The Allocation of Talent Across Mutual Fund Strategies

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Abstract

We propose a theory of mutual fund managers self-selection into stock “picking” and market “timing”. Since a picking strategy entails making multiple idiosyncratic bets, while a timing strategy betting on the aggregate market, investors can more easily learn about the skill of a picker than of a timer. With adverse selection, the equilibrium allocation of talent across strategies is such that high-skill managers always pick, while low-skill managers time with positive probability. We confirm in the data the predictions that pickers generate more value, are larger, and exhibit higher flow-performance sensitivity than timers, and that a rise in aggregate volatility skews the allocation of talent by inducing a higher fraction of low-skill managers to time the market.

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1 Introduction

Mutual fund managers seek to generate value for their shareholders through stock picking and market timing. These are distinct strategies: picking requires a manager to acquire and analyze information about individual stocks, while timing requires a manager to analyze the general market environment. Funds differ in their reliance on picking or timing strategies, and this naturally gives rise to different mutual fund styles. For example, value funds, which invest in stocks trading at a discount relative to their fundamentals, rely on picking to create value for their shareholders. In contrast, global macro funds, which predict broad macro-economic trends like interest rates and commodity prices, rely on market timing to create value for their shareholders.

Despite the volume of literature exploring whether mutual fund managers are skilled and add value for their investors (e.g., Grinblatt and Titman (1989); Gruber (1996); Chen, Narasimhan, and Wermers (2000); Fama and French (2010); Bollen and Busse (2001); Elton, Gruber, and Blake (2012); Berk and van Binsbergen (2015)), little is known about how managers choose which strategy to adopt. Our paper complements this literature by developing a deeper understanding of managers’ choice of strategy depends on investment skill. Why do certain managers choose picking strategies and others choose timing? If the two strategies differ in terms of their ability to showcase managerial skill, then managers with different skills might optimally self-select into one of the strategies. How does such self-selection affect the observed performance of the two strategies? These questions are largely unanswered, and our paper aims to answer them.

To this end, we propose a dynamic theory of fund managers’ self-selection of picking and timing strategies. Our theory of self-selection exploits a difference in the correlation between investments that constitute a picking strategy, and those that are part of a timing strategy. Because a picking strategy entails making multiple investments or bets on the idiosyncratic components of various stocks, the returns on these investments represent independent signals about the manager’s skill, which investors try to infer by observing fund performance. In contrast, a timing strategy requires a fund manager to predict fluctuations of the aggregate market, or of a specific sector, or factors. The returns on timing investments are thus positively correlated, as they are driven by a common component, and the corresponding fund performance conveys a noisier signal to investors. For this reason, compared to timing strategies, picking strategies reveal more information about the skill of the fund manager. We exploit this distinguishing feature to answer our questions.

1 Even within a narrow mandate like that of growth funds, managers that try to identify profitable growth stocks and hence undertake a picking strategy are distinguishable from those who time the benchmark by betting against the fluctuations of a growth index.
We embed our dynamic theory of fund managers’ self-selection into strategies within an equilibrium setting with endogenous fund flow, in the spirit of [Berk and Green (2004)]. We consider a representative fund manager whose investment skill can be high or low. While the manager knows her own skill, it is unknown to a representative investor, who tries to infer it by observing the manager’s performance. A skilled manager, in expectation, delivers a better performance, since investment skill positively affects the expected returns on investments. Besides observing the manager’s performance, the investor also observes the strategy employed by the manager (picking vs. timing), and updates his beliefs about her skill in a Bayesian way.²

Whether the manager chooses to be a picker or a timer, we assume that she takes \( n \) bets to implement her chosen strategy. However, while picking bets are assumed to be independent of each other (reflecting their idiosyncratic nature), timing bets are positively correlated with each other. Intuitively, the correlation structure among timing bets can arise through a common aggregate component that drives their returns. Allowing for mixed-strategies, we characterize a hybrid semi-separating equilibrium in which a high-skill manager chooses a picking strategy with probability 1, and a low-skill manager always chooses a timing strategy with positive probability. The intuition for the equilibrium self-selection is as follows.

A high-skill manager always chooses the investment strategy that allows her to better reveal her skill. This is achieved by picking, because a high-skill manager expects to perform well, and because the performance of a picking strategy delivers a more informative signal to the investor. A low-skill manager, instead, has the incentive to hide her lesser investment ability from the investor. To achieve this, she can either hide behind the high-skill manager by picking (“pool by picking”), or she can hide behind a noisier strategy by timing. Pooling by picking has the benefit of rewarding a low-skill manager with a disproportional boost to her reputation following a good performance because, in equilibrium, the investor may mistake her for a high-skill manager. At the same time, picking is risky and exposes her to drastic damage to reputation following poor performance. Adopting a timing strategy, instead, has the benefit of being less revealing, and thus tends to preserve the manager’s reputation even after poor performance. However, it also makes it difficult for the manager to boost her reputation when there is a good performance. In equilibrium, a low-skill manager balances these tradeoffs, resulting in a mixed strategy.

²We provide empirical evidence in support of our assumption that fund investors know the fund strategy (picking vs. timing). Specifically, we document that fund flows are more sensitive to the component of fund performance associated with the fund’s core strategy. Our evidence is also consistent with the fact that fund managers communicate their strategy throughout regulatory reporting cycles. Prospectuses, statements of additional information, annual and semi-annual reports, all contain information that allows investors to reasonably understand the nature of the strategy employed by the fund managers.
Using CRSP data on mutual funds for the period 1999-2017, we first test that the equilibrium delivering a self-selection mechanism in the model holds true in the data. We use a factor model in the spirit of [Treynor and Mauzy (1966)] and [Bollen and Busse (2001)] to extract the picking and timing values generated by a fund in a given year. We then use these values, together with their statistical significance, to classify any funds as pickers or timers and to assign them a continuous measure between 0 and 1 capturing their degree of picking (dop). The data confirms that high-skill managers, identified as managers who are at the top of the distribution of the average risk-adjusted total value generated over the entire sample period, are more likely to be pickers than timers. The likelihood of picking in a given year is about 40% for low-skill managers, and about 85% for high-skill managers. Moreover, we provide novel evidence that investors’ capital flows respond more to the performance generated by a fund’s core strategy, suggesting that on average investors have the ability to identify these strategies.

Given the endogenous choice of the investment strategy by managers of different skill levels, our model delivers a rich set of predictions. The equilibrium self-selection has immediate implications for the relative performance of picking and timing strategies. Specifically, since high-skill managers self-select into picking strategies, pickers should, on average, outperform timers. We document this in the data, and estimate that the outperformance by pickers is in the range of 6% to 12% per year, in terms of risk-adjusted return, and around $25 million per year, in terms of real dollar value. Given that, in equilibrium, some low-skill managers try to “pool by picking,” the model also predicts that the cross-sectional dispersion of performance across pickers should be higher than that across timers. In the data, the average cross-sectional dispersion of performance across pickers over the sample period is 6.47% while the average cross-sectional dispersion across timers is only 4.19%, and this difference is statistically significant.

Our theory has additional implications for fund flows and fund size. In particular, our model predicts that investors’ capital flows should be more sensitive to the performance associated with picking strategies than with timing strategies, because a manager’s skill is less accurately revealed by a timing strategy. Moreover, picking funds should, on average, be larger than timing funds, since pickers on average are more skilled, and hence receive more capital in equilibrium. In our empirical investigation, we show that the fund flow sensitivity to performance can be twice as large for picking funds, and we confirm that, after controlling for other fund characteristics, picking funds are approximately 60% larger than timing funds.

We also emphasize some dynamic aspects of our model. Our equilibrium shows that, as the reputation of a low-skill manager improves, the probability that this manager adopts a timing strategy increases. Since capital flows are less sensitive to the performance of timing strategies,
being a timer allows a low-skill manager to preserve her current reputation, which is particularly desirable when her reputation is high. We test this dynamic prediction in the data using a first-difference model to trace the changes in fund reputation. Our measure $dop$, capturing a fund’s degree of picking, reduces on average by almost 40% as the reputation of a low-skill manager improves from the lowest 30% to the highest 30%. Moreover, in line with the idea that switching between strategies maybe be easier for funds belonging to large fund families (where funds have access to a variety of sources of information), we show that the change in the degree of picking, due to a change in reputation, is significantly higher for these funds.

Finally, we extend the model by introducing time-variation in aggregate volatility and generate the following predictions. Since high aggregate volatility increases the correlation among timing bets (e.g., Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016); Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016)), it makes timing strategies more desirable for low-skill managers. This is because a higher correlation among timing bets translates into a noisier signal conveyed by the fund performance. We confirm this finding in the data and show that a rise in aggregate volatility reduces the likelihood of picking for low-skill managers by almost 28%, that is, going from 58% when volatility is low to 30% when it is high. As a cross-sectional implication, the average skill within the group of timers decreases during periods of high aggregate volatility, whereas it increases within the group of pickers. We uncover that in these volatile periods the estimated timing skill of timers decreases by 50%, while the estimated picking skill of pickers (i.e., $\alpha$) increases by almost 4% per year.

1.1 Related Literature

The mutual fund literature has focused extensively on the measurement of skill in the industry, but has obtained mixed results. On one hand, Gruber (1996) documents that the performance of actively managed funds is inferior to that of index funds. In the same vein, Fama and French (2010) shows that only a very few actively managed funds exhibit sufficiently large risk-adjusted returns to cover their costs to investors. On the other hand, Berk and van Binsbergen (2015) finds that the average mutual fund adds $2 million per year, and that this skill persists over 10 years. Chen, Narasimhan, and Wermers (2000) documents that the stocks bought by mutual funds outperform the stocks sold by mutual funds. Grinblatt and Titman (1989) documents the existence of skill for small and growth funds. Glode (2011) provides a theory that investors value mutual fund performance differently across states. Since mutual funds tend to outperform in recession, investors are willing to invest in these funds despite their negative average net-performance.
Many papers in this literature also attempt to decompose fund skill into stock picking and market timing. Distinguishing between these two skill-sets is important, because the presence of market timing can distort the measurement of a manager’s picking ability, as discussed in Dybvig and Ross (1985) and Elton, Gruber, and Blake (2012). Treynor and Mauzy (1966) and Henriksson and Merton (1981) formulate a parametric factor model to estimate timing skills. Following their approach, Busse (1999) and Bollen and Busse (2001) find evidence of timing skill and show that mutual funds are able to time market volatility. Using high frequency holding data, Elton, Gruber, and Blake (2012) also supports the presence of timing abilities, while Mamaysky, Spiegel, and Zhang (2008) finds some timing skill using Kalman filtering. Also Goetzmann, Ingersoll, and Ivkovic (2000), which proposes an adjustment to correct the bias arising from monthly measurement of daily timing, documents that mutual funds exhibit timing ability. However, several others papers in this literature find no evidence of timing skills. Examples include Ferson and Schadt (1996), Graham and Harvey (1996), Daniel, Grinblatt, Titman, and Wermers (1997), and Kacperczyk and Seru (2007). The contribution of this paper is that it goes beyond issues of measurement, and proposes an economic mechanism to understand the determinants that induce a fund manager to choose a particular investment strategy. Our model of self-selection predicts that picking, on average, creates more value than timing since only low-skill managers self-select into timing strategies. This helps explaining the persistent lack of timing skill documented in the literature.

Our paper is closely related to the seminal contributions by Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) that, to our knowledge, are the only studies of managers’ optimal choice between picking and timing. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) provides a micro-founded framework based on limited attention, in which a manager optimally allocates more attention to aggregate shocks when market volatility is high. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) provides empirical evidence supporting these dynamics. In particular, it shows that managers who are good pickers during expansions are also good timers during recessions. Our work is complementary, as we provide a different channel (based on self-selection) to explain the optimal choice of fund managers between picking and timing strategies. A further theoretical contribution is Detemple and Rindisbacher (2013), that analyzes the endogenous dynamics of timing strategies in response to the private information of fund managers. A recent paper by Zambrana and Zapatero (2018) discusses the role of specialists vs. generalists in the mutual fund industry, showing that pickers are more likely to be specialists, whereas timers are more likely to be generalists.

Our paper also relates to the large literature studying mutual fund flows. Many papers in this literature, including for instance Chevalier and Ellison (1997), Sirri and Tufano (1998), and
Huang, Wei, and Yan (2012), document how fund characteristics such as age, size, volatility, and type of classes (institutional vs retail) affect flow-performance sensitivity. More recently, Franzoni and Schmalz (2017) documents that fund flows become less sensitive to fund performance when aggregate risk-factor realizations are extreme, proposing that investors do not observe funds’ exposure to systematic risk, and hence the ability to learn about fund managers’ skill is high only when systematic risk is muted. Our paper makes two contributions to this literature. First, we present new evidence that flows have differential sensitivity across picking and timing strategies. Second, we introduce the concept of core-value, which is the value added using the core strategy of the manager. By identifying the core strategy of mutual funds in the data, we show that fund flows are at least two times more sensitive to the core value of the fund, as opposed to its non-core value. The fact that flows are more sensitive to a particular component of the total value added is new, and confirms that investors are sufficiently informed about their manager’s strategy.

Self-selection is an important theme in economics. Starting from Roy (1951), it is widely recognized that agents choose a particular actions to signal information about their skills or attributes. Recent contributions of self-selection in financial markets include Malliaris and Yan (2018) and Bond and Dow (2019). Malliaris and Yan (2018) considers a setting where fund managers are concerned about their reputation, and shows that low- and high-skill managers pool by choosing nickel strategies (negatively skewed) before black-swan strategies (positively skewed) in order to hedge the risk of being fired. In our model, mutual fund managers separate themselves from each other even when the available strategies have the same expected profitability. Bond and Dow (2019) considers a model in which high-skill traders optimally choose to predict frequent events while low-skill traders opt to predict rare-disasters. The key economic force at play is that position limits hinders high-skill traders from placing large short positions on rare events. Our self-selection mechanism, instead, is based on the ability of fund managers to influence investors by selecting different investment strategies. Compared to these papers, we also bring our theory to the data and test the self-selection predictions.

Other recent contributions on flow-performance sensitivity include Spiegel and Zhang (2013) and Choi, Kahraman, and Mukherjee (2016). Spiegel and Zhang (2013) shows that fund flows are more sensitive to the performance of “hot” funds, which tend to be young and small. Choi, Kahraman, and Mukherjee (2016) studies fund managers managing two funds and documents that flows into one of the manager’s fund are predicted by past performance of the other fund.

Spence (1973) highlights the role of education as a signaling device in the job market, whereas Borjas (1987) shows how wages differ across natives and migrants since the decision to migrate is by itself a signal of the quality of the worker.
2 A Theory of Self-selection

In this section we propose a parsimonious theoretical model explaining the mechanism through which mutual fund managers’ self-selection into investment strategies may occur. Our theory is based on the notion that investors learn about fund managers’ unobservable investment skills. Notably, it predicts a full or partial separating equilibrium in which timing strategies are only adopted by low-skill managers. We cast our theory within a rational expectations equilibrium with endogenous fund flows, in the spirit of Berk and Green (2004), and we generate implications for fund performance, fund flows, and other endogenous fund characteristics.

2.1 Economic Setting

Agents. We consider a discrete-time economy with time indexed by \( t = 0, 1, 2, \ldots \). The economy consists of a mutual fund manager \((M)\) and an investor \((I)\). Both agents are risk-neutral price-takers, and can be interpreted as a continuum of identical investors and fund managers. The fund manager is born with an investment skill, denoted by \( s \), which can be either High or Low, \( s \in \{H, L\} \). The investment skill \( s \) is private information to the fund manager, and is not observable by the investor. The investor tries to infer the manager’s level of skill by observing her performance over time. We denote by \( \phi_t \) the investor’s posterior probability at time \( t \) that the manager has high-skill, \( \mathbb{P}_I(s = H) \), and we refer to it as the manager’s reputation at time \( t \). We assume that the investor’s prior about \( s \) at time 0 is diffuse, that is, the manager is ex-ante equally likely to be of either type, \( \phi_0 = 1/2 \).

Strategies. The fund manager can generate value for the investor by adopting one of two strategies: Picking and Timing. We denote by \( a_t \in \{P, T\} \) the mutually exclusive investment strategy adopted by the fund manager at time \( t \), and we assume that \( a_t \) is observable by the investor, as in Malliaris and Yan (2018). A picking strategy consists of a portfolio of \( n \) assets that allows a manager, who is able to identify mispricings, to bet on the idiosyncratic component of these assets. In contrast, a timing strategy consists of a portfolio of \( n \) assets that allows a manager, who is able to predict aggregate fluctuations, to bet on the systematic component of these assets. The investment skill of a manager, therefore, manifests into her ability to identify mispricings or

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5 The mandate of a fund is often explicit enough for the investors to know the strategy implemented (e.g., value fund vs global-macro fund). Additionally, the fund prospectus and the manager’s commentary provide a valuable source of information regarding the underlying strategy. Furthermore, investors are able to infer a manager’s strategy by observing the fund performance over time. In our empirical analysis, we provide novel evidence, based on fund flows, that supports our assumption.
to predict aggregate fluctuations, depending on the chosen strategy. In what follows, we refer to the $n$ positions in the assets characterizing a picking strategy as picking bets, and likewise we refer to the $n$ positions of a timing strategy as timing bets.

The investor assesses the fund manager’s performance differently depending on whether the manager is a picker or a timer. If the manager is a picker, the investor ignores the aggregate component of the return generated by the fund manager and evaluates her solely based on her ability to generate “alpha,” i.e., the performance of her picking bets. If, instead, the manager is a timer, the investor’s assessment is based upon the manager’s ability to increase the fund exposure to the aggregate market when the market is expected to grow, and to reduce it when it is expected to decline, i.e., the performance of her timing bets.$^6$

A fundamental difference between picking and timing strategies, therefore, is their exposure to different sources of risk. While picking strategies are exposed to idiosyncratic risk, timing strategies are exposed to systematic risk. As a consequence, by definition, the returns of the $n$ picking bets in each period are independent of each other, whereas the returns of the $n$ timing bets are positively correlated with each other, as they are driven by common factor(s). This distinguishing feature between picking and timing strategies is central to our theory.

**Returns.** We abstract from the specifics of the implementation of picking and timing strategies, and model in reduced form the net payoffs of the bets associated with these strategies. Specifically, the gross return at time $t$ of an individual bet $i = 1,..,n$ of strategy $a$ (chosen at time $t-1$) is given by

$$R^a_{it} \sim N(\mu_s, \sigma^2)$$ (1)

where the expected return $\mu_s$ depends on the investment skill $s$, with $\Delta \mu \equiv \mu_H - \mu_L > 0$, but the return volatility is not affected by it. We denote the average expected return across investment skills by $\bar{\mu} \equiv (\mu_L + \mu_H)/2$. Gross returns of individual bets should be understood as risk-adjusted returns relative to a passive benchmark and risk factors, i.e., in excess of their passive and systematic components. The pairwise correlation between any two bets of investment strategy $a$ is given by

$$\rho^a = \rho 1_{\{a=T\}},$$ (2)

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$^6$We note that for specialized funds, market timing refers to ability to predict the movements of the benchmark that is in line with the mandate of the fund, rather than the overall market. Although this does not play any role in our theoretical analysis, we take this into account in our empirical investigation.
where $\rho > 0$. So, while the returns of picking bets are uncorrelated, the returns of timing bets comove positively.

