The Economics of Mutual Fund Marketing *

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Abstract

We uncover a significant relationship between the persistence of marketing and investment skills among U.S. mutual fund companies. Using regulatory filings, we calculate the share of marketing-oriented employees to total employment and reveal a large heterogeneity in its level and persistence. A framework based on costly signaling and learning helps explain the observed marketing decision. The model features a separating equilibrium in which fund companies' optimal marketing employment share responds to their past performance differently, conditional on the skill level. We confirm the model prediction that the volatility of the marketing employment share negatively predicts the fund companies' long-term performance.

Keywords: Marketing Employment Share, Persistence in Marketing, Learning, Costly Signaling, Fund Skill

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1 Introduction

Although mutual funds are expected to generate superior investment returns, fund companies spend a tremendous amount of resources on marketing and distribution. Fund companies not only post advertisements, but also—and more importantly—hire and train sales representatives who actively engage in client networking, develop distribution channels, and provide customer services. It is essential to the operations of the asset management business to allocate various types of human capital. However, little is known about how mutual fund companies determine the share of human capital dedicated to marketing versus other central tasks, including trading, research, and operation, and how the marketing decision shapes mutual fund firms' performance, asset growth, and size distribution.

In this paper, we document stylized facts about companies' marketing efforts by developing a new, labor-based measure: the ratio of mutual fund companies' marketing-oriented employees to total employment (labeled as marketing employment share, or *MKT*). We uncover a significant predictive relationship between the persistence of marketing employment share and mutual fund performance in our sample. We then propose a framework to understand the economics of mutual fund marketing. In the model, fund companies strategically choose marketing strategy based on their true investment skill and past fund performance. Marketing not only lowers costs of information acquisition for investors, but also sends costly signals to persuade fund flows by changing investors' beliefs about their skill level. Our model can reconcile the stylized empirical patterns from the data and offer unique testable predictions.

Our data are from the SEC's Form ADV filings, through which fund companies have been required to report information on their employees' profiles since 2011. The key variable that we examine, *MKT*, equals the fraction of employees who have the legal qualification of sales, and *MKT* is measured at the fund company level.[1] The new data

[1]This is natural given the typical organizational structure of mutual fund companies, in which services

on mutual funds' marketing efforts reveal several interesting stylized facts.

First, marketing efforts are substantially different across fund companies. On average, 24% of fund companies' employees are marketing-oriented, but the cross-sectional standard deviation is significant at 25%. Conventional wisdom typically views marketing as "gloss[ing] over the fact."[2] That is, marketing could influence and convenience investors in a psychological way (naive persuasion). However, this naive persuasion can hardly explain the cross-sectional heterogeneity; otherwise, one would expect all fund companies to hire a sizeable marketing force. Furthermore, the level of *MKT* does not signal funds' performance, which aligns with previous studies using other measures of marketing (e.g., Jain and Wu (2000)).

Second, there exists heterogeneity in the persistence of *MKT*. That is, some funds tend to actively adjust their marketing employment share, while others choose to maintain a stable *MKT* over time. Such a pattern suggests a separation in fund companies' optimal marketing strategy. On average, one observes the persistence of mutual fund marketing in the data, in the presence of the known lack of persistent performance (Carhart, 1997). More interestingly, this persistence of marketing employment ratios is correlated with fund companies' long-term performance. The persistence of marketing, rather than its level, reveals funds' investment skills.

To reconcile the puzzling facts on fund companies' marketing, we propose an economic framework to understand fund companies' strategic allocation of human capital to marketing. Our framework also produces novel and testable implications on the relationships among marketing, fund flows, and fund performance. In our model, marketing matters for the following two reasons. First, in a world with information frictions and performance-chasing investors, marketing helps lower the information acquisition cost

such as marketing, operations, and compliance are shared among the funds within the company. For a more detailed discussion, see Gallaher, Kaniel and Starks (2006).

[2] Vanguard founder John C. Bogle claims that marketing is particularly important when fund performance is largely based on luck. He mentioned that "luck played a bigger role in mutual fund returns than most people understand and that fund marketing often glossed over that fact." – as quoted in *The New York Times* (Gray (2011)).

for investors (*learning*). This is a common view of marketing in the mutual fund industry (e.g., Roussanov, Ruan and Wei (2021); Huang, Wei and Yan (2007)). Second, the marketing effort is a costly signal. Fund companies persuade fund flows through marketing strategies that affect investors' allocation by only changing their beliefs (*costly signaling*). The joint force of learning and signaling is novel to the literature and key to the non-monotonicity of the marketing–performance relationship. Instead of the level of marketing, the persistent effort of marketing indicates the skill type. Depending on the realized past performance and the skill of fund managers, either learning or signaling can be the dominating mechanism that drives fund companies' optimal allocation on marketing.

We see our paper's broad contribution as twofold. The literature on mutual funds finds little support for the existence of persistent superior performance. Regardless of the tremendous effort that fund companies devote to marketing, not surprisingly, we have not identified a significant relationship between marketing effort and fund performance (Jain and Wu, 2000; Bergstresser, Chalmers and Tufano, 2009).[3] We partially fill this gap by recognizing the importance of the persistence of this strategic decision and its link to information available only to the fund company. The persistence of marketing strategy robustly predicts future performance. Our labor-based measure also highlights the company-level marketing policy, which complements the fee-based measures (e.g., broker distribution expense or 12b-1 fee). Second, we theoretically analyze the interaction of the learning and signaling mechanisms and characterize the equilibrium marketing strategy as a non-monotonic function of past performance. Our particular insight can be extended to other industries where the learning of product quality is not perfect.[4]

In our model, fund companies have heterogeneous investment skills (high versus low).[5] There are three periods. At date 0, the fund company observes its type and chooses

[3]Similar findings exist in other product markets. Empirically, advertising or marketing does not seem informative about the product or fund quality.

[4]The theoretical analysis of marketing as a signal argues that advertising conveys (in)direct information about product qualities in various settings (e.g., Nelson (1974); Kihlstrom and Riordan (1984); Milgrom and Roberts (1986)), while empirical evidence is inclusive.

[5]We study the average investment skills at the fund company level instead of the fund level. At the fund

a marketing strategy, a policy that maps each skill type into a marketing employment ratio (the signal). The optimal marketing strategy maximizes the fund company's expected profits, which is the fee from the investors' flow minus the cost of the marketing force. There are two types of investors: performance chasers and sophisticated investors. Both investors do not observe the skill type. They face different information sets and make portfolio allocation decisions at date 1. Sophisticated investors start with more precise prior information sets than the performance chasers. Performance chasers only update their prior beliefs about this unknown type based on past performance. Sophisticated investors can update their beliefs based on past performance and the additional signal of the marketing employment strategy chosen by the fund company. We show a separating equilibrium exists that strictly benefits the fund company.

Performance chasers learn from past performances. At date 0, performance chasers obtain a noisier prior about the skill type than sophisticated investors. However, at date 1, they can pay a participation cost to obtain more precise information about the skill level—the same as sophisticated investors have. Hiring more marketing employees can lower the participation cost, but it is more costly given marketing employees' fixed wages. With a participation cost, the classic result from learning indicates that performance chasers only allocate capital (positive flows) when past performance surpasses a specific threshold. As a result, fund companies only choose to build up a marketing labor force when the past performance is good enough.

Sophisticated investors observe fund companies' marketing strategies in addition to past performance. They update their beliefs about the fund company's skill type after observing the realization of past performances and the marketing employment strategy at date 1. The marketing employment strategy, optimally chosen by the fund companies, then contains information about fund type beyond past performance. In this way, com-

company level, the performance may not be subject to decreasing returns to scale, as previous studies find fund family size to be positively correlated with fund returns (e.g., Chen, Hong, Huang and Kubik (2004)). One can interpret fund companies' skills in a broad sense, which refers to not only trading skills, but also the ability to attract talented fund managers, set up efficient trading infrastructure, and so on.

panies use their overall marketing effort as a costly signal to shape investors' beliefs and persuade flows. The signaling mechanism is the foundation of the persistence of marketing strategies.

Our analysis focuses on pure strategy Nash equilibrium. We show that a separating equilibrium exists when past performance is stronger than a threshold return. The reason is that, when past performance is weak, the information-acquisition channel of marketing is insignificant; in other words, poor performance cannot persuade large inflows from performance chasers. The expected profits of fund companies mainly stem from the flows from sophisticated investors, and the problem is a classic costly signaling game. With the identical marginal marketing cost, the low type always mimics the high type and the equilibrium is pooling. However, when past performance is strong enough, a separating equilibrium exists, in which the high type can achieve a larger inflow from sophisticated investors by hiring a different number of marketing employees and separating themselves from the low type. With even stronger past performance, there is a larger potential benefit of marketing employment through lower participation costs for the low type. Performance chasers' additional inflow makes the marketing signal productive (Spence, 2002). Although the marginal cost of hiring is identical across firms, when past performance is strong, the net cost (net of the profit from the performance chaser's flow) is concave. Hence, the single-cross condition is satisfied and guarantees the separating equilibrium. With the concave cost function, the separating equilibrium is not unique. We show that the efficient equilibrium is the one where the high type chooses to separate from the low type by hiring slightly fewer marketing employees than the low-type funds (and it is too costly for the low-type to mimic, as they would lose flows from performance chasers with less marketing).

The novel implication of our model is a positive relationship between fund companies' long-term performance and marketing persistence. The equilibrium marketing employment policy is a function of historical performance. Building up the marketing labor force is costly. Low-type funds would not want to adopt a high marketing employment share because performance chasers are unlikely to invest after observing a sequence of low performance in the past (smaller potential benefits from performance chasers' flow). However, high-type funds maintain a high marketing employment share and do so even after poor past performance because the commitment to sending investors signals benefits them in the long run. They know that poor performance is likely to be temporary. Therefore, under a reasonable range of parameter values, the volatility of the marketing employment share should be negatively correlated with fund skills. This is our model's central prediction that we later test and confirm in the data.

Costly signaling is key to the marketing persistence and skill relationship: The distinguished persistence in marketing strategy, instead of past performance, reveals the type of investment skills. Models with only costly learning imply the need to vary marketing effort monotonically with respect to past performance for all fund companies. Our model, however, implies that fund companies' marketing employment share is neither monotonic in past performance nor predictive of future performance. High-type funds maintain a stable level of market employment share even following poor performance, while low-type funds only hire following superior performance. When past performance is strong, the high-type funds may efficiently choose a lower level of marketing employment ratio to separate themselves from the low type and still benefit from large sophisticated investors' flow. The persistence, instead of the level of marketing employment share, indicates the skill level.

Our model also implies that fund companies' marketing employment shares are positively correlated with fund company flows. In an environment where marketing strategies signal the fund skill, sophisticated investors do not necessarily withdraw following poor past performance. In other words, signaling dampens the flow response to past performance for high-type funds. On the other hand, through the learning channel, marketing employees help lower the participation cost for performance chasers and, hence, introduce larger new inflows on average for both types of funds. Taking the two effects together, our model implies MKT predicts subsequent fund flow.

We find robust evidence in our sample consistent with our model predictions. We measure marketing persistence by the standard deviation of the marketing employment share over the years, denoted as $Vol(MKT)$. A testable hypothesis from our model is that fund companies with low $Vol(MKT)$ should exhibit superior performance in the long term due to high investment skills. Since a fund company might manage funds investing in various assets and/or with different styles, we adjust fund raw returns with a 6-factor model, which augments Carhart's 4-factor model with an international market factor and a bond market factor. We then take the value-weighted average of alphas of all funds within a firm and regress on $Vol(MKT)$ and a set of fund characteristics as controls, including family size, age, expense ratio, and past performance.

We find significant and supportive evidence. A one-standard-deviation increase in $Vol(MKT)$ is associated with a 3.75 bps lower 6-factor gross alpha per month. Such an effect is economically meaningful given that the average monthly 6-factor gross alpha of fund companies in our sample is -2 bps. We show that this relationship between $Vol(MKT)$ and firm returns is also predictive, where $Vol(MKT)$ is calculated based on MKT observed over a rolling time window. This finding is robust to using alternative risk-adjusted returns and different measurements of marketing persistence. Furthermore, consistent with the model prediction that the level of MKT is an ambiguous signal of fund type, MKT itself is not significantly correlated with the fund alpha. In addition, we show that our findings are not the results of the potential correlation between large labor adjustment costs and fund skills: We find that neither the volatility of total employment nor the volatility of investment-oriented employment share can forecast fund performance.

Our theoretical implication is not restricted to the company's hiring decision of marketing force. We show that the results are robust using the fee-based measure for marketing intensity, such as 12b-1 fees. Also, a natural auxiliary prediction is that $Vol(MKT)$

should be correlated with more value-added, which proxies for skills (Berk and van Binsbergen, 2015). Our evidence supports this conjecture.

In our second empirical test, we focus on another unique model prediction—namely, that the level of *MKT* is unambiguously related to fund company size or fund flow. Such a correlation arises through two channels: (1) high-type funds, which adopt a persistently high level *MKT* distinct from low-type funds, tend to exhibit better performance and more inflow, and (2) low-type funds may increase *MKT* upon good past performance and attract subsequent fund inflow. In the pooled regression, we find this is indeed the case. Funds with high *MKT* tend to experience more fund inflow and AUM growth than low marketing funds. Furthermore, the signaling mechanism is driven by fund skill type, which is likely time-invariant. In this sense, if we add firm fixed effects into the pooled regression, the total effect should be weaker. The empirical evidence confirms this conjecture. Taken together, these results provide additional support to our model as a relevant economic mechanism in the real world.

Literature review Our paper contributes to the literature in the following ways.

Theoretically, we propose a novel framework and uncover the strategic role of marketing in the mutual fund literature. Marketing strategies are used not only as a tool to facilitate information acquisition but also for signaling. Like the work of Huang, Wei and Yan (2007), which emphasized the importance of participation costs in driving the fund flow, we extend the learning model with costly signaling to understand the optimal choice of mutual funds' marketing strategy. Recent work by Roussanov, Ruan and Wei (2021) showed that marketing is as important as performance in determining mutual fund size. Our paper complements theirs by highlighting the dominant role of signaling through marketing policy for fund companies. We focus on the relationship between the persistence of marketing efforts and the performance of fund companies. Other non-investment-related decisions also reveal essential information. Stein (2005) shows that the choice of being open-ended can be a signal of high quality so both high and low-quality funds pool to open-end in order not to lose their flows. van Binsbergen, Han, Ruan and Xing (2021) studied mutual fund investing under managers' career concerns and showed that the choice of investment horizons also reveals the quality of managers.

Although costly signaling is a workhorse in the theoretical marketing literature, it has not been used to study fund companies' non-investment-related decisions. A classic costly signaling framework tends to conclude that the marketing effort conveys the direct and indirect product quality information (Kihlstrom and Riordan, 1984; Milgrom and Roberts, 1986). Unlike those classic settings, the quality of mutual funds is not verifiable, and marketing as a signal is costly and productive. The imperfect learning then allows the optimal marketing policy to depend on the observed past performance, which is key to understanding the heterogeneity of the marketing effort across fund companies. Consistent with Jain and Wu (2000), who showed no performance-related signal in advertisements, our theory predicts that it is the persistence of the marketing effort, instead of the level of marketing effort, that contains information about management skills. More generally, our results can be extended to other dimensions of fund companies' strategic decisions beyond investment management.[6]

Ours is not the first paper to analyze mutual funds' marketing efforts. Most previous work has used expense ratios, 12b-1 fees, or expenditures on advertisements as a proxy for mutual funds' marketing activities. Sirri and Tufano (1998), for example, found that higher total fees are associated with stronger flow-performance sensitivity in the high-performance range, but they identified a negative relationship between fees and fund flows. Meanwhile, Gallaher et al. (2006) showed that advertising expenditures do not directly affect the subsequent fund flows at the fund family level. However, our results based on human capital confirm that marketing effort does increase in fund family size

[6] Recent work by Buffa and Javadekar (2022) adopts the signaling framework to understand mutual fund managers' choice of different dimensions of activeness. However, ours focuses on the non-investment-related choices of fund families.

and predicts subsequent flows. For robustness purposes, we also use the fee-based measure to construct the persistence of marketing effort and confirm the model prediction. Our findings complement existing works on advertising and marketing in financial markets, which focus on whether the broker or advertising helps investors find better financial products due to the potential conflicts of interest (Christoffersen, Evans and Musto (2005), Bergstresser et al. (2009), Gurun, Matvos and Seru (2016)).

Our paper is also related to the literature on the role of fund families. Previous studies have found that fund companies might take various strategic actions to enhance funds' performance or value added to the family, including cross-fund subsidization (Gaspar, Massa and Matos, 2006), style diversification (Pollet and Wilson, 2008), insurance pool for liquidity shocks (Bhattacharya, Lee and Pool, 2013), and matching capital to labor (Berk, van Binsbergen and Liu, 2017). We show that fund companies can strategically choose their marketing strategies to enhance fund flow.

2 Data and Stylized Facts

In this section, we describe the main stylized facts of mutual fund marketing using the new dataset we constructed based on the SEC's Form ADV filings. Investment companies that manage more than $100 million in assets must file Form ADV annually. Item 5 in Part 1A of Form ADV requires investment companies to report employment information, including the total number of employees (Item 5.A) and the breakdown by functions. We are interested in Item 5.B(2), which reports the number of employees who are registered representatives of a broker-dealer. Legally conducting trading and sales of mutual fund shares in the U.S. requires being a registered representative.[7] The key variable of our paper, marketing employment share (*MKT*), is defined as the fraction of registered represen-

[7]A representative who has passed the Series 6 exam can only sell mutual funds, variable annuities, and similar products, while the holder of a Series 7 license can sell a broader array of securities. According to a communication with the SEC, the number reported in Item 5.B(2) includes both types of brokers.

tatives to total employees.[8] Given that the asset management industry is human capital intensive (its production function features various types of human capital or skills as the inputs), our labor-based measure *MKT* captures how much human resources the fund allocates toward marketing and sales versus other key functions, such as investment, research, and operations. In Item 5.B(1), companies report their number of employees who perform investment advisory functions (including research).[9]

MKT can potentially better capture funds' marketing efforts at the company level, where most of the meaningful marketing strategy is determined. In fund companies, portfolio management and investment decisions are typically made at the fund level, while the company is responsible for marketing, operations, and compliance for all funds. Based on this distinction, measures of marketing efforts should refer to the company level (Gallaher et al., 2006). In comparison, fee- or expenditure-based measures, such as 12b-1 or advertisement spending, capture the marketing cost that individual funds pay to external partners. For example, 12b-1 fees refer to the fund's expenses on distribution channels and advertisements. In addition, the 12b-1 fee is a cost of fund flows, so fund companies compete by charging lower fees to attract flows. Hence, a higher 12b-1 fee is likely to capture lower marketing strength (Barber, Odean and Zheng, 2005).[10]

Our labor-based measure complements the commonly used fee-based measures. We acknowledge *MKT* might not capture the entire cost of marketing and likely leads to an underestimation of a firm's actual allocation to marketing (as employees without the broker representative license can still serve clients). For most of our analysis, we also offer evidence using fee-based measures to ensure robustness.

Form ADV includes advisers to all types of investment vehicles, such as mutual funds, hedge funds, private equity, and pension funds. As this paper focuses on mutual fund

[8]We drop obvious data errors here, such as when *MKT* is larger than one. The dropped observations account for less than 2% of the whole sample.

[9]Kostovetsky and Manconi (2018) used employment data from Form ADV and found that investment-related employees contribute little to fund performance.

[10]In the data, the fee-based measures are negatively correlated with fund size and flows.

advisers, we manually merge Form ADV data with the CRSP Survivor-Bias-Free US Mutual Fund Database to implement our empirical tests. The merge is conducted using the names of fund advisory companies.[11] More details on Form ADV, the variable *MKT*, and our sample construction are in Appendix C. Finally, our sample includes 711 unique fund companies and 3,776 company–year observations from 2011 to 2020.

Next, we document several stylized facts regarding mutual funds' marketing efforts, measured by both *MKT* and 12b-1 fees. The first is the sizeable cross-sectional variation of *MKT*. Panel A of Table I reports the summary statistics of *MKT*. *MKT* is on average 23.7% with a substantial cross-sectional variation, standard deviation of 24.4%. This suggests that fund companies adopt different strategies in allocating human capital to marketing. The fund company level 12b-1 fee as a ratio of AUM also exhibits a significant cross-sectional variation: The mean of *Firm 12b-1* is 0.33% with a standard deviation of 0.17%.

