# Volatility Managers

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**Abstract**

We propose a theory and empirics to understand the state dependent learning and mutual fund dynamics when manager is endowed with picking and timing skill

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# 1 Introduction

Mutual funds aim to create value for their investors through diverse set of strategies using superior information about different type of shocks. For example, such information can be about asset-specific shocks (picking), systematic shocks (factor timing) or even volatility of systematic shocks (volatility timing). The type of strategy followed by the manager matters for investors. While timing strategies exposes investors more to systematic shocks, a skilled timer might better protect investors from downside risk — a protection investors value as documented by Glode (2011) and Polkovnichenko, Wei, and Zhao (2019). Additionally, timing strategy can be more useful when investors perceive higher aggregate uncertainty or when markets are conditionally highly volatile. During such uncertain times, investors would like to re-allocate their capital to the manager with proven timing abilities. Moreover, fund managers can be deferentially skilled across these various strategies given their educational background or prior experience as a money manager. Zambrana and Zapatero (2018) document that skilled timers are more likely to have PhD while pickers are likely to have MBA degree.

Given this, investors have a strong incentives to learn about manager's *strategy-specific* skill so as to invest with money managers better aligned with their own preferences as well as re-allocate capital efficiently in response to the time-varying aggregate state. Yet, surprisingly hardly any prior work in the mutual fund literature explicitly incorporates this important learning task that investors face. The goal of the paper is precisely to fill this gap by constructing a model of investor learning where managers have diverse set of skills which are deferentially useful across aggregate states and by providing the evidence that investors do re-allocate capital incorporating this learning.

In our model, manager has *picking* as well as *timing* skill — for us timing skill can include either level-timing (Treynor and Mazuy (1966) or Henriksson and Merton (1981)) or volatility-timing (Busse (1999), Ferson and Mo (2016)). For investors, need to learn about strategy-specific skill of the manager arises as the value to timing skill is time-varying — increasing in the aggregate uncertainty/volatility. This is a novel feature not highlighted by the prior literature that even if skill is constant through time, the value of the skill can potentially change across aggregate states.

The second novel feature of the model is the *state-dependent learning* capturing a very intuitive idea that investors learn more about a particular skill-set of the manager when manager had the opportunity to exhibit the skill. For example, investors can learn about manager's volatility management skills only after observing a highly volatile market phase Or about manager's downside protection skills only after a market downturn. Anecdotally, Michael Burry – manager of Scion

Capital shot to fame and was considered as a *trusted* manager to beat the down-market only after his stellar performance during the Global Financial Crises (GFC) of 2008. Our model formalizes this intuition. Formally, the variation in fund's return explained by the timing skill rises with aggregate volatility, leading investors to learn more about timing abilities after volatile period. On the other hand, when the market exhibits low volatility, picking skill becomes relatively more important generating superior learning about manager's picking skill after tranquil periods.

In spite of this intuitive appeal, a well-established view in the literature is that uncertainty dampens the learning. In Franzoni and Schmalz (2017), uncertainty about fund's *passive* systematic exposure to the market amplifies when market outcome is extreme – either very high or very low market return, leading to slow investor learning about manager's *skill*. Starks and Sun (2019) present a mechanism where manager's ability could be *policy-specific*. A period when policy uncertainty is high also magnifies uncertainty about manager's value to the investors, leading to slower learning and dampened flow-sensitivity to the performance. In contrast, we present a mechanism where investors learn more about at least timing abilities during more volatile times — the times when manager had the opportunity to exhibit his timing skill.

A noteworthy exception in the literature is Schmalz and Zhuk (2018) where news during downturns affect stock prices more — the signals during upturns are ambiguous as a good performance could a result of high firm alpha or high firm beta (which risk-averse investors dislike). But a good performance during downturns indicate either higher alpha or lower beta, both of which are preferred by investors. Though it is important to note that in their paper, even if stock price reacts more during downturns, the learning about firm alpha (the skill) is time-invariant. In contrast, we generate time-varying learning about alpha and *active beta* of the fund which translates into fund-flows. Moreover, our set-up generates results even with risk-neutral investors.

The fund-flows in the model are state-dependent not only because learning is state-dependent but also because the value of the timing skill is state-dependent. In particular, in the model, fund-flows per unit of update to estimate of the timing skill is directly proportional to the conditional aggregate volatility. Additionally, during periods with high aggregate uncertainty, investors reallocate capital towards the managers with proven timing abilities in the past. In other words, the stock of estimated timing skill gets *marked-to-market* every period given the aggregate state. Rising number of papers document investor's preference towards downside risk protection, which leads them to park *unconditionally* higher capital with managers having better downside protection ability.[1] In contrast, our model highlights conditional (time-varying) valuation and fund-flows to timers. Additionally, this valuation effect shows up even for risk-neutral investor.

Paper by Custódio, Ferreira, and Matos (2013) also shares the flavor that investors/agents care about the nature of skill and that they value certain skill-sets more during certain times. They document a cross-section of CEO's in terms of generalist vs specialist skill-sets. Generalist CEOs — with experience in diverse industries/firms — are paid higher in general but more so when hired to perform tasks such as mergers & acquisitions, adopting to new business environment or within industries hit by a shocks, or within distressed firms. These are exactly a times when generalist's skill sets are valued the highest – akin to how a timer in our model is valued during volatile times.

Next, we test our model predictions in the data and obtain strong evidence in favor of the mechanisms highlighted by the model. As a methodology, we employ parsimonious dynamic factor model estimated via Kalman Filter to measure fund's picking, factor-timing (or level-timing) and volatility-timing performance. We also present robustness where timing performance is measured using portfolio-holdings data. In support of model's learning channel, we document that fund-flow sensitivity (fps) to fund's picking performance (picking-fps) declines while the timing-fps increases as the aggregate market volatility rise during performance-period. In conformity with the model, we also highlight complementarity in learning — if picking and timing skills are correlated then learning about one skill feeds into learning about other skill. As volatility rises at first, higher learning about timing skill feeds into higher learning about picking skill too. This effects fades as the volatility rises further, generating a humped-shape learning about picking skill in aggregate volatility.

We find strong evidence that when different measures of conditional volatility rises in the flow-period, then *timing-fps* rises. This effect is over and above the impact performance-period volatility has on the *timing-fps*. We consider, VIX, market volatility as well as real-time recession indicators to measure conditional volatility. In particular, we use the average of these indicators in the first month of the flow-quarter to measure conditional volatility capturing that first month of the quarter matter more for fund-flows. We present novel episodic evidence on how investors value past-timers more during challenging times. In particular, we show that the funds having higher historic timing performance (timing-reputation) receive significantly more flows during Global Financial Crises (GFC), European Banking Crises as well as during COVID as highlighted by first quarter of year 2020 compared to the control group.

[1] See Glode (2011), Polkovnichenko, Wei, and Zhao (2019), De Andrade (2009), Bond and Dow (2019), Artavanis, Eksil, and Kadlec (2019)

We employ another test to highlight the channel. We document that funds having better timing-performance during GFC, not only receive more capital unconditionally in the post-GFC period[2], but more importantly as predicted by the model, receive even more capital on top of that when conditional volatility shoots up. The additional effect is twice as strong than unconditional effect. In particular, a one standard deviation higher GFC timing performance bring 1.48% capital quarterly or roughly 6% annually unconditionally. If the standardized conditional volatility rises by 1 unit, then one standard deviation higher GFC timing bring additionally 12% capital annually.

Other robustness tests in the data —-

Our paper is directly related to the vast literature on the mutual fund-flows. Chevalier and Ellison (1997), Sirri and Tufano (1998), **?**

Investor sophistication issue? statistics on intermediated / via-advisors investments —

Literature Comparison

BARBER ODEAN Approach — strange that investors would learn only about CAPM alpha?

Comparison with preference papers — Kadlec, Polvo, Glode etc

In contrast, most of the literature on the fund-flows has predominanantly analyzed investor's capital allocation decisions in a more abstract context where mutual funds are assumed to have uni-dimensional skill set. In theoretical models such as Berk and Green (2004), this shows up when manager's return is assumed to be his *skill* plus some error. In the empirical studies starting from Chevalier and Ellison (1997) and more recently in Berk and van Binsbergen (2015) or Barber, Huang, and Odean (2016), this shows up in simple flow-performance regressions where fund flows are regressed against fund's risk-adjusted or net of benchmark performance. But how investors react to the strategy-specific components of performance is largely unknown. We provide theory in which rational investors place differential value on strategy-specific components of manager's performance across market states which results not only in differential but time-varying flow-performance sensitivity to these strategy-specific components across aggregate states. We also provide robust evidence to support the theory.

[2]Consistent with Artavanis, Eksil, and Kadlec (2019)

# 2 Model

In this section, I present a parsimonious model of a mutual fund manager who is endowed with both picking and timing skill. The model is dynamic and cast in equilibrium framework of Berk and Green (2004). Investors learn about dual skill set of the manager over time and respond by adjusting capital flows to the fund. The model features time varying aggregate or factor volatility.

### Set-Up

The economy is populated by a representative mutual fund manager and continuum of investors. Time is discrete, denoted by $t = 0, 1, 2, ...$ Time period $t$ captures a reasonable frequency over which investors evaluate managers, say a quarter or a year and $\tau \in t$ denotes a more high-frequency time period, say day within a quarter. Manager is endowed with two types of skills - Picking and Timing. In spirit of Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), we think of picking and timing skill as having superior information about asset specific and aggregate shocks respectively. Such information about aggregate shocks need not be limited to the direction of shock over $t$. It can also include information about high-frequency movements over $\tau \in t$ or about volatility of shocks over $t$.

