The Economics of Mutual Fund Marketing *

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Abstract

We uncover a significant relationship between the persistence of marketing employment strategy and fund performance in the U.S. mutual fund industry. Using regulatory filings, we show a large heterogeneity in fund companies' marketing employment share, which refers to the fraction of employees devoted to marketing and sales. Not only does the marketing employment share increase in family size and predict subsequent fund flows, but it is also persistent across fund families. A framework based on Bayesian persuasion and costly learning helps explain the observed strategic marketing decision. Regarding an optimal marketing plan, fund companies with different skill types commit to heterogeneous marketing employment strategies. Conditional on the skill level, fund companies' optimal marketing employment share responds to their past performance differently. Low-skill funds only conduct marketing following good-enough past performance, whereas high-skill funds maintain a high marketing employment share even with very poor past performance. 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.

Keywords: Marketing Employment Share, Persistence Marketing, Bayesian Persuasion, Costly Learning

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1 Introduction

While mutual funds are expected to generate superior investment returns, it is a salient observation that 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 operation of the asset management business to allocate various types of human capital. However, little is known about how mutual fund companies decide the share of human capital dedicated to marketing versus other more essential tasks, including trading, research, and operation, and how such a marketing decision shapes mutual fund firms' performance, future growth, and size distribution.

In this paper, we first document some stylized facts about companies' marketing efforts by developing a ratio of mutual fund companies' marketing-oriented employees to total employment. We uncover a significant relationship between the persistence of marketing employment strategy and mutual fund performance in our sample. We then propose a framework to understand the economics of mutual fund marketing. We argue that fund companies strategically choose marketing plans based on their true investment skill and their past fund performance. Marketing strategies not only lower costs of information acquisition for investors, but are also used to persuade fund flows by changing investors' beliefs about the skill level. Our model can reconcile the stylized empirical patterns from the data as well as offer unique testable predictions.

Our data are from the SEC's Form ADV filings, which have required fund companies to report information on their employees' profiles since 2011. The key variable that we examine is the fraction of employees who have the legal qualification of sales, labeled as marketing employment share (*MKT*, hereafter). Note that *MKT* is measured at the fund company level; this is natural given the typical organizational structure of mutual fund companies, in which services such as marketing, operation, and compliance are shared among the funds within the company.[1]

The new data on mutual funds' marketing efforts highlight several interesting stylized facts. First, on average, 24% of fund companies' employees are marketing-oriented, but the cross-sectional heterogeneity is significant with a standard deviation of 25%. Conventional wisdom typically views marketing as "gloss[ing] over the fact."[2] In other words, marketing activities could influence and convenience investors in a psychological way (naive persuasion). However, this naive persuasion can hardly explain the cross-sectional heterogeneity; if such naive persuasion is effective, one should expect all fund companies to be equipped with a sizeable marketing force.

Second, in the lack of persistent performance, the marketing strategy is persistent, meaning that fund companies that choose to have a high (low) marketing employment share this year tend to exhibit high (low) *MKT* in subsequent years, while such a pattern does not exist for fund performance (consistent with the well-known findings in the literature; e.g., Carhart (1997)). Moreover, the persistence of the marketing employment ratio across fund companies exhibits substantial heterogeneity. Third, *MKT* is *positively* correlated with fund company size (measured with total assets under management). Larger and better-known fund companies tend to allocate more human resources toward marketing.

Existing literature views marketing as an effort to lower investors' participation or search cost (e.g., Roussanov, Ruan and Wei (2021); Huang, Wei and Yan (2007); Sirri and Tufano (1998)). However, as large fund families are subject to low search costs, one should expect large fund companies to conduct less—not more—marketing. In addition, explanations based on costly learning or search theories imply the need to vary marketing with respect to past performance rather than persistent marketing. For example, poorly

[1] For a more detailed discussion, see Gallaher, Kaniel and Starks (2006).

[2] A comment by the founder of Vanguard, 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." – *The New York Times*(Gray (2011)).

performing funds have little incentive to spend on marketing to lower the search costs compared to a fund with moderately good returns. Taken together, this discussion suggests that, at a minimum, the search cost channel would not be enough to fully explain a fund company's marketing decision.

To reconcile the puzzling patterns, we propose an economic framework to understand fund companies' optimal allocation of human capital to marketing. Our framework also produces rich, 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 for investors (*learning*). Second, fund companies persuade fund flows through marketing strategies that affect investors' allocation by only changing their beliefs (*Bayesian persuasion*). Depending on the realized past performance and the skill of fund managers, either learning or persuasion can be the dominating mechanism that drives fund companies' optimal allocation on marketing.

In our model, fund companies have heterogeneous investment skills (high versus low).[3] There are three periods, and two types of investors: existing investors and new investors. *Before* observing the type at date 0, the fund company fully commits to a marketing plan, a policy that maps each skill type into a distribution over the marketing employment strategies. The optimal marketing plan maximizes the fund company's expected profits. At date 1, fund companies observe their skill level and choose the marketing employment strategy conditional on past performance, as they committed.

Investors do not observe the skill type, but each period, existing investors update their beliefs about this unknown type based on past performance and the specific marketing employment strategy chosen by the fund company. Following Kamenica and Gentzkow

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

(2011), we show that there exists a truth-telling persuasion mechanism that strictly benefits the fund company. Fund companies reveal their marketing plans to their existing investors at date 0. Existing investors then update their beliefs about the fund company's skill type after observing the realization of the marketing employment strategy at date 1 to infer the type of the fund company. The marketing employment strategy thus contains important information about fund type, and fund companies benefit from sending those signals to investors. In this way, companies use their overall marketing effort to shape investors' beliefs and persuade flows. This result is the foundation of the persistence of marketing strategies.

To pin down the heterogeneous optimal marketing strategies given the fund type, fund companies maximize the new investors' flow. At date 0, new investors obtain a noiser signal about the skill type than the existing investors. However, at date 1, they can pay a participation cost to obtain a better signal about the skill level, the same as existing investors observe. Hiring more marketing employees can lower the participation cost, but the labor cost is higher, given marketing employees' fixed wages. With a participation cost, the classic result from learning indicates that new investors only allocate capital (positive flows) when past performance is better than a specific threshold (e.g., Huang, Wei and Yan (2007)). Given the convex nature of the new flow and the cost of marketing employees, fund companies only choose to build up a marketing labor force when the past performance is good enough ($r_1 > \tilde{r}$). We show that with the separating persuasion mechanism, the low-type fund has a much higher $\tilde{r}$ than the high-type fund.

Our model implies a positive relationship between fund companies' long-term performance and marketing persistence. Building up the marketing labor force is costly. Low-type funds would not want to adopt a high marketing employment share because investors are unlikely to invest after observing a sequence of low performance in the past. However, high-type funds maintain a high marketing employment share and do so even after the poor past performance, because the commitment to sending investors signals benefits them in the long run. They know that poor performance is only 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.

Bayesian persuasion 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. Our model implies that fund companies' marketing employment strategy is neither monotonic in past performance nor predictive of future performance. Marketing employment share can be high for the low-type funds after a sequence of superior past performance. Therefore, it is persistence instead of the level of marketing employment share that indicates the skill level.

