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# Performance and incentives In mutual fund industry

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# PERFORMANCE AND INCENTIVES IN MUTUAL FUND INDUSTRY

by

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*Research is to see what everybody else has seen, and to think what nobody else has thought.*

Albert Szent-Gyorgyi

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**PERFORMANCE AND INCENTIVES IN MUTUAL FUND INDUSTRY**

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ABSTRACT

I study various aspects of mutual funds in my thesis. These are divided over four chapters. The first chapter is an introduction to the thesis and sets out an executive summary of my research. The second to fourth chapters each deal with a new concept.

The second chapter shows that the sensitivity of an investor's reaction to a mutual fund's recent performance increases with the fund's historical performance. Put differently, bad (good) performance combined with a good-history for a fund results in a greater fraction of capital outflows (inflows) relative to a fund with a poor past history. The evidence is puzzling as we would expect investors to stick with a fund having a good-history, even after a single bad performance. I solve this problem using a model with investors of differing attentiveness. In equilibrium, fund owner's attentiveness increases the historical record of a fund. With this mechanism, the model can explain the higher sensitivity of outflows for the good-history funds. The chapter is important in that it shows that return-chasing behavior is not ubiquitous. It also provides a clear evidence where the market is slow to incorporate the new information into decision making.

The third chapter studies the managerial side of the mutual funds industry regarding the risk-taking behavior of the mutual funds. Mutual fund managers are compared against a benchmark or with the peers. The employment, as well as investor's capital flows, depends

on how the manager fares in the competition. I present new evidence in the chapter that the exposure of a manager to these risks is heterogeneous, and manager's historical performance governs it. The evidence implies that the risk-appetite and behavior of a manager depends on his historical performance. I find strong support in the data for this hypothesis. I show that funds with poor historical performance do not boost the portfolio risk to catch up with the peers if they are lagging at the interim date. In general, the risk appetite of the poor-history manager is less driven by their interim performance. But the good-history managers respond to their midyear position and more so during the bull years. The evidence on risk-shifting is consistent with the evidence on how each incentive behaves for good and poor history managers over bull and bear phases.

The fourth chapter shows that capital movement in and out of a mutual fund is more sensitive to fund performance during periods of high market volatility. I explain this result using a model where the manager has picking as well as timing skill. A volatile market presents an opportunity to generate timing value and to that extent produces speedy learning about managerial timing ability. Persistence in volatility boosts the sensitivity of flows to performance during such times. Given the counter-cyclical nature of market volatility, the model predicts that the flow sensitivity is higher during the recessions. Data supports the model prediction. The chapter provides a clear example when the trade volume (here capital flows) is linked positively with the volatility. Usually, literature has shown how the volatile periods slows the learning and hence trade volumes too. But my model indicates that there could be substantial learning going on during volatile times about critical economics parameters, mainly because those parameters are revealed only during volatile times.

# Contents

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# List of Symbols

| | | |
|---|---|---|
| AUM | ...... | Assets Under Management |
| FLOW | ...... | Fund flows measured as a fraction of fund size |
| $Perf_{it}$ | ...... | Rank of fund $i$ for it's recent performance at time $t$ |
| $repute_{it}$ | ...... | Reputation rank for fund $i$ ending time $t$ |
| $Mkt_{it}$ | ...... | Market share of fund $i$ at the end of time $t$ |
| AA | ...... | Always Attentive |
| OA | ...... | Occasionally Attentive |
| $f$ | ...... | Per Dollar fee charged by the fund |
| $RSR_{it}$ | ...... | Risk-Shifting Ratio by fund $i$ during time $t$ |

# Chapter 1

# Introduction

My thesis studies various aspects of mutual fund industry. It focuses on the investor's and the manager's decisions in the context of mutual funds. All the three chapters are closely related to each other and studies incentives within mutual fund industry.

## 1.1 Overview of Mutual Fund Economics

Mutual funds industry has grown at an astonishing speed over last two decades. According to Investment Company Institute (ICI) fact book, total assets held by US mutual funds is 18.2 trillion $ at the end of 2015, up from 4.8 trillion $ in 1997. Moreover, this rise of mutual fund assets in dollar terms has been inclusive. Roughly 24% of household finance is managed by investment companies, and 43% of the US households owns median of four mutual funds. Mutual funds have become a dominant intermediary in asset markets. The mutual fund industry has been pivotal in changing the structure of the US financial markets from primarily being directly owned to being intermediated one. Mutual funds own 30% of the US equity value and 46% of the commercial paper market. [1]

Studying capital flow structure and managerial risk choices are important for understanding the behavior of asset prices. Intermediation implies a two-step demand for financial assets. First, investors invest in a mutual fund and then a fund manager chooses the portfo-

[1] All the numbers are from ICI 2015 fact book

lio on behalf of the investors. It implies that asset prices are a function of investor's capital flows into and out of the mutual funds on one hand and portfolio choice made by fund managers on the other. Additionally, mutual fund flows reflect investor's decisions given their information set. Because mutual fund data is widely available, an econometrician can approximate the investor's information set pretty well. Therefore, it provides a great laboratory to study the behavioral traits and compare the patterns to the existing models. At the same time, studying managerial risk choices is important. The remuneration structure, as well as the investor's behavior, shapes the incentives for fund managers. Studying how these incentives translate into the risk choices of fund managers is important from a regulatory perspective. With this motivation, I explore three aspects of the mutual fund industry. First is to understand how investors react to the fund performance. The second chapter studies explore the role of the historical fund performance in determining how investors respond to the recent performance. In the third chapter, I examine the managerial risk-shifting behavior in response to the incentives they face. In the fourth chapter, I study how investor's reaction to the fund performance change as the state of the financial markets change.

Research in the area of mutual funds gained traction with the growth of mutual fund business. Starting from (Jensen, 1968), and subsequent findings of (Gruber, 1996), among others have documented underperformance by mutual funds compared to the benchmark index. (Carhart, 1997) documents lack of performance persistence for mutual funds. Taken together, these findings imply that an average mutual fund underperforms a pure passive benchmarking strategy and even if a fund outperforms during a particular period then it is not likely to repeat the performance in subsequent years. In light of this, it was found puzzling when following papers by (Sirri and Tufano, 1998), and (Chevalier and Ellison, 1997), among others, found that investor chase past winner funds. This behavior is termed as *Return Chasing*. (Berk and Green, 2004) solved this puzzle using the model with decreasing returns to the scale. They reasoned that lack of performance persistence is a result of return-chasing behavior. Their argument is based on the premise of decreasing returns to scale at the fund level. If a fund is expected to provide a positive return, then investors invest in such a fund until operating cost per dollar rise to bring the expected return to zero level. The reverse process results in capital outflow for a fund with negative expected returns. In equilibrium, every fund is sized such that expected return is zero. This process rationalizes the co-existence of performance chasing and lack of performance persistence. (Sirri and Tufano, 1998) and (Chevalier and Ellison, 1997) documented that fund flows or capital flows respond non-linearly to the recent fund performance. In particular, they found that flow-schedule (fund flows as a function of recent fund performance) is convex implying that sensitivity of flows to performance increases with performance. Because fund flows shapes the compensation of the manager, (Carpenter, 2000), (Chen, 2009), (Basak et al., 2007), among others explored the impact of this option like compensation on managerial risk shifting. (Brown et al., 1996) document the evidence that midyear losing funds increase the risk during the second half of the year. (Kempf et al., 2009) show that employment incentives dominate compensation incentives during severe market periods and vice-versa. They provide the evidence that midyear losing managers increase risk relative to leading managers during the times where compensation incentives dominate and decrease the risk otherwise.

In the second chapter of my thesis, I begin with the premise that the way investors react to the recent fund performance depend crucially upon the way that fund has performed historically. Model of (Berk and Green, 2004) for example imply that investors respond only to the recent performance as they have already reacted to the past performance. But if the way investor reads new signals depend upon the past performance or if investors were inattentive in the past then their reaction to the recent signal depends upon the past performance. With this view, I explore the impact of past performance on the link between new performance and subsequent investor's reaction. Contrary to the common belief that investors would stay put with a good-history manager even after a single bad performance, I find that good-history funds are more vulnerable to capital outflows after a bad performance. I solve this puzzle using a model with some of the investors being non-attentive. These investors stick to the poorly performing funds as they fail to pay attention to the fund performance. On the contrary, attentive investors always shift to the funds with a better recent performance. The relative attentiveness heterogeneity implies that the good-history funds are populated dominantly by attentive investors. If such a fund performs poorly, the investors shift out immediately, generating the observed sensitivity of capital outflows to a bad performance for good-history funds. The model also implies that a poor-history fund is over-sized relative to the competitive size and to that extent it underperforms on an average, given that mutual funds face decreasing return to scale. I test this prediction in the data and validate it.

In the third chapter, I turn my attention to the managerial side. I explore the role of historical performance for managerial risk-taking behavior. First, I document that the probability of managerial firing is affected by the long-term fund performance together with the recent performance. The evidence in the second chapter shows that capital flow incentives also depend upon the historical performance of the fund. As both the incentives for the manager gets determined by the past performance, I conjecture that the risk-taking behavior of poor-history and good-history funds could be very different. From the data, I find the same. In particular, I show that the portfolio choice of the poor-history funds is less driven by the compensation incentives. In particular, a poor-history fund with the losing midyear position always reduces the risk relative to the a midyear winner. On the other hand, a fund with a good-history engages in positive risk-shifting to catch up with the peers.

In the fourth chapter, I study how the investors reaction to the fund performance is a function of the aggregate state of the economy or the stock market. I document that capital flow is more sensitive to the performance during the periods with high conditional volatility. Traditionally, volatile periods are associated with slow learning due to increased noise and hence muted reaction. I propose a model where investors learn about different dimensions of managerial skill during different aggregate states. A manager is endowed with *picking* as well as *timing* skill. Volatile periods give the manager an opportunity to use his timing skills and to that extent, investors learn about one component of the managerial skill during high volatility periods, generating sensitivity of flows to performance during such times. To my knowledge, this is the first attempt to solve a model where a manager has timing skill.

# Chapter 2

# How the Historical Performance Shape the Mutual Fund Flows?

## 2.1 Introduction

In this chapter, I study the importance of a mutual fund's historical performance 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 the historical performance affects fund flows in general and *flow-schedule* in specific. This is the focus of the present paper.

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. [(Sirri and Tufano, 1998) ; (Chevalier and Ellison, 1997)]. To the contrary, I present a novel evidence that *return-chasing* is prominent only for the funds with a sufficiently good historical performance. For the funds with a low level of historical performance, flows are weakly responsive to recent performance. In short, the responsiveness of fund flows to the current performance is largely shaped by a fund's historical performance and that the *return-chasing* is not ubiquitous. These results present a new perspective to understand mutual fund flows. My paper underscores the importance of past performance in

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

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 up to time $t-1$. The idea is that long-term performance up to $t-1$ serves as a prior about the manager's ability and time $t$ performance serves as the signal. The objective is to understand how much of the time $t+1$ flows can be attributed to each of the following three sources: current performance at time $t$, past performance upto time $t-1$, 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 the current performance and the past performance, my regression estimates strongly support the hypothesis of *return chasing* of (Ippolito, 1992) and (Sirri and Tufano, 1998). 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 the past performance as in (Chevalier and Ellison, 1997).

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 the interaction terms between the past and the current performance. For example, a fund with a $10^{th}$ percentile historical performance 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, the interaction term between the past performance and every quantile of current performance is statistically significant and economically large. For example, the coefficient on interaction between the past and the 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 historical performance 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 historical performance 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 good-history funds. This way, my estimation finds an entirely novel source of fund flows.

4. **Flows are sensitive for good-history funds:** Interaction terms rise monotonically over the quantiles of recent performance. This implies that the gap between fund flows accruing to good-history and the poor-history funds increase with the level of the current performance. In other words, flow-schedule is more sensitive for the good-history funds. Because all the interaction terms are significant, it implies that flow-schedule for a good-history fund is sensitive even at the lower end of the recent performance. This is not the case for a poor-history fund. 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 historical performance. On the other hand, a similar jump brings 4% to 5.5% additional flows for a fund with $90^{th}$ percentile of historical performance. This is in line with (Berk and Tonks, 2007). But what is novel is that the good-history funds have more sensitive right end

of flow-schedule.

5. **Stand-alone of *historical performance*:** Fifth, the independent effect of the past performance on the level of fund flows is strongly positive; a fund experiences asset growth to the tune of 7% to 8% for having a better history, independent of recent performance. This implies that the historical performance shifts the flow-schedule up. This result is consistent with some earlier regression models including those of (Chevalier and Ellison, 1997). This effect may possibly capture the impact of better promotions in the following year after a winning year for mutual fund.

(Berk and Green, 2004) 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. These two features together imply that the fund flows are independent of the historical performance in that model. But my evidence suggests that past matters for fund flows.

To this end, I construct an equilibrium model with heterogeneous investors. Model is in spirit of (Berk and Green, 2004) 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 (Berk and Green, 2004) 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 in terms of investor attentiveness differs sub-

[2]size where expected net returns are zero

stantially across good-history and poor-history funds as the horizon over which history is measured increases. This implies that the interaction effects between the past and the current performance should become more significant and dominant as the horizon for history measurement increases. It must be mentioned at this stage that my model explains how the past performance interacts with the recent performance in shaping flows. But it is not a model to understand independent effect of the fund's historical performance .

I employ two indirect tests to confirm the model mechanism that the historical performance 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 good and poor history funds is diminished after replacement of fund manager. The data exactly supports this hypothesis. Interaction term is almost insignificant after the replacement event. Second test exploits the structure of the 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 should diminish for such funds. Again the data confirm the hypothesis.

## 2.2 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 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. (Chevalier and Ellison, 1997) use historic performance as a control, and fail to consider interactions. The reason to control for the historical performance 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 the past 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 (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 flow schedule 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). 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 historical performance 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.

(Berk and Tonks, 2007) 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 the historical performance more generally and not only at the lower range of recent performance. Second, (Berk and Tonks,

2007) use one year of historic performance. I show that dependence of flow-schedule on the historical performance increases with the period over which the history is computed. Third, (Berk and Tonks, 2007) 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 the fund's historical performance has been explored other contexts. For example, (Khorana, 1996a),(Chevalier and Ellison, 1999), and (Kostovetsky and Warner, 2015) 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 historical performance and only 12% of the replaced managers belong to top quintile of historical performance.[3] Hence, the historical performance 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's historical performance. 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 (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, (Berk and Green, 2004) show that investors chase positive

[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.

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 thr past performance. I augment the (Berk and Green, 2004) framework with the presence of inattentive investors to break the independence of flows and the historical performance to match the fact observed in the data. (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.

