Career Concerns, Short-Termism, and Real Options: The Case of Delegated Money Management*

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Abstract

We study real options in the labor market for investment management talent and show their importance for understanding the delegated investment management market. We solve and calibrate a dynamic equilibrium model featuring investment opportunities with differing maturities that interact with managers' career concerns. Managers strategically choose the horizon of their investment opportunities, and thereby affect the speed by which their skill is revealed. Short-term investment strategies benefit fund managers (particularly new ones) by accelerating skill revelation, while the downside risk is managed by manager exit. In the steady state, a large number of new and unskilled managers exploit the value of this call option, driving down the short-term value added of each manager in equilibrium. A small number of experienced and skilled managers exploit scalable long-term investment opportunities, adding substantial value. We empirically confirm our theoretical predictions using US mutual fund data. Our findings also have important implications for other industries where strategic task choice interacts with skill revelation.

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1 Introduction

We combine insights from the real options literature with recent advances in the delegated investment management literature to illustrate the important interaction between strategic task choice and employee skill revelation. We solve a dynamic equilibrium model of delegated investing featuring investment opportunities with differing maturities that interact with managers' career concerns. Because managers can strategically choose the investment opportunities they pursue, they can affect the speed by which their skill is revealed. Short-term investment opportunities, by their nature, reveal the skill of the manager more quickly than long-term investment opportunities do. This gives the manager control over the speed by which she and investors learn about her skill. Further, the downside risk is managed through manager exit. This mechanism can help explain an important stylized fact in U.S. mutual fund data: the simultaneous occurrence of a large number of new managers pursuing high turnover strategies with low value added, and a small number of experienced and skilled managers that exploit scalable long-term investment opportunities and who add substantial value. As such, while short-termism often results from irrational behavior both theoretically and empirically, in our model the choice to invest in short-term investment opportunities results from managers optimally choosing to accelerate skill revelation in a dynamic equilibrium setting.[1] This mechanism has wider applications in labor and product markets. For example, internship programs are popular among new graduates, despite their lower salaries and less important short-term tasks compared with a full-time job. Also, companies launch a large amount of new products every year. They initially charge low prices and spend a lot on these products' marketing. While many of these products do not survive, a few generates large long-term value added.

While the theoretical real options literature has made important strides in recent decades, finding their empirical counterparts has been proven to be more challenging. In particular, quantifying the value of real options in a learning context is difficult due to measurement problems related to the performance of individual employees (or the quality of a

[1] See also Shleifer and Vishny (1990, 1997) for mechanisms that induce institutional investors and corporate managers to focus more on the short term rather than the long term.

product), the relevant information set and, as a result, the speed of learning. An advantage of the mutual fund industry is that both the performance of a mutual fund as well as the amount of capital flowing into or out of it are public information.[2] Since this information is available at different frequencies, we can measure the speed of learning for funds using high- and low- turnover strategies separately. This allows us to provide direct empirical evidence to our model's key mechanism: investing in short-term investment opportunities accelerates skill revelation. Furthermore, the speed of learning is of great importance to fund managers, as it takes years or even decades for them to reveal their skill (e.g., Berk and Green [2004]).[3]

Armed with these insights, we use the mutual fund industry to quantify the value from a higher speed of learning about employees' skills: a strategy accelerating the revelation of an employee's skill increases her growth potential, while the downside risk is managed by the possibility to exit. This call-option-like payoff embeds a *real growth option.* Because the value of this real growth option is large for new employees, they are willing to accept a lower current payoff from this strategy. Put differently, the "option to learn" is valuable for making more informed decisions under imperfect information (Grenadier and Malenko [2010]). According to our estimates, for a new manager, the present value of this real growth option from investing in short-term strategies is about \$4.9 million each quarter, whereas the one-period payoff from investing in short- (long-) term strategies is \$0.09 (\$0.57) million per quarter. For an average fund manager, the present value of this option is at least \$3.5 million.

We analyze a dynamic equilibrium model of multiple fund managers with career concerns.[4] Our model builds on that of Berk and Green (2004), but deviates from it by

[2]As shown in the model of Berk and Green (2004), investors learn of a fund manager' skill from her past performance. The result of this learning can be measured by the capital flows into and out of the fund, and the speed of learning can be measured by the sensitivity of capital flows to fund performance (i.e., flow-performance sensitivity).

[3]Another paper investigating the real option value from learning is Grenadier and Malenko (2010), which shows that the "option to learn" uncertainty over the permanence of past shocks is valuable.

[4]Our new career incentive is related to but different from existing career incentives of fund managers studied in the literature (e.g., risk shifting of fund managers documented in Brown, Harlow, and Starks [1996], Basak, Pavlova, and Shapiro [2007], and Huang, Sialm, and Zhang [2011]; window dressing in Agarwal, Gay, and Ling [2014]). Sockin and Xiaolan (2022) document that the commonality in compensation incentives across funds distorts price informativeness, which feeds back into fund manager behavior. To our best

featuring investment opportunities with different horizons, whose returns are endogenously determined by competition among managers. The key mechanism we study arises from the strategic interaction between managers' career concerns regarding skill revelation and their investment horizon: investing in short-term investment opportunities allows fund managers to reveal their skill faster at the cost of lower value added. In our model, fund managers with a finite lifespan optimally sacrifice short-term profitability to maximize the expected (lifetime) stream of management fees. In equilibrium, a large number of new and unskilled fund managers compete for short-term opportunities to exploit the value of this real growth option, driving down short-term value added to a level lower than those of long-term opportunities. A small number of experienced and skilled managers exploit scalable long-term investment opportunities, adding substantial value. These model predictions are consistent with three salient empirical regularities left unexplained in the mutual fund literature.[5] First, the majority of funds' profits come from their long-term holdings as opposed to short-term trades.[6] Second, a small number of large funds with low-turnover strategies manage the majority of assets, while the industry continuously features a large number of constantly changing small funds with high-turnover strategies. Finally, older fund managers have lower fund turnover than newer fund managers on average. In addition, we provide direct empirical evidence to our model's new mechanism using funds' flow-performance sensitivity as a measure of the speed of learning. We find that the flow-performance sensitivity of high-turnover funds decays faster over time than that of low-turnover funds, and this decay is faster for the returns in the past quarter/year than for returns in the past three years.

To formalize the aforementioned ideas, we consider an infinite-horizon, discrete-time

knowledge, Chen, Jiang, and Xiaolan (2023) is the only other paper studying the interaction between funds' strategies and the speed of skill revelation, where they focus on their marketing strategies.

[5] The mutual fund literature has made important progress in explaining several stylized facts in mutual fund data. For example, Berk and Green (2004) use rational learning of fund manager skill to explain the stylized fact that investors' capital chase past fund performance. Berk and van Binsbergen (2015) further distinguish the value added by a fund manager (the product of fund gross alpha and assets under management) from the net returns shared with fund investors, and they document that funds' value added, as a measure of fund skill, is on average positive and persistent over time, whereas net alphas are not. Because the Berk and Green model is a single-fund model with exogenous investment opportunities it is unable to address the strategic interactions that we study in this paper.

[6] As documented in Van Binsbergen, Han, Ruan, and Xing (2022), mutual funds' holdings longer than a year make more profits than holdings shorter than a year do in the aggregate.

model with a continuum of fund managers, who have access to investment opportunities that may deliver excess returns (alphas) over the passive benchmark. There are two types of investment opportunities: short-term and long-term opportunities. The investment opportunities can be interpreted as investment strategies that exploit mispricing in the financial market. For example, investment in those opportunities will deliver alphas over the passive benchmark when prices converge to their fundamental value. A short-term investment opportunity converges to the fundamental value more quickly, whereas a long-term investment opportunity converges more slowly.[7] As such, short-term opportunities are much less affected by limits-to-arbitrage type of concerns compared to long-term opportunities; the latter may first deviate further from fundamental value before converging (Shleifer and Vishny [1997]). In summary, our model extends the setting of Berk and Green by introducing a strategic interaction between career concerns and managers' investment horizons among a continuum of fund managers.

There are overlapping generations of fund managers in our economy, who randomly die in each period. They may also voluntarily exit if the value of continuing operations falls below the outside option. New managers enter the economy so that the total mass of fund managers in the economy is constant. Following Berk and Green (2004), we assume that fund managers' talents are initially unknown to everyone in the economy. Given the history of performance, investors and fund managers update their beliefs about fund managers' talents. Under updated beliefs, investors' money flows to and from each fund until its expected net alpha becomes zero. Therefore, fund sizes are tied to perceived talents of managers under the assumption of rational expectations.

As mentioned above, fund managers can choose to either exit or continue fund operation in each period. In case they continue, they can choose to invest in either a short-term or a long-term investment opportunity. Fund managers maximize their expected utility of consuming the stream of fund management fees after costs. By investing in short-term opportunities, they can accelerate the revelation of their talents, which are either good or

[7] Because funds can immediately deploy their capital from realized existing investment to a new opportunity, short-term investment is equivalent to high-turnover strategy in our model. Likewise, long-term investment is equivalent to low-turnover strategy.

bad with the same probability conditioning on the current information set. The value of a higher learning speed of short-term investment arises from the option to exit, and the fact that their lifespan is finite. Fund managers can exploit the possibility of higher fund growth in case of good performance before their career is over, but can still limit the adverse impact of bad performance by choosing to exit from the industry. This value from a higher learning speed (i.e., the value of the real growth option) is larger if managers are new, because there is little known about their talents. This implies that new fund managers are willing to accept lower value added of short-term opportunities relative to those of long-term opportunities due to the extra option value of the short-term opportunities. On the margin, the total value added (i.e., the sum of value added and the option value) is equalized between short-term and long-term opportunities.

We show that fund managers choose to exit when their perceived talents are sufficiently low, and older fund managers with the same perceived talents are more likely to exit than new managers because they have a smaller growth potential. As a consequence, the stationary distribution of surviving fund managers' talents becomes on average higher than the initial distribution of talents. As fund managers become older or perceived as more skilled by investors, they switch to long-term investment opportunities leading to slower talent revelation. The stationary distribution of perceived talents determines the distribution of fund sizes, leading to a large number of small (high-turnover) funds and a small number of large (low-turnover) funds in the economy.

Another important feature of our model is that the gross alpha of a fund's investment is affected by the manager's talent as well as the decreasing returns to scale at the aggregate level; the excess return of a fund's investment over the passive benchmark increases in the level of its skill, but decreases in the magnitude of competition among funds in the same type of opportunities. Decreasing returns to scale at the aggregate level is equivalent to strategic substitutability in investment. It is well known in the literature that informed arbitrageurs are strategic substitutes for each other (Grossman and Stiglitz [1980]). The feature that the decreasing returns to scale parameter depends on the aggregate level of assets under management (AUM) further enriches the Berk and Green framework, as in their model funds' investment profits do not depend on the AUM of the fund's competitors.[8]

Consequently, the amount of capital invested in (and the resulting excess returns of) investment opportunities are determined by the distribution of funds' perceived skills. In our model, fund manager choices are a function of two state variables: the perceived skill (the posterior mean of the skill distribution) as well as the precision of beliefs regarding this skill (the inverse of the posterior variance). This allows us to construct a parsimonious Markov transition function of fund manager states. The steady state is computed using the stationary distribution of the state variables. Under this stationary distribution, there are many new and relatively unskilled funds in the economy. They invest in short-term opportunities for growth options, which drive the value added of short-term opportunities down to a level lower than long-term opportunities. As a result, old and skilled fund managers optimally choose to invest in long-term opportunities to exploit higher profits. The average value added of investing in short-term opportunities is smaller because of both the competition for growth and the low average skill of new managers, whereas the average value added of investing in long-term opportunities is larger because of both the lack of competition and the high average skill of experienced managers.

Empirically, we use 59 years of US mutual fund data to confirm our model predictions and estimate the value of the real growth option. Consistent with our model prediction that high-turnover strategies reveal fund managers' talents faster, we find that the flow-performance sensitivity of high turnover funds decays faster over time than that of low turnover funds, and the results are stronger for the returns in the past quarter or year than returns in the past three years. The value of the real growth option is large to new managers according to our parametric model calibrated to US data. For most new fund managers, the present value of the real growth option given by short-term investing is larger than the higher payoff given by long-term investing. As a result, most new fund managers prefer short-term to long-term investing. This option value decreases as a manager gets more experienced, since the precision regarding a manager's talent increases over time. This option value

[8] Berk and Green (2004) assume decreasing returns to scale at the fund level. For more studies exploring the importance of decreasing returns to scale at the fund level see Chen, Hong, Huang, and Kubik (2004), Zhu (2018), Pastor, Stambaugh, and Taylor (2020), and Barras, Gagliardini, and Scaillet (2021).

also has a hump-shaped relation with the perceived skill of a manager, because the growth option is less useful to fund managers who are either close to unskilled, or skilled enough to shift to long-term strategies for a larger payoff. Moreover, the joint distribution of fund size, manager tenure, and turnover in the data confirms the predictions in our model. New and small funds are more likely to choose high-turnover strategies, while old and large funds are more likely to choose low-turnover strategies. Old and small funds are more likely to exit. Since the fund managers perceived by investors as skilled attract more capital and are likely to switch to low-turnover strategies, low-turnover funds manage substantially more assets than high-turnover funds do. For high-turnover funds, the number of new managers is substantially more than the number of old managers, whereas for low-turnover funds, the total amount of assets managed by old managers is substantially more than the amount managed by new managers. Lastly, as our model predicts, because high-turnover strategies offer higher future growth potential, new and small fund managers are willing to accept lower current value added for high-turnover strategies. The value added of high-turnover funds (close to zero) is substantially smaller than the value added of low-turnover funds under both the CAPM and the Vanguard benchmarks.

The paper is organized as follows. In Section 2, we review related literature. In Section 3, we describe our theoretical model. In Section 4, we solve for equilibrium of our model. In Section 5, we provide main theoretical findings and test them empirically, and we also quantify the value of the real growth option using a parametric model. In Section 6, we conclude.

2 Literature

Our paper belongs to a body of literature that applies the real options approach to a wide set of economic problems (see, for example, Dixit and Pindyck [1994], Trigeorgis [1996], and Lambrecht [2017] for surveys). Drawing from research such as Bernanke (1983), Abel and Eberly (1994, 1996), and Caballero and Pindyck (1996), the real options approach underscores the importance of postponing investment until uncertainties are resolved. This "option to wait" can be augmented with an "option to learn" about learning the existing but unknown reality rather than the future (as in Grenadier and Malenko [2010] and this paper). Real options also induce participants to choose different strategies over their life cycles (or career paths). For example, young individuals (often entrepreneurs) or firms experiment when young to exploit the real option value of either expanding or abandoning the current choice depending on the flow of new information (Bernado and Chowdhry [2002]; Manso [2016]; Bouvard [2014]). In our paper, we investigate how the value of the option to learn changes across the life cycle of employees, as well as its effect on the distribution of their value added. We use the mutual fund industry as a natural laboratory to empirically examine the implications of our theoretical predictions within the context of the real options approach.

Our paper closely relates to the literature on agency conflict between fund managers and investors. Our new career incentive is related to but different from existing career incentives of fund managers studied in the literature. For example, Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), and Basak, Pavlova, and Shapiro (2007) document that because investors' capital is directed more to funds with higher performance, mid-year underperforming managers tend to gamble in the later part of an annual assessment period.[9] More recently, Huang, Sialm, and Zhang (2011) argue that fund managers risk shift to increase their personal compensation, and Agarwal, Gay, and Ling (2014) document that fund managers window dress to attract capital. Guerrieri and Kondor (2012) find that fund managers' career concerns can generate countercyclical reputational premium in bond returns, and Sockin and Xiaolan (2022) document that the commonality in compensation incentives across funds distorts price informativeness, which feed back into fund manager behavior. Relating to fund managers' age or life-cycle consideration, Almazan, Brown, Carlson, and Chapman (2004) show that manager age is significantly related to the use of direct investment restrictions in the mutual fund management process, and Chapman, Evans, and Xu (2010) introduce life-cycle and longer-term learning effects into fund managers' portfolio choices, which focuses on the effect of learning on portfolio choice, instead of the effect of funds' strategies on learning as in our paper. To our best knowledge, Chen, Jiang, and

[9]Chevalier and Ellison (1999) further show that to avoid being terminated, young managers on average hold less unsystematic risk and have more conventional portfolios.

Xiaolan (2023) is the only other paper studying the interaction between funds' strategies and the speed of skill revelation, where they focus on funds' marketing strategies instead of investment horizon.

Our paper also relates to the literature on short-termism, particularly among institutional investors, which has garnered significant attention in academic and practitioner circles due to its potential impact on economic outcomes (Graves and Waddock [1990]; Porter [1992]; Bushee [1998,2001]). Theoretical literature highlights the inefficiency caused by short-termism arising from various incentive schemes in both corporate and delegated investment setups (Stein [1989]; Scharfstein and Stein [1990]; Froot, Scharfstein, and Stein [1992]; Dow and Gorton [1994]; Shleifer and Vishny [1997]; Gümbel [2005]; Allen, Morris, and Shin [2006]; Burkart and Dasgupta [2021]; Dow, Han, and Sangiorgi [2021]; Dow, Han, and Sangiorgi [2023]).[10] Numerous empirical studies have indeed documented the myopic focus of institutional investors on short-term returns, potentially neglecting long-term value creation (Edelen [1999]; Manconi, Massa, and Yasuda [2012]; Cella, Ellul, and Giannetti [2013]; Callen and Fang [2013]; Kim, Su, and Zhu [2017]). Our paper aligns with the common theme in existing literature by highlighting the rationality of short-termism as a response to incentive schemes. However, our paper differs itself by identifying the source of short-termism as the option value of learning under career concerns in a delegated investment setup. By deliberately passing more profitable long-term opportunities, short-term investments seek to enhance future investment values by increasing the likelihood of attracting larger fund flows through the channel of accelerated learning.

This paper contributes to the large corpus of literature on decreasing returns to scale of mutual funds, including Berk and Green (2004), Chen, Hong, Huang, and Kubik (2004), Zhu (2018), and Barras, Gagliardini, and Scaillet (2021). Our paper emphasizes the importance of decreasing returns to scale at the investment opportunity level to the distribution of mutual funds and their value added.[11]

[10]For instance, Scharfstein and Stein (1990) show that short-term incentive contracts can lead to herding behavior and disregard of private information, resulting in inefficiency. Shleifer and Vishny (1997) find that fund managers, influenced by short-term fund flows, may overlook profitable long-term opportunities.

[11]While Pastor and Stambaugh (2012) and Pastor, Stambaugh, and Taylor (2015) have investigated the decreasing returns to scale at the industry level, our paper focuses on the decreasing returns to scale at the investment opportunity level and its interaction with fund managers' career concerns.

Our paper also contributes to a growing literature on learning fund managers' talents under rational expectations. Scharfstein and Stein (1990) show that fund managers may rationally mimic others' investment decisions to avoid adverse career outcomes. By contrast, Avery and Chevalier (1999) show that talented managers may differentiate their investments to signal their abilities when they have sufficiently private information about their abilities.[12] Choi, Kahraman, and Mukherjee (2016) show that fund flow to a manager's fund can be sensitive to his performance in other funds because of investors' learning across funds. Gervais and Strobl (2020) study a model where funds signal their private information on their own ability via fund transparency. They find that transparent funds are run by managers with more average talent whereas low- and high- skilled managers choose opaque investment. Kaniel and Orlov (2020) study a model where a fund can churn managers who have private information on own ability. They find that the fund churns unskilled managers frequently to help retained managers build reputation fast, and also expropriates managers' ability by threatening to fire them. Our paper shares the common mechanism of fund flows under rational expectations with existing papers in this line of literature. In particular, we focus on how the investment horizon choices of fund managers evolve through their careers under rational expectations. Our paper further compliments this literature by studying the resulting feedback between optimal investment choices of fund managers and equilibrium returns across those opportunities under the joint stationary distribution of talent and tenure.

Our paper is related to both theoretical and empirical literature on investment and performance in different horizons. Theoretically, Shleifer and Vishny (1990) and Dow and Gorton (1994) show that long-term assets should have larger mispricing wedge than short-term assets because investors can redeploy their capital faster. Dow, Han, and Sangiorgi (2021) microfound equilibrium capital distributions in a dynamic model, and show how mispricing wedge should be determined in equilibrium. Building on this intuition, our model shows that fund performance difference across horizons arise from equilibrium distribution

[12]The results of Avery and Chevalier (1999) imply that young managers may want to herd whereas old managers may want to "anti-herd" to signal their talents. While this mechanism is different from ours, these two mechanisms could coexist. Moreover, our papers share a common theme of career concern in that young managers may want to sacrifice investment profits whereas old managers do not have such incentives.

of fund skills. Our model further suggests larger mispricing wedges can arise from an alternative channel of career concern unlike above papers in the literature; fund managers are willing to accept smaller trading profits in short-term investments for growth options.

Empirically, our paper focuses on the relation between fund turnover and the perceived skill of a fund manager, measured by value added as proposed in Berk and van Binsbergen (2015). In contrast, previous studies investigate the relation between fund turnover and the abnormal return received by investors, measured by net alphas, or gross alphas, and the empirical evidence on this relation is mixed. For example, Pastor, Stambaugh, and Taylor (2017) document a positive relationship in both the time series and the cross-section. In contrast, Elton, Gruber, Das, and Hlavka (1993), as well as Carhart (1997), find a negative relationship, whereas Wermers (2000), Kacperczyk, Sialm, and Zheng (2005), and Edelen, Evans, and Kadlec (2007) find no significant relationship. Cremers and Pareek (2016) and Lan, Moneta, and Wermers (2019) construct direct measures for the average investment horizon of a fund and find that long-horizon funds outperform short-horizon funds in the cross-section, which is consistent with the finding in Van Binsbergen, Han, Ruan, and Xing (2022) that mutual funds' holdings longer than a year make more profits than holdings shorter than a year do in the aggregate.[13] Our model predicts that low-turnover funds do have more skilled managers than high-turnover funds in equilibrium, since managers that are new or perceived as unskilled prefer high-turnover strategies, which reveal their skills faster. However, the larger amount of capital managed by low-turnover funds have brought their net alphas to zero because of the decreasing returns to skill (as in Berk and Green [2004]). Starks, Venkat, and Zhu (2022) document that long-horizon investors tilt their portfolios towards firms with high-ESG profiles and behave more patiently toward these firms. The results in our paper suggest that old skilled managers are more likely to invest in long horizon and, thus, more likely to invest in firms with high-ESG profiles.

[13]Connecting funds' investment horizons with market mispricing, Cella, Ellul, and Giannetti (2013) show that institutional investors with short investment horizons sell more during market turmoil, and this creates price pressure for stocks held mostly by short-horizon investors. Giannetti and Kahraman (2018) provide evidence that open-end organizational structures undermine incentives for asset managers to attack long-term mispricing.

3 Model

We consider an infinite-horizon model in discrete time featuring fund managers' career concerns. Our model builds on the model of Berk and Green (2004), but unlike theirs, our model features a continuum of managers who face investment opportunities with different investment horizons and whose returns are endogenously determined by competition under strategic substitutability.

3.1 Mutual Funds and Investment Opportunities

There is a continuum of mutual fund managers in the economy indexed by j who each manage a single fund. We denote the set of all active funds operating in period t by $\mathcal{J}_t$. Mutual funds have access to investment opportunities that may deliver excess returns (alphas) over the passive benchmark.