Our model also implies that fund companies' marketing employment shares are positively correlated with fund family size and flows. In an environment where marketing strategies signal the fund skill, existing investors do not necessarily withdraw following poor past performance. This is, Bayesian persuasion 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 new investors and hence introduce larger new inflows on average for both types of funds. Taking the two effects together, our model implies 1) there is a positive correlation between the level of MKT and fund company size, consistent with the observed stylized fact; 2) high MKT predicts subsequent fund flow.

Next, we test these predictions of our model. The Form ADV data cover all fund advisory firms in the U.S. with an AUM of more than \$100 million. In the year 2015, the total number of employees by mutual fund companies sums up to 78,808, and 23,199 (or 29.4%) of them were legally qualified and licensed to conduct sales and marketing activities (as we discuss more later, those are "registered representatives"). We calculate the marketing employment share MKT for each firm and merge the employment information from Form ADV with CRSP's mutual fund database via adviser names. CRSP provides information on mutual fund size, performance, style, fees, and others. As MKT is measured at the fund advisory firm level, most of our analyses are conducted using firm-level information.

The key prediction from the Bayesian persuasion channel is full disclosure at equilibrium; high-type funds adopt persistent marketing plans, whereas low-type counterparts' marketing efforts vary with past performance. 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 alpha of all funds a firm manages and regress on $Vol(MKT)$ and a set of fund characteristics as controls, including 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 0.48% higher 6-factor alpha per year. Such an effect is economically meaningful given that the average annual 6-factor alpha of fund companies in our sample is -1.14%. We show that this relationship between $Vol(MKT)$ and firm returns is also predictive. This finding is robust to using alternative risk-adjusted returns and variations in the measurement 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 our second empirical test, we focus on another unique model prediction, that is, the level of MKT is unambiguously related to fund company size or fund flow. Such correlation arises through two channels: (1) high-type funds, which adopt persistently high level MKT to separate 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 cross-section, we expect MKT to be positively correlated with subsequent fund flow or asset growth. 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 persuasion mechanism through committing to a marketing strategy 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 appears to be consistent with this conjecture. The correlation between MKT and subsequent fund flow remains positive in most specifications but becomes insignificant. 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. We analyze fund companies' strategic decisions on marketing based on skill type and past performance, which is key to understanding the heterogeneity of the marketing effort across fund companies. We propose the new economics of mutual fund marketing and uncover the strategic role of marketing in the mutual fund literature. Marketing strategies are used as a tool for information design. We apply Bayesian persuasion in modeling information design Kamenica and Gentzkow (2011). Our paper is complementary to Huang, Wei and Yan (2007), which emphasizes the importance of participation costs in driving the fund flows. We extend the learning model with Bayesian persuasion to understand the optimal choice of mutual funds' marketing strategy. Recent work by Roussanov, Ruan and Wei (2021) shows that marketing is as important as performance in determining mutual fund size. We instead focus on how marketing strategies are chosen by fund companies. We emphasize the relationship between the persistence of marketing efforts instead of the level and average performance of fund companies.

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

Our paper is also related to the literature on the role of fund families. The previous studies find 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 plans to enhance fund flow.

A contemporaneous paper by Kostovetsky and Manconi (2018) also used the employment data from Form ADV and found that investment and research-related employees contribute little to fund performance. Our paper focuses on marketing-oriented employees and uncovers their crucial role in keeping fund companies growing in the face of a lack of persistent superior performance.

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 SEC's Form ADV filings. Investment companies that manage more than $100 million in assets must file Form ADV annually. Item 5 of Part 1A of Form ADV require investment companies to report employment information, including the number of total employees and the breakdown by functions. We are interested in Item 5. B(2), which reports the number of employees that are registered representatives of a broker-dealer. To legally conduct trading and sales of securities in the U.S., being a registered representative is a necessary license. The key variable of our paper, marketing employment share (*MKT*), is defined as the fraction of registered representatives to total employees.[4] We acknowledge that this is a rather narrow definition and likely lead to an underestimation of a firm's actual allocation to marketing, as employees without the broker representative license can still serve clients. The employment data from Form ADV are available annually from 2011 to 2019. More details on Form ADV and the variable *MKT* are in Appendix B.

MKT can potentially better capture funds' marketing efforts than the fee-based measures. Given that the asset management industry is human capital intensive (its production function features various types of human capital or skills as the inputs), *MKT* captures how much human resources the fund allocates toward marketing and sales versus other key functions, such as investment, research, operation, and so on. By comparison, 12b-1 fee refers to the fund's spending on distribution and advertisement, but it does not take into account the labor cost of internally hired sales. Also, the variable *MKT* is a company-level measure, not the individual fund level. In fund companies, portfolio management and investment decisions are typically made at the fund level, while the company is responsible for marketing, operation, and compliance for all funds. In nature, measures of marketing efforts should refer to the company level.

Form ADV includes advisers to all types of investment vehicles, such as mutual funds, hedge funds, private equity, pension funds, and so on. As this paper focuses on mutual fund advisers, we manually merge Form ADV data with the CRSP Survivor-Bias-Free US

[4]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.

Mutual Fund Database to implement our empirical tests. The merge is conducted using firm names.[5] Details about the sample construction is in Appendix B. Finally, our sample includes 692 unique fund companies and 3,426 company–year observations from 2011 to 2019.

Next, we document several stylized facts regarding *MKT* and also compare them with the fee-based measures that some previous studies use. The first one is the large cross-sectional variation of *MKT*. Panel A of Table I reports the summary statistics of *MKT*. The average of *MKT* is 0.24, and the median is 0.25. There is a significant cross-sectional variation: The 25th percentile is zero, while the 75th and 90th percentiles are 0.39 and 0.62, respectively. This suggests that fund companies adopt different strategies in the allocation of human capital to marketing skills. Previous studies use 12b-1 fee ratio (or total expense ratio) as a proxy for fund companies' market efforts (e.g., Roussanov et al. (2021)). 12b-1 fee refers to the annual marketing or distribution fee on a mutual fund. The fund company level 12b-1 fee as a ratio of AUM also exhibits a significant cross-sectional variation: the mean of *Firm 12b1* is 0.18% with a standard deviation of 0.19%.

The second stylized fact is the persistence of *MKT*. Following the procedure of Carhart (1997), we sort fund companies into quintiles based on *MKT* (fund performance, i.e., average fund returns within the company) at each year and track the average *MKT* (fund performance) of each quintile over the next five years in the upper (lower) panel of Figure X. 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 that there is weak persistence in performance (the pattern is robust using risk-adjusted returns). We refer the empirical fact shown in Figure X as "persistent marketing in lack of persistent performance."

Moreover, there is substantial heterogeneity in the persistence of *MKT*. Panel A of

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

Table I reports the summary statics of the standard deviation of MKT, $Vol(MKT)$. The standard deviation of $Vol(MKT)$ is 0.07 given the mean is 0.08. The variation of MKT exhibits a large difference. The difference of $Vol(MKT)$ between the bottom and the top quintile is 0.15, more than double of its standard deviation. It is then an interesting question why some fund companies choose a stable and persistent marketing employment ratio, but others don't.

