The Allocation of Talent Across Mutual Fund Strategies

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Abstract

We propose a theory of self-selection by mutual fund managers into stock "picking" and market "timing." With adverse selection, investors learn more easily about the skill of picking funds than of timing funds, since picking investments are less correlated than timing investments. The equilibrium allocation of talent across strategies is such that high-skill managers always pick, while low-skill managers time with positive probability. We empirically confirm the prediction that picking funds outperform timing funds, even though picking does not outperform timing as a strategy. Consistent with the investors' learning in our model, picking funds exhibit higher flow-performance sensitivity than timing funds, and low-skill managers have the incentive to rely more on timing strategies when their reputation, or aggregate volatility, increase.

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. Despite the volume of literature exploring whether mutual fund managers are skilled and add value for their investors, little is known about how managers choose which strategy to adopt. Our paper complements this literature by developing a deeper understanding of how manager's choice of strategy depends on investment skill. Why do certain managers choose picking strategies and others choose timing? What is the resulting allocation of talent across strategies in the mutual fund industry? If investment strategies differ in terms of their ability to showcase managerial skill, then managers with different skills might optimally self-select into different strategies. How does such self-selection affect the observed mutual fund performance? 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.

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.[1]

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[1]We 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

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 allocation of talent across strategies 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.

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. Since picking funds actively deviate from their benchmark by taking idiosyncratic risk, while timing funds deviate by exposing themself to systematic risk, we use the measure of fund intention (to pick or to time) introduced by Buffa and Javadekar (2019), and infer a fund's investment strategy in each quarter by measuring the relative contribution of idiosyncratic risk to the volatility of quarterly active returns (i.e., a fund's gross excess return over its benchmark). A fund's degree of picking (dop) is the ratio of the idiosyncratic variance of active returns to its total variance, and, accordingly, we label pickers and timers those funds with high and low dop, respectively.

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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.

Given the endogenous choice of the investment strategy by funds of different skill levels, and the resulting allocation of talent, 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 funds 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 2.2% to 3.5% per year, in terms of active returns, and between $20million and $29 million, in terms of value added over the benchmark. The incremental value added of pickers relative to the median fund size in the sample is estimated at $235 million.

We confirm that the outperformance of pickers is not a result of either size effects (i.e., decreasing returns to scale), or the fact that highly performing styles have high exposure to idiosyncratic shocks, or simply favorable return distributions of picking strategies. Notably, we show that the observed positive relationship between fund strategy (*dop*) and fund performance (active returns) in the cross-section of mutual funds disappears within fund. When a fund relies more on picking strategies, its active returns do not significantly differ from those generated when the fund relies more on timing strategies. This implies that, although picking funds outperform timing funds, picking strategies do not outperform timing strategies, thus pointing towards a composition effect through self-selection as the mechanism responsible for the outperformance of pickers over timers.

Our theory has additional implications for fund flows. 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. In our empirical investigation, we show that the fund flow sensitivity to performance is three times as large for funds with high degree of picking. We further confirm that this result holds even when controlling for fund fixed effects, revealing that a fund faces far more responsive flows at times when it picks compared to when it times. The differential flow-performance sensitivity is therefore indicative of a differential information content revealed by the two investment strategies.

We also emphasize some dynamic aspects of our model. Our equilibrium shows that, as the reputation of a low-skill manager improves, the allocation of talent shifts, since the probability that this manager adopts a timing strategy increases. Because 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 by measuring how changes in fund flows, as proxy for changes in fund reputation, affect the degree of picking in the near future. We confirm that for low-skill funds, an increase in fund flows decreases their degree of picking by 3.2% in the subsequent quarter, and by 7.2% in the subsequent year. Moreover, in line with the idea that switching between strategies

may be easier for funds belonging to diverse fund families (where funds adopt more heterogenous degrees of picking) because they have access to a larger variety of sources of information, we show that the change in the investment strategy (*dop*), 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 (measured by either the VIX index, market volatility, or fund benchmark volatility) reduces the degree of picking of low-skill funds by 6% to 11.5%, depending on the measure of volatility. We further show that, consistently with the model prediction, the outperformance of pickers becomes stronger at times of high volatility.

1.1 Related Literature

The mutual fund literature has focused extensively on the measurement of skill in the industry, and on the decomposition of skill into stock picking and market timing abilities.[2] 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 strate-

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[2]Contributions to the debate on the ability of mutual funds to create value for their shareholders include Grinblatt and Titman (1989), Gruber (1996), Chen, Jegadeesh, and Wermers (2000), Fama and French (2010), Glode (2011), Elton, Gruber, and Blake (2012), and Berk and van Binsbergen (2015). Distinguishing between picking and timing skills 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 Mazuy (1966) and Henriksson and Merton (1981) formulate similar parametric factor model to estimate timing skills. While some studies find evidence of timing skill (e.g., Busse (1999); Goetzmann, Ingersoll, and Ivkovic (2000); Bollen and Busse (2001); Mamaysky, Spiegel, and Zhang (2008); Elton, Gruber, and Blake (2012)), others conclude that mutual funds exhibit no timing ability (e.g., Ferson and Schadt (1996); Graham and Harvey (1996); Daniel, Grinblatt, Titman, and Wermers (1997)).

gies. 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.[3] Adopting the economic framework in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), Abis (2017) studies equilibrium learning of quantitative and discretionary funds over the business cycle, and using fund prospectuses to identify a funds investment strategy, shows that quantitative funds consistently display picking ability, compared to discretionary funds which, instead, switch between picking and timing. Buffa and Javadekar (2019) proposes *dop* — the degree of picking of mutual funds in every quarter — as a new measure of the intention of funds to rely on picking strategies, relative to timing strategies. We adopt the this measure in this paper in order to test the self-selection predictions of our theory. 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.[4] 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.

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[3]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.

[4]Other recent contributions on flow-performance sensitivity include Spiegel and Zhang (2013), which shows that fund flows are more sensitive to the performance of "hot" funds, which tend to be young and small, and Choi, Kahraman, and Mukherjee (2016), which 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.

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.[5] 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, instead, 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.

The rest of the paper is organized as follows. Section 2 presents our theory of self-selection and characterizes the equilibrium allocation of talent. Section 3 introduces and discusses the predictions of the equilibrium. Section 4 describes the data and our empirical methodology, and tests the model predictions. Section 5 concludes.

2 Model

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.

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[5]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.

2.1 Economic Setting

Agents. We consider a discrete-time economy with time indexed by $t = 0, 1, 2, ...$ 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 ϕ_t the investor's posterior probability at time t that the manager has high-skill, $\mathbb{P}_t^I(s = H)$, 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).[6] 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 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

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[6]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 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.[7]

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

$$R_{it}^a \sim \mathcal{N}(\mu_s, \sigma^2) \tag{1}$$

where the expected return μ_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 $\bar{\mu} \equiv (\mu_L + \mu_H)/2$. The pairwise correlation between any two bets of investment strategy a is given by

$$\rho^a = \rho \mathbb{1}_{\{a=T\}}, \tag{2}$$

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_t^a, is distributed as

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

Gross returns should be understood as active returns, that is in excess of a passive benchmark. Despite the different correlation structure characterizing the returns within each investment strat-

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[7]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.

egy, 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,

$$\mathbb{E}_t \left[R_{t+1}^P | s \right] = \mathbb{E}_t \left[R_{t+1}^T | s \right] = \mu_s. \tag{4}$$

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

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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, $\mathbb{E}_t^I\left[r_{t+1}^a\right] > 0$. 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*

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

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 ϕ_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.[8] 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 κ 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.[9]

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

$$\mathcal{V}_t(s) = \max_{a_t \in \{P,T\}} \ (1-\kappa)\,\mathbb{E}_t^M\left[f \cdot q_{t+1}(a_t)|s\right] + \kappa \left(\frac{\mathbb{E}_t^M\left[f \cdot q_{t+1}(P)|s\right] + \mathbb{E}_t^M\left[f \cdot q_{t+1}(T)|s\right]}{2} \right) \quad (8)$$

$$s.t. \ \ q_{t+1}(a_t) = \frac{1}{c}\left(\mu_L + \Delta\mu \cdot \phi_{t+1}(R_{t+1}^a) - f\right), \quad (9)$$

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 κ, 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.

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[8]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.

[9]As an alternative to the noisy action, a separating equilibrium can also be sustained when the manager has an *intrinsic* preference for one of the two strategies. This preference, for instance, could reflect the education of the manager, as documented by Zambrana and Zapatero (2018).

Since the assets under management q_t are affine in the manager's reputation ϕ_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

$$a_t(s) = \underset{a_t \in \{P,T\}}{\arg\max} \ v_t(a_t|s), \tag{10}$$

where

$$v_t(a_t|s) = \mathbb{E}_t^M \left[\phi_{t+1}(R_{t+1}^a)|s \right] = \int_{-\infty}^{\infty} \phi_{t+1}(R_{t+1}^a) \ \varphi_t(R_{t+1}^a|a_t, s) \ dR_{t+1}^a, \tag{11}$$

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

$$\phi_{t+1} = \phi_t \cdot \left(\frac{1}{\phi_t + (1 - \phi_t)\Lambda_t(R_{t+1}^a|a_t)\Lambda_t(a_t)} \right), \tag{12}$$

where ϕ_t is the investor's prior and $\Lambda_t(\cdot) = \frac{\mathbb{P}_t(\cdot|s=L)}{\mathbb{P}_t(\cdot|s=H)}$ 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 ϕ_{t+1} depends on her current reputation ϕ_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

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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 $\Lambda_t(R_{t+1}^a|a_t)$. 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 κ) 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, the allocation of talent is such that a high-skill manager always chooses a picking strategy, while a low-skill manager chooses a picking strategy with probability η_t, and a timing strategy with probability $(1 - \eta_t)$. Consistent with this hy-

brid equilibrium, a low-skill manager is indifferent between picking and timing. The following proposition characterizes the equilibrium.

Theorem 1 (**Equilibrium**). *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 η_t^*. The probability η_t^* is unique, < 1, and solves the following equation*

$$\sqrt{1 + (n-1)\rho} \int_{-\infty}^{\infty} \phi_{t+1}(R_{t+1}^P) \; e^{-\frac{(R_{t+1}^P - \mu_L)^2}{2\nu^P}} dR_{t+1}^P = \int_{-\infty}^{\infty} \phi_{t+1}(R_{t+1}^T) \; e^{-\frac{(R_{t+1}^T - \mu_L)^2}{2\nu^T}} dR_{t+1}^T, \quad (13)$$

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

$$\phi_{t+1}(R_{t+1}^a) = \phi_t \cdot \left[\phi_t + (1 - \phi_t) \; e^{-\frac{\Delta\mu}{\nu^a}\left(R_{t+1}^a - \bar{\mu}\right)} \left(\eta_t^* + (1 - \eta_t^*) \left(\frac{\kappa}{2 - \kappa} \right)^{1 - 2\mathbb{1}_{\{a_t = T\}}} \right) \right]^{-1}. \quad (14)$$

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 hid 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 η_t^*.