There are two types of investment opportunities: short-term and long-term. We index each type of investment opportunity by $i \in \{S, L\}$ where S denotes short-term and L denotes long-term. The investment opportunities can be interpreted as investment strategies that exploit mispricings that resolve over different horizons. Investing in those opportunities will deliver alphas when prices converge (at different speeds) to the fundamental value. For example, in Shleifer and Vishny (1997), long-term opportunities may first deviate further from fundamental value before converging. In this case, the price will only be informative about fund managers' skill after it has converged. For simplicity, we assume that an investment opportunity yields a zero excess return over the passive benchmark until its payoff realizes. More formally, each fund j's investment in a type i opportunity yields a random excess return over the benchmark before costs and fees between period t and $t+1$, which has two independent components as follows:

$$e^j_{t+1,i} R^j_{t+1,i}, \tag{1}$$

where $R^j_{t+1,i}$ is the fund's excess return conditional on the realization of payoff, and $e^j_{t+1,i}$ is an identically and independently distributed (i.i.d.) random variable that is equal to one with probability d_i, and zero with probability $1 - d_i$. A short-term investment opportunity is more likely to realize early compared to a long-term investment opportunity, i.e., $0 < d_L < d_S \leq 1$. The inverse of d_i can be interpreted as the investment duration (i.e., the payoff takes on average $1/d_i$ periods to realize). We also assume that the realization of the payoff is public information.

As in Berk and Green (2004), we assume that the cost of actively managing funds in each investment opportunity increases convexly in its size, and is independent of the manager's talent; investing an amount q in each opportunity creates a cost of $C(q)$ for the fund in the current period where $C'(\cdot) > 0, C''(\cdot) > 0$, and $C(0) = 0$. Note that the cost function is assumed to be identical for both investment opportunities for simplicity.[14] The assumption of increasing cost in the fund's size of active management can be motivated by costs related to price impact or illiquidity when acquiring, rebalancing, and liquidating its positions (e.g., Kyle [1985]), and the convexity ensures a unique interior optimum.

We further assume that a fund can hold only one type of investment opportunity at a time. This is a technical assumption that facilitates analysis on funds' choice of investment horizons. Although funds may diversify among different types of investment opportunities in the data, they typically specialize in either short- or long- term opportunities. We also assume that both the type and the amount of investment of each fund are observable to investors.

In our model, the gross alpha of a fund's investment is affected by the manager's talent as well as the capacity constraint at the aggregate level; the excess return of a fund's investment over the passive benchmark increases in the level of talent, but decreases in the magnitude of competition among funds in the same type of opportunities. The capacity constraint at the aggregate level is equivalent to strategic substitutability in investment. It is well-known in the literature that informed arbitrage leads to strategic substitutability as more participation in informed trading eliminates mispricing (e.g., Grossman and Stiglitz [1980]). See, for example, Dow, Han, and Sangiorgi (2021) for a microfoundation of strategic

[14]For ease of exposition, we shut down the channel of heterogeneity in fund-level decreasing returns to scale for investment opportunities. This allows us to focus on heterogeneity in aggregate-level decreasing returns to scale. Van Binsbergen, Han, Ruan, and Xing (2022) investigate the difference in fund-level decreasing returns to scale between high- and low- turnover funds. It is worth noting that although high-turnover strategy gives a lower value added than low-turnover strategy in equilibrium, heterogeneity in fund-level decreasing returns to scale allows the former to have a higher gross alpha and fee than the latter.

substitutability with investment opportunities under different horizons.

Formally, we denote by $q^j_{t,i}$ the amount of fund j's investment in a type i opportunity, and by $\mu_{t,i}$ the fraction of capital invested in type i opportunity in period t:

$$\mu_{t,i} \equiv \frac{\int_{j\in\mathcal{J}_t} q^j_{t,i} dj}{\int_{j\in\mathcal{J}_t} q^j_{t,S} dj + \int_{j\in\mathcal{J}_t} q^j_{t,L} dj}.$$

Using the fraction of capital rather than the amount of capital invested in each investment opportunity reduces the number of state variables, thereby greatly simplifying our analysis.[15] The fraction of investment $\mu_{t,i}$ captures the magnitude of competition of funds in opportunity i. After all, the higher the value of $\mu_{t,i}$, the larger the total amount of capital competing for the opportunity i, which lowers the equilibrium abnormal return of investing in that opportunity.[16] Fund j's excess return on a type i investment opportunity increases in the talent parameter ϕ^j, which captures the fund manager's true ability of generating alpha and value,[17] and decreases in the magnitude of competition $\mu_{t,i}$:

$$R^j_{t+1,i}(\mu_{t,i}, \phi^j) \equiv g_i(\mu_{t,i})(\phi^j + \epsilon^j_{t+1}),$$

where $g_i(\mu_{t,i})$ is a non-negative, decreasing function of $\mu_{t,i}$ which captures the idea that the profitability of a type i investment opportunity decreases as the competition between similar funds increases. The term ϵ^j_{t+1} is a mean-zero idiosyncratic noise component specific to fund j's investment strategy with variance $1/\omega^j_t$. For now, we assume that the marginal return on an investment opportunity is infinite if no one invests in the opportunity, i.e., $g_i(0) = \infty$ for all $i \in \{S, L\}$, but we will relax this assumption in our empirical work.

Each fund is terminated randomly with a probability $1 - \kappa$ every period, but may also

[15] Our qualitative results are robust with different choices of modeling as long as there exists strategic substitutability in returns.

[16] We show later in our regression analysis in Table A1 that the effect of industry level decreasing returns to scale (DRS) becomes insignificant after including the investment opportunity level DRS into the same regression. Fund level DRS remains significant.

[17] Given that the DRS parameter is assumed to be the same across funds, this talent parameter ϕ^j can also be interpreted as the future potential of a fund manager that needs to be learned about not only by investors, but also by the fund manager themselves. We assume the same talent parameter ϕ^j for investing in short- and long- term opportunities to focus on the difference in speed of learning provided by these two opportunities and abstract away from their specializations. Please refer to Van Binsbergen, Han, Ruan, and Xing (2022) for the effect of specialization (i.e., heterogeneous talents for short- and long- term investing) on the distribution of funds' value added.

voluntarily shut down its operation when the continuation value is lower than the outside option. All funds that exit the economy are replaced by the same mass of new funds that enter the economy. This simplifying assumption gives us more tractability by preventing the mass of funds from becoming another state variable in the economy. At the birth of a new fund (indexed by j), the fund manager in fund j is endowed with a skill level ϕ^j. As in Berk and Green (2004), we assume that this talent parameter ϕ^j is known to neither investors nor managers, and follows an i.i.d. normal prior distribution with mean ϕ_0 and variance $1/\gamma$ where γ is the precision of the prior belief on ϕ^j's.

3.2 Fund Performance and Belief Updates on Skills

The fund manager in fund j is paid a management fee f_t^j in each period t, which is a fraction of its asset under management $q_{t,i}^j$. The fund's excess total payout to investors over the passive benchmark in the subsequent period is

$$TP_{t+1}^j \equiv q_{t,i}^j e_{t+1,i}^j R_{t+1,i}^j - C(q_{t,i}^j) - q_{t,i}^j f_t^j.$$

Then, the excess return of fund j after fees is given by

$$r_{t+1}^j \equiv \frac{TP_{t+1}^j}{q_{t,i}^j} = e_{t+1,i}^j R_{t+1,i}^j - \frac{C(q_{t,i}^j)}{q_{t,i}^j} - f_t^j, \tag{2}$$

where $c_i(q_{t,i}^j)$ is the unit cost associated with investing in fund j that actively manages the size of investment $q_{t,i}^j$ in opportunity i:

$$c_i(q_{t,i}^j) \equiv \frac{C(q_{t,i}^j)}{q_{t,i}^j} + f_t^j.$$

Therefore, the fund's excess return with the choice of investment in opportunity i can be represented as

$$r_{t+1}^j = e_{t+1,i}^j \left(\phi^j + \epsilon_{t+1}^j\right) g_i(\mu_{t,i}) - c_i(q_{t,i}^j). \tag{3}$$

Because the size of the fund as well as the type of investment opportunity, which is summarized by $q_{t,i}^j$, are observable for all funds, the aggregate amount of investment, $\mu_{t,i}$, is common knowledge for each type of investment opportunity $i \in \{S, L\}$. This also implies other quantities like $c_i(q^j_{t,i})$ and $g_i(\mu_{t,i})$ are also common knowledge for each opportunity i and fund j in equilibrium. Therefore, we can define a new variable ξ^j_{t+1} which is a known function of observable variables:

$$\xi^j_{t+1} \equiv \frac{r^j_{t+1} + c_i(q^j_{t,i})}{g_i(\mu_{t,i})}. \tag{4}$$

Then, Eqs. (1) and (2) imply that all relevant information regarding r^j_{t+1}, $c_i(q^j_{t,i})$, and $g_i(\mu_{t,i})$ is summarized in variable ξ^j_{t+1} whenever the payoff realizes, and it takes the value zero otherwise:

$$\xi^j_{t+1} = \begin{cases} \phi^j + \epsilon^j_{t+1} & \text{if } e_i = 1 \\ 0 & \text{if } e_i = 0. \end{cases}$$

All agents update their posterior belief on each fund's talent on the basis of the entire history of ξ^j_t in a Bayesian manner. Let the posterior mean of fund j's talent in period t be denoted as

$$\hat{\phi}^j_t \equiv \mathrm{E}_t[\phi^j] = \mathrm{E}[\phi^j | \xi^j_1, ..., \xi^j_t],$$

and let τ^j_t denote the number of payoff realizations (or the number of belief updates) of fund j by period t. That is, there is τ^j_t informative signals in the sequence $\xi^j_1, ..., \xi^j_t$. Because by assumption, investors only learn from strategies' realized payoffs, they have more precise information about fund j for larger values of τ^j_t. In this setting, the number of realized payoffs captures the fund manager's track record in investing.

The following lemma derives the law of motion for the posterior belief on the fund manager's talent. For simplicity, we assume from here on that the idiosyncratic noise ϵ^j_{t+1} is normally distributed with a constant variance $1/\omega^j_t = 1/\omega$ for both investment opportunities.[18]

[18]This assumption helps us focus on the effect of investment horizons on the speed of learning in our model. Since the dispersion in funds' investment horizons between high- and low- turnover funds is substantially larger than the dispersion in return volatility, investment horizon has a first-order effect on the difference in the speed of learning between high- and low- turnover funds, whereas the effect of idiosyncratic noise appears second-order. The average investment horizon of funds in turnover quintile 5 is about five years, which is about ten times the investment horizon of funds in quintile 1. Whereas, the standard deviation of monthly returns for funds in turnover quintile 5 is 4.9%, which is close to the 5.7% for funds in qunitile 1. Moreover, if it is the noise at the time of realization that affects investors' learning, the variance term $1/\omega^j_t$ should not be very different for short- and long- term opportunities. For example, the realization of a short-term strategy

Lemma 1. *The posterior belief* $\hat{\phi}_t^j$ *about fund* j*'s talent parameter* ϕ^j *is given as a function of the prior belief* $\hat{\phi}_{t-1}^j$*, the number of payoff realizations* τ_t^j*, and the sufficient statistic for performance in the previous period* ξ_t^j *as follows:*

$$\hat{\phi}_t^j = \hat{\phi}_{t-1}^j + e_{t,i}^j \left(\frac{\omega}{\gamma + \tau_t^j \omega} \right) (\xi_t^j - \hat{\phi}_{t-1}^j). \tag{5}$$

Proof. Given the realization of $e_{t,i}^j$, Bayes' rule implies

$$\hat{\phi}_t^j = (1 - e_{t,i}^j)\hat{\phi}_{t-1}^j + e_{t,i}^j \left[\frac{\gamma + (\tau_t^j - 1)\omega}{\gamma + \tau_t^j \omega} \hat{\phi}_{t-1}^j + \frac{\omega}{\gamma + \tau_t^j \omega} \xi_t^j \right]$$

□

3.3 Fund Manager's Optimization Problem

In period t, each fund j can choose its investment type $i \in \{S, L\}$ and its fee f_t^j,[19] to maximize the present value of its expected utility of receiving the stream of fees such that

$$\mathrm{E}_t \left[\sum_{s=t}^{T^j} u \left(q_{s,i}^j f_s^j \right) \right], \tag{6}$$

where T^j is the last period in which the fund operates before exiting, and $u(\cdot)$ is a twice-differentiable, bounded utility function with $u' > 0, u'' < 0$ and $u(0) = 0$.[20] [21]

betting on a firm's earnings becomes public instantly after an earnings announcement, and the realization of a long-term strategy betting on a long-term R&D project becomes public instantly after an announcement of its success or failure. Only the return noises around the time of these announcements affect the learning, and the return noises in other time periods have no such effect.

[19]If fund managers are allowed to invest a portion of their fund in the passive benchmark (i.e., "closet indexing") as in Berk and Green (2004), fund managers can choose any fee lower than or equal to the optimal fee f_t^j* in the current problem. In this case, the problem of each fund j becomes choosing the optimal amount $q_{s,i}^j$ to invest actively into opportunity $i \in \{S, L\}$ instead, and invest the rest of capital in the passive benchmark. The maximum value added of each manager and the fee revenue that she could earn stays the same as in our current setting. While the percentage fee and fund size are no longer individually uniquely determined when indexing is allowed, their product is.

[20]The assumption that the utility function is bounded and concave does not affect our results qualitatively. Because a fund manager's perceived talent, which follows a normal distribution, is unbounded, their performance is also possibly unbounded. This causes technical difficulty in our analysis because the value function becomes potentially unbounded. By bounding rewards to finite values, we can ensure that the value function is bounded. Under the boundedness of the utility function, from which the concavity follows, we can obtain existence of the value function using the standard Banach fixed point theorem (see the proof of Theorem 3 in Appendix A). Furthermore, the concavity does not affect the choice of size (See Eq. (13) and footnote 22).

[21]As reported in Ibert, Kaniel, van Nieuwerburgh and Vestman (2018), a fund manager's compensation on average increases with the fee revenue of a fund. Our general form of utility function guarantees that our

Following the rational expectations assumption in the literature, as in the seminal paper by Berk and Green (2004), we similarly assume that there is a continuum of investors who can invest either in funds by paying fees or in the passive benchmark without any cost. We assume that investors are unconstrained (or equivalently, their supply of capital is infinitely elastic for any investment opportunity with positive excess returns). Therefore, investors' capital will flow to and from funds until each fund j has a zero net expected excess return over the passive benchmark after fees (net alpha):

$$\mathrm{E}_t[r^j_{t+1}] = 0, \tag{7}$$

where r^j_{t+1} is the excess return of fund j's investment in time t. Substituting Eq. (3) into Eq. (7) yields

$$d_i \hat{\phi}^j_t g_i(\mu_{t,i}) = c_i(q^j_{t,i}) = \frac{C(q^j_{t,i})}{q^j_{t,i}} + f^j_t. \tag{8}$$

That is, the fund flow equates the average excess return with the average cost in equilibrium. Therefore, Eq. (8) implies the revenue of the fund is given by

$$q^j_{t,i} f^j_t = d_i \hat{\phi}^j_t g_i(\mu_{t,i}) q^j_{t,i} - C(q^j_{t,i}). \tag{9}$$

We focus our analysis on the stationary equilibrium. The fund manager's optimal choice can fully be characterized by two state variables: the perceived talent $\hat{\phi}$ and the number of payoff realizations τ. Since, in the stationary equilibrium, every endogenous variable is time-invariant (by definition), we will drop the time subscript t. We will also drop fund index j for notational convenience. Then, we can represent the maximization problem in Eq. (6) in a recursive form; the value of continuing the operation of an individual fund given the state variables $\hat{\phi}, \tau$ can be written as

$$V(\hat{\phi}, \tau) \equiv \max \left\{ V_S(\hat{\phi}, \tau), V_L(\hat{\phi}, \tau) \right\}, \tag{10}$$

findings also hold for the specific case where a fund manager maximize its life-time compensation, which is an increasing function of the fund's total fee revenue.

where $V_i(\hat{\phi}, \tau)$ is the value of choosing a type i investment opportunity such that

$$
\begin{aligned}
V_i(\hat{\phi}, \tau) \equiv \sup_{q_i \in [0,\infty)} & u\left(d_i \hat{\phi} g_i(\mu_i) q_i - C(q_i) - F\right) \\
& + \kappa \left((1 - d_i) \max\left\{ V(\hat{\phi}, \tau), u_0 \right\} + d_i \operatorname{E}\left[\max\left\{ V(\hat{\phi}', \tau + 1), u_0 \right\} \middle| \hat{\phi}, \tau \right] \right),
\end{aligned}
\tag{11}
$$

and $\hat{\phi}'$ denotes the posterior of the perceived talent after the next payoff realization:

$$
\hat{\phi}' = \hat{\phi} + \left(\frac{\omega}{\gamma + (\tau + 1)\omega} \right) (\xi - \hat{\phi}). \tag{12}
$$

The fund manager chooses to exit when the fund's continuation value of operation becomes less than or equal to a reservation utility u_0 for the first time as shown in Eq. (10). The reservation utility u_0 is the utility that a fund managers can get from their outside option. In other words, it is their opportunity cost of running a fund. If the fund manager decides to continue, it chooses either the long-term or the short-term opportunity, and decides the investment size by setting the fee f. The possibility of exit has option value, which is reflected in the continuation value in Eq. (11). This optionality is the key to fund manager behavior as is shown in the next section.

4 Equilibrium

4.1 Equilibrium Fund Flow

In this subsection, we analyze equilibrium fund flow. Given the choice of investment type $i \in \{S, L\}$, the first order condition in Eq. (11) implies that the optimal fund size q_i^* should solve

$$
d_i \hat{\phi} g_i(\mu_i) = C_i'(q_i^*). \tag{13}
$$

[22] That is, the fund sets its size so that the expected excess return on the marginal dollar equal to the marginal cost of expansion.

[22]Note that the total revenue in Eq. (9) is a deterministic function of the chosen fee by the fund, so the monotonic transformation $u(\cdot)$ of a deterministic function does not alter the optimization problem in any other way. This is why the concavity of the utility function does not affect the fund's choice of size. But the concavity and the boundedness of $u(\cdot)$ help achieve existence of the value function by preventing it from exploding with high values of $\hat{\phi}$.

We denote by $q_i^*(\hat{\phi})$ the solution of Eq. (13) given the values of $\hat{\phi}$. Then, it is immediate that $q_i^*(\hat{\phi})$ increases in the perceived talent $\hat{\phi}$ because $C' > 0$. Furthermore, $q_i^*(0) = 0$ because the marginal benefit is less than the marginal cost, i.e., $0 = d_i \hat{\phi} g_i(\mu_i) \leq C_i'(q_i)$ with $\hat{\phi} = 0$ (the fund size becomes zero when $\hat{\phi} = 0$).[23]

Because the size of a fund increases in the perceived skill of its fund manager (Eq. (13)) and a manager is perceived to be more skilled with better performance (Lemma 1), it is immediate that fund flow increases in its excess return between the current and the previous periods.

Lemma 2. *Given investment type i, the fund flow sensitivity to excess return for a fund with size q_i^* and experience τ is given by*

$$\frac{\partial q_i^*}{\partial r_i} = \left(\frac{d_i}{C''(q_i^*)}\right)\left(\frac{\omega}{\gamma + \tau\omega}\right) > 0. \tag{14}$$

Proof. See Appendix. □

Eq. (14) implies that fund flow sensitivity to net performance is increasing in the payoff frequency d_i. All else equal, fund flow for a given amount of net performance should be more sensitive for short-term investments than for long-term ones. This simply reflects the fact that trading profits are more likely to realize for short-term investments. In addition, Eq. (14) implies that the fund flow sensitivity should be higher for newer managers (i.e., τ low) because there is a larger degree of belief updating given new information regarding skill. *Most importantly*, Eq. (14) further implies that the flow-performance sensitivity of high-turnover funds decreases faster with an increase of τ than that of low-turnover funds. That is, the learning of fund skill is faster for high-turnover funds than for low-turnover ones.

4.2 Optimal Choice

Using the optimal size derived under a given investment opportunity, we can represent the indirect value of choosing each type $i \in \{S, L\}$ of investment opportunity in Eq. (11) as

[23] We show later that new fund managers with negative perceived skill still have a positive value from the real growth option, since they have a chance of proving themselves to be skilled ($\hat{\phi} > 0$) in the future.

follows:

$$V_i(\hat{\phi},\tau) = \Pi_i(\hat{\phi}) + \kappa(1-d_i)V(\hat{\phi},\tau) + \kappa d_i \operatorname{E}\left[\max\left\{V(\hat{\phi}',\tau+1), u_0\right\} \middle| \hat{\phi},\tau\right], \tag{15}$$

where $\Pi_i(\hat{\phi})$ is the expected utility of the fund's payoff in the current period:

$$\Pi_i(\hat{\phi}) \equiv u\left(d_i\hat{\phi}g_i(\mu_i)q_i^* - C(q_i^*)\right), \tag{16}$$

and q_i^* is the implicit solution for Eq. (13).

Given the results presented above, we can establish existence and uniqueness of the value function, and also characterize it.

Theorem 3. *There exists a unique value function V that solves Eqs. (10)-(12). Furthermore, V strictly increases in $\hat{\phi}$ for each $\tau \in \mathbb{N}$, and strictly decreases in τ for each $\hat{\phi} \in \mathbb{R}$ (i.e., $V(\hat{\phi},\tau) > V(\hat{\phi},\tau+1)$ for each $\hat{\phi}$ and τ).*

Proof. See Appendix A. □

We can use the properties of the value function found in Theorem 3 to characterize the fund manager's optimal choice regarding exit and whether to invest long-term or short-term. In the following two theorems, we show that the fund manager uses threshold strategies for both choices.

4.2.1 Optimal Exit Choice

The fund manager chooses to exit whenever the maximum value of continuing investment is less than the reservation utility for the outside option, i.e., $V(\hat{\phi},\tau) < u_0$. Then, Theorem 3 implies that, given τ, the fund manager chooses to exit if and only if the perception of talent is sufficiently low, i.e., $\hat{\phi}$ is less than a threshold $\hat{\phi}_E(\tau)$ which is the solution to

$$V(\hat{\phi}_E(\tau),\tau) = u_0. \tag{17}$$

Furthermore, it is immediate that $\hat{\phi}_E(\tau)$ strictly increases in τ (because V is continuous), strictly decreases in $\hat{\phi}$, and strictly decreases in τ (Theorem 3). That is, the exit threshold of perceived talent increases as the posterior variance regarding skill decreases. We summarize the results by the following theorem.

Theorem 4. *(Exit choice) A fund manager with perceived talent $\hat{\phi}$ and the number of belief updates τ exits if and only if $\hat{\phi} < \hat{\phi}_E(\tau)$. Furthermore, the exit threshold $\hat{\phi}_E(\tau)$ increases in τ.*

The fund manager's incentive to continue operation with a low perception of talent becomes weaker if the perception is more precise. Intuitively, the value of the growth option decreases as the variance of the underlying goes down. That is, a new fund perceived as unskilled may continue operation even with continued underperformance, hoping for better performance that will upgrade their talent perception. But, an old, unskilled fund is likely to exit with continued underperformance.

4.2.2 Optimal Investment Choice

Similarly, the value of the growth option also drives the fund manager's choice of investment opportunities. Conditioning on continuing the operation (i.e., $\hat{\phi} \geq \hat{\phi}_E(\tau)$), the fund manager strictly prefers short-term investment if and only if $V_S(\hat{\phi}, \tau) > V_L(\hat{\phi}, \tau)$, or equivalently:

$$(d_S - d_L)\kappa \left\{ \mathrm{E}\left[\max\left\{ V(\hat{\phi}', \tau + 1), u_0 \right\} \middle| \hat{\phi}, \tau \right] - V(\hat{\phi}, \tau) \right\} > \Pi_L(\hat{\phi}) - \Pi_S(\hat{\phi}). \tag{18}$$

The left hand side (LHS) of Eq. (18) represents the incremental continuation value (growth potential) provided by the higher speed of skill revelation of short-term relative to long-term investment opportunities, whereas the right hand side (RHS) represents the difference in compensation in the current period. The benefit of revealing talent arises from the protection against downward risk due to the optionality of manager exit. The fund manager enjoys higher expected payoff in the future in case of good performance, but can minimize the impact of bad performance by simply exiting from the industry. By choosing the short-term investment, a fund can exploit the option value of exiting, though the value of the real growth option decreases as the precision regarding the manager's talent increases.

Using Eq. (18), we can show that the fund manager strictly prefers the short-term investment whenever their perceived talent is low enough at the given level of belief precision.