The third stylized fact is about the correlation with fund company size. At the end of each year of our sample, we sort all fund companies into five size groups based on total assets that a fund company manages (denote as *Firm Assets*). For each size group, we calculate the median MKT and plot it in the upper panel in Figure VIII. Group 1 represents the smallest fund companies in AUM, and Group 5 the largest. One can find that MKT is positively correlated with fund company size: The median MKT_Ratio of Group 5 is approximately 24%, while the median of Group 1 is zero. This pattern is consistent with the observation that large fund companies tend to spend more on marketing and sales.

In the lower panel of Figure VIII, we plot each group's median expense ratio, which is a commonly used proxy for marketing expenditure in the literature. Contrary to the pattern shown in the upper panel, the expense ratio is negatively correlated with fund company size: expense ratio decreases from 1.56% for Group 1 to approximately 0.7% for Group 5. This pattern is robust using alternative fee measures, such as 12b-1 fees.

In Panel C of Table I, we conduct analogous regression analyses in order to obtain more quantitative estimates about the relation and to control for the effect of other covariates. We regress MKT on the contemporaneous fund company size and age (denote as *Log Firm Assets* and *Log Firm Age*, respectively), with year fixed effects. In Column (1), the only dependent variable is *Log Firm Assets*, and we find that the coefficient is significantly positive, with a t-statistic of 4.51. A one standard deviation increase in fund companies' total assets is associated with a 3.9% increase in MKT, which is a 16% increase from the mean. In Column (2), the right-hand-side variable is the *Log Firm Age*, which can be considered as an alternative measure of a fund company's reputation. We find that companies with more records on the market also appear to hire more marketing employees. In Column (3), we include both size and age into the regression, and we find that only the coefficient of *Log Firm Assets* remains significantly positive. In Columns (4) to (6), we replace *Expense* as the dependent variable. Consistent with Figure VIII, we find that *Expense* strongly decreases with company size and age.

The negative correlation between fees and firm size could be driven by the economy of scale for larger companies, which leads to lower costs and fees per dollar asset under management. The existing literature rationalizes this phenomenon by interpreting marketing as an effort to lower investors' search costs. In this sense, since large fund families are subject to low search costs, they should conduct less marketing. However, using our measure of marketing share of human capital, we find that the correlation between *MKT* and firm size appears to be the opposite. This suggests that, at the minimum, the search cost channel would not be enough to explain a fund company's marketing decision. We next propose a model of mutual fund marketing to reconcile these findings and provide rich and testable implications on the relations between marketing, fund size, and performance.

3 A 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 plan also acts as an important signal for the manager's ability through Bayesian persuasion.

3.1 Environment

Consider a partial equilibrium 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 fund company and mutual fund and its manager are all indexed by i.[6] The return on the risk-free bond r_f is normalized to zero for each period. Mutual funds differ in 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:

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

where $\alpha_i \in \Omega$ stands for the unobservable ability of the manager of fund i [7] 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: existing investors and new investors. The population mass is normalized to one for existing investors (indexed by e) and λ_i for new investors (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,

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

Existing investors are endowed with initial wealth W_0 and $X_{i0}^e > 0$ unit of fund i at date 0. They have a prior that $\alpha_i = \alpha_h$ with probability q. Existing investors can update

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

[7] In practice, a fund company can manage more than one fund. So α_i can be interpreted as the best manager's ability in the family or the value-weighted average ability of the managers in the family.

their posterior belief given the information set I_1^e. Based on the posterior, they choose the optimal allocation X_{i1}^{e*} of fund i at date 1.

New investors 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 which is drawn from a uniform distribution $\mathcal{U}[0, 1]$. In other words, new investors know there are two types $\{\alpha_h, \alpha_l\}$ of fund managers but they don't observe the true q. Instead, the probability of each type for new investors is indifferent between 0 and 1. We denote the prior of this probability for the new investor is $\tilde{q}$.

In addition, at date 1, new investors can improve their information set by paying participation cost c_i to learn about the expected value of α_i (more specifically, q). Based on their improved information set I_1^n, new investors also optimally allocate their wealth as X_{i1}^{n*} at date 1.

Marketing Fund managers maximize the revenue via choosing different marketing strategies by hiring a certain amount of marketing employees. 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 *new* investors. Let R be some sufficiently large set of marketing employment realizations, and the participation cost is a function of the number of marketing employees $m_i \in R$. We assume that the participation cost function $c_i = c(m_i)$ is decreasing and concave in m_i, i.e.,

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

This assumption is made in much of the economic analysis. The more marketing employees hired, the lower the participation cost. The marginal benefit of hiring one more marketing employee goes down when the fund company already has a large marketing group. Investors' objective function is usually convex in signal precision in the literature on information acquisition. The more marketing employees the fund hires, the more precise the signal to investors.

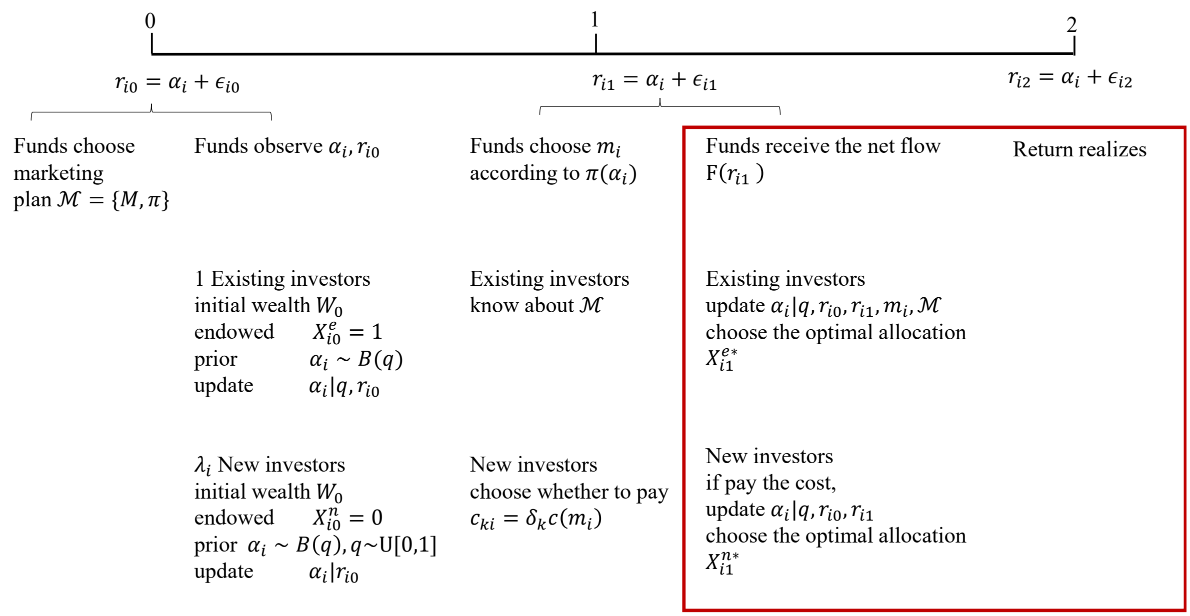
Second, marketing matters for fund flows through Bayesian persuasion. Marketing persuades rational investors by controlling their information environment (Kamenica and Gentzkow, 2011): how much effort a fund company puts into marketing itself can reveal relevant information for investors' portfolio decisions. Beyond communicating with the marketing force about the fund's past performance, investors update their beliefs about the quality from the observed marketing intensity performed by a fund company. Marketing influences the investor's behavior via information design. There is substantial empirical evidence that persuasive communication shapes consumers' and investors' beliefs and behaviors.[8]