(Carhart, 1997) presents the evidence of lack of performance persistence for mutual funds. 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. I show that poor-history of performance predicts poor future 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 (Huang, 2007). My paper takes an agnostic view about why some investors are inattentive.[4]

## 2.3 Data and Empirical Methodology

### 2.3.1 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

[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

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]

### 2.3.2 Variables

The main variable of interest is fund flows. In line with more recent literature [(Berk and Green, 2004); (Huang et al., 2012)], I define fund flows as percentage growth in assets under management (AUM) due to capital flows.[8] In particular,

$$FLOW_{it} = \frac{AUM_{it} - [AUM_{it-1} \times (1 + r_{it})]}{AUM_{it-1} \times (1 + r_{it})}, \tag{2.1}$$

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

[6] See data appendix for further details.

[7] Following (Huang et al., 2012), 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.

[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.

are ranked within their investment style following (Sirri and Tufano, 1998) or (Spiegel and Zhang, 2013). Though some recent papers use four-factor model of (Carhart, 1997) to measure fund performance (Berk and Van Binsbergen, 2014) 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. (Chevalier and Ellison, 1997) use excess returns as a performance measure without considering any risk adjustment. (Sirri and Tufano, 1998) 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 past performance. At any year-end, recent performance is computed using data for the recent period, which is the year currently ending, and the index of historical performance 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 serves as the history window. The recent raw return denoted by $r_{it}^{st}$ is the annual raw return of a fund over the recent period and the historical performance index using raw returns denoted by $r_{it}^{lt}$ is computed using aggregate raw return over the historical performance 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:

$$r_{i\tau} - RF_{\tau} = \alpha_{it,k} + \beta_{it,k} \times (r_{m,\tau} - RF_{\tau}) + \varepsilon_{i\tau} \tag{2.2}$$

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

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

I compute recent period risk using the recent period's monthly return observation. A measure of long-term risk is volatility of returns over history window. Other variables used are log of fund age, fund size, expense ratio, and turnover ratio. Following (Sirri and Tufano, 1998), 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.

### 2.3.3 Summary Statistics

Basic summary statistics are presented in table 2.1. Funds are sorted in to bottom quintile (Low), top quintile (Top) and middle three quintiles (Med), according to their year-end historical performance rank. The table also provides overall statistics for entire sample.

The first two columns exhibit the spread in performance across various historical performance quintiles. The mean spread between the *low* and *top* historical performance 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 historical performance quintile. The mean and median size of the poor-history group is three times smaller than that of the good-history 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 the quantiles of the past performance. This makes it easier to estimate regression models, as most of the control variables need not be interacted with the past performance.

### 2.3.4 Empirical Methodology

The objective is to understand how the historical performance affects the link between the current 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 (Sirri and Tufano, 1998), (Chevalier and Ellison, 1997), and (Huang et al., 2012), I divide the funds into quintiles according to their recent time $t$ performance given by $\text{Perf}_{it}$. Let $Q_{jt}$ be the dummy variable indicating that a fund lies in $j^{th}$ quantile when sorted on the basis of $\text{Perf}_{it}$. I run following regression.

$$FLOW_{it+1} = a + \sum_{j=2}^{J} \phi_j Q_{jit} + \sum_{j=2}^{J} \psi_j \left( Q_{jit} \times repute_{it-1} \right) + \gamma \times repute_{it-1} + CONTROL_{it} + \varepsilon_{it+1}, \tag{2.3}$$

$CONTROL_{it}$ 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 $t$ performance and the historical performance index up to and including time $t-1$. Second, because the model has an intercept we lose the coefficient $\phi_1$ on the first quintile of recent performance. Because the equation identifies the independent effect of $repute_{it-1}$ through $\gamma$, we lose $\psi_1$ too on the first quintile of recent performance in interaction terms. Given this structure, we can interpret each of the coefficients as follows: For $j = 2, 3, 4, 5$, $\phi_j$ captures the incremental $FLOW_{it}$ to $j^{th}$ quintile over first quantile $Q_1$. Similarly, $\psi_j$ captures the incremental interaction effect for $j^{th}$ quantile over and above that of the interaction effect on first quantile.[10]

## 2.4 Empirical Evidence

### 2.4.1 Main Results

Results are reported in the table 2.2 and table 2.3. The table 2.2 uses the raw returns measure, while the Table 2.3 uses CAPM-Alpha. In each of the tables, the first model considers only the impact of the current performance, the second model controls for the past performance, and the third model includes the interaction terms between the past and the current performance quintiles. I discuss the results in a series of hypothesis. All the hypotheses are formally tested and presented in table 2.10.

**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 2.2 and table 2.3. 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

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

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

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

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 (Ippolito, 1992) and (Sirri and Tufano, 1998) and others that fund flows are positively linked to recent performance.

**Hypothesis 2** ***(Return Chasing is valid even after controlling for the historical performance)***

*Hypothesis 1 is valid even after controlling for the historical performance.*

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. (Chevalier and Ellison, 1997) control for the historic performance and find a positive coefficient on the same. To understand the stand-alone effect of the history, I include the history 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 past 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 historical performance rank, and each of the quintiles of recent performance. Including the interaction uncovers the heterogeneity in the fund-flow schedules across the good-history and poor-history funds.

**Hypothesis 3** ***(Interactions reduce the strength of return-chasing effect)***

*The magnitude of additional fund flows attributable to better recent performance is re-*

*duced by more than half after inclusion of the interaction effect. Additionally, the stand-alone effect of the past 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 poor-history 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 interaction with the past. In other words, the quantitative importance of the *return chasing effect* identified by previous papers is greatly reduced. Similarly, the coefficient on historical performance 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 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 to a good-history fund. 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 history rank ($repute_{t-1} = 0.10$) but leads to 5.5%-6.5% additional asset growth due to flows for a $90^{th}$ percentile 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 history 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 the *interaction -effect* is far more important than *return-chasing effect* for a good-history fund.

**Hypothesis 5** ***(Sensitivity of flows and the past performance)***
*Interaction terms between the recent and the past performance increase monotonically as we move to higher quantiles of the 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 the good-history and the poor-history funds at each quintile of the recent performance. The fact that interaction terms rise monotonically suggests that the gap between flow-schedules for the good-history and the poor-history funds grows as we move to the higher quintiles of recent performance. In other words, the sensitivity of the flow-schedule increases in the past performance. Also because interaction terms rise monotonically over each quintile, fund flows are more sensitive for reputed funds over the whole range of recent performance. (Berk and Tonks, 2007) document lack of flow sensitivity at the left end of the flow-schedule for repeat losers. But my results indicate that a poor-history 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 *past performance 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 both the current and the past performance. This is the main result in the paper. The fund flow-schedule for a good-history fund is not only more sensitive, 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 the past and the recent performance. To better visualize the results, I plot the fund flow schedules for the good-history and the poor-history funds against recent performance in figure 2.1. In summary, flows are not very sensitive to the recent performance for poor-history funds. Sensitivity increases with the the good-history and the poor-history funds, and for the good-history funds, the *interaction-effect* becomes the dominant explanation of fund flows due to performance, and not the *return chasing effect*.

### 2.4.2 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, (Spiegel and Zhang, 2013) 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 2.3 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 2.4. All the main results carry over to this new dependent variable. Column 1 of each panel, where I regress $\Delta Mkt_{t+1}$ 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 poor-history fund loses market share with better recent performance. This is possibly indicative of liquidation out of poor-history funds following at least a 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 good-history 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 a good-history funds. These results speak even more strongly about the importance of the *interaction effect* for capturing market share or investor's capital. (Spiegel and Zhang, 2013) 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, I identify the good-history funds with sensitive flow schedule and the poor-history funds with less a sensitive flow schedule. But the good-history funds are not young and small compared to the poor-history funds. On the contrary, fund size is increasing in the historical performance. A fund belonging to top quintile of the past performance is roughly three times larger as compared to a fund belonging to the bottom quintile of the past performance. On the other hand, the age profile is more or less independent of the past performance as shown in summary table 2.1. 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 (Chevalier and Ellison, 1997) among others, and the theoretical model of (Berk and Green, 2004) show that the small and young funds have more sensitive flows. Though mean age across good-history and the poor-history funds is almost the same (around 12 years), mean size of a good-history fund (top 20% of past performance) is almost three times larger than that of a poor-history fund (bottom 20% of past performance). If anything, the results of (Chevalier and Ellison, 1997) suggests that a good-history fund should have lower flow sensitivity as they are larger. This means that the higher sensitivity of a good-history funds is a pretty strong result. To show that the past performance factor is a genuine separate effect not subsumed by age and size, I rerun the regression across the age and size bins. The results are presented in table 2.5 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. (Chevalier and Ellison, 1997), (Sirri and Tufano, 1998) , (Berk and Green, 2004) and others have discussed these effects. But this effect is true for a fund with any level of past performance. 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 past performance, 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. **Extended Recent 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 effect of the past. 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 the historical performance using the immediately preceding four year window. I drop one year from history window to have matching time frame with earlier regression estimates. Results are presented in table 2.7. All the results are valid even with longer evaluation period to compute recent performance.

   First, without interactions, (columns 1 and 3), 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 the recent performance has no bearing on flows for the poor-history 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.

## 2.5 Model

The model modifies (Berk and Green, 2004) 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 past performances.

### 2.5.1 Set-Up

The model has two types of investors with a total unit mass of which $\mu$ 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 $\alpha$, and it generates gross return as follows;

$$R_t = \alpha + \varepsilon_t, \tag{2.4}$$

Investors learn about $\alpha$ by observing $R_t$. But noise $\varepsilon_t$ hinders learning about $\alpha$ from observing $R_t$. Noise has following structure;

$$\varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right), \tag{2.5}$$

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, $\alpha$ 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

$$r_t = (h_{t-1}R_t) - f - \eta\left[\frac{(h_{t-1} \times q_{t-1})^2}{q_{t-1}}\right], \tag{2.6}$$

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.

### 2.5.2 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;

$$E_t(r_{t+1}) = 0, \tag{2.7}$$

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

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

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 2.7. Formally, manager solves

$$\max_{h_t \geq 0} \{f \times q_t\}, \tag{2.8}$$

subject to equilibrium condition 2.7 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*

$$h_t \equiv h(\phi_t) = \frac{2f}{\phi_t}, \tag{2.9}$$

Substituting the optimal policy given in equation 2.9 into equilibrium condition given in equation 2.7 we get equilibrium fund size;

$$q_t \equiv q(\phi_t) = \frac{\phi_t^2}{4\eta f}. \tag{2.10}$$

This expression ties $q_t$ with $\phi_t$ directly. Given the solution of $q_t$ in terms of $\phi_t$, fund flows are easily computed using equation 2.1. To compute $q_{t+1}$, we need to know how investors update skill from $\phi_t$ to $\phi_{t+1}$. 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*

$$\phi_{t+1} = \phi_t + \left(\frac{r_{t+1}}{h_t}\right)\left(\frac{\sigma_t^2}{\sigma_t^2 + \sigma_\varepsilon^2}\right). \tag{2.11}$$

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

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

### 2.5.3 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 $\mu$ 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 $\mu$ 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 $\lambda_0$ is given by

$$\lambda_0 = \frac{\mu}{\mu + (1 - \mu)\delta}. \tag{2.12}$$

In general, $\lambda_t$ 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

$$z_t = [\lambda_{t-1} + (1 - \lambda_{t-1})\,\delta]\,\widehat{q_t}. \tag{2.13}$$

To see this, note that all the AA-type investors are attentive whose fraction of ownership is $\lambda_{t-1}$. Additionally, out of OA-type investors, the $\delta$ 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 $\Omega_t$, competitive fund size denoted by $q_t(\Omega_t, h_t)$ or $q_t^*$ for short satisfies the zero expected net returns condition.

$$E_t\left[r_{t+1}|\Omega_t, h_t, q_t(\Omega_t, h_t)\right] = 0 \tag{2.14}$$

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

$$e(\Omega_t, h_t) \equiv e_t^* = q_t^* - q_{t-1}(1 + r_t). \tag{2.15}$$

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 oversized relative to its competitive benchmark given $\Omega_t$ 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 $\lambda_{t-1}$ 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, $\lambda_{t-1}$ 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 $\lambda_0$ serves as an upper limit of $\lambda_{t-1}$. Consider $t = 1$. If $e_1^* > 0$, then AA-type contributes $\lambda_0$ fraction of it which is same as their existing share of ownership given by $\lambda_0$. 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 $\lambda_2$ is a weighted average of $\lambda_1$ and $\lambda_0$ 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, $\lambda_t$ is a weighted average of $\lambda_{t-1}$ and $\lambda_0$. 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 $\alpha$ 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 A.2.

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

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 the past performance $\phi_{t-1}$. It is more likely that lower $\phi_{t-1}$ 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, $\phi_t$ 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 $\phi_{t-1}$. 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 $\phi_t$ 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 $\psi_{t-1}$ 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*

$$E_t(r_{t+1}) = -\eta h_t^2 q_t^* \psi_t. \tag{2.16}$$

With this expression, we can derive an expression for equilibrium fund flows. There are two cases. Given $\Omega_t$, $r_t$ 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 $\Omega_t$, and $\psi_{t-1}$, equilibrium flows are given by*

$$FF_t = \begin{cases} \frac{1}{(1+\psi_{t-1})(1+r_t)}\left[1 + \omega_{t-1}\left(\frac{r_t}{2f} + \frac{\psi_{t-1}}{2}\right)\right]^2 - 1 & \textit{If } z_t > |e^*_t| \\ -\frac{z_t}{q_{t-1}(1+r_t)} & \textit{otherwise} \end{cases} \tag{2.17}$$

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, $\psi_{t-1}$ is implicitly a function of the performance history. For poor history funds, $\psi_{t-1}$ 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 $\omega_{t-1}$ and the size-distortion parameter $\psi_{t-1}$. I calibrate these parameters in the next section and compare the fund schedules.

## 2.6 Performance Persistence, Size Distortion and Calibration

(Carhart, 1997), and (Berk and Tonks, 2007) 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 (Berk and Green, 2004) 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 (Carhart, 1997).

At the end of each year, I sort the funds according to four-factor alpha computed using a five-year window. Then I form 10 equally weighted portfolios each representing a decile of the past performance. 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 2.11.

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: good-history funds are optimally sized and produce zero net returns on average. But poor-history funds are over-sized and produce negative net returns on average.

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

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

where $\psi_t$ 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 $E_t(r_{t+1}) = -f\psi_t$. 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 (Chen, 2009) or (Berk and Green, 2004), 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 2.11, 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% $\times\, \psi_t$ 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 the size distortion for funds within other deciles of past performance. In particular for the top decile of past performance, 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 levels of the past performance. Some model parameters can be directly estimated, and others are estimated using moment fitting exercise.