### Return Processes

Let $f_{\tau t}$ denote the day $\tau \in t$ return on aggregate factor or simply the market. We adopt a reduced-form representation linking the manager's skill to the *value* he generates. For a risk-neutral investor, the value is given by the excess return over the benchmark. For a risk-averse investor, value denotes the certainty-equivalent of the excess utility. Here, we directly model value as a linear function of manager's skill as follows

$$V_t = \alpha + \psi g\left(\{f_{\tau t}\}_{\tau \in t}\right) + \varepsilon_t \tag{1}$$

where $\{f_{\tau t}\}_{\tau \in t}$ can be thought of as the sequence of daily market returns within period $t$ and for ease of notation, I denote it by $g\left(\{f_{\tau t}\}_{\tau \in t}\right)$ by $g_t$. We do not model the explicit strategy or dynamics of market beta that generates the value here, though we provide examples in the next-subsection. $\alpha$ and $\psi$ captures the picking and timing skill for the manager respectively and $\varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right)$ is a normally distributed noise in the return process. Picking skill ($\alpha$) generates value independently of market. Manager with timing skill ($\psi$) on the other hand creates value by either correctly predicting the market returns or more broadly predicting other useful moments/properties of market as captured by function $g(.)$ — for example market volatility. In this sense, we model timing more broadly than just being limited to predicting market returns. Next, I provide two parametric examples of $g(.)$

**Low-frequency Timing:** First example I consider is a classical market timing considered in Treynor and Mazuy (1966) or Henriksson and Merton (1981) where manager times the *level* of the market returns. This case is captured by letting

$$g\left(\{f_{\tau t}\}_{\tau \in t}\right) = f_t^2 \tag{2}$$

where $f_t = \sum_{\tau \in t} f_{\tau t}$ is the aggregate return for time $t$. One can derive this representation explicitly by assuming that the fund's return process is

$$R_t = \alpha_t + \beta_t f_t + \varepsilon_t^R \tag{3}$$

and modeling the portfolio beta as a linear function of the market returns $f_t$

$$\beta_t = \psi_t f_t \tag{4}$$

Substituting the process for beta yields $R_t = \alpha_t + \psi_t f_t^2 + \varepsilon_t^R$. For a risk-neutral investor, $R_t \equiv V_t$ in this case. The source of value is the covariance between periodic beta $(\beta_t)$ and the market returns $(f_t)$ given by $\psi_t$. In this case, a manager with timing skill creates value for investor by correctly anticipating the *average* market movement over time $t$. Implicit is the assumption that a manager is able to create timing value irrespective of the direction in which market moves. A manager with superior information about conditional market returns can exploit it by ex-ante adjusting market beta $(\beta)$ of his portfolio up or down. In this case, $\psi$ measures the value addition per unit of squared market movement over the quarter $t$. Without loss of generality, I assume that market has unconditional mean of zero: $\mathbb{E}\left(f_t\right) = 0$. I further assume that conditional on investors' information set $I$ at time $t$, market has conditional mean of zero as well i.e., $\mathbb{E}_t^I\left(f_{t+1}\right) = 0$ for any $t$.

This return process is a good description of a low-frequency timing strategy employed at frequency $t$. In particular, $\psi$ captures manager's ability to adjust his time $t$ portfolio $\beta$ up or down in response to predicted market returns for time $t$. In this case, manager's $\beta$ could be constant within the time period, yet he can create timing value for his investors by correctly anticipating direction of $f_t$. The covariance between portfolio holdings and subsequent systematic component of stock returns as proposed by Jiang, Yao, and Yu (2007), or Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) capture this type of market timing ability in the data.

**High-frequency Timing:** Mutual funds and hedge funds can engage in a high-frequency market timing by trading based upon say daily/weekly market movements as suggested by Goetzmann, Ingersoll, and Ivkovic (2000) and documented by Patton and Ramadorai (2013) in the context of hedge funds. For example, Patton and Ramadorai (2013) show that hedge funds adjust portfolio beta to even target certain days of weeks. Such high frequency timing could be more important even in the mutual fund industry with the advent of quantitative/algorithmic mutual funds as documented by Abis (2017). In this case, a skilled manager is likely produce *timing value* when market exhibits large daily volatility over the period, even if markets produce zero return on average over that period. Unlike a daily timer, a low-frequency timer, may not be able to create timing value over the period if markets stay flat. In other words, the value through high-frequency timing is more intricately linked to intra-period volatility rather than the average level of market returns over that period. To represent this case we write

$$g\left(\{f_{\tau t}\}_{\tau \in t}\right) = \widetilde{\sigma}_t^2 \tag{5}$$

where $\widetilde{\sigma}_t^2$ denotes the realized daily volatility of market returns over time $t$. What dynamic beta strategy produces $R_t \equiv V_t$ in this case for a risk-neutral investor? This representation can be derived starting from a model for fund returns and fund beta similar to equation 2 and 4 but written at daily level to get,

$$R_\tau = \alpha_\tau + \tilde{\psi}_t^f \times f_\tau^2 + \varepsilon_\tau \quad \text{for} \quad \tau \in t, \tag{6}$$

Consistent with the case of low-frequency timing, I assume that $\mathbb{E}_{t-1}^I(f_\tau) = \mathbb{E}(f_\tau) = 0 \quad \text{for} \quad \tau \in t$. Then summing over $\tau \in t$, equation 6 can be equivalently re-written as

$$R_t = \alpha_t + \psi_t \times \widetilde{\sigma}_t^2 + \varepsilon_t \tag{7}$$

where $R_t$ and $\varepsilon_t$ denote the aggregate fund return and the shock during period $t$, $\widetilde{\sigma}_t^2 = \frac{\sum_{\tau \in t} f_{\tau t}^2}{N_t}$ is the realized market variance over the period $t$ with $N_t$ being the number of days in period $t$ and $\psi_t = \tilde{\psi}_t^f \times N_t$. This equivalence holds as the daily returns are assumed to have zero-mean.[3] I take

[3]The assumption of daily return having zero-mean is without loss of generality - as pointed out by Goyal and Santa-Clara (2003), the missing term which is the square of daily mean ($\overline{f}_{\tau t}^2$) is likely to be very small

equation 7 as a representation of high-frequency timing strategy. Again, for risk-neutral investors $R_t \equiv V_t$ in this case — i.e, $V_t$ represents the physical units of excess returns earned by the investor.

**Volatility Management** As emphasized by Busse (1999) and Ferson and Mo (2016), fund managers can add value by timing the market volatility and often this version of timing ability is overlooked while assessing the mutual funds. Admati, Bhattacharya, Pfleiderer, and Ross (1986) and Busse (1999) both show that optimal portfolio beta is decreasing in expected market volatility. A manager with superior information regarding future market volatility will thus lower his exposure to the market, thereby creating value to its investors by reducing portfolio volatility more consistently than his peers or benchmark. Letting $g\left(\{f_{\tau t}\}_{\tau \in t}\right) = \widetilde{\sigma}_t^2$ can also capture the value generated through *volatility timing* in a reduced-way.

Concern for return distribution and volatility arises only for a risk-averse investor. In this case, $V_t$ in equation 1 can be interpreted as the value expressed in terms of certainty-equivalent for appropriate underlying preferences where investors care about volatility of the portfolio returns. It is important to note that $\psi$ in this case loses the physical meaning — it no longer captures the *active* portfolio beta loading on the volatility. Note that, empirically, Busse (1999) and Chen and Liang (2007) model the volatility timing explicitly by letting beta to be linear in excess volatility which generates following return process

$$R_t = \alpha_t + \gamma_t^{\sigma}\left(\widetilde{\sigma}_t - \overline{\sigma}\right) + \varepsilon_t^R \tag{8}$$

Here negative $\gamma^{\sigma}$ captures the ability of the manager to time the market volatility.

### Discussion of Value and Return

Several comments are in order. First, for a risk-neutral investors, the value process coincides with physical return process of the manager for the case of low- and high-frequency timing strategies. We explicitly derive the $V_t$ in these cases. In particular, $\psi$ has a meaning in terms of excess units of portfolio beta. On the other hand, we capture the value created via volatility timing in a reduced form given the underlying risk-averse preferences. Following Ferson and Mo (2016), one can derive the *value* in utility terms by applying the appropriate stochastic discount factor (SDF). In what follows, we abstract away from the exact underlying beta strategy or the preferences that has generated the $V_t$ and treat $V_t \equiv R_t$ and further assume that investors are risk-neutral.

Second, we have abstracted away from modeling the time-invariant exposure to the market ($\beta^{passive}$) unrelated to manager's timing skill. This is equivalent to assuming that investors know the passive beta and hence while learning about the manager skill, they net out the part of the return due to passive systematic exposure, namely $\beta^{passive} \times f_t$. In Franzoni and Schmalz (2017), market $\beta$ plays an important role as investors can't observe it. Instead, the focus in this paper is on differential learning about picking and timing skill across market states.

Third, the case of low-frequency timing when $g_t = f_t^2$ implicitly precludes any strategies that allow the manager to generate value when market does not move. This assumption is reasonable given the strict mandates on the use of cash/leverage/derivative that most equity funds face. For example, to maintain a large cash-position for the entire quarter in anticipation of market producing minimal returns may not be possible for a pure equity fund.

Fourth, low- and high-frequency timing strategies are more connected than is apparent on the face of it. Denote the conditional volatility over time $t+1$ with respect to investor's information set by $\sigma_t$. More precisely denoting $I$ to mean investor's information set we have, $\sigma_t \equiv \mathbb{E}_t^I\left(\widetilde{\sigma}_{t+1}\right)$ – that is $\sigma_t$ is the $time-t$ expected market volatility over time $t+1$. Due to the assumption of zero conditional mean of market, $\mathbb{E}_t^I\left(f_{t+1}^2\right) \equiv \sigma_{t,I}^2(f_{t+1})$. But by definition, $\sigma_{t,I}^2(f_{t+1}) \equiv \mathbb{E}_t^I\left(\widetilde{\sigma}_{t+1}\right) = \sigma_t$. Hence, given the investor's beliefs, in expectation both the models underline the fact that timing skill is more useful when market is conditionally more volatile.

## Capital Flows and Optimal Fund Size

Similar to Berk and Green (2004), I assume that investors are risk-neutral and have deep-pockets[4]. In addition, model features decreasing returns to scale (DRS) capturing the idea that per Dollar trading/impact costs are rising in fund size while investment opportunity set of implementable strategies is shrinking in fund size. Manager charges fixed fee of $k$ per Dollar of investment. This implies that *net return* earned by the investor ($r_t$) is given by

$$r_t = R_t - \frac{1}{\eta} q_{t-1} - k \tag{9}$$

where $q_t$ is the time $t$ fund size and $\eta$ is the inverse of the degree of DRS.

Risk neutrality implies that if funds' expected net return denoted by $\mathbb{E}_t\left(r_{it+1}\right)$ is positive, investors move capital in the fund until *DRS* pushes-down the expected net return to zero. Deep

[4]In what follows, we abstract away from the exact underlying beta strategy or the preferences that has generated the $V_t$ and treat $V_t \equiv R_t$ and further assume that investors are risk-neutral.

pocket assumption imply that investors can continue investing as long as expected return is positive. On the other hand, if $\mathbb{E}_t(r_{it+1}) < 0$, investors move money out of the fund until DRS brings the expected net return back to zero.[5] Hence, fund size adjusts to keep expected return at zero and in equilibrium we have

**Lemma 1** (Fund Size)**.** *In equilibrium, for any $g_t$,*

$$\mathbb{E}_t^I(r_{it+1}) = 0 \tag{10}$$

*Let $\alpha_t$ and $\psi_t$ denote investor's mean estimate of picking skill ($\alpha$) and timing skill ($\psi$) respectively. Then the equilibrium fund size is given by*

$$q_t = \eta\left(\alpha_t + \psi_t\sigma_t^2 - k\right) \tag{11}$$

*where $\sigma_t^2$ denotes the conditional market volatility.*

The expression is very intuitive. As in Berk and Green (2004), investors put more capital in the fund when their estimate of managerial skill is higher. This holds true for both the types of skills - picking and timing. But unlike Berk-Green framework, the conditional market volatility affects fund size in this model through estimated timing skill of the manager. Intuitively, given amount of timing skill is more useful when market is expected to be volatile. More formally, timing skill matters when conditional volatility of market returns is high.