The fund company comes up with a marketing plan at date $t = 0$ before observing their type. A marketing plan $\mathcal{M}$ is defined by the finite set M and a function π that maps each ability type α into a distribution over marketing strategies, $\pi : \Omega \to \Delta(M)$. $\pi(m|\alpha)$ stands for the probability that the fund i hires m marketing employees when he observes his type α. In other words, π is a distribution that specifies the statistical relationship between truth ($\alpha \in \Omega$) and the fund company's choice ($m \in M$). We will discuss in detail in Section 3.2 how fund companies strategically choose the marketing plan to reveal their types and attract flows. A marketing plan is a tool of information design and fund companies commit to their marketing plans. We assume that fund companies have the ability to commit to the marketing plan $\mathcal{M}$ after observing their types.

Timing Figure I summarizes the timing of the model. At $t = 0$, mutual fund companies then choose the marketing plan $\mathcal{M}$ *before* observing their types. After the realization of r_{i0}, both the existing investors and new investors update their prior. We use q_0^j to denote the posterior probability for $j = e, n$, where $q_0^n = Prob(\alpha_i = \alpha_h | r_0, q \sim Unif[0,1])$, $q_0^e = Prob(\alpha_i = \alpha_h | r_0, q)$. At $t = 1$, after observing their types, mutual fund companies commit to a certain marketing strategy $\pi(\alpha_i)$, which is the distribution of the number of marketing employees. Funds choose m_i with probability $\pi(m_i|\alpha_i)$. The existing investors

[8]See DellaVigna and Gentzkow (2010) for an extensive survey.

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 $1 - q$).

observe the marketing plan $\mathcal{M}$ and the realization m_i. The information set of existing investors is $I^e_1 = \{q, r_{i0}, r_{i1}, \mathcal{M}, m_i\}$, and the existing investors update their posterior q^e_1 based on I^e_1. The new investors make participation decisions after observing r_{i1}. An important assumption here is that it takes time for the fund company to communicate its marketing plan. New investors would only learn about the probability of being high type q after paying the cost at date 1, but not the marketing plan $\mathcal{M}$. Thus the information set $I^n_1 = \{q, r_{i0}, r_{i1}\}$ is different from the information set I^e_1 of existing investors. New investors update their posterior q^n_1 based on I^n_1. Both new investors and existing investors choose the optimal allocation based on their information set. Returns realize at $t = 2$.

At $t = 0$, two important optimization decisions are made regarding the marketing policy. Mutual fund companies choose the optimal marketing plan $\mathcal{M}$ by maximizing the flows of *existing* investors. We first show that in Section 3.2, funds with different types commit to distinct marketing strategies, i.e., there exists a separation equilibrium.

After establishing the separation property, we then solve the mutual funds' optimization problem backward. First, we derive the new investors' fund flows given the realized separating strategy π at date 1 in Section 3.3, and hence we obtain the mutual funds' optimal marketing plan at date 0. After obtaining the optimal choice, we discuss the model mechanism and the impact of marketing on fund size in the equilibrium and how it is related to the funds' returns in Section 3.4.

3.2 Optimal Marketing Plan

In this section, we investigate the optimal marketing decision by the fund company. We start by first solving the portfolio allocation problem of investors at date 1. We then show that the optimal marketing strategy is truth-telling.

3.2.1 Portfolio Allocation

At date 1, new investors choose to pay the cost, and existing investors allocate their capital to the fund based on their information set. For simplicity, we assume that each investor only invests in one fund. Henceforth, we abstract the subscript i in the investor's problem. As mentioned above, the new investors who pay the cost have the information set as $I_1^n = \{q, r_{i0}, r_{i1}\}$. And existing investors' information set is $I_1^e = \{q, r_{i0}, r_{i1}, \mathcal{M}, m_i\}$. 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 $W_1^j = W_0 + X_0^j(1 + r_1), j = e, n$. The following lemma summarizes the optimal allocation.

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* $q_1^j := Prob(\alpha_i = \alpha_h | I_1^j)$ *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.[9]

Only new investors who choose to pay the cost would have investments in funds. Given the posterior belief of new investors after paying the cost, q_1^n in equation (A.2), Lemma 1 indicates that there exists a threshold of $\hat{r}_1$ such that the optimal allocation of new investors $X_1^{n*} = x(q_1^n)$ is positive only if $r_1 > \hat{r}_1$. Intuitively, only when the expected return of the fund is positive, $q_1^n \alpha_h + (1 - q_1^n)\alpha_l > 0$, which is equivalent to say that the return at date 1 is higher than a certain threshold, investors would like to hold the fund.

$$X_1^{n*} = \begin{cases} x(q_1^n) & if \quad r_1 > \hat{r}_1 \\ 0 & if \quad r_1 \leq \hat{r}_1 \end{cases} \tag{3}$$

where $\hat{r}_1 = \frac{\alpha_h + \alpha_l}{2} - \frac{\sigma^2}{\alpha_h - \alpha_l} \ln(\frac{q_0^n}{1 - q_0^n}(-\frac{\alpha_h}{\alpha_l}))$ so that $q_1^n \alpha_h + (1 - q_1^n)\alpha_l = 0$, where $q_0^n := Prob(\alpha_i = \alpha_h | r_0)$ in equation A.3.

3.2.2 Separating Strategy

Next, we study the flow of existing investors and determine the optimal marketing strategy based on their portfolio allocation in the second sub-period of date $t = 1$ (within the red box of Figure I). At date 0, the fund company reveals a marketing plan $\mathcal{M}$ to their existing investors, which is a mapping plan from possible ability type α to the distribution of marketing employees:

$$\mathcal{M} = \{\pi \in \Delta(M) | \pi(M = m | \alpha = \alpha_i), i = h, l\} \tag{4}$$

Note that fund company comes up with their optimal marketing plan before observing their type. The marketing plan is chosen to maximize the expected profits.

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

After observing the realization of the marketing plan at date 1, the probability of being type α_h is perceived to be q_1^e and the existing investors allocate $X_1^e(q_1^e)$ by lemma 1.