That is, given the precision of talent perception, the fund manager chooses the short-term investment if the perception of talent is sufficiently low, i.e., $\hat{\phi}$ is less than a threshold $\hat{\phi}_S(\tau)$ which is the lowest value (in case of multiple solutions) of $\hat{\phi}_S(\tau)$ that solves

$$V_S(\hat{\phi}_S(\tau), \tau) = V_L(\hat{\phi}_S(\tau), \tau). \tag{19}$$

It is difficult to characterize general properties of the threshold due to the nature of the problem that does not allow a closed-form solution. But, we can still characterize them in a limiting case where short-term investment only offers growth potentials without profit (i.e., $g_S(\mu_S)$ is sufficiently small), and long-term investment only offers profits without growth potentials (i.e., d_L is sufficiently small with $d_L g_L(\mu_L)$ being fixed to a positive constant). Our findings in this special case are consistent with the results from numerical analyses of the general model in Section 5.

Theorem 5. *(Investment choice) Under the condition that d_L and $g_S(\mu_S)$ are sufficiently small with $d_L g_L(\mu_L)$ being fixed to a positive constant, there exists $\hat{\phi}_S(\tau)$ such that a fund manager with perceived talent $\hat{\phi}$ and the number of belief updates τ chooses the short-term investment if $\hat{\phi}_E(\tau) \leq \hat{\phi} < \hat{\phi}_S(\tau)$, and the threshold $\hat{\phi}_S(\tau)$ strictly decreases in τ.*

Proof. See Appendix A. □

The intuition of this theorem is as follows. Fund managers choose to invest short-term to exploit the value of the real growth option if their talent is perceived to be low. When fund managers are perceived to be skilled, however, they invest long-term to exploit high profits. Furthermore, fund managers tend to invest short-term if they are newer (lower values of τ). Newer fund managers whose talent is less known can exploit the value of the real growth option better than old managers whose talent is already better known. That is, the transition threshold to long-term investment becomes lower as a fund manager becomes more experienced.

4.2.3 Real Growth Option

In this section, we define the value of the real growth option provided by short-term investment strategies. It is worth noting that the exit option in Section 4.2.1 is similar to a put option with a strike price $K = u_0$ that expires in the next period. If the probability of having a belief update is 100% (i.e, $d_i = 1$), the value function Eq. (15) has a payoff similar to the value of a put option plus the value of the underlying asset $V(\hat{\phi}, \tau)$. Representing this in the standard put-call parity framing, we obtain:

$$Put + V = \kappa K + Call + Div, \tag{20}$$

where Div is the dividends paid by the asset before the execution of the option. In Eq. (15), the Div term corresponds to the manager's current payoff $\Pi_i(\hat{\phi})$. The other term left in Eq. (15), $\kappa\, \mathrm{E}\left[\max\left\{V(\hat{\phi}', \tau+1), u_0\right\} \middle| \hat{\phi}, \tau\right]$, corresponds to the present value of the strike price plus the value of a call option (i.e., $\kappa K + Call$). If the strike price gets close to zero (i.e., $K = u0 \to 0$), the value of $\kappa\, \mathrm{E}\left[\max\left\{V(\hat{\phi}', \tau+1), u_0\right\} \middle| \hat{\phi}, \tau\right]$ is similar to the value of a call option.[24]

If the probability of having a belief update is zero (i.e, $d_i = 0$), the value function Eq. (15) becomes the value of a perpetuity:

$$V = \kappa V + Div. \tag{21}$$

Therefore, the option value of short-term strategies, which have a higher probability of a belief update $d_S > d_L$, comes from the call option value from the term $\kappa\, \mathrm{E}\left[\max\left\{V(\hat{\phi}', \tau+1), u_0\right\} \middle| \hat{\phi}, \tau\right]$ in Eq. (15) relative to the value of continuing with the same value $V(\hat{\phi}, \tau)$ as before. To capture this option value, we define *the value of the real growth option* provided by the short-term strategies as the LHS of Eq. (18):

$$Option\,Value = (d_S - d_L)\kappa \left\{ \mathrm{E}\left[\max\left\{V(\hat{\phi}', \tau+1), u_0\right\} \middle| \hat{\phi}, \tau\right] - V(\hat{\phi}, \tau) \right\}, \tag{22}$$

which captures the value of higher learning speed provided by short-term investing. As we

[24]Different from a typical American call option, which cannot be canceled once executed, our real growth option allows exiting at any time.

have shown in Eq. (18), a fund manager would choose short-term investing if and only if the value of the real growth option (i.e., the LHS of Eq. (18)) is larger than the RHS, which represents the difference in compensation between long- and short- term investing in the current period.

4.2.4 Equilibrium Value Added under Career Concern

The choice between short-term and long-term investment in Eq. (18) has important implications for equilibrium value added. Because the short-term investment offers higher growth potential, long-term investment opportunities should compensate with higher profits than those of short-term investment, offering higher value added for a given posterior mean of the fund manager's talent. Otherwise, no manager will choose to invest long-term. Therefore, in equilibrium, the long-term investment will generate higher value added (which equals fee revenues) than the short-term investment when managers are risk-neutral as in Berk and Green (2004):

Theorem 6. *In equilibrium, the value added of long-term investment is strictly greater than that of short-term investment fixing the perceived talent level, i.e.,* $\Pi_L(\hat{\phi}) > \Pi_S(\hat{\phi})$ *for all* $\hat{\phi} \in (0, \infty)$.

Proof. See Appendix A. □

Theorem 6 shows that endogenous returns with capacity constraints driven by strategic substitutability play a key role in achieving equilibrium. The short-term investment will attract fund managers until its value added has eroded to below that of the long-term investment where the difference captures the option value attached to it. This option value is therefore a contributor to investors' myopia induced by misaligned incentives between delegated investors and ultimate owners of assets.[25] Even though investors want to exploit higher value added in long-term investment opportunities, there is limited access to long-term investment relative to short-term investment due to fund managers' career concerns.

[25] See, for example, Dow, Han, and Sangiorgi [2021a] and Dow, Han, and Sangiorgi [2021b] for further discussion on other possible sources of investor short-termism. Active investors (or informed investors) may prefer short-term investment because they can redeploy their capital faster to new opportunities (Dow, Han, and Sangiorgi [2021a]) or they have exposure to potential liquidity shocks (Dow, Han, and Sangiorgi [2021b]).

Theorem 5 implies that, at the given precision of talent perception, fund managers investing long-term should be perceived to be more talented than those investing short-term under the given assumptions of the theorem. This in turn implies that, at the given level of precision of talent perception, those investing long-term should create greater value added than those investing short-term due to Theorem 6. Therefore, the following corollary is immediate from the two previous theorems.

Corollary 7. *Under the assumptions of Theorem 6, the value added of a fund investing long-term is strictly greater than that of a fund investing short-term holding the number of belief updates τ constant.*

4.3 Markov Transition Function and Stationary Distribution

In the previous sections, we show that the optimal decision of a fund manager is completely specified by the state variables $\hat{\phi}$ and τ: the perceived talent and the number of belief updates. In this subsection, we construct the transition function of these two state variables. For ease of exposition, we introduce the following new notation. We denote by $I(\hat{\phi}, \tau)$ an indicator function which equals one if a fund with $(\hat{\phi}, \tau)$ continues its operation and zero otherwise. We denote by $d(\hat{\phi}, \tau)$ the probability of payoff realizations per period given the optimal choice under $(\hat{\phi}, \tau)$, i.e., $d(\hat{\phi}, \tau) = d_S$ if the short-term strategy is chosen and $d(\hat{\phi}, \tau) = d_L$ otherwise. Finally, we denote by $\tau = X$ the state of exit.

The state process of each individual fund manager follows a Markov process. Using the results in Section 4.2, we can represent the transition probabilities between different states as follows:

Lemma 8. *The Markov transition function Z from current state $(\hat{\phi}, \tau)$ to future state $(\hat{\phi}', \tau')$ is given by*

$$Z\left(\hat{\phi}', \tau' \middle| \hat{\phi}, \tau\right) = \begin{cases} \kappa I(\hat{\phi}, \tau) d(\hat{\phi}, \tau) n\left((\gamma + \tau\omega)\left(\hat{\phi}' - \hat{\phi}\right)\right) & \text{if } \tau' = \tau + 1; \\ \kappa I(\hat{\phi}, \tau)(1 - d(\hat{\phi}, \tau)) & \text{if } \tau' = \tau; \\ 1 - \kappa I(\hat{\phi}, \tau) & \text{if } \hat{\phi}' = \hat{\phi}, \tau' = X; \\ 0 & \text{otherwise,} \end{cases} \tag{23}$$

where $n(\cdot)$ is the probability density function of the standard normal distribution.

Proof. See Appendix A. $\square$

The first line in Eq. (23) provides the probability of having a transition to $(\hat{\phi}', \tau')$ from $(\hat{\phi}, \tau)$ with return realizations. The second line provides the probability of having no transition at state $(\hat{\phi}, \tau)$. The third line provides the probability of exit at state $(\hat{\phi}, \tau)$. The fourth line is the probability of having a transition to any other state than the three categories specified above, and is zero when those are unreachable states from $(\hat{\phi}, \tau)$ (for example, $\tau - 1$ cannot be reached from τ).

We denote by $\nu(\hat{\phi}, \tau)$ the joint density of the state $(\hat{\phi}, \tau)$ in the current period. Because the perceived talent is continuous and the realization of payoffs is discrete, $\nu(\cdot, \cdot)$ is a mixed joint density function. Given $\nu(\hat{\phi}, \tau)$ in the current period, we can represent $\nu(\hat{\phi}', \tau')$ in the subsequent period using the transition function in Lemma 8:

$$T\nu(\hat{\phi}', \tau') = \begin{cases} \sum_{\tau=0}^{\infty} \int_{\hat{\phi}_E(\tau)}^{\infty} Z\left(\hat{\phi}', \tau' \middle| \hat{\phi}, \tau\right) d\nu(\hat{\phi}, \tau) & \text{for } \tau' \geq 1 \text{ and } \tau' \neq X; \\ \begin{pmatrix} \kappa(1 - d(\hat{\phi}, \tau))\nu(\phi_0, 0) \\ +1 - \kappa \sum_{\tau=0}^{\infty} \int_{\hat{\phi}_E(\tau)}^{\infty} I(\hat{\phi}, \tau) d\nu(\hat{\phi}, \tau) \end{pmatrix} & \text{for } (\hat{\phi}, \tau') = (\phi_0, 0); \\ 0 & \text{otherwise.} \end{cases} \tag{24}$$

In Eq. (24), the density of any state $\hat{\phi}', \tau'$ in the subsequent future can be generally calculated by counting all flows to that state. In the second line, we treat one exception of the first line, which is the initial entry point $\hat{\phi} = \phi_0, \tau = 0$. The first component in the second line captures the remaining mass of managers after the transition, and the second component captures the mass of new managers who enter the economy to replace exiting managers.

By definition, in a stationary equilibrium, the distribution of types is time-invariant. That is, the density of state variables in the subsequent period should be equal to that in the current period:

$$\nu(\hat{\phi}', \tau') = T[\nu(\hat{\phi}', \tau')]. \tag{25}$$

Next, we prove that a unique stationary distribution of the state variables exists. That is, for any given initial distribution, the equilibrium will converge to the stationary distribution of the state variables.

Theorem 9. *There exists a unique stationary distribution ν that solves Eq. (25).*

Proof. See Appendix A. □

4.4 Stationary Equilibrium

The steady state equilibrium is pinned down by the fractions of fund managers investing in each investment opportunity (μ_S, μ_L). Because it is sufficient to use one of the two $(\mu_S + \mu_L = 1)$, we use $\mu \equiv \mu_S$, which is the fraction of managers investing in the short-term opportunity, as the state variable. Let us define $q_i(\hat{\phi}, \tau; \mu)$ as the optimal size of investment in investment opportunity i given fund manager type $\hat{\phi}, \tau$ and state variable μ_S. Likewise, let $I(\hat{\phi}, \tau; \mu)$ be the exit choice that equals one if a fund optimal chooses to stay and zero otherwise given $\hat{\phi}, \tau$ and μ. In a stationary equilibrium, the equilibrium mapping is given by the fraction of fund managers investing in opportunity S given μ:

$$H(\mu) \equiv \frac{\sum_{\tau=0}^{\infty} \int_{\hat{\phi}_E(\tau)}^{\infty} q_S(\phi, \tau; \mu) d\nu(\hat{\phi}, \tau)}{\sum_{\tau=0}^{\infty} \int_{\hat{\phi}_E(\tau)}^{\infty} \left[q_S(\phi, \tau; \mu) + q_L(\phi, \tau; \mu)\right] d\nu(\hat{\phi}, \tau)}, \tag{26}$$

where $\mathcal{J}$ denotes the set of all fund managers. The fixed point of the mapping in Eq. (26) solves the following equation:

$$H(\mu) = \mu. \tag{27}$$

We denote by $\sigma(\hat{\phi}, \tau)$ the optimal investment decision of a fund with $\hat{\phi}, \tau$ such that $\sigma \in \{X, S, L\}$ where X, S, L stand for exit, short-term investment, and long-term investment, respectively. Now, we define stationary equilibrium as follows:

Definition 10. *A stationary equilibrium consists of the optimal investment decision $\sigma(\hat{\phi}, \tau)$, optimal size $q_i(\hat{\phi}, \tau)$, value function $V(\hat{\phi}, \tau)$, transition probabilities $Z(\hat{\phi}', \tau' | \hat{\phi}, \tau)$, stationary distribution $\nu(\hat{\phi}, \tau)$, fraction of fund managers investing in short-term opportunity μ such that*

1. *Value function $V(\hat{\phi}, \tau)$ solves the recursive problem in Eqs. (10)-(12);*

2. *Transition probabilities $Z(\hat{\phi}', \tau' | \hat{\phi}, \tau)$ are given by Eq. (24);*

3. *The stationary distribution solves the functional equation in Eq. (25);*

4. *The fraction of fund managers investing in short-term opportunity solves Eq. (27).*

Focusing on the class of equilibria defined in Definition 10, we solve the equilibrium numerically in the next section.

5 Main Findings and Empirical Tests

In this section, we solve and calibrate our theory model and evaluate its main predictions. We then test those predictions empirically.

5.1 Parametric Model

We first numerically solve our stationary equilibrium model using several parametric assumptions. For simplicity, we assume a cost function which is quadratic for each opportunity $i \in \{S, L\}$:

$$C(q_{t,i}) = \frac{a}{2} {q_{t,i}}^2, \tag{28}$$

and a returns to scale function that is linear in $\mu_{t,i}$:

$$g_i(\mu_{t,i}) = b_{0,i} + b_{1,i}\mu_{t,i}. \tag{29}$$

Under these assumptions, we have the optimal investment amount q_i^* and value added Π_i for each opportunity $i \in \{S, L\}$ per period in Eqs. (13) and (16) as

$$q_i^* = \frac{d_i \hat{\phi} g_i}{a} \quad \text{and} \quad \Pi_i = \frac{(d_i \hat{\phi} g_i)^2}{2a}, \tag{30}$$

when the perceived skill $\hat{\phi}$ is positive. When $\hat{\phi}$ is negative, the fund stops operation, and both q_i^* and Π_i become zero.

We assume a linear utility function of fund managers (as in Berk and Green [2004]) in our numerical analysis:[26]

$$u(w) = w. \tag{31}$$

Table 1 shows the parametric values of the model employed in our numerical analysis. Given the parameter values provided in the table, we can numerically solve for the fixed point in Eq. (27).

We define each period t as a quarter in our numerical analysis, and all dollar values are in billions of dollars. Correspondingly, we pick $d_S = 0.4$ and $d_L = 0.05$ such that they translate into the annual turnover of $(0.4 \times 4 =)$ 1.6 for the high turnover strategy and $(0.05 \times 4 =)$ 0.2 for the low turnover strategy. These numbers are approximately the average turnovers of high-turnover funds in turnover quintile 5 and low-turnover funds in turnover quintiles 1 in our empirical analysis. We pick the average skill parameter of new entering funds $\phi_0 = 0.02/4$ and normalize the $b_{0,L} \times d_L = 1$. Under these parameters, the quarterly gross alpha of long-term investing on the first dollar (i.e., before the deteriorating effects of both fund-level and opportunity-level decreasing returns to scale) is 0.5% per quarter (i.e., 2% per year).[27] We pick a higher gross alpha on the first dollar of 8% per year for short-term investing (i.e. $b_{0,S} \times d_S = 4$). We choose this higher number to ensure that we do not have a lower return of short-term investing to start with, thus the lower return in equilibrium is caused by a more fierce competition for short-term investing. We choose the prior precision of talent ϕ as $\gamma = 400 \times 4^2$ corresponding to a 5% standard deviation in annual gross alpha before decreasing returns to scale. Our choice of ϕ_0 and γ are close to the ϕ_0 of 0.065 and γ of 277 per year in Berk and Green (2004). We adjust these two number slightly to match the smaller average gross returns and return volatility in the data. We pick the precision of idiosyncratic noise ϵ as $\omega = 300 \times 4^2$ to make sure the learning of fund skill is largely

[26] Alternatively, we could assume a bounded concave utility function as $u(w) = \left[\bar{u} - \frac{\bar{u}}{1+\frac{1}{\bar{u}}w}\right]$ to guarantee the existence of the value function using the standard Banach fixed point theorem (see the proof of Theorem 3 in Appendix A). Parameter $\bar{u}$ is the upper bound of the utility function, which is set to be an arbitrarily large number in our numerical analysis. Note that the level of utility at the given level of w converges to the risk-neutral one $u(w) = w$ as $\bar{u}$ diverges to infinity, so using this bounded concave utility function does not change our numerical result.

[27] This quarterly gross alpha of 0.5% is derived by taking the expectation of the first term of Eq. (3), and substituting the parameter values $\phi_0 = 0.02/4$, $b_{0,L} \times d_L = 1$, and $b_{1,L} = 0$ into this equation.

completed within 25 years, which is similar to the data in Figure 4.[28] We pick a quarterly survival rate $\kappa = 0.95$ for the random exiting of fund managers, and we set the reservation utility $u_0 = 0.02$, so the annual survival rates of high- and low- turnover funds are close to those observed in the data (Table 6).[29] We follow Pastor, Stambaugh and Taylor (2015) and Zhu (2018) in estimating the decreasing returns to scale (DRS) parameters at the fund level and investment opportunities level jointly. According to our estimates, we get a fund-level DRS parameter $a = .00503$, and parameters $b_{1,S} = -61.92$ and $b_{1,L} = -14.80$ in the DRS functions of short- and long- term investment opportunities, $g_i(\mu_{t,i})$. More details about the estimation of DRS parameters are provided in Section A.2 and Table A1 in the Appendix.

[Insert Table 1 about here]

5.2 Data

For empirical tests, we obtain mutual fund data from the Center for Research in Security Prices (CRSP) survivor-bias-free database and the fund manager tenure data from Morningstar Direct. Following the data cleaning process of Kacperczyk, Sialm, and Zheng (2008), we remove bond, money market, balanced, index, ETFs/ENFs, international, and sector funds. We merge funds with multiple share classes into a single fund. We end up with a sample of 3,390 actively managed US equity mutual funds from 1961 to 2019 that only invest in US domestic equities.

Table 2 reports the summary statistics for our sample of mutual funds. Fund size and value added are adjusted by inflation to January 1, 2020 dollars. Our sample has an average fund size of 1,374 million dollars and an average turnover of 81% per year. The average manager tenure is 5.7 years and the average age of a fund is 12.9 years. Manager

[28]Note that 25 years corresponds to 40 short-term investment realizations. After all, the probability that a short-term investment opportunity realizes in a quarter is 0.4, so 40 realizations on average take $40/0.4 = 100$ quarters, which is $100/4 = 25$ years.

[29]A reservation utility of $u_0 = 0.02$ corresponds to a perpetuity of receiving one million dollars per quarter under the survival rate $\kappa = 0.95$ (0.001/(1-0.95)=0.02 in billion dollars). We show later in Panel B1 of Appendix Figure A2 that the value of the real growth option of new managers almost stays the same when $u_0 = 0$. Therefore, we are conservative in our estimate of the value of the real growth option by choosing $u_0 = 0.02$. Panel B1 of Appendix Figure A2 further shows that increasing u_0 to 0.18 does not have a substantial effect on this option value either.

tenure is the number of years a manager has worked in a given fund. If a fund is team managed, we use the average manager tenure of all its managers for our analyses. The results are similar when using the highest or lowest manager tenure of a fund's managers for our analyses. The value added of a fund under both the CAPM model and the Vanguard benchmarks are positive, which are consistent with the numbers in Berk and van Binsbergen (2015). Since the asset pricing literature is still debating on whether pricing factors such as value and momentum are risk factors or anomalies, we use the CAPM model and the four Vanguard US index funds including S&P 500 Index (VFINX), Extended Market Index (VEXMX), Small-Cap Index (NAESX), and Mid-Cap Index (VIMSX) in our benchmark analyses. Our main findings still hold after including value and momentum factors or the factors corresponding to the Vanguard index funds.

[Insert Table 2 about here]

5.3 New Mechanism: Investor Learning of High-/Low- Turnover Funds

We first use the flow-performance sensitivity as an empirical measure of learning, as in Berk and Green (2004), to show that investing in short-term opportunities speeds up investors' learning of funds' skill. In particular, we test the prediction in Lemma 2 that the flow-performance sensitivity of high-turnover funds decreases faster with an increase of manager tenure than that of low-turnover funds.

Following Pool, Sialm, and Stefanescu (2016) and Berk and van Binsbergen (2016), we estimate the fund flows of mutual fund j in quarter t as

$$Flow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1} * (1 + R_{j,t})}{TNA_{j,t-1} * (1 + R_{j,t})} \tag{32}$$

where $TNA_{j,t}$ is the CRSP TNA value for fund j at the end of quarter t, and $R_{j,t}$ is the quarterly return of fund j during quarter t. When all the money of a fund is withdrawn by its investor ($TNA_{j,t} = 0$), this measure of fund flow is -100%. Following Huang, Wei, and Yan (2007), we winsorize the fund flows at the 2.5 percent level at both tails to avoid errors associated with mutual fund mergers and splits in the CRSP mutual fund database.

We then estimate the flow-performance sensitivity (FPS) coefficient β_f by running the following regression.

$$Flow_{j,t} = \beta_f * Ret\ Rank_{j,t-1} + \beta_c * ln(TNA)_{j,t-1} + \upsilon_t + \varepsilon_{j,t}, \tag{33}$$

where *Ret Rank* is the return rank from 0 (the lowest) to 1 (the highest) based on past quarter benchmark-adjusted returns.[30] We use CAPM as the benchmark in Panel A of Figure 1 and four Vanguard index funds in Panel B. Variable $ln(TNA)$ is the ln value of the fund's total net assets at the end of the last quarter, as a control variable. Similar to Barber, Huang, and Odean (2016), we run this regression nine times for funds with a manager tenure shorter than two to ten years separately, and for fund turnover quintiles 1 and 5 separately.[31] We exclude funds with less than one year of manager tenure from this analysis because of the large noise in their quarterly estimates of the flow-performance sensitivity. An FPS coefficient β of 0.10 indicates that the quarterly fund flow is 10% of fund TNA higher for the fund with the highest last-quarter return ($Ret\ Rank = 1$) compared to the fund with the lowest ($Ret\ Rank = 0$).

As shown in Panel A of Figure 1, the flow-performance sensitivity of high-turnover funds (Q5) decreases from 0.108 for funds with a manager tenure of two years to about 0.082 for funds with a manager tenure of less than ten years on average. This decrease is substantially larger than the decrease of low-turnover funds (Q1) from 0.094 to 0.079, supporting our model prediction that high-turnover strategies speed up investors' learning about fund skill. Further, the flow-performance sensitivity of high-turnover funds is on average higher than that of low-turnover funds, especially for new fund managers, as predicted in Lemma 2. The results are similar in Panel B, where we use Vanguard index funds as the benchmark.