I estimate $\omega_t$ 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 $\lambda$ and $\delta$ is not possible in this model. I call $\lambda + (1 - \lambda)\delta$ the *attentiveness index* for a fund. To estimate $\omega_t$, we need two inputs: $\sigma_\varepsilon$, which indicates fund return volatility, and $\sigma_t$, which captures belief uncertainty about the mean level of $\alpha$ or managerial skill. Summary statistics in table 2.1 show that fund return volatility is almost invariant across the past performance deciles. Uncertainty in beliefs about $\alpha$ can be measured using cross-sectional dispersion of alpha. Again, such cross-sectional dispersion in performance is not very different across various past performance deciles. Given this, I estimate a common $\omega_t$ across all the deciles of the past performance but a separate *attentiveness index* given by $\lambda + (1 - \lambda)\delta$ for various deciles of the past performance. 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 bottom decile of the past and five data points for the top decile of the past performance. 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 a good-history fund is $\lambda_{high} + (1 - \lambda_{high})\delta_{high} = 0.490$ and that for a poor-history funds is $\lambda_{low} + (1 - \lambda_{low})\delta_{low} = 0.201$. The estimated value for $\omega_t$ looks reasonable.(Berk and Green, 2004) use a value of $\omega_t = 0.0955$. Using a similar procedure as in (Berk and Green, 2004),[12] a direct estimate of $\omega_t$ in my sample is around 0.18, which generates an attentiveness index of 0.20 for a poor-history funds and 0.42 for a good-history funds. This puts credence on the estimated value for an attentiveness index estimated earlier. This is the first paper to my knowledge 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 a good past performance and only 20% for the funds with a poor past performance.

Using these parameter estimates, I plot fund-flow schedules implied by the model for good and poor history funds. For these estimated parameter values, the model reproduces the empirical fact that flow-schedule sensitivity is increasing in the historical performance. 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 2.2.

## 2.7 Three Thought Experiments

In this section, I carry out three experiments to validate model mechanism. The model predicts that the funds differ in terms of the type of investors who own them as a function of its past performance. This heterogeneity in the investor base explains heterogeneous fund flow patterns. Statistically, this mechanism implies that fund flows are determined

[12] First parameter to estimate is $\sigma_\varepsilon$ which is the volatility of $R_t$ conditional on $\alpha$. In the model, $\alpha$ 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 $\omega_t$. Calculations are similar with CAPM-$\alpha$ or 4-factor $\alpha$. (Berk and Green, 2004) use empirical fund return volatility to match signal volatility $\sigma_\varepsilon$. Mean annual volatility of fund excess returns is around 17.37% in the sample. Second parameter to estimate is $\sigma_t$ which indicates uncertainty in beliefs about mean level of $\alpha$ or ability. I use cross-sectional dispersion in raw returns computed using 5-yearly window to estimate it. Using this measure, $\sigma_t$ 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-$\alpha$ and 4-factor $\alpha$, $\omega_t$ is around 0.36, 0.30 and 0.32 respectively using similar computation.

by the interaction between the past and the current 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 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 past performances reduces after the replacement episode and this should cut the influence of the past performance 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 the past performance 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.

$$FLOW_{it+1} = a + b_1 Perf_{it} + b_2 (Perf_{it} \times repute_{it-1}) + b_3 \times repute_{it-1} + CONTROL_{it} + \varepsilon_{it+1} \tag{2.18}$$

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 $\mathrm{Perf}_t$ and $repute_{t-1}$ instead of analyzing interaction within each quintile. Results are presented in table 2.8. Panel A uses raw returns, and panel B uses CAPM-$\alpha$ 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 term lose its 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: $\mathrm{Perf}_t$ 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 the poor-history 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 the funds with poor-history have sensitive flow schedule after the 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 the interaction between the past and the current performance 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 2.18 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 2.9. 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, a longer sequence of poor (good) performance generates more heterogeneity across the poor and the good history 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 2.3 with a shorter history window, say three years or one year and then to compare the strength of the interaction effects. According to the model, it should diminish.

[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.

To this end, I re-run the regression model using one year history window preceding that of recent performance instead of five-year window used earlier. Results are presented in table 2.6.

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

## 2.8 Conclusion

This paper presents a novel fact that mutual fund flow sensitivity to recent performance is weak for funds with poor past performance. Additionally, for the good-history funds, the bulk of the flows are attributable to the interactions between the past and the current performance. 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-history if required as most investors are inattentive which implies that the poor-history funds are above the size implied by the competitive equilibrium. Decreasing returns to scale together with the second implication results in negative expected returns for the poor-history funds.

I calibrate the model and find that roughly half of the capital is attentive for good-history funds but only 20% for the poor-history funds. I also estimate that the poor-history 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 the past performance has less bearing on flow sensitivity for funds experiencing managerial replacements, and for the funds with high front loads.

# Table 2.2: Historical Raw Performance and Fund Flows

Table presents estimation of the equation 2.3 with $FLOW_{it}$ as the dependent variable defined in the equation 2.1. $Q_{jit} = 1$ if recent performance at time $t$ denoted by $\text{Perf}_{it}$ lies in the $j^{th}$ quintile. $repute_{it-1}$ denotes the normalized past performance 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 $t+1$ ($\text{Perf-Half}_{t+1}$), 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 2.2:** 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*** |

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Table 2.2 – **Continued from previous page**

| | **Panel A: Raw Returns** | | |
|---|---|---|---|
| | (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) |
| Size (t) | -0.006*** | -0.017*** | -0.017*** |
| | (0.002) | (0.002) | (0.002) |
| Expense Ratio (t) | -0.183 | 0.062 | -0.016 |

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Table 2.2 – **Continued from previous page**

| | **Panel A: Raw Returns** | | |
|---|---|---|---|
| | (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 2.1:** 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 past performance rank based on raw return measure. Statistics are over the entire sample from 1981 to 2014.

| **Reputation** | **Excess Ret**$^{LT}$ | $\alpha^{LT}$ | **Exp Ratio** | **Front Load** | **Turn over** | $\sigma^{LT}$ | **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 2.3: Historical CAPM-Alpha and Fund Flows

Table presents estimation of the equation 2.3 with $FLOW_{it}$ as the dependent variable defined in the equation 2.1. $Q_{jit} = 1$ if recent performance at time $t$ denoted by $\text{Perf}_{it}$ lies in the $j^{th}$ quintile. $repute_{it-1}$ denotes the normalized past performance 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 $t+1$ ($\text{Perf-Half}_{t+1}$), 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 2.3:** 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) |

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Table 2.3 – **Continued from previous page**

| | **Panel A: Raw Returns** | | |
|---|---|---|---|
| $Q_{4t} - Q_{1t}$ | 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* |
| | (0.250) | (0.251) | (0.252) |
| Size (t) | -0.006*** | -0.016*** | -0.016*** |
| | (0.002) | (0.002) | (0.002) |

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Table 2.3 – **Continued from previous page**

| | **Panel A: Raw Returns** | | |
|---|---|---|---|
| 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 2.4: 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 $\text{Perf}_t$ lies in the $j^{th}$ quintile. $repute_{it-1}$ denotes the normalized past performance 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 $t + 1$ ($\text{Perf-Half}_{t+1}$), 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 2.4:** 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) |
| $repute_{t-1} \times (Q_{4t} - Q_{1t})$ | | 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) |

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Table 2.4 – **Continued from previous page**

| | **Panel A: Raw Returns** | | **Panel B: CAPM Alpha** | |
|---|---|---|---|---|
| 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 2.5: Fund Flows Across Age and Size Bins

Table presents estimation results where I interact age (young vs old) and size (small vs large) dummies to the 2.3. Dependent variable is as defined in equation 2.1. $Q_{jit} = 1$ if recent performance at time $t$ denoted by $\text{Perf}_t$ lies in the $j^{th}$ quintile. $repute_{it-1}$ denotes the normalized past performance 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 (ctrl dum) indicates whether fund is young or small. Panel A and B uses raw return measure and CAPM-Alpha to sort the funds. Control variables include half yearly performance during $t+1$ ($\text{Perf-Half}_{t+1}$), 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 2.5:** Fund-Flows Across Age and Size Bins

| | **Panel A: Returns** | | **Panel B: Alpha** | |
|---|---|---|---|---|
| Ctrl Dum | **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) |

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Table 2.5 – **Continued from previous page**

| | **Panel A: Returns** | | **Panel B: Alpha** | |
|---|---|---|---|---|
| Ctrl Dum | **Young=1** | **Small=1** | **Young=1** | **Small=1** |
| $Q_{3t} - Q_{1t}$ | 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) |
| $Q_{5t} - Q_{1t}$ | 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*** |

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Table 2.5 – **Continued from previous page**

| | **Panel A: Returns** | | **Panel B: Alpha** | |
|---|---|---|---|---|
| Ctrl Dum | **Young=1** | **Small=1** | **Young=1** | **Small=1** |
| | (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) |
| $repute_{t-1} \times (Q_{2t} - Q_{1t})$×Ctrl Dum | -0.028 | 0.038 | 0.014 | 0.014 |
| | (0.042) | (0.042) | (0.042) | (0.042) |
| $repute_{t-1} \times (Q_{3t} - Q_{1t})$×Ctrl Dum | -0.022 | 0.083* | 0.017 | 0.017 |
| | (0.046) | (0.045) | (0.053) | (0.053) |
| $repute_{t-1} \times (Q_{4t} - Q_{1t})$×Ctrl Dum | 0.083 | 0.088 | 0.031 | 0.031 |
| | (0.054) | (0.061) | (0.055) | (0.055) |
| $repute_{t-1} \times (Q_{5t} - Q_{1t})$×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 ×$repute_{t-1}$ | -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) |

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Table 2.5 – **Continued from previous page**

| | **Panel A: Returns** | | **Panel B: Alpha** | |
|---|---|---|---|---|
| Ctrl Dum | **Young=1** | **Small=1** | **Young=1** | **Small=1** |
| Expense Ratio(t) | -0.113 | -0.098 | 0.126 | 0.113 |
| | (0.705) | (0.699) | (0.722) | (0.718) |
| 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 2.6: Short Horizon of Reputation and Fund Flows

Table presents estimation results for the equation 2.3 with $Flow_{it}$ and $\Delta Mkt_{it}$ as dependent variables in Panel A and B respectively and where past performance index is computed using one-year window instead of five years. $Q_{jit} = 1$ if recent performance at time $t$ denoted by $\text{Perf}_t$ lies in the $j^{th}$ quintile. For each dependent variable, I use raw-returns (Raw) and Capm-Alpha (Alpha) to measure the performance. Control variables include half yearly performance during $t+1$ ($\text{Perf-Half}_{t+1}$), 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 2.6:** Short Horizon of Reputation and Fund Flows

| | **Panel A: Flow$_{t+1}$** | | **Panel B: $\Delta Mkt_{t+1}$** | |
|---|---|---|---|---|
| | **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** |

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Table 2.6 – **Continued from previous page**

| | **Panel A: FLOW$_{t+1}$** | | **Panel B: $\Delta Mkt_{t+1}$** | |
|---|---|---|---|---|
| | **Raw** | **Alpha** | **Raw** | **Alpha** |
| | (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) |
| 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) |

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Table 2.6 – **Continued from previous page**

| | **Panel A: FLOW$_{t+1}$** | | **Panel B: $\Delta Mkt_{t+1}$** | |
|---|---|---|---|---|
| | **Raw** | **Alpha** | **Raw** | **Alpha** |
| 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 2.7: Flows With Longer Horizon for Recent Performance

Table presents estimation result for 2.3 with a modification that Perf$_{it}$ is measured over two-year window instead of one-year and past performance is measured over a four-year window previous to the recent performance window. $Q_{jit} = 1$ 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 2.7:** Flows With Longer Horizon for Recent Performance

| | **Panel A: Returns** | | **Panel B: Alpha** | |
|---|---|---|---|---|
| $Q_{2t} - Q_{1t}$ | 0.008 | 0.005 | 0.029*** | 0.001 |
| | (0.008) | (0.015) | (0.008) | (0.014) |
| $Q_{3t} - Q_{1t}$ | 0.042*** | 0.021 | 0.041*** | 0.017 |
| | (0.009) | (0.016) | (0.008) | (0.017) |
| $Q_{4t} - Q_{1t}$ | 0.074*** | 0.024 | 0.097*** | 0.035* |
| | (0.009) | (0.018) | (0.010) | (0.018) |

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Table 2.7 – **Continued from previous page**

| | **Panel A: Return** | | **Panel B:Alpha** | |
|---|---|---|---|---|
| $Q_{5t} - Q_{1t}$ | 0.177*** | 0.048* | 0.173*** | 0.034 |
| | (0.013) | (0.028) | (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) | 0.283*** | 0.283*** | 0.277*** | 0.277*** |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| Risk(t) | -0.579* | -0.576* | | 0.104 |
| | (0.300) | (0.298) | (0.308) | (0.306) |
| Size(t) | -0.014*** | -0.015*** | -0.014*** | -0.015*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Exp Ratio(t) | -1.089 | -1.136 | -0.891 | -0.927 |
| | (0.727) | (0.723) | (0.736) | (0.735) |
| Age(t) | -0.031*** | -0.030*** | -0.032*** | -0.031*** |
| | (0.006) | (0.006) | (0.007) | (0.006) |

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Table 2.7 – **Continued from previous page**

| | **Panel A: Return** | | **Panel B:Alpha** | |
|---|---|---|---|---|
| Cat Flow(t+1) | 0.105*** | 0.105*** | 0.104*** | 0.104*** |
| | (0.026) | (0.025) | (0.026) | (0.025) |
| Intercept | -0.035 | -0.005 | -0.074** | -0.037 |
| | (0.036) | (0.036) | (0.036) | (0.037) |
| N | 9384 | 9384 | 9384 | 9384 |
| Adj. $R^2$ | 0.343 | 0.347 | 0.339 | 0.344 |

# Table 2.8: Reputation and Managerial Replacements

Table presents estimation of the following regression equation

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

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 $t+1$ (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 2.8:** Reputation and Managerial Replacements

| | **Panel A: Returns** | | **Panel B: Alpha** | |
|---|---|---|---|---|
| **Replace** | **Yes** | **No** | **Yes** | **No** |

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Table 2.8 – **Continued from previous page**

| | **Panel A: Returns** | | **Panel B: Alpha** | |
|---|---|---|---|---|
| **Replace** | **Yes** | **No** | **Yes** | **No** |
| $\text{Perf}_t$ | 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 |
| $\text{Perf}_t \times repute_{t-1}$ | 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 |

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Table 2.8 – **Continued from previous page**

| | **Panel A: Returns** | | **Panel B: Alpha** | |
|---|---|---|---|---|
| **Replace** | **Yes** | **No** | **Yes** | **No** |
| N | 1136 | 7014 | 1136 | 7014 |
| Adj $R^2$ | 0.158 | 0.21 | 0.152 | 0.208 |