The fund flow of the company at $t = 1$ from the existing investors is:

$$v(X_1^e, \alpha | X_0^e) \equiv X_1^e - X_0^e \cdot (1 + r_1).$$

At date $t = 0$, the fund company chooses its marketing plan to maximize the expected size of its funds. Given X_0^e is normalized to 1, the equivalent objective of the fund company is to maximize the capital inflows at $t = 1$ of its funds:

$$\max_{\pi \in \Pi} E_{\alpha \sim B(q)} E_{m \sim \pi(\alpha)} v(X_1^e(q_1^e(\cdot|\pi, m)), \alpha) \tag{5}$$

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

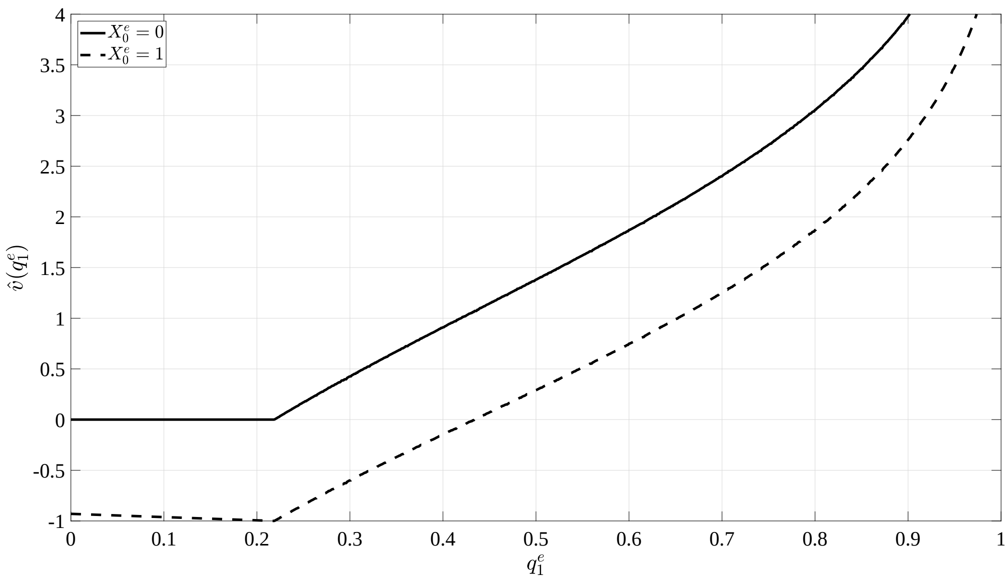
Note that the design of the optimal marketing plan is only determined by the expected date-one flow of the existing investors since only the existing investors can observe the marketing plan and be influenced by it. This assumption also simplifies the solution to the Bayesian persuasion problem by allowing reformulation. However, the marketing strategies, conditional on the fund type, could potentially impact the participation decision of the new investors through its impact on the participation cost. The participation decision of new investors then shapes the optimal marketing strategy, which will be discussed in Section 3.3.

Optimal Marketing Plan To find the optimal marketing plan, we follow Kamenica and Gentzkow (2011) and perform the reformulation. Intuitively the fund company would like to choose the optimal marketing plan from a particular class of marketing plans that produce a "recommended portfolio allocation," and investors follow the recommendation. We first compute the mutual fund company's expected utility $\hat{v}(q_1^e) = E_{\alpha \sim q_1^e} v(X_1^{e*}(q_1^e), \alpha)$, which is defined as expected date-1 optimal allocation by the existing investors X_1^{e*} before the fund company observes the fund type. From the definition of $\hat{v}$

and lemma 1 above, the optimal choice X_1^{e*} is a nonlinear function of q_1^e and not zero if and only if $q_1^e\alpha_h + (1-q_1^e)\alpha_l > 0$, i.e., $\hat{v}$ is a convex function. Hence we have the following proposition.

Figure II. Relation Between Investors' Beliefs and Expected Profits

The solid line corresponds to the mutual fund's expected utility when the initial position of existing investors $X_0^e = 0$, and the dashed line corresponds to the expected utility when $X_0^e = 1$. Other parameters are $\gamma = 1, \lambda = 1, \beta = 1, \sigma_\epsilon = 0.2, \alpha_h = 0.25, \alpha_l = -0.07, q = 0.5, w = 0.1$, where γ is the risk aversion of the CARA investor, and λ is the relative population weight of new investors. 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. After observing the marketing information at date 1, existing investors update their belief that $\alpha = \alpha_h \quad w.p \quad q_1^e$. Mutual funds receive fund flows from them and their expected utility is $\hat{v}(q_1^e)$.



Proposition 1. *Given the optimal allocation of existing investors from lemma 1, the mutual fund's expected utility $\hat{v}$ is convex:*

$$\hat{v}(q_1^e) = \begin{cases} x(q_1^e) - X_0^e(1 + q_1^e\alpha_h + (1-q_1^e)\alpha_l) & if \quad q_1^e\alpha_h + (1-q_1^e)\alpha_l > 0 \\ -X_0^e(1 + q_1^e\alpha_h + (1-q_1^e)\alpha_l) & if \quad q_1^e\alpha_h + (1-q_1^e)\alpha_l \leq 0 \end{cases}$$

Based on Corollary 2 in Kamenica and Gentzkow (2011), the optimal marketing plan is ***full disclosure****, i.e., a mutual fund company's optimal marketing strategy is heterogeneous conditional on their types: $\pi^*(m|\alpha_h) \neq \pi^*(m|\alpha_l)$.*

See Appendix A.2 for the formal proof. By the simulation, we can describe the relationship between the investor's belief and the mutual fund's expected utility as Figure II. The optimal marketing plan for high-type mutual fund companies is to commit to a hiring policy of marketing employees that is different from the policy adopted by the low-type fund companies. By choosing heterogeneous marketing strategies, fund companies fully reveal their types of ability. The fully revealing strategy implies the posterior for existing investors at date 1 follows the following rule:

$$q_1^e = \begin{cases} 1 & if \quad \pi^*(m|\alpha_h) > \pi^*(m|\alpha_l) \\ 0 & if \quad \pi^*(m|\alpha_h) \leq \pi^*(m|\alpha_l) \end{cases} \tag{6}$$

Next, we explore the participation decisions of new investors and pin down the optimal marketing strategies for different types of funds.

3.3 Participation Decision and Marketing Strategies

Mutual fund companies maximize the existing investors' expected flow and commit to a truth-telling marketing plan. However, the specific strategy, the number of marketing employees to hire given the fund type, is pinned down by its impact on the participation cost of new investors and hence the new investors' flow.

3.3.1 Participating Decision

New investors make the optimal decision by comparing the expected benefit with the participation cost if they pay. We assume that once they exert the participation cost, they'll acquire the information about the probability q and make investment decisions. The expected benefit is their investment outcome based on the new information set.

At date 0, new investors observe the risky return r_0 and update their belief on the distribution of the manager's ability q_0^n based on equation (A.3). Then investors observe fund return r_1, and update their beliefs based on the available information. If they pay the cost, they would learn the prior and q as the existing investors. The updated belief is q_1^n defined in equation (A.2). Note that the participating new investors do not observe the company's marketing strategies, so their posterior is not based on the marketing plan $\mathcal{M}$.