Instead, the value that investors put on the estimated picking skill is independent of market state. The equilibrium size expression also makes it clear that any rational investor would want to separately learn about picking and timing abilities of a manager rather than learning about the *composite skill* in an environment where aggregate volatility is time-varying.

## Investor Learning

In Berk and Green (2004), investors learn about *skill* of the manager ($\alpha$) as reflected in the intercept of the return process. In Franzoni and Schmalz (2017), investors learn about manager's skill ($\alpha$) and the unknown (passive) market exposure ($\beta^{passive}$). On the other hand, investors in the current model are tasked with learning about the two-dimensional skill set of a manager ($\alpha$, and $\psi$). Intuitively, because return process is state-dependent, learning will inherit this state-

[5] If expected net return remains negative even after losing entire money, we assume that the fund closes-down

dependency. To see it more clearly, I assume investor's time $t$ prior beliefs about $s \equiv (\alpha, \psi)'$ are jointly normally distributed as follows

$$\begin{pmatrix} \alpha \\ \psi \end{pmatrix} \equiv s \sim N \left[ s_t = \begin{pmatrix} \alpha_t \\ \psi_t \end{pmatrix}, \;\; \Sigma_t(s) = \begin{pmatrix} \sigma^2_{\alpha,t} & \sigma_{\alpha\psi,t} \\ \sigma_{\alpha\psi,t} & \sigma^2_{\psi,t} \end{pmatrix} \right] \tag{12}$$

At the end of time $t+1$, investors observe the fund performance given by $r_{t+1}$ (or equivalently $R_{t+1}$) which acts as a noisy signal about managerial skill. Investors also observe each $f_\tau$ for $\tau \in t+1$. Hence they can compute appropriate moment of the realized market return $g_{t+1}$ – either the average market returns $f_{t+1}$ or the realized market volatility $\widetilde{\sigma}_{t+1}$as the case may be. Using these two sources of information – $R_{t+1}$ and $g_{t+1}$ – investors update their beliefs. Recall that $R_{t+1} = \alpha + \psi g_{t+1} + \varepsilon_{t+1}$. Conditional on $g_{t+1}$ and given that the investor's prior beliefs about $(\alpha, \psi)$ are jointly normal, $R_{t+1}$ is also normally distributed.[6] Given that the priors on $s$ as well as the signal $R_{t+1}$ both are normally distributed, standard projection results for normal distribution as in Basak and Buffa (2019) or Franzoni and Schmalz (2017) leads to convenient belief dynamics as summarized by following lemma 2.

**Lemma 2** (Investor Learning)**.** *Let $\mathcal{I}_{t+1} = \{g_{t+1}, priors_t\}$ be the investor's information set at $t+1$ after observing $g_{t+1}$ but before observing $R_{t+1}$. Then, conditional on $\mathcal{I}_{t+1}$ and after additionally observing $R_{t+1}$, the investor's posterior beliefs about manager's skills are given by*

$$\alpha_{t+1} = \alpha_t + \lambda_{\alpha t+1} \left[ r_{t+1} - \psi_t \left( g_{t+1} - \sigma^2_t \right) \right] \tag{13}$$

*and*

$$\psi_{t+1} = \psi_t + \lambda_{\psi t+1} \left[ r_{t+1} - \psi_t \left( g_{t+1} - \sigma^2_t \right) \right] \tag{14}$$

*The sensitivity parameters $\lambda_{\alpha t+1}$ and $\lambda_{\psi t+1}$ are given by*

$$\lambda_{\alpha t+1} = \frac{\mathbb{C}\text{ov}\left[\alpha, R_{t+1} | \mathcal{I}_{t+1}\right]}{\mathbb{V}\text{ar}\left(R_{t+1} | \mathcal{I}_{t+1}\right)} = \frac{\sigma^2_{\alpha,t} + g_{t+1}\sigma_{\alpha\psi,t}}{\sigma^2_{\alpha,t} + g^2_{t+1}\sigma^2_{\psi,t} + 2g_{t+1}\sigma_{\alpha\psi,t} + \sigma^2_\varepsilon} \tag{15}$$

*and*

$$\lambda_{\psi t+1} = \frac{\mathbb{C}\text{ov}\left(\psi, R_{t+1} | \mathcal{I}_{t+1}\right)}{\mathbb{V}\text{ar}\left(R_{t+1} | \mathcal{I}_{t+1}\right)} = \frac{g_{t+1}\sigma^2_{\psi,t} + \sigma_{\alpha\psi,t}}{\sigma^2_{\alpha,t} + g^2_{t+1}\sigma^2_{\psi,t} + 2g_{t+1}\sigma_{\alpha\psi,t} + \sigma^2_\varepsilon} \tag{16}$$

[6] In particular $R_{t+1} | \left(g_{t+1}, \; priors_t\right) \sim N\left(\overline{R}_{t+1}, \sigma^2_{R,t+1}\right)$ where the mean is $\overline{R}_{t+1} = \alpha_t + \left[\psi_t \times g_{t+1}\right]$ and the variance is $\sigma^2_{R,t+1} = \sigma^2_{\alpha t} + g^2_{t+1}\sigma^2_{\psi t} + 2\sigma_{\alpha\psi t}g_{t+1} + \sigma^2_\varepsilon$

*The equilibrium fund flows, defined as the change in the equilibrium fund size, is given by*

$$q_{t+1} - q_t \equiv \Delta q_{t+1} = \eta \left[ \left( \lambda_{\alpha t+1} + \lambda_{\psi t+1} \sigma_{t+1}^2 \right) \left( r_{t+1} - \psi_t \left( g_{t+1} - \sigma_t^2 \right) \right) + \psi_t \left( \sigma_{t+1}^2 - \sigma_t^2 \right) \right] \tag{17}$$

**Mechanism Behind Learning - Case of High-Frequency Timing/Volatility Timing**

Here we discuss the intuition and learning mechanism for the case where $g = \widetilde{\sigma}$ – i.e, the case of either high-frequency or volatility timing. Observing $R_{t+1}$, investors use equations 13 and 14 to update beliefs about picking and timing skill. Estimated skill update is a product of unexpected/surprise performance, which is given by $r_{t+1} - \psi_t \left( g_{t+1} - \sigma_t^2 \right)$ and the sensitivity to this performance, given by $\lambda_{\alpha t+1}$ and $\lambda_{\psi t+1}$ for picking and timing skill respectively. As in Berk and Green (2004), a mutual fund is expected to earn zero net return in equilibrium. Hence any non-zero $r_{t+1}$ is a surprise. But our model feature another source of surprise due to unexpected component of realized $g_{t+1}$. Note that the fund size $q_t$ at the end of time $t$ in equilibrium reflects investor's time-$t$ expectation of $g_{t+1}$, which in this case is $\sigma_t^2$. In the model, $g_{t+1}$ can be though of as the quantity of opportunity available to the manager with timing skill. If the realized volatility $\widetilde{\sigma}_{t+1}$ differs from the expectation of it, then investors correctly attribute part of surprise performance $r_{t+1}$ to this unexpected realization, rather than to the skill of the manager. Hence, investors net-off $\psi_t \left( g_{t+1} - \mathbb{E}_t^I \left( g_{t+1} \right) \right)$ before updating the skill estimates. Note that $\mathbb{E}_t^I \left( g_{t+1} \right) = \mathbb{E}_t^I \left( \widetilde{\sigma}_{t+1}^2 \right) = \sigma_t^2$. Hence, the surprise performance in this model is given by $r_{t+1} - \psi_t \left( f_{t+1}^2 - \sigma_t^2 \right)$.[7] In short, any performance attributable to *excess* market volatility or movement is not attributable to the manager.

Next, let's study the behavior of learning sensitivities given by $\lambda_{\alpha t+1}$ and $\lambda_{\psi t+1}$ for picking and timing skill respectively. Intuitively, investors react more to the surprise performance if that surprise is largely attributable to the manager's skill. More formally, sensitivity is proportional to the relative variation in surprise due to skill. This quantity is precisely given by $\mathbb{C}\mathrm{ov} \left( s_i, R_{t+1} | \mathcal{I}_{t+1} \right)$,

[7] To see more formally, write out $R_{t+1}$ and $E_t^I \left( R_{t+1} \right)$

$$R_{t+1} - E_t^I \left( R_{t+1} \right) = r_{t+1} + \frac{1}{\eta} q_t + k - \left( \alpha_t + \psi_t \sigma_t^2 \right) \tag{18}$$

$$= r_{t+1} + \frac{1}{\eta} q_t - \left( \frac{1}{\eta} q_t + \psi_t \left( g_{t+1} - \sigma_t^2 \right) \right) \tag{19}$$

$$= r_{t+1} - \psi_t \left( g_{t+1} - \sigma_t^2 \right) \tag{20}$$

In the first line I substituted the gross return $R_{t+1}$ with net return $r_{t+1}$ from equation 9 and then from it subtracted the expected gross return given the priors at time $t$. Note that this expectation is taken at time $t$, hence not conditional on $f_{t+1}$. In the second line, I substituted out the beliefs with the equilibrium fund size using equation 11 which delivers the result.

