Mutual Fund Flows When Manager Has Timing And Picking Skill

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April 20, 2016

Abstract

Mutual fund manager can generate value either by *picking* profitable assets and earning *alpha* or by *timing* the market by adjusting the portfolio *beta*. While traditional theories have studied *alpha* component of the manager's skill, I build a model where manager has both these types of skills. In this set-up investor's learning about managerial skill is a function of performance as well as the state of the aggregate market. A period of high (low) market volatility is more informative about timing (picking) skill. This learning together with persistent and counter-cyclical conditional market volatility implies that fund flows are more sensitive during the periods characterized by high volatility and low market return. I test and confirm these predictions in the data.

JEL classification: G10, G11, G23.
Keywords: Mutual fund flows, Timing skill, Picking Skill, Bayesian Learning.

1 Introduction

Typically a mutual fund manager is assessed based on his ability to produce alpha (α). α captures per Dollar value generated by a manager after adjusting for market exposure of the portfolio.[1] α 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 (β) 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 [1] solves for equilibrium capital flows when the manager has only *picking* skill. Because *picking* ability generates the value independent of the market movements, the

I am grateful to Rui Albuquerque, Simon Gilchrist and Andrea Buffa for their constant guidance and support. I acknowledge financial support from Department of Economics and School of Management at Boston University.

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

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 [1] 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 does not represent the skill. In other words, investor care only about α of the manager. Unknown β 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 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

[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.

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. [4] 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 [**?**]. [6] 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.

2 Model

2.1 Set-Up

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

$$R_{it} = \alpha_i + \psi_i f_t^2 + \varepsilon_{it} \tag{1}$$

where $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$ is an error that hinders learning about skill. There are two skill components. α_i is manager's *picking* skill. It is independent of market return which is denoted by f_t. On the other hand, ψ_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 β 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

[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 ψ_i.

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 α_i and ψ_i respectively, the expected value is given by

$$E_{t-1}(R_t|\alpha_i, \psi_i) = \alpha_i + \left(\psi_i \times \Sigma_{t-1}^t\right) \tag{2}$$

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 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

$$r_{it} = R_{it} - \frac{1}{\eta} q_{it-1} \tag{3}$$

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 [7]. Their estimate of η is 0.22×10^6.

2.2 Learning

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

$$\begin{pmatrix} \alpha_i \\ \psi_i \end{pmatrix} \sim N\left(\begin{pmatrix} \alpha_{it} \\ \psi_{it} \end{pmatrix}, \begin{pmatrix} \sigma_{\alpha t}^2 & 0 \\ 0 & \sigma_{\psi t}^2 \end{pmatrix}\right) \tag{4}$$

The simplistic assumption is that $\sigma_{\alpha\psi 0} = 0$ for analytical tractability. [5] 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,

$$\alpha_{it+1} = \alpha_{it} + \lambda_{\alpha,t}\left[R_{it+1} - E_t(R_{it+1})\right] \tag{5}$$

where

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

and similarly

$$\psi_{it+1} = \psi_{it} + \lambda_{\psi,t}\left[R_{it+1} - E_t(R_{it+1})\right] \tag{6}$$

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.

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.

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

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 1 ***Equilibrium Fund Size:*** *Equilibrium fund size is given by*

$$q_{it} = \eta \left(\alpha_{it} + \psi_{it} \Sigma_t^{t+1} \right) \tag{8}$$

Proof. Using equation 3

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

Taking expectations and setting it to zero gives

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

Solving for q_{it} we get

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

■

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 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 2 ***Equilibrium Flows:*** *Under the assumption of competitive capital markets, equilibrium fund flows are given by*

$$q_{it} - q_{it-1} = \eta\left[\left(\lambda_{\alpha,t} + \lambda_{\psi,t}\Sigma_t^{t+1}\right) r_{it} + \psi_{it-1}\Delta\Sigma_t^{t+1}\right] \tag{9}$$

where $\lambda_{\alpha,t}$ *and* $\lambda_{\psi,t}$ *are given in equation 5 and 6 and* $\Delta\Sigma_t^{t+1} = \Sigma_t^{t+1} - \Sigma_{t-1}^{t}$.