The second stylized fact is the persistence of *MKT*. Following the procedure of Carhart (1997), we sort fund companies into quintiles based on *MKT* at each year and track the average *MKT* of each quintile over the next five years in the upper panel of Figure VII. One can find that high *MKT* companies continue to have high *MKT* over the following years. The lower panel replicates the finding of Carhart (1997) at the fund company level, using gross returns to measure performance. We find that there is weak persistence in performance. The empirical facts shown in both panels of Figure VII suggest that mutual fund companies exhibit persistent marketing in the lack of persistent performance.

More importantly, there is substantial heterogeneity in the persistence of *MKT*. That is, although some fund companies tend to make persistent marketing efforts, others choose to adjust *MKT* frequently over time. To measure the persistence of *MKT*, we calculate the standard deviation of *MKT* over time for each company, labeled as $Vol(MKT)$. In the upper panel of Figure VIII, we sort fund companies into quintiles based on $Vol(MKT)$, and the y-axis plots the distribution (i.e., the minimum, maximum, median, and the first

[11]For simplicity, we use the terms fund family, fund company, and fund advisory firm interchangeably in this paper.

and third quartiles) within each quintile. One can see that Group 1, the most persistent one, exhibits little variation in *MKT*, while Group 5 shows high variation of *MKT* over time. In the lower panel, we repeat the same analysis using the 12b-1 fee ratio: the pattern is similar, while there is little heterogeneity in the low $Vol(12b1)$ groups in the sample.

Motivated by the stylized fact, in the next section we develop a model to analyze fund companies' optimal choice of marketing efforts and determine why and how fund companies' persistence of *MKT* is related to fund type.

3 Model of Mutual Fund Marketing

In this section, we propose a model in which mutual funds choose their marketing policy to maximize the fund profits. In our model, marketing facilitates learning, and the mutual fund's marketing effort also acts as a signal for the manager's ability.

3.1 Environment

Consider an economy with three periods: $t = 0, 1, 2$. Investors allocate their wealth between a risk-free bond and an array of active mutual funds managed by fund companies. For simplicity, we assume that each fund company manages the portfolio of a mutual fund with one manager, and henceforth the fund company and mutual fund and its manager are all indexed by i.[12] The return on the risk-free bond r_f is normalized to zero for each period. Mutual funds differ according to their manager's ability to generate returns. The mutual fund i produces a risky return of r_{it} at time $t = 0, 1, 2$ according to the following process:

$$r_{it} = \alpha_i + \epsilon_{it},$$

[12] The marketing strategy is set at the fund company level. In practice, mutual fund companies typically manage more than one fund. We assume that each fund company manages only one mutual fund for simplicity. We interpret the mutual fund performance r_{it} as the average fund performance or the performance of the flagship fund in a fund company.

where $\alpha_i \in \Omega$ stands for the unobservable ability of the manager of fund i and ϵ_{it} represents the idiosyncratic noise in the return of fund i, which is i.i.d. both over time and across funds with a normal distribution, $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$. Suppose there are two types of fund managers, $\Omega = \{\alpha_l, \alpha_h\}$, where $\alpha_1 < 0 < \alpha_h$, and the fund i manager's type α_i could only be observed *privately* by the manager.

There are two types of rational investors: performance chasers and sophisticated investors. The population mass is normalized to one for sophisticated investors (indexed by s) and λ_i for performance chasers (indexed by n) for fund i. Both types of investors have CARA utility function and maximize their utilities over the terminal wealth W_2^j at date 2,

$$U^j = E(-e^{-\gamma W_2^j}), \quad j = s, n.$$

Sophisticated investors are endowed with initial wealth W_0 and $X_{i0}^s > 0$ unit of fund i at date 0. They have a prior that $\alpha_i = \alpha_h$ with probability q. Sophisticated investors can update their beliefs based on past performance and additional information regarding the company's marketing strategy. We discuss the information set I_1^s next in detail. Based on the posterior, they choose the optimal allocation X_{i1}^{s*} of fund i at date 1. Sophisticated investors can be thought of as existing fund investors (with $X_{i0}^s > 0$), who have better information of q and understand the signaling game of marketing.

Performance chasers are endowed with the same initial wealth W_0 and $X_{i0}^n = 0$ unit of fund i at date 0. They only know that $\alpha_i = \alpha_h$, with probability drawn from a uniform distribution $\mathcal{U}[0, 1]$. In other words, performance chasers know there are two types of fund managers, $\{\alpha_h, \alpha_l\}$, but they do not have the same prior probability q as sophisticated investors. Instead, the probability of each type for performance chasers is indifferent between 0 and 1. We denote the prior of this probability for the performance chaser as $\tilde{q}$. In addition, at date 1, performance chasers can improve their information set by paying the participation cost c_i. More specifically, they learn the actual q, the same prior as sophisticated investors. Based on their improved information set I_1^n, performance chasers optimally allocate their wealth as X_{i1}^{n*} at date 1. Performance chasers can be viewed as potential new buyers of mutual funds.

Marketing Fund companies maximize revenues generated from choosing different marketing strategies by hiring a certain number of marketing employees.[13] Marketing can increase fund flow through two channels. First, marketing facilitates learning. Marketing can lower the information acquisition cost c_i of fund i for performance chasers. Let M be some sufficiently large set of marketing employment realizations, and the participation cost is a function of the number of marketing employees $m_i \in M$. We assume that the participation cost function $c_i = c(m_i)$ is decreasing and concave in m_i—that is,

$$c(\cdot) > 0, \quad c'(\cdot) < 0, \quad c''(\cdot) < 0 \tag{1}$$

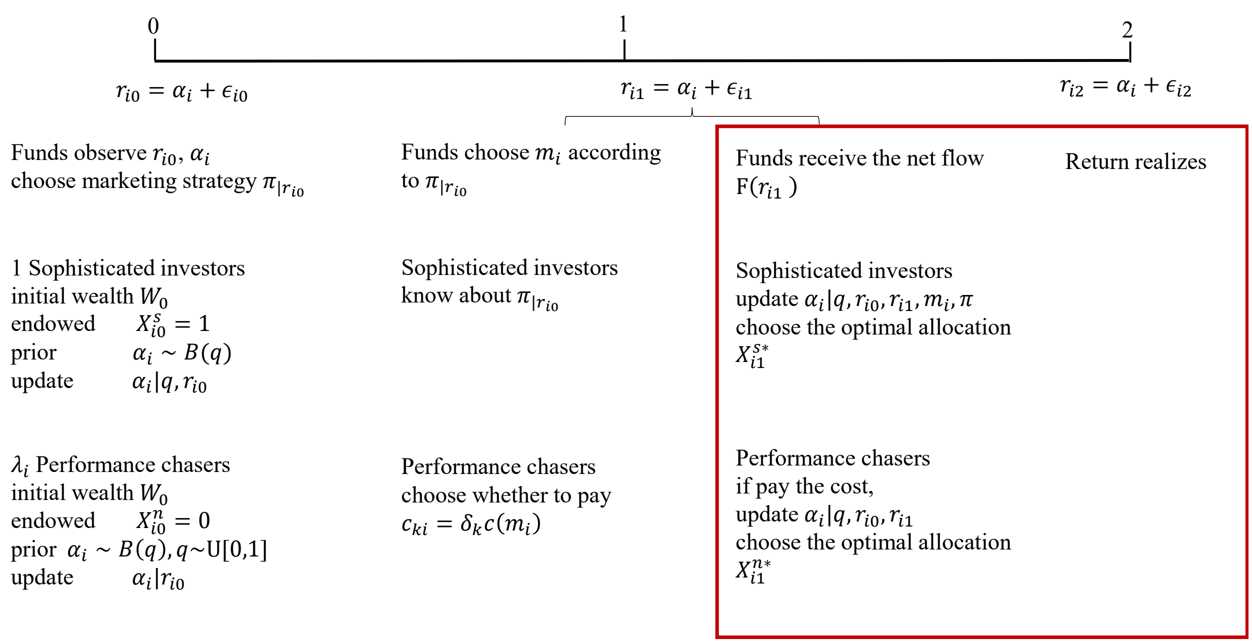
This assumption is made in many economic analyses. The more marketing employees hired, the lower the participation cost. The marginal benefit of hiring one more marketing employee decreases when the fund company already has a large marketing group. This property is also consistent with the assumption made in the literature on information acquisition that investors' objective function is usually convex in signal precision. The more marketing employees the fund hires, the lower the participation cost and the more precise the signal investors are likely to gain.

Second, marketing is also a signaling device. How much effort a fund company puts into marketing can reveal relevant information for investors' portfolio decisions. Beyond communicating with the marketing force about the fund's performance and trading strategies, investors update their beliefs about its quality from the observed marketing intensity performed by a fund company. Marketing as a signaling device is costly, and it has been shown that marketing can be informative about product qualities, both directly and indirectly (Nelson, 1974; Kihlstrom and Riordan, 1984; Milgrom and Roberts, 1986).

[13]The M can be broadly interpreted as the overall marketing effort, encompassing both advertisement strategies and distribution channel costs. Our model is not confined to marketing employment policies; it has the versatility to address general strategic decisions of fund companies' marketing efforts.

In our setting, the fund company observes r_0 and its type, and then determines a marketing strategy at date $t = 0$. A marketing strategy is a function $\pi : \Omega \times M \to [0,1]$ such that $\sum_{m \in M} \pi(\alpha, m) = 1$. $\pi(\alpha, m)$ stands for the probability that the fund i hires m marketing employees when it observes its type α. The marketing employment m is the costly signal. In other words, π is a density function that specifies the statistical relationship between truth ($\alpha \in \Omega$) and the fund company's choice ($m \in M$). The fund company's choice $m(\cdot)$ is allowed to be the policy as a function of other state variables. We will discuss in detail in Section 3.2.3 how fund companies strategically choose the marketing strategy to reveal their types and attract flows.

Figure I. Decision Making Process



Note: $B(q)$ is the prior distribution of α (i.e. $\alpha = \alpha_h$ with probability q, $\alpha = \alpha_l$ with probability $1 - q$).

Timing Figure I summarizes the timing of the model. At $t = 0$, mutual fund companies choose the marketing strategy π *after* observing r_{i0} and their types. After the realization of r_{i0}, both the sophisticated investors and performance chasers update their prior. We use q^j_t to denote the posterior probability for $j = s, n$ at date t. At date $t = 0$, both investors update their belief based on the observed performance r_0, so $q^n_0 = Prob(\alpha_i = \alpha_h | r_0, \tilde{q} \sim$

$Unif[0,1]$), $q_0^s = Prob(\alpha_i = \alpha_h | r_0, q)$. At $t = 1$, funds choose m_i with probability $\pi(\alpha_i, m_i)$. The sophisticated investors observe the marketing strategy π and the realization m_i. The information set of sophisticated investors then becomes $I_1^s = \{q, r_{i0}, r_{i1}, m_i, \pi\}$, and the sophisticated investors again update their posterior q_1^s based on I_1^s. The performance chasers make participation decisions after observing r_{i1}. An important assumption here is that performance chasers do not pay attention to the company's marketing strategy, and they only learn from past performances. Performance chasers only have to decide whether to pay for the participation cost to learn about q at date 1. Thus, the information set $I_1^n = \{q, r_{i0}, r_{i1}\}$ is different from the information set I_1^s of sophisticated investors. Performance chasers update their posterior q_1^n based on I_1^n. Marketing acting as a signal of funds' skill is only known by sophisticated investors. Both performance chasers and sophisticated investors choose the optimal allocation based on their information set. Returns are realized at $t = 2$.

At date $t = 0$, mutual fund companies choose the marketing strategy $\pi(\alpha, m)$ given investors' optimal portfolio allocation. We solve the marketing strategies in equilibrium backward in the next section.

3.2 Marketing Strategy in the Equilibrium

In this section, we derive the equilibrium in the signaling game in three steps. We start by first deriving the optimal portfolio allocation of investors as a function of their beliefs at date 1. Second, we solve the performance chasers' participation problem to construct the fund's utility, which equals the management fees from managing investors' assets minus the salary paid to the marketing employees. Third, we show that the optimal marketing strategy at date 0 in the equilibrium is truth-telling when the past performance is sufficiently strong.

3.2.1 Portfolio Allocation

At date 1, performance chasers choose to pay the cost, and sophisticated investors allocate their capital to the fund based on their information set. As previously mentioned, the performance chasers who pay the cost have the information set as $I_1^n = \{q, r_{i0}, r_{i1}\}$. Meanwhile, sophisticated investors' information set is $I_1^s = \{q, r_{i0}, r_{i1}, m_i, \pi\}$. For simplicity, we assume that each investor only invests in one fund. Henceforth, we abstract the subscript i in the investor's problem. Problem (2) solves for the optimal portfolio allocation:

$$\max_{X_1^j \geq 0} \quad E(-e^{-\gamma W_2^j} | I_1^j) \qquad\qquad s.t \quad W_2^j = W_1^j + X_1^j r_2, \tag{2}$$

where $W_1^j = W_0 + X_0^j(1 + r_1), j = s, n$. The following lemma summarizes the optimal allocation for both sophisticated investors and performance chasers.

Lemma 1. *At date $t = 1$, the optimal allocation of any investors who have a posterior belief that the fund manager has a higher ability with probability $q_1^j := Prob(\alpha_i = \alpha_h | I_1^j), j = s, n$ is*

$$X_1^{j*} = \begin{cases} x(q_1^j) & if \quad q_1^j \alpha_h + (1 - q_1^j)\alpha_l > 0 \\ 0 & if \quad q_1^j \alpha_h + (1 - q_1^j)\alpha_l \leq 0 \end{cases}$$

where $x(q_1^j) > 0$ and strictly increases in q_1^j.[14]

Lemma 1 indicates that there exists a threshold of $\hat{r}_1^j, j = s, n$ such that the optimal allocation $X_1^{j*} = x(q_1^j)$ is positive only if $r_1 > \hat{r}_1^j$. Intuitively, only when the expected return of the fund is positive, $q_1^j \alpha_h + (1 - q_1^j)\alpha_l > 0$, indicating that the return at date 1 is higher than a certain threshold, investors would like to hold the fund.

3.2.2 Participation Decision

Performance chasers make the optimal decision by comparing the expected benefit with the participation cost if they pay. At date 0, performance chasers observe the risky

[14]See appendix B.1 for detailed proof and properties of $x(q_1^j)$.

return r_0 and update their belief on the distribution of the manager's ability q_0^n based on equation (B.3). Investors then observe fund return r_1 and update their beliefs based on the available information. They would learn about the prior q as sophisticated investors if they pay the cost. The updated belief is q_1^n defined in equation (B.4). Note that the participating performance chasers do not observe the company's marketing strategies, so their posterior is not based on the marketing plan $\mathcal{M}$.

We allow each performance chaser to have different levels of financial sophistication and different learning costs. To capture the heterogeneity, we follow Huang et al. (2007) and assume that performance chaser, indexed by k, has the participation cost $c_k = \delta_k c(m)$, where $\delta_k \sim \mathcal{U}[0,1]$. Given the optimal investment allocation to the mutual fund in Lemma 1, we can calculate the certainty-equivalent wealth gain from investing in new funds:

$$\max_{X_1^n \geq 0} \quad E(-e^{-\gamma W_2^n} | r_0, r_1) = \exp(-\gamma(g(r_1; r_0) - c_k))).$$

Performance chaser k chooses to participate if and only if the wealth gain is larger than the learning cost c_k.

Lemma 2. *Given r_0, the certainty-equivalent wealth gain $g(r_1; r_0)$ satisfies*

$$\exp(-\gamma g(r_1; r_0)) = \int_0^{+\infty} e^{\frac{1}{2}\gamma^2 \sigma_\epsilon^2 X_1^{n*}} (\tilde{q}_1^n e^{-\gamma \alpha_h X_1^{n*}} + (1 - \tilde{q}_1^n) e^{-\gamma \alpha_l X_1^{n*}}) f(z) dz$$

where

$$\tilde{q}_1^n \equiv Pr(\alpha = \alpha_h | r_0, r_1) = \frac{q_0^n(z)}{q_0^n(z) + (1 - q_0^n(z)) \exp(-\frac{(2r_1 - \alpha_h - \alpha_l)(\alpha_h - \alpha_l)}{2\sigma^2})} \tag{3}$$

$q_0^n, f(z)$ are defined by equation (B.3), X_1^{n*} by lemma 1.

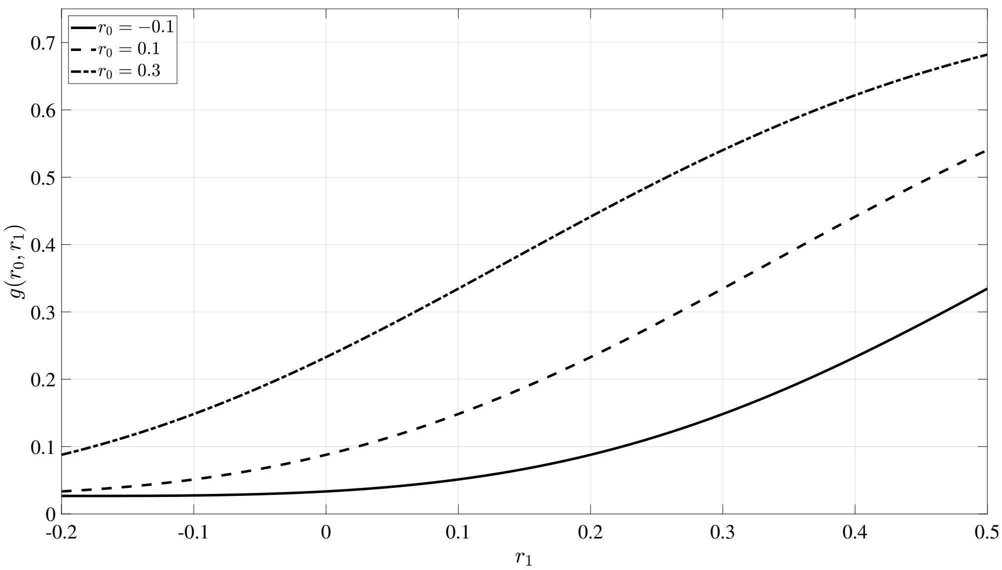
Performance chasers base their participation decision only on the fund's past performance $\{r_1; r_0\}$. We obtain the certainty-equivalent wealth gain $g(r_1; r_0)$ as a function of q_0^n and r_1. q_0^n is monotonically increasing in r_0. $g(r_1; r_0)$ is increasing in both r_1 and r_0, as plotted in Figure II.[15] For performance chaser k with the participation cost $c_k = \delta_k c(m)$, there exists a unique cutoff return $\hat{r}(c_k)$ such that the investor chooses to participate if and

[15] See Appendix B.2 for the proof.

only if $r_1 \geq \hat{r}(c_k)$.

Figure II. Relation Between the Gain Function and Fund Returns

The solid line corresponds to investors' wealth gain $g(r_1)$ as a function of r_1 when the past return $r_0 = -0.1$, the dashed line corresponds to the gain function $g(r_1)$ when $r_0 = 0.1$, and the dotted line corresponds to $r_0 = 0.3$. Other parameters are $\gamma = 1, \lambda = 1, \sigma_\epsilon = 0.2, \alpha_h = 0.25, \alpha_l = -0.07, q = 0.5, w = 0.1$, where γ is the risk aversion of the CARA investor, and λ is the relative population weight of performance chasers. Fund return is $r_{it} = \alpha_i + \epsilon_{it}$, where $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ is i.i.d. over time and across funds. After observing the marketing information at date 1, performance chasers have the certainty-equivalent wealth gain $g(r_0, r_1)$ based on their updated belief.



3.2.3 Separating Equilibrium

Given the optimal portfolio allocation in Section 3.2.1 and participation decision in Section 3.2.2, we now determine the optimal marketing strategy at date 0.