# Table 2.9: Impact of Reputation With Various Fee Structures

Table presents estimation of the following regression equation

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

$\text{Perf}_t$ and $repute_{it-1}$ denote normalized ranks for recent performance and past performance 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 $t+1$ ($\text{Perf-half}_{t+1}$) ,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 2.9:** Impact of Reputation With Various Fee Structures

| | **Panel A: Raw Returns** | | **Panel B: CAPM-Alpha** | |
|---|---|---|---|---|
| **Front Load** | **Low** | **High** | **Low** | **High** |

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Table 2.9 – **Continued from previous page**

| | **Panel A: Raw Returns** | | **Panel B: CAPM Alpha** | |
|---|---|---|---|---|
| **Front Load** | **Low** | **High** | **Low** | **High** |
| $\text{Perf}_t$ | 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) |

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Table 2.9 – **Continued from previous page**

| | **Panel A: Raw Returns** | | **Panel B: CAPM Alpha** | |
|---|---|---|---|---|
| **Front Load** | **Low** | **High** | **Low** | **High** |
| N | 2581 | 2785 | 2581 | 2785 |
| Adj $R^2$ | 0.239 | 0.169 | 0.223 | 0.164 |

# Table 2.10: Hypothesis Testing For Main Results

This table presents the hypothesis tests for the main results in table 2.2 and 2.3. 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 2.10:** 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 2.11 Reputation and Performance Persistence

At the end of each year, funds are sorted based on their historic four-factor alpha computed using five-year window. Ten equally weighted portfolios are formed to represent each decile of the past performance . 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 2.11:** 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 2.1:** Reputation and Fund Flow Schedule

The figure plots fund flow-schedule for funds with the top and the bottom quantile of past performance, 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

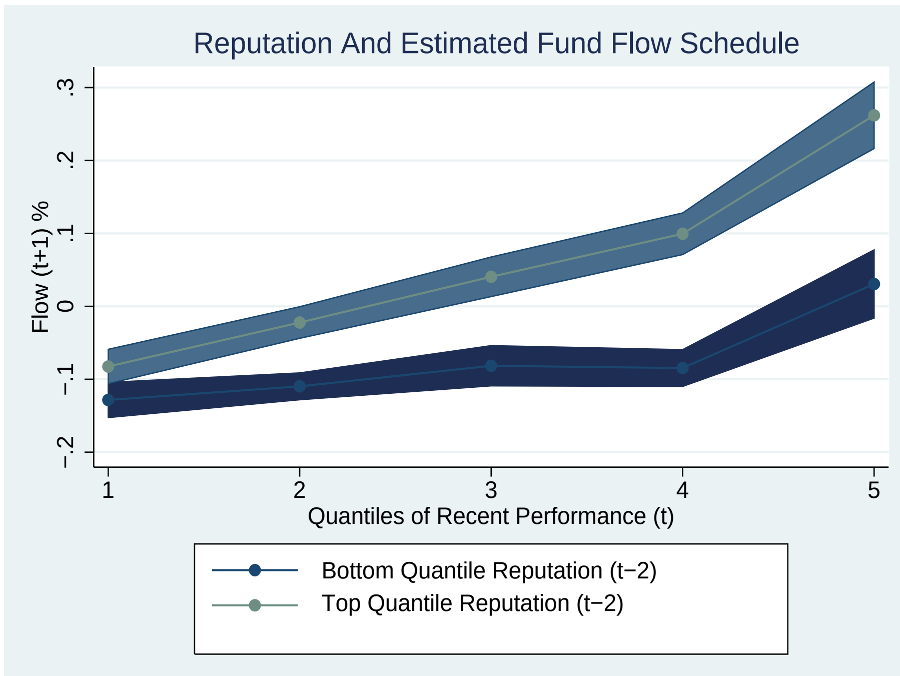
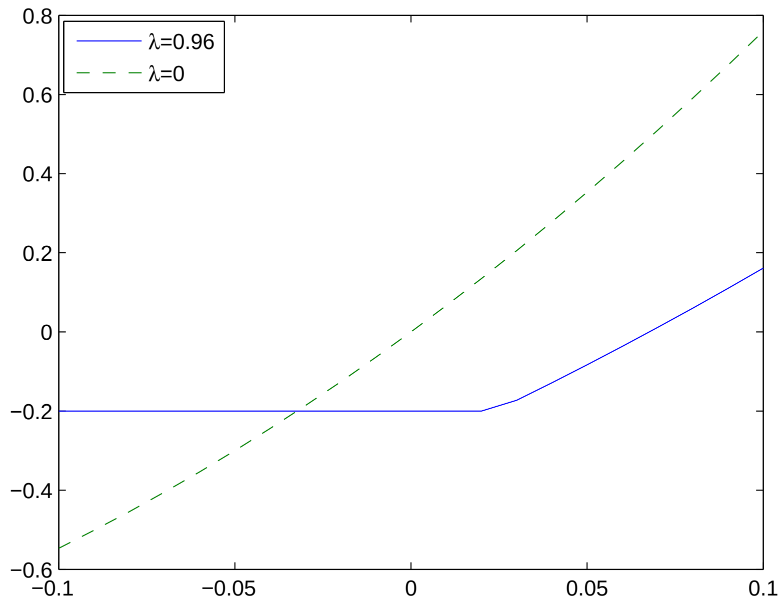


**Figure 2.2:** Model Implied Fund Flows

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



# Chapter 3

# Historical Performance and Risk-Shifting In Mutual Fund Industry

## 3.1 Introduction

I study the risk-taking or the risk-shifting behavior of the mutual fund managers in response to the multi-dimensional managerial incentives. On one hand, investors determine their mutual fund holdings given the fund's recent performance which, in turn, shapes the manager's compensation as often managers are compensated in the proportion of growth in the fund's assets. I term this as *compensation incentive*. On the other hand, manager's *employment incentives* arise from the fact that the fund company determines whether to continue the employment contract with the same manager or to terminate him given his performance. I empirically show that both these incentives are a function of the fund's historical performance and not just affected by the recent performance. Given this, I conjecture that the risk-taking behavior of the managers depends on their historical performance. For brevity, managers with a good (poor) historical performance are called *good-history* (poor-history) managers.

(Brown et al., 1996), using the data from 1985 to 1991, documents that a midyear losing manager increase the portfolio risk more than a midyear winning manager during the second half of the year, to catch up with the peers. (Kempf et al., 2009) document that risk-shifting behavior depends on whether the compensation incentives or the employment incentives dominate during a given year. I uncover a new channel namely the historical performance of the manager that has the explanatory power for the risk-taking behavior. Once I consider the past performance, I document a dramatic heterogeneity in the way managers respond to their midyear rank. None of the earlier papers have documented this heterogeneity in the risk-taking behavior.

(Javadekar, 2016) documents that the fund-flow level and the sensitivity both increases in the fund's historical performance. This fact implies that the *good-history managers* have an incentive to take the risk to capture the higher level of flows that accrue to them after a good performance. On the other hand, the poor-history managers face relatively insensitive fund-flows and to that extent, they are not motivated by the fund-flow incentives. Turning to the employment incentives, (Chevalier and Ellison, 1999) and (Khorana, 1996b) both documents an inverse relationship between recent performance and the firing probability. Contrary to that, I document the dependence of managerial firing on the historical performance. First, I show that for any level of recent performance, the firing probability is decreasing in the historical performance. Second, I show that the traction of the recent performance on the firing probability becomes weaker with the historical performance. These two observations imply that the poor-history managers face a more severe unemployment risk, but at the same time they can increase the chances of employment continuation with a better recent performance. On the other hand, the good-history managers neither face significant unemployment risk nor can they alter the likelihood of firing by improving their yearly performance. In this sense, a good-history manager is not motivated by the employment incentives. In summary, we have that a good-history manager is primarily affected by the *compensation incentive* and a poor-history manager by the *employment incentives*.

Given that historical performance shapes the manager's incentives, his portfolio choice is highly likely to be influenced by his historical record. In the data, I exactly find this to be the case. First, a poor-history manager acts more risk-averse as compared to the good-history manager during both the bull and the bear periods. A good-history manager always engages in the risk-shifting. That is amongst the class of the good-history managers, the ratio of the portfolio risk of the second half to the first half of the year is more for a midyear loser than a midyear winner. The extent of this tendency is more pronounced during bull years as fund flow level is much higher during the bull periods. Note that the nature of the unemployment incentive is virtually unchanged across bull and bear periods for the good-history managers. Hence, the change in risk-shifting intensity across bull and bear periods can be attributed to the compensation or fund flow incentives. Second, a poor-history manager never engages in risk-shifting. During bull phases, he acts neutral in the sense that a midyear performance has no traction on the risk-shifting ratio. During the bear phases, given the extremely high unemployment risk, a poor-history manager infact enegages in the reverse risk-shifting. That is amongst the class of the poo-history managers, the ratio of the portfolio risk of the second half to the first half of the year is less for a midyear loser than a midyear winner. These findings are important in that they showcase the fact that manager's risk-taking behavior is linked to the basic incentives they face. Simple linear risk-shifting technology describes managerial behavior.

## 3.2 Literature Review

The focus of the risk-shifting literature has been on trying to understand how the managers change the portfolio risk during the second half of the year in response to their midyear position. The presence of fund flow incentives and employment incentives rationalize risk-shifting motive. (Chevalier and Ellison, 1997) and (Sirri and Tufano, 1998) both documents that the fund flow schedule is convex. (Carpenter, 2000) and (Chen, 2009) show that the midyear losing managers have an incentive to increase the risk during the second half of the year given these convex incentives. (Basak et al., 2007) show that managers shift the tracking error of the portfolio over a finite range of midyear performance, especially around the kink of the fund flow schedule. The empirical literature has given a mixed evidence at the best. (Brown et al., 1996) document that a midyear losing manager increases relative risk during the second half of the year. (Chevalier and Ellison, 1997) document that young managers are likely to adjust the risk in response to mid-year peer adjusted position. (Kempf et al., 2009) stresses the distinctive role of employment incentives and compensation incentives for managerial risk taking. They show that when employment (compensation) incentives dominate, then midyear losing managers reduce (increase) the risk during the second half of the year more than the midyear winning managers. (Hu et al., 2011) provides a model with U-shaped risk choice in midyear performance and find similar support in the data.

Motivated by the impact of the past performance on both types of managerial incentives, I propose conditioning of the risk-shifting results on the fund's historical performance.

## 3.3 Data and Variables

### 3.3.1 Data

I use CRSP Survivor-Bias-Free Mutual Fund Database, covering a period from 1999 to 2014 at an annual frequency. Sample selection is in line with the earlier literature. I focus on the US domestic open-ended equity funds. I exclude sector, index, and specialty funds. Because names or styles may not reflect the actual nature of the fund, I also exclude funds whose mean equity holdings are less than 70%. I rule out any funds where size is smaller than 15 million USD and also any fund whose age is three 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 the earlier literature, I aggregate all the share classes belonging to one fund. The size of the fund is the sum of sizes of all the share classes, and fund age is the age of the oldest share class. Other variables like turnover, expense ratio, returns, etc. are computed on size-weighted average basis.

I use daily fund returns data which is available starting from 1999. For each fund, I compute daily excess return over the mean daily return of the investment category to which that fund belongs. Then $\sigma(r_{it,k} - b_{t,k})$ is just the standard deviation of these excess return computed for $k = 1, 2$.

### 3.3.2 Splitting The Sample

Following (Kempf et al., 2009), I split the sample according to whether the midyear stock market return is positive or negative. For this purpose, I use CRSP's value-weighted stock market index. I label the years with negative (positive) midyear stock market return as bear (bull) years. The basic conjecture is that the compensation (employment) incentives dominate during bull (bear) years. Market returns proxies the state of the industry to a good extent. Aggregate capital flows are low following a bear market (Karceski, 2002). That is during the bear markets, a manager can attract not a great deal of new capital flow even with a good performance. Manager's compensation depends on the size of the fund which does not grow drastically during the bear markets. Also, bonus payments are linked to the profitability of the fund family (Farnsworth and Taylor, 2006) which is low during the bear markets. In this sense, the compensation incentives are weaker during bear years. On the contrary, firing probability is higher during bear markets (Chevalier and Ellison, 1999). Therefore, employment incentives are stronger during bear markets. It is easy to see that the compensation incentives are more important during bull markets by reversing the arguments above.

### 3.3.3 Risk-Shifting Measure

It is important to fix on the notion of the risk before computing risk-shifting. For example, if an active fund benchmarks his portfolio completely, then his portfolio volatility is equal to the market volatility. If market volatility goes up during the second half of the year, then manager's portfolio volatility goes up as well. If the measure of risk is raw volatility of portfolio return, then the risk seems to have been shifted. But from a strategic perspective, portfolio benchmarking is unchanged. Which measure of risk is more appropriate? Because managers adjust the risk to outperform, the answer to the question depends on what notion of outperformance they are targeting. Fund companies evaluate managers in comparison to the pre-defined benchmark. On the other hand, the empirical evidence shows that investor assesses the manager based upon risk-adjusted or peer adjusted performance (Berk and Van Binsbergen, 2014). Given this, the appropriate notion of the risk-shifting is the extent to which the portfolio is similar to the portfolio of peers or appropriate benchmark. One quick way to measure how similar the portfolio was is to compute the volatility the fund returns are around mean returns of the peers.

Using this background and following (Kempf et al., 2009) and (Brown et al., 1996), I construct the first measure of risk-shifting as follows

$$RSR_{it} = \frac{\sigma(r_{it,2} - b_{t,2})}{\sigma(r_{it,1} - b_{t,1})} \tag{3.1}$$

where $r_{it,k} - b_{t,k}$ indicates the excess fund return over the benchmark during $k^{th}$ half of the year.

For my measure, $b_{t,k}$ is the mean return over all the funds belonging to similar investment objective during $k^{th}$ half of the year $t$.

## 3.4 Dependence of Incentives on Historical Performance

### 3.4.1 Unemployment Incentives

Table 3.1 presents the evidence about firing probabilities as a function of the recent performance and historical performance. I perform the analysis for the bear and the bull periods separately. Panel A shows the firing incidences for the bear years, and Panel B shows it for thebull years. First, a poor-history manager faces a severe risk of getting replaced after a recent poor performance. The probabilities are 8.37% and 14.48% during bull and bear years respectively. These are economically large probabilities in absolute terms as well as relative to the corresponding firing probabilities for a good-history manager which are almost a third in magnitude for a similar recent performance. Second, the table shows that firing probabilities drop significantly with recent performance for a poor-history manager. For example, if a poor-history manager ranks within top third during the current period then the probability is reduced to mere 2.53%, down from 14.48% during the bear years. But same is not true for a good-history manager. Firing probabilities hardly vary across the range of the current performance. These two observations show that poor-history managers are affected by the employment risk and recent performance can help them reduce the risk. On the other hand, a good-history manager is not very much concerned about the unemployment risk for two reasons: one is that the probability of firing is low in absolute terms, and he can't reduce it with a better recent performance. [1]

### 3.4.2 Compensation Incentives

Fund-flows drive compensation incentives to a large extent for the mutual fund managers. Evidence on *Return chasing* on the part of the mutual fund investors is well documented by (Ippolito,

[1]Some of the good-history managers might leave the fund voluntarily for a bigger contract after one more good performance. This might account for higher replacement probabilities at the top end of recent performance for a good-history manager.

