	-1.012	1.372
Q2	-1	0.32	-0.955	1.273
Q3	0.3	0.077	-1.193	1.29
Q4	3.4	0.197	-1.099	1.35
Q5	8.9	-0.161	-1.501	1.436

Figure 1: Long Term Fund Performance and Fee Changes

The graph shows an estimated relationship between change in the expense ratio (given by expense ratio (t) - expense ratio (t-1)) and the lagged long-term fund performance as measured by LT Perf (t-1). LT Perf (t) is the average gross alpha over the preceding 5 years including t. Fee Change is measured in basis points. Estimation controls for log of assets, log of fund age, the level of expense ratio

Figure 2: Predicted Probabilities of Fee Changes

Fee Changes are grouped in three bins: Negative fee changes corresponding to bottom 25% of the fee change distribution, moderate fee changes corresponding to middle 50 % of the fee change distribution and Positive fee changes corresponding to top 25% of the fee change distribution. Graph shows the estimated probabilities from logit model that a fee change falls in one of the three groups as a function of *LT Perf (t-1)*. Control variables are log assets, log of fund age, year and style fixed effects, fund turnover, and fund volatility.

Table 12: Impact of Fee Changes on Fund Flows

The table presents regression of fund flows on the indicator of past fee changes. I split the fee change distribution in to three quintiles: LOW (bottom 25% of fee changes), MED (middle 50%) and TOP (top 25%). Other control variables are as defined in table 4. All the models have time and investment-style fixed effects and standard errors are clustered at the share class level. *, ** and *** indicates significance at 10%, 5% and 1% respectively.

Dep Var →	Flow% Panel A	Flow% Panel B	Flow% Panel C
MED Fee Change (t-1)	-4.010***	-1.409	-1.542
	(0.580)	(1.060)	(1.065)
TOP Fee Change (t-1)	-5.827***	-1.910	-1.959
	(0.715)	(1.369)	(1.357)
Rank LT Perf (t-2)		25.758***	25.508***
		(1.668)	(1.665)
MED Fee Change (t-1)*Rank LT Perf (t-2)		-2.979	-2.903
		(1.894)	(1.900)
TOP Fee Change (t-1)*Rank LT Perf (t-2)		-4.687*	-4.837**
		(2.406)	(2.389)
H1 Perf (t)	1.339***	1.359***	1.362***
	(0.036)	(0.036)	(0.036)
Perf (t-1)	1.413***	1.532***	0.847***
	(0.057)	(0.057)	(0.092)
Perf (t-1)*Rank LT Perf (t-2)			1.330***
			(0.180)
Market Perf (t-1)	-22.508***	-20.148***	-20.270***
	(1.173)	(1.116)	(1.117)
Perf Volatility (t-1)	-0.994***	-0.734***	-0.716***
	(0.130)	(0.124)	(0.124)
Expense Ratio (t)	-1.338**	-1.695***	-1.659***
	(0.634)	(0.614)	(0.611)
Log Assets (t-1)	-0.909***	-1.823***	-1.817***
	(0.175)	(0.179)	(0.178)
Log Age (t-1)	-1.770***	-0.675	-0.665
	(0.489)	(0.466)	(0.465)
Turnover (t-1)	-1.393***	0.090	-0.107
	(0.469)	(0.472)	(0.469)
Intercept	714.158***	627.211***	630.878***
	(37.267)	(35.367)	(35.415)
N	17231	17231	17231
adj. R-sq	0.359	0.388	0.390

B Proofs

Proof of lemma 1

Consider equilibrium condition given in equation 9. Substituting r_{t+1} from equation 8 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 $R_{t+1} - \phi_t$

$$R_{t+1} - \phi_t = \frac{r_{t+1}}{h_t} + \frac{f}{h_t} + \eta h_t q_t - \left(\frac{E_t(r_{t+1})}{h_t} + \frac{f}{h_t} + \eta h_t q_t\right) = \frac{r_{t+1} - E_t(r_{t+1})}{h_t} \tag{20}$$

Substituting in Bayesian formula, we get

$$\phi_{t+1} = \phi_t + \left(\frac{r_{t+1} - E_t(r_{t+1})}{h_t}\right)\left(\frac{\sigma_t^2}{\sigma_t^2 + \sigma_\varepsilon^2}\right) \tag{21}$$

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

$$E_t\left(r_{t+1}\right) = -\eta h_t^2 q_t^* \psi_t \tag{22}$$

Proof of lemma 7

Define fund flows as Define Fund flows (FF_t) by

$$FF_t = \frac{q_t}{q_{t-1}(1 + r_t)} - 1 \tag{23}$$

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 12, 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 11 and $E_{t-1}(r_t)$ from equation 22, 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 $q_t = q_t^*$

$$FF_t = \frac{1}{(1+\psi_{t-1})(1+r_t)}\left[1 + \omega_{t-1}\left(\frac{r_t}{2f} + \frac{\psi_{t-1}}{2}\right)\right]^2 - 1 \tag{24}$$

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

$$FF_t = -\frac{z_t}{q_{t-1}(1+r_t)} \tag{25}$$

Figure 3: Model Implied Fund Flows

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

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