At date 0, the type of ability is revealed to fund managers. Given their abilities and date 0 performance r_0, fund companies choose the optimal marketing strategy $\pi^*(\alpha, m)$, and marketing employment m^* to maximize the net profits, equal to the expected flow of sophisticated investors and performance chasers minus the salary paid to marketing employees. As participation cost is a function of the level of marketing force m given the observed past return r_0, m directly impacts the expected net profits by altering the flow of performance chasers and wage costs. At date 0, fund companies maximize the *expected* *net profits* $U^F(\alpha_i, m, X_1^s)$ in equation (4) for a given ability type α_i and r_0,

$$U^F(\alpha_i, m, X_1^s) = f \int_{-\infty}^{\infty} \left[X_1^s + \lambda \min(1, \frac{g(r_1; r_0)}{c(m)}) X_1^{n*} \right] \phi(r_1|\alpha_i, \sigma_\epsilon) dr_1 - wm, \tag{4}$$

where $r_1 \sim N(\alpha_i, \sigma_\epsilon)$, $\phi(r_1|\alpha_i, \sigma_\epsilon)$ is the corresponding probability density function, $i = h, l$. f is the management fee charged by the fund, and w is the wage per marketing employee. The optimal allocation rule for sophisticated investors X_1^s follows Lemma 1. We assume that the cost of hiring managers and other skilled employees is fixed in this context for simplicity.[16] The overall expected revenue consists of two parts: (1) the expected revenue from the sophisticated investors and (2) the expected revenue from the performance chasers. Based on the insight of Lemma 1, improved revenue from sophisticated investors can be achieved through either a stronger past performance, denoted as r_0, or an increased belief among investors that the likelihood of being a high-type investment is high. The second component is the income generated from the information acquisition channel. Based on Lemma 2, both the participation decision and the strength of past performance play a key role to increase this part of income.

We focus on pure strategies. We define the Nash Equilibrium in Appendix A. The equilibrium is characterized by the schedule of marketing profits, the sophisticated investor's portfolio allocation X_1^s, and optimized employment choice given the portfolio allocation of sophisticated investors. The following proposition shows the conditions of the existence of the separating equilibrium in the space of pure strategy.

Proposition 1. *Given $r_0 \geq \hat{r}$, the single crossing property is satisfied. A separating equilibrium exists and satisfies the intuitive criterion. A mutual fund company's optimal marketing strategy*

[16]We abstract from the employment decision of investment managers and other occupations within fund companies. Thus, the number of marketing employees, denoted by m, can be seen as the proportion of marketing employees relative to the number of fund managers, assuming that the count of portfolio managers remains constant. The wage w represents the ratio of marketing employees' wages to those of fund managers.

is heterogeneous conditional on its types.

$$q_1^s = \begin{cases} 1 & if \quad \pi^*(m, \alpha_h) > \pi^*(m, \alpha_l) \\ 0 & if \quad \pi^*(m, \alpha_h) \leq \pi^*(m, \alpha_l) \end{cases}$$

Proposition 1 shows that a separating equilibrium exists when past performance r_0 is not too weak, $r_0 \geq \hat{r}$. The proof is in Appendix B.3.

Figure III illustrates the intuition behind Proposition 1. We plot the expected profits as a function of the marketing employment m given different levels of past performances, r_0. The expected profit function is non-convex in m. First, the equilibrium is pooling when the past performance is weak, $r_0 < \hat{r}$. When the historical performance is poor, performance chasers are unlikely to invest even if marketing employees can lower information acquisition cost $c(m)$. The information-acquisition channel of marketing is insignificant. The weak performance also deters the flow from sophisticated investors. Hence, the expected profit U^F strictly decreases in m given the cost of marketing employees as in Panel A of Figure III. This scenario is close to a classic costly signaling setting (Spence, 1973), where signals do not directly affect the output. Given that the marginal cost of signal, w, is identical for both high and low types, the single crossing property is not satisfied, and the separating equilibrium doesn't exit. The optimal marketing employment $m_h^* = m_l^* = 0$ (i.e., the m that maximizes expected profits) is zero for both high and low types. If the high type chooses to hire $m_h^* > 0$ in the equilibrium, the low type would always deviate. When mimicking the high type, the expected profit for the low type is improved by paying a marketing cost and getting the expected flow from sophisticated investors. Choosing $m > 0$ is costly and not profitable for the high type.

However, the benefits of the separating equilibrium are more pronounced when past performance is relatively strong ($r_0 > \hat{r}$). Facing a high r_0, the potential profits from new flows can be large if fund companies lower the participation cost $c(m)$. In this case, the signaling directly contributes to the return of the fund, and the profit function is concave in m. For a concave objective, the high type can achieve a larger inflow by hiring $m > 0$

and separating them from the low type. However, it is not a dominant strategy for the low type to mimic because maintaining a large marketing force is costly. Depending on how strong the past performance is, the low type might choose not to hire or hire a positive number of marketing employees to lower the participation cost for its performance chasers. Panels B and C of Figure III concern the two different scenarios, which we will discuss in Section 3.2.4.

3.2.4 Optimal Marketing Employment Policy

In this section, we characterize the optimal marketing policies $m_i^*, i = h, l$ in the separating equilibrium. The employment policy, for a given type, varies with respect to past performance r_0, and is described in the following proposition.

Proposition 2. *In any separating equilibrium $r_0 \geq \hat{r}$, a high-type manager always chooses to hire marketing employees, $m_h^* = m^*(\alpha_h; r_0) > 0$, while a low-type manager's policy is the following:*

$$m_l^* = \begin{cases} m^*(\alpha_l; r_0) & if \quad r_0 > \tilde{r} \\ 0 & if \quad r_0 \leq \tilde{r} \end{cases} \tag{5}$$

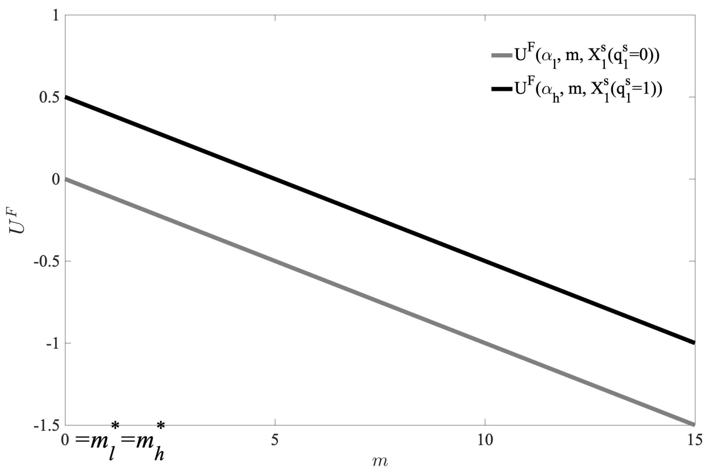
where $\hat{r} < \tilde{r}$. Moreover, when r_0 is large enough, there exists a separating equilibrium such that $m_l^* > m_h^* > 0$.

From Proposition 1, the optimal number of marketing employees for both ability types is zero when the return is lower than the threshold $r_0 < \hat{r}$ at time $t = 0$, and the equilibrium is pooling. When the past performance r_0 is stronger than the threshold return $\hat{r}$, high-type funds start building their marketing force $m_h^* > 0$. However, for the low-type funds to have a positive marketing force, it requires a much higher return threshold $\tilde{r} > \hat{r}$. Proof of Proposition is in Appendix B.4. We discuss two scenarios of this proposition and illustrate the separating equilibrium in Figure IV.

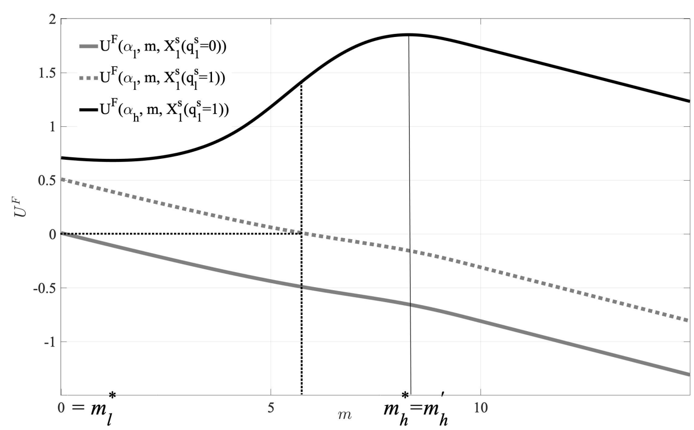
Figure III. Expected Profits When Signaling is Costly and Productive

The solid lines represent the mutual funds' expected profits in the equilibrium. The black line represents the profits when the fund has a higher ability, and the gray line represents the profits when the fund has a lower ability. The dotted line corresponds to the profits of the low-type fund when it decides to mimic the marketing strategy of the high-type fund. Panel A corresponds to the situation when $r_0 = -1$, Panel B corresponds to the profits when $r_0 = -0.1$, and Panel C corresponds to the profits when $r_0 = 0.3$. Other parameters are $\gamma = 1, \lambda = 1, f = 1, \sigma_\epsilon = 0.2, \alpha_h = 0.25, \alpha_l = -0.07, q = 0.5, w = 0.1$, where γ is the risk aversion of the CARA investor, and λ is the relative population weight of performance chasers. Fund return is $r_{it} = \alpha_i + \epsilon_{it}$, where $\alpha_i = \alpha_h \quad w.p \quad q$ and $\alpha_i = \alpha_l \quad w.p \quad 1-q$ is the prior about the managerial ability and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ is the i.i.d. noise over time and across funds. The cost function is $c(m) = \exp(1 - 0.3m - 0.01m^2)$.

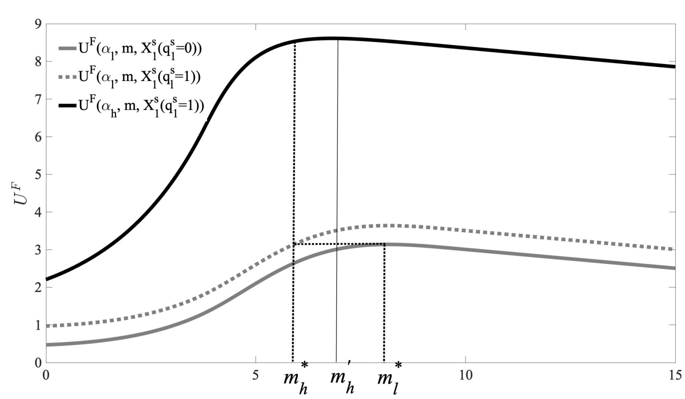
Panel A: $r_0 < \hat{r}$ Pooling



Panel B: $\tilde{r} > r_0 > \hat{r}$ Separating



Panel C: $r_0 > \tilde{r}$ Separating



Scenario I: $\tilde{r} > r_0 > \hat{r}$**.** When the past performance is moderately strong ($\tilde{r} > r_0 > \hat{r}$), the high type will hire $m_h^* > 0$, while the low type stays away from marketing $m_l^* = 0$. Intuitively, fund companies will attract little flows from performance chasers when past performance r_0 is not strong, even with the substantial marketing effort. Both the expected return at date $t = 1$ and signaling costs matter for the expected profits. High-type funds are more confident in signaling themselves even if the realized past return is not outstanding because their expected return at date 1 is good. The low-type funds could mimic the high-type funds to hire the same number of marketing employees. However, once the low-type funds deviate from the separating equilibrium, they are still unlikely to profit, given their low expected return and costly marketing. There exists a threshold $\tilde{r}$ so that a low-type is indifferent in mimicking or not—that is the IC constraint is binding in Equation (6).

$$U^F(\alpha_l, m_h^*, X_1^{s^*}(q_1^s = 1)) \leq U^F(\alpha_l, m_l^*, X_1^{s^*}(q_1^s = 0)) \tag{6}$$

This scenario is shown in Panel B of Figure III. The dotted line plots the left side of the IC constraint, i.e. the expected profits of low-type funds, when the low type mimics the high type and sophisticated investors, allocate given they observed m_h^* and believe the manager as the high-type ($q_1^s = 1$). The right side of the IC constraint is the expected profits of the low type in the separating equilibrium. Since $U^F(\alpha_l, m_h^*, X_1^s(q_1^s = 1))$ is increasing in r_0, so $\tilde{r}$ is the threshold performance level that the IC constraint is binding. When $\tilde{r} > r_0 > \hat{r}$, the high type will hire m_h^* to maximize the expected profits. Given the costly signaling, the best response of low-type funds is to not hire any marketing employees $m_l^* = 0$.

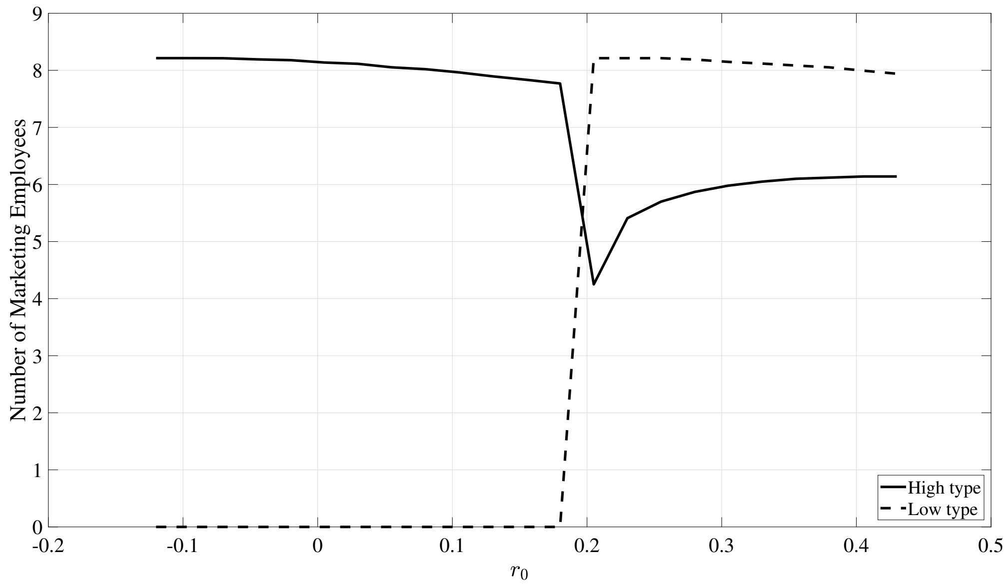
Scenario II: $r_0 > \tilde{r}$**.** Low-type funds will only hire to lower the participation costs and attract inflows from performance chasers when the past performance is strong enough $r_0 > \tilde{r}$. To ensure a separating equilibrium, the high-type fund now deviates from its optimal marketing employment level (the m_h' that maximizes the expected profits for the high-type fund) to the equilibrium m_h^* in Panel C of Figure III, so that it becomes too costly for the low-type fund to mimic. The dotted line in the figure shows the expected profits for the low-type fund if it mimics such efforts. Hiring m_h^* makes it indifferent for the low-type fund to mimic. Optimally and efficiently, the high type should hire any number less than m_h^* to ensure that the benefit of pooling equilibrium is smaller than the separating equilibrium. As a result, the low-type fund stays at m_l^* to enjoy the maximized flow from the performance chasers.

We next discuss the equilibrium uniqueness. Note that, in the case of Panel C of Figure III, there exists one more separating equilibrium given the concave profit function. In signaling games with two types, we use the intuitive criterion proposed in Cho and Kreps (1987) to get the unique equilibrium: the best separating equilibrium. This refinement is particularly relevant when $r_0 > \tilde{r}$. Given the concave profit function, the high-type fund faces two options to achieve separation. The first is what is shown in Panel C, an equilibrium $m_h^* < m_h'$ on the left of the profit-maximizing marketing level m_h'. The second is a $m_h^* > m_h'$ on the right of the profit-maximizing marketing level. That is, the high-type funds may be better off choosing a slighter higher or lower number of marketing employees than m_h'. Given the intuitive criterion, the separating equilibrium with the most efficient m_h^* would be the unique equilibrium in this signaling game where $m_h^* < m_h'$ as long as $m_h^* > 0$. Under specific choices of the parameter set, $m_h^* > m_h'$ can be the only available equilibrium if choosing a lower amount of marketing force is not feasible.

Figure IV summarizes the marketing employment policy of both high type and low type within the reasonable regime of the realized returns. The high-type fund keeps the size of its marketing force relatively persistent. A high-type fund maintains its marketing force even if it experiences negative past returns because it knows that the low return is a small probability event. A low-type fund chooses to enhance its marketing force after the realization of a strong past performance. In the separating equilibrium, it could even build up a larger marketing force than the high-type fund to attract flows from the

Figure IV. Optimal Marketing Plans for Two Types of Abilities

The solid line corresponds to the mutual fund's optimal marketing plan when it has the higher ability, and the dashed line corresponds to the optimal marketing plan when it has the lower ability. Other parameters are $\gamma = 1, \lambda = 2, \beta = 1, \sigma_\epsilon = 0.25, \alpha_h = 0.25, \alpha_l = -0.07, q = 0.5, w = 0.2$, where γ is the risk aversion of the CARA investor, and λ is the relative population weight of performance chasers. Fund return is $r_{it} = \alpha_i + \epsilon_{it}$, where $\alpha_i = \alpha_h \quad w.p \quad q$ and $\alpha_i = \alpha_l \quad w.p \quad 1-q$ is the prior about the managerial ability and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ is the i.i.d. noise over time and across funds. The cost function is $c(m) = \exp(1 - 0.3m - 0.01m^2)$. These optimal marketing plans are announced to sophisticated investors at time 0.



performance-chasing investors. This implication shares a similar insight as in Roussanov et al. (2021)—namely, that the low-skilled funds over-market themselves, leading to misallocation between capital and skill.

3.3 Testable Model Implications

With imperfect learning and costly signaling, our model implies that the persistence of marketing strategies can indicate mutual funds' skill level within the reasonable regime of realized returns r_0. The past performance is not monotonic in the choice of optimal marketing strategy and, hence, does not fully reveal the type of mutual funds.

3.3.1 Persistence of Marketing Strategy and Fund Manager Skill

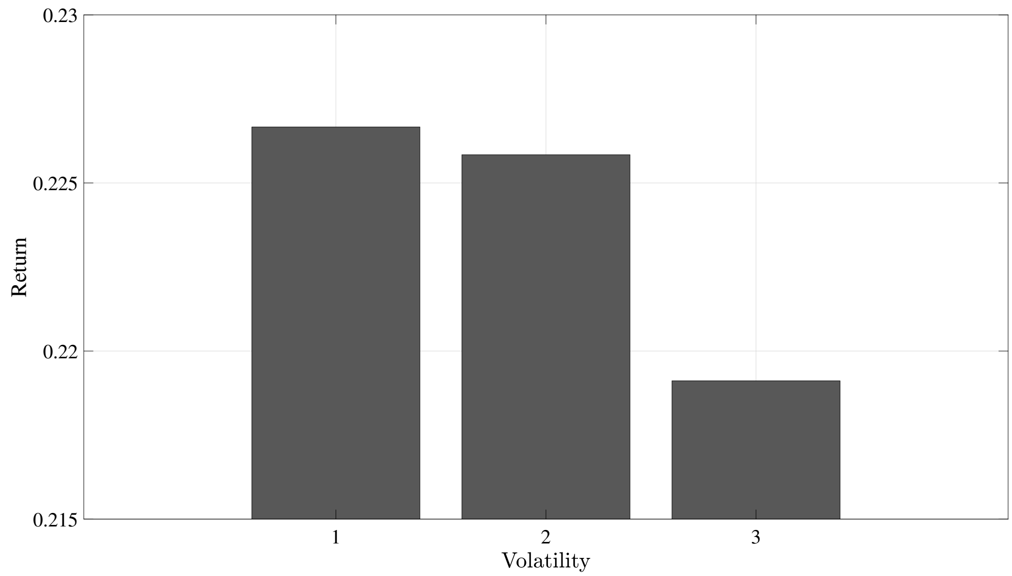
As our Proposition 1 indicates, fund companies optimally fully reveal their types via the optimal marketing strategy when past performance is not too weak. In Figure IV, high-type fund companies signal themselves by hiring a large marketing force even when the past performance was poor. As long as the performance is higher than the threshold return for the separating equilibrium, high-type funds enhance their marketing force. This is because they are confident in their future performance after observing their type at date 0. However, this is not the case for low-type fund companies. The optimal marketing effort is zero if the return at time 0 is lower than the threshold, and this threshold is much higher for the low-type fund companies to maintain a positive scale of the marketing labor force. Suppose the average performance for the high-type fund is superior enough. In that case, its optimal marketing employment policy will not experience a non-marketing regime over the observed realized past returns, making them much more persistent than the strategies adopted by the low-type funds. This insight from the model yields the following testable implication:

Remark 1. Persistent Marketing Strategies. Given that $\alpha_l \leq \alpha_h$ and ϵ_{it} is normally distributed, there is a smaller variation in the marketing labor force $\sigma(m_h^*)$ in the high-type fund companies than that in the low-type fund companies.