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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

$$\Lambda_t(a_t) = \eta_t + (1 - \eta_t) \left(\frac{\kappa}{2 - \kappa} \right)^{1 - 2\mathbb{1}_{\{a_t = T\}}}. \tag{15}$$

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 η_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 η_t^*, such that $v_t(P|L) = v_t(T|L)$. Notably, in both panels, picking value decreases with η_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 η_t is the fraction of low-skill managers who choose to pick in a given period. Therefore, our self-selection mechanism gives rise to an endogenous allocation of talent across strategies. In particular, it predicts that all high-skill managers plus a fraction η_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 $1/2\left[1 + \eta_t\left(1 - \kappa\right)\right] > 1/2$. 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.[10]

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[10]An alternative interpretation of η_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.
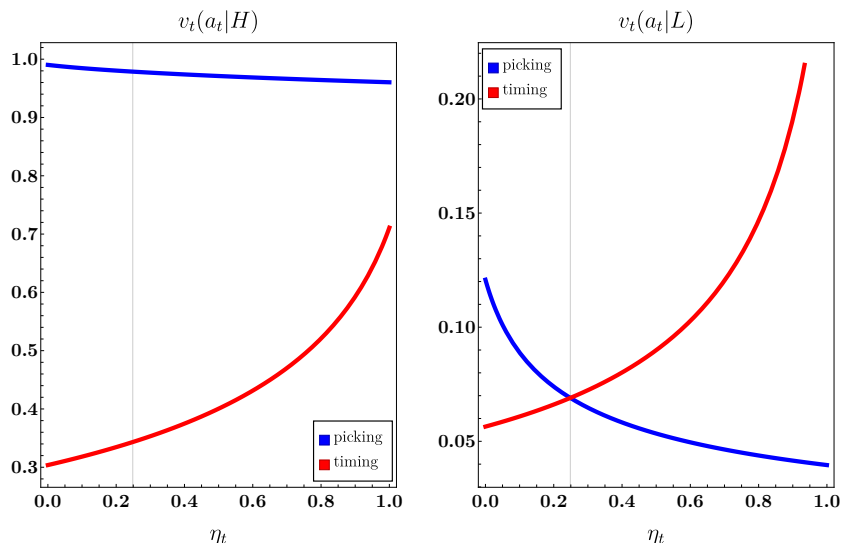
Figure 1: Self-selection

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 η_t. The thin vertical lines represent the equilibrium strategy η_t^*. Parameter values are: $\mu_L = 0.02$, $\mu_H = 0.15$, $\sigma = 0.15$, $\rho = 0.25$, $\kappa = 0.15$, $n = 20$, $\phi_t = 0.5$.

3   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

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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, η_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 η_t, the average performance of timers improves with η_t. Indeed, as η_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, η_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 η_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:

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

The next proposition presents our results on fund flows and size.

Proposition 2 (**Fund Flows and Size**). *Given the fund reputation ϕ_t, the threshold of fund performance $\mathcal{R}^a_{t+1}$ that induces positive fund flows, $F_{t+1}(\mathcal{R}^a_{t+1}) = 0$,*

$$\mathcal{R}^a_{t+1} = \bar{\mu} + \frac{\nu^a}{\Delta\mu} \log \left(\eta^*_t + (1 - \eta^*_t) \left(\frac{\kappa}{2 - \kappa} \right)^{1 - 2\mathbb{1}_{\{a_t = T\}}} \right),$$ (17)

is lower for pickers than timers, $\mathcal{R}_{t+1}^P < \bar{\mu} < \mathcal{R}_{t+1}^T$. Moreover, the flow-performance sensitivity

$$\frac{\partial F_{t+1}}{\partial R_{t+1}^a} = \frac{\Delta\mu^2 \phi_{t+1}(1 - \phi_{t+1})}{\nu^a(\mu_L + \Delta\mu \cdot \phi_t - f)} \tag{18}$$

is always positive for both pickers and timers, and is higher for pickers for the same level of fund flows $F_{t+1}(R_{t+1}^P) = F_{t+1}(R_{t+1}^T)$.

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 $\mathcal{R}_{t+1}^P$ and $\mathcal{R}_{t+1}^T$.

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.

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

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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 $F_{t+1}(\mathcal{R}_{t+1}^a) = 0$. 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" 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, $\partial \eta_t^* / \partial \phi_t \leqslant 0$.*

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 Nieuwerburgh, and Veldkamp (2016); Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016)). 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 σ_{mt}, as a binary *iid* process with $\sigma_{mt} \in \{\underline{\sigma}_m, \overline{\sigma}_m\}$,

where $\overline{\sigma}_m > \underline{\sigma}_m$, and assume that the dynamics of the pairwise correlation between any two bets of investment strategy a is given by

$$
\rho_t^a = \begin{cases} \rho \mathbb{1}_{\{a_t=T\}} & \text{if} \quad \sigma_{mt} = \underline{\sigma}_m \\ (\rho + \Delta_\rho)\mathbb{1}_{\{a_t=T\}} & \text{if} \quad \sigma_{mt} = \overline{\sigma}_m, \end{cases} \tag{19}
$$

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 $\sigma_{mt} = \overline{\sigma}_m$. 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, $\partial \eta_t^*/\partial \rho \leqslant 0$. Consequently, when market volatility is high, $\sigma_{mt} = \overline{\sigma}_m$, 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 differential cross-sectional performance between picking and 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 η_t^* decreases with the correlation ρ, as illustrated by the bottom-right panel in Figure 2.

The endogenous dependence between η_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 change in the allocation of talent, 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.
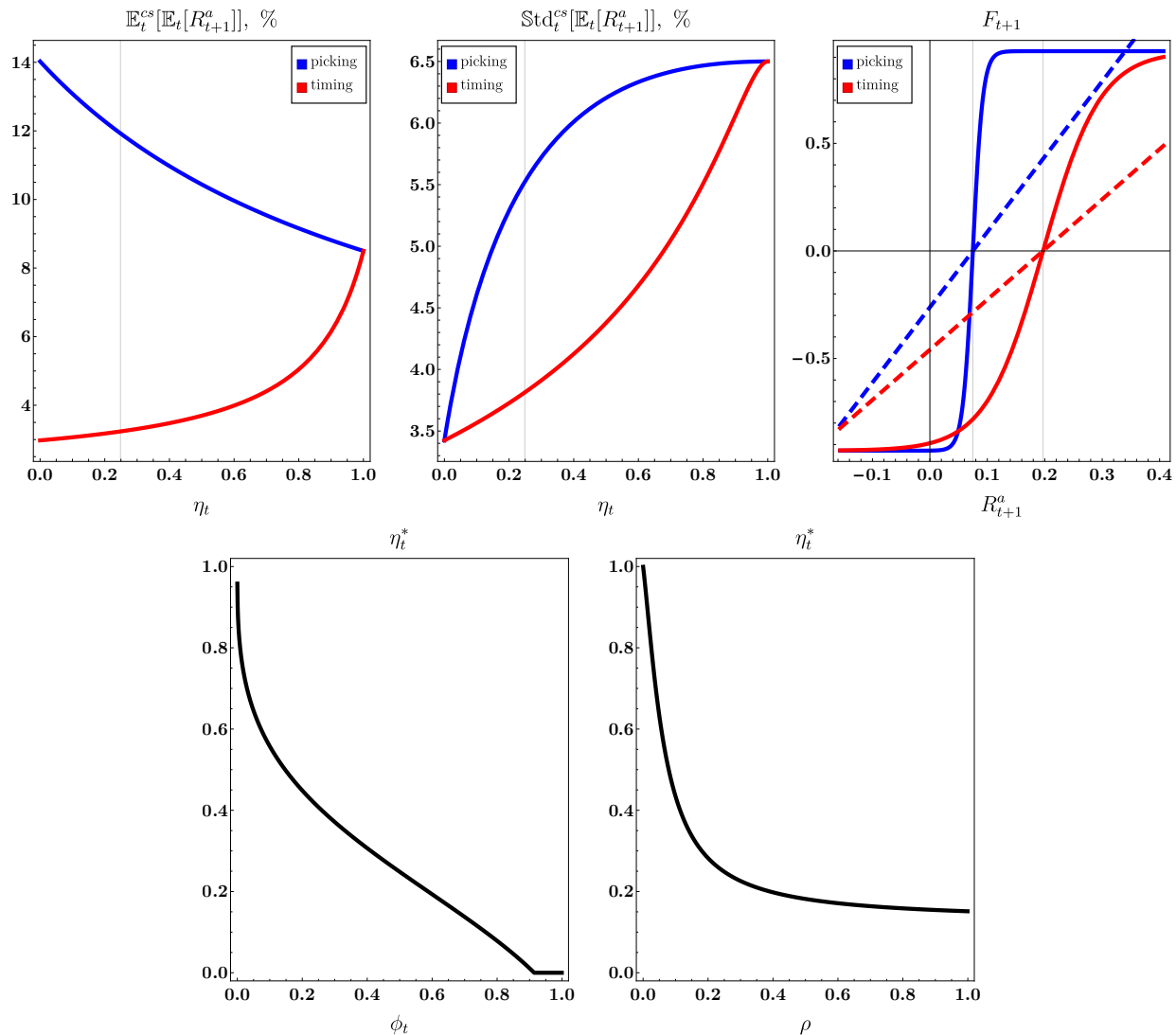
Figure 2: Implications of self-selection

In the top-left and top-middle panels we plot respectively the cross-sectional average of fund expected performance $\mathbb{E}_t^{cs}[\mathbb{E}_t[R_{t+1}^a]]$ and its cross-sectional dispersion $\mathbb{S}\mathrm{td}_t^{cs}[\mathbb{E}_t[R_{t+1}^a]]$, as a function of the picking probability η_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 $\mathbb{E}_t^{cs}\mathbb{E}_t[\partial F_{t+1}/\partial R_{t+1}^a]$ and the intercept such that $F_{t+1}(\mathcal{R}_{t+1}^a) = 0$ (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 η_t^* as a function of the manager's reputation ϕ_t (bottom-left panel), and as function of the correlation among timing bets ρ (bottom-right panel). Parameter values are as in Figure 1 and $f = 0.015$.

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4 Empirical Analysis

4.1 Data and Methodology

Data description. We use CRSP survivor-bias-free data on mutual funds over the period 1999-2018, and focus on the US open ended active 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). We exclude sector and speciality funds, as well as target-date or accrual funds, and funds with restrictions on sales.

A mutual fund might have multiple share classes reflecting different fees and marketing structures. However, all share classes belonging to the same fund have identical gross returns. Since we focus on the gross performance of the 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 (AUM) 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 for a given time period.

To obtain our final sample, we filter our data even further as follows. First, fund holdings may be misaligned with respect to the fund's stated mandate (e.g., diBartolomeo and Witkowski (1997); Kim, Shukla, and Tomas (2000)). Hence to correctly identify equity oriented funds, we require that a fund's average equity share be at least 80%. To filter out funds employing leveraged strategies, we also exclude the funds with average equity exposure of more than 105% 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 very small funds - In particular we exclude fund-quarters with real assets of less than 20 million $. Real assets are assets expressed in 2011 average fund size.[11] Finally, we require that each fund appear in the data for at least eight quarters, ensuring a sufficiently long time-series of fund performance to allow us to reliably identify the skill of a fund manager.[12] Our final sample contains 3,772 funds and 159,106 fund-quarter observations: there are 1,644 growth funds, 991

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[11]Very 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).