1992), (Chevalier and Ellison, 1997), and (Sirri and Tufano, 1998), among others. But (Javadekar, 2016) finds that the pattern of fund flows is determined primarily by the interaction between recent and historical fund performance. Table 3.5 reproduces the main findings of that paper. The first model in Panel A regresses flows on the current performance without considering the historical performance. The positive coefficient on the recent performance variable indicates return chasing. In the second column of Panel A, I include the interaction between the recent and the historical performance. First, the impact of the return chasing is drastically weaker. Coefficient reduces from 0.35 to 0.16, a drop of more than 50%. Second, the coefficient on the interaction term equals 0.29. It is statistically and economically large. In fact, it is bigger than the coefficient of the recent performance. The evidence shows how the historical performance determines the sensitivity of fund flows. In particular, the fund flows are sensitive for the managers with high historical rank. In panel B, I repeat the regressions with a split sample. The results are valid across bull and bear years. Therefore, the results indicate that a poor-history manager has relatively weaker incentive to improve the performance to attract new capital. This finding is valid across various market states.

## 3.5 Hypothesis Development

The basic logic behind the following hypothesis is that the good-history managers are driven by the compensation incentives while the poor-history managers are driven primarily by the employment incentives.

**Hypothesis 7** *The extent to which a midyear loser increases the risk relative a midyear winner fund is more for the category of the good-history managers than for the category of the poor-history managers. Formally, for* $r_1 > r_2$

$$RSR_{good,t}(r_2) - RSR_{good,t}(r_1) > RSR_{poor,t}(r_2) - RSR_{poor,t}(r_1)$$

*where* $r_1$ *and* $r_2$ *indicate the level of midyear performance.*

This hypothesis conjectures that a good-history manager has more appetite to shift the risk up during the year in response to his weak midyear performance as compared to a poor-history manager. There are two channels at work here. First, during any market state, a good-history manager is relatively less concerned about the unemployment risk. At the same time, for a good-history manager, the level, the sensitivity and the convexity of flow-schedule is higher relative to a poor-history manager. Both these channels lead to the unambiguous conclusion that for a given weak midyear performance, a good-history manager would deviate more from the benchmark portfolio as compared to a poor-history manager.

**Hypothesis 8** *For any type of manager, the extent of risk-shifting given a midyear losing position is lower during the bear years than the bull years. Formally, for* $r_1 > r_2$

$$[RSR_{i,t}(r_2) - RSR_{i,t}(r_1)]_{bull} > [RSR_{i,t}(r_2) - RSR_{i,t}(r_1)_{bear}$$

*where* $r_1$ *and* $r_2$ *indicate the level of midyear performance.*

This follows because unemployment risk increases during the bear markets. Even for a good-history manager, it increases relative to the bull years.

**Hypothesis 9** *The difference in risk-shifting ratio between good-history and poor-history manager widens during bear years as compared to the bull years. Formally, for any* $r_1$*,*

$$[RSR_{good,bear}(r_1)] - RSR_{poor,bear}(r_1)] > [RSR_{good,bull}(r_1)] - RSR_{poor,bull}(r_1)]$$

The rise in the unemployment risk is more dramatic for the poor-history managers during the bear years. The flow-schedule is invariant in terms of how flows react to the recent performance across the bear and the bull phases. This suggests that the poor-history managers would become relatively more risk-averse during the bear phases as compared to the bull phases, widening the difference in the risk-shifting ratio between the good-history and the poor-history managers.

## 3.6 Results

### 3.6.1 Contingency Tables

I present the primary results using traditional $2 \times 2$ contingency tables using the midyear performance and the risk-shifting ratio as two dimensions. Each fund with below (above) median midyear performance is classified as midyear loser (midyear winner). Similarly, a fund with below (above) median risk-shifting ratio is classified as having low (high) RSR. The median for both the variables is computed over all the funds following a particular investment category. I additionally sort the funds using its historical performance. To this end, I consider last year's performance as a historical record. A fund is called good-history (bad-history) if its performance ranked amongst top (bottom) 20% of the funds within their investment segment during last year.

The evidence is presented in the table 3.2 for bull years and 3.3 for the bear years. First, comparing panel A, B and C across tables 3.2 and 3.3, we see that a midyear loser is more likely to have a low RSR if belonging to the class of poor-history managers. During the bull years, 53.60% of the midyear losers have below median RSR within the class of poor-history managers as compared to 47.93% for the class of good-history managers. The numbers are 57.17% and 50.87% respectively for the bear years. Next, comparing the bear and bull numbers for the same class of managers, we see that a more fraction of midyear losing managers has lower RSR during bear years. The numbers are 53.60% and 57.17% for bull and bear years for the poor-history managers and 47.93% and 50.87% for the good-history managers. Third, comparing the absolute fractions, we see that the poor-history midyear losers are always more likely to act risk-averse. Within the class of the poor-history managers, during both the bear and the bull years, more than half of the midyear losers have lower RSR. On the other hand, good-history managers act as risk-takers during bull years.

Note that when we do not condition on the historical performance, both the extent and the direction of the risk-shifting behavior becomes obscure to understand. Evidence in panel C of both the tables suggests that during the bull years, midyear losers are more likely to have high risk-shifting ratio (51.70% as against 48.20%), but during bear years the reverse is true. During bear years, midyear losers are less likely to have higher risk-shifting ratio (48.06% as against 51.89%). This evidence is consistent with (Kempf et al., 2009) who were the first to point out that the risk-shifting behavior is different during the bear and the bull years. The contribution of this paper is to show that there is one more level of heterogeneity that is masked behind these numbers.

### 3.6.2 Regression

I test the hypothesis using regression approach in this section. In particular, I estimate the following regression model for the bear and the bull years separately.

$$
\begin{aligned}
RSR_{it} = {} & \beta_0 + \beta_1 \times (r_{it,1} - b_{t,1}) + \beta_2 \times \text{Rank}(r_{it-1} - b_{t-1}) \\
& + \beta_3[(r_{it,1} - b_{t,1}) \times \text{Rank}(r_{it-1} - b_{t-1})] + Controls_{it} + \varepsilon_{it}
\end{aligned}
$$

where $r_{it,k} - b_{t,k}$ denotes the benchmark-adjusted fund performance during the k$^{th}$ half of the year and $r_{it} - b_t$ denotes the benchmark-adjusted fund performance for the full year $t$. Rank($x$) denotes the normalized rank of the fund when sorted by variable $x$ that lie between 0 and 1. The estimates are presented in table 3.4. The panel A estimates the equation without considering the historical performance while the Panel B include historical performance and its interaction with the midyear performance. Column head indicates the state of the market (bull or bear).

First, consider panel A. The results are consistent with (Kempf et al., 2009). The coefficient on the midyear performance is negative for the bull years, and it is positive for the bear years. A negative coefficient suggests that the risk-shifting ratio ($RSR_{it}$) is decreasing in the midyear performance; a midyear loser increases the risk more than a midyear winner. (Kempf et al., 2009) argues that compensation incentives dominate during the bull years which leads to risk-shifting by midyear losers to catch up with the peers and get additional capital. But during the bear years, unemployment risk shoots up. Therefore, a midyear loser is more averse to shift the risk up as compared to a midyear winner, leading to a positive coefficient on midyear performance. These are the findings without considering the historical performance.

In the panel B, I include the historical performance along with the midyear performance. Hypothesis 7 implies that $\beta_3$ is negative. Hypothesis 8 implies twin conditions: $\beta_1$(bear) > $\beta_1$(bull) for the poor-history managers and $[\beta_1 + \beta_3]$(bear) > $[\beta_1 + \beta)3]$(bull). Hypothesis 9 implies that $[\beta_1 - \beta_3]$(bear) > $[\beta_1 - \beta_3]$(bull). From the table we see that, all the conjectures or hypothesis are confirmed. A poor-history manager has a lower RSR during any given market state. Any given manager is more risk-averse in the bear phase and that the heterogeneity in risk-shifting widens during the bear phase across the good-history and the poor-history managers. Analyzing the absolute values of coefficients we see that, the coefficient on $Perf_{it,1}$ is always non-negative indicating that only the midyear performance does not induce risk-shifting on the part of the midyear losers. It's only for the good-history managers that a weak midyear performance causes positive risk-shifting. The fact that $[\beta_1 + \beta_3]$ is negative for both the phases confirms the fact.

## 3.7 Conclusion

The paper analyzes the risk-shifting behavior of the mutual fund managers and finds that the historical performance matters in the determination of the risk-shifting patterns. This dependence comes from the fact that the managerial incentives are dependent on the historical performance. Paper documents the dependence of unemployment incentives on the past performance. Next, the paper shows that the conjectured behavior is valid in the data. In particular, the poor-history managers are more averse to increase the risk in response to midyear performance. Moreover, managers, in general, are more reluctant to shift the risk up during the bear phases. Additionally, I find the cross-sectional variation in risk-shifting is higher during the bear phases. The difference mostly comes from the fact that the poor-history managers turn dramatically risk-averse mainly due to the corresponding disproportionate increase in the unemployment risk for these managers during the bear phase. In terms of the contribution, this paper shows that risk-shifting behavior can be explained without non-linear models once we condition on the historical performance of the fund.

**Table 3.1:** Performance and Probability of Firing

| $(r_{it-1} - b_{t-1}) \rightarrow$ | Poor History (t-1) | | | Good History (t-1) | | |
|---|---|---|---|---|---|---|
| $(r_{it} - b_t) \rightarrow$ | Poor | Med | Top | Poor | Med | Top |
| | | | **Bear Years** | | | |
| Not Fired | | | | | | |
| N | 124 | 446 | 231 | 334 | 1,054 | 381 |
| % | 85.517 | 91.206 | 97.468 | 94.084 | 95.126 | 95.012 |
| Fired | | | | | | |
| N | 21 | 43 | 6 | 21 | 54 | 20 |
| % | 14.482 | 8.793 | 2.531 | 5.915 | 4.873 | 4.987 |
| | | | **Bull Years** | | | |
| Not Fired | | | | | | |
| N | 328 | 1,056 | 391 | 568 | 1,647 | 639 |
| % | 91.620 | 94.369 | 96.543 | 96.928 | 96.259 | 97.856 |
| Fired | | | | | | |
| N | 30 | 63 | 14 | 18 | 64 | 14 |
| % | 8.379 | 5.630 | 3.456 | 3.071 | 3.740 | 2.143 |

**Table 3.2:** Contingency Table For Risk-Shifting During Bull Years

| | Poor-History (A) | | Good-History (B) | | Full Sample (C) | |
|---|---|---|---|---|---|---|
| | Mid Low | Mid High | Mid Low | Mid High | Mid Low | Mid High |
| Low RAR (N) | 439 | 433 | 728 | 860 | 2022 | 2164 |
| % | 53.60 | 52.36 | 47.93 | 54.16 | 48.30 | 51.80 |
| High RAR (N) | 380 | 394 | 791 | 728 | 2164 | 2014 |
| % | 46.40 | 47.64 | 52.07 | 45.84 | 51.70 | 48.20 |
| Column Total | 819 | 827 | 1519 | 1588 | 4186 | 4178 |
| Chi2 | 0.26 | | 12.06 | | 10.19 | |
| p-value | 0.61 | | 0.00 | | 0.00 | |

**Table 3.3:** Contingency Table For Risk-Shifting During Bear Years

| | Poor-History (A) | | Good-History (B) | | Full Sample (C) | |
|---|---|---|---|---|---|---|
| | Mid Low | Mid High | Mid Low | Mid High | Mid Low | Mid High |
| Low RAR (N) | 319 | 177 | 349 | 460 | 1153 | 1067 |
| % | 57.17 | 52.99 | 50.87 | 50.94 | 51.94 | 48.11 |
| High RAR (N) | 239 | 157 | 337 | 443 | 1067 | 1151 |
| % | 42.83 | 47.01 | 49.13 | 49.06 | 48.06 | 51.89 |
| Column Total | 558 | 334 | 686 | 903 | 2220 | 2218 |
| Chi2 | 1.47 | | 0.00 | | 6.51 | |
| p-value | 0.23 | | 0.98 | | 0.01 | |

**Table 3.4:** Midyear Risk-Shifting By Fund Managers

The table presents the evidence on managerial risk-shifting. The dependent variable is midyear risk-shifting. Panel A regresses risk-shifting measure on midyear performance without the interactions with historical performance. Panel B considers the interaction between midyear performance and the historical performance. $\text{Perf}_{i,1t}$ denotes the peer-adjusted performance of the fund in the first half of the year t and $\text{repute}_{it-1}$ indicates the historical performance of that fund at the start of the year $t$. Bull (Bear) denotes the years when midyear stock market return is positive (negative). All the regressions have time and fund investment category fixed effects. Standard errors are clustered at share class level.

| | Panel A | | Panel B | |
|---|---|---|---|---|
| | Bull | Bear | Bull | Bear |
| $\text{Perf}_{i1,t}$ | -0.351*** | 0.253*** | -0.118 | 0.776*** |
| | (0.082) | (0.079) | (0.131) | (0.146) |
| $\text{repute}_{i,t-1}$ | | | -0.021** | 0.013 |
| | | | (0.011) | (0.014) |
| $\text{Perf}_{i1,t}\times$ $\text{repute}_{i,t-1}$ | | | -0.512** | -1.052*** |
| | | | (0.228) | (0.251) |
| Log Size (t-1) | -0.003 | 0.008*** | -0.002 | 0.007*** |
| | (0.002) | (0.003) | (0.002) | (0.003) |
| Expense Ratio (t-1) | -0.717 | 1.205 | -0.765 | 1.164 |
| | (0.527) | (0.885) | (0.526) | (0.879) |
| Log Age (t-1) | 0.003 | -0.014* | 0.003 | -0.013* |
| | (0.006) | (0.008) | (0.006) | (0.008) |
| Intercept | 1.027*** | 0.947*** | 1.038*** | 0.944*** |
| | (0.020) | (0.031) | (0.021) | (0.032) |
| N | 6465 | 3704 | 6465 | 3704 |
| Adj. R-sq | 0.595 | 0.603 | 0.595 | 0.605 |

**Table 3.5:** Historical Performance and Fund Flows

The table presents the regression of fund flows at time $t+1$ on the performance at time $t$ given by Rank($r_{it} - b_t$) and the performance at the time $t-1$ given by Rank($r_{it-1} - b_{t-1}$). Ranks are normalized to lie between 0 and 1. Control variables include age, size, and expense ratio. All the models have time and style fixed effects. Standard errors are clustered at the fund level.