Figure V shows that the volatility of marketing employment level m in our calibrated numerical example is correlated with the fund performance. There is more volatility in marketing labor forces/actions in the low-type mutual funds. The persistence of marketing strategy, instead of past performance, then reveals the fund company's average skill. The Remark 1 stands as the unique implication of costly signaling and learning, and we test this result in our next section. Note that in Remark 1, it is essential for α_l not to be significantly smaller than α_h. If there is a substantial difference, investors can reasonably infer the fund's type based on past performance alone, leading the low-type fund to consistently choose $m_l^* = 0$ in equilibrium. In our calibrated numerical example, we set α_l and α_h as one standard deviation below and above the mean of net return in the sample. We argue that a broad range of reasonable choices of mean and standard deviation for the return distribution would yield results exhibiting a similar pattern as in Figure V. In our

Figure V. Return Predictability of Marketing Strategy Volatility

This figure reports the relationship between the volatility of marketing employment policies and the expected return r_1 at time 1. Other parameters are $\gamma = 1, \lambda = 2, \beta = 1, \sigma_\epsilon = 0.25, \alpha_h = 0.25, \alpha_l = -0.07, q = 0.5, w = 0.2$, where γ is the risk aversion of the CARA investor, and λ is the relative population weight of performance chasers. Fund return is $r_{it} = \alpha_i + \epsilon_{it}$, where $\alpha_i = \alpha_h \quad w.p \quad q$ and $\alpha_i = \alpha_l \quad w.p \quad 1-q$ is the prior about the managerial ability and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ is the i.i.d. noise over time and across funds. The cost function is $c(m) = \exp(1 - 0.3m - 0.01m^2)$.



empirical test, we exclude funds with a marketing employment share of zero throughout the sample.

3.3.2 Marketing Strategies and Fund Flow

Given the optimal marketing strategy $\pi(m^*, \alpha_i)$ and the fund company's past performance, we can write down mutual funds' expected fund flows under optimal choices.

Remark 2. Expected flow under optimal choices. The fund flow $F(r_1)$ at time $t = 1$ is written as

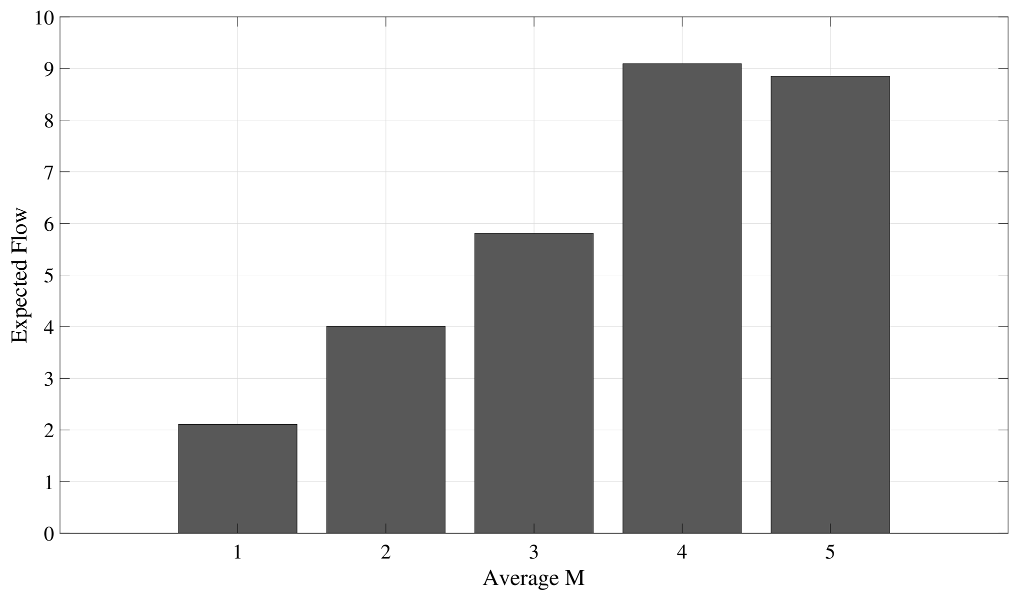
$$F(r_1) = (X_1^{s*} - X_0^s(1 + r_1)) + \lambda \min[1, \frac{g(r_1; r_0)}{c(m)}] X_1^{n*},$$

where X_1^{s*} and X_1^{n*} are defined in Lemma 1, and the gain function $g(r_1; r_0)$ is from Lemma 2.

Figure VI describes the total expected flow of mutual funds given their past performance and optimal marketing employment policy. Noticeably, the expected fund flow is increasing in the number of marketing employees given the fund's past performance r_0. The average number of marketing employees is the expected number weighted by the probability of ability types of mutual funds. The learning channel drives this positive correlation between the expected fund flow and marketing policy. The more marketing employees are hired, the lower the participation costs for performance chasers and, hence, larger new inflows on average. Given X_0^s, the relative comparative statics for fund flow is equivalent to that for the fund size.

Figure VI. Relationship between Expected Flow and the Optimal Marketing Employment

This figure reports the expected flow of mutual funds under the optimal marketing strategy. The parameters are the same, $\gamma = 1, \lambda = 2, \beta = 1, \sigma_\epsilon = 0.25, \alpha_h = 0.25, \alpha_l = -0.07, q = 0.5$, where γ is the risk aversion of the CARA investor, and λ is the relative population weight of performance chasers. Fund return is $r_{it} = \alpha_i + \epsilon_{it}$, where $\alpha_i = \alpha_h \quad w.p \quad q$ and $\alpha_i = \alpha_l \quad w.p \quad 1-q$ is the prior about the managerial ability and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ is the i.i.d. noise over time and across funds. The cost function is $c(m) = \exp(1 - 0.3m - 0.01m^2)$. The optimal marketing strategy varies with the past performance r_0 and funds skill type. Hence we know the relationship between the average number of marketing employees and the expected flow.



4 Tests of Model Predictions

In this section, we test several unique predictions from our model. We first test the hypothesis about the relationship between marketing persistence and fund company performance. Then, we examine the predictions of optimal m^* on equilibrium (i.e., MKT)

that we observe on fund flow. The results support our model as a relevant economic force in the real world.

4.1 Marketing Persistence and Fund Performance

Our model implies a full disclosure of marketing strategies by high- and low-type mutual funds if past performance is not too weak. That is, high alpha funds should exhibit persistent marketing efforts with respect to fund performance, while low-type funds' marketing input tends to change with past performance. A testable implication from this model prediction is that funds with more persistent MKT should exhibit better long-term fund performance as shown in Figure V.

Our primary measure of marketing persistence is the volatility of MKT, calculated as the standard deviation of MKT through the sample period of 2011 to 2020 (denoted as $Vol(MKT)$). We require a fund company to have at least three-year records in the data. We also exclude fund companies that report zero marketing employees in all years. As Form ADV only provides employment information at the annual level, $Vol(MKT)$ captures little high-frequency variations in MKT. According to our model predictions, fund companies with low $Vol(MKT)$ should perform better on average than funds with high $Vol(MKT)$. To test this hypothesis, we run the following Fama-MacBeth regression:

$$\text{Firm Return}_{i,t+1} = Vol(MKT)_i + \text{Firm Return}_{i,t} + Control_{i,t} + v_t + \epsilon_{i,t+1}. \tag{7}$$

Firm $\text{Return}_{i,t+1}$ refers to the value-weighted average returns of mutual funds that fund company i manages in month $t+1$. As a fund company may manage mutual funds with different styles and asset focuses, including domestic equity, fixed income, international, and balanced, we adjust fund return with a 6-factor model, which augments Carhart's 4-factor model with an international market factor and a bond market factor, as our baseline measure.[17] We also use CAPM-adjusted fund returns and raw returns as alternative mea-

[17] The 6-factor model includes Fama–French three factors (MKTRF, SMB, and HML), Carhart momentum factor (MOM), Barclays US Aggregate Bond Index (BABI) return as our bond factor, and the Morgan Stanley

sures. We control for Firm Return at year t and fund company characteristics, including size, age, the number of managed funds, and the expense ratio. We show the Fama and MacBeth (1973) estimates of monthly fund firms' performance regressed on firm characteristics lagged one month. The t-statistics are adjusted for serial correlation using Newey and West (1987) lags of order 12. Note that this is not a test of forecasting fund returns, as $Vol(MKT)_i$ is calculated using full sample information.

Table II reports the results. In Panel A, gross fund returns are used, as the before-fee returns presumably better measure fund skills. In column (1), we use 6-factor adjusted fund returns and find that the coefficient before $Vol(MKT)$ is significantly negative (t-stat = 4). In terms of economic magnitude, a one-standard-deviation decrease in $Vol(MKT)$ is associated with a 3.75 bps higher 6-factor gross alpha per month. This is sizeable given that the average monthly 6-factor gross alpha of fund companies in our sample is -2 bps. The coefficient before past firm return (6-factor Alpha_t) is significantly positive, consistent with the smart money effect (e.g., Zheng (1999)). The firm expense ratio is not correlated with higher gross fund returns, and firm size is positively correlated with performance; the two patterns are consistent with the findings in the literature (e.g., Chen et al. (2004)). The coefficient of firm age is insignificant.

In column (2), we use the level of $MKT_{i,t}$ instead of $Vol(MKT)$ in regression (7). This is motivated by one of the model implications that the level of MKT should be an ambiguous indicator of fund type, as low-type funds may also hire more marketing employees following good past performance (as shown in Figure IV with model simulation). Consistent with the model prediction, the coefficient of MKT is not significantly different from zero. This finding also echoes the results of Jain and Wu (2000) and Bergstresser et al. (2009), who showed the level of marketing efforts is not correlated with performance. In column (3), we further include both MKT and $Vol(MKT)$ into the right-hand side of the regression, and the coefficients of MKT and $Vol(MKT)$ are virtually unchanged com-

Capital International index (MSCI) return to proxy the performance of international markets.

pared with columns (1) and (2). In columns (4)–(6) and (7)–(9), we repeat the analysis with CAPM-adjusted gross returns and raw fund gross returns, respectively, and the results are robust. In Panel B, we repeat the regressions using net-of-fee fund returns; the results are virtually the same.

We also test whether the relationship between $Vol(MKT)$ and firm returns is predictive. We estimate the $Vol(MKT)_t$ using past 3 years $\{MKT_{t-2}, MKT_{t-1}, \text{and } MKT_t\}$, and regress firm return at $t+1$ on the past $Vol(MKT)_t$. Table III reports the regression results. The results are similar to the regression results in Table II. The coefficient of $Vol(MKT)_t$ is significantly negative when predicting 6-factor adjusted fund returns in column (1). The economic magnitude is even larger: a one-standard-deviation increase in $Vol(MKT)_t$ is associated with 4.9 bps decrease in the 6-factor adjusted gross Alpha. In column (4) and column (7), we report the regression results for CAPM Alpha and raw returns, and in Panel B the results using net fund returns; in all specifications, fund performance is significantly predicted by $Vol(MKT)_t$.

Next, we conduct several robustness tests. In Panel A of Table IV, we use an alternative way to measure the variability of firm MKT: the range of MKT over the past 3-year rolling window (denoted as $Range(MKT)_t$). We find that the coefficients of $Range(MKT)_t$ remain significantly negative (with t-stats between 4.5 to 5.9). In Panel B, we replace the left-hand side variable with the adjusted return of the fund company's flagship fund. Flagship fund is defined as the largest fund that the company manages based on AUM. The results are also robust: the coefficients before $Vol(MKT)_t$ are significantly negative (with t-stats between 3.05 to 6.02).

In Table V, we examine whether the volatility of total employment ($Vol(EMP)$) or the volatility of investment-oriented employment share ($Vol(INV)$) exhibits a similar predictability of fund performance. We define EMP as the number of total employees and INV as the fraction of investment-oriented employees to total employment. This is to address the concern that the volatility of marketing employment share may capture funds' labor adjustment cost or turnover rate of the general labor force, which might be related to fund investment skills. Our results show this is not the case; neither $Vol(EMP)$ nor $Vol(INV)$ exhibits significant predictability of fund returns. This finding highlights the uniqueness of marketing-oriented employees, who can lower the participation cost and be used as a signaling device of fund type.

In Table VI, we report results using the 12b-1 fee-based measure for marketing effort. To calculate $Vol(12b1)_t$, we first obtain the average of standard deviation of 12b-1 at the share class level in the past 3 years in a given fund, and then aggregate the fund-level $Vol(12b1)$ to the firm level. The results are consistent with what we find using the market employment share, albeit with lower statistical significance. The coefficients of $Vol(12b1)$ are all negative in both panels and significant at the 10% level when using 6-factor gross and net returns.

Figure IX visualizes our baseline finding in Table II. We sort all fund companies into quintiles based on $Vol(MKT)$ and plot the average firm returns on the y-axis. We use gross returns in the upper panel and 6-factor adjusted returns in the lower panel. Average fund returns decrease with $Vol(MKT)$, particularly Groups 4 and 5.

The strong and robust relationship between $Vol(MKT)$ and fund performance suggests that the low $Vol(MKT)$ strategy reveals the fund's high alpha skills. One may wonder how these findings can be reconciled with the conclusion of Berk and Green (2004) that fund managers' superior performance, if any, will be eroded by fund inflows due to diminishing returns to scale. In that sense, we would not be able to find high-skill funds exhibiting long-term alpha. Following this, Berk and van Binsbergen (2015) propose to measure fund skills with value added, calculated by multiplying fund size with fund gross alpha. One auxiliary prediction in our setting is that low $Vol(MKT)$ should be correlated with high value added.

For month t, we define fund-level $Value\ Added_t$, as a fund's 6-factor alpha (based on gross returns) times the fund's AUM at the beginning of the month. We take the value-weighted average of value added of all funds in the fund company. Then, we re-estimate the regressions (7) by replacing the dependent variable with $Value\ Added_t$. Table VII shows that the results are consistent with our conjecture. The coefficient of $Vol(MKT)$ is negative with a t-statistic around 5, while MKT itself is insignificant. In columns (4)–(6), the rolling $Vol(MKT)_t$ is used, and the results are similar, albeit at a noisier point estimation.

It is worth noting that our model analyzes the alpha skill of fund companies, not individual mutual funds. Diminishing return to scale may not be applicable to fund companies. For example, the founders or CEOs of fund companies themselves may not only have superior investment skills, but also they might have a good ability to select and attract talented fund managers to join them. In this way, despite the presence of diminishing returns to scale, high-type fund companies can potentially keep expanding by opening up more individual funds. Furthermore, previous studies have shown that fund companies might take internal strategic actions that can enhance funds' performance or value added to the family, including cross-fund subsidization (Gaspar et al. (2006)), style diversification (Pollet and Wilson (2008)), insurance pool for liquidity shocks (Bhattacharya et al. (2013)), and matching capital to labor (Berk et al. (2017)). Indeed, consistent with the observations, diminishing returns to scale do not appear at the fund family level; for example, Chen et al. (2004), as well as our analysis, found that fund family size predicts positive subsequent fund returns.

4.2 Optimal *MKT* and Fund Flows

The previous subsection shows that the optimal m^* (or, empirically, the level MKT that we observe in the data) does not necessarily reveal the funds' type. Nonetheless, our model suggests that MKT is unambiguously associated with fund companies' subsequent fund flow and asset growth. As discussed in Section 3, such an effect arises through two channels. First, high-type funds, which adopt persistently high levels of MKT to separate from low-type funds, tend to exhibit better performance and more inflow. Second, due to costly learning, low-type funds may increase *MKT* upon good past performance to attract subsequent inflow. Thus, in the cross section, we expect *MKT* to be positively correlated with subsequent fund flow or asset growth (Figure VI shows these results with model simulations). Furthermore, as the former channel (i.e., signaling) is driven by fund companies' type, which is likely time-invariant, the cross-sectional effect should be significantly attenuated after controlling for firm fixed effects.

We run the following regression for fund company j at year t:

$$Firm\ Flow_{j,t+1} = \alpha + \beta_1 MKT_{j,t} + Controls_{j,t} + \epsilon_{i,t+1}. \tag{8}$$

We control for the firm's current size ($Log\ Firm\ Assets_{j,t}$) and expense ratio ($Firm\ Expense_{j,t}$). Controls also include firm age ($Log\ Firm\ Age_{j,t}$), past year return ($Firm\ Return_{j,t}$) and year fixed effects.

Table VIII reports the results. In column (1), the coefficient of *MKT* is significantly positive, suggesting that those fund companies with high marketing employee shares tend to experience more subsequent fund flow. The coefficient of *MKT* equals 1.319 (with a t-statistic of 2.4) and is economically meaningful: A one-standard-deviation increase in *MKT* is associated with a 32.2% increase in fund flow, which equals 53% of the average growth rate (i.e., 60.7%) during our sample period.

The coefficient of $Firm\ Expense$ appears to be negative, with a t-statistics of 4.5. If $Firm\ Expense$ is a proxy for the company's spending on advertising and distribution, then it is hard to interpret this result. Nonetheless, this pattern is likely driven by investors' preference for funds with lower fees. The difference in the effect on future asset growth between *MKT* and $Firm\ Expense$ highlights the importance of measuring marketing efforts by human capital. In column (2), we add firm fixed effects into equation (8), which can rule out unobservable and time-invariant firm characteristics, such as firms' skill level. The point estimate of the coefficient of *MKT* remains positive but becomes insignificant (t-stat = 0.9), consistent with our conjecture.

Next, we examine alternative measures of firm growth. First, in columns (3) and (4), we use the growth rate of total assets under management of the fund company, denoted as $\Delta Firm\ Assets_{j,t+1}$. We find similar results that MKT forecasts the high growth of the fund company in the pooled regression, but such an effect becomes weaker and insignificant after controlling for firm effects. Second, in columns (5) and (6), we construct the growth rate of total firm revenue (assets times expense ratio), $\Delta Firm\ Revenue_{j,t+1}$ as the dependent variable. We find a highly similar pattern that hiring more marketing employees is associated with higher revenue. Overall, the evidence shown in Table VIII provides additional support to our model.

5 Conclusion

We analyze the allocation of human capital toward marketing among U.S. mutual fund companies. Mutual fund companies adopt very distinct marketing strategies, resulting in a large heterogeneity in fund companies' marketing employment share and in its persistence. We uncover a significant relationship between the persistence of marketing employment share and fund performance in the U.S. mutual fund industry.

We propose a framework based on costly learning and signaling to explain the observed strategic marketing decision. Conditional on the skill level, fund companies' optimal marketing employment share responds to their past performance differently. Low-skill funds only conduct marketing following a sufficiently good past performance, while high-skill funds maintain a high marketing employment share even with very poor past performance. The persistence of marketing employment strategy reveals the skill type. Consistent with the model prediction, we show that the volatility of the marketing ratio is negatively correlated with the long-term performance of fund companies.

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A Equilibrium

The environment described above represents a signaling game between funds and sophisticated investors. The allocation strategy for sophisticated investors is a function μ: $M \times A \to [0,1]$ where $\sum_{X_1^s \in A} \mu(m, X_1^s) = 1$ for all m. $\mu(m, X_1^s)$ is the probability that sophisticated investors allocate X_1^s unit of capital into fund i following the signal m. A Nash equilibrium of this game is defined as follows.