Given the homogenous nature of the return distribution of all the bets within a strategy, the fund manager splits the total investment of the fund equally over the $n$ bets. Therefore, the fund’s gross return at time $t$ from strategy $a$, denoted by $R^a_t$, is distributed as

$$R^a_t \sim \mathcal{N}(\mu_s, \nu^a) \quad \text{where} \quad \nu^a = \frac{\sigma^2}{n} \left(1 + (n - 1)\rho^a\right). \quad (3)$$

Despite the different correlation structure characterizing the returns within each investment strategy, the expected return of picking and timing – i.e., the expected performance of a picking and a timing fund – is the same for a given investment skill $s$,

$$\mathbb{E}_t [R^P_{t+1} | s] = \mathbb{E}_t [R^T_{t+1} | s] = \mu_s. \quad (4)$$

The two strategies, therefore, are equally profitable from the perspective of the fund manager.

Our parsimonious way to model the cross-sectional correlation among timing bets maintains a tractable setting, yet captures a fundamental feature of investment strategies that differentiates market timing from stock picking. This fundamental feature is responsible for the self-selection of fund managers into picking and timing, as it effectively makes these strategies signaling devices for the managers to reveal or hide their investment skills. Before we formally discuss the signaling game between the fund manager and the investor, we next introduce a competitive market structure to endogenize the provision of capital, that is the fund flows that the investor gives to or withdraws from the fund manager.

## 2.2 Provision of Capital

We cast our economic setting in the rational expectations framework of [Berk and Green (2004)](#), where investors’ fund flows optimally respond to fund managers’ past performance. This allows us to derive predictions for how self-selection affects the equilibrium dynamics of fund flows and other endogenous characteristics, such as fund size and fund performance.

We maintain two key elements of Berk and Green (2004): competitive (and perfectly elastic) provision of capital to fund managers by investors, and decreasing return to scale (DRS) in the “production” of value for investors by fund managers. These assumptions imply that: (i) the investor’s capital flows into (out of) the fund when the fund manager is expected to deliver
positive (negative) net returns; and (ii) net returns decrease with the size of the fund, capturing the larger price impacts and higher operational costs associated with larger trades.

We denote the fund’s assets under management at time \( t \) by \( q_t > 0 \) (i.e., its size), and we denote the management fee that the investor pays to the fund manager in every period for each dollar invested by \( f < 1 \). We incorporate DRS by assuming that actively managing a larger fund is more costly. Specifically, the cost of managing a fund of size \( q_t \) is equal to \( C(q_t) = c \cdot q_t^2 \), where \( c > 0 \) captures the degree of DRS. It follows that the net return (per dollar invested) delivered by the fund manager at time \( t + 1 \), following strategy \( a_t \), depends positively on the gross return at time \( t + 1 \), and negatively on the size of the fund at time \( t \) and its fee,

\[
  r_{t+1}^a = R_{t+1}^a - c \cdot q_t - f. \tag{5}
\]

Putting together a competitive capital market with abundance of capital and DRS, we obtain an equilibrium condition that must hold in each period,

\[
  \mathbb{E}_t^I [r_{t+1}^a] = 0, \tag{6}
\]

where \( \mathbb{E}_t^I [\cdot] \) denotes the expectation conditional on the investor’s information set at time \( t \). The intuition behind this condition is as follows. Suppose that the expected net return of the fund were positive, \( \mathbb{E}_t^I [r_{t+1}^a] > 0 \). Since the investor is risk-neutral and has deep pockets, providing capital to the fund is optimal. However, every additional dollar that the investor invests in the fund reduces the net returns by \( c \), due to the additional (marginal) cost of managing a larger fund. Inflows of capital into the fund continue until its expected net return is driven all the way down to zero. At this point, the investor has no incentive to provide additional capital. Following the same logic with negative expected net returns and capital outflows, the conclusion is that, in equilibrium, a fund cannot exhibit either positive or negative expected net returns.

This equilibrium property in \( (6) \) allows us to pin down the endogenous size of the fund, as characterized in Lemma 1.

**Lemma 1 (Fund Size).** The size of the fund at time \( t \) is equal to

\[
  q_t = \frac{1}{c} (\mu_L + \Delta \mu \cdot \phi_t - f). \tag{7}
\]

Consequently, fund size is increasing with the fund manager’s reputation at time \( t \), \( \partial q_t / \partial \phi_t > 0 \).
Lemma 1 shows that the size of the fund can only change due to changes in the reputation of the fund manager. Indeed, if after observing the net return of the fund $r_t^a$ and deducing its gross return $R_t^a$, the investor revises his beliefs about the manager’s investment skill upward, then the investor’s capital flows into the fund, and the fund’s assets under management increase. The opposite holds if the investor revises his beliefs downwards. Importantly, the equilibrium fund size in (7) also reveals that the manager’s choice of an investment strategy does not affect $q_t$ directly, but only indirectly through the manager’s reputation $\phi_t$. Indeed, the investor’s beliefs about the manager’s investment skill $s$ depend on the realized return $R_t^a$ that the fund manager obtains by implementing investment strategy $a$: $\phi_t = \phi_t(R_t^a)$.

**Manager’s problem.** The compensation that the fund manager receives at time $t$ corresponds to the total management fees $f \cdot q_t$. At each point in time, the fund manager chooses an investment strategy $a_t$ to maximize the expected compensation over the next period. We assume that there is a small probability the investment strategy that is ultimately implemented may not be the one that is chosen by the fund manager. For instance, a manager may need to comply with a strategic decision of her fund family, and hence follow a strategy different from her choice. Specifically, with probability $\kappa$ the fund manager is implementing an investment strategy which, with a 50% probability, is either picking or timing. This small amount of noise in the fund manager’s action allows us to sustain a separating equilibrium, as we discuss in more detail when we introduce our signaling game.\footnote{We also solved for the case in which the fund manager maximizes the expected discounted sum of all future compensations, and confirmed that all the results and the economic forces underlying the myopic case remain valid.}

For a given investment skill $s$, therefore, the manager solves the following problem at time $t$:

$$
V_t(s) = \max_{a_t \in \{P,T\}} \left( (1 - \kappa) \mathbb{E}_t^M [f \cdot q_{t+1}(a_t) | s] + \kappa \left( \frac{\mathbb{E}_t^M [f \cdot q_{t+1}(P) | s] + \mathbb{E}_t^M [f \cdot q_{t+1}(T) | s]}{2} \right) \right)
$$

s.t. \quad q_{t+1}(a_t) = \frac{1}{c} \left( \mu_L + \Delta \mu \cdot \phi_{t+1}(R_{t+1}^a) - f \right),

where $\mathbb{E}_t^M [\cdot]$ denotes the expectation conditional on the manager’s information set at time $t$, which crucially includes her skill $s$. The manager’s objective function in (8) is given by two components, weighted by the probabilities $(1 - \kappa)$ and $\kappa$, respectively. The first component represents the manager’s expected compensation if the strategy implemented is her optimal investment strategy, whereas the second component represents the manager’s expected compensation if the strategy implemented is not chosen by the manager. We refer to the latter component as the noise in the objective function, and we note that it is symmetric across strategies and skills.
Since the assets under management $q_t$ are affine in the manager’s reputation $\phi_t$, and since the noise in the manager’s objective function is not affected by her choice $a_t$, we can rewrite the manager’s problem as

$$a_t(s) = \arg \max_{a_t \in \{P,T\}} v_t(a_t|s),$$

where

$$v_t(a_t|s) = \mathbb{E}_t^M [\phi_{t+1}(R_{t+1}^a)|s] = \int_{-\infty}^{\infty} \phi_{t+1}(R_{t+1}^a) \varphi_t(R_{t+1}^a|a_t,s)\ dR_{t+1},$$

and $\varphi_t(\cdot)$ denotes the probability density function at time $t$ of fund return $R_{t+1}^a$, conditional on strategy $a_t$ and skill $s$, which corresponds to the probability density function of the normal distribution in (3). Intuitively, the fund manager maximizes her expected compensation by maximizing her expected reputation. This is because the higher the reputation, the greater the assets under management and, consequently, the higher the total fees.

**Investor’s learning.** As discussed thus far, the only channel through which an investment strategy affects the fund manager’s compensation is through her reputation. This reputation is endogenously determined by the investor’s beliefs about the manager’s skill, which in turn depends on the investment strategy implemented in equilibrium and on its realized performance. In our rational model, the investor updates his beliefs in a Bayesian way, by evaluating the conditional probabilities that the observed performance from a given strategy is generated by a low- or high-skill manager. Specifically, after observing the investment strategy $a_t$ and the return $R_{t+1}^a$, the posterior beliefs are given by

$$\phi_{t+1} = \phi_t \cdot \left( \frac{1}{\phi_t + (1 - \phi_t)\Lambda_t(R_{t+1}^a|a_t)\Lambda_t(a_t)} \right),$$

where $\phi_t$ is the investor’s prior and $\Lambda_t(\cdot) = \frac{\pi_t(\cdot|s=L)}{\pi_t(\cdot|s=H)}$ is a likelihood ratio conditional on the skill $s$. Intuitively, the function $\Lambda_t(x)$ tells us whether it is more or less likely that outcome $x$ is associated with a low-skill manager, as opposed to a high-skill manager. When $\Lambda_t(x) > 1$, it is more likely that it is associated with a low-skill manager, whereas, when $\Lambda_t(x) < 1$, the opposite is true.

Equation (12), which is derived in Lemma A.2 in the Appendix, shows that the investor’s update of the manager’s reputation $\phi_{t+1}$ depends on her current reputation $\phi_t$ and on two distinct likelihood ratios, capturing two distinct learning channels. The first one, $\Lambda_t(R_{t+1}^a|a_t)$, quantifies how much more likely it is that, given the observed strategy $a_t$, the gross return $R_{t+1}^a$ is delivered by
a low-skill manager, relative to a high-skill manager. The second likelihood ratio, instead, \( \Lambda_t(a_t) \), quantifies how much more likely it is that the investment strategy \( a_t \) is implemented by a low-skill manager, relative to a high-skill manager. When the product of the two ratios is sufficiently low, i.e., below one, the manager’s reputation improves (\( \phi_{t+1} > \phi_t \)), whereas when it is sufficiently high, i.e., above one, her reputation worsens (\( \phi_{t+1} < \phi_t \)).

It is important to emphasize why the investment strategy of the fund manager – and not just her performance – conveys valuable information regarding her investment skill, i.e., \( \Lambda_t(a_t) \) is not constant with respect to \( a_t \). This is because of the endogenous self-selection mechanism. Importantly, since this is an equilibrium mechanism, the fund manager (who is atomistic) does not internalize how her chosen investment strategy affects this learning channel. In contrast, the manager does fully internalize how the choice of being a picker or a timer affects the investor’s learning through \( \Lambda_t(R_{t+1}^P|a_t) \). While the cross-sectional independence of picking bets makes \( \Lambda_t(R_{t+1}^P|P) \) very sensitive to \( R_{t+1}^P \), the positive correlation across timing bets reduces the sensitivity of \( \Lambda_t(R_{t+1}^T|T) \) with respect to \( R_{t+1}^T \). Therefore, a fund manager is “attracted” towards one of the two investment strategies depending on whether she wants to increase or decrease the investor’s ability to learn about her skill.

### 2.3 Equilibrium Allocation of Talent

We next define and solve for the equilibrium characterizing the signaling game between the manager and the investor. Our notion of equilibrium is standard. We consider a perfect Bayesian equilibrium, defined by a set of investment strategies and beliefs such that: (i) the manager’s investment strategies are optimal given the investor’s beliefs, and (ii) the investor’s beliefs are derived from the investment strategies using Bayes’ rule.

We allow for mixed strategies, i.e., the manager can randomize between picking and timing strategies, and we refer to an equilibrium in which only one of the two manager types adopts a mixed strategy as hybrid semi-separating equilibrium. The small noise in the manager’s objective function (occurring with probability \( \kappa \)) prevents the equilibrium from fully revealing the manager’s type, regardless of the chosen investment strategy. This is akin to the equilibrium feature of noisy REE models.

We conjecture and verify a hybrid semi-separating equilibrium in which only a low-skill manager adopts a mixed strategy. In this equilibrium, a high-skill manager always chooses a picking strategy, while a low-skill manager chooses a picking strategy with probability \( \eta_t \), and a timing
strategy with probability \((1 - \eta_t)\). Consistent with this hybrid equilibrium, a low-skill manager is indifferent between picking and timing. The following proposition characterizes the equilibrium.

**Theorem 1 (Allocation of Talent).** There exists a hybrid semi-separating equilibrium in which at time \(t\) a high-skill manager chooses to pick with probability 1, while a low-skill manager chooses to pick with probability \(\eta_t^*\). The probability \(\eta_t^*\) is unique, < 1, and solves the following equation

\[
\sqrt{1 + (n - 1)\rho} \int_{-\infty}^{\infty} \phi_{t+1}(R_{t+1}^P) e^{-\frac{(R_{t+1}^P - \mu_L)^2}{2\sigma^2}} dR_{t+1}^P = \int_{-\infty}^{\infty} \phi_{t+1}(R_{t+1}^T) e^{-\frac{(R_{t+1}^T - \mu_L)^2}{2\sigma^2}} dR_{t+1}^T,
\]

where the manager’s reputation \(\phi_{t+1}(R_{t+1}^a)\) is given by

\[
\phi_{t+1}(R_{t+1}^a) = \phi_t \cdot \left[ \phi_t + (1 - \phi_t) e^{\frac{\Delta \mu}{\Delta R} (R_{t+1}^a - \bar{\mu})} \left( \eta_t^* + (1 - \eta_t^*) \left( \frac{\kappa}{2 - \kappa} \right)^{1 - \mathbb{1}_{(o_t = T)}} \right) \right]^{-1}.
\]

The equilibrium in Theorem 1 features a self-selection mechanism whereby a high-skill manager always chooses the investment strategy that allows her to better reveal her skill. Since driven by \(n\) independent bets, the performance of a picking strategy is a precise signal about the skill of the manager. In contrast, the signal conveyed by a timing strategy is less informative, as the underlying bets are correlated with each other. In the extreme case of perfect correlation, for instance, all bets are successful (unsuccessful) as long as one is successful (unsuccessful). This means that, although driven by \(n\) different bets, the performance of a timing strategy is effectively driven by only one bet, and hence is a noisier signal about the skill of the manager. This makes a picking strategy the optimal investment strategy for a high-skill fund manager.

While a high-skill manager wants to reveal her investment ability, a low-skill manager wants to hide it. By the opposite logic, a low-skill manager has an incentive to choose a timing strategy, and the worse her investment ability is, the stronger the incentive. In equilibrium, though, a low-skill manager may find it optimal to pick with some probability, because while choosing a timing strategy allows a low-skill manager to hide her skill, it also makes it difficult for that manager to improve her reputation, and hence to increase her compensation. So, for a low-skill manager, the advantage of picking is the possibility to hide her type by pooling with high-skill managers. Pooling by picking has the benefit of rewarding a low-skill manager with a disproportional boost in her reputation following a good performance, since the investor confuses her for a high-skill manager. At the same time, however, pooling exposes her to a drastic downgrade in reputation after poor performance. In equilibrium, a low-skill manager balances these tradeoffs, resulting in the equilibrium mixed strategy \(\eta_t^*\).
Given the equilibrium self-selection, a particular strategy becomes informative of the skill of the manager adopting that strategy. Because of this, the investor learns about the manager’s skill not only from her realized performance, but also from her strategy. This learning channel is captured by the likelihood ratio $\Lambda_t(a_t)$ in (12), which in equilibrium is equal to

$$\Lambda_t(a_t) = \eta_t + (1 - \eta_t) \left( \frac{\kappa}{2 - \kappa} \right)^{1 - 2 \mathbb{1}_{(a_t = T)}}.$$  

Equation (15) reveals that the likelihood ratio $\Lambda_t(a_t)$ is always higher than 1 for a timing strategy ($a_t = T$) and is always lower than 1 for a picking strategy ($a_t = P$). Thus, it is more likely that the fund manager implementing an observed timing strategy is a low-skill manager and that the fund manager implementing an observed picking strategy is a high-skill manager. This result follows from the fact that, in equilibrium, a high-skill manager picks with greater probability than a low-skill manager ($\eta^*_t < 1$).

The left and right panels in Figure 1 plot the value function in (11), i.e., the expected future reputation of a high- and low-skill manager, respectively, as a function of the picking probability $\eta_t$, and for the two investment strategies. The two plots illustrate the self-selection mechanism occurring in equilibrium. In particular, the vertical line represents the equilibrium value of $\eta^*_t$, such that $v_t(P|L) = v_t(T|L)$. Notably, in both panels, picking value decreases with $\eta_t$, while timing value increases with it. In particular, for values of $\eta_t < \eta^*_t$ a low-skill manager has the incentive to increase the probability of picking, whereas for values of $\eta_t > \eta^*_t$, she has the incentive to decrease it.

A natural interpretation of $\eta_t$ is the fraction of low-skill managers who choose to pick in a given period. Our self-selection mechanism then predicts that all high-skill managers plus a fraction $\eta_t$ of low-skill managers choose to pick. If the number of low- and high-skill managers is the same, it immediately follows that more than 50% of the fund managers are pickers. Formally, the fraction of pickers at time $t$ is equal to $1/2 \left[ 1 + \eta_t (1 - \kappa) \right] > 1/2$. We note that the noise in the managers’ actions, i.e., investment strategy decisions unrelated to skill, affects low- and high-skill managers symmetrically, and hence it does not qualitatively change this prediction.\footnote{An alternative interpretation of $\eta_t$ is the fraction of assets under management that a manager would invest in picking strategies. Accordingly, our equilibrium suggests that low-skill managers finds it optimal to invest in both timing and picking strategies, whereas high-skill managers prefer to invest only in picking strategies.}
Figure 1: Self-selection

In this figure we plot the fund manager’s value functions $v_t(a_t|s)$ for a high-skill manager (left panel) and a low-skill manager (right panel) depending on whether the chosen strategy is picking (blue lines) or timing (red lines). The value functions are plotted against the probability $\eta_t$. The thin vertical lines represent the equilibrium strategy $\eta_t^*$. Parameter values are: $\mu_L = 0.02$, $\mu_H = 0.15$, $\sigma = 0.15$, $\rho = 0.25$, $\kappa = 0.15$, $n = 20$, $\phi_t = 0.5$.

2.4 Model Predictions

We now present the equilibrium predictions that are induced by the endogenous self-selection of fund managers into investment strategies. The next proposition presents the cross-sectional comparison of fund performance between pickers and timers.

Proposition 1 (Fund Performance). The cross-sectional average of the expected fund performance of pickers is higher than that of timers. Moreover, the expected fund performance has a higher cross-sectional dispersion.