| | Panel A: Full Sample | | Panel B: State-Dependent | |
|---|---|---|---|---|
| | | | Bull Years | Bear Years |
| Rank($r_{it} - b_t$) | 0.357*** | 0.164*** | 0.150*** | 0.189*** |
| | (0.015) | (0.027) | (0.031) | (0.042) |
| Rank($r_{it-1} - b_{t-1}$) | | 0.061*** | 0.071*** | 0.046 |
| | | (0.021) | (0.027) | (0.031) |
| Rank($r_{it} - b_t$)× Rank($r_{it-1} - b_{t-1}$) | | 0.291*** | 0.273*** | 0.315*** |
| | | (0.047) | (0.058) | (0.075) |
| Log Size (t) | -0.018*** | -0.027*** | -0.026*** | -0.027*** |
| | (0.002) | (0.003) | (0.003) | (0.004) |
| Expense Ratio (t) | -0.496 | -0.678 | -0.406 | -0.985 |
| | (0.806) | (0.808) | (0.881) | (1.268) |
| Log Age (t) | -0.045*** | -0.014** | -0.015* | -0.011 |
| | (0.007) | (0.007) | (0.008) | (0.009) |
| Intercept | 0.067* | 0.042 | 0.061 | 0.002 |
| | (0.035) | (0.035) | (0.039) | (0.052) |
| N | 10169 | 8747 | 5327 | 3420 |
| adj. R-sq | 0.125 | 0.143 | 0.127 | 0.162 |

# Chapter 4

# Mutual Fund Flows When Manager Has Timing and Picking Skills

## 4.1 Introduction

Typically a mutual fund manager is assessed based on his ability to produce alpha ($\alpha$). $\alpha$ captures per Dollar value generated by a manager after adjusting for market exposure of the portfolio.[1] $\alpha$ measures manager's *picking skill*. But a manager can generate the value by adjusting the factor exposure of the portfolio ahead of time by forecasting factors accurately. For example, lowering portfolio beta ($\beta$) before the market downturn would produce a positive excess return which is a value created by the manager. Such skill to forecast the market movement is the *timing skill*. Much of the theoretical and empirical models analyzing mutual fund flows have focused on picking skill only. For example, the benchmark model (Berk and Green, 2004) solves for equilibrium capital flows when the manager has only *picking* skill. Because *picking* ability generates the value independent of the market movements, the implications for fund flows are independent of the state of the market. But level, as well as the sensitivity of capital flows to performance, appears to be state-dependent in the data. I introduce *timing skill* to the (Berk and Green, 2004) framework which generates state-dependent implications for capital flows.

Recent paper by (Franzoni and Schmalz, 2016) considers an environment where manager's factor exposure is unknown. In their paper, though the factor exposure is unknown, it is a constant, and it

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[1]Typically Capital Asset Pricing Model (CAPM) or Carhart's four-factor model is used for computing manager's alpha.

does not represent the skill. In other words, investor care only about $\alpha$ of the manager. Unknown $\beta$ only adds a layer of complexity to learning but does not shed light on how investors decision changes in the presence of the picking skill. In short, little is known about how the presence of timing skill impact the learning and consequently the mutual fund flows. The primary objective of this paper is to fill this gap on the theoretical and empirical front.

My model features a mutual fund manager endowed with dual skills: *timing* and *picking* skill. Both the skill components are unobservable and unknown to the investors. Investors are risk neutral and provide capital competitively. That is they have deep pockets. Risk neutrality implies that investors invest with the manager if expected return net of all fees is non-negative and liquidate their holdings otherwise. The mutual fund is subject to decreasing returns to scale indicating that per The dollar cost of operating the fund are increasing in the size of the fund. Capital move in and out of the fund to achieve zero expected net return condition which also pins down the scale of the fund. The main thrust of the model lies in the learning mechanism which I describe next.

The underlying learning mechanism is as follows: Investors learn about managers timing (picking) skill during the periods when the aggregate market is volatile (calm). A period of high market volatility presents an opportunity for the manager to generate timing value by altering the portfolio beta. Hence, the fund performance during a volatile period is more informative about manager's timing skill. On the contrary, if the factor or the market is calm with minimal volatility, then the only way to generate value is using picking skill. Hence, non-volatile periods are more informative about manager's picking skills. [2] The set-up, therefore, implies a market state-dependent learning mechanism. Because, both the skills produce the value during different market states, investors care about learning each of the skill components. For example, timing skill is valuable if the market is expected to be volatile, but not otherwise.

The model generates empirical predictions when combined with the other characteristics of the data. First, the stylized fact about market volatility is that it is persistent. It implies that during volatile times, not only investors learn more about manager's timing skill but because timing skill

[2] If these skills are correlated for the manager then learning about one skill has a spillover effect for the other skill too. I analyze two limiting cases where there is no correlation between timing and picking skill for a given manager and the other extreme, where both these skills are perfectly correlated.

is more important during volatile periods, this learning has a strong bearing on the expected returns requiring greater capital adjustment as compared to non-volatile period. It results in increased sensitivity of capital flow to the fund performance during volatile times. The second feature of the data is that market volatility is counter-cyclical. It implies that capital flow sensitivity to performance is greater during periods of low market returns. Third, because timing skill becomes more important during volatile times, whenever conditional market volatility rises compared to the past, then proportionately more capital flows accrues to the managers who have exhibited better timing skill. The paper is first to my knowledge that explores the implications of timing skill for mutual fund flows. Earlier studies have identified the impact of fund's return volatility on fund flows. (Huang et al., 2012) both empirically and theoretically find that past fund performance volatility dampens the sensitivity of flows. But to my knowledge, there is no paper which studies how market volatility affects the flow sensitivity. Including market returns or market volatility as a control in the regression of flows on the fund performance tells us whether market volatility shifts the flow schedule up or down. It is a result regarding the level of flows. To generate the implication for sensitivity we need to interact the market volatility with fund performance. Data supports the predictions of the model.

This paper is also important from the perspective of managerial incentives across market states. Aggregate fund flows are increasing in stock market returns (Warther, 1995). (Karceski, 2002) shows how this feature together with return-chasing on the part of the investors leads fund managers to prefer high beta stocks. Evidence in this paper suggests that even if aggregate flows are greater during the times of high stock market returns, the sensitivity of flows to fund performance is substantially lower during these times. On the other hand, even when aggregate flows are low during low stock return periods, the fund can lose a lot of capital if it underperforms during such period. Hence, my paper provides a drastically different view on the incentives faced by fund managers across market states.

## 4.2 Model

### 4.2.1 Set-Up

The model has a mutual fund managed by a manager who generates the gross return as follows

$$R_{it} = \alpha_i + \psi_i f_t^2 + \varepsilon_{it} \tag{4.1}$$

where $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$ is an error that hinders learning about skill. There are two skill components. $\alpha_i$ is manager's *picking* skill. It is independent of market return which is denoted by $f_t$. On the other hand, $\psi_i$ denotes the *timing* skill, which captures the manager's ability to forecast market movement. The basic idea is that whenever the market or the factor moves (either up or down) generating large $f_t^2$, a good market timer can forecast the movement and adjust portfolio $\beta$ accordingly.[3] For simplicity, I assume that $E_{t-1}(f_t) = E(f_t) = 0$.

The model introduces the timing skill in an easy way. In reality, timing skill might be captured by a more complicated process. Additionally, note that certain derivatives strategies (for example straddle) allow managers to time the market even with zero market movement. (The skill is in predicting zero market movement). But for an equity oriented mutual fund manager, investment mandates are usually tight restricting the use of complex derivative strategies. Given these mandates, the simple way to include timing skill is justifiable.

Total value generated by a manager is $\alpha_i + \psi_i f_t^2$. Note that if $\psi_i = 0$, then the manager can not earn any return from factor volatility. For a manager with timing and picking skill values of $\alpha_i$ and $\psi_i$ respectively, the expected value is given by

$$E_{t-1}(R_t|\alpha_i, \psi_i) = \alpha_i + \left(\psi_i \times \Sigma_{t-1}^t\right) \tag{4.2}$$

where $\Sigma_{t-1}^t \equiv E_{t-1}(f_t^2)$ denotes the conditional volatility of market return, given that market has zero expected return. Note that timing skill becomes more useful when the conditional volatility of

[3]One more way to understand the gross return equation is to imagine that there exists an asset with non-negative payoff $\pi = f_t^2$ and the extent to which a manager can access this privileged asset depends upon the forecasting skill given by $\psi_i$.

a factor is high: expectation is rising in conditional volatility. Note that the conditional volatility is counter-cyclical as well as persistent. These facts coupled with learning mechanism produce an asymmetric capital flow sensitivity to recent fund performance across market states. Consider a volatile period with significant adverse market shock. A fund's performance during such a time will reveal a lot about the timing skill. Because conditional volatility is persistent, timing skill also drives the expected return more prominently. On the contrary, a low volatility period with large positive market shock will no doubt reveal a lot about psi, but the timing component does not affect expected returns significantly now due to lower conditional volatility. Investor earns net return of $r_{it}$ which is given by

$$r_{it} = R_{it} - \frac{1}{\eta} q_{it-1} \tag{4.3}$$

where $q_{it-1}$ denotes the fund size at the end of $t-1$. $\eta > 0$ implies decreasing returns to scale. Existence of decreasing returns to scale is documented by (Pasto et al., 2015). Their estimate of $\eta$ is $0.22 \times 10^6$.

### 4.2.2 Learning

There are two unknowns $\alpha_i$ and $\psi_i$ to learn from one observable $R_{it}$. Investors have priors about $\alpha_i$ and $\psi_i$ as follows: At time $t$

$$\begin{pmatrix} \alpha_i \\ \psi_i \end{pmatrix} \sim N\left( \begin{pmatrix} \alpha_{it} \\ \psi_{it} \end{pmatrix}, \begin{pmatrix} \sigma^2_{\alpha t} & 0 \\ 0 & \sigma^2_{\psi t} \end{pmatrix} \right) \tag{4.4}$$

The simplistic assumption is that $\sigma_{\alpha\psi 0} = 0$ for analytical tractability. (Kacperczyk et al., 2014) document that timing and picking skills are correlated for a given manager. In the appendix, I solve the model where these skills are perfectly correlated. Consider time $t+1$ fund and market return observations $R_{it+1}$ and $f_{t+1}$. Using Bayesian updating,

$$\alpha_{it+1} = \alpha_{it} + \lambda_{\alpha,t} \left[ R_{it+1} - E_t(R_{it+1}) \right] \tag{4.5}$$

where

$$\lambda_{\alpha,t} = \left[\frac{cov_t(R_{it+1}, \alpha_i | f_{t+1})}{var_t(R_{it+1}|f_{t+1})}\right] = \left[\frac{\sigma^2_{\alpha t}}{\sigma^2_{\alpha t} + \sigma^2_{\psi t} f^4_{t+1} + \sigma^2_{\epsilon}}\right]$$

and similarly

$$\psi_{it+1} = \psi_{it} + \lambda_{\psi,t}\left[R_{it+1} - E_t(R_{it+1})\right] \tag{4.6}$$

where

$$\lambda_{\psi,t} = \left[\frac{cov_t(R_{it+1}, \psi_i | f_{t+1})}{var_t(R_{it+1}|f_{t+1})}\right] = \left[\frac{\sigma^2_{\psi t} f^2_{t+1}}{\sigma^2_{\alpha t} + \sigma^2_{\psi t} f^4_{t+1} + \sigma^2_{\epsilon}}\right]$$

I will discuss the properties of learning in the next section when I solve the model quantities with calibration.

### 4.2.3 Equilibrium Size and Fund Flows

Investors are risk neutral and provide capital competitively. $f_t$ is observable. Risk neutrality and elastic capital provisioning implies that, investors invest in a fund until expected net value (skill component) is non-negative.

$$E_t(r_{it+1}) = 0 \tag{4.7}$$

If $E_t(r_{it+1}) > (<)0$, then investors invest into (liquidate out of) the fund, which increases (decreases) per dollar cost of management reducing (increasing) net return. Process continues until expected net return hits zero level. This condition directly pins down the equilibrium fund size.

**Lemma 8** *Equilibrium fund size is given by*

$$q_{it} = \eta\left(\alpha_{it} + \psi_{it}\Sigma_t^{t+1}\right) \tag{4.8}$$

Fund size is increasing in the estimate of the *picking* skill independent of the market state. But the estimate of the *timing* skill matters only through conditional factor volatility. What matters is the multiplicative term given by $\psi_{it}\Sigma_t^{t+1}$. Low conditional volatility lowers the value investor attaches to the timing skill. Note that in equilibrium

$$E_t\left(R_{it+1}\right) = \alpha_{it} + \psi_{it}\Sigma_t^{t+1} = \frac{q_{it}}{\eta}$$

where second equality is derived by rearranging equation 4.8. Surprise element in learning therefore simplifies to

$$\begin{aligned} R_{it+1} - E_t\left(R_{it+1}\right) &= r_{it+1} + \frac{q_{it}}{\eta} - \frac{q_{it}}{\eta} \\ &= r_{it+1} \end{aligned}$$

This formulation allows us to express Bayesian updating formulas in terms of observables. With learning and equilibrium size expressed in terms of observables, it is easy to derive an expression for fund flows.