Definition A.1. *Behavior strategies (π^*, μ^*) form a Nash Equilibrium if and only if*

1) for $i = l, h$

$$\pi^*(\alpha_i, m') > 0 \quad implies \quad \sum_{X_1^s} U^F(\alpha_i, m', X_1^s)\mu^*(m', X_1^s) = \max_m \sum_{X_1^s} U^F(\alpha_i, m, X_1^s)\mu^*(m, X_1^s) \tag{A.1}$$

2) for each $m' \in M$ such that $q_1^s \pi^*(\alpha_h, m') + (1 - q_1^s)\pi^*(\alpha_l, m') > 0$,

$$\mu^*(m', X_1^{s\prime}) > 0 \quad implies \quad \sum_{\alpha_l, \alpha_h} U^s(\alpha_i, m, X_1^{s\prime})q_1^{s*}(\alpha_i, X_1^{s\prime}) = \max_{X_1^s} \sum_{\alpha_l, \alpha_h} U^s(\alpha_i, m, X_1^s)q_1^{s*}(\alpha_i, X_1^s) \tag{A.2}$$

where

$$q_1^{s*}(\alpha_h, X_1^s) = \frac{q_1^s \pi^*(\alpha_h, m)}{q_1^s \pi^*(\alpha_h, m) + (1 - q_1^s)\pi^*(\alpha_l, m)}, \quad q_1^{s*}(\alpha_l, X_1^s) = 1 - q_1^{s*}(\alpha_h, X_1^s), \quad q_1^s \equiv Pr(\alpha = \alpha_h | I_1^n) \tag{A.3}$$

Condition (A.1) says that the fund company places a positive probability only on marketing that maximizes its expected profits. Condition (A.2) represents that sophisticated investors place positive probability only on capital allocations that maximize their expected CARA utility. Condition (A.3) states that sophisticated investors update their beliefs based on the Bayes' rule.

B Proofs

B.1 Proof of Lemma 1

At date 1, investors who have a posterior belief that $\alpha = \alpha_h$ with probability q_1^j solve Problem (2):

$$\max_{X_1^j \geq 0} \quad E(-e^{-\gamma W_2^j} | I_1^j) \qquad\qquad s.t \quad W_2^j = W_1^j + X_1^j r_2, \tag{B.1}$$

where $W_1^j = W_0 + X_0^j(1+r_1), j = s, n$. Without knowing the true value of q, performance chasers update the posterior based on the Bayes rules:

$$\tilde{q}_1^n \equiv Pr(\alpha = \alpha_h | r_0, r_1) = \frac{q_0^n(z)}{q_0^n(z) + (1 - q_0^n(z)) \exp(-\frac{(2r_1 - \alpha_h - \alpha_l)(\alpha_h - \alpha_l)}{2\sigma^2})}, \tag{B.2}$$

where q_0^n is the posterior at the end of date 0 based on the observed r_0:

$$q_0^n \equiv Pr(\alpha = \alpha_h | r_0) = \frac{1}{1 + \exp(-\frac{(2r_0 - \alpha_h - \alpha_l)(\alpha_h - \alpha_l)}{2\sigma^2}) z}, \tag{B.3}$$

where $z = \frac{1-q}{q}$ and its probability density function $f(z)$ is $f(z) = \frac{1}{(z+1)^2}, z \in [0, +\infty)$.

At date 1, if performance chasers learn q, they update the belief based on the prior q and past return r_0, r_1.

$$q_1^n \equiv Pr(\alpha_i = \alpha_h | q, r_0, r_1) = \frac{q_0^s}{q_0^s + (1 - q_0^s) \exp(-\frac{(2r_1 - \alpha_h - \alpha_l)(\alpha_h - \alpha_l)}{2\sigma^2})}. \tag{B.4}$$

where q_0^s is the sophisticated investors' belief at date 0.

$$q_0^s \equiv Pr(\alpha_i = \alpha_h | q, r_0) = \frac{q}{q + (1 - q) \exp(-\frac{(2r_0 - \alpha_h - \alpha_l)(\alpha_h - \alpha_l)}{2\sigma^2})}. \tag{B.5}$$

For the simplicity of forms, we use X_1 as a general symbol of X_1^j. Given I_1^j and $r_2 = \alpha + \epsilon_2$, where $\epsilon_2 \sim N(0, \sigma_\epsilon^2)$, Problem 2 is equivalent to

$$\max_{X_1 \geq 0} \quad E(-e^{-\gamma W_2} | I_1^j) = \min_{X_1 \geq 0} e^{\frac{1}{2}\gamma^2 \sigma_\epsilon^2 X_1^2} (q_1^j e^{-\gamma \alpha_h X_1} + (1 - q_1^j) e^{-\gamma \alpha_l X_1}) \tag{B.6}$$

the first-order conditions can be written as

$$\gamma \sigma_\epsilon^2 X_1 (q_1^j e^{-\gamma \alpha_h X_1} + (1 - q_1^j) e^{-\gamma \alpha_l X_1}) - (q_1^j \alpha_h e^{-\gamma \alpha_h X_1} + (1 - q_1^j) \alpha_l e^{-\gamma \alpha_l X_1}) = 0 \tag{B.7}$$

It is a transcendental equation and has no analytical solution. To study the characteristics of the optimal allocation X_1, we start with defining $f(X_1) \equiv \gamma \sigma_\epsilon^2 X_1 (q_1^j e^{-\gamma \alpha_h X_1} + (1 - q_1^j) e^{-\gamma \alpha_l X_1})$ and $h(X_1) \equiv (q_1^j \alpha_h e^{-\gamma \alpha_h X_1} + (1 - q_1^j) \alpha_l e^{-\gamma \alpha_l X_1})$. Thus the first-order conditions (B.7) can be written as

$$f(X_1) - h(X_1) = 0$$

Notice that $f(X_1) \geq > 0, h'(X_1) < 0$,

$$h(X_1) \leq h(0) = q_1 \alpha_h + (1 - q_1^j)\alpha_l, \quad \forall X_1 \geq 0$$

- If $q_1^j \alpha_h + (1 - q_1)\alpha_l < 0$, then $h(X_1) \leq 0$ and the first order derivative is always positive. The expected utility is decreasing in X_1 and reaches the maximum when $X_1^* = 0$.

- If $q_1 \alpha_h + (1 - q_1^j)\alpha_l \geq 0$, there exists $\hat{x}$ such that $h(\hat{x}) = 0$. We know that

$$\begin{aligned} &f(X_1) \geq 0, && \forall X_1 \geq 0 \\ &h(X_1) \in (0, q_1^j \alpha_h + (1 - q_1^j)\alpha_l], && 0 \leq X_1 < \hat{x} \\ &h(X_1) \in (-\infty, 0], && X_1 \geq \hat{x} \end{aligned}$$

  where $\hat{x} = \frac{1}{\gamma(\alpha_h - \alpha_l)} \ln(-\frac{q_1^j \alpha_h}{(1-q_1^j)\alpha_l})$. Next, we go through each sub-interval of X_1 to find the optimal allocation X_1^*.

  - When $X_1 \geq \hat{x}$, $f(X_1) > 0$ and $h(X_1) \leq 0$, there is no solution to first-order conditions (B.7).

  - When $X_1 < \hat{x}$, $h(X_1) > 0$. The optimal allocation X_1^* exists such that $f(X_1^*) - h(X_1^*) = 0$ because $f(0) - h(0) = -(q_1^j \alpha_h + (1 - q_1^j)\alpha_l) < 0$, $f(\hat{x}) - g(\hat{x}) = f(\hat{x}) > 0$ and $f(X_1) - h(X_1)$ is continuous on $[0, \hat{x})$. For uniqueness, we could rewrite the first-order conditions (B.7) as

$$f(X_1) - h(X_1) = (1 - q_1^j)e^{-\gamma \alpha_l X_1}(\gamma \sigma_\epsilon^2 X_1 - \alpha_h)p(X_1) = 0 \tag{B.8}$$

    where $p(X_1) \equiv (\frac{q_1^j}{1-q_1^j} e^{-\gamma(\alpha_h - \alpha_l)X_1} + \frac{\alpha_h - \alpha_l}{\gamma \sigma_\epsilon^2 X_1 - \alpha_h} + 1)$.

    X_1^* is an optimal allocation if and only if $X_1^* < \frac{\alpha_h}{\gamma \sigma_\epsilon^2}$ and $p(X_1^*) = 0$. $p(X_1)$ is strictly decreasing in X_1 when $X_1 < \frac{\alpha_h}{\gamma \sigma_\epsilon^2}$ based on the assumptions of α_h, α_l. Hence if X_1^* exists, X_1^* must be a unique solution to the first order conditions so that $p(X_1^*) = 0$.

  In the case that $q_1^j \alpha_h + (1 - q_1^j)\alpha_l > 0$, there exists a unique optimal allocation X_1^* in $(0, \hat{x})$. We define it as $x(q_1^j)$.

To summarize, the solution to Problem (2) is

$$X_1^* = \begin{cases} x(q_1^j) & if \quad q_1^j \alpha_h + (1-q_1^j)\alpha_l > 0 \\ 0 & if \quad q_1^j \alpha_h + (1-q_1^j)\alpha_l \leq 0 \end{cases}$$

where $0 < x(q_1^j) < \min(\frac{1}{\gamma(\alpha_h-\alpha_l)} \ln(-\frac{q_1^j \alpha_h}{(1-q_1^j)\alpha_l}), \frac{\alpha_h}{\gamma\sigma_\epsilon^2})$ and

$$\frac{q_1^j}{1-q_1^j} e^{-\gamma(\alpha_h-\alpha_l)x(q_1^j)} + \frac{\alpha_h - \alpha_l}{\gamma\sigma_\epsilon^2 x(q_1^j) - \alpha_h} + 1 = 0$$

Taking the derivative of q_1^j on both sides of the equation above, we know that $x(q_1^j)$ is strictly increasing in q_1^j and convex in q_1^j. Thus X_1^* is also increasing and convex in q_1^j.□

B.2 Proof of Lemma 2

For performance chasers, $X_0^n = 0, W_1^n = W_0$. For the simplicity of symbols, we use X_1 standing for X_1^{n*} in our proof. The certainty equivalent wealth gain could be written as

$$\begin{aligned} \max_{X_1 \geq 0} \quad E(-e^{-\gamma W_2} | cost\ paid) =& E(-e^{-\gamma(W_0 + X_1 r_2 - c_k)} | \tilde{q}_1^n) \\ =& - e^{-\gamma W_0} \cdot e^{\frac{1}{2}\gamma^2\sigma_\epsilon^2 X_1^2} (\tilde{q}_1^n e^{-\gamma(X_1\alpha_h - c_k)} + (1-\tilde{q}_1^n) e^{-\gamma(X_1\alpha_l - c_k)}) \\ =& - e^{-\gamma W_0} \cdot e^{-\gamma\left[-\frac{1}{\gamma}\ln(\tilde{q}_1^n e^{-\gamma\alpha_h X_1} + (1-\tilde{q}_1^n)e^{-\gamma\alpha_l X_1}) - \frac{\gamma}{2}\sigma_\epsilon^2 X_1^2 - c_k\right]} \end{aligned}$$

From the solution to the portfolio allocation problem (2), we can define the gain function as

$$g(r_1; r_0) = \begin{cases} -\dfrac{1}{\gamma}\ln(\tilde{q}_1^n e^{-\gamma\alpha_h X_1} + (1-\tilde{q}_1^n)e^{-\gamma\alpha_l X_1}) - \dfrac{\gamma}{2}\sigma_\epsilon^2 X_1^2 & if \quad r_1 > \tilde{r}_1 \\ 0 & if \quad r_1 \leq \tilde{r}_1 \end{cases}$$

Where $r_1 > \tilde{r}_1$ can be rewritten as

$$q_0^n(z) > \frac{-\alpha_l}{\alpha_h \exp(\frac{(2r_1 - \alpha_h - \alpha_l)(\alpha_h - \alpha_l)}{2\sigma_\epsilon^2}) - \alpha_l} \Leftrightarrow z < \hat{z} \equiv -\frac{\alpha_h}{\alpha_l}\exp(\frac{(\alpha_h - \alpha_l)}{\sigma_\epsilon^2}(r_0 + r_1 - \alpha_h - \alpha_l))$$

and $f(z) = \frac{1}{(z+1)^2}$, $z \in [0, +\infty)$ by equation (B.3). Hence the certainty equivalent wealth gain is equal to

$$\begin{aligned}\exp(-\gamma g(r_1; r_0)) &= \int_0^{+\infty} (\tilde{q}_1^n e^{-\gamma\alpha_h X_1} + (1-\tilde{q}_1^n)e^{-\gamma\alpha_l X_1})e^{\frac{1}{2}\gamma^2\sigma_\epsilon^2 X_1} \cdot f(z)dz \\ &= \int_0^{\hat{z}} (\tilde{q}_1^n e^{-\gamma\alpha_h x(\tilde{q}_1^n)} + (1-\tilde{q}_1^n)e^{-\gamma\alpha_l x(\tilde{q}_1^n)})e^{\frac{1}{2}\gamma^2\sigma_\epsilon^2 x(\tilde{q}_1^n)} \cdot f(z)dz + \int_{\hat{z}}^{\infty} f(z)dz \\ &= \int_0^{\hat{z}} (\tilde{q}_1^n e^{-\gamma\alpha_h x(\tilde{q}_1^n)} + (1-\tilde{q}_1^n)e^{-\gamma\alpha_l x(\tilde{q}_1^n)})e^{\frac{1}{2}\gamma^2\sigma_\epsilon^2 x(\tilde{q}_1^n)} \cdot f(z)dz + \frac{1}{1+\hat{z}}\end{aligned}$$

where $\tilde{q}_1^n$ is defined by equation (B.2) and q_0^n is defined by equation (B.3). q_0^n is increasing in r_0. $\tilde{q}_1^n$ is increasing in r_1 and q_0^n. Notice that the integrated part is the minimum of the objective function as (B.6). For the convenience, define $Fval(X_1^{n*}) \equiv (\tilde{q}_1^n e^{-\gamma\alpha_h X_1^{n*}} + (1-\tilde{q}_1^n)e^{-\gamma\alpha_l X_1^{n*}})e^{\frac{1}{2}\gamma^2\sigma_\epsilon^2 X_1^{n*}}$.

$$\frac{\mathrm{d}\, Fval(X_1^{n*}(\tilde{q}_1^n))}{\mathrm{d}\, \tilde{q}_1^n} = \frac{\partial\, Fval(X_1^{n*}(\tilde{q}_1^n))}{\partial\, \tilde{q}_1^n} + \frac{\partial\, Fval(X_1^{n*}(\tilde{q}_1^n))}{\partial\, X_1^{n*}} X_1^{n*\prime}$$

From the first order conditions of solving the optimization problem (B.6), $\frac{\partial\, Fval(X_1^{n*}(\tilde{q}_1^n))}{\partial\, X_1^{n*}} = 0$. The integrated function $Fval(X_1^{n*}(\tilde{q}_1^n))$ is decreasing in $\tilde{q}_1^n$ because

$$\frac{\mathrm{d}\, Fval(X_1^{n*}(\tilde{q}_1^n))}{\mathrm{d}\, \tilde{q}_1^n} = e^{-\gamma\alpha_h X_1^{n*}} - e^{-\gamma\alpha_l X_1^{n*}} \leq 0$$

Hence $\exp(-\gamma g(r_1; r_0))$ is decreasing in $\tilde{q}_1^n$ which means $g(r_1; r_0)$ is increasing in $\tilde{q}_1^n$ then increasing in both r_1 and r_0. Moreover,

$$\frac{\mathrm{d}^2\, Fval(X_1^{n*}(\tilde{q}_1^n))}{(\mathrm{d}\, \tilde{q}_1^n)^2} = (e^{-\gamma\alpha_h X_1^{n*}} + e^{-\gamma\alpha_l X_1^{n*}})(-\gamma\alpha_h + \gamma\alpha_l)\frac{\mathrm{d}\, X_1^{n*}}{\mathrm{d}\tilde{q}_1^n} \leq 0$$

$\exp(-\gamma g(r_1; r_0))$ is concave in $\tilde{q}_1^n$ which means $g(r_1; r_0)$ is convex in $\tilde{q}_1^n$. □

B.3 Proof of Proposition 1

First, we discuss the utility of funds when selecting m, which equals the fee charged for the assets of sophisticated investors and performance chasers minus the salary paid to marketing employees. Only performance chasers who choose to pay the cost would have investments in funds. Given the posterior belief of performance chasers after paying the cost, q_1^n in equation (B.4), Lemma 1 indicates that there exists a threshold of $\hat{r}_1$ such that the optimal allocation of performance chasers $X_1^{n*} = x(q_1^n)$ is positive only if $r_1 > \hat{r}_1$. $\hat{r}_1$

satisfies the equation

$$\frac{1}{1+(\frac{1}{q}-1)\exp(-\frac{(\hat{r}_1+r_0-\alpha_h-\alpha_l)(\alpha_h-\alpha_l)}{\sigma^2})} = \frac{-\alpha_l}{\alpha_h-\alpha_l} \tag{B.9}$$

Intuitively, only when the expected return of the fund is positive, $q_1^n\alpha_h + (1-q_1^n)\alpha_l > 0$, indicating that the return at date 1 is higher than a certain threshold, investors would like to hold the fund. Equation (B.10) restates Lemma 1 for the performance chasers:

$$X_1^{n*} = \begin{cases} x(q_1^n) & if \quad r_1 > \hat{r}_1 \\ 0 & if \quad r_1 \leq \hat{r}_1 \end{cases} \tag{B.10}$$

The total fund flow of performance chasers who have paid the cost can be written as

$$FN(r_1, m) \equiv \min[1, \frac{g(r_1; r_0)}{c(m)}]X_1^{n*} = \begin{cases} \min[1, \frac{g(r_1; r_0)}{c(m)}]x(q_1^n) & r_1 > \hat{r}_1 \\ 0 & r_1 \leq \hat{r}_1 \end{cases}$$

For the simplicity of notation, let U_i^F denote the utility of funds with type α_i. At any separating equilibrium, the skill type is fully revealed by the marketing level m. Sophisticated investors believe they know the true type by observing m. The optimal allocation is $X_1^{s^*}(1)$ if the manager is perceived to be high type and $X_1^{s^*}(0) = 0$ if it's low type. In such cases, it's convenient to define $U_i^F(m, 1) = U^F(\alpha_i, m, X_1^{s^*}(1))$ and $U_i^F(m, 0) = U^F(\alpha_i, m, X_1^{s^*}(0))$. Given the definition of $FN(r_1, m)$, the expected profits (4) of a fund with ability α_i can be written as

$$U_i^F(m, X_1^{s^*}(I)) = fX_1^{s^*}(I) + f\lambda \int_{\hat{r_1}}^{\infty} FN(r_1, m)\phi_i(r_1)dr_1 - wm, \; I = 0 \, or \, 1, \tag{B.11}$$

where $r_1 \sim N(\alpha_i, \sigma_\epsilon)$ and $\phi_i(r_1) = \phi(r_1|\alpha_i, \sigma_\epsilon)$.

We are now going to discuss conditions for the existence of separating equilibrium.

Case I: $r_0 < \hat{r}$. First, denote $\hat{r}$ as the threshold of r_0 such that

$$g(\hat{r}_1(\hat{r}), \hat{r}) = C(0)$$

where $\hat{r}_1(\hat{r})$ is the solution to equation (B.9) given $r_0 = \hat{r}$. When $r_0 < \hat{r}$, $g(r_1; r_0) \geq c(m)$ for all $r_1 > \hat{r}_1$. In that case, the utility function (B.11) is equal to

$$U_i^F(m, X_1^{s^*}(I)) = fX_1^{s^*}(I) + f\lambda \int_{\hat{r}_1}^{\infty} x(q_1^n(r_1))\phi_i(r_1)dr_1 - wm, \; I = 0 \, or \, 1,$$

The marginal cost of sending the signal m is equal to w, which is identical to both high-type and low-type. If there exists a separating equilibrium, the low type would always want to deviate and mimic the high type. In this case, there is no separating equilibrium. Both high-type and low-type funds spend zero in marketing.

Case II: $r_0 \geq \hat{r}$**.** Second, when $r_0 \geq \hat{r}$, the strict single crossing property is satisfied. There exists a threshold $\bar{r}_1 > \hat{r}_1$ of returns at date 1 such that $g(\bar{r}_1; r_0) = c(m)$. The utility function (B.11) is equal to

$$U_i^F(m, X_1^{s^*}(I)) = fX_1^{s^*}(I) + f\lambda \int_{\hat{r}_1}^{\bar{r}_1} \frac{g(r_1; r_0)}{c(m)} x(q_1^n)\phi_i(r_1)dr_1 + f\lambda \int_{\bar{r}_1}^{\infty} x(q_1^n)\phi_i(r_1)dr_1 - wm,$$

for $I = 0$ or 1. Next, we construct a separating equilibrium as follows.