Proposition 1 asserts that in the cross-section of fund managers, the average performance of picking funds is higher than the average performance of timing funds. This finding follows from the fact that the fraction of high-skill managers is greater within the group of pickers than within the group of timers. It is important to emphasize that the outperformance of picking funds is entirely driven by the self-selection mechanism. Low-skill managers tend to be timers and consequently the
observed average performance of timing funds is lower than that of picking funds. The expected return on the two investment strategies is identical for a given skill, and does not contribute to the differential average performance. The top-left panel in Figure 2 plots the cross-sectional average performance of pickers (blue line) and of timers (red line), as a function of the probability of picking by low-skill managers, $\eta_t$. The graph shows that the blue line is above the red line for any values of $\eta_t < 1$, confirming the superior average performance of pickers. Moreover, it shows that while the average performance of pickers worsens with $\eta_t$, the average performance of timers improves with $\eta_t$. Indeed, as $\eta_t$ increases, low-skill managers switch from timing to picking strategies, thus dragging down the average performance of pickers and lifting that of timers.

Proposition 1 also highlights that pickers exhibit greater cross-sectional dispersion in their expected performance. Intuitively, the group of pickers is a more balanced group comprised of high-skill and low-skill managers. In contrast, the group of timers is largely dominated by low-skill managers, which makes the average cross-sectional performance of timers more homogenous. The top-middle panel in Figure 2 plots the cross-sectional dispersion of pickers’ performance (blue line) and of timers’ performance (red line), as a function of the probability of picking by low-skill managers, $\eta_t$. When none of the low-skill managers chooses to pick ($\eta_t = 0$) or when all of them do so ($\eta_t = 1$), the two strategies exhibit the same composition of low- and high-skill managers, and hence the average performance of the two strategies displays the same cross-sectional dispersion. However, while the cross-sectional dispersion is at its lowest when $\eta_t = 0$, it is at its highest when $\eta_t = 1$. Indeed, the graph reveals that the performance dispersion of both pickers and timers increases with $\eta_t$.

By updating his beliefs about the manager’s skill, the investor changes his expectation of the future return that the manager can generate. This, in turn, changes the size of the fund through capital inflows or outflows, as revealed in (7). For instance, a positive change in beliefs implies an inflow of capital to the fund in order to exploit the positive expected return. We define fund flows as relative changes in fund size, $F_{t+1} = (q_{t+1} - q_t)/q_t$, as in Berk and Green (2004). Given Lemma 1, fund flows are proportional to changes in beliefs about the manager’s skill:

$$F_{t+1} = \frac{\Delta \mu \cdot (\phi_{t+1} - \phi_t)}{\mu_L + \Delta \mu \cdot \phi_t - \bar{f}}.$$  \hspace{1cm} (16)

The next proposition presents our results on fund flows and size.
Proposition 2 (Fund Flows and Size). Given the fund reputation $\phi_t$, the threshold of fund performance $R^a_{t+1}$ that induces positive fund flows, $F_{t+1}(R^a_{t+1}) = 0$,\\
\[ R^a_{t+1} = \bar{\mu} + \nu^a \sum \log \left( \eta^*_t + (1 - \eta^*_t) \left( \frac{\kappa}{2 - \kappa} \right)^{1-2\xi_{t+1}} \right), \]  
(17)\\
is lower for pickers than timers, $R^P_{t+1} < \bar{\mu} < R^T_{t+1}$. Moreover, the flow-performance sensitivity\\
\[ \frac{\partial F_{t+1}}{\partial R^a_{t+1}} = \Delta \mu^2 \phi_{t+1}(1 - \phi_{t+1}) \]  
(18)\\
is always positive for both pickers and timers, and is higher for pickers for the same level of fund flows $F_{t+1}(R^P_{t+1}) = F_{t+1}(R^T_{t+1})$. In equilibrium, the cross-sectional average of fund size is larger for pickers than timers.

Proposition 2 characterizes the behavior of fund flows in our model. First, the sensitivity of fund flows to performance is always positive, regardless of whether the manager chooses a picking or a timing strategy. This is sensible, and it reflects the fact that (i) the investor updates his beliefs about the manager’s skill by observing her performance, and (ii) the manager’s performance is a positive signal about her skill. This result is also consistent with existing empirical findings (e.g., Gruber (1996); Chevalier and Ellison (1997); Sirri and Tufano (1998); Huang, Wei, and Yan (2012)). Second, controlling for reputation, a timer needs to deliver a better performance than a picker, in order to trigger positive fund flows. This implies that a picking and a timing fund with the same reputation and with the same current performance may actually experience inflows and outflows of capital, respectively. This is the case if their current performance is between $R^P_{t+1}$ and $R^T_{t+1}$.

These results are driven by two effects. The first effect captures the extensive margin of the investor’s learning. Just by observing the manager’s strategy, the investor extracts information about her skill. Indeed, since a high-skill manager picks with higher probability than a low-skill manager, observing a timing strategy skews the investor’s beliefs negatively for any level of performance. The second effect, instead, captures the intensive margin. Even when the performance of a timer is very good, part of the performance is attributed to the correlation among timing bets rather than to the investment skill of the manager. Effectively, the investor discounts a timer’s performance due to correlation. Both effects reduce the capital the investor is willing to invest in a timing fund, and hence induce a larger performance threshold for capital flows into the fund. The same logic implies that the flow-performance sensitivity is lower for timers, as the flatter fund flow
schedule in (18) reveals. Proposition 2 also reveals that picking funds are expected to be larger, because, compared to timing funds, they have more skilled managers and hence more capital, on average.

The top-right panel in Figure 2 plots the endogenous fund flows (as a percentage of assets) of a picking fund (solid blue line) and a timing fund (solid red line), as a function of their performance. Although the flow-performance relation for both pickers and timers becomes flat for extreme levels of performance, pickers exhibit higher flow-performance sensitivity than timers for the range of performance that is more likely to occur. In line with the estimated linear relation between flow and performance, commonly studied in the empirical literature, in the same panel we plot a linear flow-performance relation for both strategies (dashed lines), with a slope corresponding to the average flow-performance sensitivity, and an intercept such that $F_{t+1}(R_{t+1}^a) = 0$. This linearized version of the model-implied fund flows confirms our result.

One of the key determinants of the trade-off between “pooling by picking” and “hiding by timing”, for a low-skill manager, is the effect of her current reputation. The next proposition analyzes the relation between fund reputation and the optimal investment strategy of a low-skill manager.

**Proposition 3 (Reputation).** The equilibrium probability of picking of a low-skill manager decreases with her reputation, $\partial \eta^*_t/\partial \phi_t \leq 0$.

When the reputation of a low-skill manager is good – mostly due to luck given her poor ability to invest – that manager finds it more beneficial to adopt a timing strategy. This is because a timing strategy, by slowing the investor’s learning, allows her to hide her lack of skill and hence to “preserve” her current reputation. In contrast, when her reputation is poor, preserving it by timing becomes less beneficial. In this case, a low-skill manager has a stronger incentive to pick, as she hopes to be mistaken for a manager with high investment skills, and hence to be rewarded disproportionally in case of a good performance. This leads to a negative relation between the probability of picking for low-skill managers and their reputation. The bottom-left panel in Figure 2 illustrates this finding, and shows that for very high levels of reputation, a low skill-manager optimally chooses to adopt only timing strategies, $\eta^*_t = 0$.

We finally turn to the analysis of aggregate volatility and the role it plays in affecting the equilibrium in this economy. In particular, we consider changes in the correlation among timing bets as driven by the dynamics of aggregate volatility. Intuitively, timing bets can be thought as composed by an aggregate component and an idiosyncratic one (e.g., Kacperczyk, Van Nieuwer-
Since the common aggregate component is the driver of the correlation between timing bets, this correlation naturally increases when the aggregate component becomes more volatile.

To incorporate time-varying aggregate fluctuations in our setting, yet maintaining its tractability, we model market volatility, denoted by $\sigma_{mt}$, as a binary iid process with $\sigma_{mt} \in \{\sigma_m, \sigma_m\}$, where $\sigma_m > \sigma_m$, and assume that the dynamics of the pairwise correlation between any two bets of investment strategy $a$ is given by

$$
\rho^a_t = \begin{cases} 
\rho \mathbb{I}_{\{a_t = T\}} & \text{if } \sigma_{mt} = \sigma_m \\
(\rho + \Delta \rho) \mathbb{I}_{\{a_t = T\}} & \text{if } \sigma_{mt} = \sigma_m,
\end{cases}
$$

(19)

where $\Delta \rho > 0$. We assume that market volatility is observable, meaning that all agents in our economy know whether market volatility is high or low at any point in time. This generates a conditional version of our baseline model, in which both the investor and the fund manager can condition their actions on the fact that timing bets are more correlated with each other when $\sigma_{mt} = \sigma_m$. The next proposition presents our results on market volatility.

**Proposition 4 (Market Volatility).** The equilibrium picking probability of a low-skill manager decreases with the correlation among timing bets, $\partial \eta^*_t / \partial \rho \leq 0$. Consequently, when market volatility is high, $\sigma_{mt} = \sigma_m$, the fraction of high-skill managers increases among picking funds, whereas the fraction of low-skill managers increases among timing funds. It follows that market volatility raises the average cross-sectional performance of picking funds and reduces the performance of timing funds.

As market volatility increases, a timing strategy becomes even more appealing to a low-skill manager, since the increased correlation among timing bets further reduces the information content conveyed by the performance of this strategy. Therefore, in equilibrium, the probability $\eta^*_t$ decreases with the correlation $\rho$, as illustrated by the bottom-right panel in Figure 2.

The endogenous dependence between $\eta^*_t$ and market volatility has implications for the conditional cross-sectional performance of picking and timing strategies. Low-skill managers are less likely to pick during volatile times. Through a composition effect, this improves the average skill of pickers and worsens the average skill of timers. As a consequence, the average cross-sectional performance of pickers increases with market volatility, whereas the average cross-sectional performance of timers decreases.
Figure 2: Implications of self-selection

In the top-left and top-middle panels we plot respectively the cross-sectional average of fund expected performance $E_{t}^{cs}[E_t[R_{t+1}^a]]$ and its cross-sectional dispersion $Std_{t}^{cs}[E_t[R_{t+1}^a]]$, as a function of the picking probability $\eta_t$. In the top-right panel we plot the fund flows $F_{t+1}$ (solid lines) and a linear flow-performance relation with the slope equal to the average flow-performance sensitivity $E_{t}^{cs}[\partial F_{t+1}/\partial R_{t+1}^a]$ and the intercept such that $F_{t+1}(R_{t+1}^a) = 0$ (dashed lines), as a function of fund performance $R_{t+1}^a$. In the bottom panels we plot the equilibrium probability of picking for a low-skill manager $\eta_t^*$ as a function of the manager’s reputation $\phi_t$ (bottom-left panel), and as function of the correlation among timing bets $\rho$ (bottom-right panel). Parameter values are as in Figure 1 and $f = 0.015$. 

22
3 Empirical Analysis

3.1 Data and Methodology

Data description. We use CRSP survivor-bias-free data on mutual funds over the period 1999-2017, and focus on the US domestic equity mutual funds. In particular, we consider funds with CRSP objective codes EDCL (Large Cap), EDCM (Mid Cap), EDCS (Small Cap) together with EDCI (Micro Cap), EDYG (Growth), EDYB (Balanced/Blend), and EDYI (Income/Value). Additionally, we include sector funds from 11 sectors and we exclude index funds, closed-end funds, target-date or accrual funds, and funds with restrictions on sales.

A mutual fund might have multiple share classes reflecting different fee and marketing structures. However, all share classes belonging to the same fund have identical gross returns. Since we focus on the gross value generated by mutual funds, we follow [Huang, Wei, and Yan (2012)] and aggregate all share classes into one for each fund. We measure a fund’s total assets by the assets under management across all of its share classes, and we consider the oldest share class to measure a fund’s age. Expense ratios, loads, turnover, fees, and other fund characteristics are calculated as asset-weighted averages across all share classes.

To obtain our final sample, we filter our data as follows. First, since fund holdings may be misaligned with respect to the fund’s stated mandate (e.g., [diBartolomeo and Witkowski (1997); Kim, Shukla, and Tomas (2000)]), we require that a fund’s average equity share be between 70% and 130% of its assets. Second, to avoid the incubation bias discussed in [Evans (2010)], i.e., the tendency of fund families to publicly offer only those funds that are successful during the incubation stage, we exclude any observations pertaining to the fund’s first year. Third, as is standard in the literature, we also exclude funds that always stay within the bottom decile of the fund size distribution. Finally, we require that each fund appear in the data for at least five years, ensuring a sufficiently long time-series of fund performance to allow us to reliably identify the skill of a fund manager. Our final sample contains 2,124 funds and 14,223 fund-year observations: 948 funds are growth funds, 145 are value/income funds, 533 focus on micro-, small-, or mid-caps, and 273 are sector funds. The average life of a fund in our sample is eight years.


10Very small funds are problematic because the ratio of fund flows to assets under management tends to be very large and volatile. See, e.g., [Chevalier and Ellison (1997), Huang, Wei, and Yan (2012), and Berk and van Binsbergen (2015)].

11We note that a priori there is no reason to believe that our survival requirement would affect managers with different investment strategies differently. Indeed, all the results in this section remain valid if we do not impose this requirement.
Factor model. We follow the approach of Treynor and Mauzy (1966) and Bollen and Busse (2001) to estimate the excess returns that fund managers generate through picking and timing strategies. Specifically, we estimate the following factor model every year using daily data:

\[
R_{it\tau}^{e} = \alpha_{it} + \beta_{it}R_{bt\tau}^{e} + \gamma_{it}(R_{bt\tau}^{e})^2 + \delta_{it}X_{tr} + \varepsilon_{it\tau},
\]

(20)

where \(i, t, \tau\) indexes the fund, the year and the day, respectively. \(R_{it\tau}^{e}\) is the gross fund return in excess of the risk-free rate, \(R_{bt\tau}^{e}\) is the fund’s benchmark return in excess of the risk-free rate, and \(X_{tr}\) is a vector of risk factors. The inclusion of the square of the benchmark excess return, \((R_{bt\tau}^{e})^2\), allows us to capture a fund manager’s attempt to increase the benchmark exposure prior to a rise in the benchmark, and to decrease it prior to a fall. Effectively, a successful timing strategy is one that predicts benchmark fluctuations and adds value whenever the benchmark moves, irrespective of the direction of the movement.\(^{12}\)

The empirical specification in (20) departs from the formulation in Treynor and Mauzy (1966) in three ways. First, we risk-adjust a fund’s return using its passive exposure to its mandate-specific benchmark. This prevents us from assigning positive or negative investment skill to a manager with passive exposure to a benchmark that itself exhibits positive or negative alpha relative to the factor model. This may be particularly relevant for the sector funds in our sample. Second, in line with Bollen and Busse (2001), we orthogonalize the Fama-French and Carhart four factors (market (MKTRF), size (SMB), growth (HML) and momentum (MOM)) to avoid multicollinearity.\(^{13}\) Third, we measure timing with respect to the benchmark instead of the broad market, as in Kaplan and Sensoy (2005).

Value added and investment skill. The estimated intercept \(\hat{\alpha}_{it}\) captures the picking skill of fund \(i\) during year \(t\), and coincides with the picking value (i.e., excess return) generated by that fund in that year, \(v_{it}^{P} = \hat{\alpha}_{it}\). The estimated slope on the square of the benchmark, \(\hat{\gamma}_{it}\), instead, captures the timing skill of fund \(i\) during year \(t\). Since the value generated by a timing strategy in a year depends both on the timing skill of the manager and on the fluctuations of the benchmark

\(^{12}\)The assignment of mandate-specific benchmarks is reported in Tables B.1 in Appendix B. We use Morningstar indexes that closely match the mandate or the style of the fund.

\(^{13}\)Orthogonalization is necessary as the factors could be highly correlated with a fund’s benchmark. We follow Busse (1999) and sequentially orthogonalize the factors as follows. For a given year, we regress the market excess returns on the benchmark excess returns (including an intercept) and consider the corresponding residuals as the orthogonalized market factor. Next, we regress the SMB factor on the benchmark excess returns and the orthogonalized market factor and recover the orthogonalized SMB factor. We continue sequentially until all the remaining factors (HML, MOM) are orthogonalized.
in that year, the timing value is given by \( v_{it}^T = \tilde{\gamma}_{it} \cdot \frac{1}{N_t} \sum_{\tau=1}^{N_t} (R_{bt\tau})^2 \), where \( N_t \) is the number of trading days in year \( t \). The total value added by fund \( i \) at the end of year \( t \) is the sum of the picking and timing values during that year, \( v_{it} = v_{it}^P + v_{it}^T \).

We measure the underlying investment skill of a fund, denoted by \( s_i \), by calculating the sample-average of the total value added by the fund,

\[
s_i = \frac{1}{N_i} \sum_{t=1}^{N_i} v_{it},
\]

where \( N_i \) is the number of years that the fund is in the sample. A high-skill fund is a fund that is run by a manager who adds value in a consistent manner, thus pushing the long-run fund performance to the top of its distribution. In our leading specification, we consider the top 30% and bottom 30% of the skill distribution to identify high- and low-skill managers, respectively.\(^{14}\)

**Source of value and investment strategies.** One simple yet reasonable way to label a fund as a *picker* \( (a_{it} = P) \) or a *timer* \( (a_{it} = T) \) in a certain year is to compare its yearly picking and timing values and label it corresponding to the highest source of value. Formally, if we denote the difference \( v_{it}^P - v_{it}^T \) as \( pmt_{it} \) (for *picking-minus-timing*), the strategy of fund \( i \) at time \( t \) is given by

\[
a_{it} = P \cdot 1(pmt_{it} \geq 0) + T \cdot 1(pmt_{it} < 0).
\]

(22)

According to (22), in a given year, each manager is either a picker or a timer, so picking and timing strategies are mutually exclusive. Moreover, a fund is considered to be either a picker or a timer regardless of how large (in absolute value) \( pmt \) is, and in particular regardless of whether \( pmt \) and its components, \( v_{it}^P \) and \( v_{it}^T \), are statistically different from 0.