Each new investor has a different level of financial sophistication and faces different learning costs. To capture the heterogeneity, we follow Huang et al. (2007) and assume that new investor, 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:

$$\max_{X_1^n \geq 0} \quad E(-e^{-\gamma W_2^n} | I_1^n) = \exp(-\gamma(g(r_1; r_0) - c_k)))$$

New investor 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*

$$\exp(-\gamma g(r_1; r_0)) = \int_0^{+\infty} e^{\frac{1}{2}\gamma^2 \sigma_\epsilon^2 X_1^{n*}} (q_1^n e^{-\gamma \alpha_h X_1^{n*}} + (1 - q_1^n) e^{-\gamma \alpha_l X_1^{n*}}) f(z) dz$$

where

$$q_1^n \equiv Pr(\alpha = \alpha_h | I_1^n) = \frac{q_0^n(z)}{q_0^n(z) + (1 - q_0^n(z)) \exp(-\frac{(2r_1 - \alpha_h - \alpha_l)(\alpha_h - \alpha_l)}{2\sigma^2})} \tag{7}$$

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

New investors 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 both in r_1 and r_0, as plotted in Figure III.[10] For new investor 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 only if $r_1 \geq \hat{r}(c_k)$.

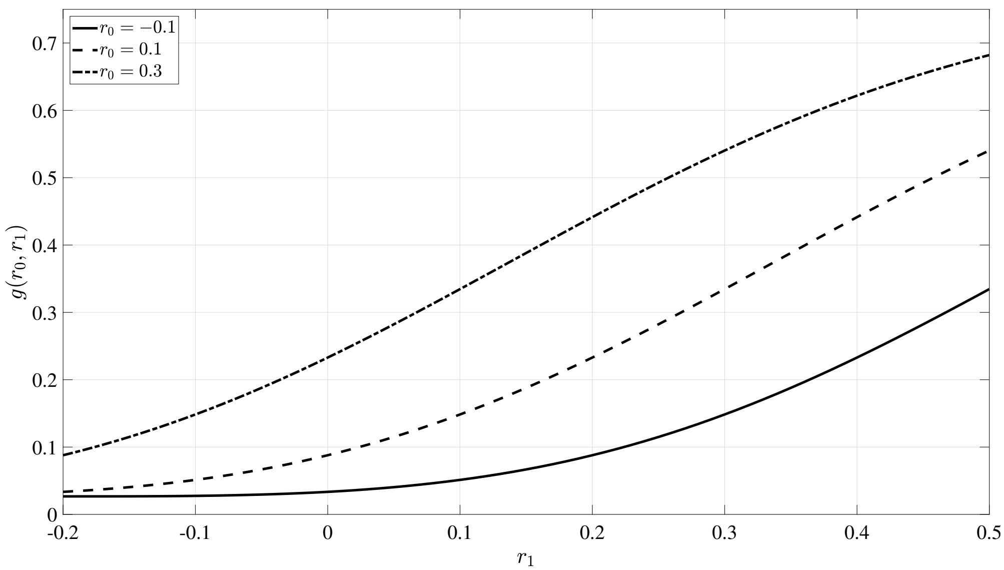
3.3.2 Optimal Marketing Strategies $\pi(m|\alpha)$

From Section 3.2, under the optimal marketing plan $\mathcal{M}$, the mutual fund company will commit to a fully-revealing strategy at date 0 and announce it to existing investors, which means there are separated marketing regimes for each type of abilities at date 1.

[10] See appendix A.3 for the proof.

Figure III. 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 $\gamma = 1, \lambda = 1, \beta = 1, \sigma_\epsilon = 0.2, \alpha_h = 0.25, \alpha_l = -0.07, q = 0.5, w = 0.1$, where γ is the risk aversion of the CARA investor, and λ is the relative population weight of new investors. 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, new investors have the certainty-equivalent wealth gain $g(r_0, r_1)$ based on their updated belief.



Fund flows from existing investors are maximized as long as the marketing strategies are distinct. So far, we haven't pinned down the specific hiring policy for marketing employees. In this section, we determine the optimal marketing strategies $\pi(m|\alpha)$ by maximizing the fund companies' flow from new investors.

At date 0, the type of ability is revealed to fund managers. Given their abilities, fund companies choose the optimal marketing force m^* to maximize the net profits, equal to the expected flow of new investors minus the salary paid to marketing employees. Since participation cost is a function of the optimal level of marketing force m^* given the observed past return r_0, the expected net profits at date 0 is then a function of m. Fund companies solve the following Problem (8) given the ability type α_i,

$$\max_{m_j \geq 0} \quad \beta\lambda \int_{\hat{r}_1}^{+\infty} \min[1, \frac{g(r_1; r_0)}{c}] X_1^{n*} \phi(r_1|\alpha_j, \sigma_\epsilon) dr_1 - w m_j, \tag{8}$$

where $r_1 \sim N(\alpha_j, \sigma_\epsilon)$, $\phi(r_1|\alpha_j, \sigma_\epsilon)$ is the corresponding probability density function, $j = h, l$ and w is the wage per marketing employee. We assume the cost of hiring managers and other skilled employees are fixed in this context for simplicity.[11]

Proposition 2. *In the case of two fund types, $\alpha_j \in \{\alpha_h, \alpha_l\}$, the optimal solution to Problem* (8) *is the following:*

$$m_j^* = \begin{cases} m^*(r_0, \alpha_j) & if \quad r_0 > \tilde{r}_0^j \\ 0 & if \quad r_0 \leq \tilde{r}_0^j \end{cases} \tag{9}$$

where $\tilde{r}_0^h < \tilde{r}_0^l$.

See Appendix A.4 for the proof. Figure IV illustrates Proposition 2 in our calibrated numerical example. For both ability types, the optimal number of marketing employees is zero when the return is lower than the threshold $r_0 < \tilde{r}^j$ at time $t = 0$. However, this threshold is much lower for the high-type funds than the low-type ones. Intuitively, fund companies will attract little flows when past performance is poor, even with a substantial amount of marketing effort. For the high-type funds, they are more confident in signaling themselves even if the realized past return is not outstanding. They know their expected returns are high. Hence in Figure IV, within the reasonable regime of the realized returns, from -20% to 50%, the high-type fund keeps the size of its marketing force very stable. A high-type fund maintains its marketing force even if they experience negative past returns because they know the low return is a small probability event. For the low-type funds, they choose to enhance the marketing after the past performance is strong enough.