[Insert Figure 1 about here]

Next, we formally test the predictions of Lemma 2 using the following regression analysis. We regress quarterly fund flows on funds' return ranks in the past quarter, year, and

[30] Since fund flows are more sensitive to return ranks than returns (as documented in Di Maggio, Franzoni, Kogan, and Xing [2023] and Fricke, Jank, and Wilke [2023]), we use return ranks for the analysis of flow-performance sensitivity to reduce the noises.

[31] Because the number of funds in the sample decreases with an increase of manager tenure, the estimates of the FPS coefficients are noisier for funds with larger manager tenure. Therefore, we estimate the FPS coefficient of funds with a manager tenure shorter than two, three, ... ten, years respectively in Figure 1. A formal regression analysis using the manager tenure of each fund (as in Eq (34)) is reported in Table 3.

three years, as well as their interactions with fund turnover and manager tenure:

$$
\begin{aligned}
Flow_{j,t} =& \beta_1 * Ret\ Rank_{j,t-1} \times Tenure_{j,t-1} \times Turnover_{j,t-1} \\
&+ \beta_2 * Ret\ Rank_{j,t-1} \times Turnover_{j,t-1} + \gamma_1 * Turnover_{j,t-1} \\
&+ \beta_3 * Ret\ Rank_{j,t-1} \times Tenure_{j,t-1} + \gamma_2 * Tenure_{j,t-1} \\
&+ \beta_4 * Ret\ Rank \times ln(TNA)_{j,t-1} + \gamma_3 * ln(TNA)_{j,t-1} \\
&+ \eta * Ret\ Rank_{j,t-1} + \upsilon_t + \varepsilon_{j,t}.
\end{aligned} \tag{34}
$$

Each quarter we rank all funds based on their past quarter (year or 3-year) returns and assign them a continuous rank ranging from zero (worst) to one (best). *Ret Rank* is the return rank, and $Tenure$ is the number of years a manager has worked in a given fund. All independent variables (except *Ret Rank*) are standardized to a mean of zero and a standard deviation of one. We use CAPM as the benchmark in Panel A and four Vanguard index funds in Panel B. The coefficient β_1 should be significantly negative if high-turnover strategies speed up investors' learning of fund skill as our model predicts.

Indeed, Table 3 shows that coefficient β_1 is significantly negative in all three settings in both Panel A and Panel B, and this effect is stronger for the flow-performance sensitivities to last quarter's return and last year's return than to the last three-year return. The coefficient of *Ret Rank* in column (1) of Panel A reports a quarterly flow-performance sensitivity of 7.4%, that is, the quarterly fund flow is 7.4% of fund TNA higher for the fund with the highest last-quarter return ($Ret\ Rank = 1$) compared to the fund with the lowest ($Ret\ Rank = 0$), and this flow-performance sensitivity is 11.2% and 10.1% for last-year's return and the last-3-year's return ranks respectively as in column (2) and (3). The coefficient of $Ret\ Rank \times Tenure \times Turnover$ in column (1) reports that the decrease of flow-performance sensitivity with a one-standard-deviation increase in manager tenure (5.1 years as reported in Table 2) is -0.75% larger for a fund with an annual turnover that is one-standard-deviation (82% per year) higher. Therefore turnover has a substantial effect on the speed by which the flow-performance sensitivity decreases in manager tenure (i.e., the speed of investors' learning of fund skill). Moreover, the coefficient of $Ret\,Rank \times Turnover$ in column (1) reports that this flow-performance sensitivity is 0.72% higher for a fund with an annual turnover that is one-standard-deviation higher. Consistent with our model prediction (as in Berk and Green [2004]), we find that manager tenure, which is positively correlated with fund age, has a negative effect on the flow-performance sensitivity. We control for quarterly fixed effects and cluster the standard errors per quarter since fund flows are positively correlated in the same quarter and we are interested in the sensitivity of fund flows to the relative performance ranks of funds. The results are similar without controlling for quarterly fixed effects, and the results are similar in Panel B, where we use Vanguard index funds as the benchmark.

[Insert Table 3 about here]

5.4 The Value of The Real Growth Option

In this section, we investigate the value of the real growth option (defined in Eq. (22)) as a function of the two state variables: perceived skill $\hat{\phi}$ and the number of realizations τ. Panel A of Figure 2 plots the value of the real growth option (the LHS of Eq. (18)) in colored solid lines against the difference in current-period payoffs between long- and short -term investing (the RHS of Eq. (18)) in gray dashed line as a function of perceived skill $\hat{\phi}$. Fund managers choose the short-term investment option if and only if the value of the real growth option is higher than the difference in current-period payoffs (gray dashed line). As shown in Panel A of Figure 2, the value of the real growth option is large and above the gray dashed line for most new fund managers (i.e., with $\tau = 0$).[32] As a result, they would prefer short-term to long-term investing.

To have a closer look at the value of the real growth option for a new fund manager and an average fund manager in the industry, we add two vertical dotted lines for the levels of perceived skill of these two types of managers (with $\hat{\phi} = 0.005$ and 0.0175 correspondingly) in Panel A. We zoom in on this region for new and average manager in Panel B1 of Figure 2. For a new manager (the intersection of blue solid and dotted lines with $\hat{\phi}$=0.005 and $\tau = 0$), the present value of this real growth option is about \$4.9 million, whereas the additional value added from investing in long- versus short- term strategies is only (0.57 - 0.09 =)

[32] More than 99% of fund managers have a perceived skill $\hat{\phi} < 0.045$ in our sample.

\$0.48 million. For an average fund manager in our sample (the intersection of the orange solid and dotted lines with $\hat{\phi}$=0.0175 and $\tau = 12$), the value of this option is about \$3.5 million. An average manager would choose long-term strategies, since this option value is smaller than the additional value added from investing in long- versus short- term strategies of (7.0 - 1.1 =) \$5.9 million.[33] This additional value added is larger for an average manager than for a new manager because of a higher perceived skill. For completeness, we also plot in Panel B2 of Figure 2 the option values of new and average managers as a function of the number of realizations τ separately. The option values of new and average managers (intersection points with vertical dotted lines) in Panel B2 coincide with Panel B1.

Similar to a call option, whose value increases with the uncertainty in the future stock price, the value of the real growth option increases with the uncertainty about a fund manager's skill, which relates to the fund manager's future payoffs (continuation value). The higher this uncertainty is, the larger the value of the real growth option becomes. Since the uncertainty regarding a manager's skill decreases as the number of realizations τ increases (as in Eqs. (5) and (12)), the value of the real growth option decreases as τ increases, as shown in Panel A and Panel B2 of Figure 2.

Panel A of Figure 2 shows that the value of the real growth option first increases with perceived skill $\hat{\phi}$ until it matches the difference in payoffs between long- and short- term strategies ($\Pi_L - \Pi_S$), and it decreases thereafter. Intuitively, the growth option is less useful to fund managers who are either close to unskilled, or skilled enough to shift to long-term strategies for a larger payoff. Our model illustrates this intuition as follows. Since a fund manager's payoff (value added) increases more than linearly with the perceived skill $\hat{\phi}$ (as in Eq. (16)),[34] a higher current perceived skill leads to a larger variation in the fund manager's future payoffs (continuation value). The decrease in payoff in case of bad performance is muted by the option to exit. As a result, the value of the real growth option first increases

[33] An average fund manager of all surviving funds in our data sample has a fund size of \$1.4 billion ($\hat{\phi}$=0.0183) and a manager tenure of 5.7 years, that is ($\tau = 5.7 \times 4\, quarters \times 0.5 =$) 11.4 realizations on average if investing in the short-term strategy ($d_s = 0.5$). To be conservative, we choose the closest grid with a lower perceived skill ($\hat{\phi} = 0.0175$) and a higher number of realizations ($\tau = 12$) for our estimation of the value of the real growth option.

[34] If we assume that the cost function is quadratic and the utility function is linear as in Eqs. (28) and (31) in our parametric model, the fund manager's payoff $\Pi_i = (d_i \hat{\phi} g_i)^2/(2a)$ as in Eq (30) increases quadratically with perceived skill $\hat{\phi}$.

with the perceived skill $\hat{\phi}$. When the perceived skill $\hat{\phi}$ is high enough to make the difference in payoffs between long- and short -term investing (the RHS of Eq. (18) in gray dashed line in Panel A of Figure 2) larger than this option value, the fund manager will optimally choose to invest in long-term strategies going forward. Since long-term strategies are less likely to realize (i.e., $d_L < d_S$) compared to short-term strategies, the variation in the fund manager's future payoffs (continuation value) becomes substantially smaller once she shifts to long-term investing. Therefore, the value of the real growth option reverses once it reaches the gray dashed line. As the perceived skill continues to increase, the option to exit becomes even less likely to be exercised, which leads to a further decrease in this option value.

Finally, it is interesting to note that new fund managers with negative perceived skill (i.e., out-of-the-money managers with $\hat{\phi} < 0$) still have a positive value from the real growth option, since they have a chance of proving themselves to be skilled in the future, whereas older managers with negative perceived skill have less value from the real growth option as the residual uncertainty regarding their skill is so much lower.

[Insert Figure 2 about here]

In Appendix Section A.2.1, we perform sensitivity analyses for the value of the real growth option with respect to the key parameters used in our calibration (including probability d_S, the precision of the prior γ, the precision of the signal ω, reservation utility u_0, survival rate κ, fund-level DRS parameter a, investment-opportunity-level DRS parameters $b_{1,S}$ and $b_{1,L}$, as well as discount rate β). We show that, for new fund managers, this option value from short-term strategies remains substantially larger than the higher payoff given by long-term strategies under most parameter values. As a result, new fund managers are better off choosing short-term strategies. The reason is that, for a new fund manager with a perceived skill as low as $\phi_0 = 0.005$, the payoff from investing in long-term strategies immediately is small compared to the substantially larger payoff from revealing her skill faster.

5.5 Main Finding 1: Optimal Investment

Theorem 4 shows that fund managers choose to exit when their perceived talents are sufficiently low, and the threshold becomes higher as fund managers get older because their growth potential becomes smaller. Also, Theorem 5 shows that, conditioning on continuing their operations, fund managers choose to invest short-term when their perceived talents are sufficiently low, the threshold becomes lower as fund managers get older because their growth potential becomes smaller. These findings are driven by the larger value of the exit option attached to short-term investment strategies compared to long-term ones. That is, the call-option-like value becomes more sensitive to the managers' choices as the option is closer to at-the-money (nearer to the exercise boundary, implying low perceived talent) or the volatility is higher (i.e., for new fund managers).

[Insert Figure 3 about here]

[Insert Figure 4 about here]

Figure 3 shows the area of optimal choice in terms of the state variables. As the trade-off demonstrated in Eq. (18), funds with new managers and small size are more likely to invest in short-term opportunities to speed up investors' learning of their talents and, thus, increase the value of their real growth option, while sacrificing some of their current-period profits. On the other hand, because the information about old fund managers' talents is more precise and the growth potential of large funds is smaller, this real growth option is less important for those older managers. As a result, funds with old managers and large size are more likely to choose long-term opportunities which prioritize current-period value added to the value of this real growth option.

In Figure 4, we show that the actual distribution of fund size and manager tenure of high- and low- turnover funds in the data resembles our model's prediction in Figure 3. Funds with new managers and small size (at the lower left corner) are more likely to choose high-turnover strategies, while funds with old managers and large size (at the top right corner) are more likely to choose low-turnover strategies.

5.5.1 Choice of Turnover

To further test the prediction of Theorem 5, we plot the average fund turnover by manager tenure for each fund size quintile separately in Figure 5 to look into the correlation between manager tenure and fund turnover controlling for fund size. It shows that fund turnover decreases almost monotonically with the increase of manager tenure for fund size quintiles 2 to 5. We formally test this correlation using the regression below:

$$Turnover_{j,y} = \beta * Tenure_{j,y} + \gamma * ln(TNA)_{j,y-1} + \upsilon_y + \varepsilon_{j,y}, \tag{35}$$

where $Turnover_{j,y}$ is the turnover of fund j in year y, and $Tenure_{j,y}$ is the (average) manager tenure. We include year fixed effects in our benchmark specification since there might be common variation in fund turnover across funds over time. Since fund turnover is highly persistent over time (as shown in Van Binsbergen, Han, Ruan, and Xing [2022]), we cluster the robust standard errors at the fund level. We find that, on average, annual fund turnover is 1.9% lower for a manager with one more year of experience (as reported in Panel A of Table 4). Since the standard deviation of manager tenure is 5.1 years as reported in Table 2, a one standard deviation increase in manager tenure on average leads to a 9.7% (1.9%*5.1) decrease in annual fund turnover. This negative correlation is statistically significant for all fund size quintiles, except quintile 1. This is because small funds always have the incentive to choose short-term opportunities which allows faster updating of investors' beliefs (as shown in Figure 3). Further, the correlation between fund size and turnover is also significantly negative which is consistent with the prediction of our model. Our results are also robust to including fund fixed effects (setting [2] of Panel B), which confirms our model prediction that funds switch from short- to long- term opportunities as they get older.

[Insert Figure 5 about here]

Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997) argue that younger fund managers have a higher propensity to take risk. To distinguish our story (that new fund managers use high-turnover strategies to speed up the learning) from this risk-taking story, we measure the fund's portfolio risk by the standard deviation of the fund's monthly excess return per year. We regress this measure of portfolio risk on manager tenure controlling for fund turnover in the same year, and report the result in setting (1) of Panel B. The results show that the correlation between manager tenure and portfolio risk is indistinguishable from zero after controlling for fund turnover, suggesting that fund managers are not simply using high-turnover strategies to increase their risk taking. Consistently, we find that the relation between fund turnover and manager tenure remains the same after including the return volatility as a control variable (as reported in setting [4] of Panel B).

Since fund age and manager tenure are positively correlated (with a correlation of 0.347), one may wonder whether high-turnover strategies are associated with new funds rather than new managers. We explore this by including both fund age and manager tenure in the same regression in setting (3) of Panel B and find that the effect of manager tenure remains the same while the effect of fund age is close to zero.

[Insert Table 4 about here]

5.5.2 Choice of Exiting

To test Theorem 4, we run a probit regression to investigate the relation between managers' exit decisions and fund size, as well as manager tenure. In particular, we regress an exit dummy on fund size and manager tenure at the annual frequency:

$$\begin{aligned} Exit\,Dummy_{j,y} =&\beta_1 * Tenure_{j,y-1} \times ln(TNA)_{j,y-1} + \beta_2 * Tenure_{j,y-1} \\ &+ \beta_3 * ln(TNA)_{j,y-1} + \beta_4 * ln(TNAfamily)_{j,y-1} + \upsilon_y + \varepsilon_{j,y}. \end{aligned} \tag{36}$$

The dependent variable $Exit\,Dummy_{j,y}$ equals one when there is a change in the manager (management team) of a fund in a year, and zero otherwise. $ln(TNAfamily)_{j,y-1}$ is the natural logarithm of the total AUM of fund j's managing firm at the end of the previous year. All independent variables are standardized to a mean of zero and a standard deviation of one.

As predicted in Theorem 4, we find in Table 5 that the chance of a manager exiting decreases significantly with an increase in fund size, especially for older managers with longer tenure. The point estimate of $ln(TNA)$ *std* suggests that a manager in the sample who has a fund size one standard deviation lower increases the probability that she will exit next year by about 4.4% on average, and the point estimate of $Tenure\ std \times ln(TNA)\ std$ suggests that this number increases by 1.5% for a manager with a tenure one standard deviation longer (5.1 years as reported in Table 2). That is, older managers with a smaller fund size are more likely to exit.

In principle, our exit dummy captures all changes in the management team of a fund including promotions, firings, demotions, or lateral moves. As documented in Chevalier and Ellison (1999), the majority of these changes reflect demotions instead of promotions because the management of an equity fund is among the pinnacle positions for portfolio managers within a fund company. As robustness checks, we use two alternative definitions of manager exit. In setting (2) of Table 5, the exit dummy equals one when a manager in a fund stops being a fund manager in our database. In setting (3) of Table 5, it equals one when a fund stops operating. Results based on these two alternative measures are consistent with our model prediction as reported in Table 5.

[Insert Table 5 about here]

[Insert Figure 6 about here]

Since our model predicts that managers of small funds are more likely to choose high-turnover strategies and, at the same time, more likely to exit (as in Figure 3), we expect that managers of high-turnover funds are more likely to exit than those of low-turnover funds. Figure 6 plots the probability that a fund-manager combination survives more than n (1-10) years conditional on this fund-manager pair staying in turnover quintiles 1 or 5. Cumulative survival rates are calculated based on the survival rates for each manager tenure in each turnover quintile reported in Table 6.[35] Consistent with our model prediction, the survival rates of low turnover fund managers are substantially higher than those of high turnover

[35] Table 6 reports the survival rates of fund-manager combinations by manager tenure and fund turnover quintiles in detail. We calculate the survival rate as the fraction of managers (management team) with (average) manager tenure n at the end of each year that continue to manage the same fund in the entire following year. A manager stops managing a fund either because he quits or the fund stops operating. In Table 6 and Figure 6, we sort all funds into quintiles with thresholds of annual turnover below 27%, between 27% and 48%, between 48% and 74%, between 74% and 117%, and above 117%. We use the same thresholds for all the years, so the results are not affected by the variation of turnover thresholds over time.

fund managers. For example, the chance that a low turnover fund manager survives more than a year (ten years) is 82% (9%), which is substantially higher than the 70% (1%) chance for high turnover fund managers correspondingly. Moreover, Figure 6 shows that, on average, the chance of managers exiting is high. Only 1% - 9% of fund managers keep managing the same funds more than ten years.

[Insert Table 6 about here]

5.6 Main Finding 2: Stationary Distribution

Figure 7 shows the stationary distribution of funds as a function of perceived skill and manager tenure for short-term and long-term funds separately. We calculate the density of funds at each manager tenure by aggregating the densities of funds for all number of payoff realizations (τ) at that manager tenure. The survival rates in Figure 7 largely match the average manager survival rates in Figure 6. Theorem 9 guarantees the existence and uniqueness of such a distribution. One can observe gradual attrition of fund managers for both voluntary and random exits. As a consequence of voluntary exits, the density of funds with small fund size (low perceived skill) decreases substantially with an increase in manager tenure. Since new and small fund managers are more likely to choose short-term strategies, as shown in Figure 3, the stationary distribution features a large number of small and high-turnover funds. It is worth noting that there is a one-to-one mapping between fund size and perceived skill in our model as in Berk and Green (2004).

[Insert Figure 7 about here]

[Insert Figure 8 about here]

Together with voluntary exiting, fast skill revelation of investing in the short-term helps to filter out the unskilled managers and keep the skilled ones in the industry. As shown in Panel A of Figure 8, the stationary distribution of true skill, which is the distribution of surviving funds, naturally contains better skilled fund managers compared to the initial distribution. This rightward shift of skill distribution main comes from funds which have shifted from short-term to long-term investing.

[Insert Figure 9 about here]

[Insert Figure 10 about here]

Figure 9 plots the steady state distributions of short-term and long-term funds for new and old fund managers separately. Panel A plots the distribution for new fund managers (with one quarter of manager tenure), and Panel B plots it for old fund managers (with 40 quarters of manager tenure). As shown in Panel A, most new fund managers choose short-term opportunities to increase the value of the real growth option. Only a small group of funds who have proved their skills through extraordinary past performance (because of either luck or skill) choose long-term opportunities. For old fund managers, in Panel B, most of them choose long-term opportunities for higher current-period value added. Only a small fraction of old fund managers with low perceived skills choose high-turnover strategies. Because of the high chance of managers exiting (as documented in Section 5.5.2), the mutual fund industry features a large number of new fund managers choosing high-turnover strategies and a small number of old managers choosing low-turnover strategies.

Next, we compare the distribution of fund sizes from actual mutual fund data with the predicted distribution from our theory. Figure 10 plots the distribution of fund size from actual mutual fund data, for high-turnover funds (quintile 5) and low-turnover funds (quintile 1) separately and for new and old managers separately. The distributions in Panel A for new managers (with tenure $<=$ 7 years) resemble the distributions in Panel A of Figure 9, where the density of high-turnover funds is higher than the density of low-turnover funds. The distributions in Panel B for old managers (with tenure $>$ 7 years) also resemble the distributions in Panel B of Figure 9, where the density of low-turnover funds is higher than the density of high-turnover funds. The average fund size of high-turnover funds is smaller than low-turnover funds in both panels. The density of high-turnover funds in Panel B is substantially lower than that in Panel A because of their managers' lower survival rates.

Next we look into the fraction of high-turnover and low-turnover funds for new and old managers separately. Figure 11 plots the number of funds and the total net assets for each fund turnover quintile and by manager tenure. As shown in Panel A, for high-turnover funds, the number of new managers (with tenure $<=$ 7 years) is about three times the number of old managers (with tenure $>$ 7 years); while for low-turnover funds, new managers are only slightly more than old managers. However, Panel B shows that, for low-turnover funds, the total amount of assets managed by old managers is more than twice the amount managed by new managers, and low-turnover funds manage substantially more assets than high-turnover funds do. These results are consistent with our conjecture that a main function/value added of the large number of small and high-turnover funds is to select skilled managers for large low-turnover funds, which add the majority of value for the mutual fund industry. There are two ways in which a manager of a small high-turnover fund can become a manager of a large low-turnover fund: (1) investors reward the fund with more capital and the fund becomes large and switches to a low-turnover strategy, and (2) the manager is hired (or reassigned by the fund family) to manage a large and low-turnover fund.

[Insert Figure 11 about here]

5.7 Main Finding 3: Equilibrium Value Added

Our model (Corollary 7) predicts that the average value added of funds investing in long-term opportunities is larger than that of funds investing in short-term opportunities, controlling for the number of believe updates. Figure 12 shows the average value added, value from real growth option, and the fraction of AUM in the steady state of our model for investments in short-term and long-term opportunities separately. Under the stationary distribution in our model, there are many new and relatively unskilled funds in the economy. They invest in short-term opportunities for the value of the real growth option, which drives the value added of short-term opportunities down to a level lower than that of long-term opportunities. As a result, old and skilled fund managers optimally choose to invest in long-term opportunities. The average value added of investing in short-term opportunities is small because of both the competition for the value of the real growth option and the lower skill level of new managers, whereas the average value added of investing in long-term opportunities is large mainly because of higher average skill. Therefore, investing in long-term opportunities adds more value than investing in short term opportunities does in equilibrium. Because short term opportunities offer a large value from real growth option, fund managers are willing to accept lower current value added for short term opportunities. As reported in the left panel of Figure 12, the value of short-term strategies is mainly from the value from real growth option ($3.7 million per quarter) represented by the green bar instead of payoffs from the short-term opportunities ($0.5 million per quarter) represented by the blue bar. Finally, competition makes short term opportunities less profitable.

[Insert Figure 12 about here]

[Insert Figure 13 about here]

Figure 13 plots the average value added for each fund turnover quintile by manager tenure. We sort funds into turnover quintiles every year based on their turnover ratios in the CRSP mutual fund database. Panel A reports the value added calculated based on the CAPM, and Panel B based on the Vanguard benchmark composed by four US Vanguard Index funds (including S&P 500 Index (VFINX), Extended Market Index (VEXMX), Small-Cap Index (NAESX), and Mid-Cap Index (VIMSX)). As our model predicts, the value added of high-turnover funds (negative and close to zero) is substantially smaller than the value added of low-turnover funds. This is because short-term opportunities offer higher future growth options, making new and small fund managers more willing to accept lower current value added in exchange for the potential growth of future values. As a consequence, the value added of low-turnover funds are mostly attributed to old and skilled managers as Figure 13 shows. The value added of relatively low-turnover funds (quintile 1 and 2) managed by old managers are significantly positive under both the CAPM and Vanguard benchmarks under the 10% significant level. The point estimate of value added of high-turnover funds (quintile 4 and 5) managed by new and old managers are negative, though only significantly so for funds in quintile 4 that are managed by old managers.

6 Conclusion

In our paper, we use the mutual fund industry as a laboratory to investigate the value of real options in labor market settings and find that they are of first order importance in explaining optimal career choice and compensation. The reason why real options play such an important role in our setting is that the employee has a choice of tasks that influences the speed by which investors and the firm management learn about the employee's skill.