We also consider an alternative labeling rule where the strategy of fund \( i \) at time \( t \) is a weighted average between picking and timing,

\[
a_{it} = P \cdot dop_{it} + T \cdot (1 - dop_{it}),
\]

(23)

\(^{14}\)We note that it is important to estimate a fund skill \( s_i \) by first estimating the values added by the fund in each year and then averaging them over the sample, rather than by running a single regression (per fund) over the fund’s entire sample period. The intuition is as follows. With the first method, the average timing value of fund \( i \) over its life is estimated as \( \mathbb{E}[\gamma_{it}(R_{bt})^2] \), whereas with the second method, it is estimated as \( \mathbb{E}[\gamma_{it}] \cdot \mathbb{E}[(R_{bt})^2] \). Unless \( \text{Cov}[\gamma_{it}, (R_{bt})^2] = 0 \), the estimated timing value using a single regression (second method) would completely ignore the ability of a fund to adjust \( \gamma_{it} \) depending on \( (R_{bt})^2 \), that is, the ability to time its benchmark precisely when it is more profitable to do so. Our yearly estimations allow us to capture to this aspect of market timing.
where the weight \( dop_{it} \) (for degree-of-picking) takes value between 0 and 1 for each fund. Intuitively, if (i) a fund’s picking value is statistically positive, (ii) it is statistically larger than the fund’s timing value, and (iii) the fund’s timing value fails to be statistically positive, then we take this as sufficient evidence that the main source of value is picking, and consequently we consider the fund a picker and set its degree of picking, \( dop \), to 1. If, instead, a fund satisfies exactly the opposite conditions, we consider the fund a timer and set \( dop \) to 0. If the conditions for neither of the two polar cases are satisfied, suggesting that the fund employs both strategies, then \( dop \) takes a value closer to 1 when relying more on picking, and closer to zero when relying more on timing. Formally,

\[
dop_{it} = \begin{cases} 
1 & \text{if } t(pmt_{it}) \geq t^* \land t(v^P_{it}) \geq t^* \land t(v^T_{it}) < t^* \\
0 & \text{if } t(pmt_{it}) \leq -t^* \land t(v^P_{it}) < t^* \land t(v^T_{it}) \geq t^* \\
\frac{pmt_{it} - lb_{it}}{ub_{it} - lb_{it}} & \text{if } (0, 1) \quad \text{otherwise,}
\end{cases}
\]

where the function \( t(x) \) is the t-statistic of \( x \), \( t^* \) is a statistical threshold which depends on the chosen level of significance, and the lower bound \( (lb_{it}) \) and upper bound \( (up_{it}) \) of \( pmt_{it} \) guarantee that the ratio \( (pmt_{it} - lb_{it})/(ub_{it} - lb_{it}) \) is greater than 1 when \( dop_{it} = 1 \), and less than 0 when \( dop_{it} = 0 \).\(^{15}\) Our proposed measure for the degree of picking of a fund is in line with the characterization of a fund strategy in Zambrana and Zapatero (2018), which also takes into account the statistical significance of picking and timing values.

It is important to emphasize that the measures we consider for assigning an investment strategy to a fund (\( \mathbb{1}(pmt_{it} \geq 0) \) and \( dop_{it} \)) are derived independently from the total value added by the fund \( v_{it} \). Intuitively, under the null hypothesis of no self-selection, the split of the value-pie generated by a manager, i.e., the split between picking and timing values, is independent of its overall size (total value). This implies that any relationship in the data between the split and the size of the pie is not mechanical, but rather evidence against the null.

Out of 14,223 fund-year observations in our data set, 7,912 fund-years have positive \( pmt \). If we consider the sample average of \( pmt_{it} \), denoted by \( \overline{pmt}_{it} \), to capture a fund’s long-term strategy, 1,357 out of 2,124 funds (about 64%) are long-term pickers (\( \overline{pmt}_{it} > 0 \)).

\(^{15}\) The lower bound of \( pmt_{it} \) is the highest value of \( pmt_{it} \) such that the joint conditions \( \{t(pmt_{it}) \leq -t^* \land t(v^P_{it}) < t^* \land t(v^T_{it}) \geq t^* \} \) hold true. The upper bound of \( pmt_{it} \), instead, is the lowest value of \( pmt_{it} \) such that the joint conditions \( \{t(pmt_{it}) \geq t^* \land t(v^P_{it}) \geq t^* \land t(v^T_{it}) < t^* \} \) are satisfied. This implies that

\[
\begin{align*}
lb_{it} &= \min \left\{ -se(pmt_{it}) \cdot t^*; v^P_{it} - se(v^T_{it}) \cdot t^*; se(v^P_{it}) \cdot t^* - v^T_{it} \right\}, \\
up_{it} &= \max \left\{ se(pmt_{it}) \cdot t^*; v^P_{it} - se(v^T_{it}) \cdot t^*; se(v^P_{it}) \cdot t^* - v^T_{it} \right\},
\end{align*}
\]

where \( se(x) \) denotes the standard error of \( x \).
Table 1: Distribution of Picking and Timing Values across Degree of Picking

This table presents the overlap between our measure of a fund’s degree of picking, dop, and the statistical significance of picking and timing values. The statistical significance is assessed at 5% level of significance.

<table>
<thead>
<tr>
<th>Statistical Significance</th>
<th>Degree of Picking</th>
</tr>
</thead>
<tbody>
<tr>
<td>Picking Value</td>
<td>Timing Value</td>
</tr>
<tr>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Total</td>
<td></td>
</tr>
</tbody>
</table>

Since our dop measure allows for the co-existence of picking and timing strategies within funds, it is informative to see how many funds are actually generating value with both strategies. Table 1 shows that, out of 14,223 fund-year observations, there are only 183 instances in which a fund has simultaneously statistically positive \( v_P^{it} \) and statistically positive \( v_T^{it} \). This corresponds to about 1.3% of all fund-year observations, and about 4% of the fund-year observations characterized by a statistically positive value for at least one of the two strategies. These numbers strongly suggest that very few funds are able to successfully adopt picking and timing strategies simultaneously. Moreover, conditional on \( v_P^{it} \) or \( v_T^{it} \) being statistically positive, the average dop\(_{it}\) is 0.95 or 0.3, respectively. This means that the vast majority of funds that generate positive value with one strategy do not generate value with the other.

3.2 Testing Model Predictions

Before focusing on the implications of self-selection, we provide evidence that seems consistent with our assumption that investors have a good understanding of a fund’s main investment strategy. To this end, we identify a fund’s core value as the value generated by the dominant strategy of the fund, and the non-core value as the difference between the total and the core values. Formally, the core value of fund \( i \) in year \( t \), denoted by \( v_C^{it} \), is defined as the convex combination

\[
v_C^{it} = v_P^{it} \cdot \omega_{it} + v_T^{it} \cdot (1 - \omega_{it}),
\]  

(25)
where the weight $\omega_{it}$ reflects the criteria to identify pickers and timers. Given the labeling rules in (22) and (23), $\omega_{it}$ in our analysis is either $1(pmt_{it} > 0)$ or $dop_{it}$. With the former, the core value is equal to $v^P_{it}$ for a picker, and to $v^T_{it}$ for a timer. With the latter, instead, the core value is closer to $v^P_{it}$ the higher the degree of picking, and to $v^T_{it}$ the lower the degree of picking.

Are investors able to distinguish between core and non-core strategies? Although there are reasons to believe that they are, e.g., they can gather information through the fund prospectus, the mandate, the historical performance and holdings data, we answer this question by looking at the response of investors to the performance generated by core and non-core strategies. If investors have no information regarding a fund’s core strategy, they should respond only to the total (risk-adjusted) performance of the fund, and as a consequence the fund flow sensitivity to core and non-core values should be the same. Therefore, any differential sensitivity of flows to core and non-core performance is indirect evidence of investors’ knowledge about the fund’s strategies.

As is standard in the literature, we define the fund flows that a fund receives in year $t$ as

$$\text{flow}_{it} = \frac{q_{it} - q_{it-1} (1 + r_{it})}{q_{t-1} (1 + r_{it})},$$

where $q_{it}$ denotes the assets under management at the end of year $t$ and $r_{it}$ is the net return the fund earned during year $t$.

Table 2 presents the estimated sensitivity of flows to core and non-core performance. In column 1, we use $1(pmt_{it} > 0)$ to classify funds as pickers or timers. With this specification, the sensitivity to core performance is 1.99 vs. 1.23 for non-core performance, where the difference is statistically significant (as reported at the bottom of the table). Column 2 shows that this result remains valid if we compute a fund’s core value using the degree of picking $dop_{it}$. Column 3 considers the same specification as in column 1 but for the restricted sample of young funds, belonging to the bottom three deciles of the fund-age distribution. That the higher flow-performance sensitivity for core value holds true even for younger funds further suggests that investors have a reasonable idea of a fund’s strategy from the outset, without necessarily relying on a long history of past performance.\textsuperscript{16}

Overall, we consider these findings as supporting evidence for the information structure assumed in the model.

\textsuperscript{16}Although fund flows are more sensitive to core performance, our findings show that investors seem to react also to non-core performance. This could reflect the presence of some unsophisticated investors who are unable to distinguish among strategies, or the fact that non-core performance may contain some valuable information.
Table 3: Distribution of Managers’ Skill into Picking and Timing Strategies

This table presents the distribution of managers’ skill into picking and timing strategies. Levels of skill are classified as low, medium and high using the bottom 30%, the middle 40%, and the top 30% of the skill distribution, respectively. Investment strategies are identified using the long-term \( pmt \), denoted by \( \overline{pmt} \), which correspond to the sample average of \( pmt \) for each fund.

<table>
<thead>
<tr>
<th>Skill</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long-term Pickers (( pmt &gt; 0 ))</td>
<td>249</td>
<td>559</td>
<td>549</td>
<td>1,357</td>
</tr>
<tr>
<td>Long-term Timers (( pmt &lt; 0 ))</td>
<td>389</td>
<td>290</td>
<td>88</td>
<td>767</td>
</tr>
<tr>
<td>Total</td>
<td>638</td>
<td>849</td>
<td>637</td>
<td>2,124</td>
</tr>
</tbody>
</table>

**Prediction 1: Likelihood of picking is higher for high-skill managers**

In the equilibrium of the model, high-skill managers always pick, while low-skill managers time with positive probability (Theorem 1). As a consequence, high-skill managers pick with higher probability than low-skill managers. We test this prediction in the data by showing that managers identified as high-skill are on average more likely to pick in any given year.

Table 3 reports the distribution of managers across skill and strategies, where we consider \( \overline{pmt} \) to identify a fund (long-term) strategy. Out of 663 high-skill managers, 567 are pickers and only 96 are timers. Out of 722 low-skill managers, 434 are timers and only 288 are pickers. This simple tabulation unveils a pattern that is consistent with the hybrid separating equilibrium of the model. Table 4 tests our hypothesis more formally. Column 1, which is our baseline specification, is based on a probit regression of \( 1(pmt_{it} > 0) \) (i.e., probability of being a picker) on the estimated skill. The coefficients are positive on medium- and high-skill dummies, 0.21 and 0.34, respectively, indicating that managers who are more skilled are more likely to pick. The estimated probability of picking for low-skill managers is 47%, which rises to 60% for high-skill managers. The regression controls for year and style fixed effects, as well as yearly controls such as fund age, size, turnover, and expense ratio.

We consider several robustness checks from our baseline specification. First, our prediction is confirmed even when using the degree of picking, \( dop \), to identify a fund’s strategy (column 2). Second, to alleviate potential concerns on the in-sample nature of the estimation, in column 3 we consider the same specification as in column 1 but we restrict the sample to only young funds. The findings suggest that high-skill managers are more likely to be pickers even during the early stages of the fund’s life. For the fund-year observations when the fund is young, the skill that is
measured using the entire sample is almost an *out-of-sample* measure of skill. Third, consistent with Berk and van Binsbergen (2015), who argue that the dollar value generated by a fund is a better measure of the ability of its fund manager, we compute the dollar skill for each fund as the sample-average of the yearly dollar value added, \( v_{it}^S = v_{it} \cdot q_{it-1} \). In column 4, we use quantiles of dollar skill and confirm the result that funds generating more dollar value are more likely to be pickers. Fourth, recognizing that the identification of strategy within a year may be noisy, we use \( \mathbb{1}(pmt_i > 0) \) to identify a fund’s long-term strategy, and we run a corresponding probit regression. Column 5 shows that the estimated probabilities of picking go up from 42% for low-skill managers to 85% for high-skill managers. Thus, averaging over the years reduces the noise and increases the statistical power of our test. Overall, our finding on self-selection is robust and the nature of equilibrium that we obtain in the model bears out in the data.

**Prediction 2: Performance of pickers is higher on average**

Our model predicts that high-skill managers are more likely to be pickers. In equilibrium, therefore, the fraction of high-skill managers within the group of pickers is larger than within the group of timers, and pickers on average generate more value than timers (Proposition 1). We test this prediction, and quantify the outperformance of pickers, by regressing the fund’s annual value added on its annual investment strategy (\( \mathbb{1}(pmt_{it} > 0) \) or \( dop_{it} \)).

Column 1 in Table 5 provides our baseline result. Using \( \mathbb{1}(pmt_{it} > 0) \), pickers generate on average 6.15% additional annual (risk-adjusted) return compared to timers. When using \( dop_{it} \) to identify a fund’s strategy, our result becomes even stronger. Column 2 shows that pure pickers (i.e., funds with \( dop_{it} = 1 \)) outperform pure timers (i.e., funds with \( dop_{it} = 0 \)) by 13% annually. Moreover, pickers outperform timers in their respective core strategy. In column 4 we regress funds’ annual core performance (i.e., picking value for pickers and timing value for timers) on their annual investment strategy, and find that pickers generate 3.40% more core value compared to timers. A comparison between columns 1 and 4 also suggests that pickers outperform timers with respect to their non-core strategy.\(^{17}\)

In column 3 of Table 5 we incorporate the role of fund size. Given the relative illiquidity of betting on idiosyncratic factors compared to aggregate factors, picking strategies can be difficult to implement on a large scale. Confirming the intuition that fund size impairs the performance of pickers, the estimated coefficient on the interaction of a dummy for picking and a dummy for large funds is -0.66. Overall, however, diseconomies of scale are small and the net result is

\(^{17}\)A fund’s non-core values, which are negative on average, can be interpreted as an indirect cost of implementing the core strategy of the fund (see, e.g., Bollen and Busse (2001)). With this view in mind, our findings imply that pickers are also better than timers in reducing these implementation costs.
Table 6: Cross-Sectional Dispersion of Picking and Timing Performance

This table presents the sample average of yearly cross-sectional dispersion of performance for pickers \((pmt > 0)\) and timers \((pmt < 0)\). A paired two-sided t-test on the difference in dispersion, with associated standard errors (s.e.) and t-score, are reported.

<table>
<thead>
<tr>
<th></th>
<th>No. of Years</th>
<th>Mean</th>
<th>s.e.</th>
<th>t-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pickers ((pmt &gt; 0))</td>
<td>18</td>
<td>6.474</td>
<td>0.595</td>
<td>10.872</td>
</tr>
<tr>
<td>Timers ((pmt &lt; 0))</td>
<td>18</td>
<td>4.191</td>
<td>0.576</td>
<td>7.270</td>
</tr>
<tr>
<td>Pickers – Timers</td>
<td></td>
<td>2.283</td>
<td>0.316</td>
<td>7.206</td>
</tr>
</tbody>
</table>

that even large picking funds outperform timing funds by an annual return of \(5.71\% = 6.37\% - 0.66\%\). Lastly, we estimate the difference in performance between pickers and timers in dollar value. Pickers generate on average $26M more value than timers do on an annual basis. Using \(dop\), pure pickers generate $60M more value than pure timers. These figures are economically large, especially if considered, for instance, in relation to the findings in Berk and van Binsbergen (2015), who report that the average fund adds $0.14M per month or roughly $17M per year.

Prediction 3: Performance of pickers has greater cross-sectional dispersion

The endogenous self-selection characterizing our model’s equilibrium generates a greater heterogeneity of skill among pickers, as compared to timers (Proposition 1). This is because, beyond the implementation of a strategy for reasons outside a manager’s control, which occurs with small probability \(\kappa\), a fraction \(\eta^*\) of low-skill managers chooses to adopt a picking strategy, while no high-skill manager chooses to adopt a timing strategy. To validate this prediction in the data, we compare the cross-sectional dispersion of average performance between pickers and timers. To this end, we compute the cross-sectional standard deviation of their total performance within a year. Table 6 shows that the cross-sectional dispersion of the average performance of pickers over the sample is 6.47%, while that of timers is only 4.19%. The difference in dispersion of 2.28% is statistically significant.

Prediction 4: Fund flows are more sensitive to the performance of pickers

In the model, correlated timing bets reveal substantially less information about the manager’s skill, compared to uncorrelated picking bets. In equilibrium, this induces low-skill managers to
use timing strategies to hide their skill level, and high-skill managers to use picking strategies to
signal theirs. The differential ability of investors to learn from the two strategies is reflected in a
lower flow-performance sensitivity of timers (Proposition 2). We test this prediction by regressing
fund flows on funds’ lagged performance $v_{it-1}$ and lagged strategy ($\mathbf{1}(pmt_{it-1} > 0)$ or $dop_{it-1}$).

Using $\mathbf{1}(pmt_{it-1} > 0)$, column 1 in Table 7 shows that the flow-performance sensitivity for
timing is 1.36, i.e., a 1% increase in lagged performance brings additional flows of 1.36% of current
asset size. However, the interaction between lagged picking and lagged performance is significantly
positive and equal to 0.49, implying that for pickers, the flow-performance sensitivity rises to
1.85% = 1.36% + 0.49%. This evidence supports the learning channel that is a the core of our
self-selection mechanism. Column 3 uses lagged dop as a robustness check. With this specification,
the flow-performance sensitivity of pickers is almost twice as large as that of timers. In column 2,
we interact the lagged dummy of picking with the lagged core and lagged non-core performance.
A result, the coefficient on core performance (not interacted with the lagged dummy of picking),
1.66, is statistically larger than the coefficient on non-core performance, 1.18, implying that fund
flows of timers are more sensitive to core performance than to non-core. Moreover, the coefficient
on the interaction of the picking strategy with core performance is statistically positive, while the
coefficient on the interaction with non-core performance is not. This highlights that the excess
flow-performance sensitivity for pickers is driven by their core performance.

The existing literature on fund flows has highlighted the role of fund age in reducing the flow-
performance sensitivity (e.g., Chevalier and Ellison (1997)). When a longer history of performance
is available, investors are able to learn more about their managers’ skill, and fund performance is
less important when investors update their beliefs. In other words, investors of older funds have
more extreme – and more precise – posterior beliefs about their managers’ investment abilities.
Given the reduced learning associated with older funds, we should also expect that the role played
by a fund’s investment strategy in conveying valuable information to investors should be less
prominent. Columns 4-6 confirm this. For older funds, the excess flow-performance sensitivity of
pickers gradually reduces and disappears for the oldest group of funds in the sample.

**Prediction 5: Fund size is larger for pickers**

Since the endogenous self-selection in our model makes pickers on average more skilled and hence
able to generate higher performance, pickers, in equilibrium, attract more inflows from investors.
This implies that the fund size of pickers is larger than that of timers (Proposition 2). This
prediction is confirmed by the data.
The average fund size of long-term pickers \( (\text{pmt} > 0) \) is $1.03B (in 2010 dollars), as opposed to an average fund size of $553M of long-term timers \( (\text{pmt} < 0) \). The median size is also higher for long-term pickers: $165M versus $114M. In Table 8, we formally test the relation between fund size and fund strategy by controlling for other annual covariates. Column 1 shows that long-term pickers manage funds that on average have $421M more assets under management. The difference in fund size between long-term pure pickers \( (\text{dop}_i = 1) \) and long-term pure timers \( (\text{dop}_i = 0) \) drastically increases to $1.48B, as revealed by column 2. In column 3, we show that the difference in fund size between strategies holds even when considering the lagged strategy followed by the manager, and controlling for the average fund performance of the inception of the fund till the current date. Finally, column 4 shows that the assets under management of long-term pickers are higher than those of long-term timers even within the group of young funds; specifically, the difference in fund size for young funds is $278M. This result is striking considering that, using \( \text{pmt} \), our results are effectively estimated out-of-sample for young funds.