Step 1. The low-type manager selects m_l^* that maximizes $U_l^F(m, X_1^{s^*}(0))$.

Step 2. Let $U_l^{F^*} \equiv U_l^F(m_l^*, X_1^{s^*}(0))$. The high-type manager selects m_h^* to solve:

$$\begin{aligned} &\max U_h^F(m, X_1^{s^*}(1)) \\ &\text{subject to } U_l^F(m, X_1^{s^*}(1)) \leq U_l^{F^*}. \end{aligned} \tag{B.12}$$

When the optimization problems in Steps 1 and 2 have solutions, we know it is a separating equilibrium. The low-type manager won't deviate from the equilibrium given that m_h^* is selected in Step 2 to satisfy the constraint in Problem (B.12). Because m_h^* is the solution to Problem (B.12) and the utility is strictly increasing in X_1^s,

$$U_h^F(m_h^*, X_1^{s^*}(1)) \geq U_h^F(m_l^*, X_1^{s^*}(1)) > U_h^F(m_l^*, X_1^{s^*}(0)).$$

The high-type manager won't deviate.

Finally, we show that there exist solutions to the optimization problems in Steps 1 and 2. Taking the derivative of $U_i^F(m, X_1^{s^*}(I))$ with respect to m, we have

$$\frac{\partial U_i^F(m, X_1^{s^*}(I))}{\partial m} = -f\lambda \frac{c'(m)}{c^2(m)} \int_{\hat{r}_1}^{\bar{r}_1} g(r_1; r_0)x(q_1^n)\phi_i(r_1)dr_1 - w \tag{B.13}$$

where $g(\bar{r}_1; r_0) = c(m) > 0$.

The solution to the optimization problem in Step 1 always exists. When $\frac{\partial U^F(\alpha_l, m, X_1^s)}{\partial m}|_{m=0} \leq 0$, $U^F(\alpha_l, m, X_1^s)$ is decreasing in m for all $m \geq 0$. The optimal choice of the low type is $m_l^* = 0$. When $\frac{\partial U_l^F(\alpha_l, m, X_1^s)}{\partial m}|_{m=0} > 0$, considering that $\frac{\partial U^F}{\partial m}|_{m\to\infty} = -w < 0$, there exists $m_l^* > 0$ such that it solves the maximization problem of the low-type fund.

The solution to the optimization problem in Step 2 exists when $r_0 \geq \hat{r}$. Given the strict single crossing property and the constraint, m_h^* is selected in the interval $[m_l^*, \infty)$. Similar to the previous discussion, $\frac{\partial U_h^F}{\partial m}|_{m\to\infty} = -w < 0$, the solution m_h^* always exist. □

B.4 Proof of Proposition 2

First, we discuss the curvature of funds' expected utility with respect to the marketing level m. From the previous equation (B.13), the second-order derivative of the utility function is equal to

$$\frac{\partial^2 U^F}{\partial m^2} = -f\lambda\left(\frac{c'(m)}{c^2(m)}\right)' \int_{\hat{r}_1}^{\tilde{r}_1} g(r_1; r_0) X_1^{n*} \phi(r_1|\alpha_i, \sigma_\epsilon) dr_1 - f\lambda \frac{c'^2(m)}{c(m)} g^{-1'}(c(m); r_0) X_1^{n*}(\tilde{r}_1) \phi(\tilde{r}_1|\alpha_i, \sigma_\epsilon)$$

By the assumption of the cost function, $\frac{c'(m)}{c^2(m)}$ is decreasing in m and the inverse gain function $g^{-1}(c(\cdot); r_0)$ is decreasing in m. When $m \to +\infty$, $\frac{\partial^2 U^F}{\partial m^2} = 0$ and $\frac{\partial U^F}{\partial m} = -w$. Hence the utility function is quasiconcave in m. More specifically, the utility is first non-decreasing then strictly decreasing in m.

Given the concavity of the utility function, we can find the optimal marketing level for the low-type fund in the separating equilibrium. The low-type fund would choose the level that maximizes its profits as if its type is fully disclosed. The first order condition gives the optimal solution m_i' as

$$m_i' = \begin{cases} m'(r_0, \alpha_i) & r_0 > \tilde{r}_{i,0} \\ 0 & r_0 \leq \tilde{r}_{i,0} \end{cases}$$

and $m'(r_0, \alpha_i)$ is the solution to the equation

$$-\frac{c'(m_i')}{c^2(m_i')} = \frac{w}{f\lambda \int_{\hat{r}_1}^{\tilde{r}_1} g(r_1; r_0)\phi(r_1|\alpha_i, \sigma_\epsilon) X_1^{n*} dr_1} \tag{B.14}$$

where $g(\tilde{r}_1; r_0) = c(m_i')$ and $g(\hat{r}_1; r_0) = 0$. When $r_0 \leq \tilde{r}_{i,0}$, the utility function is always decreasing in m. A low-type manager would choose zero investments towards marketing.

$\tilde{r}_{i,0}$ satisfies the following equation.

$$-\frac{c'(0)}{c^2(0)} = \frac{w}{f\lambda \int_{\hat{r}_1}^{g^{-1}(c(0);\tilde{r}_{i,0})} g(r_1;\tilde{r}_{i,0})\phi(r_1|\alpha_i,\sigma_\epsilon)X_1^{n*}dr_1} \tag{B.15}$$

When $r_0 > \tilde{r}_{i,0}$, notice that

$$-\frac{c'(0)}{c^2(0)} > \frac{w}{f\lambda \int_{\hat{r}_1}^{g^{-1}(c(0);r_0)} g(r_1;r_0)\phi(r_1|\alpha_i,\sigma_\epsilon)X_1^{n*}dr_1},$$

there exists a positive solution to equation (B.14). Thus for the low-type fund, the optimal marketing level m_l^* in the equilibrium is equivalent to

$$m_l^* = m_l' = \begin{cases} m'(r_0,\alpha_l) & r_0 > \tilde{r} = \tilde{r}_{l,0} \\ 0 & r_0 \leq \tilde{r} \end{cases}$$

From the equation (B.15), we know that $\tilde{r}_{h,0} < \tilde{r}_{l,0}$.

Hence when $\tilde{r}_{h,0} \leq r_0 < \tilde{r}_{l,0}$, the optimal marketing level m_l^* for the low-type is zero. In the separating equilibrium, neither type wants to deviate from the equilibrium (m_l^*, m_h^*). The high-type manger select $m_h^* = m_h'$. Considering that when $\tilde{r}_{h,0} \leq r_0$ the high-type manager won't deviate

$$U^F(\alpha_h, m_h^*, X_1^s(1)) \geq U^F(\alpha_h, 0, X_1^s(1)) \geq U^F(\alpha_h, 0, X_1^s(0)).$$

As long as

$$w \geq \frac{f}{m_h'}(X_1^s(1) - \lambda \int_{-\infty}^{+\infty} (FN(r_1, m_h') - FN(r_1, 0))\phi(r_1|\alpha_l, \sigma_\epsilon)dr_1),$$

the low-type manager would not deviate $U^F(\alpha_l, m_h', X_1^s(1)) \leq U^F(\alpha_l, 0, X_1^s(0))$. $(0, m_h')$ is the marketing strategy in the equilibrium and high type would hire more than the low type.

When $r_0 \geq \tilde{r}_{l,0} > \tilde{r}_{h,0}$, from the equation (B.14), we know that $m_h' < m_l' = m_l^*$ because $\phi(r_1|\alpha_h, \sigma_\epsilon) > \phi(r_1|\alpha_l, \sigma_\epsilon)$ and $-\frac{c'(m)}{c^2(m)}$ is increasing in m. In this case, to guarantee that funds would not deviate from the equilibrium, the optimal marketing level m_h^* satisfies the following

$$\begin{cases} U^F(\alpha_h, m_h^*, X_1^s(1)) \geq U^F(\alpha_h, m_l^*, X_1^s(0)) \\ U^F(\alpha_l, m_h^*, X_1^s(1)) \leq U^F(\alpha_l, m_l^*, X_1^s(0)) \end{cases}$$

Rewriting the inequalities, we get

$$\begin{cases} w(m_h^* - m_l^*) \leq f X_1^s(1) + f\lambda \int_{-\infty}^{+\infty} (FN(r_1, m_h^*) - FN(r_1, m_l^*))\phi(r_1|\alpha_h, \sigma_\epsilon)dr_1 \\ w(m_h^* - m_l^*) \geq f X_1^s(1) + f\lambda \int_{-\infty}^{+\infty} (FN(r_1, m_h^*) - FN(r_1, m_l^*))\phi(r_1|\alpha_l, \sigma_\epsilon)dr_1 \end{cases} \tag{B.16}$$

Thus if

$$w \leq \frac{f}{(m_h' - m_l^*)}(X_1^s(1) + \lambda \int_{-\infty}^{+\infty} (FN(r_1, m_h') - FN(r_1, m_l^*))\phi(r_1|\alpha_l, \sigma_\epsilon)dr_1)$$

then there exists the optimal marketing level $m_h^* \leq m_h'$ such that $U^F(\alpha_l, m_h^*, X_1^s(1)) = U^F(\alpha_l, m_l^*, X_1^s(0))$. m_h^* is the solution to the equation (B.17),

$$w = \frac{f}{(m_h^* - m_l^*)}(X_1^s(1) + \lambda \int_{-\infty}^{+\infty} (FN(r_1, m_h^*) - FN(r_1, m_l^*))\phi(r_1|\alpha_l, \sigma_\epsilon)dr_1). \tag{B.17}$$

In this case, the inequalities (B.16) hold. (m_l^*, m_h^*) is the marketing strategy in the equilibrium and $m_h^* \leq m_h' < m_l^*$. The high-type fund would hire less than the low-type.□

C Data and Sample Construction

C.1 Form ADV data

Form ADV is an SEC regulatory filing that is required for all investment managers who qualify as an "investment adviser" under the Investment Advisers Act of 1940. Since the passage of the Dodd–Frank Act in 2010, investment advisors who manage more than $100 million in regulatory assets under management must file Form ADV annually. In addition to employment, Form ADV also includes information about an advisory company's size, employment, ownership structure, contact information, and so on.

Item 5 in Part 1A of Form ADV reports employment information. Item 5.A. asks, "Approximately how many employees do you have? Include full- and part-time employees but do not include any clerical workers." In Items 5.B(1) to (6), the form asks about the number of employees in certain categories. For example, 5.B(1) asks "How many of the employees reported in 5.A. perform investment advisory functions (including research)?" Item 5.B(2) provides the key information for our study, asking "How many of the employees reported in 5.A. are registered representatives of a broker-dealer?"

The term registered representative refers to individuals who are licensed to sell securities, such as stocks, bonds, and mutual funds, on behalf of their customers (as a broker), for their own account (as a dealer), or for both. In a brokerage or fund company, the sales personnel (often referred to as brokers or advisors) are technically known as registered representatives. To become a registered representative, one must pass the qualification examination administrated by FINRA and must be sponsored by a broker-dealer firm.To sponsor their in-house registered representatives, mutual fund advisory companies typically either register as a brokerage firm in addition to its adviser status or set up an affiliated brokerage firm.

The number of registered representatives is a good proxy of the in-house marketing ability of a mutual fund company. Usually, registered representatives are responsible for selling mutual funds to potential investors. In addition, registered representatives, often called account executives, are responsible for providing customer service and keeping the company-client relationships.

In response to the Dodd–Frank Act, the SEC has made substantial changes to Form ADV in 2010. One important post-amendment change to this form is that advisers must provide a specific number in response to all questions in Items 5.A and 5.B. Before 2011, advisers only chose a range from six choices (i.e., 1–5, 6–10, 11–50, 51–250, 501–1000, and more than 1000). Thus, the Form ADV data we use in this paper are available annually from 2011 to 2020. The key variable of our paper, *MKT*, is defined as the fraction of registered representatives to total employees—that is, the number in Item 5.B(2) divided by the number in Item 5.A. We also define INV as the fraction of investment-oriented representatives to total employees for the robustness check, which is using the number in Item 5.B(1) divided by the number in Item 5.A.

It is worth noting that *MKT* is a noisy measure that may not reflect a firm's exact number of employees hired to perform the marketing function. It is possible that employees without the broker license may still talk to clients or promote the firm's products (they are just not allowed to sell mutual fund shares). It is also possible that some mutual funds have more complex arrangements for marketing labor force, such as outsourcing marketing to another independent or affiliated firm. Outsourcing marketing to a third-party firm might be common for a small company, while setting up an affiliated firm for marketing may be common for large firms. In this sense, one would expect *MKT* to capture the lower bound of a firm's human capital share in marketing and sales, as it counts the number of employees who have the legal qualification to work as a sales representative. The measurement error in *MKT* is likely biased against our finding any results.

The variable *MKT* is a company-level measure. In fund companies, portfolio management and investment decisions are typically made at the fund level, while the company is responsible for marketing, operations, and compliance for all funds. Based on this distinction, measures of marketing efforts must refer to the company level. Some of the previous literature has have examined the role of spending on advertising or distribution using 12b-1 fees (e.g., Khorana and Servaes (2012); Gallaher et al. (2006); Barber et al. (2005)). To the best of our knowledge, *MKT* is the first direct measure of the marketing labor force from the employment data at mutual fund companies.

Form ADV includes advisers to all types of investment vehicles, such as mutual fund, hedge fund, private equity, and pension fund. As this paper focuses on mutual fund advisers, we later manually merge Form ADV data with the CRSP Survivor-Bias-Free US Mutual Fund Database to implement our empirical tests.

C.2 Sample construction and variable definitions

We start by constructing a monthly file of mutual funds from CRSP. We download data on monthly net returns (*Fund_Return*), total net assets (TNA, *Fund Assets*), and *Expense Ratio* for each share class of a mutual fund and then collapse the share class level variables into fund level by taking the average value weighted by the previous month-end TNA. To identify a fund's different share classes, we use CRSP Class Group (crsp_cl_grp), which is available to all funds in CRSP. By comparison, the literature typically uses Mutual Fund

Links (MFlinks), which only covers domestic equity mutual funds. Because our analysis is conducted at the company level, we must include *all* mutual funds in a company.[18]

We further categorize all funds into seven groups based on Lipper Objectives (crsp_obj_name).[19] Funds with TNA less than $1 million are dropped. We calculate each mutual fund's monthly flow (*Flow*) as the percentage of new funds that flow into the mutual fund over a month. *Flow* is winsorized at both the 1% and 99% levels at each month. *Fund Age* is the number of years since the inception of the fund.

To adjust fund performance for different risk exposures, we use a 6-factor model, which augments the Fama–French three-factor model (MKTRF, SMB, HML) with a momentum factor (MOM), a bond market factor, and a factor for international stock markets. This approach aims to better adjust risk exposures for international, balanced, and fixed-income mutual funds in our sample. We use the Bloomberg Barclays US Aggregate Bond Index (BABI) return as our bond factor and the Morgan Stanley Capital International index (MSCI) return to proxy the performance of international markets. In addition, we use CAPM-adjusted return as an alternative measure. This is motivated by the finding in Berk and van Binsbergen (2016) and in Barber, Huang and Odean (2016): Investors use the CAPM-beta to adjust risk exposure when making investment decisions. For robustness, we also consider raw returns a simple measure of fund performance that an investor may use. In the regression, we adjust gross returns (the sum of the net return and the 1/12 expense ratio) and net returns of funds.

For each fund in our sample, we estimate its loading on the factors (MKTRF, SMB, HML, UMD, BABI, and MSCI) using a 5-year rolling window at the end of each year. We require a fund to have at least 36 months of returns to estimate factor loadings, which are then used to calculate that fund's risk-adjusted returns in the following year. Funds that have insufficient observations to estimate betas at the beginning of each year are excluded from our sample.

Next, we construct several company-level variables based on fund-level information. The identifier of the fund company that we use in CRSP is *adv_name*. Note that this

[18]One drawback of crsp_cl_grp is that it is only available after 1998, but this does not impact our paper.

[19]Following Chen, Hong, Jiang and Kubik (2013), we first select mutual funds with an Lipper objective of "aggressive growth" or "long-term growth" and categorize these funds as "Aggressive Growth" funds. We categorize funds with Lipper objectives of "small-cap growth" as "Small-Cap Growth" and funds with Lipper objectives of "growth- income" or "income-growth" as "Growth and Income." We classify mutual funds with Lipper objectives that contain the words "bond(s)," "government," "corporate," "municipal," or "money market" as "Fixed Income." Mutual funds that have an objective that contains the words "sector," "gold," "metals," "natural resources," "real estate," or "utility" are considered "Sector" funds. We classify funds that have an objective containing the words "international" or "global," or a name of a country or a region, as "International" unless it is already classified. Finally, we categorize "balanced," "income," "special," or "total return" funds as "Balanced" funds.

differs from the management company name normally used in the literature to identify fund families. We use the adviser name because Form ADVs are filed by advisory firms, not by a fund family.[20] We also conduct our analysis at the fund company level and find similar results.

$Vol(MKT)$ is the standard deviation of MKT during the sample years. $Range(MKT)$ is the range of MKT. We calculate *Firm Assets*, total TNA of funds that a fund company manages, and the number of funds in the company, *No. of Funds*. *Firm Revenue* is defined as the sum of all funds' revenue, which equals a fund's total net assets times its expense ratio. The calculation is based on the funds' TNA at each month end and sums up all fund-month revenues into the firm-year level. Δ*Firm Assets* is the annual log change of *Firm Assets*. Δ*Firm Revenue* is the annual log change of *Firm Revenue*. *Firm Flow* is the percentage of total new fund flows into funds of the fund company over a year–namely, for all funds $i = 1, ..., N$ in the company k, *Firm Flow* over year t is given by,

$$Firm\ Flow_{k,t} = \frac{TNA_{k,t} - \sum_{i=1}^{N} TNA_{i,t-1}(1 + r_{i,t})}{TNA_{k,t-1}}$$

$TNA_{k,t} = \sum_{i=1}^{N} TNA_{i,t}$ and TNA refers to the total net asset value. *Firm Flow* is winsorized at the 1% and 99% levels by year. The variables *Firm Expense* and *Firm Return* equal the value-weighted average of the expense ratio and the previous year's return or alpha of all funds in the company, respectively. The expense ratio is also winsorized at the 1% and 99% levels by year.

Next, we merge this dataset to the Form ADV filings. Due to the lack of a common identifier, we manually match each fund's adviser name in CRSP (*adv_name*) with that adviser's legal name on the Form ADV. To be conservative, we require both the keyword and corporation abbreviation of the two names to be the same. We allow only trivial variations in punctuation. To eliminate possible matching errors, we drop company–year observations where the firm's total asset in CRSP is more than twice or smaller than 20% of the total assets reported on Form ADV. We also require a minimum fund size of $1 million.

[20] In principle, a mutual fund's management company and advisory firm are different legal entities: The management company owns the fund, while the advisory firm manages the fund's portfolio. But for most cases, a fund's management company and its advisory firm are virtually the same. Some exceptions are the cases in which the management company may outsource portfolio management to a third-party advisor. See Chen et al. (2013) for more details.

D Figures and Tables

Figure VII. Persistence of Fund Performance and Marketing

The upper panel plots post-formation firm returns on portfolios of fund companies sorted on lagged one-year firm return. The lower panel plots post-formation *MKT* on portfolios of mutual funds sorted on lagged *MKT*. Firm return is the average 6-factor Alpha of mutual funds in the fund company, value-weighted by each fund's total assets; 6-factor Alphas are adjusted gross returns using the 6-factor model. *MKT* is the fraction of marketing employees (i.e., registered brokers) to total employees.