**Lemma 9** *Under the assumption of competitive capital markets, equilibrium fund flows are given by*

$$q_{it} - q_{it-1} = \eta\left[\left(\lambda_{\alpha,t} + \lambda_{\psi,t}\Sigma_t^{t+1}\right) r_{it} + \psi_{it-1}\Delta\Sigma_t^{t+1}\right] \tag{4.9}$$

*where $\lambda_{\alpha,t}$ and $\lambda_{\psi,t}$ are given in equation 4.5 and 4.6 and $\Delta\Sigma_t^{t+1} = \Sigma_t^{t+1} - \Sigma_{t-1}^{t}$.*

### 4.2.4 Discussion On Learning Mechanism

The sensitivity of fund flows to the performance $r_{it}$ is governed by the coefficient $\left(\lambda_{\alpha,t} + \lambda_{\psi,t}\Sigma_t^{t+1}\right)$ given in equation 9. Because both $\lambda_{\alpha,t}$ and $\lambda_{\psi_t}$ depend upon $f_t^2$, the flow sensitivity is a function of $f_t^2$ or $|f_t|$. To understand the behavior of $\lambda_{\alpha,t}$ and $\lambda_{\psi,t}$, we need three estimates: $\sigma_\varepsilon$, $\sigma_\psi$ and $\sigma_\alpha$. $\sigma_\varepsilon$ denotes the variability of fund returns around the skill level. Median fund return volatility captures this parameter. In the data median of annual fund return volatility is 0.1682 or 16.82%. Next two parameters namely $\sigma_\alpha$ and $\sigma_\psi$ can be estimated using the cross-sectional dispersion of $\alpha$ and $\psi$ estimated from factor model with timing and picking skill. To this end, I run following factor model to align the estimates with the model:

$$r_{i\tau,t} - rf_{\tau,t} = \alpha_i + \beta(f_{\tau,t} - rf_{\tau,t}) + \psi_i f_{\tau,t}^2 + \nu_{i\tau,t} \tag{4.10}$$

These numbers are 0.1141 and 2.3507 respectively. Note that the uncertainty around the estimate of timing skill $\psi$ is very large relative to picking skill. Next target is to estimate conditional volatility. Because I am interested in generating implications for sensitivity as a function of $f_t$ the market return, I estimate conditional volatility as a function of $f_t$. To this end, I estimate an exponential conditional volatility model and express conditional volatility as a function of current market performance. The conjectured model is

$$\Sigma_t^{t+1} = ae^{bf_t}$$

I proxy the conditional volatility $\Sigma_t^{t+1}$ by the realized volatility at time $t + 1$. I denote it by $\Sigma_{t+1}$ Estimates are presented in table 4.1. In data, $a = 0.159$ and $b = -4.31$. Negative coefficient on $f_t$ implies that a current low return predicts high conditional volatility next period. Given these estimates, I plot the components of the coefficient on $r_{it}$ as a function of $f_t$ in the following figure 4.1. First observation is that $\lambda_{\alpha,t} = \Delta\alpha_{it}$, which measures the learning about $\alpha_i$ is decreasing in $|f_t|$. This is true for any parametric values. This implies that with increasing $|f_t|$, greater share of a surprise return $r_{it}$ is ascribed to timing skill instead of picking skill. This happens because the contribution of $\alpha_i$ to return $R_{it}$ is independent of $|f_t|$, but $R_{it}$ becomes more variable with $|f_t|$. This means that a smaller fraction of total variability of the signal can be explained by picking skill. The flip side of this result can be seen in right top figure for $\lambda_{\psi,t}$. $\lambda_{\psi,t}$ is increasing in $|f_t|$ up to a point. This is because the contribution of timing skill $\psi_i$ to $R_{it}$ is increasing in $|f_t|$. But as $|f_t|$ rises beyond a thresh-hold, the variance of $R_{it}$ grows even faster slowing the learning even for timing skill. This explains why $\Delta\psi_{it} = \lambda_{\psi,t}$ is decreasing beyond a thresh-hold for $|f_t|$. Note that these results about the shape of the learning curves are independent of specific parametric values. Second observation is relating to the scale of $\Delta\psi_{it}$ versus scale of $\Delta\alpha_{it}$. Given that $\sigma_{\psi_i}$ is an order magnitude larger than $\sigma_{\alpha_i}$, the changes in estimates for $\psi_i$ are also an order magnitude larger than that for $\alpha_i$. Note that

$\lambda_{\psi,t}$ and $\lambda_{\alpha,t}$ are symmetric around $f_t = 0$. What generates the asymmetry in the learning across market states is the fact that conditional market volatility is counter-cyclical. Timing skill matters for expected returns via conditional market volatility. This implies that the coefficient on $r_{it}$ is far greater as conditional volatility rises over the empirically relevant range for $|f_t|$. Note that as $f_t$ rises, coefficient rises at first due to increase in $\lambda_{\psi,t}$. But as $f_t$ rises further, not only $\lambda_{\psi,t}$ starts to decrease but conditional volatility falls as well, resulting in the overall coefficient falling beyond a point, say $\overline{f}$ for positive $f_t$. The coefficient would fall even on the negative side as $f_t$ falls below a level $\underline{f} < 0$. But because conditional volatility is increasing as $f_t$ falls, $|\underline{f}| > |\overline{f}|$.

## 4.3 Data, Variables and Empirical Framework

### 4.3.1 Data

I use CRSP Survivor-Bias-Free Mutual Fund Database, covering a period from 1999 to 2014 at a quarterly frequency. Sample selection is in line with the earlier literature. I focus on the US domestic open-ended equity funds. I exclude sector, index, and specialty funds. Because names or styles may not reflect the actual nature of the fund, I also exclude funds whose mean equity holdings are less than 70%. I rule out any funds where size is smaller than 15 million USD and also any fund whose age is three 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 (Huang et al., 2012), I treat each share class as a separate panel which allows conditioning the results on fee schedules and investor type that each share class attracts.

### 4.3.2 Variables

The main variable of interest is fund flows. In line with more recent literature [(Berk and Green, 2004); (Huang et al., 2012)], I define fund flows as percentage growth in assets under management

(AUM) due to capital flows.[4] In particular,

$$FLOW_{it} = \frac{AUM_{it} - [AUM_{it-1} \times (1 + r_{it})]}{AUM_{it-1} \times (1 + r_{it})}, \tag{4.11}$$

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 $t$. In regression, I exclude all the funds with top 1% fund flows. Winsorization could be an alternative, but it is possible that such drastic high flows could be a result of some major unobservable factor such as an anticipated change in management or some institutional or high net worth client picking up a substantial stake in a smaller mutual fund. For these funds, the average link between flows and performance is not valid, and instead of winsorization, it is better to exclude them. As a robustness check, I also rerun the regressions with Dollar flows instead of percentage flows as a measure.

I measure the performance of the fund using raw returns of the fund and then ranking the funds according to raw returns across all the funds that follow similar investment mandate. This is similar to (Sirri and Tufano, 1998) or (Spiegel and Zhang, 2013). The rank is normalized to fall between 0 (lowest) and 1 (highest). I denote performance rank by $\text{Perf}_{it}$. Using a CAPM-Alpha or Four-Factor Alpha model is not appropriate in this context as we want to understand the investor's reaction to the picking as well as timing skill.

The third important variable is conditional volatility. Fortunately, empirical setting simplifies the computation of this variable. Though in a model, capital adjustment takes place at the end of time $t$, in the data we link time $t$ performance to time $t + 1$ flows. Then instead of using conditional volatility estimate at the end of $t$, we can use realized market volatility at time $t + 1$ as this is observable while investor decides to rebalanced the portfolio at time $t + 1$ in response to time $t$ performance. I denote the realized market volatility at time $t$ by $\Sigma_t$.

I compute recent period risk using the recent quarter's daily return data. Other variables used are the log of fund age, fund size, expense ratio, and turnover ratio. Following (Sirri and Tufano, 1998), I add one-seventh of the front-load and end-load to each year's management fees to compute the

[4] 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.

expense ratio. I also control for overall flows accruing to each investment style to which the fund belongs.

### 4.3.3 Can Investor Estimate Timing And Picking Skills?

Before I test the predictions of the model, it is instructive to test if investors are sophisticated enough to react to a complicated factor model with timing skill component. To this end I study how the fund flows react to various components of total fund return. First, I estimate a following factor model to break-up the total fund returns in to various components:

$$r_{i\tau,t} - rf_{\tau,t} = \alpha_i + \beta(f_{\tau,t} - rf_{\tau,t}) + \psi_i|f_{\tau,t}| + \nu_{i\tau,t} \tag{4.12}$$

where $\alpha_i$, $\psi_i$ and $\beta$ represents picking component of the skill, timing component of the skill and passive exposure to the market respectively and $\tau$ represents the day-index for quarter $t$. This factor model is estimated for each quarter separately using daily data on the fund and the market return. The estimated values of $\alpha_i$ and $\psi_i$ for quarter $t$ are denoted by $\widehat{\alpha}_{it}$ and $\widehat{\psi}_{it}$. Next, I run a simple flow-sensitivity regression at quarterly frequency as follows

$$FLOW_{it+1} = \rho_0 + \rho_1\widehat{\alpha}_{it} + \rho_2\left(\widehat{\psi}_{it} \times |f_t|\right) + \rho_3\left(\widehat{\beta}_{it} \times f_t\right) + \text{Controls}_{it} + \epsilon_{it+1}$$

The results are presented in table 4.2. Results strongly support the case for investor sophistication. Coefficients on timing and picking component are positive while coefficient on the value generated through passive exposure to the market ($\beta \times f_t$) is statistically not significant. This suggests two things: First, investors do not chase passive value. In other words, investors are able to filter out the passive component of the return not related to the managerial skill. Second, because the coefficients are positive on both timing and picking component, they identify these distinct skills and react to each.

### 4.3.4 Model Predictions

Equation 4.9 generates simple empirical predictions which are depicted in figure 4.1.
The first implication is the link between conditional volatility and subsequent fund flows. Formally

**Result 2** *For any given $|f_t|$*

$$\frac{\partial \Delta q_{it}}{\partial r_{it} \partial \Sigma_t^{t+1}} > 0$$

*That is, given the absolute market return $|f_t|$, the sensitivity of flows to fund return is increasing in conditional volatility.*

The intuition for the result is straightforward. Conditional market volatility provides an opportunity to the manager to showcase his timing skill. This intuition implies that given everything else, with the rise in conditional volatility, the impact of the learning about timing skill $\lambda_{\psi,t}$ on expected returns and also the sensitivity of flows increases.
Empirical testing of the result requires that the result must be valid for any level of market return. To this end, I split the sample into two parts. One sample with small $|f_t|$ (periods with middle third $f_t$) and second sample with large $|f_t|$ (periods with bottom and top third $f_t$).[5] On each sample, I use following regression equation

$$\begin{aligned} FLOW_{it+1} &= \rho_0 + \rho_1 Perf_{it} + \rho_2 \Sigma_{t+1} \\ &\quad + \rho_3 [Perf_{it} \times \Sigma_{t+1}] + \text{Controls}_{it} + \epsilon_{t+1} \end{aligned}$$

where $\Sigma_{t+1}$ is the realized market volatility during $t + 1$ and is a proxy for the conditional volatility $\Sigma_t^{t+1}$. I also use Dollar flows to test the hypothesis. Results are presented in the table 4.3. Note that coefficient on $Perf_{it}$ is positive for all the models suggesting a positive link between performance and flows. Stand-alone effect of market volatility at time $t + 1$ which proxies the conditional volatility $\Sigma_t^{t+1}$ in the model is insignificant for all but the first model in Panel A. This is the impact of market volatility on the level of flows. The term of interest is the interaction between $Perf_{it}$ and $\Sigma_{t+1}$. The coefficient is statistically significant and positive in all the models. The model predicts

[5] Note that market return affect the results only through $|f_t|$.

this positive link. Note that each model controls the range of absolute market return. Hence, the negative coefficient implies that for any given level of market return, the sensitivity of flows to $Perf_{it}$ amplifies as conditional market volatility increases. The coefficient is economically large. For example consider Panel A. A mere five percentage point (500 bps) rise in conditional volatility is enough to double the sensitivity of flows to performance.

The second implication is the link between market returns and fund flow sensitivity. Evidence suggest that market volatility is countercyclical and persistent, For example, (Brandt and Kang, 2004). At the same time, the model implies that investor not only learns more about the timing skill but also values it more during volatile times. Combining these two statements leads to a simple hypothesis that sensitivity of fund flows to the performance is asymmetric: greater during the times with low market returns. Formally,

**Result 3**

$$\frac{\partial \Delta q_{it}}{\partial r_{it}}(f_t = -f) > \frac{\partial \Delta q_{it}}{\partial r_{it}}(f_t = f)$$

The results are presented in the table 4.4. Again $Perf_{it}$ has a positive coefficient. The positive coefficient on Med $f_t$ and Top $f_t$ dummy variables indicate that better market returns attract more capital independent of the fund performance. The coefficient on the interaction terms is of primary interest. Interaction with Top $f_t$ dummy has a negative and economically significant coefficient. It means that the sensitivity of flows to the performance drops from 48 during Low $f_t$ times to almost 30 during Top $f_t$ times. Similar magnitude reduction is observed with percentage flow as a dependent variable. These results suggest that sensitivity of flows to the performance is countercyclical.

## 4.4 Conclusion

This paper studies the implications for mutual fund flows when the manager has picking and timing skill. The paper shows that investors are sophisticated enough to decompose the fund returns into various components. Second, the model generates implications for flow-sensitivity across volatility and market cycles. Uncertainty around the mean estimate of timing skill is vast compared to the uncertainty around the mean estimate of picking skill. Additionally, given that the timing skill is more useful during the volatile times and that these are also the times when investor learns a lot about manager's timing skill, flows are sensitive to performance during more volatile times. Given that volatility is counter-cyclical, the sensitivity of flows to performance is higher during low aggregate stock market returns. The paper provides an illustration as to why economic quantities adjust fast during volatile times. The paper also has a significant bearing on managerial incentives. It shows that boom periods are characterized by high aggregate flows but diminished flow sensitivity. So the incentive to outperform during boom periods is reduced as managers attract a substantial fraction of higher aggregate flows even with a mediocre performance. At the same time, managers face capital outflow risk during volatile or doom periods due to high flow sensitivity. It would be an interesting to study managerial risk-taking behavior across market states through the prism of evidence I show in this paper.

**Figure 4.1:** Decomposition of Coefficient on Surprise Return

This graph plots the various components of coefficient of the flows on surprise return $y_{it}$. Market return is on X-axis. Following parameterization is used to generate the plot: $\sigma_\alpha = 0.114$ which is the belief uncertainty about picking skill, $\sigma_\psi = 2.350$ which is the belief uncertainty about timing skill, and $\sigma_t = 0.168$ which is the noise in fund returns around the mean skill level. Volatility is estimated using following

$$\sigma_t(f_{t+1}) = \sqrt{252} \times e^{-4.60-(4.31\times f_t)}$$

First row plots component of flow sensitivity specific to changes in $\alpha$ and $\psi$ respectively which are given by $\lambda_\alpha = \frac{\Delta\alpha}{y_{it}}$ and $\lambda_\psi = \frac{\Delta\psi}{y_{it}}$. Second row plots the conditional volatility as a function of market returns and the resulting coefficient on $y_{it}$.