**Prediction 6: Reputation decreases the likelihood of picking for low-skill managers**

A key prediction of the model is that the equilibrium picking probability of a low-skill manager decreases monotonically with the manager’s reputation (Proposition 3). Intuitively, when the reputation of a low-skill manager is reasonably high, then the gains from pooling with high-skill managers by adopting a picking strategy are small. Indeed, in this case, the low-skill manager is more concerned about protecting his good reputation, which can be achieved by reducing investors’ ability to learn through the adoption of a timing strategy.

In order to test this prediction, we need a measure of fund reputation. An intuitive proxy for this is past fund performance. In the context of our model, for instance, fund performance moves the posterior beliefs of the investor, as revealed by equation (14). So we construct three quantiles of lagged fund performance (bottom 30%, middle 40%, and top 40%), representing low, medium, and high reputation, respectively. Column 1 in Table 9 presents the estimation results of a probit of \( 1(\text{pmt}_it > 0) \) on fund reputation for the sample of low-skill manager. As the lagged performance improves, the probability of being a picker decreases from 50% to 36%. Column 2, instead, shows that the degree of picking \( (\text{dop}_it) \) on average goes down by almost 10 basis points when fund reputation moves from low to high.

As a robustness check, we estimate a first-difference version of column 2. First-difference estimation allows us to test our prediction in a cleaner way, since changes in performance, rather than levels, might be a better approximation for changes in reputation. A change from one quantile of lagged performance to an adjacent one (e.g., from bottom to middle or from middle to top)
corresponds to a mild change in reputation, whereas a change from one quantile to a non-adjacent quantile (e.g., from bottom to top) corresponds to a strong change in reputation. In column 3, we regress changes in $dop_t$ on changes in the reputation quantile. When reputation does not change, we obtain no significant change in the degree of picking. When there is a strong decrease in the reputation of low-skill managers, their degree of picking increases by 0.15, on average. When, instead, there is a strong improvement to reputation, the degree of picking decreases by 0.39, on average. A spread of almost 0.55 is large, considering that the degree of picking is a measure between 0 and 1. Our findings also highlight the asymmetry in the way low-skill managers change strategies. The shift to timing is far more intense as a result of the reputation improvement.

It is reasonable to expect that the ability of a manager to switch between a picking and a timing strategy, or to change how much to rely on one over the other, might depend on the availability of strategy-specific information. Picking requires more stock-level information, and timing requires information on aggregate fluctuations of the market or sector. We conjecture that larger fund families, which tend to have funds operating in varied sectors and styles, are more likely to provide their managers with a wider set of information required to switch between strategies. Based on this conjecture, we should expect that switching between strategies is more pronounced in larger fund families. In columns 4 and 5 we run the same regression as in column 3 but restrict our sample to fund families with very few funds and with many funds, respectively. First, the negative relation between reputation and degree of picking continues to hold for the subsamples of funds belonging to smaller and larger families. Second, in line with our conjecture, the reduction in the degree of picking, and hence to switching towards timing strategies, after a positive change in reputation is far stronger for funds belonging to large families. Specifically, $dop_t$ goes down by 0.50, on average, for funds belonging to larger families, and only by 0.38 for funds belonging to smaller families.

**Prediction 7: Volatility decreases the likelihood of picking for low-skill managers**

In the model, the correlation parameter $\rho$ governs how correlated timing bets are with each other, and hence affects the volatility of timing strategies. As this correlation increases, low-skill managers find it more profitable to adopt timing strategies, since the ensuing increase in volatility reduces investors' ability to infer skill from performance (Proposition 4). Because the rise in aggregate volatility is an important channel through which the correlation among timing bets increases, we test the model prediction by analyzing the relation between the investment strategy ($1(pmt_t > 0)$ or $dop_t$) adopted by low-skill funds and the volatility of their benchmark.

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18 We consider the number of funds within a fund family, rather than the assets under management of the family, since our goal is to measure the variety of funds.
Column 1 in Table 10 presents our baseline result using $1(pmt_{it} > 0)$ in a probit regression. The average picking probability of low-skill managers goes from 49% to 40% during periods of high benchmark volatility (identified as top 30% of benchmark volatility distribution). Since the cumulative distribution of volatility is relatively flat in the middle – over the middle 4 deciles (4th to 7th) benchmark volatility rises from 13% to only 17% – changes in volatility in this region may not be economically large enough to induce a change in the fund strategy. To alleviate this concern, in column 2 we exclude the middle 4 deciles and compare high benchmark volatility states (top 30%) with only low volatility states (bottom 30%). With this refinement, the data reveals a much larger and statistically significant drop in the probability of picking for low-skill managers: it goes from 57% when benchmark volatility is low to 30% when it is high.

Using the continuous measure $dop_{it}$ to identify the investment strategy, we obtain similar results. Columns 3 shows that the degree of picking of low-skill managers drops on average by 15% during periods of high benchmark volatility. To better control for fund fixed effects, we estimate a first-difference version of column 3 by regressing changes in $dop$ on a dummy of increase in benchmark volatility. Column 4 shows a drop in $dop$ of 17.5%. As a last robustness check, in columns 5 and 6, we condition on low and high levels of lagged benchmark volatility, respectively. When benchmark volatility is already high, a further rise should not significantly affect the choice of the investment strategy. This is confirmed by an estimated coefficient on the dummy for the rise in benchmark volatility that is not significantly different from 0. When, instead, benchmark volatility is low, an increase in volatility makes a change in strategy more profitable, and the data show an average drop of 22% in the degree of picking. Overall, the data suggests that low-skill managers do take benchmark volatility into account when strategically choosing their investment strategies.

**Prediction 8: Volatility reduces the average skill of timers and raises that of pickers**

As low-skill managers rely more on timing strategies in periods of high benchmark volatility, the average skill within the group of timers decreases in these periods, while the average skill within the group of pickers increases (Proposition 4).

In Table 11, the data illustrates this prediction. In column 1, we regress a fund’s timing skill, measured by the estimated $\hat{\gamma}_{it}$ in equation (20), on a dummy of high volatility, and on the interaction of this dummy with the degree of picking, $dop_{it}$. When $dop_{it}$ is sufficiently low, funds’ timing skill decreases during periods of high benchmark volatility, compared to periods of low volatility. For instance, when $dop_{it} = 0$ (i.e., the fund is a pure timer), the timing skill decreases by 1.09. In column 2, instead, we regress a fund’s picking skill, measured by the estimated $\hat{\alpha}_{it}$
in equation (20), on the same set of regressors as in column 1. When \( dop_{it} \) is sufficiently high, picking skill increases during periods of high benchmark volatility. For the subset of pure pickers \(( dop_{it} = 1)\), the average \( \alpha \) increases by 3.86%.\(^{19}\) In the last column of Table \([11]\), we show the effects of benchmark volatility on the total fund performance. During periods of high benchmark volatility, the total fund value decreases for timers (low \( dop_{it} \)), whereas it increases for pickers (high \( dop_{it} \)).

Our results on volatility relate to the recent findings in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016). Their model implies that it is optimal for a fund manager to time the market when aggregate volatility is high and to pick otherwise. This is because the value of using aggregate information, as opposed to information on individual companies, becomes greater during periods of high aggregate volatility. In the presence of adverse selection, though, our model predicts that, compared to high-skill managers, low-skill managers should have stronger incentives to rely on timing strategies when volatility increases. In this case, due to a composition effect of high- and low-skill managers within investment strategies, the cross-sectional performance of pickers is expected to go up while that of timers is expected to go down.

4 Concluding Remarks

Why do some fund managers choose picking strategies and some others choose timing strategies? To answer this question, we propose a novel theory of manager self-selection into these investment strategies. Our theory of self-selection exploits the difference in the correlation between investments associated with a picking strategy as opposed to a timing strategy. While timing investments tend to be positively correlated, since they are driven by a common underlying component, picking investments are uncorrelated. In the presence of adverse selection, this salient distinction between these strategies implies that investors can more readily learn about the skill of a picker than that of a timer. Our equilibrium model with endogenous fund flows delivers a unique hybrid mixed-strategy separating equilibrium in which high-skill managers always pick, while low-skill managers time with positive probability. We validate the model in the data and confirm its rich set of empirical predictions. We find that picking funds tend to generate more value for investors, are larger, and exhibit higher fund flow sensitivity than timing funds. We also confirm the predictions that an increase in market volatility reduces the cross-sectional dispersion

\(^{19}\)We note that the F test of \( \beta [I\text{(High Volatility)}] + \beta [I\text{(High Volatility)} \times dop] = 0 \) is overwhelmingly rejected with an F score of 41 and p-value that is arbitrarily close to 0.
of performance across picking and timing strategies, and causes a higher fraction of low-skilled managers to choose a timing strategy.
Appendix A: Proofs

Proof of Lemma 1. The net fund return is given by \( r_t^{a+1} \) in (5). A competitive capital market implies that in equilibrium \( \mathbb{E}_t[R_t^{a+1}] = 0 \). This pins down the fund size \( q_t = (1/c) \cdot \mathbb{E}_t[R_{t+1}^{a} - f] \). Taking expectation at time \( t \) of \( R_{t+1}^{a} \) yields \( \mathbb{E}_t[R_t^{a+1}] = \phi_t h + (1 - \phi_t) \mu_L \). Substituting this expectation into the expression of \( q_t \) we obtain (7).

Lemma A.1 (Properties of Logit-Normal Distribution). Suppose \( Y \sim \mathcal{N}(\mu, \sigma^2) \), then \( X = e^Y/(1+e^Y) \) has a logit-normal distribution, \( X \sim \text{LogitN}(\mu, \sigma^2) \), and satisfies the following properties:

(a) \( \mathbb{E}[X] \) is increasing in \( \mu \);
(b) \( \mathbb{E}[X] \) is decreasing in \( \sigma \) if \( \mu > 0 \) and increasing in \( \sigma \) if \( \mu < 0 \);
(c) \( \mathbb{E}[X] \) is decreasing in \( \sigma \) if \( \mu = k - \sigma^2/2 \);
(d) \( \mathbb{E}[X] \) is increasing in \( \sigma \) if \( \mu = k + \sigma^2/2 \).

Proof. We express \( Y = \mu + \sigma Z \), where \( Z \sim \mathcal{N}(0,1) \). It follows that

\[
X = \frac{e^{\mu + \sigma Z}}{1 + e^{\mu + \sigma Z}} = (1 + e^{-\mu - \sigma Z})^{-1} \tag{A.1}
\]

Since \( X \) is a non-negative random variable, in what follows we rely on the Dominated Convergence Theorem to interchange the order of the expectation and derivative of \( X \) with respect to \( \mu \) and \( \sigma \).

(a) Taking the derivative of the expectation of \( X \) with respect to \( \mu \), we obtain that

\[
\frac{\partial}{\partial \mu} \mathbb{E}[X] = \mathbb{E} \left[ \frac{\partial}{\partial \mu} (1 + e^{-\mu - \sigma Z})^{-1} \right] = \mathbb{E} \left[ \frac{-e^{-\mu - \sigma Z}}{(1 + e^{-\mu - \sigma Z})^2} \right] > 0 \quad \text{since} \quad \frac{e^{-\mu - \sigma Z}}{(1 + e^{-\mu - \sigma Z})^2} > 0 \quad \forall Z.
\]

(b) Taking the derivative of the expectation of \( X \) with respect to \( \sigma \), we obtain that

\[
\frac{\partial}{\partial \sigma} \mathbb{E}[X] = \mathbb{E} \left[ \frac{\partial}{\partial \sigma} (1 + e^{-\mu - \sigma Z})^{-1} \right] = e^{-\mu} \mathbb{E} \left[ \frac{Z}{e^{\frac{\sigma Z}{2}} + e^{-\mu - \frac{\sigma Z}{2}}} \right] = e^{-\mu} \left( \mathbb{E} \left[ \frac{Z \mathbb{1}_{\{Z > 0\}}}{e^{\frac{\sigma Z}{2}} + e^{-\mu - \frac{\sigma Z}{2}}} \right] + \mathbb{E} \left[ \frac{Z \mathbb{1}_{\{Z < 0\}}}{e^{\frac{\sigma Z}{2}} + e^{-\mu - \frac{\sigma Z}{2}}} \right] \right),
\]

where the last equality follows from the fact that the random variable \( Z \sim \mathcal{N}(0,1) \) has symmetric distribution around 0. In particular, let \( \tilde{Z} = -Z \). Then, \( Z \mathbb{1}_{\{Z > 0\}} = \tilde{Z} \mathbb{1}_{\{	ilde{Z} > 0\}} \). Since \( \tilde{Z} \sim \mathcal{N}(0,1) \), it follows that \( \mathbb{E}[g(Z)] = \mathbb{E}[g(\tilde{Z})] \) for any function \( g: \mathbb{R} \to \mathbb{R} \).
Let
\[ a(Z) \equiv \left( e^{\frac{\mu}{2}Z} + e^{-\mu - \frac{\sigma^2}{2}} \right)^2 \quad \text{and} \quad b(Z) \equiv \left( e^{-\frac{\mu}{2}Z} + e^{-\mu + \frac{\sigma^2}{2}} \right)^2. \]

It follows that \( a(Z) - b(Z) = (e^{\sigma Z} - e^{-\sigma Z}) \left( 1 - e^{-2\mu} \right). \) Since we are interested only in positive values of \( Z, \) \( (e^{\sigma Z} - e^{-\sigma Z}) > 0 \) for any \( Z > 0, \) and consequently \( a(Z) > b(Z) \) if \( \mu > 0 \) and \( a(Z) < b(Z) \) if \( \mu < 0. \) This implies that

\[
\frac{\partial}{\partial \sigma} \mathbb{E}[X] = \begin{cases} 
-\mu \left( E \left[ \frac{Z1_{(Z>0)}}{a(Z)} \right] - E \left[ \frac{Z1_{(Z>0)}}{b(Z)} \right] \right) < 0 & \text{if } \mu > 0 \\
-\mu \left( E \left[ \frac{Z1_{(Z>0)}}{a(Z)} \right] - E \left[ \frac{Z1_{(Z>0)}}{b(Z)} \right] \right) > 0 & \text{if } \mu < 0
\end{cases}
\]

(c) Let \( f(Z) \) denote \( X \) in (A.1) and consider \( \mu = k - \sigma^2/2, \)
\[
f(Z) = \frac{e^{k - \frac{\sigma^2}{2} + \sigma Z}}{1 + e^{k - \frac{\sigma^2}{2} + \sigma Z}}
\]

Taking the derivative of the expectation of \( X \) with respect to \( \sigma, \) we obtain that
\[
\frac{\partial}{\partial \sigma} \mathbb{E}[X] = \mathbb{E} [f(Z)(1 - f(Z))(Z - \sigma)].
\]

In order to sign the above derivative, we make use of Stein's Lemma: if \( X \) and \( Y \) are jointly normally distributed, then \( \text{Cov}[g(X), Y] = \text{Cov}[X, Y] \cdot E[\partial g(X)/\partial X]. \) Let \( g(Z) = f(Z) (1 - f(Z)). \) Since \( Z \sim \mathcal{N}(0, 1), \) \( \mathbb{E}(Z) = 0 \) and consequently
\[
\text{Cov}[g(Z), Z] = \mathbb{E}[g(Z)Z] + \mathbb{E}[g(Z)]\mathbb{E}[Z] = \mathbb{E}[g(Z)Z].
\]

Applying Stein's Lemma and considering that \( \forall \text{Var}[Z] = 1, \)
\[
\mathbb{E}[g(Z)Z] = \text{Cov}[Z, Z] \cdot E \left[ \frac{\partial g(Z)}{\partial Z} \right] = E \left[ \frac{\partial g(Z)}{\partial Z} \right]
\]
\[
= E \left[ (1 - f(Z)) \left[ f(Z)(1 - f(Z)) \sigma \right] - f(Z) \left[ f(Z)(1 - f(Z)) \sigma \right] \right]
\]
\[
= \sigma E \left[ f(Z)(1 - f(Z)) \right] (1 - 2f(Z)).
\]

Since
\[
1 - 2f(Z) = \frac{1 - e^{k - \frac{\sigma^2}{2} + \sigma Z}}{1 + e^{k - \frac{\sigma^2}{2} + \sigma Z}} < 1 \quad \forall \ Z,
\]

it follows that \( f(Z) (1 - f(Z)) (1 - 2f(Z)) < f(Z) (1 - f(Z)). \) This implies that
\[
\mathbb{E}[f(Z)(1 - f(Z))Z] = \sigma \mathbb{E}[f(Z)(1 - f(Z)) (1 - 2f(Z))] \quad \sigma \mathbb{E}[f(Z)(1 - f(Z))]
\]
\[
\downarrow
\]
\[
\frac{\partial}{\partial \sigma} \mathbb{E}[X] = \mathbb{E} [f(Z)(1 - f(Z))(Z - \sigma)] < 0.
\]
(d) Let $f(Z)$ denote $X$ in (A.1) and consider $\mu = k + \frac{\sigma^2}{2}$,

$$f(Z) = \frac{e^{k+\frac{\sigma^2}{2}} + \sigma} {1 + e^{k+\frac{\sigma^2}{2}} + \sigma}$$

Taking the derivative of the expectation of $X$ with respect to $\sigma$, we obtain that

$$\frac{\partial}{\partial \sigma} \mathbb{E}[X] = \mathbb{E} [f(Z)(1 - f(Z))(Z + \sigma)].$$

In order to sign the above derivative, we make use of Stein's Lemma, as in property (c). Let $g(Z) = f(Z)(1 - f(Z))$. Since $Z \sim \mathcal{N}(0,1)$, it follows that

$$\mathbb{E} [f(Z)(1 - f(Z))Z] = \mathbb{Cov}[g(Z), Z] = \mathbb{E}[g(Z)Z]$$

$$= \mathbb{Cov}[Z, Z] \cdot \mathbb{E} \left[ \frac{\partial g(Z)}{\partial Z} \right] = \mathbb{E} \left[ \frac{\partial g(Z)}{\partial Z} \right]$$

$$= \mathbb{E} [(1 - f(Z)) f(Z)(1 - f(Z)) \sigma - f(Z) f(Z)(1 - f(Z)) \sigma]$$

$$= \sigma \mathbb{E} [f(Z)(1 - f(Z))(1 - 2f(Z))].$$

Therefore,

$$\frac{\partial}{\partial \sigma} \mathbb{E}[X] = \mathbb{E} [f(Z)(1 - f(Z))(Z + \sigma)]$$

$$= \sigma \mathbb{E} [f(Z)(1 - f(Z))(1 - 2f(Z))] + \sigma \mathbb{E} [f(Z)(1 - f(Z))]$$

$$= 2\sigma \mathbb{E} \left[ f(Z)(1 - f(Z))^2 \right],$$

which is always positive since $f(Z) \in [0, 1]$. \hfill \Box

**Lemma A.2 (Bayesian Learning).** The probability at time $t + 1$ that the manager is high-skill type, $\phi_{t+1}$, is given by (A.2). Moreover, conditional on the manager’s information at time $t$, $\phi_{t+1}$ has a logit-normal distribution, $(\phi_{t+1}|a_t, s) \sim \text{LogitN}(m_t^0(s), \varsigma^a)$, where

$$m_t^0(s) = \begin{cases} 
\log(\phi_t/(1 - \phi_t)) + \frac{\Delta \mu^2}{\nu^a} - \log(\Lambda_t(a_t)) & \text{if } s = H \\
\log(\phi_t/(1 - \phi_t)) - \frac{\Delta \mu^2}{\nu^a} - \log(\Lambda_t(a_t)) & \text{if } s = L, 
\end{cases}$$

(A.2)

$$\varsigma^a = \Delta \mu^2/\nu^a.$$  

(A.3)

**Proof.** Let $\phi_t$ be the prior probability at time $t$ that the manager is high-skill, $\phi_t = \mathbb{P}_t(H)$. An application of Bayes rule yields that the posterior probability $\phi_{t+1} = \mathbb{P}_{t+1}(H|R_{t+1}^a, a_t)$ is given by

$$\phi_{t+1} = \frac{\varphi_t(R_{t+1}^a|a_t, H) \cdot \mathbb{P}_t(a_t|H) \cdot \phi_t}{\varphi_t(R_{t+1}^a|a_t, H) \cdot \mathbb{P}_t(a_t|H) \cdot \phi_t + \varphi_t(R_{t+1}^a|a_t, L) \cdot \mathbb{P}_t(a_t|L) \cdot (1 - \phi_t)},$$

(A.4)
where $\varphi(t)$ is the pdf of the normal distribution in (3). Dividing (A.4) by $\varphi_t(R^a_{t+1}|a_t, H) \cdot \mathbb{P}_t(a_t|H)$ we obtain that

$$
\phi_{t+1} = \phi_t \left( \phi_t + (1 - \phi_t) \frac{\varphi_t(R^a_{t+1}|a_t, L) \mathbb{P}_t(a_t|L)}{\varphi_t(R^a_{t+1}|a_t, H) \mathbb{P}_t(a_t|H)} \right)^{-1}.
$$ (A.5)

By defining $\Lambda_t(\cdot)$ as the likelihood ratio $\mathbb{P}_t(\cdot|L)/\mathbb{P}_t(\cdot|H)$, (12) obtains.