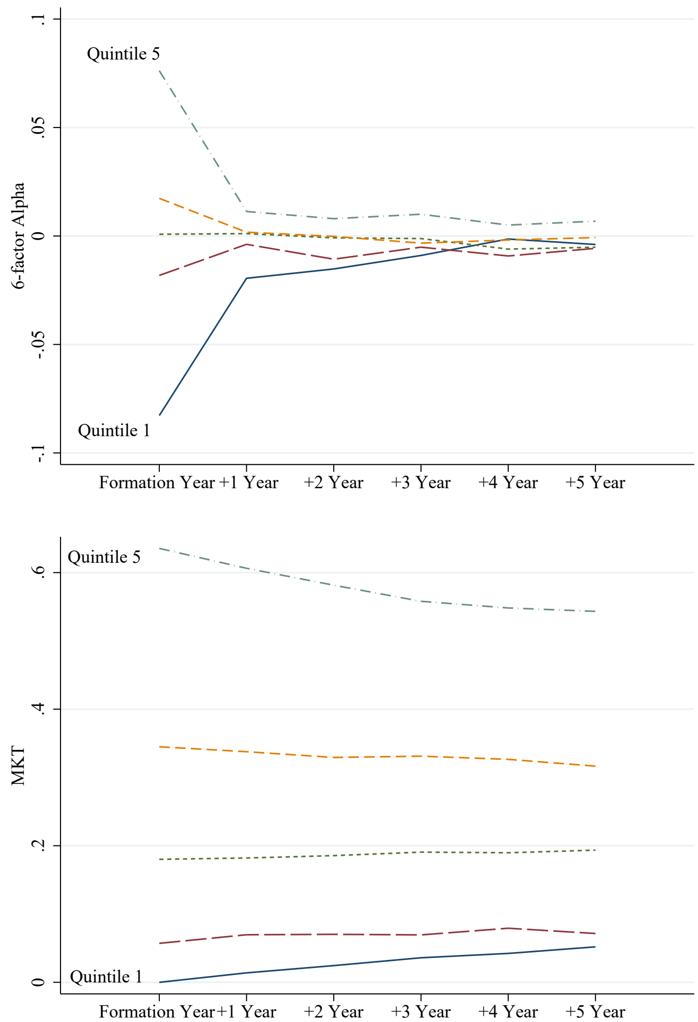

Figure VIII. Heterogeneous Persistence of Fund Marketing

This figure is the box plot of fund companies' marketing persistence using *MKT* and 12b-1 fee ratio. Fund companies are sorted into quintiles based on the persistence of marketing. In the upper graph, marketing persistence is measured by the volatility of *MKT*, *Vol(MKT)*. In the bottom graph, marketing persistence is measured by the volatility of the 12b-1 ratio, *Vol (12b1)*. Fund companies in the Group 1 are firms with the most persistent marketing strategies, and Group 5 includes firms with the least persistent marketing strategies. The box displays the persistence within each group based on the five-number summary without outliers: the minimum, the maximum, the median, and the first and third quartiles.

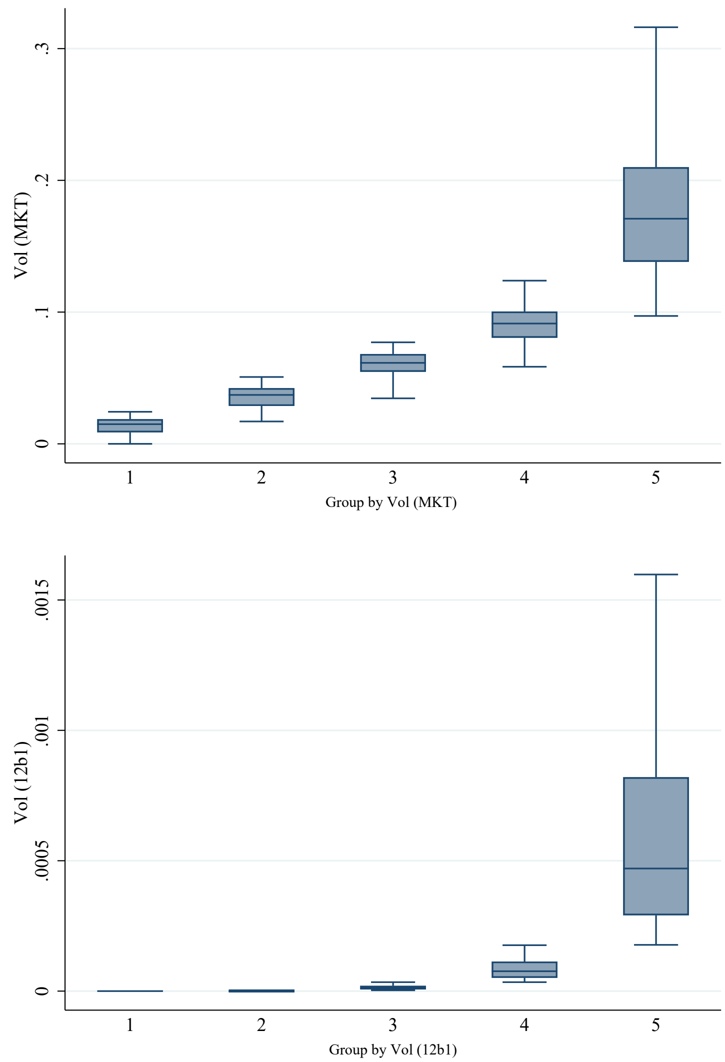

Figure IX. The Relationship between Firm Return and Marketing Persistence

Fund companies are sorted into quintiles based on the persistence of marketing. Marketing Persistence is measured by the volatility of *MKT*, *Vol(MKT)*. *Firm Return* is the average annualgross return of mutual funds of a fund company, value-weighted by each fund's total assets. *6-factor Alpha* is the average gross alpha of funds of a fund company, where the fund gross return is adjusted by the 6-factor model. Fund companies in the Group 1 are categorized as firms with the most persistent marketing strategies, and Group 5 includes firms with the least persistent marketing strategies. The y-axis plots the average firm return for each group.

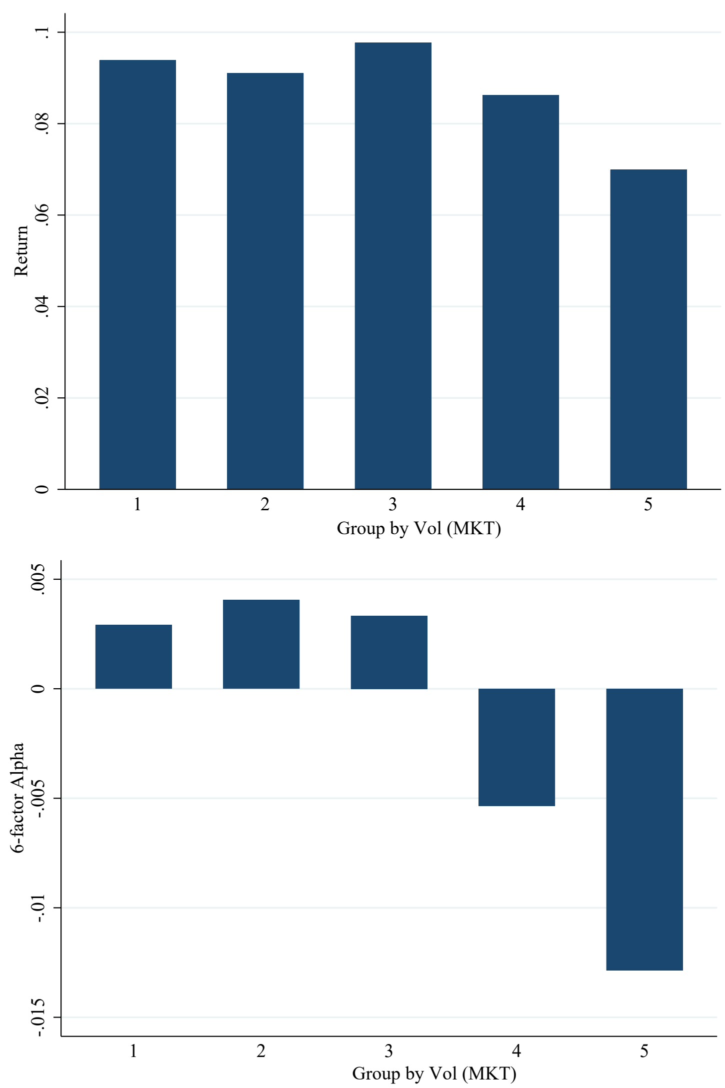

Table I. Summary Statistics

The sample period is from 2011 to 2020. Panel A shows summary statistics of annual variables at the fund company level. *MKT* is the fraction of marketing employees (i.e., registered brokers) to total employees. *Vol(MKT)* (*Range(MKT)*) is the standard deviation (range) of *MKT* during the sample period when fund companies have at least 3-year record of *MKT*. *Vol(EMP)* is the standard deviation of the total number of employees *EMP* in the last 3 years, and we drop observations with zero employees over the past 3 years. *Vol(INV)* is the standard deviation of *INV*, the ratio of the investment-oriented employees to the total number of employees in the last 3 years. *12b1* is the average 12b-1 fee ratio of mutual funds in the firm, value-weighted by each fund's total assets. *Vol(12b1)* is the average of the standard deviation of *12b1* at the share class level in the last 3 years when funds have at least 3 years of records of *12b1*. $Vol(12b1)_{vw}$ represents the value-weighted averaged standard deviation. $Vol(12b1)_{ew}$ is the equal-weighted average instead. *Firm Expense* is the average expense ratio of mutual funds in the firm, value-weighted by each fund's total assets. *Firm Flow* is the average fund flow in the firm, value-weighted by each fund's total assets. Fund flow is the percentage of total new fund flows into the company's funds over a year and is winsorzied at the 1% and 99% levels by each month. Δ*Firm Size* is the log change of *Firm Assets* over a year. Δ*Firm Revenue* is the log change of *Firm Revenue* over a year. *Firm Revenue* is the summation of each fund's total net assets times expense ratio and is winsorized at both the 2.5% and 97.5% levels by month. Panel B shows the summary statistics of monthly variables at the company level. *Firm Assets* is the total net assets (in millions USD) managed by all mutual funds in the fund company, and *Log Firm Assets* is the log of *Firm Assets*. *Log No. of funds* is the log of the total number of mutual funds (*No. of Funds*) in a fund company. *Firm Age* equals the number of years since the inception of the company's first fund. *Log Firm Age* is the log of *Firm Age*. *Firm* $Return^n$ is the average past year net return of mutual funds of a fund company, value-weighted by each fund's total assets. *Firm* $Return^g$ is the average past gross return of mutual funds within the firm, where the fund's gross return equals the sum of the net return and the 1/12 expense ratio. *CAPM* $Alpha^g$ and 6-factor $Alpha^g$ are adjusted gross returns using the CAPM or 6-factor model, respectively. *CAPM* $Alpha^n$ and 6-factor $Alpha^n$ are adjusted net returns using corresponding models. *Value added* is the average value added of mutual funds in a fund company, value-weighted by each fund's total assets. The value added of funds is calculated as the gross alpha times total assets (in millions USD) in the last month, where the gross alpha is adjusted using the 6-factor model.

Panel A: Annual Variables

Variable	Obs	Mean	Std. Dev.	P25	P50	P75
MKT	3776	23.70%	24.40%	0.00%	17.60%	38.60%
Vol (MKT)	2918	7.85%	6.80%	2.98%	6.15%	10.20%
Range (MKT)	2918	21.10%	17.20%	8.33%	16.70%	28.00%
EMP	3908	117	340	7	19	72
Vol (EMP)	2708	11.9	42.2	0.577	1.73	6.35
INV	3908	50.90%	18.90%	30.00%	46.70%	66.70%
Vol (INV)	2708	4.76%	0.00%	0.59%	2.39%	5.88%
12b1	2547	0.3340%	0.1780%	0.2500%	0.2650%	0.4050%
Vol $(12b1)_{vw}$	2338	0.0066%	0.0233%	0.0000%	0.0001%	0.0026%
Vol $(12b1)_{ew}$	2340	0.0074%	0.0244%	0.0000%	0.0002%	0.0036%
Firm Expenses	3776	1.11%	0.50%	0.77%	1.07%	1.39%
Firm $Return^n$	3776	7.55%	13.90%	-1.10%	6.21%	15.00%
Firm Flow	3776	60.70%	504.00%	-55.20%	-3.41%	72.00%
ΔFirm Size	3160	9.55%	48.90%	-9.63%	6.77%	22.50%
ΔFirm Revenue	3160	6.51%	37.50%	-7.89%	3.96%	17.00%

Panel B: Monthly Variables

Variable	Obs	Mean	Std. Dev.	P25	P50	P75
Firm Assets	43942	40687	220988	189	1263	11605
Log Firm Assets	43942	7.31	2.76	5.25	7.14	9.36
No. of Funds	43942	19.00	38.50	2.00	5.00	14.00
Log No. of Funds	43942	2.02	1.26	1.10	1.79	2.71
Firm Age	43942	20.50	17.20	7.25	17.70	27.70
Log Firm Age	43942	2.74	0.87	2.11	2.93	3.36
Firm Return^g	43942	0.70%	3.83%	-0.78%	0.71%	2.40%
6-factor Alpha^g	37998	-0.02%	1.86%	-0.55%	0.02%	0.56%
CAPM Alpha^g	37998	-0.16%	2.07%	-0.83%	-0.03%	0.61%
Firm Return^n	43942	0.61%	3.83%	-0.88%	0.63%	2.31%
6-factor Alpha^n	38244	-0.12%	1.85%	-0.64%	-0.04%	0.46%
CAPM Alpha^n	38244	-0.25%	2.06%	-0.92%	-0.10%	0.51%
Value Added	37946	-0.07	96.30	-2.88	0.08	3.81

Table II. Marketing Persistence and Fund Performance

This table presents the results of regressions of fund companies' subsequent performance on *Vol(MKT)*. *Vol(MKT)* is the standard deviation of *MKT* over the whole sample period (at least a 3-year record of *MKT*). *Log Firm Assets* is the log of one plus the total net assets (in millions USD) under management in the fund company. *Log Firm Age* is the log of *Firm Age*. *Firm Expense* is the average expense ratio of mutual funds in a fund company, value-weighted by each fund's total assets. *Log No. of Funds* is the log of the total number of mutual funds in a fund company. *Firm Return*^{n} is the average past year net return of mutual funds of a fund company, value-weighted by each fund's total assets. *Firm Return*^{g} is the average past gross return of mutual funds within the firm, where the fund's gross return equals the sum of the net return and the 1/12 expense ratio. All observations are at the firm level, and firm performance is measured by the 6-factor alpha in columns (1) (2), and (3), the CAPM alpha in columns (4) (5) and (6), and raw return in columns (7) (8), and (9). In Panel A, *CAPM Alpha*^{g} and *6-factor Alpha*^{g} are adjusted gross returns using CAPM or 6-factor model, respectively. In Panel B, *CAPM Alpha*^{n} and *6-factor Alpha*^{n} are adjusted net returns using the corresponding models. This table shows the Fama and MacBeth (1973) estimates of monthly fund companies' performance regressed on firm characteristics lagged 1 month. Observations are from January 2011 to December 2020. The *t*-statistics are adjusted for serial correlation using Newey and West (1987) lags of order 12 and are shown in parentheses.

Panel A: Performance Measured by Gross Return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	6-factor Alpha$^g_{t+1}$			CAPM Alpha$^g_{t+1}$			Firm Return$^g_{t+1}$		
Vol(MKT)	-0.552		-0.529	-0.549		-0.534	-0.828		-0.759
	(-4.00)		(-3.47)	(-4.86)		(-4.18)	(-6.80)		(-6.09)
MKT$_t$		-0.052	-0.023		-0.047	-0.004		-0.131	-0.107
		(-1.49)	(-0.58)		(-1.16)	(-0.08)		(-2.64)	(-1.84)
Log Firm Assets$_t$	0.029	0.033	0.028	0.021	0.020	0.021	0.021	0.023	0.019
	(2.77)	(3.45)	(2.79)	(1.87)	(1.89)	(1.89)	(1.53)	(2.47)	(1.41)
Log Firm Age$_t$	0.029	0.018	0.029	0.032	0.029	0.033	0.070	0.070	0.069
	(1.02)	(0.63)	(1.01)	(1.13)	(1.05)	(1.16)	(1.95)	(2.73)	(1.95)
Firm Expense$_t$	-2.383	1.128	-2.261	-5.533	-3.706	-5.478	4.185	10.024	4.366
	(-0.76)	(0.31)	(-0.73)	(-1.27)	(-0.59)	(-1.24)	(0.91)	(1.90)	(0.94)
Log No. of Funds$_t$	-0.061	-0.056	-0.061	-0.045	-0.038	-0.045	-0.070	-0.057	-0.067
	(-4.03)	(-3.61)	(-4.11)	(-2.67)	(-2.63)	(-2.90)	(-3.06)	(-2.95)	(-3.06)
6-factor Alpha^g_t	0.070	0.025	0.070						
	(2.81)	(1.09)	(2.82)						
CAPM Alpha^g_t				0.079	0.061	0.078			
				(2.42)	(2.00)	(2.40)			
Firm Return^g_t							0.051	0.049	0.051
							(1.18)	(1.21)	(1.17)
Obs.	25656	30831	25656	25656	30831	25656	27280	33558	27280
Adj. R^2	0.103	0.102	0.104	0.117	0.110	0.118	0.166	0.146	0.167

Panel B: Performance Measured by Net Return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	6-factor Alpha^n_{t+1}			CAPM Alpha^n_{t+1}			Firm Return^n_{t+1}		
Vol(MKT)	-0.556		-0.527	-0.554		-0.533	-0.859		-0.785
	(-3.63)		(-3.13)	(-4.48)		(-3.80)	(-7.07)		(-6.31)
MKT_t		-0.063	-0.029		-0.060	-0.013		-0.144	-0.116
		(-1.67)	(-0.73)		(-1.42)	(-0.26)		(-2.85)	(-2.05)
Log Firm Assets_t	0.032	0.034	0.031	0.023	0.020	0.022	0.022	0.023	0.020
	(3.15)	(3.76)	(3.16)	(2.07)	(2.01)	(2.08)	(1.66)	(2.56)	(1.52)
Log Firm Age_t	0.030	0.020	0.030	0.030	0.028	0.031	0.068	0.069	0.068
	(1.03)	(0.70)	(1.02)	(1.07)	(1.03)	(1.10)	(1.87)	(2.62)	(1.86)
Firm Expense_t	-10.028	-7.184	-9.908	-13.559	-11.997	-13.505	-4.360	1.674	-4.157
	(-3.17)	(-2.02)	(-3.16)	(-3.40)	(-2.02)	(-3.34)	(-0.92)	(0.31)	(-0.87)
Log No. of Funds_t	-0.063	-0.056	-0.062	-0.042	-0.034	-0.042	-0.068	-0.055	-0.064
	(-4.09)	(-3.64)	(-4.17)	(-2.61)	(-2.46)	(-2.83)	(-3.05)	(-2.84)	(-3.02)
6-factor Alpha^n_t	0.071	0.026	0.071						
	(2.75)	(1.09)	(2.76)						
CAPM Alpha^n_t				0.079	0.061	0.079			
				(2.43)	(2.02)	(2.41)			
Firm Return^n_t							0.051	0.050	0.051
							(1.19)	(1.23)	(1.18)
Obs.	25767	30977	25767	25767	30977	25767	27280	33558	27280
Adj. R^2	0.105	0.102	0.105	0.120	0.111	0.120	0.166	0.146	0.167

Table III. Marketing Persistence and Fund Performance: Predictive Regressions

This table presents the results of regressions of fund companies' subsequent performance on *Vol(MKT)* in the rolling window. *Vol(MKT)$_t$* is the standard deviation of *MKT* in the past 3 years. *Log Firm Assets* is the log of one plus the total net assets (in millions USD) under management in the fund company. *Log Firm Age* is the log of *Firm Age*. *Firm Expense* is the average expense ratio of mutual funds in a fund company, value-weighted by each fund's total assets. *Log No. of Funds* is the log of the total number of mutual funds in a fund company. *Firm Return^n* is the average past year net return of mutual funds of a fund company, value-weighted by each fund's total assets. *Firm Return^g* is the average past gross return of mutual funds within the firm, where the fund's gross return equals the sum of the net return and the 1/12 expense ratio. All observations are at the firm level and firm performance is measured by 6-factor alpha in columns (1) (2), and (3), the CAPM alpha in columns (4) (5), and (6), and raw return in columns (7) (8), and (9). In Panel A, *CAPM Alpha^g* and *6-factor Alpha^g* are adjusted gross returns using CAPM or 6-factor model, respectively. In Panel B, *CAPM Alpha^n* and *6-factor Alpha^n* are adjusted net returns using the corresponding models. This table shows the Fama and MacBeth (1973) estimates of monthly fund companies' performance regressed on firm characteristics lagged 1 month. Observations are from January 2011 to December 2020. The t-statistics are adjusted for serial correlation using Newey and West (1987) lags of order 12 and are shown in parentheses.