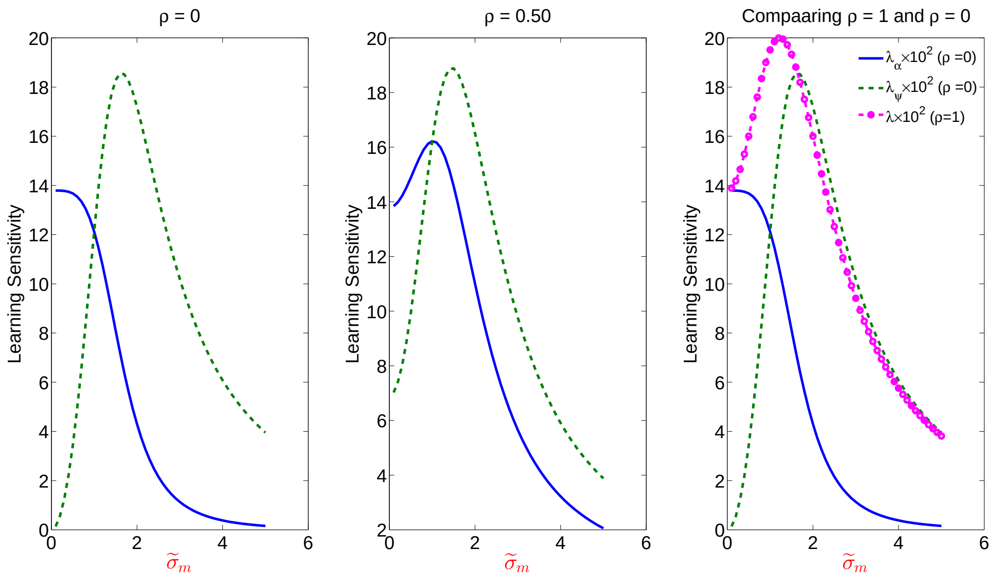


**Figure 1: Learning Sensitivity**

In this figure, I plot the learning sensitivities $\lambda_\alpha$ (solid blue line) and $\lambda_\psi$ (dashed green line) as a function of market realization $f$ for various levels of $\sigma_{\alpha\psi}$. Following parameters have been used to generate the graph; $\sigma_\alpha = 1\%$, $\sigma_\psi = 1\%$, $\sigma_\varepsilon = 8\%$ and $\sigma_{\alpha\psi}$ is parameterized by three different levels of correlation between $\alpha$ and $\psi$ with $\rho_{\alpha\psi} \in \{0, 0.20, 0.50\}$. The sensitivities are magnified by a factor of $10^2$.

for $s_i \in s = (\alpha, \psi)'$, scaled by the total variation in surprise. For the case of high-frequency market timing where $R_{t+1} = \alpha + \psi\widetilde{\sigma}^2_{t+1} + \varepsilon_t$, it is clear that timing skill is useful only when market exhibits high realized volatility. Hence intuitively, when realized market volatility is low, substantial part of the performance is attributable to manager's picking ability. That is the only way to generate value in this model when market does not move. On the other hand, performance reveals much more about managers' timing ability when market volatility is high.

For a more formal understanding of this mechanism consider the case when $\sigma_{\alpha\psi} = 0$ and recall that $\mathcal{I}_{t+1} = \{g_{t+1},\ priors_t\}$ is investor's information set prior to observing manager's return $R_{t+1}$. Uncertainty about both - picking and timing skill as respectively measured by $\sigma_{\alpha t}$ and $\sigma_{\psi t}$ contributes to the uncertainty of $R_{t+1}$ for the investors. The main difference between these two sources of uncertainties is that uncertainty about timing skill magnifies with $\widetilde{\sigma}_{t+1}$, while the uncertainty about picking skill does not. More formally, covariance between $\psi$ and $R_{t+1}$ is $\widetilde{\sigma}_{t+1} \times \sigma^2_{\psi,t}$, while covariance between $R_{t+1}$ and $\alpha$ is $\sigma^2_{\alpha t}$ and is independent of market realization. There are two reasons for this independence. First, picking skill contributes to $R_{t+1}$ independent of market outcome. Second, zero correlation between the two skills further imply that there is no complementarity in learning between these skill. This rules out any indirect dependence of market outcome (which affects the learning of timing skill) while learning about picking skill.

Hence, picking skill monotonically drives less and less variation in fund performance as the realized market volatility rises. Figure 1 plots the learning sensitivities for the high-frequency version of timing skill when $g_{t+1} = \widetilde{\sigma}^2_{t+1}$. The case of zero-correlation between skills is plotted in the leftmost panel of figure 1.

Figure 1 also plots the learning sensitivities when skills are positively correlated. Consider the middle panel where assumed correlation between two level of skills is 0.50. The basic result still holds; for low to moderate market volatility, picking sensitivity is larger than timing sensitivity while timing sensitivity dominates as realized market volatility becomes large. But when skills are positively correlated, market volatility is informative even about picking abilities due to learning complementarity. This implies that as market volatility rises at first, the steep rise in $\lambda_\psi$ reflecting improved learning about timing skill spills-over to learning about picking skill, pushing $\lambda_\alpha$ to rise as well – albeit less steeply. An important observation in this case is that the picking sensitivity achieves its maximum for lower volatility levels than that for timing sensitivity.

Figure 1 also plots the other extreme in the rightmost panel where two skills perfectly correlated. In essence, manager has a level of *skill* which he employs either for picking or timing strategies. This case is similar to the one considered in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) where manager can employ his skill either to analyze idiosyncratic or systematic information. In this case the picking and timing sensitivity are identical. I juxtaposed the case with zero correlation for comparison. The maximal learning in this case occurs for lower level of volatility compared to where the timing-sensitivity peaks for the case of zero-correlation. This reflects the fact slower learning about picking skill spills-over to learning about timing skill for higher levels of realized market volatility.

For the extremely large market volatility, both the picking and timing learning sensitivities die down and approach zero irrespective of the correlation across skills. In other words - learning stops. This happens as almost all of the variation in the gross return (conditional on investor's information set) is driven by the market and fund performance loses its informativeness about manager skill. Following lemma 3 formalizes these intuitive results.

**Lemma 3** (Sensitivity Comparison). *(i)* ***Hump-Shape:*** *Consider a symmetric case with* $\sigma_{\alpha,t} = \sigma_{\psi,t}$ *and let* $\sigma_{\alpha\psi t} > 0$. *Then* $\exists\ g^{\psi}_{t+1}$ $(g^{\alpha}_{t+1})$ *such that* $\lambda_{\psi t}$ $(\lambda_{\alpha t})$ *is increasing in* $g_{t+1}$ *upto* $g^{\psi}_{t+1}$ $(g^{\alpha}_{t+1})$ *and decreasing in* $g_{t+1}$ *thereafter. Furthermore* $\lim_{g_{t+1}\to\infty} \lambda_{\alpha t} = \lim_{g_{t+1}\to\infty} \lambda_{\psi t} = 0$

*(ii)* ***Maximal fps:*** *Moreover, for any* $\sigma_{\alpha\psi t} > 0$, *we have that* $g^{\alpha}_{t+1} < g^{\psi}_{t+1}$.

(iii) ***Uncorrelated Skills:*** *In a special case when* $\sigma_{\alpha\psi} = 0$*, then* $\lambda_{\alpha t}$ *achieves the maximum at* $g_{t+1} = 0$ *given by* $\lambda_{\alpha}^{\max} = \frac{\sigma_{\alpha,t}^2}{\sigma_{\alpha,t}^2 + \sigma_{\varepsilon}^2}$ *and monotonically decreases in* $g_{t+1}$*. On the other hand,* $\lambda_{\psi} = 0$ *when* $g_{t+1} = 0$

(iv) ***Scale:*** *Consider a symmetric case with* $\sigma_{\alpha,t} = \sigma_{\psi,t}$*. Then for any* $\rho_{\alpha\psi} > 0$*, for any* $g_{t+1} < 1$*, we have that* $\lambda_{\alpha t+1} > \lambda_{\psi t+1}$ *and vice-versa.*

### Case of Traditional Market Timing

Similar results hold for the case of traditional low-frequency timing strategy where $g_t = f_t^2$. In particular, moderate market returns reveal more about picking skill and vice-versa. It is interesting to contrast the learning with that in Franzoni and Schmalz (2017). In their paper, uncertainty about portfolio's *passive beta* monotonically slows down the investor learning about manager's *skill* when market outcomes are extreme. On the contrary in this model, extreme outcomes speeds-up the learning for at least one part of the skill component, namely, the timing ability of the manager. More interestingly, if skills are positively correlated, market volatility can actually speed-up the learning even about picking skill due to learning complementarity upto moderate levels of market outcomes.

### Implications of Time-Varying Market Volatility for Fund-Flows

Apart from learning captured by the sensitivities $\lambda_{\alpha t+1}$ and $\lambda_{\psi t+1}$, the other important quantity that determines the fund-flows is the conditional market volatility $\sigma_{t+1}$. Recall that $\sigma_{t+1} = \mathbb{E}_{t+1}^{I}\left(\widetilde{\sigma}_{t+2}\right)$ – i.e, $\sigma_{t+1}$ is the investor expected volatility over time $t+2$. The conditional volatility plays two roles in the fund-flow equation. First, conditional volatility pins down the value investors put on the estimated timing skill of the manager. If the expected future volatility is high, then investors value timing skill even more. How much investors react to the update to the timing skill given by $\lambda_{\psi t+1}$ is directly proportional to $\sigma_{t+1}$. Intuitively, investors value manager's superior information about aggregate shocks precisely when they are more uncertain about such aggregate shocks. Second, conditional volatility shows up in the last term in equation 17 given by $\psi_t\left(\sigma_{t+1}^2 - \sigma_t^2\right)$. $\psi_t$ is the manager's estimated ability upto time $t$ - reflecting the historic timing performance of the manager. If the conditional market volatility rises, investors *mark-to-market* upwards the value attached with stock of timing skill as well. In the data this effect is captured by documenting the flight of capital during challenging time periods towards funds which have proven their timing abilities in the past.

# 3 Empirical Implementation

In this section, we lay out the performance measurement that allows us to test model predictions. As model accommodates various timing strategies modeled through function $g(.)$ of market outcome including low- and high-frequency timing of market level as well as timing of market volatility, we need a performance measurement technique that allows us to capture all three abilities at once. For the purpose of the empirics, our unit of time measurement is a quarter – both for performance and subsequent fund-flows

## 3.1 Measuring Performance

To capture level as well as volatility timing and at various frequencies, we propose a parsimonious but flexible dynamic-beta factor model which we estimate using Kalman Filter following Mamaysky, Spiegel, and Zhang (2008). In particular, we postulate a daily factor-model for quarter $t$ as follows

$$\begin{aligned} R_{i\tau} &= \alpha_{i\tau} + \beta_{i\tau} R_{m\tau} + \varepsilon^{R}_{i\tau} \quad \text{for} \quad \tau \in t && (21) \\ \alpha_{i\tau} &= \alpha_{it} + \varepsilon^{\alpha}_{i\tau} \quad \text{for} \quad \tau \in t && (22) \\ \beta_{i\tau} &= \beta_{it} + \varepsilon^{\beta}_{i\tau} \quad \text{for} \quad \tau \in t && (23) \end{aligned}$$

where $\tau \in t$ denotes a day in quarter $t$ and $\varepsilon^{h}_{i\tau} \sim N\left(0, z^2_{iht}\right)$ for $h \in \{\alpha, \beta, R\}$ denotes the pairwise independent shocks to the fund's daily returns, $\alpha$ and $\beta$. Pairwise independence imply that $\varepsilon^{h}_{i\tau t} \perp \varepsilon^{h'}_{i\tau t}$ for any $h, h' \in \{\alpha, \beta, R\}$. $\alpha_{it}$ and $\beta_{it}$ denote the average $\alpha$ and $\beta$ for a given fund-quarter. The $\alpha$ and $\beta$ are potentially time-varying on daily basis and are modeled as a constant plus daily deviations from the mean. The objective is to put as little a structure as possible a-priori on how the $\alpha$ and $\beta$ for a manager moves through time and letting data guide us. The filter estimates the three variances $z^2_{i\alpha t}$, $z^2_{i\beta t}$, and $z^2_{iRt}$ and two constants $\alpha_{it}$ and $\beta_{it}$ via maximum-likelihood estimator (MLE). This estimation exercise yields time-series of daily $\alpha$ and $\beta$ for the fund over the quarter.