Let $\Phi_t$ denote the logit transformation of $\phi_t$, $\Phi_t = \log(\phi_t/(1 - \phi_t))$. Applying the logit transformation to $\phi_{t+1}$ in (A.5), we obtain that

$$
\Phi_{t+1} = \Phi_t - \log \left( \Lambda_t(R^a_{t+1}|a_t) \right) - \log (\Lambda_t(a_t))
= \Phi_t - \log \left( \frac{e^{-\frac{1}{2\sigma^2}(R^a_{t+1} - \mu_H)^2}}{e^{-\frac{1}{2\sigma^2}(R^a_{t+1} - \mu_L)^2}} \right) - \log (\Lambda_t(a_t))
= \Phi_t - \frac{1}{2\sigma^2} \left[ (R^a_{t+1} - \mu_H)^2 - (R^a_{t+1} - \mu_L)^2 \right] - \log (\Lambda_t(a_t))
= \Phi_t + \frac{\Delta \mu}{\sigma^2} \left( \frac{R^a_{t+1} - \bar{\mu}}{\nu^a} \right) - \log (\Lambda_t(a_t)).
$$ (A.6)

Since $\Phi_{t+1}$ is affine in $R^a_{t+1}$, it is normally distributed with mean and variance equal to (A.2) and (A.3), respectively: $\Phi_{t+1} \sim \mathcal{N}(\mu^a(s), \sigma^a)$.

**Proof of Theorem 1.** Given the conjectured equilibrium in which a high-skill manager picks with probability 1 and a low-skill manager picks with probability $\eta_t < 1$, a low-skill manager must be indifferent between choosing a picking and a timing strategy: $v_t(P|L) = v_t(T|L)$. Since

$$
v_t(a_t|L) = \mathbb{E}_t^M \left[ \phi_{t+1}(R^a_{t+1}|s) \right] = \int_{-\infty}^{\infty} \phi_{t+1}(R^a_{t+1}) \frac{1}{\sqrt{2\pi}\nu^a} e^{-\frac{(R^a_{t+1} - \mu_H)^2}{2\sigma^2}} dR^a_{t+1},
$$

and $\nu^T = \nu^P(1 + (n - 1)\rho)$, the conjectured equilibrium implies (13). Moreover, given the mixed strategy $\eta_t \leq 1$, the likelihood ratio $\Lambda_t(a_t)$ becomes equal to

$$
\Lambda_t(a_t) = \frac{\mathbb{P}_t(a_t|L)}{\mathbb{P}_t(a_t|H)} = \begin{cases} 
\frac{\eta_t (1 - \eta_t) + (1 - \eta_t) \frac{\varphi_t(R^a_{t+1}|a_t, L)}{\varphi_t(R^a_{t+1}|a_t, H)}}{1 - \eta_t} & \text{if } a_t = P \\
\frac{(1 - \eta_t)(1 - \eta_t) + \eta_t \frac{\varphi_t(R^a_{t+1}|a_t, L)}{\varphi_t(R^a_{t+1}|a_t, H)}}{\eta_t} & \text{if } a_t = T,
\end{cases}
$$

which can be written more concisely as (15). Substituting (15) and $\Lambda_t(R^a_{t+1}|a_t) = e^{-\frac{\Delta \mu(R^a_{t+1} - \bar{\mu})}{\sigma^a}}$ into (A.5), (14) obtains. For notational convenience, let $\lambda^a_t(\eta_t)$ denote the logarithm of the likelihood-ratio $\Lambda_t(a_t)$ in (15).

We next show that there always exists a unique probability $\eta_t < 1$ that supports the conjectured hybrid separating equilibrium. We proceed in steps.

**Step 1.** We first prove that $\eta_t = 1$ (i.e., full pooling) cannot be part of an equilibrium. Consider a low-skill manager ($s = L$). When $\eta_t = 1$, the mean of $\Phi_{t+1}$ in (A.2) becomes equal to $m^a_t(L) = \Phi_t - \Delta \mu^2/2\sigma^a$, since $\lambda^P_t(1) = \lambda^T_t(1) = 0$. Since the variance of $\Phi_{t+1}$ in (A.3) is independent of $\eta_t$ and
equal to \( \zeta^a = \frac{\Delta \mu^2}{\nu^a} \), it follows that \( (\phi_{t+1}|a_t, L, \eta_t = 1) \sim \logit(\Phi_t - (1/2)\nu^a, \nu^a) \). We use property (c) in Lemma A.1 to conclude that \( v_t(a_t|L, \eta_t = 1) \) is decreasing in \( \zeta^a \). Since \( \nu^P < \nu^T \), and hence \( \zeta^P > \zeta^T \), it follows that

\[
\begin{align*}
v_t(P|L, \eta_t = 1) < v_t(T|L, \eta_t = 1).
\end{align*}
\]

This implies that full pooling cannot be part of an equilibrium because, given the investor’s beliefs that a low-skill manager would pick with probability 1, the low-skill manager would deviate and instead adopt a timing strategy (with probability 1).

**Step 2.** We next show some useful properties of \( m^a(L) \). Consider a low-skill manager \((s = L)\). The mean of \( \Phi_{t+1} \) in \((A.2)\), \( m_t^L(L) = \Phi_t - \Delta \mu^2/2\nu^a - \lambda^2_t(\eta_t) \), is monotonically decreasing in \( \eta_t \) when \( a_t = P \) since \( \lambda^2_t(\eta_t) \) is monotonically increasing in \( \eta_t \). In contrast, \( m_t^T(L) \) is monotonically increasing in \( \eta_t \) since \( \lambda^2_t(\eta_t) \) is monotonically decreasing in \( \eta_t \). Moreover, since \( \nu^P < \nu^T \), we obtain that at the two limits of \( \eta_t \) the following holds:

\[
\lim_{\eta_t \to 1} m_t^P(L) = \Phi_t - \frac{\Delta \mu^2}{2\nu^P} < \lim_{\eta_t \to 1} m_t^T(L) = \Phi_t - \frac{\Delta \mu^2}{2\nu^T},
\]

and

\[
\lim_{\eta_t \to 0} m_t^P(L) = \Phi_t - \frac{\Delta \mu^2}{2\nu^P} - \log \left( \frac{\kappa}{2 - \kappa} \right) \geq \lim_{\eta_t \to 0} m_t^T(L) = \Phi_t - \frac{\Delta \mu^2}{2\nu^T} - \log \left( \frac{2}{\kappa} \right)
\]

depending on whether \( \kappa \leq \bar{\kappa} \), where \( \bar{\kappa} \equiv 2/\left(1 + e^{\Delta \mu^2/(\nu^T - \nu^P)}\right) \).

**Step 3.** Suppose \( \kappa < \bar{\kappa} \), so that \( \lim_{\eta_t \to 0} m_t^P(L) \geq \lim_{\eta_t \to 0} m_t^T(L) \). Given the monotonicity of \( m^a(L) \) in \( \eta_t \), this implies that there exists a probability \( \eta_t^* \) such that \( m_t^P(L, \eta_t = \tilde{\eta}_t) = m_t^T(L, \eta_t = \tilde{\eta}_t) \). Consider the following two cases:

(i) \( m_t^P(L, \eta_t = \tilde{\eta}_t) = m_t^T(L, \eta_t = \tilde{\eta}_t) < 0 \). Since the common mean \( m_t^a(L) \) at \( \eta_t = \tilde{\eta}_t \) is negative, we use property (b) in Lemma A.1 to conclude that \( v_t(a_t|L) \) is increasing in \( \zeta^a \). Therefore, since \( \nu^P \), \( \nu^T \), and hence \( \zeta^P \) \( > \zeta^T \), it follows that \( v_t(P|L, \eta_t = \tilde{\eta}_t) > v_t(T|L, \eta_t = \tilde{\eta}_t) \). Moreover, since by property (a) in Lemma A.1 \( v_t(a_t|L) \) is increasing in \( m_t^a(L) \), and since \( m_t^P(L) \) is decreasing in \( \eta_t \), \( m_t^T(L) \) is increasing in \( \eta_t \), it follows that the difference \( v_t(T|L, \eta_t = \tilde{\eta}_t) - v_t(T|L, \eta_t = \tilde{\eta}_t) \) decreases in \( \eta_t \). Since \( v_t(T|L, \eta_t = 1) - v_t|L, \eta_t = 1) < 0 \), by continuity and monotonicity of \( v_t(a_t|L) \) in \( \eta_t \), it means that there exists a unique mixed strategy \( \eta_t^* \in (\tilde{\eta}_t, 1) \) such that \( v_t(P|L, \eta_t = \eta_t^*) = v_t(T|L, \eta_t = \eta_t^*) \).

(ii) \( m_t^P(L, \eta_t = \tilde{\eta}_t) = m_t^T(L, \eta_t = \tilde{\eta}_t) > 0 \). Since the common mean \( m_t^a(L) \) at \( \eta_t = \tilde{\eta}_t \) is positive, we use property (b) in Lemma A.1 to conclude that \( v_t(a_t|L) \) is decreasing in \( \zeta^a \). Therefore, since \( \nu^P \), \( \nu^T \), and hence \( \zeta^P \) \( > \zeta^T \), it follows that \( v_t(T|L, \eta_t = \tilde{\eta}_t) > v_t(P|L, \eta_t = \tilde{\eta}_t) \). Moreover, since by property (a) in Lemma A.1 \( v_t(a_t|L) \) is increasing in \( m_t^a(L) \), and since \( m_t^P(L) \) is decreasing in \( \eta_t \), \( m_t^T(L) \) is increasing in \( \eta_t \), it follows that the difference \( v_t(T|L, \eta_t = \tilde{\eta}_t) - v_t(P|L, \eta_t = \tilde{\eta}_t) \) increases in \( \eta_t \). If \( v_t(T|L, \eta_t = 0) - v_t(P|L, \eta_t = 0) < 0 \), by continuity and monotonicity of \( v_t(a_t|L) \) in \( \eta_t \), it means that there exists a unique mixed strategy \( \eta_t^* \in (0, \tilde{\eta}_t) \) such that \( v_t(P|L, \eta_t = \eta_t^*) = v_t(T|L, \eta_t = \eta_t^*) \). If, instead, \( v_t(T|L, \eta_t = 0) - v_t(P|L, \eta_t = 0) > 0 \), then timing is preferred over picking by a low-skill manager for any \( \eta_t \in [0, 1] \). Consequently, there exists a unique pure strategy \( \eta_t^* = 0 \).
Step 4. Suppose \( \kappa > \tilde{\kappa} \), so that \( \lim_{\eta_t \to 0} m_t^P(L) < \lim_{\eta_t \to 0} m_t^T(L) \). Given the monotonicity of \( m^a(L) \) in \( \eta_t \), this implies that \( m_t^T(L) > m_t^P(L) \) for any \( \eta_t \). Following the same logic as in step 3, we consider the following cases:

(i) \( m_t^P(L, \eta_t) = 0 < 0 \). Since \( v_t(a_t|L) \) is increasing in \( \varsigma^a \) when \( m_t^a(L) \) is negative and decreasing otherwise, and since \( \varsigma^P > \varsigma^T \), it can be that \( v_t(P|L, \eta_t = 0) \geq v_t(T|L, \eta_t = 0) \). If \( v_t(P|L, \eta_t = 0) > v_t(T|L, \eta_t = 0) \), given the continuity and monotonicity of \( v_t(a_t|L) \) in \( \eta_t \), there exists a unique mixed \( \eta_t^* \in (0,1) \) such that \( v_t(P|L, \eta_t = \eta_t^*) = v_t(T|L, \eta_t = \eta_t^*) \). If, instead, \( v_t(P|L, \eta_t = 0) < v_t(T|L, \eta_t = 0) \), there exists a unique pure strategy \( \eta_t^* = 0 \).

(ii) \( m_t^P(L, \eta_t) = 0 > 0 \). Since \( v_t(a_t|L) \) is decreasing in \( \varsigma^a \) when \( m_t^a(L) \) is positive, and since \( \varsigma^P > \varsigma^T \), it follows that \( v_t(P|L, \eta_t = 0) < v_t(T|L, \eta_t = 0) \). Consequently, there exists a unique pure strategy \( \eta_t^* = 0 \).

Step 5. We next show that at the equilibrium \( \eta_t^* \) it is always optimal for a high-skill manager to choose a picking strategy. Consider a high-skill manager (\( s = H \)). Since \( \lambda_t^P(\eta_t) \) and \( \lambda_t^T(\eta_t) \) are respectively monotonically increasing and decreasing in \( \eta_t \), the mean of \( \Phi_{t+1} \) in (A.2), \( m_t^S(H) = \Phi_t + \Delta \mu^2 / 2 \nu^a - \lambda_t^P(\eta_t) \), is monotonically decreasing in \( \eta_t \) when \( a_t = P \), and monotonically increasing in \( \eta_t \) when \( a_t = T \). Moreover, since by property (a) in Lemma A.1 the value function \( v_t(a_t|H) \) is increasing in \( m_t^S(H) \), it follows that \( v_t(P|H, \eta_t = \eta_t^*) \geq v_t(P|H, \eta_t = 1) \) and \( v_t(T|H, \eta_t = 1) \geq v_t(T|H, \eta_t = \eta_t^*) \).

When \( \eta_t = 1 \), the mean of \( \Phi_{t+1} \) in (A.2) becomes equal to \( m_t^S(H) = \Phi_t + \Delta \mu^2 / 2 \nu^a \), since \( \lambda_t^P(1) = \lambda_t^T(1) = 0 \). Since the variance of \( \Phi_{t+1} \) in (A.3) is independent of \( \eta_t \) and equal to \( \varsigma^a = \Delta \mu^2 / \nu^a \), it follows that \( (a_{t+1}, a_t, H, \eta_t = 1) \sim \text{Logit}(\Phi_t + (1/2) \nu^a, \nu^a) \). We use property (d) in Lemma A.1 to conclude that \( v_t(a_t|H, \eta_t = 1) \) is increasing in \( \varsigma^a \). Since \( \nu^P < \nu^T \), and hence \( \varsigma^P > \varsigma^T \), it follows that

\[
v_t(P|L, \eta_t = 1) \geq v_t(T|L, \eta_t = 1).
\]

This implies that \( v_t(P|H, \eta_t = \eta_t^*) \geq v_t(T|H, \eta_t = \eta_t^*) \), and hence it is optimal for a high-skill manager to always adopt a picking strategy.

Proof of Proposition [1]. Given the assumption of diffuse investor’s prior about the manager’s type, we consider an equal mass of high-skill and low-skill managers. The equilibrium self-selection implies that the mass of managers implementing picking and timing strategies are given by

\[
\text{Mass}_t^P = \frac{1}{2} \left( 1 - \frac{\kappa}{2} \right) + \frac{1}{2} \left[ \eta_t^* \left( 1 - \frac{\kappa}{2} \right) + (1 - \eta_t^*) \frac{\kappa}{2} \right] = \frac{1}{2} \left[ 1 + \eta_t^* (1 - \kappa) \right] > \frac{1}{2}, \tag{A.7}
\]

\[
\text{Mass}_t^T = \frac{1}{2} \left( \frac{\kappa}{2} \right) + \frac{1}{2} \left[ \eta_t^* \frac{\kappa}{2} + (1 - \eta_t^*) \left( 1 - \frac{\kappa}{2} \right) \right] = \frac{1}{2} \left[ 1 - \eta_t^* (1 - \kappa) \right] < \frac{1}{2}, \tag{A.8}
\]

respectively. High-skill managers, who account for half of the manager’s population, always choose to pick, but given the possibility of a change of strategy out of their control, only \( (1 - \kappa/2) \) of them ends up implementing a picking strategy. Among low-skill managers, who account for the other half of the manager’s population, a fraction \( \eta_t^* \) of these managers chooses to pick, but only \( \eta_t^* (1 - \kappa/2) \) of them ends up undertaking a picking strategy. Moreover, out of the fraction \( (1 - \eta_t^*) \) of low-skill managers who chooses to time, \( (1 - \eta_t^*) \kappa/2 \) of them ends up undertaking a picking strategy. The sum of these fractions yields (A.7). Using the same logic, (A.8) obtains.
Let $M_t^a(s)$ denote the fraction of managers of skill $s$ adopting strategy $a$ at time $t$. It follows that

\[
M_t^P(H) = \frac{1}{2} \left( \frac{1}{Mass_t^P} \right) = \frac{1}{1 + \eta_t^*(1 - \kappa)},
\]

\[
M_t^T(H) = \frac{1}{2} \frac{\frac{\eta_t^*}{(1 - \kappa)}}{1 + \eta_t^*(1 - \kappa)},
\]

(A.9)

(A.10)

The cross-sectional average of the expected performance of fund $a$ at time $t$ is given by

\[
E^c_t[R_{t+1}^a] = M_t^a(H)\mu_H + (1 - M_t^a(H))\mu_L,
\]