Our model shows that a strategy (such as short-term investment) accelerating the revelation of an employee's skill increases his growth potential, while the potentially larger downside risk of this choice can be effectively attenuated by the possibility to exit. We document that the value of the real growth option (the value of a higher learning speed) is large for new employees. As a result, a large number of new fund managers exploit the value of this real growth option by investing in short-term opportunities. As the competition among new fund managers reduces value added from short-term opportunities, a small number of old skilled fund managers optimally choose to extract value from long-term opportunities instead. Lastly, long-term investing on average adds more value than short term investing does in equilibrium. Because short term opportunities offer a large value through a higher learning speed, fund managers are willing to accept lower current value added for short term opportunities. Competition makes short term opportunities less profitable (i.e., prices are more efficient). As a result, the value of high-turnover (short-term) strategies is mainly from speeding up the learning of new fund managers' skills instead of extracting value from the short-term opportunities. We empirically confirm our model predictions using half a century of US mutual fund data.

Our paper focuses on the value of an option to learn to employees. A promising future direction is to investigate how this option to learn by employees affects the welfare of the consumers of the firm. A firm's role in optimally allocating real options to its employees is also of great importance. In the mutual fund context, the question becomes how should a fund management firm optimally match high-turnover funds with fund managers. Furthermore, future research could focus on other industries where the speed of learning and skill revelation play an important role in resource allocations. For example, practitioners in law may choose short-term and less important cases earlier in their career for learning, and shift to more important cases later for skill revelation. New surgeons may start with simpler and less risky surgeries for practicing.

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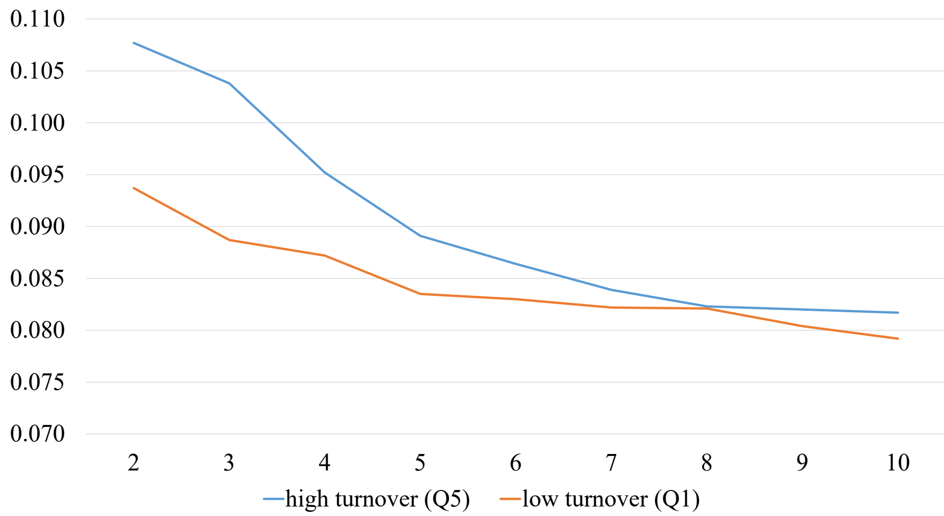
Panel A: Flow-Performance Sensitivity Based on the CAPM



Panel B: Flow-Performance Sensitivity Based on the Vanguard Benchmarks

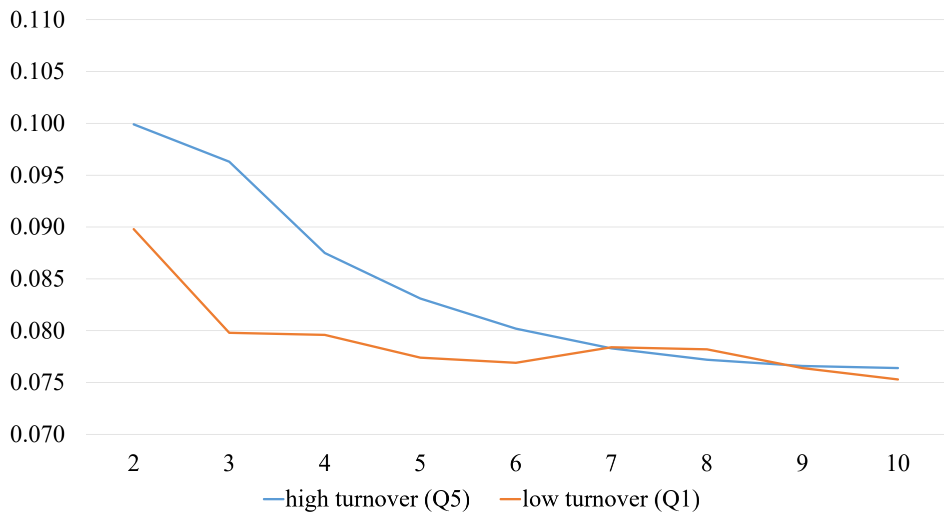
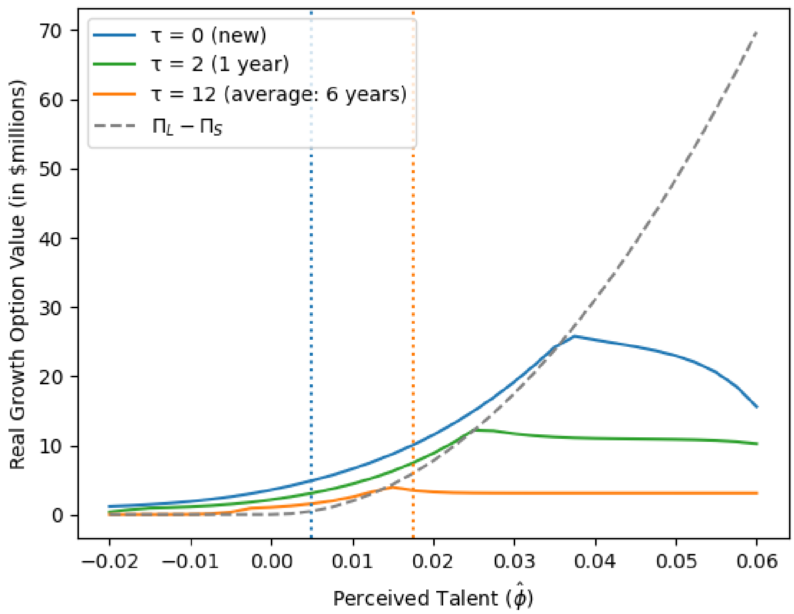


Figure 1: Decay of Flow-Performance Sensitivity over Manager Tenure by Fund Turnover

This figure plots flow-performance sensitivity (FPS) coefficient by manager tenure for fund turnover quintile 1 and 5 separately. The FPS coefficient β is estimated by running the following regression for funds with a manager tenure shorter than 2 to 10 years separately, and for fund turnover quintile 1 and 5 separately: $Flow_{j,t} = \beta * Ret\ Rank_{j,t-1} + \beta_c * ln(TNA)_{j,t-1} + \upsilon_t + \varepsilon_{j,t}$, where $Ret\ Rank$ is the return rank from 0 (the lowest) to 1 (the highest) based on past quarter benchmark-adjusted returns. We use CAPM as the benchmark in Panel A and four Vanguard index funds in Panel B. $ln(TNA)$ is the ln value of the fund's total net asset at the end of last quarter as a control variable. Manager tenure is the number of years a manager has worked in a given fund. If a fund is team managed, we use the average manager tenures of all its managers for our analysis. We sort funds into turnover quintiles every year based on their last-year turnover ratios in CRSP mutual fund database.

Panel A: Entire Distribution



Panel B1 & B2: New Manager and Average Manager

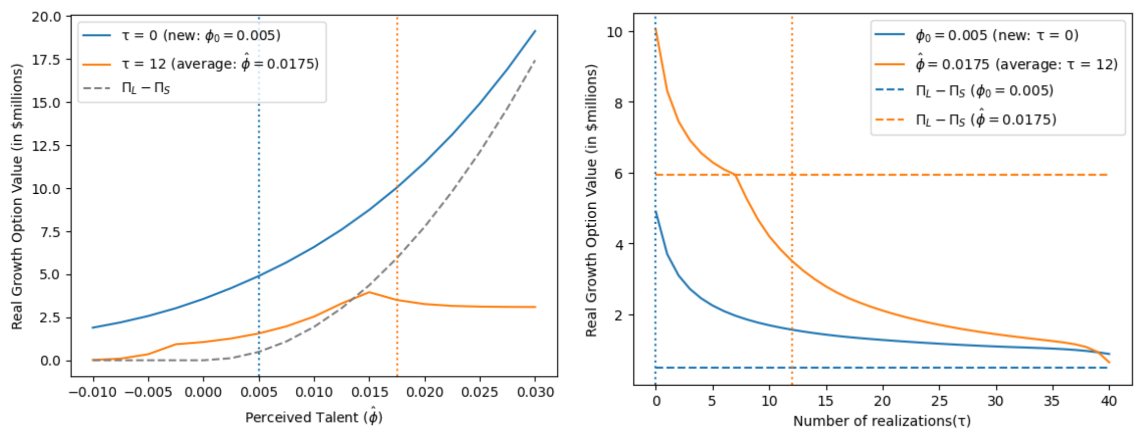


Figure 2: Value of The Real Growth Option

This figure plots the value of the real growth option as a function of perceived skill and number of realizations. The value of the real growth option is defined as the left hand side (LHS) of Eq.(18):

$$(d_S - d_L)\kappa \left\{ \mathrm{E}\left[\max\left\{ V(\hat{\phi}', \tau+1), u_0 \right\} \middle| \hat{\phi}, \tau \right] - V(\hat{\phi}, \tau) \right\} > \Pi_L(\hat{\phi}) - \Pi_S(\hat{\phi}).$$

It represents the incremental continuation value from a faster learning speed of short-term investing. Panel A plots this option value for the entire distribution of perceived skill $\hat{\phi}$ and for managers with $\tau = 0$, 2, and 12 realizations separately. The gray dashed line is the right hand side (RHS) of Eq.(18), which is the difference in current-period payoffs between investing in long- vs. short- term opportunities. Panel B1 (left) zooms in the region for a new manager (blue) with $\hat{\phi} = 0.005$ (blue dotted line) and $\tau = 0$, and for an average manager (orange) with $\hat{\phi} = 0.0175$ (orange dotted line) and $\tau = 12$. Panel B2 (right) is as a function of the number of realizations τ.

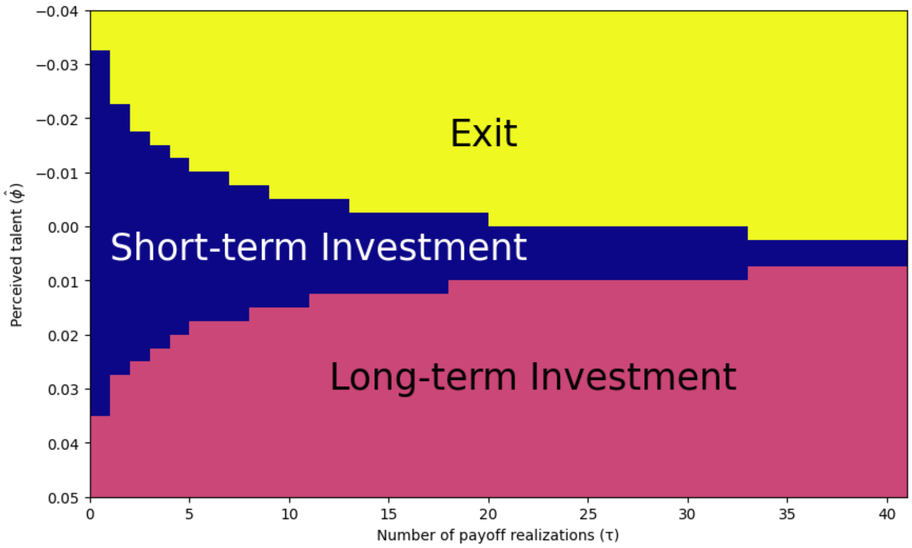


Figure 3: Optimal Choice by Perceived Skill and the Number of Belief Updates

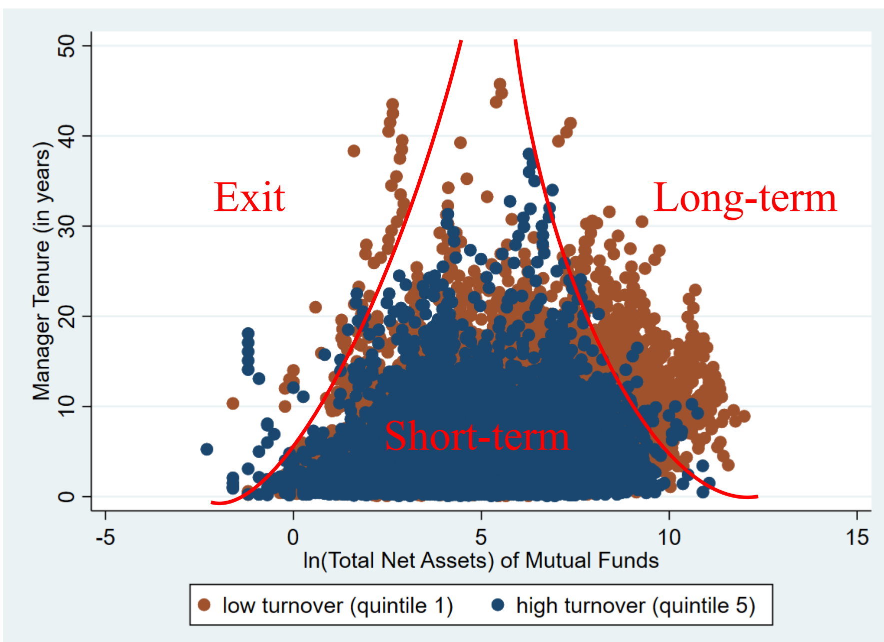


Figure 4: Scatter Plot of Manager Tenure and Total Net Assets by Fund Turnover

This figure shows the scatter plot of manager tenure versus the ln value of funds' total net assets for low-turnover funds (quintile 1) and high-turnover funds (quintile 5) separately. Manager tenure is the number of years a manager has worked in a given fund. If a fund is team managed, we use the average manager tenures of all its managers for our analysis.

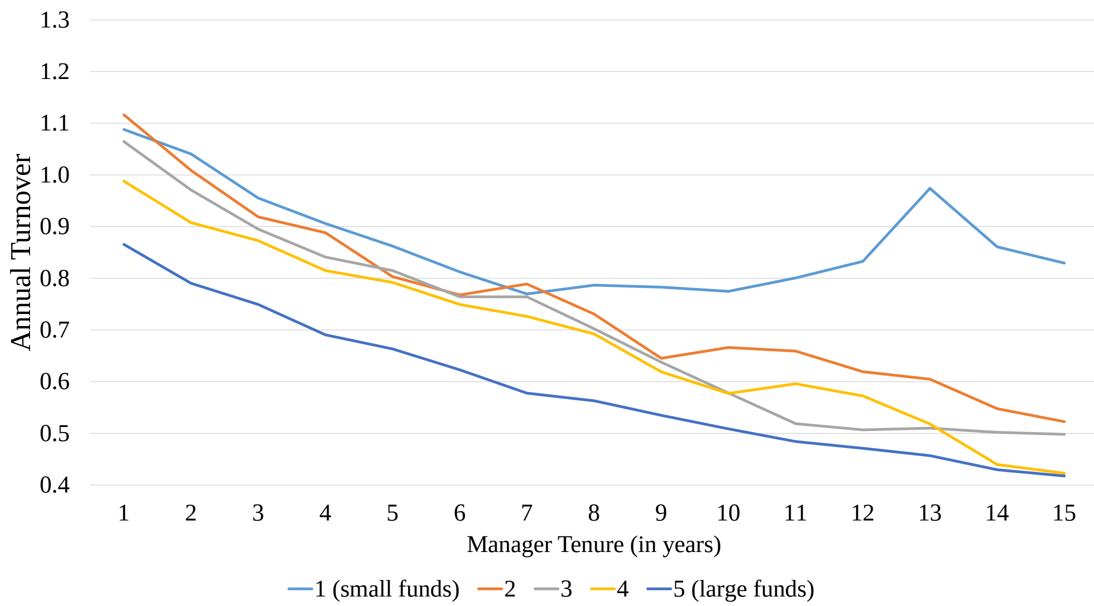


Figure 5: Fund Turnover by Manager Tenure and Fund Size Quintiles

This figure plots the average fund turnover by manager tenure for each fund size quintile separately. Manager tenure is the number of years a manager has worked in a given fund. If a fund is team managed, we use the average manager tenures of all its managers for our analysis. Every quarter, we sort funds into fund size quintiles based on their total net assets at the end of last quarter.

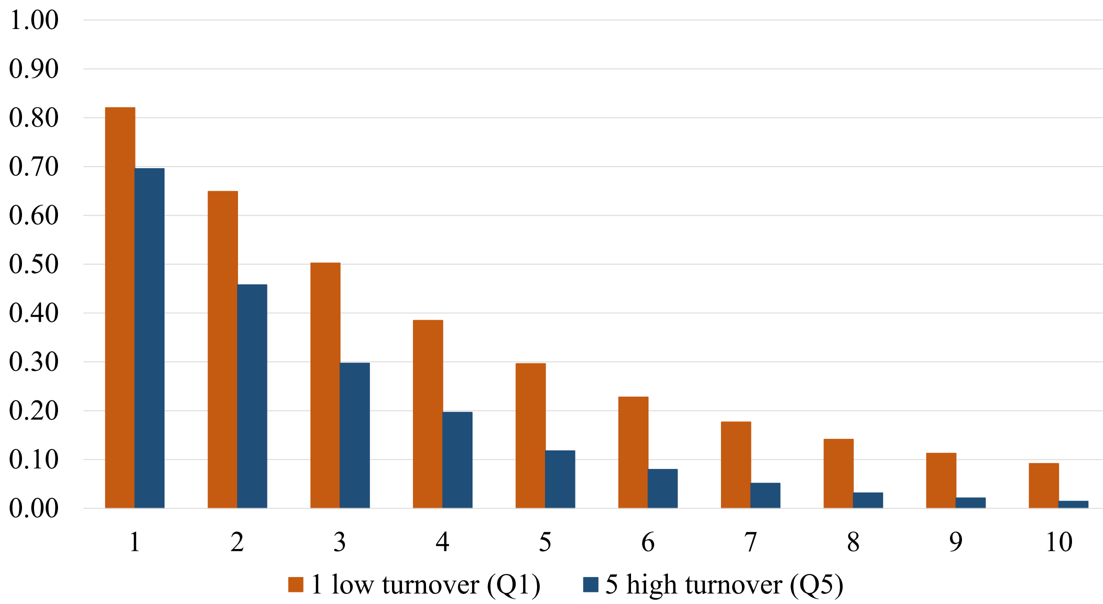


Figure 6: Fund Survival Rate by Fund Turnover and Manager Tenure

This figure plots the cumulative survival rates by manager tenure for fund turnover quintile 1 and 5 separately. Specifically, it shows the probability that a fund-manager combination survives more than n (1-10) years conditional on it stays in turnover quintile 1 or 5. Manager tenure is the (average) number of years a manager(s) has (have) worked in a given fund. Cumulative survival rates are calculated based on the survival rates for each manager tenure reported in Table 6.

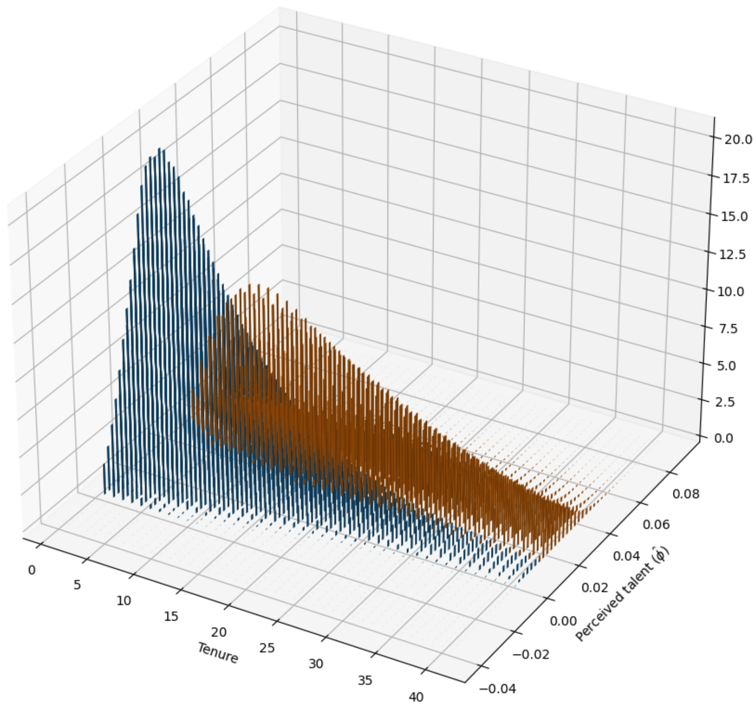


Figure 7: Stationary Distribution of Perceived Skill and Manager Tenure under the Parametric Model

This figure plots the distribution of perceived skill and manager tenure for short-term (blue) and long-term (orange) funds separately. All funds with at least one realization are included into this figure.

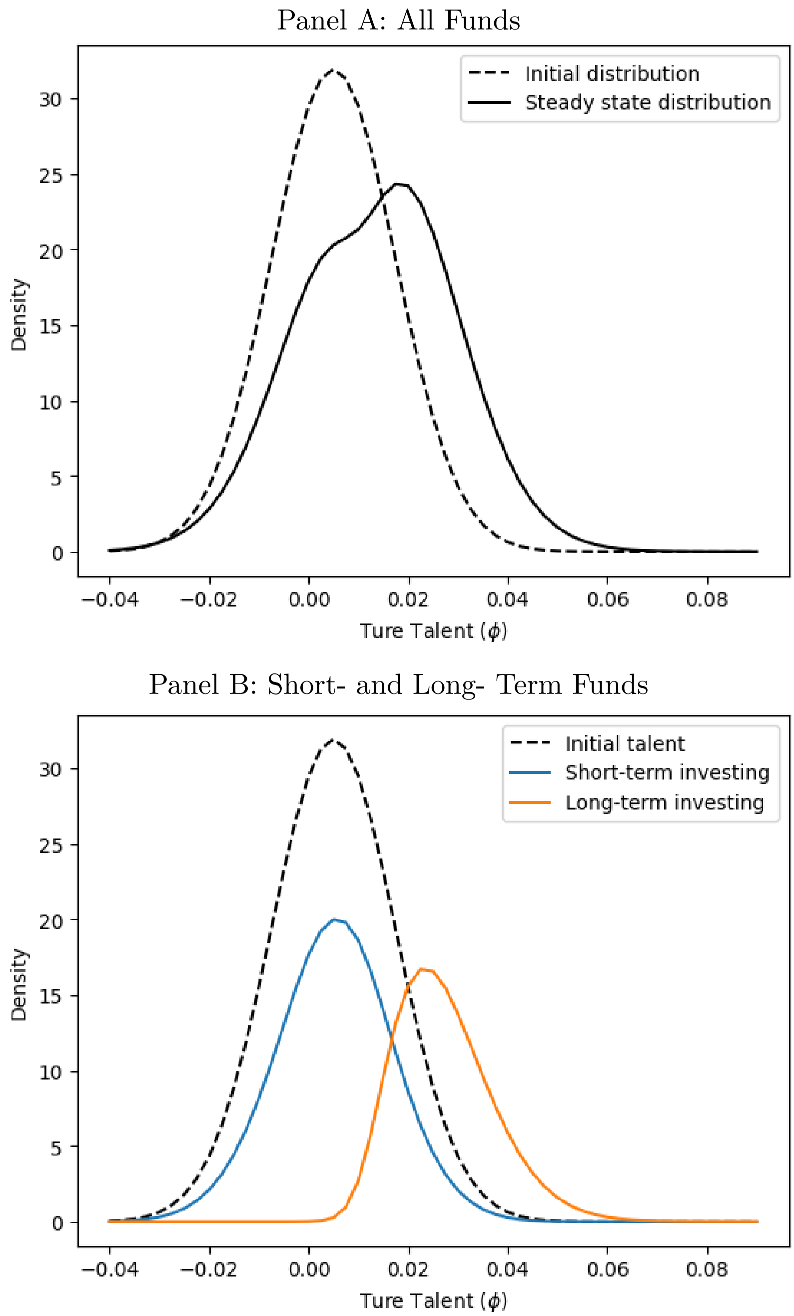
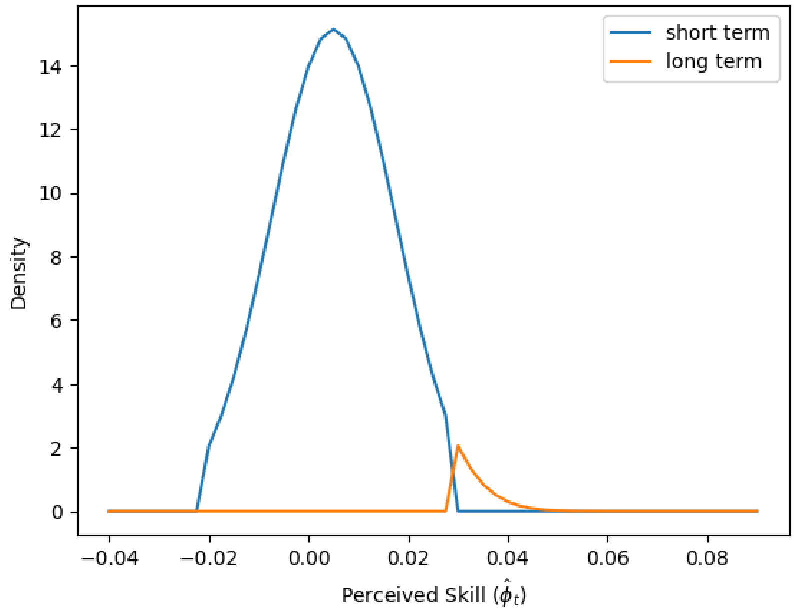


Figure 8: Stationary Distribution of True Skill under the Parametric Model

This figure plots the distribution of true talents for surviving funds in their steady state distribution (solid lines) compared with the initial distribution (dashed lines). Panel A is for all funds, and Panel B is for short-term (blue line) and long-term (orange line) funds separately.