[12]We 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.

value/income funds, 1099 focus on micro-, small-, or mid-caps. The average life of a fund in our sample is about nine years.

Investment performance. We consider two measures of investment performance at quarterly frequency for each fund in the sample. The first one is the fund's *active return* in quarter t, which is defined as the fund's gross excess return over its benchmark that is realized between the start of quarter $t-1$ and the start of quarter t,

$$R_{it}^A = R_{it} - R_{it}^B. \tag{20}$$

We note that a fund's active return measures how the fund's holdings of each asset, relative to its benchmark's holdings, comove with the asset returns: $R_{it}^A = \sum_{j=1}^{N_{t-1}}(w_{it-1}(j) - w_{it-1}^B(j))R_t(j)$, where N_{t-1} is the number of available assets at time $t-1$. So, a fund generates positive active returns if it overweights assets that perform well and underweights those that perform poorly over the next period.

The second measure is the fund's *value added* in quarter t, which is defined as the fund's active return in that quarter multiplied by the fund's AUM at the start of quarter $t-1$,

$$V_{it} = q_{it-1}R_{it}^A, \tag{21}$$

capturing the incremental dollar amount generated by the fund over its benchmark in quarter t.

Investment strategy. The distinguishing feature of picking and timing funds is the way they generate active returns and value. In particular, while picking funds actively deviate from their benchmark by taking idiosyncratic risk, timing funds deviate by taking systematic risk. Based on this insight, one should expect the volatility of active returns of picking funds to be mostly idiosyncratic and that of timing funds to be mostly systematic. Following Buffa and Javadekar (2019), we decompose the volatility of a fund's active returns – also known as the fund's tracking error – into its systematic and idiosyncratic components.[13]

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[13]In the context of (i) simulated portfolios of picking and timing funds, and (ii) a theoretical framework based on aggregate and asset-specific information processing, Buffa and Javadekar (2019) shows that picking and timing strategies are correctly identified by a fund's *dop*.

To determine whether variations in a fund's active return are explained by variations in systematic factors, we adopt the following (linear) factor model,

$$R^A_{it\tau} = \alpha_{it} + \beta'_{it} F_{t\tau} + \epsilon_{it\tau}, \tag{22}$$

where, given a vector of risk factors F, we estimate in each quarter t, for each fund i, the coefficients $(\hat{\alpha}_{it}, \hat{\beta}'_{it})$ using daily data (τ) between quarter t and $t+1$. A variance decomposition yields that

$$\mathbb{Var}_t[R^A_{it,t+1}] = \underbrace{\mathbb{Var}_t[\hat{\beta}'_{it} F_{t,t+1}]}_{\text{systematic active variance}} + \underbrace{\mathbb{Var}_t[\hat{\epsilon}_{it,t+1}]}_{\text{idiosyncratic active variance}} \tag{23}$$

where $\hat{\epsilon}_{it,t+1}$ is the time-series of residuals from (22). As a measure of investment strategy, we define the *degree of picking* of fund i in quarter t as ratio of idiosyncratic and total variance of active returns,

$$dop_{it} = \frac{\mathbb{Var}_t[\hat{\epsilon}_{it,t+1}]}{\mathbb{Var}_t[R^A_{it,t+1}]}. \tag{24}$$

Intuitively, a picking strategy is driven by the fund's intention to increase the relative exposure of its active return to idiosyncratic risk, and consequently is associated with a higher degree of picking. We note that, although in the data we measure a fund's degree of picking ex-post (i.e., after the realization of returns between t and $t+1$), we ascribe the resulting *dop* to the beginning of quarter t, because it is when the investment strategy is chosen. Given the resulting cross-sectional distribution of dop_{it}, we identify picking funds as those with a high degree of picking (top 20% of the pool distribution of *dop*) and label those with a low degree of picking (bottom 20%) as timing funds. The funds with a medium degree of picking (middle 60%) have active returns that are driven by sufficient variation in both systematic an idiosyncratic components and hence are likely to have implemented both strategies.

Investment skill. Under the model assumption that the investment strategies have the same expected profitability, the investment skill of a fund can be inferred from the long-term average of its investment performance. The idea is that, although a skilled fund may not generate a good

performance in any period, it should do so on average over its lifetime. Therefore, corresponding to the two measures of performance in (20) and (21), we consider

$$s_i = \mathbb{E}[R_{it}^A] = \frac{1}{T_i} \sum_{t=1}^{T_i} R_{it}^A, \tag{25}$$

$$s_i^{\$} = \mathbb{E}[V_{it}] = \frac{1}{T_i} \sum_{t=1}^{T_i} V_{it}, \tag{26}$$

as measures of skill, where T_i is the number of periods that fund i is in the sample. A high-skill fund is a fund that performs well in a consistent manner, thus pushing the long-term average fund performance to the top of its distribution. In our leading specification, we consider the top 20% and bottom 20% of the skill distribution to identify high- and low-skill funds, respectively.[14] We note that comparing funds based on $s_i^{\$}$, which is the measure of skill proposed by Berk and van Binsbergen (2015), takes into account cross-sectional differences in average fund size, and in the comovement between fund size and active returns: $s_i^{\$} = \mathbb{E}[q_{it-1}]s_i + \mathbb{C}\mathrm{ov}[q_{it-1}, R_{it}^A]$. Later in this section, we confirm that in the data the expected profitability across strategies is not significantly different, thus making $(s_i, s_i^{\$})$ valid proxies for a fund's investment skill.

Fund benchmarks and risk factors.   Our measures of investment performance, strategy and skill rely (i) on fund benchmarks to compute active returns, and (ii) on risk factors to decompose the variation in these returns. Following Berk and van Binsbergen (2015), we view a fund's benchmark as the next best alternative investment opportunity available to investors, and hence consider a set of Vanguard's passively managed index funds as "basis" to construct appropriate benchmarks for each active fund in each quarter. The benchmark of fund i in quarter t is defined as the closest portfolio of index funds in the Vanguard's set. Specifically,

$$R_{it}^B = \hat{\gamma}_{it-1}' R_t^I, \tag{27}$$

where R_t^I is the vector of excess returns of the index funds in quarter t, and γ_{it-1} is a vector of loadings estimated by projecting fund i's daily excess returns from quarter $t-4$ to quarter $t-1$ (one year), $R_{it-4,t-1}$, on the vector index fund's excess returns for the same period, $R_{t-4,t-1}^I$, including a constant term. In other words, for each fund in a given quarter, we use the past year of data to obtain the closest combination of index funds to that fund, and use that combination to determine the excess return of the corresponding portfolio of index funds in the next quarter.

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[14]Our results are robust to different cut-offs of the skill distribution to identify high- and low-skill funds.

As a choice of index funds, we focus on a set that capture the most prominent sources of risk in equity markets, and use them also as risk factors in (22) when determining a mutual fund's degree of picking in a given quarter. These include: Vanguard 500 Index fund, Vanguard Value Index, Vanguard Growth Index, Vanguard Mid-Cap Index, and Vanguard Small-Cap Index. Since there are no index funds available in our sample that track the momentum factor, we add the momentum portfolio by Carhart (1997) to this set of index funds. Finally, to reduce multicollinearity issues due to the high return correlation among the Vanguard's index funds, we sequentially orthogonalize them with respect to the Vanguard 500 Index, in the spirit of Busse (1999).

Summary statistics. Table 1 provides summary statistics for our measure *dop*. The median *dop* is 0.77 and it rises from 0.52 to 0.91 as we move from the bottom 20% to the top 20% quantile of the *dop* distribution. Compared to low-*dop* funds (timers), high-*dop* funds (pickers) are on average four quarters older, have $28M more in AUM, and have lower turnover, 0.48 vs. 0.67. This suggests that timers trade more frequently, possibly reflecting the volatile nature of the market segment they aim to time. High-*dop* funds also have slightly lower expense ratios, and lower tracking error, 3.23% vs. 5.01%. The last three rows in Table 1 reveal that, within each quantile of the *dop* distribution, the fraction of funds with a particular style (i.e., Value, Growth, Small Cap) is roughly the same. High-*dop* funds have only a slightly higher fraction of small cap funds and only a slightly lower fraction of growth funds.

4.2   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* performance as the performance generated by the dominant strategy of the fund, and the *non-core* performance as the difference between the total and the core performance.

Following Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014), we first decompose a fund's active return into picking return and timing return using the factor model in (22). Specifically, a fund's timing return corresponds to the systematic component of its active return, $R_{it}^T = \hat{\beta}_{it-1} F_t$, whereas the fund's picking return is given by the remainder part, $R_{it}^P = \hat{\alpha}_{it-1} + \hat{\epsilon}_{it}$. We then define

a fund's core (active) return in quarter t, denoted by R_{it}^C, as the convex combination of picking and timing returns in that quarter, weighted by its degree of picking,

$$R_{it}^C = R_{it}^P \cdot dop_{it} + R_{it}^T \cdot (1 - dop_{it}). \tag{28}$$

The non-core return is simply given by the difference $R_{it}^A - R_{it}^C$. Intuitively, the higher the contribution of the idiosyncratic component in the volatility of active returns (i.e., the higher the degree of picking), the closer the fund's core return is to its picking return.

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) active return of the fund, and as a consequence the fund flow sensitivity to core and non-core performance 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 quarter t as

$$flow_{it} = \frac{q_{it} - q_{it-1}(1 + r_{it})}{q_{it-1}(1 + r_{it})}, \tag{29}$$

where q_{it} denotes the AUM at the end of quarter t and r_{it} is the net return the fund earned during that quarter.

Table 2 presents the estimated flow-performance sensitivity to our measures of core and non-core performance. Column 1 confirms the established empirical result that fund flows are sensitive to lagged performance, measured by active returns. For a 1% of active returns, investors bring 0.135% additional assets. Column 2 breaks active returns into its core and non-core components, based on (28). Fund flows are almost four times as sensitive to core returns (0.186) as compared to non-core returns (0.047), suggesting that investors are able to identify the core and non-core strategies of a fund, and that they consider the performance of the core strategy more informative of the fund's skill. Columns 3 and 4 confirm that flows are more sensitive to core returns of both pickers and timers. Hence, investors rely more on the idiosyncratic (systematic) component of active returns when evaluating a fund with a higher (lower) degree of picking.[15] Overall, we consider these findings as supporting evidence for the information structure assumed in the model.

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[15]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.

Prediction 1: Pickers outperform timers

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 consequently pickers on average generate more value than timers (Proposition 1).

In Table 3, we regress the two measures of investment performance (active return and value added) on our measure of investment strategy *dop*, controlling for observable fund characteristics potentially affecting fund performance. Column 1 shows that the regression coefficient on *dop* when performance is measured by active returns is equal to 3.053, implying that pickers generate up to 3.053% more active returns than timers annually. In terms of value added, column 2 shows that pickers on average generate up to $29M annually more than timers. The incremental value added of pickers is large considering that the median fund size in our sample is $235M, and that the average fund adds roughly $17M per year, as reported by Berk and van Binsbergen (2015).