(A.11)

where the unscript $cs$ indicates that the average is taken cross-sectionally. Since $M_t^P(H) > M_t^T(H)$ for any $\eta_t^* \in [0, 1)$, it follows that $E^c_t[R_{t+1}^T] > E^c_t[R_{t+1}^P]$. The cross-sectional dispersion in the expected performance of strategy $a$ at time $t$, instead, is given by

\[
\text{Var}^c_t[R_{t+1}^a] = [M_t^a(H)\mu_H + (1 - M_t^a(H))\mu_L]^2 - [M_t^a(H)\mu_H + (1 - M_t^a(H))\mu_L]^2
\]

\[
= \mu_L^2 + M_t^a(H)(\mu_H^2 - \mu_L^2) - [\mu_L + M_t^a(H)\Delta\mu]^2
\]

\[
= 2M_t^a(H)\Delta\mu(\bar{\mu} - \mu_L) - [\mu_L + M_t^a(H)(\Delta\mu)]^2
\]

\[
= M_t^a(H)(\Delta\mu)^2 - M_t^a(H)^2(\Delta\mu)^2
\]

\[
= M_t^a(H)(1 - M_t^a(H))(\Delta\mu)^2.
\]

Since $M_t^a(H)(1 - M_t^a(H))$ is a symmetric concave function in $M_t^a(H)$ with its maximum achieved at $M_t^a(H) = 1/2$, and since $M_t^P(H) > 1/2 > M_t^T(H)$, it follows that

\[
\text{Var}_t^c[R_{t+1}^P] \geq \text{Var}_t^c[R_{t+1}^T] \iff \left( M_t^P(H) - \frac{1}{2} \right) \leq \left( \frac{1}{2} - M_t^T(H) \right) \iff M_t^P(H) + M_t^T(H) \leq 1.
\]

Since

\[
M_t^P(H) + M_t^T(H) = \frac{1}{1 + \eta_t^*(1 - \kappa)} + \frac{\frac{\eta_t^*}{(1 - \kappa)}}{1 - \eta_t^*(1 - \kappa)} = \frac{1 - \eta_t^*(1 - \kappa)^2}{1 - (\eta_t^*)^2(1 - \kappa)^2} \leq 1
\]

we conclude that $\text{Var}_t^c[R_{t+1}^P] \geq \text{Var}_t^c[R_{t+1}^T]$.\hfill\Box

**Proof of Proposition 2.** Let $R_{t+1}^a$ be the level of performance such that $F_{t+1}(R_{t+1}^a) = 0$. Given the fund flows in (16), it follows that $F_{t+1} \geq 0$ if and only if $\phi_{t+1} \geq \phi_t$. Given $\phi_{t+1}(R_{t+1}^a)$ in (14), we solve for $R_{t+1}^a$ by setting $\phi_{t+1}(R_{t+1}^a) = \phi_t$, which implies that

\[
\phi_t + (1 - \phi_t) e^{-\frac{\Delta\mu}{\nu_a}(R_{t+1}^a - \bar{\mu})} \left( \eta_t^* + (1 - \eta_t^*) \left( \frac{\kappa}{2 - \kappa} \right)^{1-2\mathbb{1}_{(a_t = T)}} \right) = 1,
\]

and hence that

\[
e^{-\frac{\Delta\mu}{\nu_a}(R_{t+1}^a - \bar{\mu})} \left( \eta_t^* + (1 - \eta_t^*) \left( \frac{\kappa}{2 - \kappa} \right)^{1-2\mathbb{1}_{(a_t = T)}} \right) = 1.
\]

(A.12)
Taking log(·) on both sides of (A.12), and solving for $R_{t+1}^q$, (17) obtains: $R_{t+1}^q = \bar{\mu} + (\nu^a/\Delta \mu) \lambda_t^q(\eta_t^a)$. Since $\lambda_t^q(\eta_t^a) < 0 < \lambda_t^q(\eta_t^m)$, it follows that $R_{t+1}^p < \bar{\mu} < R_{t+1}^q$.

Given the fund reputation $\phi_t$, the flow-performance sensitivity at time $t + 1$ induced by strategy $a_t$ is equal to

$$
\frac{\partial F_{t+1}}{\partial R_{t+1}^\mu} = \frac{\partial F_{t+1}}{\partial \phi_{t+1}} \cdot \frac{\partial \phi_{t+1}}{\partial R_{t+1}^\mu} = \left( \frac{\Delta \mu}{\mu_L^a + \Delta \mu \cdot \phi_t - f} \right) \cdot (\phi_{t+1}(1 - \phi_{t+1})) \cdot \left( \frac{\Delta \mu}{\mu^a} \right),
$$

which simplifies to (18). Since all three partial derivatives in (A.13) are positive for any $a_t \in \{P, T\}$, the flow-performance sensitivity is always positive for both pickers and timers. Moreover, if a picking and a timing fund have the same reputation at time $t$, $\phi_t$, and they obtain the same level of fund flows at time $t + 1$, $F_{t+1}(R_{t+1}^P) = F_{t+1}(R_{t+1}^T)$, it implies that $\phi_{t+1}(R_{t+1}^p) = \phi_{t+1}(R_{t+1}^T)$. As a consequence, the flow-performance sensitivity of the picking fund is higher than that of the timing fund since $\nu^P < \nu^T$.

The cross-sectional average of the expected fund size of a fund implementing strategy $a$ at time $t$ is given by

$$
E_t^{cs}[E_t[q_{t+1}^a]] = M_t^a(\nu_t)E_t[q_{t+1}^a|H] + (1 - M_t^a(\nu_t))E_t[q_{t+1}^a|L],
$$

where $q_{t+1}^a$ is a shortcut for $q_{t+1}(\phi_{t+1}(R_{t+1}^a))$. For a given fund reputation $\phi_t$, $E_t[q_{t+1}^a|H] > E_t[q_{t+1}^a|L]$ since $q_{t+1}^a$ is linear in $\phi_{t+1}$ and $E_t[\phi_{t+1}(R_{t+1}^a)|H] > E_t[\phi_{t+1}(R_{t+1}^a)|L]$, where the last inequality follows from property (a) of Lemma A.1 and from the fact that the mean of the logit-normal distribution of $\phi_{t+1}$ in (A.2) is such that $m_t^a(\nu_t) > m_t^a(L)$. Moreover, since $E_t[q_{t+1}^a|H] > E_t[q_{t+1}^T|H]$ (from Theorem 1), a high-skill manager always prefers $P$ over $T$ and $M_t^P(\nu) > M_t^T(\nu)$, it follows that $E_t^{cs}[E_t[q_{t+1}^P]] > E_t^{cs}[E_t[q_{t+1}^T]]$.

**Proof of Proposition 3.** TBC.

**Proof of Proposition 4.** An increase in $\rho$, increases the variance $\nu^T$ in (3), which in turns increases $m_t^T(L)$ and decreases $\varsigma_t^T$ in (A.2) and (A.3), respectively. Since $m_t^T(L)$ can be written as $\Phi_t - (1/2)\varsigma_t^T - \lambda_t^T(\eta_t)$, using property (c) in Lemma A.1, we conclude that for a given $\eta_t$,

$$
\frac{\partial v_t(T|L, \eta_t, \rho)}{\partial \rho} = \frac{\partial v_t(T|L, \eta_t, \rho)}{\partial \varsigma_t^T} \cdot \frac{\partial \varsigma_t^T}{\partial \rho} > 0.
$$

Moreover, since $\nu^P$ is not affected by $\rho$, it follows that for a given $\eta_t$, $\partial v_t(P|L, \eta_t, \rho)/\partial \rho = 0$.

Consider an equilibrium in which $\eta_t^* < 0 < \lambda_t^T(\eta_t)$ for a given $\rho$. This implies that $v_t(P|L, \eta_t^*|\rho) = v_t(T|L, \eta_t^*|\rho)$. The partial derivative in (A.15) implies that for any $\rho < \rho'$, $v_t(P|L, \eta_t^*|\rho', \rho' < v_t(T|L, \eta_t^*|\rho')$. In order to reinstate the equality of the two value functions (supporting a hybrid separating equilibrium), $\eta_t^* - \rho$ decreases since $m_t^T(L)$ and $m_t^P(L)$ are respectively increasing and decreasing in $\eta_t$, and the value functions $v_t(a_t|L)$ are continuous and monotonic in $\eta_t$. Therefore, $\eta_t^* - \rho < 0$ for any $\rho' > \rho$. If, instead, $\eta_t^* = 0$, then $\eta_t^* = 0$ for any $\rho' > \rho$. Consequently, we conclude that $\partial \eta_t^*/\partial \rho \leq 0$. 

45
Since the fractions $M^P_t(H)$ and $M^T_t(H)$ in (A.9) and (A.10) are respectively decreasing and increasing in $\eta^*_t$, they are respectively increasing and decreasing in $\rho$. Therefore, when market volatility is high, $\rho^*_t = \rho + \Delta \rho$, a higher fraction of picking funds is run by high-skill managers, whereas a higher fraction of timing funds is run by low-skill managers. This implies that the cross-sectional average of the expected performance in (A.14) of picking funds increases, whereas that of timing funds decreases. \qed
Appendix B: Data

We identify the style or mandate of the fund using CRSP reported objective of the fund. We then assign the Morningstar index appropriate for the mandate. Table B.1 shows the benchmark assignment.

### Table B.1: Assignment of Benchmarks

<table>
<thead>
<tr>
<th>Index</th>
<th>Morningstar Code</th>
<th>CRSP Objective Code</th>
<th>Objective Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>US Market</td>
<td>MSTAR</td>
<td>EDYB</td>
<td>Balanced</td>
</tr>
<tr>
<td>US Growth</td>
<td>MGRO</td>
<td>EDYG</td>
<td>Growth</td>
</tr>
<tr>
<td>US Value</td>
<td>MVAL</td>
<td>EDYI</td>
<td>Income / Value</td>
</tr>
<tr>
<td>Large Cap (Core)</td>
<td>MLCR</td>
<td>EDCL</td>
<td>Large Cap Core</td>
</tr>
<tr>
<td>Mid Cap (Core)</td>
<td>MMCR</td>
<td>EDCM</td>
<td>Mid Cap Core</td>
</tr>
<tr>
<td>Small Cap (Core)</td>
<td>MSCR</td>
<td>EDCS / EDCI</td>
<td>Small or Micro Cap Core</td>
</tr>
<tr>
<td>Basic Materials</td>
<td>MBMS</td>
<td>EDSM</td>
<td>Materials</td>
</tr>
<tr>
<td>Consumer Cyclicals</td>
<td>MCCS</td>
<td>EDSS</td>
<td>Consumer Discretionary</td>
</tr>
<tr>
<td>Consumer Defensive</td>
<td>MCDS</td>
<td>EDSG</td>
<td>Consumer Staples</td>
</tr>
<tr>
<td>Communications</td>
<td>MCSS</td>
<td>EDSA</td>
<td>Communications</td>
</tr>
<tr>
<td>Energy</td>
<td>MES</td>
<td>EDSN</td>
<td>Natural Resources and Energy</td>
</tr>
<tr>
<td>Financial Services</td>
<td>MFSS</td>
<td>EDSF</td>
<td>Financial Services</td>
</tr>
<tr>
<td>HealthCare</td>
<td>MHS</td>
<td>EDHS</td>
<td>HealthCare</td>
</tr>
<tr>
<td>Industrials</td>
<td>MIS</td>
<td>EDSI</td>
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</tr>
<tr>
<td>Real Estate</td>
<td>MRETS</td>
<td>EDSR</td>
<td>Real Estate</td>
</tr>
<tr>
<td>Technology</td>
<td>MTS</td>
<td>EDST</td>
<td>Technology</td>
</tr>
<tr>
<td>Utilities</td>
<td>MUS</td>
<td>EDSU</td>
<td>Utilities</td>
</tr>
</tbody>
</table>
Table 2: Fund Flow Sensitivity to Core and Non-Core Performance

This table shows the average fund flow sensitivity to lagged fund core and non-core values. Core value is defined as $v_{Ct} = v_{Pt}^P \cdot \omega_{it} + v_{Tt}^T \cdot (1 - \omega_{it})$, where $v_{Pt}^P$ is picking value, $v_{Tt}^T$ is timing value, and the weight $\omega_{it}$ reflects the criteria to identify pickers and timers and is either $1(pmt_{it} > 0)$ or $dop_{it}$. Non-core value is the difference between total value and core value. Flows are calculated as a percentage of lagged asset value, as defined in equation (26). All specifications include time and style fixed effects. Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

<table>
<thead>
<tr>
<th>Panel A: Regressions</th>
<th>Flows</th>
<th>Young Funds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable ($t$)</td>
<td>$pmt$</td>
<td>$dop$</td>
</tr>
<tr>
<td>Identification of Strategy Using</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample Restriction</td>
<td>($1$)</td>
<td>($2$)</td>
</tr>
<tr>
<td>Core Value ($t-1$)</td>
<td>1.998***</td>
<td>2.601***</td>
</tr>
<tr>
<td>(0.094)</td>
<td>(0.197)</td>
<td></td>
</tr>
<tr>
<td>Non-Core Value ($t-1$)</td>
<td>1.236***</td>
<td>1.322***</td>
</tr>
<tr>
<td>(0.087)</td>
<td>(0.200)</td>
<td></td>
</tr>
<tr>
<td>$dop$-weighted Core ($t-1$)</td>
<td>1.962***</td>
<td>1.962***</td>
</tr>
<tr>
<td>(0.094)</td>
<td>(0.094)</td>
<td>(0.094)</td>
</tr>
<tr>
<td>$dop$-weighted Non-Core</td>
<td>1.278***</td>
<td>1.278***</td>
</tr>
<tr>
<td>(0.091)</td>
<td>(0.091)</td>
<td>(0.091)</td>
</tr>
<tr>
<td>Log Fund Age ($t-1$)</td>
<td>-8.988***</td>
<td>-8.949***</td>
</tr>
<tr>
<td>(0.752)</td>
<td>(0.751)</td>
<td>(1.382)</td>
</tr>
<tr>
<td>Log Assets ($t-1$)</td>
<td>-1.528***</td>
<td>-1.546***</td>
</tr>
<tr>
<td>(0.244)</td>
<td>(0.245)</td>
<td>(0.518)</td>
</tr>
<tr>
<td>Expense Ratio ($t-1$)</td>
<td>-4.049***</td>
<td>-3.717***</td>
</tr>
<tr>
<td>(1.132)</td>
<td>(1.129)</td>
<td>(2.277)</td>
</tr>
<tr>
<td>Turnover ($t-1$)</td>
<td>-0.320</td>
<td>-0.336</td>
</tr>
<tr>
<td>(0.232)</td>
<td>(0.235)</td>
<td>(0.668)</td>
</tr>
<tr>
<td>Fund Return Volatility ($t-1$)</td>
<td>-0.293***</td>
<td>-0.192</td>
</tr>
<tr>
<td>(0.109)</td>
<td>(0.118)</td>
<td>(0.240)</td>
</tr>
<tr>
<td>Benchmark Returns % ($t-1$)</td>
<td>0.551***</td>
<td>0.551***</td>
</tr>
<tr>
<td>(0.073)</td>
<td>(0.074)</td>
<td>(0.117)</td>
</tr>
<tr>
<td>Benchmark Volatility ($t-1$)</td>
<td>0.125</td>
<td>0.056</td>
</tr>
<tr>
<td>(0.123)</td>
<td>(0.130)</td>
<td>(0.245)</td>
</tr>
<tr>
<td>Intercept</td>
<td>27.912***</td>
<td>29.272***</td>
</tr>
<tr>
<td>(6.197)</td>
<td>(6.258)</td>
<td>(13.627)</td>
</tr>
<tr>
<td>Fund-Year Obs</td>
<td>10165</td>
<td>10165</td>
</tr>
<tr>
<td>Adjusted R-Sq</td>
<td>0.259</td>
<td>0.260</td>
</tr>
</tbody>
</table>

Panel B: Hypothesis Testing

| $F$-test of $H_0$: $\beta_{core} = \beta_{non-core}$ |
|----------------------|-------|-------|
| Degree of Freedom | 1722 | 860 | 1267 |
| $F$-score | 38.57 | 13.45 | 20.17 |
| $p$-value (2 Tailed) | 0 | 0 | 0 |

48
Table 4: Skill and Likelihood of Picking Strategy

Panel A shows the relation between skill and the fund’s likelihood of picking or its degree of picking. Levels of skill are classified as low, medium and high using the bottom 30%, the middle 40%, and the top 30% of the skill distribution, respectively. The group of low skill serves as the base group. \( \mathbb{I}(pmt > 0) \) is a dummy for \( pmt_{it} = v^P_{it} - v^T_{it} > 0 \), while \( \mathbb{I}(\bar{pmt} > 0) \) is a dummy for \( \bar{pmt}_i = (1/N_i) \sum_{t=1}^{N_i} pmt_{it} > 0 \), where \( N_i \) is the total number of years fund \( i \) is in the sample. All the regressions include time and style fixed effects. The standard errors are clustered at the fund level. Except for column 5, which is a cross-sectional regression, all the regressions are pooled OLS at yearly frequency. Panel B reports the implied probabilities of picking from the probit models in Panel A. Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

### Panel A: Regressions

<table>
<thead>
<tr>
<th>Dependent Variable ((t))</th>
<th>( \mathbb{I}(pmt &gt; 0) )</th>
<th>( dop )</th>
<th>( \mathbb{I}(pmt &gt; 0) )</th>
<th>( \mathbb{I}(pmt &gt; 0) )</th>
<th>( \mathbb{I}(\bar{pmt} &gt; 0) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample Restriction</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>Medium Skill (Returns)</td>
<td>0.215***</td>
<td>0.061***</td>
<td>0.296***</td>
<td>0.693***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.007)</td>
<td>(0.100)</td>
<td>(0.069)</td>
<td></td>
</tr>
<tr>
<td>High Skill (Returns)</td>
<td>0.345***</td>
<td>0.105***</td>
<td>0.311***</td>
<td>1.297***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.008)</td>
<td>(0.108)</td>
<td>(0.080)</td>
<td></td>
</tr>
<tr>
<td>Medium Skill (Dollars)</td>
<td></td>
<td>0.089**</td>
<td></td>
<td></td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.037)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Skill (Dollars)</td>
<td></td>
<td>0.307***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.033)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( dop ) ((t-1))</td>
<td>0.025</td>
<td>-0.095</td>
<td>-0.016</td>
<td>-0.005</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.086)</td>
<td>(0.062)</td>
<td>(0.024)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Log Fund Age ((t-1))</td>
<td>-0.016</td>
<td>-0.006</td>
<td>-0.016</td>
<td>-0.005</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.005)</td>
<td>(0.062)</td>
<td>(0.024)</td>
<td></td>
</tr>
<tr>
<td>Log Assets ((t-1))</td>
<td>0.005</td>
<td>0.024</td>
<td>-0.016</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.028)</td>
<td>(0.024)</td>
<td>(0.010)</td>
<td></td>
</tr>
<tr>
<td>Turnover ((t-1))</td>
<td>0.007</td>
<td>0.019</td>
<td>0.019</td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.030)</td>
<td>(0.028)</td>
<td>(0.009)</td>
<td></td>
</tr>
<tr>
<td>Expense Ratio ((t-1))</td>
<td>0.087***</td>
<td>0.014*</td>
<td>0.058</td>
<td>0.105***</td>
<td>-0.888**</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.007)</td>
<td>(0.115)</td>
<td>(0.035)</td>
<td>(0.357)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.366**</td>
<td>0.366***</td>
<td>-1.219**</td>
<td>-0.269*</td>
<td>-0.888**</td>
</tr>
<tr>
<td></td>
<td>(0.154)</td>
<td>(0.045)</td>
<td>(0.490)</td>
<td>(0.162)</td>
<td>(0.357)</td>
</tr>
<tr>
<td>Fund-Year Obs</td>
<td>11929</td>
<td>11929</td>
<td>1041</td>
<td>11929</td>
<td>2124</td>
</tr>
<tr>
<td>Adjusted R-Sq</td>
<td>0.047</td>
<td>0.087</td>
<td>0.047</td>
<td>0.046</td>
<td>0.165</td>
</tr>
</tbody>
</table>

### Panel B: Estimated Probabilities of Picking

<table>
<thead>
<tr>
<th>Skill</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Skill</td>
<td>0.473***</td>
<td>0.478***</td>
<td>0.499***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Medium Skill</td>
<td>0.558***</td>
<td>0.595***</td>
<td>0.534***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.025)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>High Skill</td>
<td>0.609***</td>
<td>0.601***</td>
<td>0.619***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.029)</td>
<td>(0.009)</td>
</tr>
</tbody>
</table>
Table 5: Performance of Picking and Timing Strategies

This table shows the relation between fund strategy and fund performance. Fund strategy is identified using either $1(pmt > 0)$ or $dop$. The variable $1(Large)$ is a dummy for fund size being in the top 30% of the size distribution. Net Value in column 5 is the fund total value net of its expense ratio. All the regressions include time and style fixed effects. *, **, *** indicate significance at less than 1%, 5% and 10% respectively.