Panel A: New Funds (1 quarter)



Panel B: Old Funds (40 quarters)

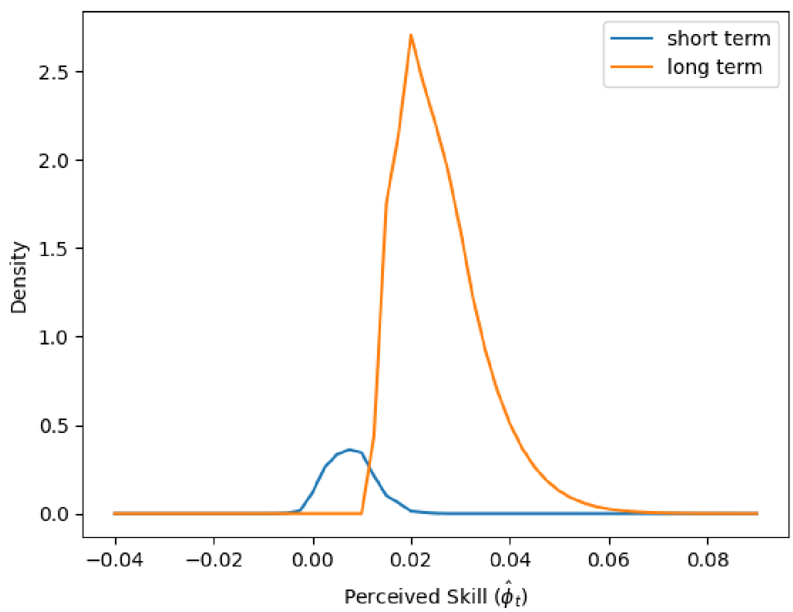
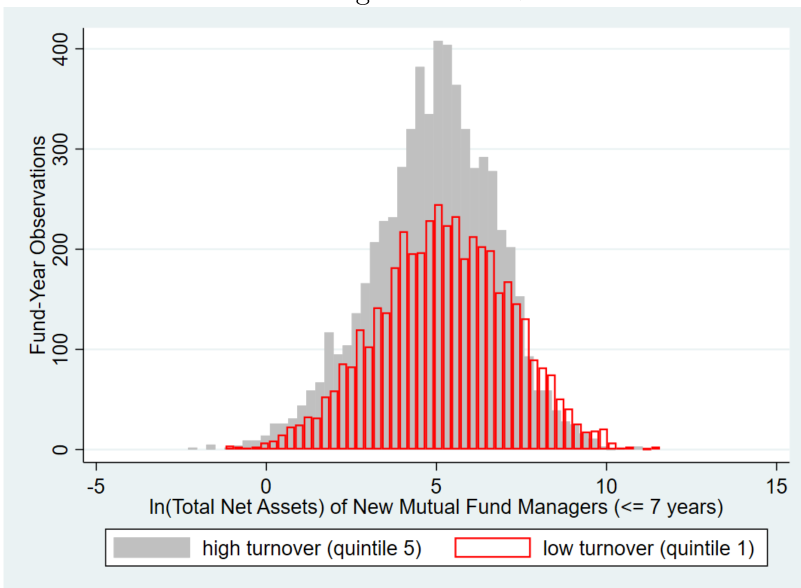


Figure 9: Distribution of Perceived Skill by Investment Horizon and Manager Tenure

This figure plots the distribution of perceived skill for short-term and long-term funds separately and for new and old managers separately. Panel A is for new fund managers with one quarter of manager tenure, and Panel B is for old fund managers with 40 quarters of manager tenure.

Panel A: Manager Tenure <= 7 Years



Panel B: Manager Tenure > 7 Years

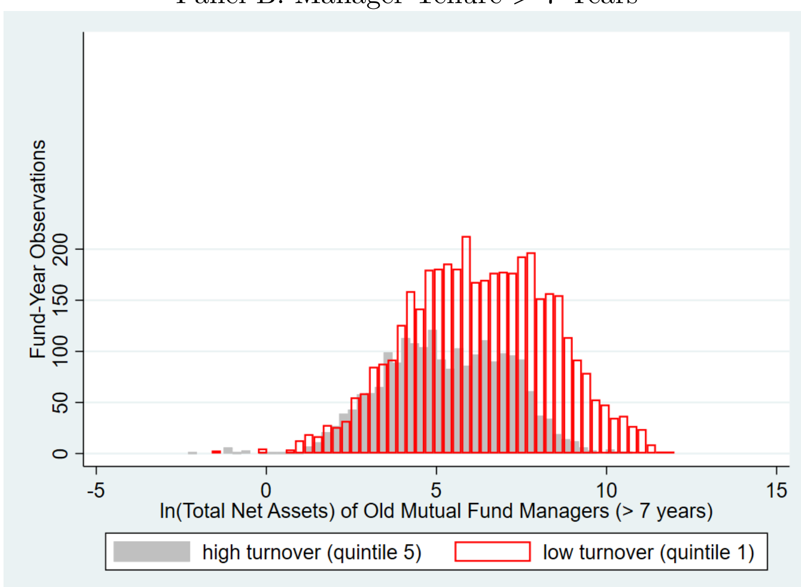
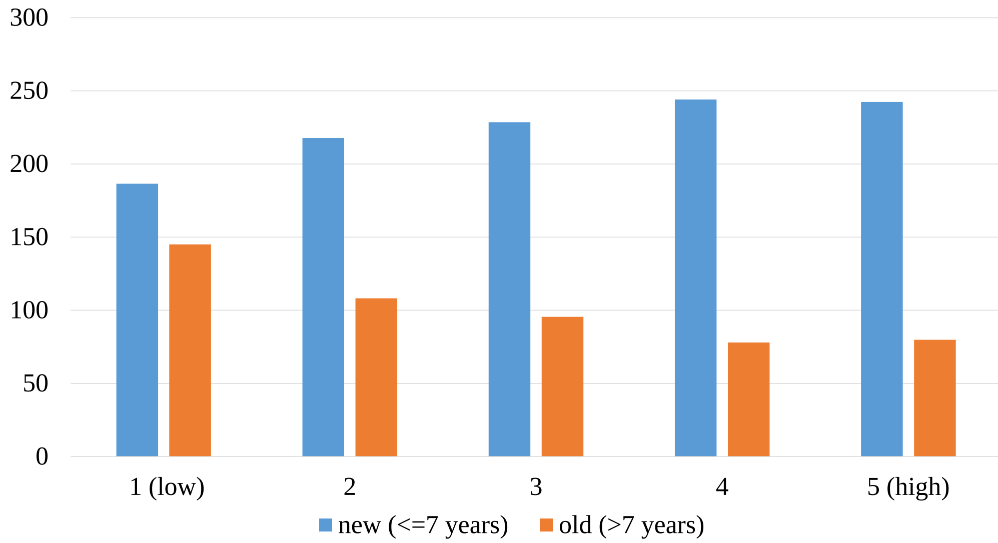


Figure 10: Distribution of Fund Size by Turnover and Manager Tenure: New (<= 7 Years) vs Old (> 7 Years)

This figure plots the distribution of fund size for high-turnover funds (quintile 5) and low-turnover funds (quintile 1) separately and for new and old managers separately. Panel A is for new managers with tenure <= 7 years, and Panel B is for old managers with tenure > 7 years. We sort funds into turnover quintiles every year based on their turnover ratios in CRSP mutual fund database. The vertical axis is the number of fund-year observations for all the funds in our sample from 1961 to 2019, and the horizontal axis is the ln value of total net assets inflation adjusted to the dollar amounts on 2020 January 1.

Panel A: Average Number of Funds per Year



Panel B: Total Net Assets (in billion $s)

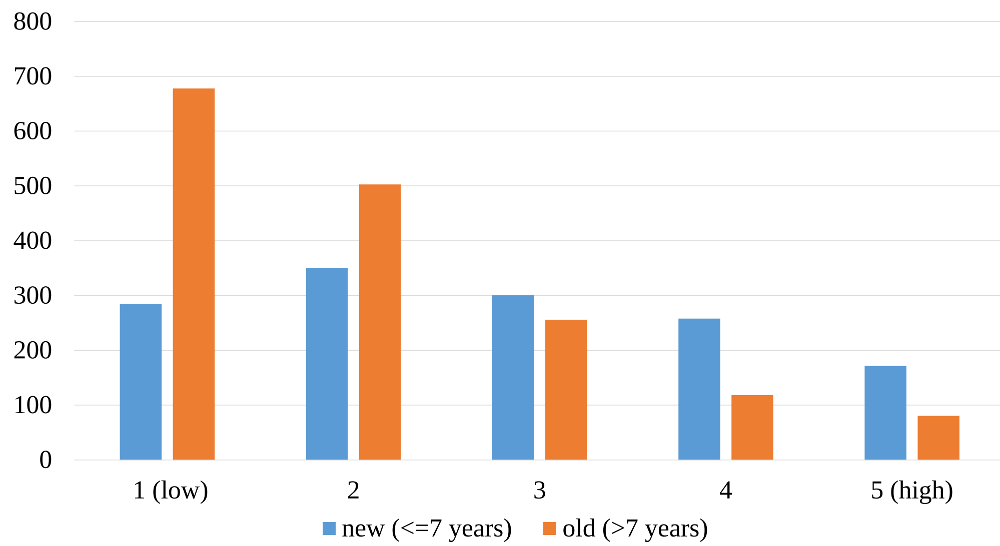


Figure 11: Number of Funds and Total Net Assets by Manager Tenure and Fund Turnover Quintiles

This figure plots the number of funds and the total net assets for each fund turnover quintile and by manager tenure. Panel A is for the average number of fund per year in each category, and Panel B is for the total net assets of all the funds in each category. We sort funds into turnover quintiles every year based on their turnover ratios in CRSP mutual fund database. Blue bars are for new managers with tenure $<=$ 7 years, and orange bars are for old managers with tenure $>$ 7 years. All dollar amounts are inflation adjusted to 2020 January 1, and all numbers are averaged across years from 1961 to 2019.

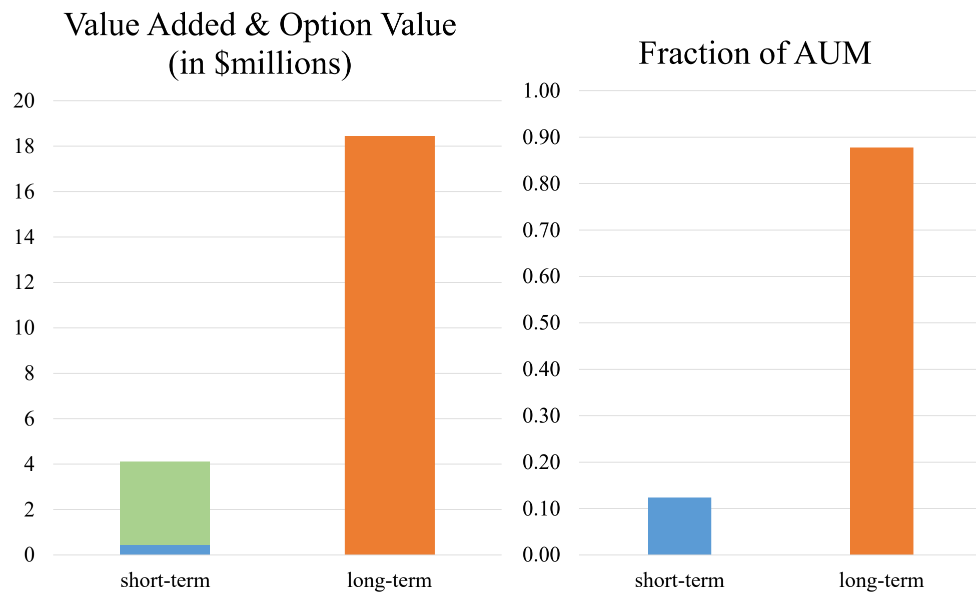
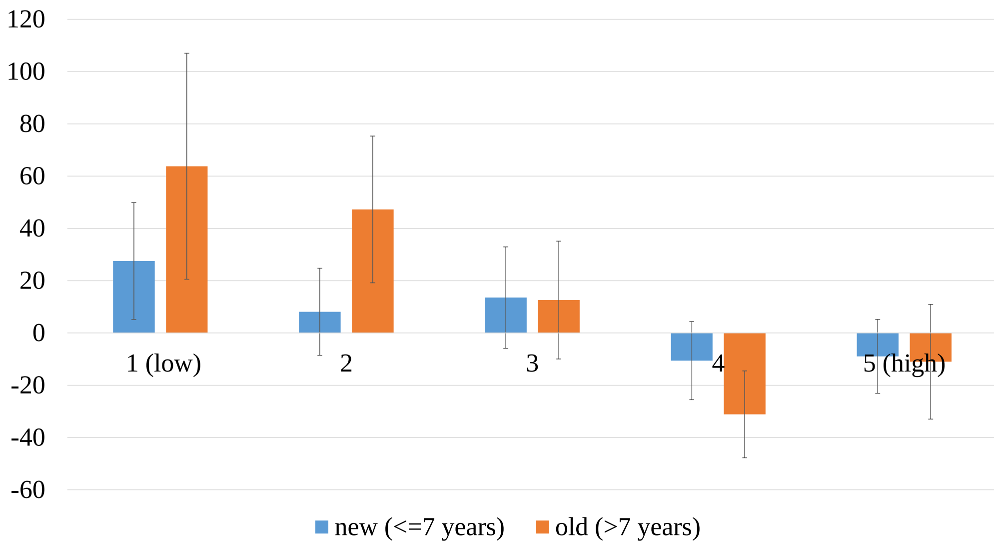


Figure 12: Value Added, Value of The Real Growth Option, and Fraction of AUM under the Parametric Model

This figure plots the average value added of mutual funds, value from real growth option (green bar), and the fraction of assets under management (AUM), for funds investing in short-term and long-term opportunities separately.

Panel A: Average Value Added Based on the CAPM (in $million)



Panel B: Average Value Added Based on the Vanguard Benchmarks (in $million)

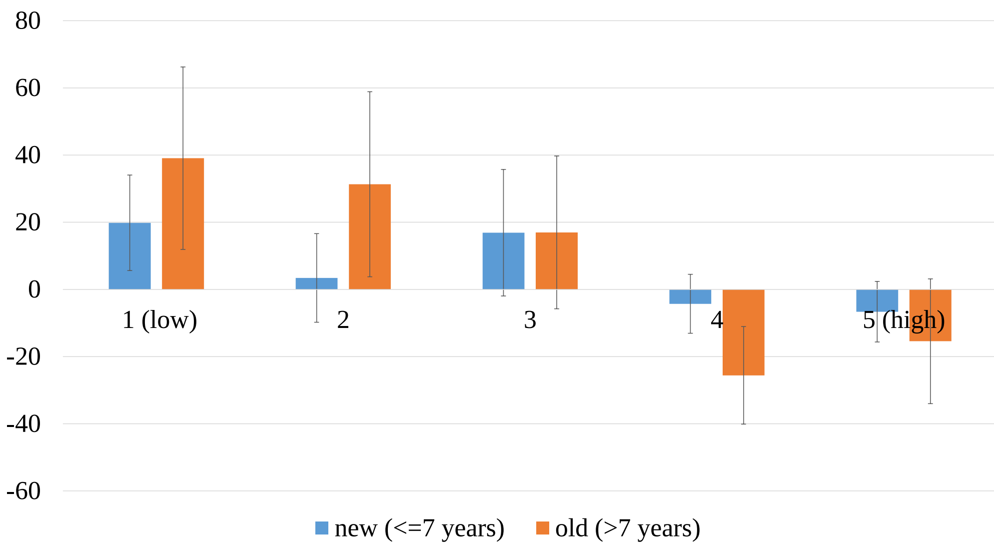


Figure 13: The Value Added by Fund Turnover Quintiles and Manager Tenure

This figure plots the average value added for each fund turnover quintiles by manager tenure. We sort funds into turnover quintiles every year based on their turnover ratios in the CRSP mutual fund database. Panel A reports the value added calculated based on the CAPM, and Panel B based on four US Vanguard Index funds as benchmarks (including S&P 500 Index (VFINX), Extended Market Index (VEXMX), Small-Cap Index (NAESX), and Mid-Cap Index (VIMSX)). Blue bars are for new managers with tenure $<= 7$ years, and orange bars are for old managers with tenure > 7 years. All dollar amounts are inflation adjusted to 2020 January 1. All numbers are averaged across months from 1961 January to 2019 December and annualized. The 90% confidence intervals are calculated across months.

Table 1: Parameter Values used in Numerical Analysis

Variable	Value	Interpretation
d_S	.5	payoff rate (turnover) of short-term opportunity
d_L	.04	payoff rate (turnover) of long-term opportunity
a	.00503	fund-level decreasing returns to scale (DRS)
$b_{0,S}$	4/.5	constant scale parameter for short-term opportunity
$b_{0,L}$	1/.04	constant scale parameter for for long-term opportunity
$b_{1,S}$	-61.92	DRS parameter for short-term opportunity
$b_{1,L}$	-14.80	DRS parameter for long-term opportunity
ϕ_0	.02/4	prior mean of talent ϕ
γ	400×4^2	prior precision of talent ϕ
ω	300×4^2	precision of idiosyncratic noise ϵ
κ	.95	probability of fund survival
u_0	.02	reservation utility for the outside option

Table 2: Summary Statistics

This table shows summary statistics for our sample of actively managed US equity mutual funds from January 1961 to 2019 for the full sample, year 1961 to 1990, and 1991 to 2019 separately. Panel A reports the mean and standard deviation of fund size, turnover from the CRSP mutual fund database, fund age, and fund manager tenure from the MorningStar at the fund-year level. Panel B reports the net fund returns, CAPM alphas, Vanguard alphas estimated using Vanguard benchmark per month in percentage per month, expense ratios per year, and value added based on CAPM and Vanguard benchmark. Fund size and value added are reported in million dollars adjusted by inflation into January 1, 2020 dollars. All numbers are equally weighted.

	Full sample		1961 - 1990		1991 - 2019	
Num. of funds	3,390		714		3,356	
	Mean	Std	Mean	Std	Mean	Std
Panel A: Fund characteristics (per fund-year)						
Fund size (in mill $s)	1,374	5,874	222	962	1,567	6,313
Turnover	0.81	0.82	0.71	0.67	0.81	0.96
Manager tenure	5.7	5.1	5.9	6.7	5.7	5.0
Age	12.9	11.6	17.2	14.7	12.7	11.4
Panel B: Return, expenses, alphas, and value added (per fund-month)						
Net return (in %)	0.78	15.31	0.57	6.56	0.79	15.61
Expense ratio (yearly, in %)	1.22	0.53	1.03	0.62	1.24	0.52
CAPM gross alpha (in %)	0.07	4.10	-0.09	2.92	0.08	4.15
Vanguard gross alpha (in %)	0.04	3.73	0.03	2.44	0.04	3.77
CAPM value added (in mill $s)	7.26	530.55	29.54	125.20	7.14	531.99
Vanguard value added (in mill $s)	0.54	126.18	-0.33	24.02	0.57	128.36

Table 3: Flow-Performance Sensitivity by Fund Turnover and Manager Tenure

This table reports the regression results of quarterly fund flows on the interaction term of fund turnover, manager tenure, and funds' return ranks in the past quarter (1), year (2), and three years (3), as described in Eq. (34). Ret Rank is the percentile of the fund's benchmark-adjusted return among all the funds, which is zero for the lowest and one for highest. We use CAPM as the benchmark in Panel A and four Vanguard index funds in Panel B. Turnover is the average turnover in the past quarter, year, and three years as reported in the CRSP database. Manager Tenure is the (average) number of years the current manager(s) has been working in this fund. ln(TNA) is the ln value of the fund's total net asset at the end of last quarter. All independent variables (except Ret Rank) are standardized to a mean of zero and a standard deviation of one. Robust standard errors are clustered per quarter. Sig. lvl: *** 0.01, ** 0.05, and * 0.1

Panel A: CAPM as the Benchmark

Dependent Variable: Fund Flow (a % of TNA)			
	(1) Last-Quarter Ret	(2) Last-Year Ret	(3) Last-3-Year Ret
Ret Rank × Tenure × Turnover	-0.0075***	-0.0048***	-0.0018*
	(-6.01)	(-4.61)	(-1.90)
Ret Rank × Turnover	0.0072***	0.0058***	0.0080***
	(3.10)	(3.43)	(4.21)
Turnover	-0.0079***	-0.0042***	-0.0036***
	(-7.53)	(-5.68)	(-4.44)
Ret Rank × Tenure	-0.0109***	-0.0134***	-0.0032**
	(-4.26)	(-5.43)	(-2.28)
Tenure	-0.0053***	0.0001	-0.0012*
	(-4.44)	(0.13)	(-1.85)
Ret Rank × ln(TNA)	-0.0112***	-0.0123***	-0.0047***
	(-6.30)	(-8.12)	(-2.75)
ln(TNA)	-0.0154***	-0.0084***	-0.0082***
	(-9.77)	(-8.28)	(-9.81)
Ret Rank	0.0737***	0.1125***	0.1012***
	(13.80)	(19.60)	(25.15)
Quarterly FE	Yes	Yes	Yes
Observations	144,218	137,333	118,196
Adjusted R2	0.099	0.119	0.101

Table 3: Flow-Performance Sensitivity by Fund Turnover and Manager Tenure (continued)