We measure the high-frequency market timing over the quarter as the covariance between daily beta and daily market returns. This captures the idea that a successful high-frequency market timer is able to move portfolio beta in response to high-frequency market movements. To this end we estimate following regression within a quarter

$$\underbrace{\beta_{i\tau} - \beta_{it}}_{\equiv \varepsilon^{\beta}_{i\tau}} = b_{0t} + \psi^{hf}_{it} \times R_{m\tau} + \epsilon_{i\tau} \quad \text{for} \quad \tau \in t \tag{24}$$

$\psi^{hf}_{it}$ is the covariance between daily beta and daily market returns scaled by the market variance — higher covariance therefore indicates manager's skill in dynamically managing the portfolio beta in response to the high-frequency market movement.

A successful low-frequency timer on the other hand tilt market beta up or down in response to his prediction about low-frequency market returns— in this case quarterly market returns. We implement this idea by computing manager's *active market beta* over the quarter and to see if the active tilt is in the correct direction. The active beta is the excess beta over the benchmark's beta which is a passive exposure from investor's perspective. In particular, we define the low-frequency timing performance as

$$\psi^{lf}_{it} = (\beta_{it} - \beta_{bt}) \times R_{mt} \tag{25}$$

Here $\beta_{bt}$ is the quarter-$t$ market beta for the appropriate benchmark. As a baseline we consider average market beta over all the funds belonging to fund's investment-objective as the benchmark beta. We further scale equation 25 by $|R_{mt}|$ to compute active beta per unit of market returns.

Next we measure the manager's volatility timing ability, i.e, the ability to protect the investors from market volatility. Intuitively, we want to measure if the manager is successful in reducing the portfolio beta during high-volatility quarters. Consequently, we measure the volatility timing of a manager over quarter $t$ as

$$\psi^{\sigma}_{it} = (\beta_{bt} - \beta_{it})\,(\widetilde{\sigma}_t - \widetilde{\sigma}) \tag{26}$$

where $\beta_{mbt}$ and $\beta_{mit}$ correspond to benchmark's market beta and fund's market beta over quarter $t$ and $\widetilde{\sigma}_t$ is the realized market volatility over quarter $t$ while $\widetilde{\sigma}$ is the mean market volatility.

## 3.2 Data

We use CRSP survivor-bias-free data on mutual funds over the period 1999(Q1)-2019(Q2) and restrict our sample to the active open-ended domestic equity mutual funds in the USA [8]. Our final sample after filtering as discussed below consists of 4348 mutual funds and 1,43,301 fund-quarters with average survival of 9 years in the sample. Multiple share classes of a fund are aggregated-up following Huang, Wei, and Yan (2012) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) [9]

We exclude sector funds (CRSP Objective Code starting with "EDS"), target-date or retirement funds, accrual funds or funds with any exit-restrictions as is standard in the mutual fund literature. Further, to correct for the possible misalignment of fund portfolio and stated objective of being an equity fund as documented by diBartolomeo and Witkowski (1997) or Kim, Shukla, and Tomas (2000), we require that a fund's average equity share be at least 80% and less than 120%. Evans (2010) documents that fund families have a tendency to offer only those funds which are successful during incubation stage and incubated fund performance exhibits some persistence for first year after its public offer. To tackle this incubation bias, we consider data only from second year after the fund public offer. We also exclude any fund-quarters where asset size is smaller than $5Mn.

CRSP provides daily returns data for mutual funds starting from 1999 and we use it to implement factor model. For the holding-based measure, I use *S-12* filings of mutual funds as provided by Thomsons. This data is available for periods prior to 1999 as well and I use data starting from 1980 in this case. I match the Thomsons holdings data to CRSP mutual fund data using MFLINK files at CRSP Class Group - quarter level. The portfolio weights are computed as fraction of reported assets in Thomsons.

As is standard in the literature, I compute fund flows as quarter-over-quarter percentage change in fund size net off fund returns as follows

$$flows_{it+1} = \frac{q_{it+1} - q_{it}\,(1 + R_{it+1})}{q_{it}\,(1 + R_{it+1})} \tag{27}$$

where $q$ denotes fund size and $R$ denotes realized gross returns for the fund.

[8]Specifically, I drop any funds having CRSP Objective Code not starting *ED*. To drop passive/index funds, I drop funds where fund name contains word "Index" or if CRSP Index Fund Flag is either B, D, or E.

[9]Multiple share classes of a fund typically have varied fee schedule but gross (before fees) return is identical for all of them. Hence, we aggregate all the share classes of a fund following. Fund assets are aggregate assets of all the share classes, fund age is the age of the oldest share class, expense ratio, loads, turnover and fees are are calculated as asset-weighted averages across all share classes for a given time period.

### 3.3 Summary

# 4 Results

The main focus of the paper is on how investors react to manager's timing skills during the volatile market states – either aggressive timing skills when manager engages in high-frequency timing or more defensive skills whereby manager lowers the portfolio beta. In this section, we present the evidence that main predictions of the model are valid in the data and are very robust. In all the predictions, the dependent variable is fund-flows as defined in equation 27. The period of time if a quarter – both performance-period and flow-measurement period. The quarterly picking and timing performance is measured using daily Kalman filter as outlined in equations 21 to 26. A baseline specification absorbs Style×Time fixed effects to wash out the style-specific flows every quarter and clusters the standard errors at fund-level. We include standard controls with one lag that have been found associated with fund-flows. These includes flows, expense ratio, log of fund size and age, and turnover.

The first important prediction model generates is that investors learn more about manager's aggressive or defensive volatility timing skills after a period with high market volatility. This happens as the picking skill drives the variation in fund's return when market is not volatile but as the volatility rises, the market accounts for larger variation in fund's return and reveals more about manager's timing abilities. In fact, when the two types of skills are uncorrelated, the *picking-fps* should decrease monotonically in market volatility. This leads to following first prediction

**Prediction 1** (Realized Volatility and $fps$ )**.** *For a manager, the picking-fps decreases while timing-fps increases as a function of realized market volatility.*

Table 1 documents the evidence for prediction 1. Column 1 confirms the usual positive *fps* documented in the literature, except that we present component-by-component *fps*. Berk and van Binsbergen (2015) and Barber, Huang, and Odean (2016) suggests that investors evaluate fund-performance using CAPM factor model but reward exposure to other aggregate factors like size or value, while Agarwal, Clifton, and Ren (2018) report that hedge fund investors reward even passive exotic risk exposures. Column 1 suggests that investors are able to recognize the value generated using dynamic beta as against passive beta and reward the manager appropriately for his timing skill.

Column 2 provides the main evidence to support the prediction. We interact the picking and timing performances with the performance-period market volatility.[10] The interaction of realized volatility during performance period and picking performance is negative — a one unit rise in standardized market volatility during performance quarter reduces *picking-fps* by 3.2 basis points or by about 20%. On the other hand, fund-flows become more sensitive to volatility timing performance as market volatility rises as seen through positive interaction. The *fps* for aggressive timing performance increases by 45 points or almost 60%. The *fps* for defensive volatility timing increases by 98 points almost by 150%. In fact, when realized market volatility is very low, then investor's reaction to defensive volatility timing as measured by flows *fps* is not even significant statistically. This provides a strong confirmation of the model prediction.

The results are robust to clustering the standard errors by fund and time both (Column 3).[11] In column 4, we estimate the specification within a fund. Results indicate that picking-fps is lower and timing-fps is higher for the same fund during higher-volatility periods compared to the lower-volatility periods. This addresses the concern that perhaps the underlying sample of funds which operate during volatile periods and non-volatile periods is inherently different due to entry-exit of the funds.

We also use two alternate measures of volatility – VIX index in column 5 and real-time recession probability index of Chauvet (1998) and Chauvet and Piger (2005). Both the measures are the averages of daily indexes over the quarter and further standardized. Using either of these measure, we find that picking-fps reduces while timing-fps increases with realized proxies of volatility. With a one unit rise in standardized recession index, picking-fps drops by 75% while *fps* to both types of timing performance rise enormously – the coefficients on interaction are multiples of the stand-alone coefficients.

If the picking and timing skills are correlated instead, the learning about timing skill feeds into learning about picking skill, resulting in a hump-shaped *picking-fps* as a function of market volatility. This is the complementarity in learning that our model features. In this case as the volatility rises moderately, performance of the manager reveals more about his timing skill, but also reveals little bit more about his picking skills. This leads to following prediction

**Prediction 2** (Complementarity in Learning)**.** *As the market volatility rises upto a threshhold, investors learn more about both timing and picking skills of the manager. Learning about picking skill reduces as the volatility rises beyond the threshold.*

[10]The market volatility refers to the volatility of CRSP Value-Weighted Index.

[11]As we absorb *Style* × *Quarter* fixed effects, if the true underlying time effects are constant across the style, then our time effects completely absorb the within-time correlation following Petersen (2009).

Table 2 documents the results. In column 1, we estimate the fps on sub-sample of performance-quarters where the realized market volatility is in the lowest quartile of the volatility distribution. The *picking-fps* is positive and has a positive interaction coefficient on realized volatility suggesting the spill-over in learning process. But as we re-estimate the *fps* over the performance quarters with quatiles 2-4 of the realized market volatility, the interaction of picking performance with volatility turns negative — suggesting that the spill-over in learning is dominated beyond the point. First two columns suggests that picking and timing skills are correlated and that *picking-fps* is hump-shaped in market volatility.

In column 3, we test the hypothesis more formally estimating a piecewise-linear regression. We construct our variables following Sirri and Tufano (1998). We chose bottom quartile of the volatility distribution as the cut-off and estimate the *fps* over two ranges of the volatility. To this end, we define two variables - $LOWVOL = \max{(a, \sigma_m)}$ where a is the $25^{th}$ percentile cut-off of the volatility distribution and $HIGHVOL$ is then defined as $HIGHVOL = \max{(0, \sigma_m - a)}$. Column 3 shows that *picking-fps* is positive till $\sigma_m < a$ while it turns negative after that cut-off. On the other hand, in column 4, we interact, *timing-fps* for both types with the LOWVOL and HIGHVOL. *Timing-fps* is rising over HIGHVOL for both types of timing performances. Column 5 shows that same results holds for alternate volatility measures such as VIX.