Proof. Using equation 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 5 and $\Delta\alpha_{it} = \lambda_{\alpha,t} r_{it}$ and using equation 6, $\Delta\psi_{it} = \lambda_{\psi,t} r_{it}$. Substituting this in the expression for fund flows we get

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

■

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 2. Because both $\lambda_{\alpha,t}$ and λ_{ψ_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: σ_ε, σ_ψ and σ_α. σ_ε 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 σ_α and σ_ψ can be estimated using the cross-sectional dispersion of α and ψ estimated from factor model with timing and picking skill. To this end, I run following factor model to align the estimates with the model:

$$r_{i\tau,t} - rf_{\tau,t} = \alpha_i + \beta(f_{\tau,t} - rf_{\tau,t}) + \psi_i f_{\tau,t}^2 + \nu_{i\tau,t} \tag{10}$$

These numbers are 0.1141 and 2.3507 respectively. Note that the uncertainty around the estimate of timing skill ψ 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 Σ_t^{t+1} by the realized volatility at time $t+1$. I denote it by Σ_{t+1} Estimates are presented in table 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 1.

First observation is that $\lambda_{\alpha,t} = \Delta\alpha_{it}$, which measures the learning about α_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 α_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 ψ_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 σ_{ψ_i} is an order magnitude larger than σ_{α_i}, the changes in estimates for ψ_i are also an order magnitude larger than that for α_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, $|\underline{f}| > |\overline{f}|$.

3 Data, Variables and Empirical Framework

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 [4], 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.

3.2 Variables

The main variable of interest is fund flows. In line with more recent literature [[1]; [4]], I define fund flows as percentage growth in assets under management (AUM) due to capital flows.[4] In particular,

$$FLOW_{it} = \frac{AUM_{it} - [AUM_{it-1} \times (1 + r_{it})]}{AUM_{it-1} \times (1 + r_{it})}, \tag{11}$$

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 [8] or [9]. The rank is normalized to fall between 0 (lowest) and 1 (highest). I denote performance rank by 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 Σ_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 [8], 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.

[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.

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:

$$r_{i\tau,t} - rf_{\tau,t} = \alpha_i + \beta(f_{\tau,t} - rf_{\tau,t}) + \psi_i|f_{\tau,t}| + \nu_{i\tau,t} \tag{12}$$

where α_i, ψ_i and β represents picking component of the skill, timing component of the skill and passive exposure to the market respectively and τ 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 α_i and ψ_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 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.

3.4 Model Predictions

Equation 9 generates simple empirical predictions which are depicted in figure 1.

The first implication is the link between conditional volatility and subsequent fund flows. Formally

Result 1 *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

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

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

where Σ_{t+1} is the realized market volatility during $t+1$ and is a proxy for the conditional volatility Σ_t^{t+1}. I also use Dollar flows to test the hypothesis. Results are presented in the table **??**. 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 Σ_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 Σ_{t+1}. The coefficient is statistically significant and positive in all the models. The model predicts 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, [2]. 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 2

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

The results are presented in the table 4. 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 counter-cyclical.

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.

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Figure 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 α and ψ 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}.

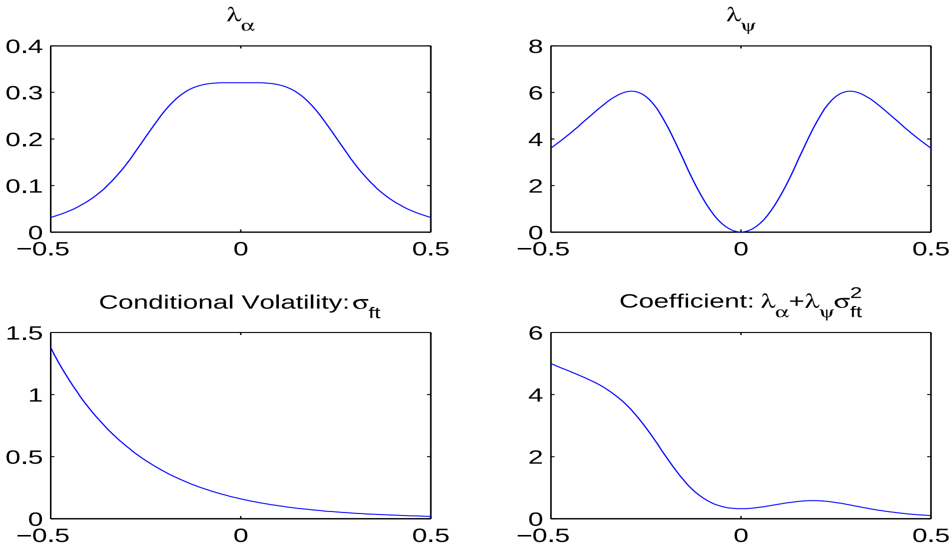

Table 1: Conditional Factor Volatility Model

Table presents the estimates for the following conditional volatility model

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

where Σ_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 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 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 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***
	(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 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. Σ_{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 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)
Σ_{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)
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: 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. Σ_{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: 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)
$\sigma(R_{it})$	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