Panel A: Performance Measured by Gross Return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	6-factor Alpha$^g_{t+1}$			CAPM Alpha$^g_{t+1}$			Firm Return$^g_{t+1}$		
Vol(MKT)$_t$	-0.720		-0.741	-0.588		-0.624	-0.723		-0.721
	(-5.45)		(-5.70)	(-4.61)		(-4.71)	(-4.29)		(-4.60)
MKT$_t$		-0.052	0.039		-0.047	0.072		-0.131	-0.043
		(-1.49)	(1.14)		(-1.16)	(1.28)		(-2.64)	(-0.57)
Log Firm Assets$_t$	0.017	0.033	0.017	0.019	0.020	0.020	0.006	0.023	0.006
	(1.25)	(3.45)	(1.31)	(1.63)	(1.89)	(1.72)	(0.35)	(2.47)	(0.29)
Log Firm Age$_t$	0.037	0.018	0.039	0.065	0.029	0.068	0.096	0.070	0.098
	(1.41)	(0.63)	(1.45)	(2.09)	(1.05)	(2.12)	(2.41)	(2.73)	(2.44)
Firm Expense$_t$	-3.844	1.128	-3.998	-4.277	-3.706	-4.474	1.808	10.024	1.650
	(-0.93)	(0.31)	(-0.97)	(-0.89)	(-0.59)	(-0.92)	(0.31)	(1.90)	(0.28)
Log No. of Funds$_t$	-0.037	-0.056	-0.039	-0.036	-0.038	-0.039	-0.034	-0.057	-0.034
	(-1.96)	(-3.61)	(-2.06)	(-2.17)	(-2.63)	(-2.46)	(-1.56)	(-2.95)	(-1.58)
6-factor Alpha^g_t	0.049	0.025	0.049						
	(2.00)	(1.09)	(1.99)						
CAPM Alpha^g_t				0.043	0.061	0.043			
				(1.80)	(2.00)	(1.76)			
Firm Return^g_t							0.013	0.049	0.013
							(0.27)	(1.21)	(0.27)
Obs.	17523	30831	17523	17523	30831	17523	17803	33558	17803
Adj. R^2	0.101	0.102	0.102	0.117	0.110	0.118	0.172	0.146	0.174

Panel B: Performance Measured by Net Return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	6-factor Alpha^n_{t+1}			CAPM Alpha^n_{t+1}			Firm Return^n_{t+1}		
Vol(MKT)_t	-0.779		-0.798	-0.646		-0.679	-0.781		-0.777
	(-5.32)		(-5.50)	(-4.56)		(-4.55)	(-4.65)		(-4.94)
MKT_t		-0.063	0.035		-0.060	0.063		-0.144	-0.050
		(-1.67)	(1.02)		(-1.42)	(1.13)		(-2.85)	(-0.67)
Log Firm Assets_t	0.019	0.034	0.020	0.020	0.020	0.021	0.009	0.023	0.008
	(1.47)	(3.76)	(1.51)	(1.80)	(2.01)	(1.87)	(0.48)	(2.56)	(0.41)
Log Firm Age_t	0.032	0.020	0.034	0.059	0.028	0.062	0.089	0.069	0.091
	(1.20)	(0.70)	(1.24)	(1.87)	(1.03)	(1.89)	(2.27)	(2.62)	(2.30)
Firm Expense_t	-12.908	-7.184	-13.075	-13.875	-11.997	-14.089	-7.653	1.674	-7.806
	(-3.02)	(-2.02)	(-3.07)	(-3.10)	(-2.02)	(-3.09)	(-1.30)	(0.31)	(-1.32)
Log No. of Funds_t	-0.041	-0.056	-0.043	-0.036	-0.034	-0.039	-0.034	-0.055	-0.034
	(-2.12)	(-3.64)	(-2.21)	(-2.16)	(-2.46)	(-2.43)	(-1.56)	(-2.84)	(-1.57)
6-factor Alpha^n_t	0.050	0.026	0.049						
	(2.05)	(1.09)	(2.05)						
CAPM Alpha^n_t				0.042	0.061	0.042			
				(1.74)	(2.02)	(1.70)			
Firm Return^n_t							0.012	0.050	0.011
							(0.25)	(1.23)	(0.24)
Obs.	17584	30977	17584	17584	30977	17584	17803	33558	17803
Adj. R^2	0.104	0.102	0.105	0.120	0.111	0.122	0.172	0.146	0.173

Table IV. Marketing Persistence and Fund Performance: Robustness Tests

This table presents the results of the robustness check for the relationship between marketing persistence and subsequent performance. Panel A shows the regressions of fund companies' subsequent performance on an alternative measure of marketing persistence, *Range(MKT)*. *Range(MKT)* is the range of *MKT* in the past 3 years. Panel B shows the regressions of the flagship fund's subsequent performance on *Vol(MKT)* in the rolling window. Firm performance is measured by the performance of the fund with the largest assets in a fund company. *Log Firm Assets* is the log of *Firm Assets*. *Log Firm Age* is the log of *Firm Age*. *Firm Expense* is the average expense ratio of mutual funds in a fund company, value-weighted by each fund's total assets. *Log No. of funds* is the log of the total number of mutual funds in a fund company. All observations are at the firm level and firm performance is measured by gross return in columns (1), (2), and (3), and net return in columns (4), (5), and (6). In columns (1) (2), and (3) of each panel, firm return is measured by gross return, and *CAPM Alpha* and *6-factor Alpha* are adjusted gross returns using CAPM or 6-factor model, respectively. In columns (4), (5), and (6) of each panel, firm return is measured by net return, and *CAPM Alpha* and *6-factor Alpha* are adjusted net returns using corresponding models. This table shows the Fama and MacBeth (1973) estimates of monthly fund companies' performance regressed on firm characteristics lagged one month. Observations are from January 2011 to December 2020. The t-statistics are adjusted for serial correlation using Newey and West (1987) lags of order 12 and are shown in parentheses.

Panel A: Alternative Measure of Marketing Persistence

	Gross Return			Net Return		
	(1)	(2)	(3)	(4)	(5)	(6)
	6-factor Alpha_{t+1}	CAPM Alpha_{t+1}	Firm Return_{t+1}	6-factor Alpha_{t+1}	CAPM Alpha_{t+1}	Firm Return_{t+1}
Range(MKT)_t	-0.407	-0.351	-0.403	-0.440	-0.383	-0.435
	(-5.88)	(-4.79)	(-4.49)	(-5.66)	(-4.61)	(-4.79)
MKT_t	0.040	0.074	-0.041	0.036	0.065	-0.047
	(1.18)	(1.31)	(-0.55)	(1.07)	(1.16)	(-0.64)
Log Firm Assets_t	0.017	0.020	0.005	0.020	0.021	0.008
	(1.31)	(1.71)	(0.29)	(1.51)	(1.87)	(0.41)
Log Firm Age_t	0.038	0.068	0.097	0.033	0.061	0.091
	(1.44)	(2.12)	(2.43)	(1.22)	(1.89)	(2.29)
Firm Expense_t	-4.026	-4.525	1.594	-13.117	-14.157	-7.874
	(-0.98)	(-0.93)	(0.27)	(-3.08)	(-3.11)	(-1.33)
Log No. of Funds_t	-0.039	-0.039	-0.034	-0.042	-0.038	-0.034
	(-2.04)	(-2.43)	(-1.55)	(-2.19)	(-2.40)	(-1.54)
6-factor Alpha_t	0.049			0.049		
	(1.99)			(2.04)		
CAPM Alpha_t		0.043			0.042	
		(1.76)			(1.69)	
Firm Return_t			0.013			0.011
			(0.26)			(0.24)
Obs.	17523	17523	17803	17584	17584	17803
Adj. R^2	0.102	0.118	0.174	0.106	0.122	0.173

Panel B: Flagship Fund Performance

	Gross Return			Net Return		
	(1)	(2)	(3)	(4)	(5)	(6)
	6-factor Alpha$_{t+1}$	CAPM Alpha$_{t+1}$	Firm Return$_{t+1}$	6-factor Alpha$_{t+1}$	CAPM Alpha$_{t+1}$	Firm Return$_{t+1}$
Vol(MKT)$_t$	-1.188	-1.024	-0.933	-1.234	-1.099	-0.986
	(-5.80)	(-4.49)	(-3.05)	(-6.02)	(-4.72)	(-3.35)
MKT$_t$	0.032	0.027	-0.114	0.030	0.024	-0.114
	(0.56)	(0.45)	(-1.25)	(0.51)	(0.40)	(-1.22)
Log Firm Assets$_t$	0.028	0.013	0.006	0.027	0.012	0.005
	(1.46)	(0.78)	(0.22)	(1.39)	(0.68)	(0.19)
Log Firm Age$_t$	-0.004	0.062	0.113	-0.006	0.061	0.110
	(-0.12)	(1.54)	(2.11)	(-0.18)	(1.45)	(2.05)
Firm Expense$_t$	-7.738	-14.970	-2.212	-17.440	-25.206	-12.293
	(-1.19)	(-2.51)	(-0.31)	(-2.56)	(-4.26)	(-1.64)
Log No. of Funds$_t$	-0.050	-0.050	-0.043	-0.048	-0.049	-0.041
	(-1.72)	(-1.98)	(-1.17)	(-1.66)	(-1.89)	(-1.12)
6-factor Alpha$_t$	0.022			0.021		
	(0.68)			(0.65)		
CAPM Alpha$_t$		0.040			0.039	
		(1.52)			(1.50)	
Firm Return$_t$			0.007			0.007
			(0.17)			(0.17)
Obs.	16149	16149	17147	16208	16208	17147
Adj. R^2	0.114	0.117	0.152	0.116	0.118	0.152

Table V. Employment Persistence and Fund Performance

This table presents the results of the robustness check for the relationship between alternative employment persistence and subsequent performance: *Vol(EMP)* in Columns (1)(2) and *Vol(INV)* in Columns (3)(4). *Vol(EMP)* is the standard deviation of the total number of employees *EMP* in the past 3 years. *Vol(INV)* is the standard deviation of *INV*, the ratio of the investment-oriented employees to the total number of employees in the past 3 years. *Log Firm Assets* is the log of *Firm Assets*. *Log Firm Age* is the log of *Firm Age*. *Firm Expense* is the average expense ratio of mutual funds in a fund company, value-weighted by each fund's total assets. *Log No. of Funds* is the log of the total number of mutual funds in a fund company. All observations are at the firm level. In columns (1) and (3), firm return is measured by adjusted gross returns using 6-factor model. In columns (2) and (4), firm return is measured by adjusted net returns using the 6-factor model. This table shows the Fama and MacBeth (1973) estimates of monthly fund companies' performance regressed on firm characteristics lagged one month. Observations are from January 2011 to December 2020. The t-statistics are adjusted for serial correlation using Newey and West (1987) lags of order 12 and are shown in parentheses.

	(1)	(2)	(3)	(4)
	6-factor Alpha$^g_{t+1}$	6-factor Alpha$^n_{t+1}$	6-factor Alpha$^g_{t+1}$	6-factor Alpha$^n_{t+1}$
Vol(EMP)$_t$	-0.000	-0.000		
	(-1.10)	(-0.60)		
EMP$_t$	0.000	0.000		
	(0.33)	(0.06)		
Vol(INV)$_t$			-0.060	-0.037
			(-0.32)	(-0.20)
INV$_t$			-0.041	-0.050
			(-1.15)	(-1.49)
Log Firm Assets$_t$	0.022	0.024	0.019	0.021
	(2.40)	(2.62)	(2.02)	(2.16)
Log Firm Age$_t$	0.042	0.038	0.041	0.037
	(1.35)	(1.17)	(1.39)	(1.22)
Firm Expense$_t$	-2.832	-11.982	-3.159	-12.360
	(-0.69)	(-3.04)	(-0.78)	(-3.20)
Log No. of Funds$_t$	-0.045	-0.048	-0.045	-0.048
	(-2.53)	(-2.68)	(-2.47)	(-2.60)
6-factor Alpha^g_t	0.010		0.011	
	(0.46)		(0.52)	
6-factor Alpha^n_t		0.010		0.011
		(0.45)		(0.51)
Obs.	23955	24074	23955	24074
Adj. R^2	0.091	0.093	0.097	0.099

Table VI. Marketing Persistence and Fund Performance: 12b1 Fee

This table presents the results of the robustness check for the relationship between marketing persistence and subsequent performance. It shows regressions of funds' subsequent performance on an alternative measure of marketing persistence: *Vol(12b1)* in the rolling window. *Vol(12b1)* is the average of the standard deviation of *12b1* at the share class level in the last 3 years when funds have at least 3-year of records of *12b1*. Columns (1) and (2) represents the results when using the value-weighted averaged standard deviation as the measure of persistence. Columns (3) and (4) use the equal-weighted average instead. *Log Firm Assets* is the log of *Firm Assets*. *Log Firm Age* is the log of *Firm Age*. *Firm Expense* is the average expense ratio of mutual funds in a fund company, value-weighted by each fund's total assets. *Log No. of Funds* is the log of the total number of mutual funds in a fund company. All observations are at the firm level. In columns (1) and (3), firm return is measured by adjusted gross returns using 6-factor model. In columns (2) and (4), firm return is measured by adjusted net returns using the 6-factor model. This table shows the Fama and MacBeth (1973) estimates of monthly fund companies' performance regressed on firm characteristics lagged one month. Observations are from January 2011 to December 2020. The t-statistics are adjusted for serial correlation using Newey and West (1987) lags of order 12 and are shown in parentheses.

	Value-weighted		Equal-weighted	
	(1)	(2)	(3)	(4)
	6-factor Alpha^g_{t+1}	6-factor Alpha^n_{t+1}	6-factor Alpha^g_{t+1}	6-factor Alpha^n_{t+1}
Vol(12b1)_t	-143.611	-155.299	-117.032	-130.828
	(-2.07)	(-2.31)	(-1.92)	(-2.07)
12b1_t	-3.588	-2.300	-3.974	-2.474
	(-0.59)	(-0.41)	(-0.65)	(-0.44)
Log Firm Assets_t	0.025	0.027	0.025	0.027
	(3.56)	(3.68)	(3.54)	(3.64)
Log Firm Age_t	0.015	0.014	0.015	0.014
	(0.35)	(0.35)	(0.35)	(0.35)
Firm Expense_t	-4.285	-13.045	-4.279	-13.169
	(-1.34)	(-4.12)	(-1.36)	(-4.21)
Log No. of Funds_t	-0.053	-0.053	-0.052	-0.053
	(-2.82)	(-2.90)	(-2.79)	(-2.86)
6-factor Alpha^g_t	0.039		0.039	
	(1.16)		(1.16)	
6-factor Alpha^n_t		0.041		0.041
		(1.14)		(1.15)
Obs.	20547	20626	20571	20650
Adj. R^2	0.141	0.143	0.139	0.141

Table VII. Marketing Persistence and Fund Performance: Value Added

This table presents the results of the robustness check for the relationship between marketing persistence and subsequent value added. *Value Added* is the average value added of mutual funds in a fund company, value-weighted by each fund's total assets. The value added of funds is calculated as the gross alpha times total assets in the last month, where the gross alpha is adjusted using the 6-factor model. *Log Firm Age* is the log of *Firm Age*. *Firm Expense* is the average expense ratio of mutual funds in a fund company, value-weighted by each fund's total assets. In columns (1), (2), and (3), *Vol(MKT)* is the standard deviation of *MKT* in the past 3 years. In columns (4), (5), and (6), *Vol(MKT)* is the standard deviation of *MKT* during the whole sample period. *Log Firm Assets* is the log of *Firm Assets*. All observations are at the firm level. This table shows the Fama and MacBeth (1973) estimates of monthly fund companies' performance regressed on firm characteristics lagged 1 month. Observations are from January 2011 to December 2020. The t-statistics are adjusted for serial correlation using Newey and West (1987) lags of order 12 and are shown in parentheses.

	Value Added$_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Vol(MKT)	-12.953		-12.843			
	(-5.28)		(-5.72)			
Vol(MKT)$_t$				-32.305		-33.695
				(-1.78)		(-1.82)
MKT$_t$		-1.016	-0.760		-1.016	-0.686
		(-0.68)	(-0.53)		(-0.68)	(-0.28)
Log Firm Assets$_t$	2.503	2.157	2.517	2.491	2.157	2.527
	(2.93)	(2.91)	(2.97)	(1.69)	(2.91)	(1.73)
Log Firm Age$_t$	-2.134	-1.347	-2.095	-2.541	-1.347	-2.478
	(-2.73)	(-1.71)	(-2.65)	(-2.31)	(-1.71)	(-2.23)
Firm Expense$_t$	246.872	267.091	251.517	173.580	267.091	175.742
	(1.31)	(1.65)	(1.34)	(0.58)	(1.65)	(0.58)
Log No. of Funds$_t$	-4.099	-3.637	-4.125	-3.865	-3.637	-3.939
	(-7.34)	(-5.08)	(-7.45)	(-3.44)	(-5.08)	(-3.55)
Value Added$_t$	0.063	0.055	0.062	0.002	0.055	0.002
	(1.22)	(1.21)	(1.21)	(0.06)	(1.21)	(0.05)
Obs.	25633	30799	25633	17508	30799	17508
Adj. R^2	0.176	0.172	0.175	0.157	0.172	0.155

Table VIII. Regressions of Future Firm Revenue on MKT

This table presents the results of regressions of fund companies' changes in size, flow, and subsequent revenue on *MKT*. All observations are at the firm–year level. Δ*Firm Size* is the log change of *Firm Assets* over a year. *Firm Flow* is the percentage of total new fund flows into the company's funds over a year and is winsorzied at the 1% and 99% levels. Δ*Firm Revenue* is the log change of *Firm Revenue* over a year. *Log Firm Assets* is the log of *Firm Assets*. *Log Firm Age* is the log of *Firm Age*. *Firm Expense* is the average expense ratio of mutual funds in a fund company, value-weighted by each fund's total assets. Δ*Firm Expense* is the change of *Firm Expense* over a year. *Firm Return*^{n} is the average past year net return of mutual funds of a fund company, value-weighted by each fund's total assets. *Log No. of Funds* is the log of the total number of mutual funds in a fund company. The dependent variable is Δ*Firm Size* in columns (1) and (2), *Firm Flow* in columns (3) and (4), and Δ*Firm Revenue* in columns (5) and (6). All dependent variables are at year $t+1$, while independent variables are at year t. Year fixed effects are included in all columns, and firm fixed effects are added in columns (2), (4), and (6). Observations are at the company level annually from 2011 to 2020. Standard errors are clustered by firm, and the corresponding t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm Flow$_{t+1}$		ΔFirm Size$_{t+1}$		ΔFirm Revenue$_{t+1}$	
MKT$_t$	1.319	1.258	0.090	-0.017	0.074	0.051
	(2.39)	(0.94)	(2.62)	(-0.19)	(2.95)	(0.71)
Log Firm Assets$_t$	0.122	-1.895	-0.004	-0.245	-0.003	-0.159
	(1.02)	(-3.39)	(-0.75)	(-9.17)	(-0.80)	(-9.48)
Log Firm Age$_t$	-1.239	0.275	-0.111	-0.178	-0.067	-0.086
	(-5.37)	(0.51)	(-8.63)	(-3.34)	(-6.69)	(-2.37)
Firm Expense$_t$	-163.042	-242.285	-13.255	-20.688	-10.699	-31.372
	(-4.51)	(-2.34)	(-5.37)	(-2.15)	(-6.05)	(-4.24)
Firm Return$_t^n$	1.006	2.919	0.691	0.356	0.494	0.325
	(0.83)	(2.14)	(7.92)	(4.92)	(7.75)	(5.44)
Firm FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2976	2890	2976	2890	2976	2890
Adj. R^2	0.059	0.292	0.166	0.410	0.150	0.335