Our measure of *dop* is particularly meaningful when a fund is truly active. The presence of closet indexers (i.e., active funds that are effectively passive by tracking very closely their benchmarks), therefore, may blur our results as the *dop* of these funds may not capture their intention to choose a particular strategy. To alleviate this concern, columns 3 and 4 report the same regression coefficients as in columns 1 and 2, respectively, but excluding fund-quarters with bottom 20% of tracking error. The results remain statistically and economically strong for both active returns and value added. The outperformance of pickers over timers is indeed coming from active pickers outperforming active timers.

Table 4 show that our key result — the superior performance of pickers — is robust. First, we want to rule out that the outperformance of pickers is driven by style effects. It could be that mutual funds employ picking and timing strategies by selecting investment styles that are particularly suitable for these strategies, and hence the outperformance of pickers may simply reflect the outperformance of the style employed by pickers. Although summary statistics in Table 1 already reveal a quite uniform distribution of styles across levels of *dop*, we explicitly control for *style×time* fixed effects in columns 1 and 2. The regression coefficients on *dop* remain statistically significant and economically large (2.215 vs. 3.053 for active returns, and $21.07M vs. $29.007M for value added), thus providing evidence that the outperformance of pickers is also present within investment styles.

Another potential explanation for the superior performance of picking funds over timing funds might be related to size effects induced by decreasing returns to scale. For instance, it could be that funds with high *dop* are smaller on average, possibly because it may be more difficult to exploit stock-level mispricing at a large scale. To address this concern, column 5 interacts *dop*

with a dummy for large funds (i.e., funds with size above the median of the size distribution in every quarter). While the coefficient on *dop* remains statistically and economically significant (1.92 for active returns), the coefficient on its interaction with size is not. This confirms that the difference in performance between pickers and timers is not driven by their size differential.[16] Finally, columns 3 and 4 show that picking funds outperform timing funds, in terms of both active returns and value added, even after accounting for potential differences in expense ratios. This implies that high-*dop* funds seem to generate incremental performance also for their investors.

Our model assumes that fund level performance is purely determined by a fund's skill, and not by differences in the return distribution of picking and timing strategies. Under this assumptions, therefore, these strategies should generate similar performance for a given fund of any skill level. In Table 5, we test this key implication of our theory by showing that the observed positive relationship between *dop* and performance in the cross-section disappears *within fund*. We do so by estimating a first-difference model of active returns on *dop*. The idea is to see whether a fund's active returns change significantly when a fund changes its strategy from one quarter to the next. If investment strategies were to differ in terms of return distributions, then changes in strategy across adjacent quarters would on average generate a change in active returns, given that the fund's skill is unlikely to have significantly changed across the two quarters.[17] Column 1 shows that changes in *dop* have on average an insignificant effect on active returns from one quarter to the next, with a small negative coefficient of -0.73. If anything, when a fund relies more on picking strategies, its active returns tend to fall. To test for potential asymmetries, columns 2 and 3 use dummies for drop and rise in *dop*, respectively. Active returns within fund do not change on average from one quarter to the next due to either a rise or a drop in *dop*. We note that all specifications in Table 5 include *style×time* fixed effects to alleviate the legitimate concern that funds could employ different strategies during different market conditions.

The empirical evidence that picking strategies do *not* outperform timing strategies provides support to the equilibrium mechanism of our theory, and at the same time validates the long-term averages of investment performance as appropriate measures of skill. Therefore, as a further evidence of the self-selection of mutual funds into investment strategies, we directly show the *composition effect* in the cross-section of funds whereby the group of pickers has a higher fraction of high-skill funds. The table below shows the joint distribution of skill and average *dop*:

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[16]By explicitly estimating the decreasing return to scale (DRS), Buffa and Javadekar (2019) conclude that it is not significantly different across picking and timing strategies.

[17]We note that with a fund fixed effects model, the resulting demeaning is performed using the entire life-time of a fund, over which the fund's skill may actually evolve. Therefore, if a fund's skill is time-varying, a fund fixed effects model would not be able to control for this unobservable fund characteristic. However, since a fund's skill can be reasonably assumed not to drastically change across adjacent quarters, a first-difference model better controls for possible variations in fund skill.

Average *dop*	Skill (Average Active Return)		Skill (Average Value Added)	
	Bottom 20% (Low-skill Funds)	Top 20% (High-skill Funds)	Bottom 20% (Low-skill Funds)	Top 20% (High-skill Funds)
Bottom 20% (Timers)	247	52	246	51
	83%	17%	83%	17%
Top 20% (Pickers)	78	220	78	218
	26%	74%	26%	74%

We restrict the sample to bottom and top 20% of the skill distribution, where fund skill is measured either by the long-term average of active returns generated by a fund over its life-time, s_i in (25), or by its average value added, $s_i^\$$ in (26). For both measures of fund skill, we find that 74% of pickers (high-*dop* funds) are high-skill funds, whereas 83% of timers (low-*dop* funds) are low-skill funds. We note that there are potentially other incentives or mechanisms, outside our theory, for which high-skill managers optimally rely on timing strategies. These may include intrinsic preferences for specific strategies as in Zambrana and Zapatero (2018), or information choices as in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016). Importantly, though, the fraction of high-skill funds within the group of pickers is on average significantly higher than that within the group of timers.

Overall, the findings in Tables 3, 4 and 5, corroborate that pickers outperform timers, even though picking strategies do *not* outperform timing strategies. This is in line with our theory, and makes a strong case for self-selection as an important mechanism responsible for the documented outperformance of picking funds.

Prediction 2: Fund flows are more sensitive to the performance of pickers

In the model, correlated timing bets reveal substantially less information about the fund's investment skill, compared to uncorrelated picking bets. In equilibrium, this induces low-skill funds to use timing strategies to hide their skill level, and high-skill funds 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 conditional on their investment strategy.

Table 6 estimates the flow-performance sensitivity conditional on *dop*. Since fund flows are measured in quarter t, and fund performance is measured in quarter $t-1$, we consider as control variable the investment strategy that has generated that performance, that is the degree of picking

between period $t-1$ and t, i.e., dop_{it-1}. Column 1 shows that the regression coefficient on (lagged) active returns is equal to 0.076, while the coefficient on the interaction of active returns and *dop* is 0.171. This implies that the flow-performance sensitivity of pickers can be up to three times as large as that of timers. This confirms our prediction that investors are more responsive to the performance of funds with higher relative exposure to idiosyncratic shocks. In column 2, we estimate the same regression but controlling for fund fixed effects and obtain that, when a fund picks, the ensuing flow-performance sensitivity is about four times as large as compared to when it times. Controlling for fund fixed effects is important. Indeed, it rules out the possibility that the two strategies have different flow-performance sensitivities because of some confounding forces that might comove with the degree of picking in the cross-section (e.g., clientele effects). The finding in column 2 implies that the differential sensitivity is likely to be the result of the differential information content that is revealed by the two strategies.

Columns 3 and 4 shows that this result holds true for young and old funds alike, where we adopt the median age cutoff to identify young and old funds. Consistent with the age effects documented by Chevalier and Ellison (1997) and others, the flow-performance sensitivity tends to be slightly lower for the group of older funds on average, but it remains twice as large for pickers within that group.

Prediction 3: Reputation decreases the degree of picking of low-skill managers

A key prediction of the model is that the equilibrium probability of picking of a low-skill fund decreases monotonically with the fund's reputation (Proposition 3). Intuitively, when a low-skill fund increases its reputation, the gains from pooling with high-skill funds by adopting a picking strategy become smaller. Indeed, in this case, the low-skill fund is more concerned about preserving its reputation, which is achieved by reducing the investors' ability to learn from the fund performance, through the adoption of a timing strategy.

We consider past fund flows as a measure of fund reputation. In the context of our model, and similar to Berk and Green (2004), fund flows are a direct measure of the change in the posterior beliefs of investors. Accordingly, we construct a normalized flows measure (which is between 0 and 1) and is computed by sorting funds within each style in each period. Column 1 in Table 7 shows that higher normalized flows (i.e., higher increase in reputation) for low-skill funds, leads to a degree of picking which is 3.22% lower in the next quarter. Given the possibility that funds change their investment strategy with delay, in column 2 we consider the average of normalized flows over last four quarters to better capture changes in reputation, and we consider the average degree of picking over the next four quarters to better capture the change in strategy. This

specification yields a drop in the average *dop* over the next year of about 7.21%, as the average normalized flows move from 0 to 1.

Switching between picking and timing strategies imposes high information requirement on a fund. Picking strategies rely more on stock-level information, whereas timing strategies rely more on aggregate-level information. We conjecture that funds that belongs to *diverse* fund families, i.e., fund families that have funds that span a wider range of strategies (measured as fund families in the top 20% of within family-quarter cross-sectional standard deviation of *dop*), are more likely to have access to a wider set of information, which might facilitate the switch between strategies. Based on this conjecture, we expect that the change in strategy following a change in reputation is more pronounced for funds that belongs to diverse fund families. Column 3 confirms the conjecture. An increase in reputation of low-skill funds in the past year leads to a decrease in their average *dop* over the subsequent year which is stronger (an additional 3% drop) when they operate in fund families that include funds with more heterogenous strategies.

Our model predicts that high-skill funds always pick, thereby changes in their reputation should result in no substantial change in their strategies. Column 4 confirms this prediction since the change in future *dop* induced by past normalized flows is not statistically significant.[18]

Prediction 4: Volatility decreases the degree of picking of low-skill managers

The correlation parameter ρ in the model governs the correlation across timing bets. Higher ρ makes timing returns more volatile and consequently low-skill funds 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 relationship between the investment strategy of low-skill funds and different measures of volatility.

Table 8 presents the results. In columns 1-3 we regresses quarterly *dop* of low-skill funds on contemporaneous measures of aggregate volatility. Specifically, we consider three quantiles of the volatility distribution, computed using three different measures of volatility: the VIX index, the

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[18]Column 5 shows positive coefficient on lagged average normalized flows. The increase in the degree of picking for high-skill funds following an increase in reputation is outside our model. In a richer version of the model, one can imagine an equilibrium in which both low- and high-skill managers adopt mix strategies. This could be the case when the high-skill manager has an intrinsic preference for one of the two strategies and would optimally decide not to adopt her preferred strategy because of self-selection considerations. In this setting, an increase in reputation may induce the high-skill manager with an intrinsic preference for timing to increase the probability of picking as this allows her to separate more from a low-skill manager (who instead would find it optimal to decrease the probability of picking).

volatility of the CRSP Value-weighted Index, or the fund benchmark volatility. All the regressions control for fund fixed effects. An increase in volatility leads to a large drop in the degree of picking of low-skill funds, which ranges between 6% and 11.5% depending on the measure of volatility considered. Since these are within-fund regressions, the results should be interpreted as strong evidence supporting the prediction that funds with low investment skill dynamically switch across fund strategies in response to changes in volatility.

Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) predict and document that *smart* managers switch from picking to timing strategies during high volatility regimes. This occurs as managers find it more useful to gather aggregate information, given that, in those regimes, aggregate shock explains a larger component of stock returns. Our model adds a complementary layer to their mechanism, by predicting a switch from picking to timing strategies of low-skill funds due to self-selection and signaling incentives. In column 4, we regress quarterly *dop* on different volatility regimes and interact this with a dummy for high-skill funds. The estimate coefficients confirm that also high-skill funds switch from picking to timing, as predicted by Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014), but they highlight that it is low-skill funds that switch more aggressively. Specifically, while the degree of picking of low-skill funds drops by roughly 13% in very volatile periods, that of high-skill funds only drops by 11.6%. Moreover, when volatility increases only moderately (i.e., entering its middle range), the degree of picking of low-skill funds still drops by almost 5%, whereas it remains unchanged for high-skill funds.

Prediction 5: Volatility increases the outperformance of pickers

As low-skill funds time more aggressively during periods of high volatility, the average skill within the group of timers decreases in these periods, thus pulling their average performance down. At the same time, the group of pickers becomes more dominated by high-skill funds, which improves the average performance in that group. Overall, our model predicts that pickers outperform timers by a wider margin during periods of high volatility.

We test this prediction in column 5 of Table 8. We regress quarterly funds' active returns on volatility regimes, and we further condition on the quarterly degree of picking *dop*. Timing funds (low-*dop*) see their active returns drop by a large 11% as we move from low- to high-volatility regime. The interaction of high-volatility and high-*dop* is significantly positive at around 10.2%, implying that the performance of picking funds is unaffected by volatility, and hence their outperformance over timing funds increases by a larger margin (about 11%) during high volatility regimes. This magnitude is economically very significant, considering that the average

outperformance is around 3% (Table 3). Therefore, our empirical findings provide evidence in support of the model prediction.

5   Concluding Remarks

This paper studies the allocation of talent across investment strategies in the mutual fund industry. To this end, we propose a novel theory of manager self-selection into stock picking and market timing strategies. Our theory 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 instead uncorrelated. In the presence of adverse selection, the 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 outperform timing funds, even though pricking strategies do not outperform timing strategies, thus uncovering an important composition effect in the cross-section of mutual funds. We also show that picking funds exhibit higher fund flow sensitivity than timing funds, and confirm the dynamic predictions that an increase in fund reputation, or in market volatility, causes low-skilled managers to rely more on timing strategies, thus increasing the cross-sectional dispersion of performance across funds.

Our analysis lays the foundation for further work on the efficiency of the allocation of talent in the asset management industry. Given the amount of wealth this industry invests, understanding whether talent is potentially misallocated within the industry is important from a normative perspective. Future research could study and characterize conditions under which a misallocation of talent might carry long-term consequence for the efficient allocation of capital.

Appendix A: Proofs

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

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, $X \sim \mathcal{L}ogit\mathcal{N}(\mu, \sigma^2)$, and satisfies the following properties:*

(a) $\mathbb{E}[X]$ is increasing in μ;

(b) $\mathbb{E}[X]$ is decreasing in σ if $\mu > 0$ and increasing in σ if $\mu < 0$;

(c) $\mathbb{E}[X]$ is decreasing in σ if $\mu = k - \sigma^2/2$;

(d) $\mathbb{E}[X]$ is increasing in σ if $\mu = k + \sigma^2/2$.

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

$$X = \frac{e^{\mu + \sigma Z}}{1 + e^{\mu + \sigma Z}} = \left(1 + e^{-\mu - \sigma Z}\right)^{-1} \tag{A.1}$$

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 μ and σ.

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

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

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

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

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, $Z\mathbf{1}_{\{Z<0\}} = \tilde{Z}\mathbf{1}_{\{\tilde{Z}>0\}}$. Since $\tilde{Z} \sim \mathcal{N}(0, 1)$, it follows that $\mathbb{E}[g(Z)] = \mathbb{E}[g(\tilde{Z})]$ for any function $g: \mathbb{R} \to \mathbb{R}$.

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Let

$$a(Z) \equiv \left(e^{\frac{\sigma}{2}Z} + e^{-\mu-\frac{\sigma}{2}Z}\right)^2 \quad \text{and} \quad b(Z) \equiv \left(e^{-\frac{\sigma}{2}Z} + e^{-\mu+\frac{\sigma}{2}Z}\right)^2.$$

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

$$\frac{\partial}{\partial \sigma}\mathbb{E}\left[X\right] = \begin{cases} e^{-\mu}\left(\mathbb{E}\left[\frac{Z\mathbf{1}_{\{Z>0\}}}{a(Z)}\right] - \mathbb{E}\left[\frac{Z\mathbf{1}_{\{Z>0\}}}{b(Z)}\right]\right) < 0 & \text{if } \mu > 0 \\[2ex] e^{-\mu}\left(\mathbb{E}\left[\frac{Z\mathbf{1}_{\{Z>0\}}}{a(Z)}\right] - \mathbb{E}\left[\frac{Z\mathbf{1}_{\{Z>0\}}}{b(Z)}\right]\right) > 0 & \text{if } \mu < 0 \end{cases}$$

(**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 σ, we obtain that

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

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

$$\mathbb{C}\text{ov}[g(Z), Z] = \mathbb{E}[g(Z)Z] + \mathbb{E}[g(Z)]\mathbb{E}[Z] = \mathbb{E}[g(Z)Z].$$

Applying *Stein's Lemma* and considering that $\mathbb{V}\text{ar}[Z] = 1$,

$$\begin{aligned} \mathbb{E}[g(Z)Z] &= \mathbb{C}\text{ov}[Z, Z] \cdot \mathbb{E}\left[\frac{\partial g(Z)}{\partial Z}\right] = \mathbb{E}\left[\frac{\partial g(Z)}{\partial Z}\right] \\ &= \mathbb{E}\left[(1 - f(Z))\left[f(Z)(1 - f(Z))\sigma\right] - f(Z)\left[f(Z)(1 - f(Z))\sigma\right]\right] \\ &= \sigma\mathbb{E}\left[f(Z)(1 - f(Z))(1 - 2f(Z))\right]. \end{aligned}$$

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

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

$$\Downarrow$$

$$\frac{\partial}{\partial \sigma}\mathbb{E}[X] = \mathbb{E}\left[f(Z)(1 - f(Z))(Z - \sigma)\right] < 0.$$

(**d**) 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 σ, we obtain that

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

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

$$
\begin{aligned}
\mathbb{E}\left[f(Z)(1 - f(Z))Z \right] &= \mathbb{C}\text{ov}[g(Z), Z] = \mathbb{E}[g(Z)Z] \\
&= \mathbb{C}\text{ov}[Z, Z] \cdot \mathbb{E}\left[\frac{\partial g(Z)}{\partial Z} \right] = \mathbb{E}\left[\frac{\partial g(Z)}{\partial Z} \right] \\
&= \mathbb{E}\left[(1 - f(Z)) \left[f(Z)(1 - f(Z))\sigma \right] - f(Z) \left[f(Z)(1 - f(Z))\sigma \right] \right] \\
&= \sigma \mathbb{E}\left[f(Z)(1 - f(Z))(1 - 2f(Z)) \right].
\end{aligned}
$$

Therefore,

$$
\begin{aligned}
\frac{\partial}{\partial \sigma} \mathbb{E}[X] &= \mathbb{E}\left[f(Z)(1 - f(Z))(Z + \sigma) \right] \\
&= \sigma \mathbb{E}\left[f(Z)(1 - f(Z))(1 - 2f(Z)) \right] + \sigma \mathbb{E}\left[f(Z)(1 - f(Z)) \right] \\
&= 2\sigma \mathbb{E}\left[f(Z)(1 - f(Z))^2 \right],
\end{aligned}
$$

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

Lemma A.2 (**Learning**). *The probability at time $t + 1$ that the manager is high-skill type, ϕ_{t+1}, is given by (12). Moreover, conditional on the manager's information at time t, ϕ_{t+1} has a logit-normal distribution, $(\phi_{t+1}|a_t, s) \sim \mathcal{L}ogit\mathcal{N}(m_t^a(s), \varsigma^a)$, where*

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

$$\varsigma^a = \Delta\mu^2/\nu^a. \tag{A.3}$$

Proof. Let ϕ_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

$$\phi_{t+1} = \frac{\varphi_t\left(R_{t+1}^a|a_t, H\right) \cdot \mathbb{P}_t\left(a_t|H\right) \cdot \phi_t}{\varphi_t\left(R_{t+1}^a|a_t, H\right) \cdot \mathbb{P}_t\left(a_t|H\right) \cdot \phi_t + \varphi_t\left(R_{t+1}^a|a_t, L\right) \cdot \mathbb{P}_t\left(a_t|L\right) \cdot (1 - \phi_t)}, \tag{A.4}$$

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

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

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

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

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

Since Φ_{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: $\Phi_{t+1} \sim \mathcal{N}(m^a_t(s), \varsigma^a)$. $\qquad\square$

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

$$v_t(a_t|L) = \mathbb{E}^M_t\left[\phi_{t+1}(R^a_{t+1})|L\right] = \int_{-\infty}^{\infty} \phi_{t+1}(R^a_{t+1}) \frac{1}{\sqrt{2\pi\nu^a}} e^{-\frac{(R^a_{t+1} - \mu_L)^2}{2\nu^a}} dR^a_{t+1}, \tag{A.7}$$

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

$$\Lambda_t(a_t) = \frac{\mathbb{P}_t(a_t|L)}{\mathbb{P}_t(a_t|H)} = \begin{cases} \frac{\eta_t\left(1 - \frac{\kappa}{2}\right) + (1 - \eta_t)\frac{\kappa}{2}}{1 - \frac{\kappa}{2}} & \text{if } a_t = P \\[2mm] \frac{(1 - \eta_t)\left(1 - \frac{\kappa}{2}\right) + \eta_t\frac{\kappa}{2}}{\frac{\kappa}{2}} & \text{if } a_t = T, \end{cases}$$

which can be written more concisely as (15). Substituting (15) and $\Lambda_t(R^a_{t+1}|a_t) = e^{-\frac{\Delta\mu\left(R^a_{t+1} - \bar{\mu}\right)}{\nu^a}}$ 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 Φ_{t+1} in (A.2) becomes equal to $m^a_t(L) = \Phi_t - \Delta\mu^2/2\nu^a$, since $\lambda^P_t(1) = \lambda^T_t(1) = 0$. Since the variance of Φ_{t+1} in (A.3) is independent of η_t and

equal to $\varsigma^a = \Delta\mu^2/\nu^a$, it follows that $(\phi_{t+1}|a_t, L, \eta_t = 1) \sim \mathcal{L}ogit\mathcal{N}(\Phi_t - (1/2)v^a, v^a)$. We use property *(c)* in Lemma A.1 to conclude that $v_t(a_t|L, \eta_t = 1)$ is decreasing in ς^a. Since $\nu^P < \nu^T$, and hence $\varsigma^P > \varsigma^T$, it follows that

$$v_t(P|L, \eta_t = 1) < v_t(T|L, \eta_t = 1).$$

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 Φ_{t+1} in (A.2), $m_t^a(L) = \Phi_t - \Delta\mu^2/2\nu^a - \lambda_t^a(\eta_t)$, is monotonically decreasing in η_t when $a_t = P$ since $\lambda_t^P(\eta_t)$ is monotonically increasing in η_t. In contrast, $m_t^T(L)$ is monotonically increasing in η_t since $\lambda_t^T(\eta_t)$ is monotonically decreasing in η_t. Moreover, since $\nu^P < \nu^T$, we obtain that at the two limits of η_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

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

depending on whether $\kappa \lessgtr \bar{\kappa}$, where $\bar{\kappa} \equiv 2/\left(1 + e^{\frac{\Delta\mu^2(\nu^T - \nu^P)}{4\nu^P\nu^T}}\right)$.