Panel B: Four Vanguard Index Funds as the Benchmark

Dependent Variable: Fund Flow (a % of TNA)			
	(1) Last-Quarter Ret	(2) Last-Year Ret	(3) Last-3-Year Ret
Ret Rank × Tenure × Turnover	-0.0071***	-0.0046***	-0.0020**
	(-6.07)	(-4.61)	(-2.02)
Ret Rank × Turnover	0.0068***	0.0041**	0.0062***
	(3.39)	(2.61)	(3.25)
Turnover	-0.0075***	-0.0035***	-0.0029***
	(-7.87)	(-4.03)	(-4.05)
Ret Rank × Tenure	-0.0116***	-0.0142***	-0.0035**
	(-4.91)	(-5.90)	(-2.24)
Tenure	-0.0045***	0.0006	-0.0014**
	(-4.34)	(0.67)	(-2.17)
Ret Rank × ln(TNA)	-0.0117***	-0.0099***	-0.0017
	(-6.96)	(-6.33)	(-0.92)
ln(TNA)	-0.0132***	-0.0080***	-0.0086***
	(-9.10)	(-7.14)	(-10.14)
Ret Rank	0.0725***	0.1118***	0.1052***
	(15.67)	(21.21)	(26.26)
Quarterly FE	Yes	Yes	Yes
Observations	140,216	132,986	113,097
Adjusted R2	0.093	0.117	0.108

Table 4: Fund Turnover and Manager Tenure

This table reports the regression results of annual fund turnover on manager tenure as in Eq. (35), for all funds and funds in each size quintile separately. Panel A reports the benchmark regression results. Panel B reports the robustness checks including (1) regressing return volatility (measured by the standard deviation of fund monthly returns per year), instead of turnover, on manager tenure to rule out the risk-taking story, (2) fund fixed effects, (3) controlling for fund age, and (4) controlling for return volatility. Fund turnover is reported in the CRSP mutual fund database, and the manager tenure is from the Morningstar. Robust standard errors are clustered at fund level. Sig. lvl: *** 0.01, ** 0.05, and * 0.1

Panel A: Regressions of fund turnover on manager tenure

Dependent Var.	Turnover	by Fund Size Quintiles				
	(all)	1 (small)	2	3	4	5 (large)
Tenure	-0.019***	-0.005	-0.027***	-0.030***	-0.020***	-0.017***
	(-8.09)	(-0.80)	(-5.82)	(-10.99)	(-4.08)	(-4.94)
ln(TNA)	-0.044***	-0.050**	-0.072***	-0.050**	-0.058**	-0.082***
	(-8.86)	(-2.27)	(-2.76)	(-2.06)	(-1.99)	(-5.63)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,586	7,361	8,052	8,307	8,664	9,465
Adjusted R^2	0.061	0.025	0.040	0.071	0.055	0.112

Panel B: Robustness Checks

Dependent Var.	Volatility	Turnover		
	(1)	(2)	(3)	(4)
Tenure	-0.000	-0.011***	-0.019***	-0.019***
	(-0.20)	(-5.86)	(-8.02)	(-8.24)
ln(TNA)	-0.000***	-0.053***	-0.043***	-0.043***
	(-3.26)	(-9.12)	(-8.25)	(-8.84)
Turnover	0.003***			
	(8.66)			
Age			-0.001	
			(-0.72)	
Volatility				9.096***
				(10.88)
Year FE	Yes	No	Yes	Yes
Fund FE	No	Yes	No	No
Observations	42,209	42,586	42,583	42,209
Adjusted R^2	0.623	0.539	0.061	0.089

Table 5: Manager Exit and Fund Turnover

This table reports the probit regression results of exit dummy on fund size and manager tenure at year frequency, as described in Eq. (36). In setting (1), exit dummy equals one when there is any change in the manager (management team) of a fund in a year, and zero otherwise. In setting (2), it equals one when any manager in a fund stops being a fund manager in our database. In setting (3), it equals one when a fund stops operating. Turnover is the average turnover reported in the CRSP database. Manager Tenure is the (average) number of years the current manager(s) has been working in this fund. ln(TNA) is the ln value of the fund's total net asset at the end of last year, and ln(TNA family) is the ln value of the fund managing firm's total net asset at the end of last year. All independent variables are standardized to a mean of zero and a standard deviation of one. Robust standard errors are clustered per year. Sig. lvl: *** 0.01, ** 0.05, and * 0.1

	(1) Fund-Manager Exit	(2) Manager Termination	(3) Fund Termination
Tenure × ln(TNA)	-0.044***	-0.034**	-0.135***
	(-2.65)	(-2.10)	(-4.58)
ln(TNA)	-0.127***	-0.038**	-0.556***
	(-5.68)	(-2.56)	(-22.06)
Tenure	-0.021	-0.090***	-0.089***
	(-1.36)	(-4.96)	(-4.60)
ln(TNA_family)	0.166***	0.061***	0.179***
	(11.99)	(3.84)	(9.16)
Year FE	Yes	Yes	Yes
Observations	38,587	39,192	37,147
Pseudo R2	0.019	0.012	0.14

Table 6: Survival Rates by Manager Tenure and Fund Turnover

This table reports the survival rates of fund-manager combinations by manager tenure and fund turnover. We calculate the survival rate as the fraction of managers with manager tenure n at the end of each year that continue to manage the same fund in the following entire year. A manager stops managing a fund either because he quits or the fund stops operating. First column is the manager tenure (1-15), which is the number of years a manager has worked in the current fund. Second column reports the survival rates for all the fund-manager combinations in our sample. Column three to seven report the survival rates for each turnover quintile separately, and colume eight (5-1) reports the difference between quintile five and one. In this analysis, we define turnover quintiles as funds with an annual turnover below 27%, between 27% and 48%, between 48% and 74%, between 74% and 117%, and above 117%. We use the same thresholds for all the years, so the results are not affected by the variation of turnover thresholds over time.

		Turnover Quintiles					
Tenure	All	1 (low)	2	3	4	5 (high)	5-1
1	0.76	0.82	0.79	0.79	0.76	0.70	-0.12
2	0.71	0.79	0.73	0.71	0.68	0.66	-0.13
3	0.71	0.77	0.76	0.71	0.67	0.65	-0.12
4	0.70	0.77	0.71	0.70	0.67	0.66	-0.10
5	0.69	0.77	0.74	0.72	0.63	0.60	-0.17
6	0.70	0.77	0.70	0.67	0.67	0.68	-0.09
7	0.72	0.78	0.75	0.76	0.65	0.64	-0.13
8	0.73	0.80	0.77	0.73	0.68	0.62	-0.18
9	0.74	0.80	0.78	0.70	0.71	0.67	-0.13
10	0.74	0.81	0.73	0.72	0.71	0.68	-0.13
11	0.74	0.78	0.79	0.73	0.72	0.63	-0.14
12	0.78	0.80	0.78	0.80	0.74	0.75	-0.05
13	0.78	0.83	0.79	0.80	0.76	0.66	-0.17
14	0.77	0.80	0.74	0.74	0.79	0.78	-0.01
15	0.84	0.87	0.81	0.86	0.84	0.74	-0.14

A Appendix

A.1 Proofs

Proof of Lemma 2:

Let

$$\psi(\hat{\phi}, q_i^*) \equiv d_i \hat{\phi} g_i(\mu_i) - C_i'(q_i^*).$$

Then, $\hat{\phi}$ and q_i^* satisfy $\psi(\hat{\phi}, q_i^*) = 0$ under the optimal choice. By the implicity function theorem, we have

$$\frac{\partial q_i^*}{\partial \hat{\phi}} = -\frac{\frac{\partial \psi}{\partial \hat{\phi}}}{\frac{\partial \psi}{\partial q_i^*}} = \frac{d_i g_i(\mu_i)}{C''(q_i)} > 0, \tag{A.1}$$

because $C'' > 0$.

Using the chain rule, we can now represent the fund flow sensitivity using the results in Eqs. (4), (5), and (A.1) as follows:

$$\frac{\partial q_i^*}{\partial r_i} = \frac{\partial q_i^*}{\partial \hat{\phi}} \frac{\partial \hat{\phi}}{\partial \xi} \frac{\partial \xi}{\partial r_i} = \left(\frac{d_i g_i(\mu_i)}{C''(q_i^*)} \right) \left(\frac{\omega}{\gamma + \tau\omega} \right) \left(\frac{1}{g_i(\mu_i)} \right) = \left(\frac{d_i}{C''(q_i^*)} \right) \left(\frac{\omega}{\gamma + \tau\omega} \right).$$

□

Proof of Theorem 3:

Let $X \equiv \Phi \times \mathbb{N}$ where Φ is the set of perceived talents in $\mathbb{R}$. Let $\mathbf{C}(X)$ be the space of functions that are bounded on X, and continuous on Φ. The space $\mathbf{C}(X)$ is equipped with the sup norm. We define an operator T on $\mathbf{C}(X)$ by

$$TV(\hat{\phi}, \tau) \equiv \max \left\{ V_S(\hat{\phi}, \tau), V_L(\hat{\phi}, \tau) \right\}, \tag{A.2}$$

where $V_i(\hat{\phi}, \tau)$ denotes the value of choosing opportunity $i \in \{S, L\}$:

$$V_i(\hat{\phi}, \tau) \equiv \Pi_i(\hat{\phi}) + \kappa(1 - d_i)V(\hat{\phi}, \tau) + \kappa d_i \operatorname{E} \left[\max \left\{ V(\hat{\phi}', \tau + 1), 0 \right\} \middle| \hat{\phi}, \tau \right], \tag{A.3}$$

and $\hat{\phi}'$ is the posterior of perceived talent in case of a successful belief update:

$$\hat{\phi}' \equiv \hat{\phi} + \left(\frac{\omega}{\hat{\gamma} + \omega} \right) (\xi - \hat{\phi}), \quad \text{and} \quad \hat{\gamma}' \equiv \hat{\gamma} + \omega.$$

We prove our first main result of the theorem.

Theorem A.11. *There exists a unique value function $V \in \mathbf{C}(X)$ which solves $TV = V$.*

Proof. Suppose that $V \in \mathbf{C}(X)$. Then, $\mathrm{E}\left[\max\left\{V(\hat{\phi}', \tau+1), 0\right\} \middle| \hat{\phi}, \tau\right]$ is bounded. Because $u(\cdot)$ is bounded, Π_i is bounded from Eq. (16). These findings together with Eq. (A.3) imply that V_S and V_L are bounded. Then, Eq. (A.2) implies that TV is bounded because the maximum of two bounded functions is bounded.

Likewise, because V is continuous in $\hat{\phi}$ at any given τ by the supposition that $V \in \mathbf{C}(X)$, $\mathrm{E}\left[\max\left\{V(\hat{\phi}', \tau+1), 0\right\} \middle| \hat{\phi}, \tau\right]$ is continuous in $\hat{\phi}$. From Eq. (13), it is immediate that q^* is continuous in $\hat{\phi}$ on $[0, \infty)$ because $C'(\cdot) > 0, C''(\cdot) > 0$. Therefore, Eq. (16) implies that Π_i is continuous in $\hat{\phi}$. These findings together with Eq. (A.3) imply that V_S and V_L are continuous in $\hat{\phi}$. Then, TV is continuous in $\hat{\phi}$ because the maximum of two continuous functions is continuous.

Therefore, T maps $\mathbf{C}(X)$ to $\mathbf{C}(X)$. It is straight forward to show that the monotonicity and the discounting conditions are satisfied for the Blackwell's sufficient conditions. Because $\mathbf{C}(X)$ is a complete normed space, the contraction mapping theorem implies that T has a unique fixed point on $\mathbf{C}(X)$, i.e., there exists a unique value function V^* in $\mathbf{C}(X)$. □

We now turn to our second main result that V strictly increases in $\hat{\phi}$. Given the result of Theorem A.11, it is sufficient to show that the mapping T defined in Eqs. (A.2)-(A.3) maps the subset of $\mathbf{C}(X)$ that increase in $\hat{\phi}$ into the subset of $\mathbf{C}(X)$ that strictly increases in $\hat{\phi}$ under the hypothesis (see Corollary 1 to Theorem 3.2 in Stokey and Lucas (1989).)

Lemma A.12. *$TV(\hat{\phi}, \tau)$ is strictly increasing in $\hat{\phi}$ at any given level of τ.*

Proof. The first term in Eq. (A.3) strictly increases in $\hat{\phi}$ because applying the Envelope theorem to Eq. (16) yields

$$\frac{d\Pi_i(\hat{\phi})}{d\hat{\phi}} = u'\left(d_i \hat{\phi} g_i(\mu_i) q_i^*(\hat{\phi}) - C^*(q_i^*) - F\right) d_i g_i(\mu_i) q_i^*(\hat{\phi}) > 0, \tag{A.4}$$

which implies Π_i is strictly increasing in $\hat{\phi}$. The second term in Eq. (A.3) increases in $\hat{\phi}$ because of the supposition that V increases in $\hat{\phi}$.

Because the sufficient statistic for the fund's performance ξ follows a conditional normal distribution with mean $\hat{\phi}$ and variance $1/\hat{\gamma} + 1/\omega$ given $\hat{\phi}$ and τ, we can represent

$$\hat{\phi}'\Big|_{\hat{\phi},\tau} = \left[\hat{\phi} + \left(\frac{\omega}{\hat{\gamma}+\omega}\right)(\xi - \hat{\phi})\right]\Bigg|_{\hat{\phi},\tau} = \hat{\phi} + \left(\frac{\omega}{\hat{\gamma}+\omega}\right)\left(\frac{1}{\hat{\gamma}} + \frac{1}{\omega}\right)\theta = \hat{\phi} + \frac{1}{\hat{\gamma}}\theta, \tag{A.5}$$

where θ is a random variable follows the standard normal distribution. Then, we can obtain the conditional expectation of continuation value of managing the fund as follows:

$$\begin{aligned} \mathrm{E}\left[\max\left\{V(\hat{\phi}', \tau+1), 0\right\}\Big|\hat{\phi}, \tau\right] &= \int_{-\infty}^{\infty} \max\left\{V\left(\hat{\phi}', \tau+1\right), 0\right\} n(\theta) d\theta \\ &= \int_{-\infty}^{\infty} \max\left\{V\left(\hat{\phi} + \frac{1}{\hat{\gamma}}\theta, \tau+1\right), 0\right\} n(\theta) d\theta, \end{aligned} \tag{A.6}$$

where $n(\cdot)$ is the standard normal density function. Because $V\left(\hat{\phi} + (1/\hat{\gamma})\theta, \tau+1\right)$ increases in $\hat{\phi}$ at any level of θ and τ under the supposition that V increases in $\hat{\phi}$, Eq. (A.6) implies that the third term in Eq. (A.3) increases in $\hat{\phi}$. □

We prove that V strictly decreases in τ. Again, it is sufficient to show that the mapping T defined in Eqs. (A.2)-(A.3) maps the subset of $\mathbf{C}(X)$ that decrease in τ into the subset of $\mathbf{C}(X)$ that strictly decreases in τ under the hypothesis.

Lemma A.13. *$TV(\hat{\phi}, \tau)$ is strictly decreasing in τ at any given level of $\hat{\phi}$.*

Proof. The first term in Eq. (A.3) is unaffected by τ. The second term in Eq. (A.3) decreases in τ because of the supposition that V decreases in τ. Similarly as in the proof of Lemma A.12, because $V\left(\hat{\phi} + (1/\hat{\gamma})\theta, \tau+1\right)$ decreases in τ at any level of θ and $\hat{\phi}$ under the supposition that V decreases in τ, Eq. (A.6) implies that the third term in Eq. (A.3) decreases in τ. □

This finishes the proof. □

Proof of Theorem 5:

We first prove two useful lemmas under the condition that d_L and $g_S(\mu_S)$ are sufficiently small and $d_L g_L(\mu_L)$ is fixed to be a positive constant.

Lemma A.14. *$V_S(\hat{\phi}_E(\tau), \tau) > V_L(\hat{\phi}_E(\tau), \tau)$.*

Proof. Suppose not (i.e., $V_S(\hat{\phi}_E(\tau),\tau) \le V_L(\hat{\phi}_E(\tau),\tau)$). Then, from Eq. (A.3), we have

$$0 = V_L(\hat{\phi}_E(\tau),\tau) = \Pi_L(\hat{\phi}_E(\tau)) + \kappa d_L \, \mathrm{E}\left[\max\left\{V(\hat{\phi}',\tau+1),0\right\}\middle|\hat{\phi}_E(\tau),\tau\right],$$

which implies $\Pi_L(\hat{\phi}_E(\tau)) < 0$ and

$$\kappa \, \mathrm{E}\left[\max\left\{V(\hat{\phi}',\tau+1),0\right\}\middle|\hat{\phi}_E(\tau),\tau\right] = -\frac{1}{d_L}\Pi_L(\hat{\phi}_E(\tau)). \tag{A.7}$$

Using $V(\hat{\phi}_E(\tau),\tau) = 0$ and Eq. (18), the supposition that $V_S(\hat{\phi}_E(\tau),\tau) \le V_L(\hat{\phi}_E(\tau),\tau)$ also implies that

$$(d_S - d_L)\kappa \, \mathrm{E}\left[\max\left\{V(\hat{\phi}',\tau+1),0\right\}\middle|\hat{\phi}_E(\tau),\tau\right] \le \Pi_L(\hat{\phi}_E(\tau)) - \Pi_S(\hat{\phi}_E(\tau)). \tag{A.8}$$

Substituting Eq. (A.7) into Eq. (A.8) yields

$$\Pi_S(\hat{\phi}_E(\tau)) \le \frac{d_S}{d_L}\Pi_L(\hat{\phi}_E(\tau)) < 0.$$

Then $\Pi_S(\hat{\phi}_E(\tau))$ should be arbitrarily small as d_L approaches zero. But this contradicts because $\Pi_S(\cdot)$ is bounded below by $u(-F)$ due to Eq. (16). □

Lemma A.15. *$V_S(\hat{\phi},\tau) < V_L(\hat{\phi},\tau)$ when $\hat{\phi}$ is sufficiently large.*

Proof. As $\hat{\phi}$ goes to infinity, $\Pi_L(\hat{\phi})$ converges to $\bar{u}$ where

$$\bar{u} \equiv \sup_w u(w).$$

Then, Eq. (15) implies that $V_L(\hat{\phi},\tau)$ converges to $\bar{u}/(1-\kappa)$. Likewise, Eqs. (10) and (15) imply that

$$V_S(\hat{\phi},\tau) \le u(-F) + \kappa\frac{\bar{u}}{1-\kappa} < \frac{\bar{u}}{1-\kappa}.$$

Therefore, $V_S(\hat{\phi},\tau) < V_L(\hat{\phi},\tau)$ when $\hat{\phi}$ becomes sufficiently large. □

By the result of Lemmas A.14-A.15, and the continuity of V in $\hat{\phi}$, the intermediate value theorem implies that there exists a solution for Eq. (19) on the interval $(\hat{\phi}_E(\tau),\infty)$ to Eq. (19). Furthermore, because $V_S(\hat{\phi},\tau)$ crosses $V_L(\hat{\phi},\tau)$ from above at $\hat{\phi} = \hat{\phi}_S(\tau)$ and

$V_L(\hat{\phi},\tau)$ is strictly increasing in $\hat{\phi}$ (Theorem 3), we conclude that $\hat{\phi}_S(\tau)$ strictly decreases in τ. □

Proof of Theorem 6:

Because the marginal return is infinity if no one invests in opportunity i (i.e., $g_i(0)=\infty$), the aggregate amount invested in each opportunity S and L should be positive in equilibrium, i.e., $\mu_S>0$ and $\mu_L>0$, in which case there are some fund managers strictly prefer long-term investment to short-term investment.

Therefore, Eq. (18), which is the condition for choosing short-term investment, implies that, for those who prefer long-term investment, the following should be true:

$$(d_S-d_L)\kappa\left\{\mathrm{E}\left[\max\left\{V(\hat{\phi}',\tau+1),0\right\}\middle|\hat{\phi},\tau\right]-V(\hat{\phi},\tau)\right\}<\Pi_L(\hat{\phi})-\Pi_S(\hat{\phi}). \tag{A.9}$$

The L.H.S of Eq. (A.9) is the smallest and equal to zero when $\tau=\infty$. Because there exists at least some fund managers investing long-term in equilibrium, there should be some $\hat{\phi}$ such that Eq. (A.9) is satisfied with $\tau=\infty$ (otherwise it won't be satisfied by τ less than infinity.) This implies that $\Pi_L(\hat{\phi})>\Pi_S(\hat{\phi})$ given that level of $\hat{\phi}$.

By the definition of Π_i in Eq. (16) and the monotonicity of $u(\cdot)$, $\Pi_L(\hat{\phi})>\Pi_S(\hat{\phi})$ is true if and only if

$$d_L\hat{\phi}g_L(\mu_L)q_L^*-C(q_L^*)>d_S\hat{\phi}g_S(\mu_S)q_S^*-C(q_S^*), \tag{A.10}$$

where q_i^* solves $d_i\hat{\phi}g_i(\mu_i)=C'(q_i^*)$ for $i\in\{S,L\}$, which is the first order condition in Eq. (13). We define

$$\Psi(y)\equiv yC'^{-1}(y)-C\left(C'^{-1}(y)\right).$$

Then, Eq. (A.10) is equivalent to

$$\Psi(d_L\hat{\phi}g_L(\mu_L))>\Psi(d_S\hat{\phi}g_S(\mu_S)). \tag{A.11}$$

But $\Psi(\cdot)$ is a strictly increasing function because $C' > 0$:

$$\Psi'(y) = C'^{-1}(y) + y\frac{1}{C''\left(C'^{-1}(y)\right)} - C'\left(C'^{-1}(y)\right)\frac{1}{C''\left(C'^{-1}(y)\right)} = C'^{-1}(y) > 0,$$

which implies Eq. (A.11) is true if and only if $d_L\hat{\phi}g_L(\mu_L) > d_S\hat{\phi}g_S(\mu_S)$, or equivalently

$$d_Lg_L(\mu_L) > d_Sg_S(\mu_S).$$

Therefore, if $\Pi_L(\hat{\phi}) > \Pi_S(\hat{\phi})$ is true for some $\hat{\phi}$, it is true for any value of $\hat{\phi} \in (0, \infty)$ where the lower bound of $\hat{\phi}$ is zero because it is the minimum value that ensures existence of a non-negative solution for q_i^* in Eq. (13). □

Proof of Lemma 8:

We first calculate the transition function for the case of exit. From Theorem 4, the optimal voluntary exit becomes a function of state variable $\hat{\phi}, \tau$, which is captured by $I(\hat{\phi}, \tau)$. Then, given state $\hat{\phi}, \tau$, the transition function for the case of exit is

$$Z(\hat{\phi}' = \hat{\phi}, \tau + 1 = X|\hat{\phi}, \tau) = (1 - \kappa) + \kappa(1 - I(\hat{\phi}, \tau)) = 1 - \kappa I(\hat{\phi}, \tau).$$

Conditioning on no exit, the probability of payoff realization is determined by the choice of investment opportunity. From Theorem 5, the choice of investment is a function of state variable $\hat{\phi}, \tau$. Therefore, the probability of payoff realization can be represented as a function of state variable $d(\hat{\phi}, \tau)$. Then, given state $\hat{\phi}, \tau$, the transition function for the case of no update is

$$Z(\hat{\phi}' = \hat{\phi}, \tau + 1 = \tau|\hat{\phi}, \tau) = \kappa I(\hat{\phi}, \tau)(1 - d(\hat{\phi}, \tau)).$$

Now, we work on the case for the belief update conditioning on no exit and payoff realization. Similarly as in Eq. (A.5), we can represent the conditional distribution of $\hat{\phi}'$ given $\hat{\phi}$ and τ as

$$\hat{\phi}'\Big|_{\hat{\phi},\tau} = \hat{\phi} + \frac{1}{\gamma + (\tau + 1)\omega}\theta.$$

where θ is a random variable follows the standard normal distribution. Then, $\hat{\phi}'$ is obtained if

$$\theta = (\gamma + (\tau + 1)\omega)(\hat{\phi}' - \hat{\phi}).$$

Then, given state $\hat{\phi}, \tau$, the transition function for the case of update is

$$Z(\hat{\phi}', \tau + 1 = \tau + 1|\hat{\phi}, \tau) = \kappa I(\hat{\phi}, \tau)(1 - d(\hat{\phi}, \tau))n\left((\gamma + (\tau + 1)\omega)(\hat{\phi}' - \hat{\phi})\right).$$

Finally, all other states than those states in the above can not be reached, which implies the value of the transition function should be zero. □

Proof of Theorem 9:

We first state a stronger condition (henceforth condition M) that implies Doeblin's condition (see, for example, Stokey and Lucas [1989] for further discussion on the condition). Let $Z^N(A|s) \equiv Z$ be the probability of transition from state $s = (\hat{\phi}, \tau)$ to a set A in N steps.