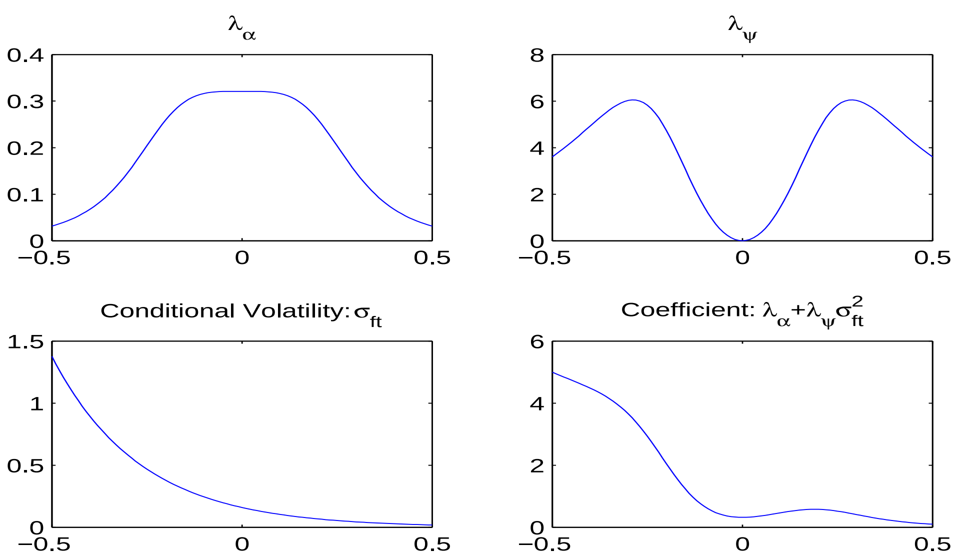

**Table 4.1:** Conditional Factor Volatility Model

Table presents the estimates for the following conditional volatility model

$$\log(\Sigma_t^{t+1}) = \log(a) + \kappa f_t + \nu_{t+1}$$

where $\Sigma_t^{t+1}$ is computed as realized daily volatility over the next month $(t + 1)$ Factor considered is market excess return. Robust standard errors are in parenthesis and *, ** and *** denote significance of coefficient at 10%, 5% and 1% level respectively. Because above model generates estimate of conditional volatility at daily frequency, to generate annualized conditional volatility, I multiply the estimate by $\sqrt{252}$.

| Dependent Variable | Log Factor Risk (t+1) |
|---|---|
| Lagged Market Return | -4.312*** |
| | (0.868) |
| Constant | -4.601*** |
| | (0.032) |
| N | 191 |
| Adj. R-sq | 0.158 |

# Table 4.2: Fund Flow Sensitivity to Components of Fund Returns

The table represents the regression of fund flows on various components of the net fund returns. The components namely timing, picking and beta exposure are estimated using a factor model in equation 4.12. Style Growth is the average flow growth over all the funds within same investment category. Other controls are log of age, log of size, turnover, expense ratio, fund's return volatility which is denoted by $\sigma(r_{it})$. All the regressions have quarter-year dummies. Standard errors are clustered at share class level.

**Table 4.2:** Fund Flow Sensitivity to Components of Fund Returns

| | **Dollar Flows** | **Percentage Flow** |
|---|---|---|
| Intercept | 122.290*** | 0.113*** |
| | (20.405) | (0.007) |
| $\widehat{\psi}_{it} \times \lvert f_t \rvert$ (Timing Component) | 190.326*** | 0.248*** |
| | (19.229) | (0.012) |
| $\widehat{\alpha}_{it}$ (Picking Component) | 45.364*** | 0.070*** |
| | (4.780) | (0.003) |
| $\widehat{\beta}_{it} \times f_t$ (Beta Component) | 66.977* | 0.036 |
| | (37.170) | (0.025) |
| Risk (t) | 471.814 | -1.388*** |
| | (455.862) | (0.277) |
| Log Size (t) | -11.888*** | -0.001** |
| | (2.442) | (0.000) |
| Expense Ratio (t) | -294.681 | -0.771*** |
| | (403.239) | (0.155) |
| Age (t) | -18.346*** | -0.024*** |

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Table 4.2 – **Continued from previous page**

| | **Dollar Flows** | **Percentage Flows** |
|---|---|---|
| | (3.539) | (0.001) |
| Turnover (t) | -1.903* | -0.002* |
| | (1.127) | (0.001) |
| Style Growth(t+1) | 224.070*** | 0.111*** |
| | (61.235) | (0.024) |
| N | 72316 | 71612 |
| Adj R-sq | 0.042 | 0.087 |

# Table 4.3: Market Volatility and Flow Sensitivity

The table presents the results of the regression of flows on fund performance and market volatility. Panel A uses percentage flow definition while Panel B uses Dollar flow definition. In both the Panels, $Perf_{it}$ is the quarter $t$ normalized rank of a fund within its investment style. $\Sigma_{t+1}$ is the realized market volatility during quarter $t+1$ and it proxies conditional volatility estimate at time $t$. Style Growth is the average flow growth over all the funds within same investment category. Other controls are the log of age, log of size, turnover, expense ratio, fund's return volatility which is denoted by $\sigma(R_{it})$. All the regressions have quarter-year dummies. Standard errors are clustered at share class level.

**Table 4.3:** Market Volatility and Flow Sensitivity

| | **Panel A: Percentage Flow** | | **Panel B: Dollar Flow** | |
|---|---|---|---|---|
| | **Large $\lvert f_t\rvert$** | **Small $\lvert f_t\rvert$** | **Large $\lvert f_t\rvert$** | **Small $\lvert f_t\rvert$** |
| Intercept | 0.138*** | 0.055*** | 75.646* | 78.703*** |
| | (0.020) | (0.010) | (39.816) | (18.555) |
| $Perf_{it}$ | 0.042*** | 0.045*** | 26.032*** | 23.299*** |
| | (0.004) | (0.004) | (6.929) | (5.558) |
| $\Sigma_{t+1}$ | -7.950*** | 1.753* | 1531.778 | 455.160 |
| | (2.257) | (0.919) | (3922.456) | (788.410) |
| $Perf_{it} \times \Sigma_{t+1}$ | 0.706*** | 1.602*** | 938.982** | 1235.180** |
| | (0.264) | (0.381) | (405.919) | (482.218) |
| $\sigma(R_{it})$ | -1.311*** | -2.641*** | 569.453 | -214.986 |
| | (0.286) | (0.350) | (497.675) | (483.850) |
| Log Size | -0.001** | -0.001** | -13.687*** | -10.721*** |
| | (0.001) | (0.000) | (2.802) | (2.404) |

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Table 4.3 – **Continued from previous page**

| | **Panel A: Percentage Flow** | | **Panel B: Dollar Flow** | |
|---|---|---|---|---|
| | **Large** $\lvert f_t \rvert$ | **Small** $\lvert f_t \rvert$ | **Large** $\lvert f_t \rvert$ | **Small** $\lvert f_t \rvert$ |
| Expense Ratio | -0.780*** | -0.786*** | -401.864 | -221.339 |
| | (0.182) | (0.166) | (436.340) | (414.513) |
| Log Age | -0.022*** | -0.026*** | -16.244*** | -20.076*** |
| | (0.002) | (0.002) | (3.634) | (3.884) |
| Turnover | -0.002* | -0.002* | -0.489 | -3.045** |
| | (0.001) | (0.001) | (1.539) | (1.181) |
| Style Growth | 0.128*** | 0.289*** | 251.583*** | 261.770*** |
| | (0.026) | (0.044) | (71.531) | (57.677) |
| N | 29303 | 42309 | 29603 | 42713 |
| Adj R-Sq | 0.106 | 0.093 | 0.048 | 0.040 |

# Table 4.4: Market Returns and Flow Sensitivity

The table presents the results of the regression of flows on fund performance and market return. In both the Panels, $Perf_{it}$ is the quarter $t$ normalized rank of a fund within its investment style. Med $f_t$ and Top $f_t$ are dummies indicating that market return during time $t$ belong to middle and top third quintiles as per the historical market return data. A bottom third quintile is a base group. $\Sigma_{t+1}$ is the realized market volatility during quarter $t+1$ and it proxies conditional volatility estimate at time $t$. Style Growth is the average flow growth over all the funds within same investment category. Other controls are the log of age, log of size, turnover, expense ratio, fund's return volatility which is denoted by $\sigma(R_{it})$. All the regressions have quarter-year dummies. Standard errors are clustered at share class level.

**Table 4.4:** Market Returns and Flow Sensitivity

| | **Dollar Flows** | **Percentage Flow** |
|---|---|---|
| Intercept | 59.110*** | 0.069*** |
| | (18.593) | (0.009) |
| $Perf_{it}$ | 48.031*** | 0.063*** |
| | (5.598) | (0.003) |
| Med $f_t$ | 21.847** | -0.011* |
| | (9.006) | (0.006) |
| Top $f_t$ | 27.918*** | 0.016*** |
| | (8.469) | (0.006) |
| $Perf_{it} \times \text{Med} f_t$ | -12.895** | -0.003 |
| | (5.391) | (0.003) |
| $Perf \times \text{Top} f_t$ | -18.805*** | -0.023*** |
| | (5.965) | (0.004) |

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Table 4.4 – **Continued from previous page**

| | **Dollar Flows** | **Percentage Flows** |
|---|---|---|
| $\sigma(R_{it})$ | 432.418 | -1.593*** |
| | (435.016) | (0.274) |
| Log Size | -11.918*** | -0.001*** |
| | (2.441) | (0.000) |
| Expense Ratio | -304.984 | -0.800*** |
| | (400.633) | (0.154) |
| Log Age | -18.451*** | -0.024*** |
| | (3.541) | (0.001) |
| Turnover | -2.114* | -0.002** |
| | (1.138) | (0.001) |
| Style Growth | 257.590*** | 0.164*** |
| | (63.286) | (0.025) |
| N | 72316 | 71612 |
| adj. R-sq | 0.043 | 0.098 |

# Chapter 5

# Conclusions

## 5.1 Summary of the Chapters

The thesis studies three aspects of mutual funds. It shows that the mutual fund's historical performance is crucial in determining the capital flow patterns for that fund as well manager's firing probability given his recent performance. The thesis finds a novel empirical fact that the good-history funds are more vulnerable to capital outflows after a recent poor performance. The thesis also presents a theoretical model providing the mechanism to generate the observed capital flow patterns. The basic conjecture is that the investors differ in their attentiveness, and the fund's historical performance determines the average attentiveness of the investors who own it. In equilibrium, good-history funds are prominently owned by the attentive investors and vice versa. The thesis also finds that the poor-history funds are more likely to perform poorly in near future. The thesis also studies aspects of risk-taking from managerial perspective. It studies how fund managers adjust the portfolio risk in response to their midyear position. Because, the historical performance has a bearing on not only the capital flow patterns but also the unemployment risk, it conjectures that the risk-taking behavior is dependent upon the past performance. It shows using the data that the good-history funds shift the risk upwards more than the poor-history managers if they are in a midyear losing position. In absolute terms, good-history managers increase the risk during the second half of the year in response to the weak midyear performance, but the poor-history funds do not adjust the risk during the bull years and shift the risk downwards if they are in a midyear losing position during bear periods. The chapter also presents the evidence that the gap between the risk-taking behavior of the good-history and the poor-history managers widens during the bear phases. In summary, I explore the impact of fund's historical performance for its capital flow patterns and risk-shifting by the managers.

The thesis also presents interesting empirical observation that the sensitivity of capital flows to the recent fund performance is increasing in the conditional volatility of aggregate stock market. I present a model where investors learn about the managerial picking skill during calm periods and learn about timing skill during volatile periods. Using the persistence of conditional market volatility, the model is able to generate asymmetric capital flow sensitivity. To the best of my knowledge, this is the first study to understand and explain the link between market volatility and capital flow sensitivity.

# Appendix A

# Proofs

## A.1 Proofs For Chapter II

**Proof of lemma 1**

Consider equilibrium condition given in equation 2.7. Substituting $r_{t+1}$ from equation 2.6 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 $\phi_t$. 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 $\phi_t$ from expected net return equation, we get following for $R_{t+1} - \phi_t$

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

Substituting in Bayesian formula, we get

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

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

$$E_t\left(r_{t+1}\right) = -\eta h_t^2 q_t^* \psi_t \tag{A.3}$$

**Proof of lemma 7**

Define fund flows as Define Fund flows ($FF_t$) by

$$FF_t = \frac{q_t}{q_{t-1}(1+r_t)} - 1 \tag{A.4}$$

This definition is identical to one tested in empirical section. Now consider a fund with $\Omega_t$, $h_{t-1}$ and $\psi_{t-1}$. 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 2.10, 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 $\phi_t$ in terms of $\phi_{t-1}$ 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 2.9 and $E_{t-1}(r_t)$ from equation A.3, 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 $q_t = q_t^*$

$$FF_t = \frac{1}{(1+\psi_{t-1})(1+r_t)}\left[1 + \omega_{t-1}\left(\frac{r_t}{2f} + \frac{\psi_{t-1}}{2}\right)\right]^2 - 1 \tag{A.5}$$

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

$$FF_t = -\frac{z_t}{q_{t-1}(1+r_t)} \tag{A.6}$$

## A.2 Proofs For Chapter IV

**Proof of lemma 8**

Using equation 4.3

$$r_{it+1} = \alpha_i + \psi_i f_{t+1}^2 + \varepsilon_{it+1} - \frac{1}{\eta} q_{it}$$

Taking expectations and setting it to zero gives

$$\begin{aligned} E_t\left(r_{it+1}\right) &= 0 \\ \implies & E_t\left(\alpha_i + \psi_i f_{t+1}^2 + \varepsilon_{it+1} - \frac{1}{\eta} q_{it}\right) = \alpha_{it} + \psi_{it}\Sigma_t^{t+1} - \frac{1}{\eta} q_{it} = 0 \end{aligned}$$

Solving for $q_{it}$ we get

$$q_{it} = \eta\left(\alpha_{it} + \psi_{it}\Sigma_t^{t+1}\right)$$

**Proof of lemma 9**

Using equation 4.8 and subtracting equations at $t+1$ and $t$ we get

$$\begin{aligned} q_{it} - q_{it-1} &= \eta\left(\alpha_{it} - \alpha_{it-1} + \psi_{it}\Sigma_t^{t+1} - \psi_{it-1}\Sigma_{t-1}^{t}\right) \\ &= \eta\left(\Delta\alpha_{it} + \Delta\psi_{it}\Sigma_t^{t+1} + \psi_{it-1}\Delta\Sigma_t^{t+1}\right) \end{aligned}$$

where second line is obtained by adding and subtracting $\psi_{it}\Sigma_t^{t+1}$. Using equation 4.5 and $\Delta\alpha_{it} = \lambda_{\alpha,t} r_{it}$ and using equation 4.6, $\Delta\psi_{it} = \lambda_{\psi,t} r_{it}$. Substituting this in the expression for fund flows we get

$$q_{it} - q_{it-1} = \eta \left[ \left( \lambda_{\alpha,t} + \lambda_{\psi,t} \Sigma_t^{t+1} \right) r_{it} + \psi_{it-1} \Delta\Sigma_t^{t+1} \right]$$

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Chartered Accountant (Financial Auditor), 2001-2005
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Research Assistant (Equity Valuation) to *Prof. Scott Stewart*, Boston University, 2011-2012
Equity Researcher at *Wealth Managers (India) Pvt. Ltd*, 2005-2006
Audit and Taxation Internship at *B.L. Phatak & Co.* for Chartered Accountancy program, 2002-2005

## Teaching Experience

Lecturer (*International Finance*), Questrom School of Business, Boston University, 2014-2015

Teaching Fellow, Microeconomic Analysis, Department of Economics, Boston University, Fall 2011

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## Working Papers

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## Work in Progress

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## Media & Presentations

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