Step 3. Suppose $\kappa < \bar{\kappa}$, 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 η_t, this implies that there exists a probability $\tilde{\eta}_t$ 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 ς^a. Therefore, since $\nu^P < \nu^T$, and hence $\varsigma^P > \varsigma^T$, 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 η_t and $m_t^T(L)$ is increasing in η_t, it follows that the difference $v_t(P|L, \eta_t) - v_t(T|L, \eta_t)$ decreases in η_t. Since $v_t(P|L, \eta_t = 1) - v_t(T|L, \eta_t = 1) < 0$, by continuity and monotonicity of $v_t(a_t|L)$ in η_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 ς^a. Therefore, since $\nu^P < \nu^T$, and hence $\varsigma^P > \varsigma^T$, 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 η_t and $m_t^T(L)$ is increasing in η_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 η_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 η_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 $\kappa > \bar{\kappa}$, 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 η_t, this implies that $m_t^T(L) > m_t^P(L)$ for any η_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 ς^a when $m_t^a(L)$ is negative and decreasing otherwise, and since $\varsigma^P > \varsigma^T$, it can be that $v_t(P|L, \eta_t = 0) \gtrless v_t(T|L, \eta_t = 0)$. 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 η_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 ς^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 η_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 η_t, the mean of Φ_{t+1} in (A.2), $m_t^a(H) = \Phi_t + \Delta \mu^2 / 2\nu^a - \lambda_t^a(\eta_t)$, is monotonically decreasing in η_t when $a_t = P$, and monotonically increasing in η_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 $m_t^a(H)$, it follows that $v_t(P|H, \eta_t = \eta_t^*) \geqslant v_t(P|H, \eta_t = 1)$ and $v_t(T|H, \eta_t = 1) \geqslant v_t(T|H, \eta_t = \eta_t^*)$.

When $\eta_t = 1$, the mean of Φ_{t+1} in (A.2) becomes equal to $m_t^a(H) = \Phi_t + \Delta \mu^2 / 2\nu^a$, since $\lambda_t^P(1) = \lambda_t^T(1) = 0$. Since the variance of Φ_{t+1} in (A.3) is independent of η_t and equal to $\varsigma^a = \Delta \mu^2 / \nu^a$, it follows that $(\phi_{t+1}|a_t, H, \eta_t = 1) \sim \mathcal{L}ogit\mathcal{N}(\Phi_t + (1/2)v^a, v^a)$. We use property *(d)* in Lemma A.1 to conclude that $v_t(a_t|H, \eta_t = 1)$ is increasing in ς^a. Since $\nu^P < \nu^T$, and hence $\varsigma^P > \varsigma^T$, it follows that

$$v_t(P|L, \eta_t = 1) \geqslant v_t(T|L, \eta_t = 1).$$

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

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

$$Mass_t^P = \frac{1}{2}\left(1 - \frac{\kappa}{2}\right) + \frac{1}{2}\left[\eta_t^*\left(1 - \frac{\kappa}{2}\right) + (1 - \eta_t^*)\frac{\kappa}{2}\right] = \frac{1}{2}\left[1 + \eta_t^*\left(1 - \kappa\right)\right] > \frac{1}{2}, \qquad (A.8)$$

$$Mass_t^T = \frac{1}{2}\left(\frac{\kappa}{2}\right) + \frac{1}{2}\left[\eta_t^*\frac{\kappa}{2} + (1 - \eta_t^*)\left(1 - \frac{\kappa}{2}\right)\right] = \frac{1}{2}\left[1 - \eta_t^*\left(1 - \kappa\right)\right] < \frac{1}{2}, \qquad (A.9)$$

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 η_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.8). Using the same logic, (A.9) obtains.

Let $M_t^a(s)$ denote the fraction of managers of skill s adopting strategy a at time t. It follows that

$$M_t^P(H) = \frac{\frac{1}{2}\left(1 - \frac{\kappa}{2}\right)}{Mass_t^P} = \frac{1 - \frac{\kappa}{2}}{1 + \eta_t^*\left(1 - \kappa\right)}, \tag{A.10}$$

$$M_t^T(H) = \frac{\frac{1}{2}\left(\frac{\kappa}{2}\right)}{Mass_t^T} = \frac{\frac{\kappa}{2}}{1 - \eta_t^*\left(1 - \kappa\right)}. \tag{A.11}$$

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

$$\mathbb{E}_t^{cs}[\mathbb{E}_t[R_{t+1}^a]] = M_t^a(H)\mu_H + (1 - M_t^a(H))\mu_L, \tag{A.12}$$

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 $\mathbb{E}_t^{cs}[\mathbb{E}_t[R_{t+1}^P]] > \mathbb{E}_t^{cs}[\mathbb{E}_t[R_{t+1}^T]]$. The cross-sectional dispersion in the expected performance of strategy a at time t, instead, is given by

$$
\begin{aligned}
\mathbb{V}\mathrm{ar}_t^{cs}[\mathbb{E}_t[R_{t+1}^a]] &= \left[M_t^a(H)\mu_H^2 + (1 - M_t^a(H))\mu_L^2\right] - \left[M_t^a(H)\mu_H + (1 - M_t^a(H))\mu_L\right]^2 \\
&= \mu_L^2 + M_t^a(H)\left(\mu_H^2 - \mu_L^2\right) - \left[\mu_L + M_t^a(H)\Delta\mu\right]^2 \\
&= \mu_L^2 + M_t^a(H)2\bar{\mu}\Delta\mu - \left[\mu_L^2 + M_t^a(H)^2\left(\Delta\mu\right)^2 + 2\mu_L M_t^a(H)\Delta\mu\right] \\
&= 2M_t^a(H)\Delta\mu\left(\bar{\mu} - \mu_L\right) - M_t^a(H)^2\left(\Delta\mu\right)^2 \\
&= M_t^a(H)\left(\Delta\mu\right)^2 - M_t^a(H)^2\left(\Delta\mu\right)^2 \\
&= M_t^a(H)\left(1 - M_t^a(H)\right)\left(\Delta\mu\right)^2.
\end{aligned}
$$

Since $M_t^a(H)\left(1 - M_t^a(H)\right)$ 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

$$\mathbb{V}\mathrm{ar}_t^{cs}[\mathbb{E}_t[R_{t+1}^P]] \geqslant \mathbb{V}\mathrm{ar}_t^{cs}[\mathbb{E}_t[R_{t+1}^T]] \Leftrightarrow \left(M_t^P(H) - \frac{1}{2}\right) \leqslant \left(\frac{1}{2} - M_t^T(H)\right) \Leftrightarrow M_t^P(H) + M_t^T(H) \leqslant 1.$$

Since

$$M_t^P(H) + M_t^T(H) = \frac{1 - \frac{\kappa}{2}}{1 + \eta_t^*(1 - \kappa)} + \frac{\frac{\kappa}{2}}{1 - \eta_t^*(1 - \kappa)} = \frac{1 - \eta_t^*(1 - \kappa)^2}{1 - (\eta_t^*)^2(1 - \kappa)^2} \leqslant 1$$

we conclude that $\mathbb{V}\mathrm{ar}_t^{cs}[\mathbb{E}_t[R_{t+1}^P]] \geqslant \mathbb{V}\mathrm{ar}_t^{cs}[\mathbb{E}_t[R_{t+1}^T]]$. $\qquad\square$

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

$$\phi_t + (1 - \phi_t)\, e^{-\frac{\Delta\mu}{\nu^a}\left(\mathcal{R}_{t+1}^a - \bar{\mu}\right)}\left(\eta_t^* + (1 - \eta_t^*)\left(\frac{\kappa}{2 - \kappa}\right)^{1 - 2\mathbb{1}_{\{a_t = T\}}}\right) = 1,$$

and hence that

$$e^{-\frac{\Delta\mu}{\nu^a}\left(\mathcal{R}_{t+1}^a - \bar{\mu}\right)}\left(\eta_t^* + (1 - \eta_t^*)\left(\frac{\kappa}{2 - \kappa}\right)^{1 - 2\mathbb{1}_{\{a_t = T\}}}\right) = 1. \tag{A.13}$$

Taking $\log(\cdot)$ on both sides of (A.13), and solving for $\mathcal{R}_{t+1}^a$, (17) obtains: $\mathcal{R}_{t+1}^a = \bar{\mu} + (\nu^a/\Delta\mu)\lambda_t^a(\eta_t^*)$. Since $\lambda_t^T(\eta_t^*) < 0 < \lambda_t^P(\eta_t^*)$, it follows that $\mathcal{R}_{t+1}^P < \bar{\mu} < \mathcal{R}_{t+1}^T$.