Condition M. There exists $\epsilon > 0$ and an integer $N > 1$ such that for any $A \in \mathbb{R} \times \mathcal{T}$, either $Z^N(A|s) \geq \varepsilon$, for all $s \in S$, or $Z^N(A^c|s) \geq \varepsilon$, all $s \in \mathbb{R} \times \mathcal{T}$.

Let $\varepsilon \equiv \kappa(1 - d_S) = \kappa \min(1 - d_S, 1 - d_L)$. From Lemma 8 and Eq. (24), it is immediate that $Z^N(\hat{\phi}, X|\hat{\phi}, \tau) \geq \varepsilon$ for all $\hat{\phi}, \tau$. Because, for any $A \subset S$, it is either $\hat{\phi}, X \in A$ or $\hat{\phi}, X \in A^c$, we have either $Z^N(A|\hat{\phi}, \tau) \geq Z^N(\hat{\phi}, X|\hat{\phi}, \tau) \geq \varepsilon$ or $Z^N(A^c|\hat{\phi}, \tau) \geq Z^N(\hat{\phi}, X|\hat{\phi}, \tau) \geq \varepsilon$. Then, due to Theorem 11.12 in Stokey and Lucas (1989), there exists a unique stationary distribution ν that solves the functional equation in Eq. (25). □

A.2 Estimation of Decreasing Returns to Scale Parameters

In this section, we provide a detailed description of our estimation procedure of decreasing returns to scale (DRS) parameters at fund level and at investment opportunity level.

We estimate parameters $b_{1,S}$ and $b_{1,L}$ in the decreasing returns to scale functions of different types of investment opportunities, $g_i(\mu_{t,i})$, as follows. We construct a proxy for $\mu_{t,i}$ in the following way. Using data from 1999 to 2018, we generate the quintile break points based on fund-level turnover ratios in this sample period. We label a fund in a given quarter as high turnover if its turnover ratio is higher than the 80th percentile in this sample period and as low turnover if it is lower than the 20th percentile. Then, for each quarter, we compute the ratio between the sum of AUM across all funds labeled either as high or low turnover in our sample, and the aggregate capitalization of all the CRSP stocks. We denote this ratio for high turnover funds as $\mu_{t,S}$, and for the low turnover funds as $\mu_{t,L}$. In addition, to capture the industry level decreasing returns to scale, following Pastor, Stambaugh and Taylor (2015), we also construct the $\mu_{t,tot}$ which is the sum of AUM across all funds in our sample, divided by the aggregate capitalization of all the CRSP stocks. We find that, over the time series, there exist trends in these ratios (μ). Hence, we de-trend $\mu_{t,S}$, $\mu_{t,L}$, and $\mu_{t,tot}$ using a Hodrick-Prescott (HP) Filter with the smoothing parameter set at 1600 (given our data is at the quarterly frequency).

We follow Zhu (2018) in estimating the decreasing returns to scale parameters at the fund level a, the investment opportunities level, and the industry level. More specifically, we first recursively forward-demean the following variables: the lagged $\mu_{t,S}$, $\mu_{t,L}$, and $\mu_{t,tot}$, the dependent variable (fund alphas), and the fund size. We define the recursively forward-demeaned variables for a given fund as

$$\overline{x}_{t-1} = x_{t-1} - \frac{1}{T-t+1}\sum_{s=t}^{T} x_{s-1}, \tag{A.12}$$

where x represents one of the aforementioned five variables and T denotes the total length of the fund. To address the endogeneity issue of the fund size, following Zhu (2018), we regress forward-demeaned fund size ($\overline{q}_{t-1}$) onto actual fund size (q_{t-1}) and use its predicted value ($\overline{q}^{*}_{t-1}$) in the later estimation.[36] The regression equation is as follows:

$$\overline{q}_{t-1} = \psi + \rho q_{t-1} + \nu_{t-1}. \tag{A.13}$$

[36] Please refer to Pastor, Stambaugh and Taylor (2015) for more details of the finite-sample bias introduced by the correlation between fund size and benchmark-adjusted fund returns. As documented in Pastor, Stambaugh and Taylor (2015), industry size can instrument for itself in the estimation of decreasing returns to scale at the industry level, since the correlation between industry size and benchmark-adjusted fund returns is sufficiently small (with a R-squared about 0.006 in their panel regression). The same argument holds at the investment opportunities level as well.

Our estimation equation for decreasing returns to scale at various levels is then given by:

$$\overline{r}_t = b_S \overline{\mu}_{t-1,S} + b_L \overline{\mu}_{t-1,L} + b_{tot} \overline{\mu}_{t-1,tot} + a \overline{q}^*_{t-1} + \epsilon_t. \tag{A.14}$$

In estimating the above equation, we only keep the subsample of fund's observations that belong to either high or low turnover quintiles (i.e., its turnover ratio is either higher than the 80th percentile or lower than the 20th percentile in the sample period).

For high turnover funds, the left hide side variable of the regression $\overline{r}_t$ is the forward-demeaned quarterly CAPM alpha. For the low turnover funds, $\overline{r}_t$ is the forward-demeaned average CAPM alpha over the next 12 quarters. Consistent with the fact that a fund is competing with other funds within the same type of investment strategy, we set $\overline{\mu}_{S,t-1}$ ($\overline{\mu}_{L,t-1}$) to zero for low (high) turnover funds.

[Insert Table A1 about here]

Estimation results are provided in Appendix Table A1. Firstly, consistent with Zhu (2018), we find a significantly negative coefficient in front of $\overline{q}^*_{t-1}$ which indicates that there exists fund-level DRS. Our estimate of this fund-level DRS is $a = .00503$ when fund size is in billion dollars. Secondly, the coefficients in front of both $\overline{\mu}_{t-1,S}$ and $\overline{\mu}_{t-1,L}$ are negative and statistically significant. This result suggests that the intensity of competition for a given type of investment opportunity significantly affects the equilibrium abnormal return of investing in that opportunity. Lastly, we find that the coefficient in front of $\overline{\mu}_{t-1,tot}$ is negative but insignificant. It indicates that the intensity of the two types of investment opportunities captures the majority of the impacts of the mutual fund industry size on the individual fund's returns.

Notice that, when we construct the empirical proxy for $\mu_{t,i}$, we scale the total fund AUM of high- and low- turnover funds by the aggregate capitalization of all the CRSP stocks, instead of the total fund AUM of the mutual fund industry as in our model. Therefore, we multiply b_S and b_L by 16.2%, the average ratio between mutual funds total AUM and the total stock market, to adjust for this difference and get $b_S = -0.294$ and $b_L = -0.016$. Then, we search for the $b_{1,S}$ and $b_{1,L}$ that give $d_S E(\phi_S) b_{1,S} = -0.294$ and $d_L E(\phi_L) b_{1,L} = -0.016$ iteratively under the current set of parameters and get $b_{1,S} = -61.92$ and $b_{1,L} = -14.80$.

Under these two values, we have the average skill of short-term funds at the steady state as $E(\phi_S) = 0.0095$, and that of long-term funds as $E(\phi_L) = 0.0272$.

A.2.1 Sensitivity Tests for The Value of Real Growth Option

Next, we perform sensitivity analyses for the value of the real growth option with respect to the probability d_S, the precision of the prior γ, and the precision of the signal ω. Since we are more interested in this option value for new managers with an initial level of perceived skill, we do this sensitivity test for new managers that have no payoff realization yet ($\tau = 0$) as a function of perceived skill $\hat{\phi}$ in the left panels (Panel A1, B1, and C1) of Figure A1, and managers with initial level of perceived skill ($\hat{\phi} = \phi_0 = 0.005$) as a function of d_S, γ, and ω correspondingly in the right panels (Panel A2, B2, and C2) of that figure.

As reported in Figure A1, this option value remains substantial for new fund managers (with $\tau = 0$ and $\hat{\phi} = 0.005$) under a large range of parameter values of d_S, γ, and ω. This option value from short-term investing stays larger than the higher payoff given by long-term investing (dashed gray lines) for new managers. For example, in Panel A1, the intersection of the dotted blue vertical line and the orange curve ($d_S = 0.1$) stays above the dashed gray curve even if the probability d_S is set to a value of 0.1, close to that of the long-term opportunity ($d_L = 0.04$). As Eq. (18) predicts, this option value increases monotonically with the probability d_S (as shown in Panel A2 of Figure A1), and it mostly stays above the dashed gray line when $d_S \geq 0.1$. Consistent with Lemma 1, the value of the real growth option decreases with an increase in the precision of the prior γ (Panel B2) or the precision of the signal ω (Panel C2). Since an increase in either the precision of the prior or the precision of the signal decreases the uncertainty in a manager's skill, it decreases the value of the real growth option. Because in the belief-updating equation (Eq.(12)) the loading on return outperformance is given by $\frac{\omega}{\gamma+(\tau+1)\omega}$, the option value decreases with γ more for new managers ($\tau = 0$) than for older managers, whereas it decreases with ω more for older managers than for new managers.

[Insert Figure A1 about here]

[Insert Figure A2 about here]

In Appendix Figure A2, we also perform sensitivity analyses with respect to discount rate β, survival rate κ, reservation utility u_0, fund-level DRS parameter a, and investment-opportunity-level DRS parameters $b_{1,S}$ and $b_{1,L}$. The results show that, for new fund managers with a perceived skill of $\phi_0 = 0.005$ (dotted vertical blue line), this option value from short-term strategies remains substantially larger than the higher payoff given by long-term strategies under most parameter values.

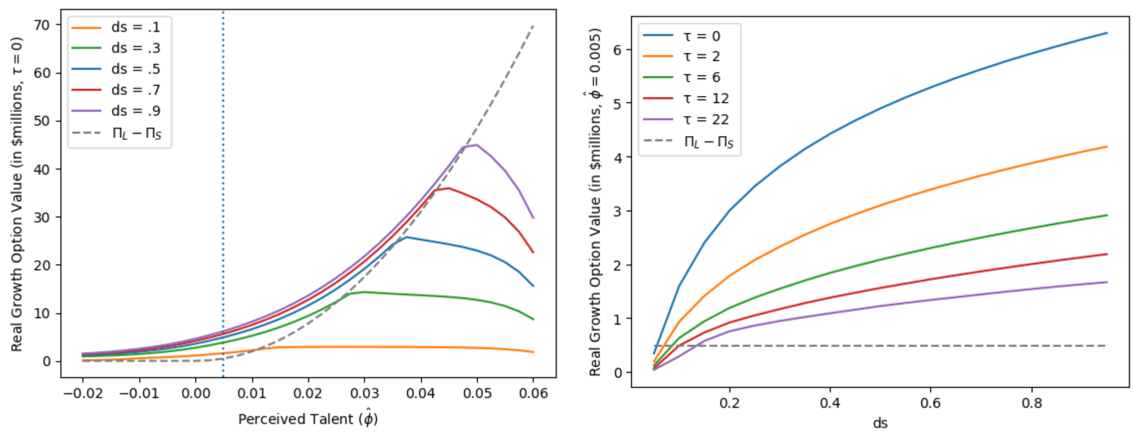
In Panel A1, we perform a sensitivity analysis regarding the discount rate β. Up until now, we have assumed it to be one since a discount rate below one is mathematically isomorphic to a lower survival rate κ in the manager's optimization. As reported in Panel A1, we find that the value of the real growth option of new managers stays large for a discount rate β between 0.91 and 0.99 per quarter. For example, the value of the real growth option for a new manager (with $\hat{\phi}$=0.005 and $\tau = 0$) only decreases modestly from \$4.9 million to \$4.0 million as we decrease the discount rate β from 1 to 0.95 per quarter (0.81 per year), which is substantially smaller than the usual discount rates used in the literature. It remains larger than the dashed gray line (i.e., the higher payoff given by long-term strategies) of \$0.5 million for new mangers. Similarly, this option value stays large for new managers with a survival rate κ between 0.91 and 0.99 (as reported in Panel A2).

In Panel B1, we perform a sensitivity analysis regarding the utility value of the outside option u_0. We find that the value of the real growth option for new manages stays roughly the same when there is zero utility from the outside option (line $u_0 = 0$ in Panel B1), suggesting that the large option value is not caused by a high utility from the outside option. The option value does increase with u_0 if we increase u_0 from 0.02 to as large as 0.18, especially for new managers with a relatively low perceived skill, since they have a higher chance of exiting.

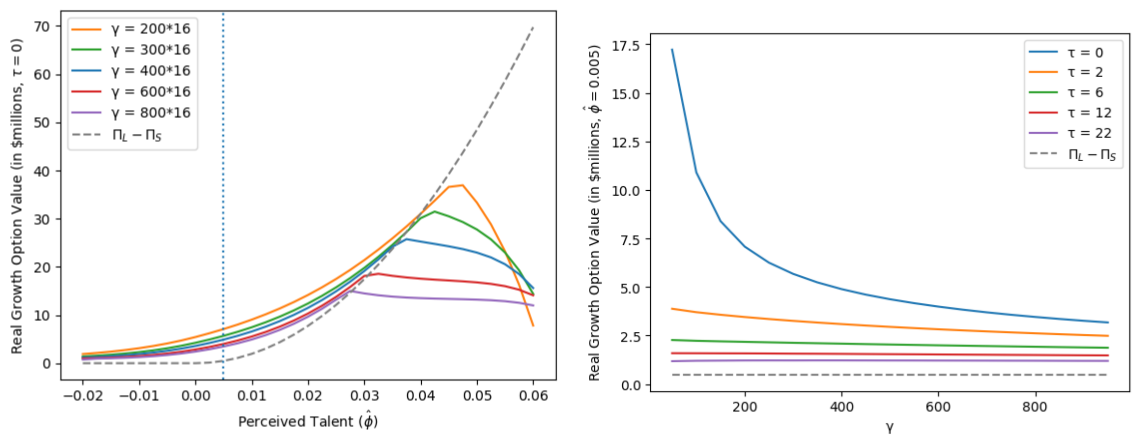
As reported in Panel B2 & C2, the value of the real growth option increases substantially if either the fund-level DRS parameter a or the DRS parameter for long-term opportunities $b_{1,L}$ becomes smaller. The reason is that this option value depends largely on the value added of investing in long-term strategies once a manager has proved herself to be skilled, and a decrease in either of these two DRS parameters increases the value added of investing in long-term strategies substantially. Therefore, compared with the literature which generally uses relatively larger DRS parameters, our estimate of the option value is conservative. For example, if we use the fund-level DRS parameter $a = .001455$ from Zhu (2018), instead of $a = .00503$, this option value would be close to \$20 million per quarter.[37] Meanwhile, since new fund managers have a low perceived skill of $\phi_0 = 0.005$, their additional payoff from investing in long-term strategies (dashed gray curve) does not depend much on these DRS parameters and is close to zero in all scenarios. As a result, this option value stays above the dashed gray curve for new managers under different DRS parameter values. In contrast, the value of the real growth option does not change much with the DRS parameter for short-term opportunities $b_{1,S}$ (as shown in Panel C1), since, in equilibrium, the direct payoff of investing in short-term strategies is always pushed down to a low level by the large option value embedded.

[37]The regression coefficient in column 4 of Table 3 of Zhu (2018) is 0.485 using monthly returns. This value means that for every one hundred million dollars increase in the fund size, the expected monthly alpha will be decreased by 0.485 bps, corresponding to $0.485 \times 3 = 1.455$ bps per quarter. Thus, a one billion dollar increase in the fund size leads to a decrease in quarterly alpha of 0.001455 (i.e., 14.55bps).

Panel A1 & A2: Sensitivity Test of d_S



Panel B1 & B2: Sensitivity Test of γ



Panel C1 & C2: Sensitivity Test of ω

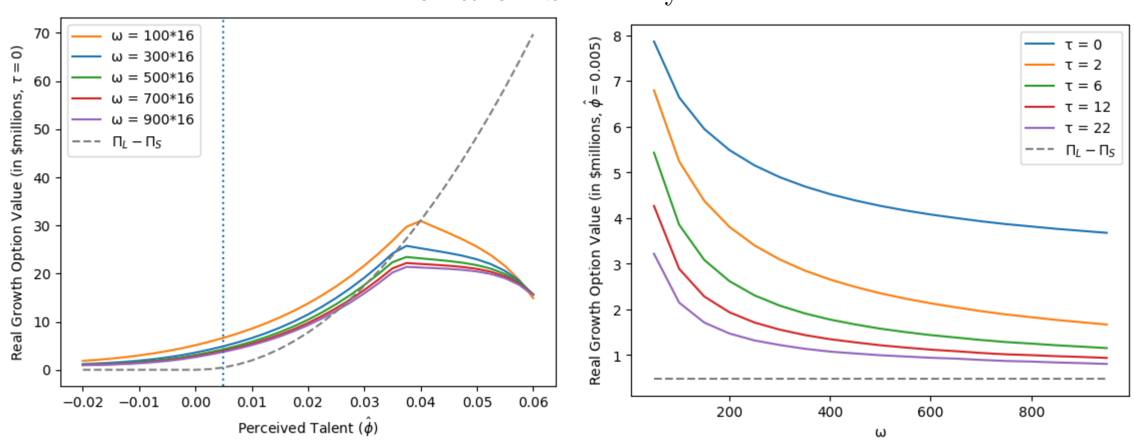


Figure A1: Sensitivity Tests

These figures plot the value of the real growth option for different values of d_S (Panel A), γ (Panel B), and ω (Panel C). The left panels (Panel A1, B1, and C1) are as a function of perceived skill $\hat{\phi}$, given $\tau = 0$. Dotted vertical blue lines are initial level of perceived skill $\phi_0 = 0.005$. The right panels (Panel A2, B2, and C2) are as a function of variable d_S, γ, and ω under investigation for different values of τ, given $\hat{\phi} = 0.005$.

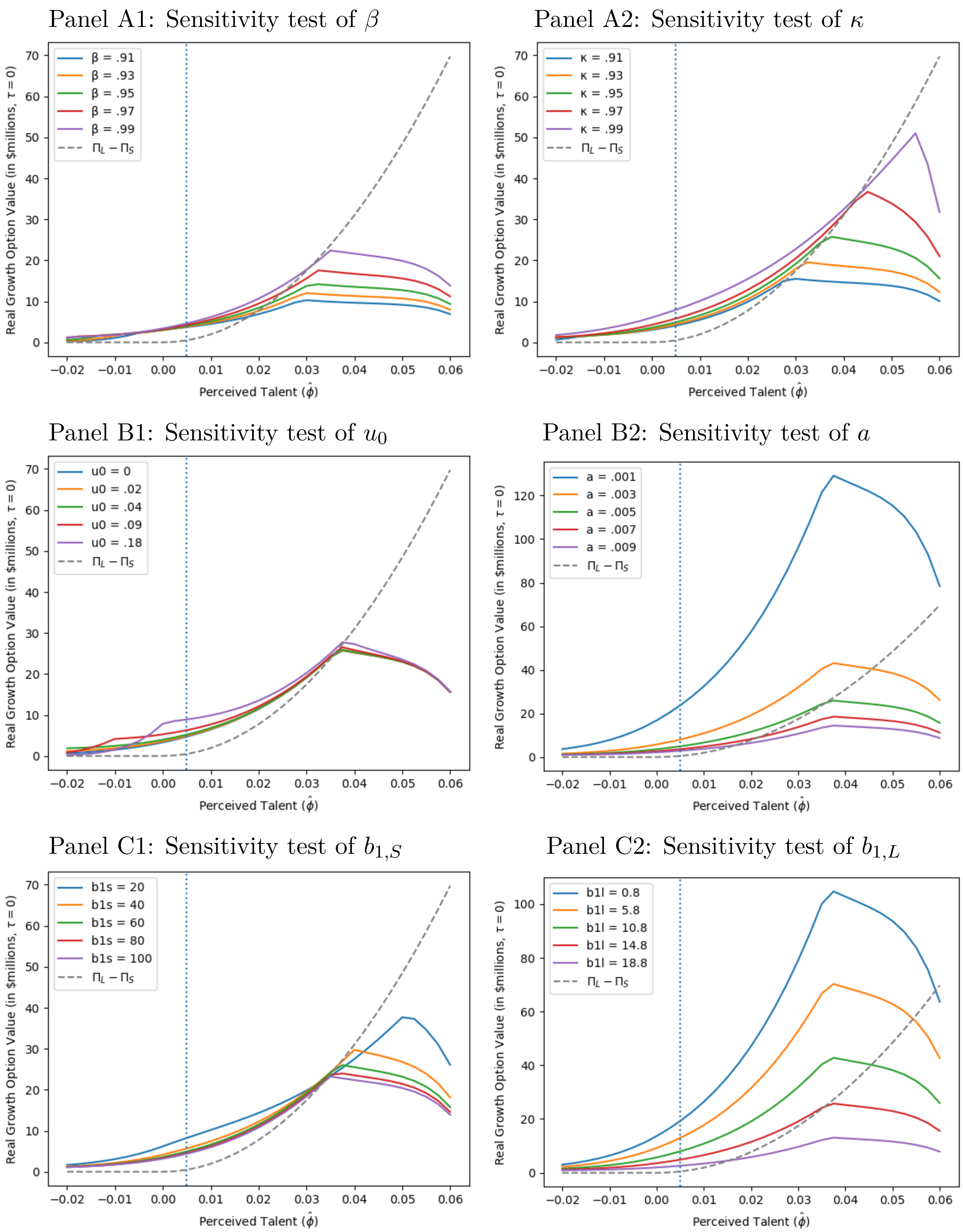


Figure A2: Sensitivity Tests

These figures plot the value of the real growth option for discount rate β, survival rate κ, reservation utility u_0, fund-level DRS parameter a, and investment-opportunity-level DRS parameters $b_{1,S}$ and $b_{1,L}$, as a function of perceived skill $\hat{\phi}$, given $\tau = 0$. Dotted vertical blue lines are initial level of perceived skill $\phi_0 = 0.005$.

Table A1: Estimation of decreasing returns to scale at various levels

This table reports the estimates of decreasing returns to scale at fund level, investment opportunities level, and industry level using Eq. (A.14):

$$\overline{r}_t = b_S \overline{\mu}_{t-1,S} + b_L \overline{\mu}_{t-1,L} + b_{tot} \overline{\mu}_{t-1,tot} + a \overline{q}^*_{t-1} + \epsilon_t,$$

where $\mu_{t-1,S}$, $\mu_{t-1,L}$, and $\mu_{t-1,tot}$ are de-trended lagged total assets under management (AUM) of short-term funds (in top fund turnover quintile), long-term funds (in bottom fund turnover quintile), and all funds correspondingly divided by the aggregate capitalization of all the CRSP stocks. Variable q_{t-1} is lagged fund size in million dollars. Dependent variable r_t is quarterly CAPM alpha for high-turnover funds and average CAPM alpha over the next 12 quarters for low turnover funds. Following Zhu (2018), all variables are forward-demeaned as described in Eq. (A.12), and we use the estimate ($\overline{q}^*_{t-1}$) of regressing forward-demeaned fund size ($\overline{q}_{t-1}$) onto actual fund size (q_{t-1}) as described in Eq. (A.13) to address the endogeneity issue. Consistent with the fact that a fund is competing with other funds within the same type of investment strategy, we set $\overline{\mu}_{S,t-1}$ ($\overline{\mu}_{L,t-1}$) to zero for low (high) turnover funds. Standard errors are clustered at the fund level.

	Value	t-statistics
b_S	-1.809	-9.87
b_L	-0.099	-1.73
b_{tot}	-0.083	-1.28
a	-5.03e-6	-5.23