In summary, data shows strong support for the learning mechanism proposed by the model suggesting that investors do learn about multi-dimensions of the managerial skill across market states and further suggests that these two skills are correlated.

POLYNOMIAL RESULT??? WILL LOOK NICE THEORY == DATA Fps

The next set of predictions are in terms of state-contingent allocation of capital across funds. Learning about manager's skill pins down the reputation for a manager. But the value of each unit of timing skill is time-varying and state-dependent in the model. If the markets are expected to be volatile, then we should expect investors to provide capital to funds having higher timing reputation. In the model this shows up in two ways. First, conditional volatility magnifies the effect of learning on the flows. Recent change in the investor's estimate of timing skill is acted with a higher multiple if conditional volatility is high. Second, when conditional volatility rises, funds having acquired good timing reputation in the past receive more flows. This can be thought of as a mark-to-market adjustment to the fund size to reflect state of the market. We test both these hypothesis in the following two predictions

**Prediction 3** (Conditional Volatility and Flows)**.** *The timing-fps is higher (lower) during periods with higher (lower) conditional volatility, fixing the learning constant. Moreover, investors provide* *more (less) capital to the funds high (low) past/historic timing performance when conditional volatility rise.*

Table 3 test this prediction and report the evidence. We want to measure the conditional volatility at the time investors are making the capital flow adjustments. As a proxy, we consider the average VIX or real-time recession index during the first month of the flow-quarter. This implicitly assumes that capital reallocation in response to the quarterly performance happens primarily early during following quarter (the flow-quarter).[12] Column 1 reports the timing-fps interacted with proxy of conditional volatility using VIX index. Positive coefficient of 0.22 on the interaction between timing performance and the conditional volatility indicates that investors react more strongly to latest timing performance if timing skill is more useful in near future. Column 2 reports the same using first month's average of recession index as a proxy and again confirms the result with positive coefficient on the interaction.

The obvious concern with this baseline specification is that volatility is persistent. Hence, it is not clear if this interaction is picking up the effect of lagged volatility of conditional volatility. In other words, is this positive interaction a result of learning-channel due to high lagged volatility or a reflection of state-dependent usefulness of timing skill? To isolate these two channels, we perform two robustness. In column 3, we consider sub-sample of performance-quarters for which realized volatility is below mean. This suppresses the learning-channel in the sense that learning about timing skill is moderate. Even then, the conditional volatility interacts with timing performance positively. In column 4, we construct orthogonal component of conditional volatility with respect to lagged realized volatility and use only this orthogonal component of conditional volatility. The interaction between timing performance and conditional volatility is still positive. The overall evidence supports the capital re-allocation prediction. To test the second part of the prediction, we let theory guide construction of our measure of fund's timing reputation. Model suggests that investors learn more about fund's timing ability during the periods with high market volatility — the period in which manager had ample opportunity to generate timing value. Consistent with this, for a given quarter flow-quarter $t$, we define timing reputation as average of timing performance between quarter $t-9$ and $t-2$ provided the quarterly volatility was above the mean of in-sample distribution of the volatility.

Table 4 present the evidence. Column 1 regresses the fund flows on the lagged picking and timing performances alongwith timing reputation and its interaction with the conditional volatility measures introduced earlier. Timing reputation affects flows independently of recent performance

[12]Results are valid even if we consider average VIX/Volatility/Recession Index over entire flow-quarter on one end and over first one-week of the flow-quarter on the other.

with positive coefficient of 0.628. This is consistent with the overall evidence in the literature (De Andrade (2009), Glode (2011), Polkovnichenko, Wei, and Zhao (2019)) that investors prefer managers who can protect the downside risk or volatility better. But timing reputation affect flows even more so when conditional volatility is high. A one standard deviation increase in conditional volatility increases the reputation-fps by 31 basis points or by about half. This is the mark-to-market adjustment.

This result holds valid even after considering the interaction of recent timing performance with the conditional volatility (Column 2). In Column 3, we consider a more aggressive measure of timing reputation where average is taken only over the quarters where volatility in the performance-quarter was one standard deviation above the mean of the volatility distribution. The impact of this aggressive timing-reputation is even more during volatile periods. Overall, column 1-3 provide strong evidence that investors re-allocate capital to the funds having better timing/volatility management skills as exhibited by the past performances.

In columns 4-5, we exploit the prediction of the model using important economic/financial episodes over last decade to highlight the importance of timing reputation in explaining fund-flows. Column 4 interacts timing reputation with three such episodes; first is the Global financial crises (GFC) defined by Q3-Q4 of 2008 and Q1-Q2 of 2009, second is the European banking crises defined over Q3-Q4 of 2011 and third is the Taper tantrum episode spanning Q2-Q3 of 2013. As column 4 shows, the funds having good timing reputation received excess capital-flows during each of these episodes. The coefficient on interaction is economically significant — "90-10" percentile difference of timing reputation is 2.13 units implying that during GFC funds with $90^{th}$ percentile of timing reputation received 1.34% more capital quarterly or 5.36% annually relative to the funds with $10^{th}$ percentile of timing reputation.

In column 5, we test the model prediction in a novel way that helps deliver the main point of the model intuitively. For every fund operating during GFC period, we compute the average timing performance and label it as "Timing During GFC". Then we study the fund-flows to these funds during EU banking crises and Taper episode relative to the other years post GFC.[13] There are two important points. First is that the standalone coefficient on "Timing During GFC" of 0.534 indicates that funds having better timing performance during GFC are rewarded unconditionally in the years following GFC — again using "90-10" percentile difference in the GFC timing performance distribution generates a difference of 3.07% in annual fund-flows.

The second implication and closer to what model delivers is that the funds with better GFC timing performance experienced even higher fund-flows during EU banking crises and Taper episodes.

[13] Hence the sample for the last column is restricted to $year > 2009$

In fact during Taper, “90-10” percentile difference in the GFC timing performance distribution generates a difference of 5.70% of fund-flows over the two quarters of Tape or expressed annually the difference in flows is to the tune of 11%. This results highlights the important mechanism of the model — as the volatility and uncertainty in the market rises, investors shift their capital even more towards those funds which are known to be good volatility managers. This also shows that investors have long memory. The performance during 2008 matters even after 5 years during Taper episode.

# 5 Concluding Remarks

# Appendix A: Proofs

**Proof of Lemma 1**. In equilibrium, the net expected net returns must equal zero, given the investor information set: $\mathbb{E}_t^I[r_{it+1}] = 0$. Also given that with respect to investor's information set, market is conditionally zero mean, we have that $\mathbb{E}_{t,I}\left(f_{t+1}^2\right) = \sigma_{t,I}^2\left(f_{t+1}\right) = \sigma_t^2$. Taking expectation of equation 9, we get

$$
\begin{aligned}
E_t^I\left(r_{it+1}\right) &= \alpha_t + \psi_t E_t^I(f_{t+1}^2) - \frac{1}{\eta}q_t - k && \text{(A.1)}\\
&= \alpha_t + \psi_t \sigma_t^2 - \frac{1}{\eta}q_t - k && \text{(A.2)}
\end{aligned}
$$

where we used the fact that with respect to investor's information set, market return is conditionally mean zero. Hence $\mathbb{E}_t^I\left(f_{t+1}^2\right) = \sigma_{t,I}^2\left(f_{t+1}\right) = \sigma_t^2$. Setting $E_t^I\left(r_{it+1}\right)$ equal to zero and solving for $q_t$ gives equation 11 $\square$

**Proof of Lemma 2**. The proof of this lemma is a direct application of projection theorem of of the jointly normally distributed variables. If $(Z, X)$ are jointly normal as follows

$$
\begin{pmatrix} Z \\ X \end{pmatrix} = \left[\begin{pmatrix} \overline{Z} \\ \overline{X} \end{pmatrix} \quad \begin{pmatrix} \Sigma_{zz} & \Sigma_{zx} \\ \Sigma_{xz} & \Sigma_{xx} \end{pmatrix}\right]
$$

then the mean and variance of Z conditional on X is given by

$$
\begin{aligned}
\mathbb{E}\left(Z|x\right) &= \overline{Z} + \Sigma_{zx}\Sigma_{xx}^{-1}\left(x - \overline{X}\right)\\
\mathbb{V}\mathrm{ar}\left(Z|x\right) &= \Sigma_{zz} - \Sigma_{zx}\Sigma_{xx}^{-1}\Sigma_{xz}
\end{aligned}
$$

The fund's gross returns given the priors are normally distributed

$$
\begin{aligned}
R_{t+1}|priors_t, g_{t+1} &\sim N\left(\overline{R}_{t+1}, \Sigma_{Rt+1}\right)\\
\text{where} \quad \Sigma_{Rt+1} &= \sigma_{\alpha t}^2 + g_{t+1}\sigma_{\psi,t}^2 + 2g_{t+1}\sigma_{\alpha\psi t} + \sigma_\varepsilon^2\\
\overline{R}_{t+1} &= \alpha_t + \psi_t g_{t+1}
\end{aligned}
$$

Taking $Z = (\alpha, \psi)'$, $X = R_{t+1}$ and denoting $\mathcal{I}_{t+1} = \{g_{t+1}, priors_t\}$ the investor's information set at the end of time $t+1$ the application of Projection theorem above yields

$$
\mathbb{E}\left( \begin{array}{c} \alpha \\ \psi \end{array} \middle| \mathcal{I}_{t+1} \right) = \begin{pmatrix} \alpha_t \\ \psi_t \end{pmatrix} + \begin{pmatrix} \Sigma_{\alpha,R_{t+1}} \\ \Sigma_{\psi,R_{t+1}} \end{pmatrix} \times \frac{1}{\Sigma_{Rt+1}} \times \left(R_{t+1} - \overline{R}_{t+1}\right)
$$

where $\Sigma_{\alpha R_{t+1}}$ gives the covariance between $\alpha$ and $R_{t+1}$ conditional on $\mathcal{I}_{t+1}$ and similarly $\Sigma_{\psi,R_{t+1}}$ gives the conditional covariance between $\psi$ and $R_{t+1}$. In the equilibrium using equation 11 we have

$$\begin{aligned}
R_{t+1} - E_t^I\left(R_{t+1}\right) &= r_{t+1} + \frac{1}{\eta}q_t + k - \left(\alpha_t + \psi_t\sigma_t^2\right) && \text{(A.3)}\\
&= r_{t+1} + \frac{1}{\eta}q_t - \left(\frac{1}{\eta}q_t + \psi_t\left(g_{t+1} - \sigma_t^2\right)\right) && \text{(A.4)}\\
&= r_{t+1} - \psi_t\left(g_{t+1} - \sigma_t^2\right) && \text{(A.5)}
\end{aligned}$$