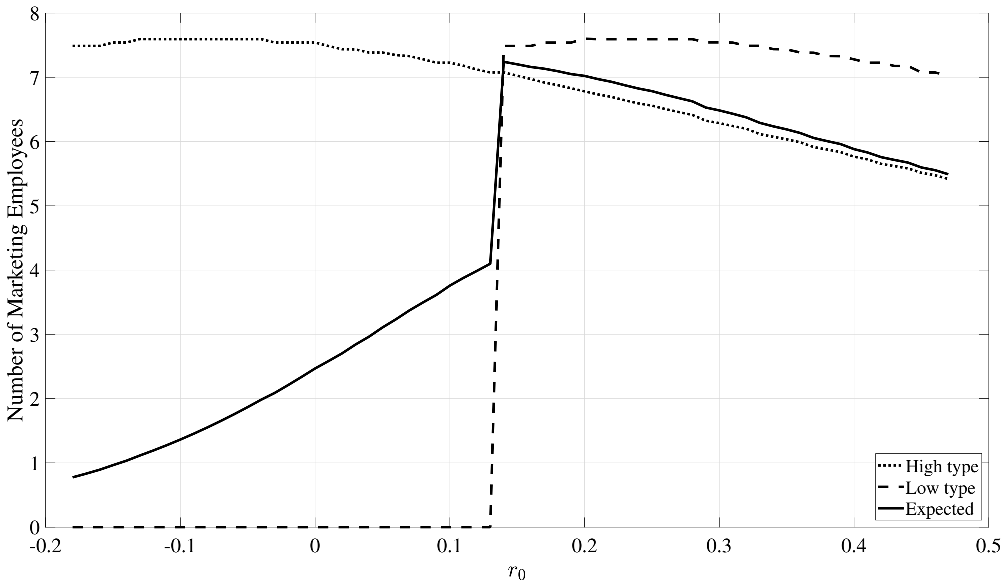
3.4 Discussion: Marketing Strategy and Model Implications

With learning and Bayesian persuasion, our model implies that the marketing strategy is persistent and is an indicator of mutual funds' skill level. The past performance is not monotonic in the choice of optimal marketing strategy and hence does not fully reveal the type of mutual funds.

[11] Equivalently, the number of marketing employees m can be interpreted as the relative ratio of marketing employees to total employees, and we can interpret the wage level w to be relative wages as well.

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 $\gamma = 1, \lambda = 1, \beta = 1, \sigma_\epsilon = 0.2, \alpha_h = 0.25, \alpha_l = -0.07, q = 0.5, w = 0.1$, where γ is the risk aversion of the CARA investor, and λ is the relative population weight of new investors. 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 existing investors at time 0.



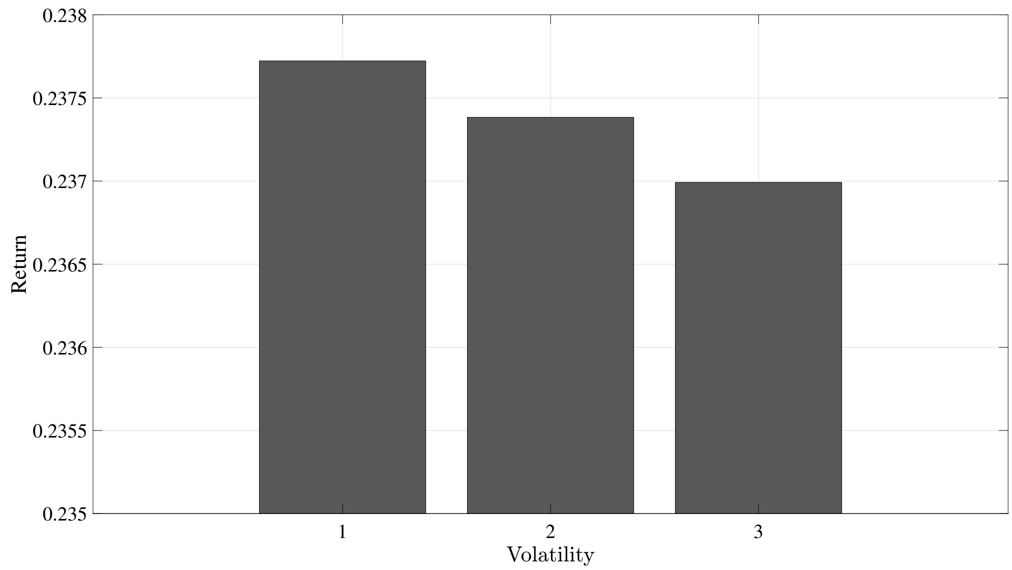
3.4.1 Persistence of Marketing Strategy and Fund Manager Skill

As the classic Bayesian persuasion result indicates, fund companies optimally fully reveal their types via the optimal marketing plan. As shown in Figure IV, high-type fund companies signal themselves by hiring a large marketing force even when the past performance was poor. The threshold return (to enhance marketing force) for high-type fund companies is very low 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. Suppose the average performance for the high-type fund is superior enough. In that case, their optimal marketing strategies will not experience 0 over the observed realized past returns and hence is much more persistent than the strategies adopted by the low-type funds.

Corollary 3.1. ***Persistent Marketing Strategies*** Given $\alpha_l \leq \alpha_h$ and ϵ_{it} is normally dis-

Figure V. Return predictability of marketing strategy volatility

This figure reports the relation between the volatility of marketing strategies and the expected return r_1 at time 1. Other parameters are $\gamma = 1, \lambda = 1, \beta = 1, \sigma_\epsilon = 0.2, \alpha_h = 0.25, \alpha_l = -0.07, q = 0.5, w = 0.1$, where γ is the risk aversion of the CARA investor, and λ is the relative population weight of new investors. 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 $c(m) = \exp(1 - 0.3m - 0.01m^2)$.



tributed, there is smaller variation in the marketing labor force $\sigma(m_h^*)$ in the high-type fund companies than that in the low-type fund companies.

Observationally, 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. Figure V shows that the volatility of marketing strategies in our calibrated numerical example is correlated with the fund performance. Corollary 3.1 is the unique implication of Bayesian persuasion, and we test this result in our next section.

3.4.2 Learning vs. Bayesian Persuasion

The key driver of the heterogeneous persistence of marketing strategies is Bayesian persuasion. To see the mechanism from learning and Bayesian persuasion separately, we plot the relation of fund flows and past performance under the setting of pure learning and pure Bayesian persuasion in Figure VI.

In Figure VI Panel (a) where we allow both types of fund companies to choose the same level of marketing force m^*. The flow is more sensitive to performance for low-type funds (larger convexity) when performance is high. When learning is the dominant channel, flow is driven primarily by the posterior belief after observing the fund returns. Given the performance-chasing nature of flow, larger inflow following better performances, especially for the low-type funds, is the direct result of learning. Learning improves the flow to performance sensitivity.

In Panel (b) of Figure VI, we shut down the impact of learning by increasing the noise of signals. In this case, Bayesian persuasion is the dominant mechanism. With Bayesian persuasion, the flow is much less sensitive to performance because the most important information is contained in the company's choice of marketing strategy. Hence, high-type funds always have much higher inflows than the low-type funds from the fully-revealing property of Bayesian persuasion. The effect of Bayesian persuasion differs from the learning-only result in Panel (a). Instead of improving the flow-to-performance sensitivity, Bayesian persuasion reduces the sensitivity and numbs the impact of performance on flow.

Our result indicates what matters to predict fund performance is the revealed persistence of marketing strategy instead of the level of marketing effort. In fact, we show that fund companies' marketing strategy is not necessarily monotonic in past performance and future performance (See Section C). As we test in the next section, this is indeed the case in data.