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

$$
\begin{aligned}
\frac{\partial F_{t+1}}{\partial R_{t+1}^a} &= \frac{\partial F_{t+1}}{\partial \phi_{t+1}} \cdot \frac{\partial \phi_{t+1}}{\partial \Phi_{t+1}} \cdot \frac{\partial \Phi_{t+1}}{\partial R_{t+1}^a} \\
&= \left(\frac{\Delta\mu}{\mu_L + \Delta\mu \cdot \phi_t - f} \right) \cdot (\phi_{t+1}(1 - \phi_{t+1})) \cdot \left(\frac{\Delta\mu}{\nu^a} \right),
\end{aligned}
\tag{A.14}
$$

which simplifies to (18). Since all three partial derivatives in (A.14) 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, ϕ_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 $\nu^P < \nu^T$. $\square$

Proof of Proposition 3. Let the function $W_t^{\phi}(\cdot)$ denote the difference in the value function of a low-skill manager from implementing a picking and a timing strategy,

$$
W_t^{\phi}(\eta_t, \phi_t) \equiv v_t(P|L, \eta_t, \phi_t) - v_t(T|L, \eta_t, \phi_t).
$$

The equilibrium η_t^* is such that $W_t^{\phi}(\eta_t^*, \phi_t) = 0$. Using the *implicit function theorem*, we obtain that

$$
\frac{\partial \eta_t^*}{\partial \phi_t} = - \frac{\partial W_t^{\phi}(\eta_t^*, \phi_t)/\partial \phi_t}{\partial W_t^{\phi}(\eta_t, \phi_t)/\partial \eta_t}
$$

Since by property *(a)* in Lemma A.1 $v_t(a_t|L, \eta_t, \phi_t)$ is increasing in $m_t^a(L)$, and since $m_t^P(L)$ is decreasing in η_t and $m_t^T(L)$ is increasing in η_t, it follows that $W_t^{\phi}(\eta_t, \phi_t)$ decreases in η_t, $\partial W_t^{\phi}(\eta_t, \phi_t)/\partial \eta_t < 0$. Therefore,

$$
\text{sgn}\left(\frac{\partial \eta_t^*}{\partial \phi_t} \right) = \text{sgn}\left(\frac{\partial v_t(P|L, \eta_t^*, \phi_t)}{\partial \phi_t} - \frac{\partial v_t(T|L, \eta_t^*, \phi_t)}{\partial \phi_t} \right).
$$

An increase in ϕ_t, increases the mean $m_t^a(L)$ in (A.2). Using property *(a)* in Lemma A.1, we conclude that for a given η_t,

$$
\frac{\partial v_t(a_t|L, \eta_t, \phi_t)}{\partial \phi_t} = \frac{\partial v_t(a_t|L, \eta_t, \phi_t)}{\partial m_t^a(L)} \cdot \frac{1}{\phi_t(1 - \phi_t)} > 0,
\tag{A.15}
$$

for $a_t = P, T$. Since both $v_t(P|L, \eta_t, \phi_t)$ and $v_t(T|L, \eta_t, \phi_t)$ increase with ϕ_t, we need to establish which of the two value functions increases more at the equilibrium η_t^*. To to so, we first note that, since $(\phi_{t+1}|a_t, s) \sim \mathcal{L}ogit\mathcal{N}(m_t^a(s), \varsigma^a)$ with $m_t^a(s)$ and ς^a as in (A.2) and (A.3), respectively, the value function in (A.7) can be written as $v_t(a_t|L, \eta_t, \phi_t) = \mathbb{E}_t^M[f^a(Z)]$, where

$$
f^a(Z) = \frac{e^{-(1/2)\varsigma^a + \sqrt{\varsigma^a}Z}}{\frac{1-\phi_t}{\phi_t}\Lambda_t(a_t) + e^{-(1/2)\varsigma^a + \sqrt{\varsigma^a}Z}},
$$

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and $Z \sim \mathcal{N}(0,1)$. When $\phi_t \to 0$, $m_t^a(L) \to -\infty$, and consequently

$$v_t(a_t|L, \eta_t, \phi_t) \to 0 \tag{A.16}$$

for both $a_t = P$ and $a_t = T$. Similarly, when $\phi_t \to 1$, $m_t^a(L) \to \infty$, and consequently

$$v_t(a_t|L, \eta_t, \phi_t) \to 1 \tag{A.17}$$

for both $a_t = P$ and $a_t = T$. Therefore, as a function of ϕ_t, both value functions start at 0 and monotonically go to 1. Analyzing the derivative in (A.15) when $\phi_t \to 0$, we obtain that

$$
\begin{aligned}
\lim_{\phi_t \to 0} \frac{\partial v_t(a_t|L, \eta_t, \phi_t)}{\partial \phi_t} &= \lim_{\phi_t \to 0} \mathbb{E}_t^M \left[f^a(Z) \cdot (1 - f^a(Z)) \cdot \frac{1}{\phi_t(1 - \phi_t)} \right] \\
&= \lim_{\phi_t \to 0} \mathbb{E}_t^M \left[\frac{\Lambda_t(a_t)e^{(1/2)\varsigma^a + \sqrt{\varsigma^a}Z}}{\left((1 - \phi_t)\Lambda_t(a_t)e^{(1/2)\varsigma^a} + \phi_t e^{\sqrt{\varsigma^a}Z}\right)^2} \right] \\
&= \frac{1}{\Lambda_t(a_t)} \mathbb{E}_t^M \left[e^{-(1/2)\varsigma^a + \sqrt{\varsigma^a}Z} \right] \\
&= \frac{1}{\Lambda_t(a_t)},
\end{aligned}
$$

where the last equality follows from the expectation of a log-normal random variable. Since $\Lambda_t(P) < 1 < \Lambda(T)$, it follows that

$$\left. \frac{\partial v_t(P|L, \eta_t, \phi_t)}{\partial \phi_t} \right|_{\phi_t \to 0} > \left. \frac{\partial v_t(T|L, \eta_t, \phi_t)}{\partial \phi_t} \right|_{\phi_t \to 0}. \tag{A.18}$$

From Theorem 1, we know that for any $\phi_t \in (0, 1)$ there always exists a unique $\eta_t^* < 1$. This means that, given η_t^*, the two value functions $v_t(P|L, \eta_t^*, \phi_t)$ and $v_t(T|L, \eta_t^*, \phi_t)$ must cross at a value of ϕ_t between 0 and 1. We denote this value by ϕ_t^*. Putting together (A.16), (A.17), and (A.18), it implies that

$$\left. \frac{\partial v_t(T|L, \eta_t^*, \phi_t)}{\partial \phi_t} \right|_{\phi_t = \phi_t^*} > \left. \frac{\partial v_t(P|L, \eta_t^*, \phi_t)}{\partial \phi_t} \right|_{\phi_t = \phi_t^*},$$

and hence that $\partial \eta_t^* / \partial \phi_t \leqslant 0$. $\qquad \square$

Proof of Proposition 4. Let the function $W^\rho(\cdot)$ denote the difference in the value function of a low-skill manager from implementing a picking and a timing strategy,

$$W_t^\rho(\eta_t, \rho) \equiv v_t(P|L, \eta_t, \rho) - v_t(T|L, \eta_t, \rho).$$

The equilibrium η_t^* is such that $W_t^\rho(\eta_t^*, \rho) = 0$. Using the *implicit function theorem*, we obtain that

$$\frac{\partial \eta_t^*}{\partial \rho} = -\frac{\partial W_t^\rho(\eta_t^*, \rho)/\partial \rho}{\partial W_t^\rho(\eta_t, \rho)/\partial \eta_t}$$

Since by property *(a)* in Lemma A.1 $v_t(a_t|L, \eta_t, \rho)$ is increasing in $m_t^a(L)$, and since $m_t^P(L)$ is decreasing in η_t and $m_t^T(L)$ is increasing in η_t, it follows that $W_t^\rho(\eta_t, \rho)$ decreases in η_t, $\partial W_t^\rho(\eta_t, \rho)/\partial \eta_t < 0$. Therefore,

$$\text{sgn}\left(\frac{\partial \eta_t^*}{\partial \rho}\right) = \text{sgn}\left(\frac{\partial v_t(P|L, \eta_t^*, \rho)}{\partial \rho} - \frac{\partial v_t(T|L, \eta_t^*, \rho)}{\partial \rho}\right).$$

An increase in ρ, increases the variance ν^T in (3), which in turns increases $m_t^T(L)$ and decreases ς^T in (A.2) and (A.3), respectively. Since $m_t^T(L)$ can be written as $\Phi_t - (1/2)\varsigma^T - \lambda_t^T(\eta_t)$, using property *(c)* in Lemma A.1, we conclude that for a given η_t,

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

Moreover, since ν^P is not affected by ρ, it follows that for a given η_t, $\partial v_t(P|L, \eta_t, \rho)/\partial \rho = 0$. This implies that $\partial \eta_t^*/\partial \rho \leqslant 0$.

Since the fractions $M_t^P(H)$ and $M_t^T(H)$ in (A.10) and (A.11) are respectively decreasing and increasing in η_t^*, they are respectively increasing and decreasing in ρ. Therefore, when market volatility is high, $\rho_t^T = \rho + \Delta_\rho$, 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.12) of picking funds increases, whereas that of timing funds decreases. $\qquad\square$

Table 1: Summary Statistics

Averages	Low-*dop* (bottom 20%) (1)	Medium-*dop* (middle 60%) (2)	High-*dop* (top 20%) (3)	Full Sample (4)
		Distribution of *dop*		
Degree of Picking (*dop*)	0.52	0.77	0.91	0.77
Age (Q)	35	37	39	37
Size ($M)	208	239	252	236
Family Funds	11	11	11	11
Turnover	0.67	0.52	0.48	0.54
Expense Ratio (%)	1.15	1.11	1.11	1.12
Tracking Error (%)	5.01	3.47	3.23	3.64
Fraction of Small Cap Funds	0.29	0.32	0.35	0.32
Fraction of Growth Funds	0.46	0.42	0.39	0.42
Fraction of Value Funds	0.03	0.03	0.03	0.03

Table 2: Fund Flow Sensitivity to Core and Non-Core Performance

This table shows the quarterly fund flow sensitivity to lagged fund's total, core and non-core performance measured as active returns, in percentage. Flows are calculated as a percentage of lagged asset value at quarterly frequency and then annualized. Column 3 and 4 uses the sub-sample of funds with above and below median *dop*, respectively. All specifications include time and style fixed effects. Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

	Panel A: Regressions			
Dependent Variable	% Fund Flows (t)			
Sample	All Funds		Pickers	Timers
	(1)	(2)	(3)	(4)
Active Return (t-1)	0.135***			
	(0.006)			
Core Active Return (t-1)		0.186***	0.244***	0.150***
		(0.008)	(0.010)	(0.011)
Non-Core Active Return (t-1)		0.047***	0.075***	0.046**
		(0.015)	(0.019)	(0.020)
Tracking Error (t-1)	0.164***	0.161***	0.131***	0.161***
	(0.025)	(0.026)	(0.032)	(0.027)
Log Assets (t-1)	0.032	0.029	0.053	-0.011
	(0.041)	(0.041)	(0.047)	(0.043)
Log Fund Age (t-1)	-4.015***	-4.007***	-4.081***	-3.932***
	(0.099)	(0.099)	(0.116)	(0.111)
Expense Ratio (t-1)	-0.704**	-0.724**	-0.446	-1.027***
	(0.314)	(0.314)	(0.374)	(0.222)
Turnover (t-1)	-0.301***	-0.304***	-0.209**	-0.387***
	(0.086)	(0.087)	(0.094)	(0.082)
Intercept	11.094***	11.048***	11.426***	11.523***
	(0.798)	(0.804)	(0.970)	(0.992)
Fund-Quarter Obs	147787	147786	74729	73047
Adjusted R-Sq	0.122	0.124	0.126	0.124
	Panel B: Hypothesis Testing			
		F-test of H_0: $\beta_{core} = \beta_{non\text{-}core}$		
Degree of Freedom		3707	3660	3680
F-score		49.52	4535	13.77
p-value (2 Tailed)		0	0	0.0002

Table 3: Performance of Pickers and Timers

This table shows the relationship between fund performance and degree of picking (*dop*). Columns 1-2 regress quarterly active return and value added on quarterly *dop*. Columns 3-4 do the same but excluding the *fund-quarters* having bottom 20% of tracking error. All the columns controls for time fixed effects. Standard errors are clustered at fund level. Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