Denoting $\frac{\Sigma_{\alpha,R_{t+1}}}{\Sigma_{Rt+1}} \equiv \lambda_{\alpha t+1}$ and $\frac{\Sigma_{\psi,R_{t+1}}}{\Sigma_{Rt+1}} \equiv \lambda_{\psi t+1}$, we obtain

$$\begin{aligned}
\mathbb{E}\left(\alpha|\mathcal{I}_{t+1}, R_{t+1}\right) &= \alpha_{t+1} = \alpha_t + \lambda_{\alpha t+1}\left[r_{t+1} + \psi_t\left(g_{t+1} - \sigma_t^2\right)\right] && \text{(A.6)}\\
\mathbb{E}\left(\psi|\mathcal{I}_{t+1}, R_{t+1}\right) &= \psi_{t+1} = \psi_t + \lambda_{\psi t+1}\left[r_{t+1} + \psi_t\left(g_{t+1} - \sigma_t^2\right)\right] && \text{(A.7)}
\end{aligned}$$

These are our belief update equations 13 and 14 Substituting the equilibrium size in the above equation we get

$$\begin{aligned}
q_{t+1} - q_t &= \eta\left(\alpha_{t+1} + \psi_{t+1}\sigma_{t+1}^2\right) - \eta\left(\alpha_t + \psi_t\sigma_t^2\right)\\
&= \eta\left[\Delta\alpha_{t+1} + \Delta\psi_{t+1}\sigma_{t+1}^2 + \psi_t\Delta\sigma_{t+1}^2\right]\\
&= \eta\left[\left(\lambda_{\alpha t+1} + \lambda_{\psi t+1}\sigma_{t+1}^2\right)\left(r_{t+1} - \psi_t\left(g_{t+1} - \sigma_t^2\right)\right) + \psi_t\left(\sigma_{t+1}^2 - \sigma_t^2\right)\right]
\end{aligned}$$

where in the last line we used the belief-update equations 13 and 14 to arrive at equation 17. Next we derive the explicit expressions for $\lambda_{\alpha t+1}$ and $\lambda_{\psi t+1}$

$$\begin{aligned}
\mathbb{C}\text{ov}\left(\Sigma_{\alpha,R_{t+1}}|\mathcal{I}_{t+1}\right) &= \mathbb{C}\text{ov}\left(\alpha_t + \psi_t g_{t+1}, \alpha_t\right) && \text{(A.8)}\\
&= \sigma_{\alpha t}^2 + \sigma_{\alpha\psi t}g_{t+1} && \text{(A.9)}
\end{aligned}$$

and similarly

$$\begin{aligned}
\mathbb{C}\text{ov}\left(\Sigma_{\psi,R_{t+1}}|\mathcal{I}_{t+1}\right) &= \mathbb{C}\text{ov}\left(\alpha_t + \psi_t g_{t+1}, \psi_t\right) && \text{(A.10)}\\
&= \sigma_{\alpha\psi t} + \sigma_{\alpha t}^2 g_{t+1} && \text{(A.11)}
\end{aligned}$$

This completes the proof. □

**Proof of Lemma 3**. Consider the symmetric case with $\sigma_{\alpha t} = \sigma_{\psi t} \equiv \sigma_t$ and let the correlation between $\alpha$ and $\psi$ be denoted by $\rho$. Taking the derivative of sensitivities with respect to $g_{t+1}$ gives

$$\frac{\partial\lambda_{\alpha t+1}}{\partial g_{t+1}} = \frac{\rho_{\alpha\psi}\sigma_t^2}{\Sigma_{Rt+1}} - \sigma_t^2\left(1 + g_{t+1}\rho_{\alpha\psi}\right)\underbrace{\left(\frac{\partial\Sigma_{Rt+1}}{\partial g_{t+1}}\right)\left(\frac{1}{\Sigma_{Rt+1}^2}\right)}_{\equiv\ x} \tag{A.12}$$

Similarly

$$\frac{\partial\lambda_{\psi t+1}}{\partial g_{t+1}} = \frac{\sigma_t^2}{\Sigma_{Rt+1}} - \sigma_t^2\left(g_{t+1} + \rho_{\alpha\psi}\right)x \tag{A.13}$$

Setting the respective derivatives to zero and denote by $g_{t+1}^{\alpha}$ and $g_{t+1}^{\psi}$ the levels of $g_{t+1}$ which satisfies this first order condition

$$\begin{aligned} g_{t+1}^{\alpha} &= \frac{1}{x\Sigma_{\alpha R_{t+1}}} - \frac{1}{\rho_{\alpha\psi}} \\ g_{t+1}^{\psi} &= \frac{1}{x\Sigma_{\alpha R_{t+1}}} - \rho_{\alpha\psi} \end{aligned}$$

Hence

$$g_{t+1}^{\alpha} < g_{t+1}^{\psi} \iff -\frac{1}{\rho_{\alpha\psi}} < -\rho_{\alpha\psi} \iff \frac{1}{\rho_{\alpha\psi}} > \rho_{\alpha\psi}$$

This is clearly holds for any value of $\rho_{\alpha\psi} \in (0,1)$. Hence, the maximum of picking-fps occurs before the maximum of timing-fps. when $\sigma_{\alpha\psi t} = 0$, then from equation A.12 it is clear that $\frac{\partial\lambda_{\alpha t+1}}{\partial g_{t+1}} < 0$, and $\lambda_{\alpha t+1}$ achieves its maximal when $g_{t+1} = 0$ and then decreases monotonically. At $g_{t+1} = 0$, $\lambda_{\psi t+1} = 0$ The last part of the proof compares the scale of picking and timing sensitivities with each other. Consider the symmetric case as before with $\sigma_{\alpha t} = \sigma_{\psi t} \equiv \sigma_t$. Substituting this in the definition of $\lambda_{\alpha t+1}$ and $\lambda_{\psi t+1}$. we get

$$\lambda_{\alpha t+1} = \frac{\sigma_t^2 \left(1 + g_{t+1}\rho_{\alpha\psi}\right)}{\Sigma_{Rt+1}} \tag{A.14}$$

$$\lambda_{\psi t+1} = \frac{\sigma_t^2 \left(g_{t+1} + \rho_{\alpha\psi}\right)}{\Sigma_{Rt+1}} \tag{A.15}$$

Hence, $\lambda_{\alpha t+1} > \lambda_{\psi t+1} \iff g_{t+1} < 1$ (provided $\rho_{\alpha\psi} \neq 1$). This completes the proof

□

# Appendix B: Tables

## Table 1: Market State and Learning

This table reports the quarterly flow-sensitivity to the picking and timing performance. The performance is estimated from a CAPM factor model implemented via Kalman filer model allowing for daily variation in fund's beta. Timing is defined as the coefficient of the regression of daily estimated CAPM betas on the market excess returns. Picking is the residual after netting out the timing and passive market returns from the total fund returns for the quarter. Market volatility and VIX are standardized and one unit of each represents one standard deviation. Columns 1-5 absorb $Style \times Time$ fixed effects and column 6 control for Fund and Time fixed effects. All the columns excepting column 5 cluster the standard errors at Fund level. In column 5 standard errors are clustered at fund and time level. for All errors are clustered at $Firm \times Month$ level. Superscripts ***, ** ,* indicate significance at the 1%, 5%, and 10% level.

| | Flows % | | | | | |
|---|---|---|---|---|---|---|
| Volatility Measure | | Market Vol | | | VIX | Recession Index |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Picking (-1) | 0.157*** | 0.158*** | 0.158*** | 0.138*** | 0.157*** | 0.168*** |
| | (0.008) | (0.009) | (0.016) | (0.009) | (0.009) | (0.009) |
| Level Timing (-1) | 0.569*** | 0.706*** | 0.706*** | 0.589*** | 0.674*** | 0.523*** |
| | (0.033) | (0.040) | (0.073) | (0.038) | (0.038) | (0.033) |
| Vol Timing (-1) | 1.040** | 0.615 | 0.615 | -0.376 | 0.589 | 0.411 |
| | (0.473) | (0.512) | (1.096) | (0.639) | (0.508) | (0.527) |
| Picking × Volatility (-1) | | -0.032*** | -0.032** | -0.031*** | -0.023*** | -0.118*** |
| | | (0.008) | (0.013) | (0.008) | (0.008) | (0.031) |
| Level Timing × Volatility (-1) | | 0.458*** | 0.458*** | 0.314*** | 0.336*** | 0.882*** |
| | | (0.052) | (0.092) | (0.048) | (0.043) | (0.163) |
| Vol Timing × Volatility (-1) | | 0.989*** | 0.989*** | 1.069*** | 1.015*** | 3.564*** |
| | | (0.241) | (0.349) | (0.277) | (0.228) | (1.107) |
| Log Assets (-1) | -0.070** | -0.068* | -0.068 | -2.423*** | -0.069** | -0.071** |
| | (0.035) | (0.035) | (0.041) | (0.118) | (0.035) | (0.035) |
| Log Fund Age (-1) | -1.913*** | -1.923*** | -1.923*** | -5.119*** | -1.924*** | -1.917*** |
| | (0.081) | (0.081) | (0.111) | (0.273) | (0.081) | (0.081) |
| Turnover (-1) | -0.101 | -0.072 | -0.072 | 0.199 | -0.073 | -0.093 |
| | (0.088) | (0.087) | (0.124) | (0.163) | (0.087) | (0.088) |
| Expense Ratio (-1) | -0.065 | -0.065 | -0.065 | 0.386 | -0.069 | -0.071 |
| | (0.209) | (0.206) | (0.222) | (0.266) | (0.207) | (0.209) |
| Flows (-1) | 0.252*** | 0.252*** | 0.252*** | 0.200*** | 0.252*** | 0.252*** |
| | (0.008) | (0.008) | (0.012) | (0.008) | (0.008) | (0.008) |
| Fixed Effects | Style×Time | Style×Time | Style×Time | Fund, Time | Style×Time | Style×Time |
| Clustering | Fund | Fund | Fund, Time | Fund | Fund | Fund |
| Fund-Quarters | 127957 | 127957 | 127957 | 127952 | 127957 | 127957 |
| Adj R-Sq | 0.129 | 0.130 | 0.130 | 0.171 | 0.130 | 0.130 |

## Table 2: Complementarity in Learning (High Frequency Model)

This table reports the quarterly piece-wise linear estimation of flow-sensitivity to the picking and timing performance conditional on of various measures of volatility/uncertainty. The performance is estimated from a CAPM factor model implemented via Kalman filer model allowing for daily variation in fund's beta. Timing is defined as the coefficient of the regression of daily estimated CAPM betas on the market excess returns. Picking is the residual after netting out the timing and passive market returns from the total fund returns for the quarter. Market volatility and VIX are expressed in units of its standard deviation. For a given threshhold $k$ for any random variable $x$, $LOWx = \min(x, K)$ and $HIGHx = (x - K)\,\mathbb{1}(x > K)$. K corresponds to the $25^{th}$ percentile of the respective distribution of market volatility and vix for the purpose of defining LOW and HIGH segments. All the models include Style×Time fixed effects. All the columns cluster the standard errors at Fund level. Superscripts ***, ** ,* indicate significance at the 1%, 5%, and 10% level.