<table>
<thead>
<tr>
<th>Dependent Variable ($t$)</th>
<th>Total Value</th>
<th>Core Value</th>
<th>Net Value</th>
<th>Dollar Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>(0.124)</td>
<td>(0.150)</td>
<td>(0.089)</td>
<td>(0.124)</td>
</tr>
<tr>
<td>$dop$ ($t$)</td>
<td></td>
<td>13.371***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.210)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1(Large)$ ($t-1$)</td>
<td></td>
<td>0.283</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.176)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1(pmt &gt; 0)$ ($t$) × $1(Large)$ ($t-1$)</td>
<td>-0.664***</td>
<td></td>
<td>0.283</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.243)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Fund Age ($t-1$)</td>
<td>-0.161</td>
<td>-0.126</td>
<td>-0.220**</td>
<td>-0.137*</td>
</tr>
<tr>
<td></td>
<td>(0.106)</td>
<td>(0.097)</td>
<td>(0.104)</td>
<td>(0.082)</td>
</tr>
<tr>
<td>Log Assets ($t-1$)</td>
<td>-0.106***</td>
<td>-0.130***</td>
<td>-0.125***</td>
<td>-0.103***</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.034)</td>
<td>(0.031)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Turnover ($t$)</td>
<td>-0.214***</td>
<td>-0.203***</td>
<td>-0.205***</td>
<td>-0.049</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.065)</td>
<td>(0.066)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>Expense Ratio ($t$)</td>
<td>-0.372**</td>
<td>-0.355**</td>
<td>-0.272*</td>
<td>0.754***</td>
</tr>
<tr>
<td></td>
<td>(0.147)</td>
<td>(0.140)</td>
<td>(0.143)</td>
<td>(0.134)</td>
</tr>
<tr>
<td>Fund Ret Volatility ($t$)</td>
<td>-0.163***</td>
<td>-0.121***</td>
<td>-0.164***</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.016)</td>
<td>(0.017)</td>
<td>(0.016)</td>
</tr>
<tr>
<td></td>
<td>(0.885)</td>
<td>(0.885)</td>
<td>(0.876)</td>
<td>(0.824)</td>
</tr>
<tr>
<td>Fund-Year Obs</td>
<td>11929</td>
<td>11929</td>
<td>11929</td>
<td>11929</td>
</tr>
<tr>
<td>Adjusted R-Sq</td>
<td>0.291</td>
<td>0.405</td>
<td>0.291</td>
<td>0.205</td>
</tr>
</tbody>
</table>
Table 7: Fund Flow Sensitivity of Picking and Timing Strategies

This table shows the average fund flow sensitivity to the lagged fund performance for the subsample of funds with assets under management > $20M. All the regressions include time and style fixed effects. Standard errors are clustered at fund level. Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

<table>
<thead>
<tr>
<th>Dependent Variable (t)</th>
<th>Flows</th>
<th>Youngest</th>
<th>Oldest</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Total Value (t-1)</td>
<td>1.366***</td>
<td>1.049***</td>
<td>0.984***</td>
</tr>
<tr>
<td></td>
<td>(0.097)</td>
<td>(0.118)</td>
<td>(0.262)</td>
</tr>
<tr>
<td>If (pmt &gt; 0) (t-1)</td>
<td>0.932</td>
<td>-0.101</td>
<td>1.746</td>
</tr>
<tr>
<td></td>
<td>(0.760)</td>
<td>(0.924)</td>
<td>(2.344)</td>
</tr>
<tr>
<td>If (pmt &gt; 0) × Value (t-1)</td>
<td>0.495***</td>
<td></td>
<td>1.728***</td>
</tr>
<tr>
<td></td>
<td>(0.123)</td>
<td></td>
<td>(0.349)</td>
</tr>
<tr>
<td>Core Value (t-1)</td>
<td>1.661***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.160)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If (pmt &gt; 0) × Core Value (t-1)</td>
<td>0.420**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.183)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Core Value(t-1)</td>
<td>1.180***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If (pmt &gt; 0) × Non-Core Value (t-1)</td>
<td>0.101</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.163)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>dop (t-1)</td>
<td></td>
<td>3.930***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.465)</td>
<td></td>
</tr>
<tr>
<td>dop × Value (t-1)</td>
<td></td>
<td>0.976***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.184)</td>
<td></td>
</tr>
<tr>
<td>Log Fund Age (t-1)</td>
<td>-8.950***</td>
<td>-8.975***</td>
<td>-8.961***</td>
</tr>
<tr>
<td></td>
<td>(0.754)</td>
<td>(0.753)</td>
<td>(0.754)</td>
</tr>
<tr>
<td>Log Assets (t-1)</td>
<td>-1.552***</td>
<td>-1.536***</td>
<td>-1.569***</td>
</tr>
<tr>
<td></td>
<td>(0.246)</td>
<td>(0.245)</td>
<td>(0.246)</td>
</tr>
<tr>
<td>Expense Ratio (t-1)</td>
<td>-3.464***</td>
<td>-4.074***</td>
<td>-3.577***</td>
</tr>
<tr>
<td></td>
<td>(1.138)</td>
<td>(1.131)</td>
<td>(1.136)</td>
</tr>
<tr>
<td>Turnover (t-1)</td>
<td>-0.338</td>
<td>-0.328</td>
<td>-0.342</td>
</tr>
<tr>
<td></td>
<td>(0.234)</td>
<td>(0.230)</td>
<td>(0.231)</td>
</tr>
<tr>
<td>Fund return Volatility (t-1)</td>
<td>-0.175</td>
<td>-0.266**</td>
<td>-0.174</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.073)</td>
<td>(0.073)</td>
</tr>
<tr>
<td>Benchmark Returns (t-1)</td>
<td>0.542***</td>
<td>0.553***</td>
<td>0.552***</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.073)</td>
<td>(0.073)</td>
</tr>
<tr>
<td>Benchmark Volatility (t-1)</td>
<td>0.033</td>
<td>0.106</td>
<td>0.050</td>
</tr>
<tr>
<td></td>
<td>(0.130)</td>
<td>(0.123)</td>
<td>(0.129)</td>
</tr>
<tr>
<td>Intercept</td>
<td>30.179***</td>
<td>27.375***</td>
<td>27.873***</td>
</tr>
</tbody>
</table>

Fund-Year Obs 10165 10165 10165 1298 3502 2807
Adjusted R-Sq 0.258 0.260 0.260 0.200 0.256 0.272
Table 8: Fund Size of Pickers and Timers

This table shows the relation between fund strategy and fund size. Column 4 considers the subsample of funds that belongs to the first 3 deciles of the age distribution. Assets are in terms of 2010 USD. The variable $\tau$ till $(x)$ is the average value added since the inception of the fund till time $x$. Standard errors are clustered at the fund level. Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

<table>
<thead>
<tr>
<th>Dependent Variable $(t)$</th>
<th>Assets</th>
<th>Young Funds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample Restriction</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$I(pmt &gt; 0)$</td>
<td>421.503***</td>
<td>278.453***</td>
</tr>
<tr>
<td></td>
<td>(146.302)</td>
<td>(95.645)</td>
</tr>
<tr>
<td>$dop$</td>
<td></td>
<td>1489.568***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(413.856)</td>
</tr>
<tr>
<td>$I(pmt &gt; 0) (t-1)$</td>
<td></td>
<td>153.16***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(59.427)</td>
</tr>
<tr>
<td>$\tau$ till $(t-1)$</td>
<td></td>
<td>12.49***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(7.151)</td>
</tr>
<tr>
<td>Log fund Age $(t)$</td>
<td>893.605***</td>
<td>896.697***</td>
</tr>
<tr>
<td></td>
<td>(189.991)</td>
<td>(193.307)</td>
</tr>
<tr>
<td>Expense Ratio $(t)$</td>
<td>-1456.283***</td>
<td>-1456.789***</td>
</tr>
<tr>
<td></td>
<td>(250.717)</td>
<td>(248.838)</td>
</tr>
<tr>
<td>Flows $(t)$</td>
<td>1.584***</td>
<td>1.406**</td>
</tr>
<tr>
<td></td>
<td>(0.528)</td>
<td>(0.553)</td>
</tr>
<tr>
<td>Gross Fund Return $(t)$</td>
<td>5.754***</td>
<td>4.586**</td>
</tr>
<tr>
<td></td>
<td>(1.980)</td>
<td>(1.898)</td>
</tr>
<tr>
<td>Intercept</td>
<td>636.205**</td>
<td>119.945</td>
</tr>
<tr>
<td></td>
<td>(316.355)</td>
<td>(360.197)</td>
</tr>
<tr>
<td>Fund-Year Obs</td>
<td>12221</td>
<td>12221</td>
</tr>
<tr>
<td>Adjusted R-Sq</td>
<td>0.089</td>
<td>0.089</td>
</tr>
</tbody>
</table>
Table 9: Fund Reputation and Likelihood of Picking Strategy for Low-Skill Managers

This table shows the relation between fund reputation and likelihood of picking or degree of picking, for the subsample of low-skill managers (bottom 30% of the skill distribution). The variable Repute is defined as the lagged performance and is divided into three quantiles: bottom 30% (low), middle 40% (medium) and top 30% (high). Strong (mild) rise and drop in Repute is a dummy for the reputation quantile rising or dropping by 2 (1) quantiles between $t - 2$ and $t - 1$. No change in Repute indicates that the quantile of reputation is the same between $t - 2$ and $t - 1$. Column 1 is a Probit estimation while columns 3 to 5 are first-difference versions of column 2. In columns 3-5, all other covariates are first-differenced. Large (small) family is a dummy for a fund belonging to a fund family in the highest (lowest) 30% of the distribution of number of funds within the family. The variables $dop_i$ and $pmt_{it}$ denote sample averages of $dop_i$ and $pmt_{it}$ for each fund. All regression include time effects. Columns 1-2 also include style effects. Standard errors are clustered at the fund level. Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

Panel A: Regressions

<table>
<thead>
<tr>
<th>Dependent Variable $(t)$</th>
<th>$1(pmt &gt; 0)$</th>
<th>$dop$</th>
<th>First-Difference of $dop$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample Restriction</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Medium Repute $(t-1)$</td>
<td>-0.078</td>
<td>-0.037***</td>
<td></td>
</tr>
<tr>
<td>High Repute $(t-1)$</td>
<td>-0.354***</td>
<td>-0.098***</td>
<td></td>
</tr>
<tr>
<td>Rolling Value $(t-2)$</td>
<td>-0.009**</td>
<td>-0.003***</td>
<td>-0.004***</td>
</tr>
<tr>
<td>$1(pmt &gt; 0)$</td>
<td>0.510***</td>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>$dop$</td>
<td>1.046***</td>
<td>(0.028)</td>
<td></td>
</tr>
<tr>
<td>Strong Drop in Repute $(t-1)$</td>
<td>0.147***</td>
<td>0.143***</td>
<td>0.137***</td>
</tr>
<tr>
<td>Mild Drop in Repute $(t-1)$</td>
<td>0.089***</td>
<td>0.124***</td>
<td>0.052</td>
</tr>
<tr>
<td>No Change in Repute $(t-1)$</td>
<td>0.055</td>
<td>0.085</td>
<td>-0.066</td>
</tr>
<tr>
<td>Mild Rise in Repute $(t-1)$</td>
<td>-0.189***</td>
<td>-0.156***</td>
<td>-0.238***</td>
</tr>
<tr>
<td>Strong Rise in Repute $(t-1)$</td>
<td>-0.393***</td>
<td>-0.386***</td>
<td>-0.495***</td>
</tr>
<tr>
<td>Log Assets $(t-1)$</td>
<td>0.014</td>
<td>-0.002</td>
<td>-0.073***</td>
</tr>
<tr>
<td>Log Fund Age $(t-1)$</td>
<td>0.033</td>
<td>0.005</td>
<td>-0.009</td>
</tr>
<tr>
<td>Expense Ratio $(t-1)$</td>
<td>-0.027</td>
<td>-0.016**</td>
<td>0.111</td>
</tr>
<tr>
<td>Turnover $(t-1)$</td>
<td>-0.006</td>
<td>-0.001</td>
<td>-0.004</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.136</td>
<td>0.004</td>
<td></td>
</tr>
<tr>
<td>Fund-Year Obs</td>
<td>2645</td>
<td>2645</td>
<td>2112</td>
</tr>
<tr>
<td>Adjusted R-Sq</td>
<td>0.0843</td>
<td>0.233</td>
<td>0.234</td>
</tr>
</tbody>
</table>

Panel B: Estimated Probabilities of Picking

<table>
<thead>
<tr>
<th></th>
<th>Low Reputation</th>
<th>High Reputation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.497***</td>
<td>0.359***</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.024)</td>
</tr>
</tbody>
</table>

53
Table 10: Volatility and Likelihood of Picking Strategy for Low-Skill Managers

This table shows the relation between benchmark volatility and likelihood of picking or degree of picking, for the subsample of low-skill managers (bottom 30% of the skill distribution). Benchmark volatility is divided into three quantiles: bottom 30% (low), middle 40% (medium) and top 30% (high). Columns 2-3 exclude the middle quantile of benchmark volatility. Columns 4-6 run a first-difference model on dop, where \( I(\text{Rise in Volatility}) \) is a dummy for rise in benchmark volatility over the last year. Panel B reports the estimated probabilities for the probit regressions in columns 1-2. Standard errors are clustered at the fund level. Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

<table>
<thead>
<tr>
<th>Dependent Variable (t)</th>
<th>Sample of Low-Skill Managers</th>
<th>First-Difference of dop</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I((pmt &gt; 0))</td>
<td>dop</td>
</tr>
<tr>
<td>Volatility Quantiles</td>
<td>All</td>
<td>Low and High</td>
</tr>
<tr>
<td>Lagged Volatility</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>I(\text{High Volatility}) (t)</td>
<td>-0.212* (0.122)</td>
<td>-0.726** (0.302)</td>
</tr>
<tr>
<td>I(\text{Rise in Volatility}) (t)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Fund Age (t-1)</td>
<td>0.004 (0.049)</td>
<td>0.072 (0.062)</td>
</tr>
<tr>
<td>Log Assets (t-1)</td>
<td>0.013 (0.017)</td>
<td>-0.004 (0.023)</td>
</tr>
<tr>
<td>Expense Ratio (t-1)</td>
<td>0.032 (0.057)</td>
<td>0.030 (0.072)</td>
</tr>
<tr>
<td>Turnover (t-1)</td>
<td>0.010 (0.011)</td>
<td>0.018 (0.012)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.294 (0.302)</td>
<td>-0.235 (0.490)</td>
</tr>
<tr>
<td>Fund-Year Obs</td>
<td>3292</td>
<td>1895</td>
</tr>
<tr>
<td>Adjusted R-Sq</td>
<td>0.052</td>
<td>0.060</td>
</tr>
</tbody>
</table>

Panel B: Estimated Probabilities of Picking

<table>
<thead>
<tr>
<th></th>
<th>Sample of Low-Skill Managers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Volatility</td>
<td>0.483*** (0.016)</td>
</tr>
<tr>
<td></td>
<td>0.576*** (0.057)</td>
</tr>
<tr>
<td>High Volatility</td>
<td>0.400*** (0.035)</td>
</tr>
<tr>
<td></td>
<td>0.297*** (0.056)</td>
</tr>
</tbody>
</table>
Table 11: Volatility, Skill and Performance

This table shows how the relation between skill and performance changes as a function of benchmark volatility. All the regressions exclude the middle four deciles of benchmark volatility. Timing and picking skills correspond to \( \hat{\gamma}_{it} \) and \( \hat{\alpha}_{it} \) estimated in equation (20), respectively. All the regressions include time and style fixed effects. Standard errors are clustered at the fund level. Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

<table>
<thead>
<tr>
<th>Dependent Variable ((t))</th>
<th>Timing Skill ((1))</th>
<th>Picking Skill ((2))</th>
<th>Total Value ((3))</th>
</tr>
</thead>
<tbody>
<tr>
<td>( I(\text{High Volatility}) \ (t) )</td>
<td>-1.093*** (0.166)</td>
<td>-5.124*** (0.598)</td>
<td>-2.356*** (0.710)</td>
</tr>
<tr>
<td>( dop \ (t) )</td>
<td>-3.932*** (0.079)</td>
<td>16.950*** (0.282)</td>
<td>11.237*** (0.269)</td>
</tr>
<tr>
<td>( dop \times I(\text{High Volatility}) \ (t) )</td>
<td>2.685*** (0.085)</td>
<td>8.983*** (0.399)</td>
<td>4.649*** (0.484)</td>
</tr>
<tr>
<td>Log Assets ((t-1))</td>
<td>0.007 (0.010)</td>
<td>-0.088*** (0.032)</td>
<td>-0.082* (0.045)</td>
</tr>
<tr>
<td>Log Fund Age ((t-1))</td>
<td>0.016 (0.029)</td>
<td>0.079 (0.093)</td>
<td>0.035 (0.128)</td>
</tr>
<tr>
<td>Turnover ((t))</td>
<td>-0.036*** (0.012)</td>
<td>-0.166*** (0.045)</td>
<td>-0.282*** (0.083)</td>
</tr>
<tr>
<td>Expense Ratio ((t))</td>
<td>-0.213*** (0.039)</td>
<td>-0.161 (0.154)</td>
<td>-0.744*** (0.188)</td>
</tr>
<tr>
<td>Intercept</td>
<td>2.033*** (0.336)</td>
<td>-0.609*** (0.886)</td>
<td>-8.122*** (1.429)</td>
</tr>
<tr>
<td>Fund-Year Obs</td>
<td>6965</td>
<td>6965</td>
<td>6965</td>
</tr>
<tr>
<td>Adjusted R-Sq</td>
<td>0.410</td>
<td>0.714</td>
<td>0.389</td>
</tr>
</tbody>
</table>
References


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