Sample	All Funds		Excluding Indexers	
Dependent Variable	Return (t)	Value (t)	Return (t)	Value (t)
	(1)	(2)	(3)	(4)
dop (t)	3.053***	29.007***	3.437***	27.821***
	(0.344)	(9.397)	(0.400)	(10.217)
Log Assets (t-1)	-0.182***	4.921*	-0.236***	1.516
	(0.030)	(2.594)	(0.037)	(2.825)
Log Fund Age (t-1)	0.151**	-0.809	0.224***	-0.871
	(0.061)	(1.172)	(0.073)	(1.369)
Expense Ratio (t-1)	0.489***	2.736	0.192	-1.495
	(0.117)	(2.037)	(0.165)	(2.901)
Turnover (t)	-0.225***	-2.089***	-0.285***	-2.665**
	(0.067)	(0.806)	(0.094)	(1.054)
Intercept	5.642***	35.364*	6.104***	62.984***
	(0.620)	(20.983)	(0.675)	(23.025)
Time FE	Yes	Yes	Yes	Yes
Fund-Quarter Obs	149462	149462	119395	119395
Adjusted R-Sq	0.059	0.013	0.064	0.013

Table 4: Performance of Pickers and Timers: Additional Effects

In this table we regress quarterly fund performance (measured either as active returns or dollar value) on quarterly *dop*. All columns include style×time fixed effects. Columns 3 and 4 use net-of-fees performance. The variable Large is a dummy for funds with above median fund size. Standard errors are clustered at fund level. Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

Effect	Style		Expense Ratio		Size
Dependent Variable	Return (t)	Value (t)	Net Return (t)	Net Value (t)	Return (t)
	(1)	(2)	(3)	(4)	(5)
dop (t)	2.215***	21.070**	2.228***	23.363**	1.921***
	(0.342)	(9.572)	(0.343)	(9.628)	(0.499)
Large (t-1)					0.895*
					(0.509)
Large (t-1) × *dop* (t)					0.523
					(0.604)
Log Assets (t-1)	-0.175***	5.112**	-0.169***	-7.451***	-0.478***
	(0.030)	(2.571)	(0.031)	(2.234)	(0.048)
Log Fund Age (t-1)	0.074	-2.755**	0.067	-2.895**	0.087
	(0.059)	(1.211)	(0.061)	(1.207)	(0.059)
Expense Ratio (t-1)	0.057	-1.967	-0.874***	-7.789***	0.035
	(0.162)	(2.703)	(0.198)	(2.727)	(0.163)
Turnover (t)	-0.214***	-1.717**	-0.218***	-1.481**	-0.214***
	(0.070)	(0.802)	(0.071)	(0.731)	(0.070)
Intercept	44.554***	38.360**	44.427***	98.506***	45.789***
	(5.100)	(19.306)	(5.102)	(20.588)	(5.087)
Style×Time FE	Yes	Yes	Yes	Yes	Yes
Fund-Quarter Obs	149443	149443	149443	149443	149443
Adjusted R-Sq	0.117	0.020	0.117	0.021	0.117

Table 5: Performance of Picking and Timing Strategies Within Fund

This table exhibits the relationship between quarterly active returns and degree of picking (*dop*) using a first-difference model. For a given variable x, $\Delta x_t \equiv x_t - x_{t-1}$. Drop (Rise) in *dop* ($t$) is a dummy with value of 1 if $dop_t - dop_{t-1} < (>)0$. All columns include style×time fixed effects. Standard errors are clustered at fund level. All the models control for quarterly time fixed effects. Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

Dependent Variable	Δ Return (t)		
	(1)	(2)	(3)
Δ *dop* (t)	-0.736**		
	(0.348)		
Δ Log Assets (t-1)	-13.342***	-13.351***	-13.349***
	(0.557)	(0.557)	(0.557)
Δ Expense Ratio (t-1)	-1.138**	-1.140**	-1.140**
	(0.484)	(0.484)	(0.484)
Δ Turnover (t)	0.082	0.083	0.082
	(0.156)	(0.156)	(0.156)
Drop in *dop* (t)		0.080	
		(0.096)	
Rise in *dop* (t)			-0.101
			(0.093)
Intercept	-35.190***	-35.248***	-35.171***
	(8.437)	(8.436)	(8.430)
Style×Time FE	Yes	Yes	Yes
Fund-Quarter Obs	146127	146127	146127
Adjusted R-Sq	0.116	0.116	0.116

Table 6: Fund Flow Sensitivity of Picking and Timing Strategies

This table shows the quarterly fund flow sensitivity to the lagged fund performance, measure as quarterly active return. Both active returns and flow variables are winsorized at 1%. Young (old) funds denote the group of funds with a fund age below (above) median during the performance period. All columns include style×time fixed effects. Column 2 additionally includes fund fixed effects. Standard errors are clustered at fund level. Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

Dependent Variable	% Fund Flows (t)			
Sample	All Funds		Young Funds	Old Funds
	(1)	(2)	(3)	(4)
Active Return (t-1)	0.076***	0.037**	0.084***	0.046**
	(0.019)	(0.018)	(0.028)	(0.019)
Active Return (t-1) × dop (t-1)	0.171***	0.167***	0.197***	0.154***
	(0.026)	(0.025)	(0.039)	(0.026)
dop (t-1)	-0.063	0.172	-0.458	1.619***
	(0.353)	(0.330)	(0.594)	(0.327)
Tracking Error (t-1)	0.135***	0.145***	0.167***	0.040
	(0.032)	(0.038)	(0.051)	(0.029)
Log Assets (t-1)	-0.049	-2.983***	-0.389***	-0.026
	(0.044)	(0.131)	(0.071)	(0.040)
Log Fund Age (t-1)	-4.223***	-7.600***	-6.585***	-0.808***
	(0.109)	(0.249)	(0.199)	(0.176)
Expense Ratio (t-1)	-0.607*	-0.290	-0.705	-0.502**
	(0.345)	(0.426)	(0.521)	(0.202)
Turnover (t-1)	-0.320***	0.010	-0.323***	-0.139*
	(0.092)	(0.094)	(0.100)	(0.084)
Intercept	12.794***	46.163***	20.098***	-5.889
	(4.885)	(1.484)	(5.398)	(4.278)
Style×Time FE	Yes	Yes	Yes	Yes
Fund FE		Yes		
Fund-Quarter Obs	147387	147387	73054	74333
Adjusted R-Sq	0.111	0.157	0.117	0.041

Table 7: Fund Reputation and Investment Strategy

This table shows the relation between fund reputation as measured by past fund flows and degree of picking (dop). Flows are double sorted within quarter and style and normalized between 0 and 1. Columns 1 and 4 use quarterly dop and lagged normalized flows while columns 2, 3 and 5 use average dop from t to $t+3$ and average normalized flows between $t-4$ and $t-1$. Low-skill (high-skill) funds are funds within bottom (top) 20% of the long-term average of active returns quantile. Diverse fund family is a dummy that takes 1 if within family-quarter standard deviation of dop falls within top 20%. All columns include fund fixed effects and style×time fixed effects. Standard errors are clustered at the fund level. Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

Sample	Low-Skill Funds			High-Skill Funds	
Dependent Variable	dop (t)	$\overline{dop}$ (t, $t+3$)		dop (t)	$\overline{dop}$ (t, $t+3$)
	(1)	(2)	(3)	(4)	(5)
Normalized Flows (t-1)	-3.216***			0.188	
	(0.461)			(0.391)	
Average Normalized Flow (t-4, t-1)		-7.206***	-6.164***		1.279**
		(0.661)	(0.648)		(0.523)
Diverse Fund Family (t-1)			-1.646***		
			(0.461)		
Diverse Fund Family (t-1) × Average Normalized Flow (t-4, t-1)			-3.002***		
			(0.835)		
Log Assets (t-1)	-0.031	-0.405*	-0.483**	1.200***	0.925***
	(0.241)	(0.226)	(0.219)	(0.134)	(0.134)
Expense Ratio (t-1)	2.032**	2.078**	2.042**	0.500*	0.388
	(0.976)	(0.964)	(0.948)	(0.266)	(0.254)
Turnover (t)	-0.163			-0.779	
	(0.188)			(0.500)	
Turnover (t, $t+3$)		-0.358	-0.336		-1.049
		(0.276)	(0.265)		(0.647)
Intercept	72.514***	76.107***	76.664***	68.664***	69.181***
	(1.964)	(1.955)	(1.909)	(1.055)	(0.912)
Style×Time FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Fund-Quarter Obs	28799	29387	29387	29577	30027
Adjusted R-Sq	0.003	0.025	0.038	0.006	0.011

Table 8: Volatility, Investment Strategy and Fund Performance

This table shows the relationship between aggregate volatility and investment strategies, and between aggregate volatility and fund performance. Aggregate volatility is measured in three ways: (i) average level of VIX index during a quarter; (ii) quarter volatility of CRSP value-weighted index (i.e., market volatility); (iii) quarter volatility of fund benchmarks. A quarter in the sample is categorized in one of the following three volatility quantiles: low (bottom 20%), medium (middle 60%) and high (top 20%). Superscripts *, **, and *** indicate significance at less than 1%, 5% and 10%, respectively.

Dependent Variable		*dop* (*t*)			Active Return (*t*)
Sample		Low-Skill Funds		Low-Skill and High-Skill Funds	Low-Skill and High-Skill Funds
Volatility Measures	VIX	Market	Benchmark	Benchmark	Benchmark
	(1)	(2)	(3)	(4)	(5)
Medium-Vol (*t*)	-0.171	-0.459*	-4.048***	-4.684***	0.076
	(0.329)	(0.259)	(0.219)	(0.243)	(0.728)
High-Vol (*t*)	-6.218***	-5.965***	-11.534***	-13.194***	-10.963***
	(0.421)	(0.349)	(0.350)	(0.387)	(1.275)
High-Skill				2.879***	
				(0.309)	
Medium-Vol (*t*) × High-Skill				0.459	
				(0.294)	
High-Vol (*t*) × High-Skill				1.546***	
				(0.476)	
dop (*t*)					6.202***
					(0.769)
Medium-Vol (*t*) × *dop* (*t*)					-1.725*
					(0.914)
High-Vol (*t*) × *dop* (*t*)					10.193***
					(1.680)
Log Assets (*t*-1)	-1.242***	-0.607***	-0.470**	-0.369***	-0.227***
	(0.225)	(0.219)	(0.217)	(0.081)	(0.068)
Log Fund Age (*t*-1)	3.522***	3.276***	2.318***	1.069***	0.423***
	(0.262)	(0.264)	(0.261)	(0.129)	(0.130)
Expense Ratio (*t*-1)	2.224**	2.569***	1.829**	-1.147***	0.497***
	(0.872)	(0.872)	(0.875)	(0.423)	(0.185)
Turnover (*t*)	-0.163	-0.201	-0.160	-0.553**	-0.235**
	(0.180)	(0.189)	(0.175)	(0.243)	(0.094)
Intercept	65.148***	62.520***	69.115***	77.184***	-2.661***
	(1.902)	(1.829)	(1.866)	(0.692)	(0.763)
Fund FE	Yes	Yes	Yes		
Fund-Quarter Obs	29335	29335	29335	59179	59179
Adjusted R-Sq	0.041	0.040	0.064	0.087	0.026

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