| | Flows % | | | | |
|---|---|---|---|---|---|
| Volatility Measure | Market Volatility | | | | VIX |
| Quartiles of Lagged Volatility | Bottom (Q1) | Non-Bottom (Q2-Q4) | | | |
| | (1) | (2) | (3) | (4) | (5) |
| Picking (-1) | 0.362*** | 0.172*** | 0.012 | 0.053 | 0.105*** |
| | (0.103) | (0.010) | (0.039) | (0.039) | (0.039) |
| Picking×Volatility (-1) | 0.266** | -0.045*** | | | |
| | (0.125) | (0.009) | | | |
| Level Timing (-1) | 0.351*** | 0.695*** | 0.567*** | | 0.566*** |
| | (0.046) | (0.042) | (0.033) | | (0.033) |
| Volatility Timing (-1) | 0.307 | 1.559*** | 1.221** | | 1.161** |
| | (0.839) | (0.539) | (0.474) | | (0.475) |
| Picking×LOWVOL(-1) | | | 0.409*** | 0.315*** | 0.188** |
| | | | (0.091) | (0.091) | (0.095) |
| Picking×HIGHVOL(-1) | | | -0.042*** | -0.044*** | -0.026*** |
| | | | (0.009) | (0.009) | (0.008) |
| Level Timing×LOWVOL(-1) | | | | 0.934*** | |
| | | | | (0.093) | |
| Level Timing×HighVOL(-1) | | | | 0.417*** | |
| | | | | (0.060) | |
| Vol Timing×LOWVOL(-1) | | | | -1.093 | |
| | | | | (1.573) | |
| Vol Timing×HighVOL(-1) | | | | 1.150*** | |
| | | | | (0.272) | |
| Log Assets (-1) | 0.006 | -0.093** | -0.070** | -0.067* | -0.071** |
| | (0.077) | (0.037) | (0.035) | (0.035) | (0.035) |
| Log Fund Age (-1) | -2.212*** | -1.822*** | -1.912*** | -1.919*** | -1.915*** |
| | (0.151) | (0.086) | (0.081) | (0.081) | (0.081) |
| Turnover (-1) | -0.267* | -0.063 | -0.104 | -0.071 | -0.101 |
| | (0.153) | (0.097) | (0.088) | (0.087) | (0.088) |
| Expense Ratio (-1) | -0.059 | -0.072 | -0.068 | -0.063 | -0.069 |
| | (0.560) | (0.136) | (0.208) | (0.206) | (0.208) |
| Flows (-1) | 0.221*** | 0.264*** | 0.252*** | 0.252*** | 0.252*** |
| | (0.013) | (0.009) | (0.008) | (0.008) | (0.008) |
| Style*Time FE | Y | Y | Y | Y | Y |
| Fund-Quarters | 31526 | 94907 | 127957 | 127957 | 127957 |
| Adj R-Sq | 0.104 | 0.138 | 0.129 | 0.130 | 0.129 |

## Table 3: Conditional Volatility and Capital Reallocation

This table reports the quarterly estimation of flow-sensitivity to the lagged picking and timing performance as a function of conditional volatility. The performance is estimated from a CAPM factor model implemented via Kalman filer model allowing for daily variation in fund's beta. Timing is defined as the coefficient of the regression of daily estimated CAPM betas on the market excess returns. Picking is the residual after netting out the timing and passive market returns from the total fund returns for the quarter. Conditional volatility is proxied by the average VIX and recession index in the first month of the quarter in which flows are measured in columns 1, 3. Column 2 uses average recession index in the first month of the quarter in which flows are measured. Column 3 estimates column 1 on sub-sample of data where VIX in the performance measurement period is below mean. Column 4 residualizes the first-month's average VIX with respect to average VIX over performance measurement period. All the models include Style×Time fixed effects. All the columns cluster the standard errors at Fund level. Superscripts ***, ** ,* indicate significance at the 1%, 5%, and 10% level.

| | Flows % | | | |
|---|---|---|---|---|
| Measure of Conditional Volatility | VIX | | | Recession Index |
| | | $VIX(-1) < Mean$ | VIX Shock | |
| | (1) | (2) | (3) | (4) |
| Picking (-1) | 0.152*** | 0.176*** | 0.156*** | 0.156*** |
| | (0.008) | (0.013) | (0.008) | (0.008) |
| Level Timing(-1) | 0.633*** | 0.667*** | 0.571*** | 0.584*** |
| | (0.035) | (0.063) | (0.033) | (0.034) |
| Volatility Timing(-1) | 0.070 | -1.357 | 1.062** | 0.577 |
| | (0.506) | (1.674) | (0.473) | (0.499) |
| Level Timing(-1)× Conditional Volatility | 0.250*** | 0.416*** | 0.137*** | 0.138*** |
| | (0.035) | (0.083) | (0.048) | (0.039) |
| Volatility Timing(-1)× Conditional Volatility | 1.873*** | -1.238 | 1.664*** | 0.796*** |
| | (0.308) | (2.120) | (0.587) | (0.273) |
| Log Assets (-1) | -0.066* | -0.064 | -0.069** | -0.070** |
| | (0.035) | (0.047) | (0.035) | (0.035) |
| Log Fund Age (-1) | -1.918*** | -2.222*** | -1.913*** | -1.913*** |
| | (0.080) | (0.105) | (0.081) | (0.081) |
| Turnover (-1) | -0.069 | -0.260** | -0.098 | -0.095 |
| | (0.087) | (0.113) | (0.088) | (0.088) |
| Expense Ratio (-1) | -0.059 | 0.005 | -0.063 | -0.065 |
| | (0.208) | (0.297) | (0.209) | (0.209) |
| Flows (-1) | 0.252*** | 0.243*** | 0.252*** | 0.252*** |
| | (0.008) | (0.010) | (0.008) | (0.008) |
| Style×Time FE | Y | Y | Y | Y |
| Fund-Quarters | 127957 | 80063 | 127957 | 127957 |
| Adj R-Sq | 0.130 | 0.118 | 0.129 | 0.129 |

## Table 4: Past Timing Reputation and Flows During Crises Periods

This table reports the quarterly estimation of flow-sensitivity to the picking and timing performance conditional timing reputation. Conditional volatility is proxied by the average VIX during first month of the period for which flows are measured in columns 1-3. In all the columns (except column 3), Timing reputation for a given quarter $t$ is the average of timing performance over all the quarters between quarters $t-9$ to $t-2$ for which VIX was above mean. In column 3, the average is conditional on quarter having Vix at least one-$\sigma$ above its mean. $\mathbb{1}(GFC)$ indicates Q3-Q4 of 2008a and Q1-Q2 of 2009 and captures the period corresponding to Global Financial Crises. $\mathbb{1}(EUBankingCrises)$ indicates dummy for EU banking crises defined by Q3-Q4 of 2011 and $\mathbb{1}(Taper)$ is a dummy for Taper Tantrum episode defined over Q2-Q3 of 2013. "Timing During GFC" indicates the average timing performance of a fund during GFC period. All the models include Style×Time fixed effects. All the columns cluster the standard errors at Fund level. Superscripts ***, ** ,* indicate significance at the 1%, 5%, and 10% level.

| | Flows % | | | | | |
|---|---|---|---|---|---|---|
| Rolling Timing | Level Timing | | | Volatility Timing | | |
| Sample | | | Post GFC | | | Post GFC |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Picking(-1) | 0.148*** | 0.147*** | 0.133*** | 0.125*** | 0.126*** | 0.116*** |
| | (0.009) | (0.009) | (0.015) | (0.009) | (0.009) | (0.015) |
| Vol Timing (-1) | 1.527*** | 1.584*** | 1.665** | -0.969 | 0.253 | -0.090 |
| | (0.488) | (0.495) | (0.678) | (0.636) | (0.529) | (0.806) |
| Level Timing(-1) | 0.533*** | 0.534*** | 0.468*** | 0.568*** | 0.574*** | 0.519*** |
| | (0.038) | (0.038) | (0.040) | (0.038) | (0.038) | (0.040) |
| Timing(-9,-2) | 0.729*** | 0.668*** | | 4.790*** | 4.795*** | |
| | (0.061) | (0.060) | | (0.715) | (0.755) | |
| Timing(-9,-2)×Conditional Vol | 0.322*** | | | 3.922*** | | |
| | (0.054) | | | (1.038) | | |
| Timing(-9,-2)×$\mathbb{1}$(GFC) | | 0.617*** | | | 7.772** | |
| | | (0.231) | | | (3.855) | |
| Timing(-9,-2)×$\mathbb{1}$(European Crises) | | 1.365*** | | | 7.068 | |
| | | (0.442) | | | (5.888) | |
| Timing(-9,-2)×$\mathbb{1}$(Covid) | | -2.079*** | | | 11.812** | |
| | | (0.639) | | | (4.939) | |
| GFC Timing | | | 1.047*** | | | 1.480*** |
| | | | (0.134) | | | (0.467) |
| GFC Timing×Conditional Volatility | | | 0.567*** | | | 3.044*** |
| | | | (0.159) | | | (0.667) |
| Log Assets (-1) | -0.087** | -0.076* | -0.096** | -0.070* | -0.069* | -0.086* |
| | (0.039) | (0.039) | (0.048) | (0.039) | (0.039) | (0.048) |
| Log Fund Age (-1) | -1.505*** | -1.505*** | -0.950*** | -1.559*** | -1.556*** | -1.003*** |
| | (0.087) | (0.087) | (0.142) | (0.088) | (0.088) | (0.143) |
| Turnover (-1) | -0.080 | -0.069 | -0.120 | -0.080 | -0.089 | -0.275* |
| | (0.098) | (0.098) | (0.151) | (0.098) | (0.098) | (0.150) |
| Expense Ratio (-1) | 0.153 | 0.156 | -0.423* | 0.154 | 0.156 | -0.417* |
| | (0.233) | (0.235) | (0.232) | (0.233) | (0.233) | (0.235) |
| Flows (-1) | 0.266*** | 0.267*** | 0.189*** | 0.270*** | 0.270*** | 0.191*** |
| | (0.010) | (0.010) | (0.014) | (0.010) | (0.010) | (0.014) |
| Style×Time FE | Y | Y | Y | Y | Y | Y |
| Fund-Quarter Obs | 91625 | 91625 | 53631 | 91625 | 91625 | 53631 |
| Adj R-Dq | 0.125 | 0.125 | 0.062 | 0.124 | 0.124 | 0.061 |

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