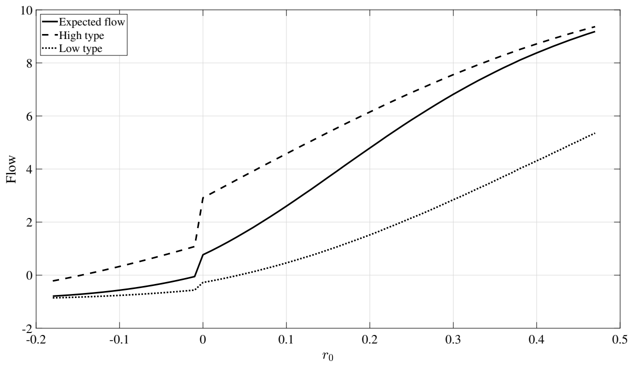
3.4.3 Marketing Strategies and Fund Size

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.

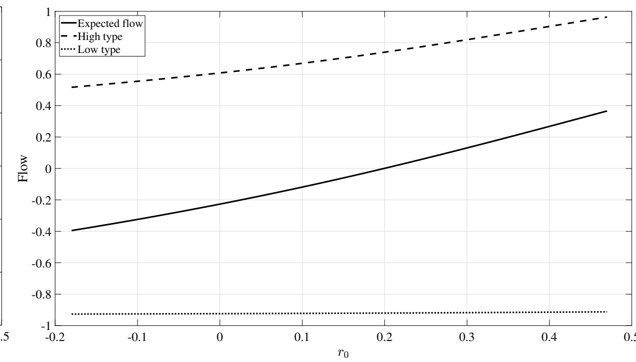
Proposition 3. ***Expected flow under optimal choices.*** *The fund flow $F(r_1)$ at time $t = 1$ is*

Figure VI. The relation of fund flow and past performance under different settings

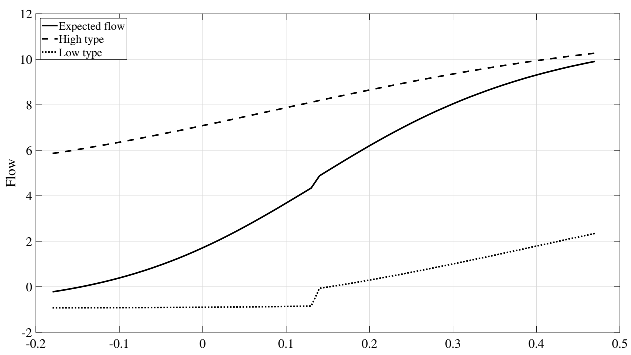
Panel(a) plots the relation under a pure learning setting where the fund manager maximizes the expected flow by choosing a uniform number of employees for each r_0. Panel(b) plots the relation under mainly Bayesian Persuasion setting by letting the noise of signals sufficiently large, $\sigma_\epsilon = 0.4$. Panel(c) plots the relation under the current setting, which combines learning and Bayesian Persuasion channels. Panel(d) compares the expected flows among all three settings. Other parameters are the same across the different settings, which are $\gamma = 1, \lambda = 1, \beta = 1, \alpha_h = 0.25, \alpha_l = -0.07, q = 0.5, w = 0.1$, where γ is the risk aversion of the CARA investor, and λ is the relative population weight of new investors. $\sigma_\epsilon = 0.2$ for panel(a)(c)(d). 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 existing investors at time 0.



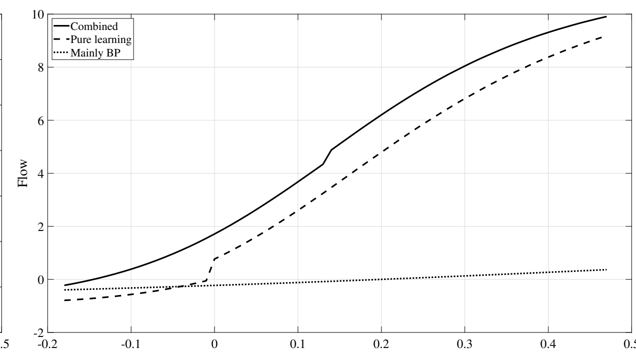
(a) Pure learning



(b) Mainly BP



(c) Combined



(d) Expected flows

written as

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

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

Note that given $X_0^e = 1$, the relative comparative statics for fund flow is equivalent to that for the fund size. Figure VII describes the total expected size of mutual funds given their past performance and optimal marketing policy. Noticeably, the expected fund size is increasing in the number of marketing employees given the fund's past performance r_0 in all four panels. 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 size and marketing policy. More marketing employees are hired, lower the participation costs for new investors and hence larger new inflows on average.

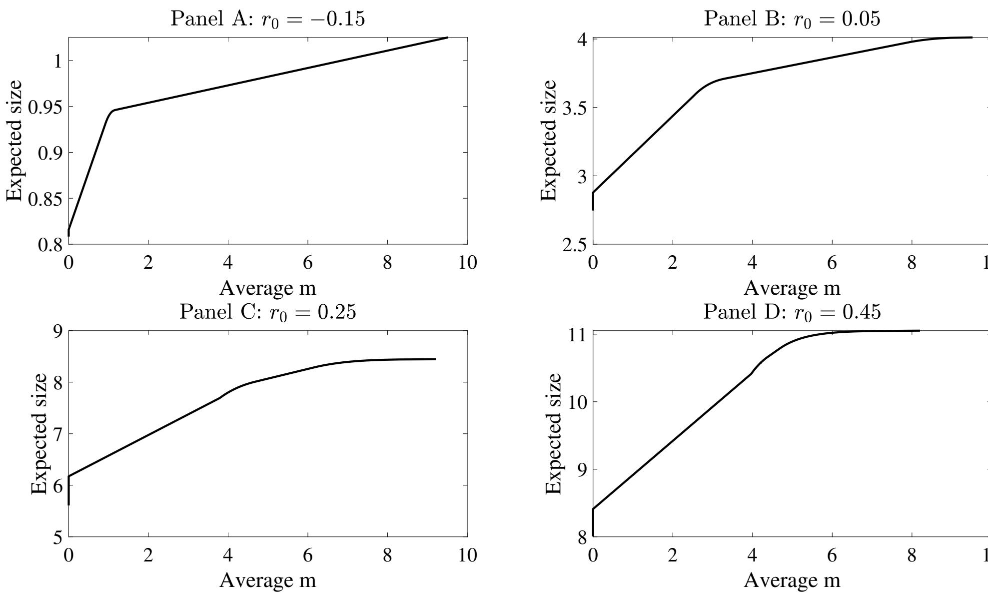
Another distinct feature from Figure VII is that, conditional on different levels of past returns r_0, the marginal impact of hiring one more marketing employee on the expected fund flow, hence the expected fund size, is different. The impact is much larger for a fund with a better past performance. This implies a more convex flow-to-performance sensitivity for high m fund companies.

Marketing Strategies and Fund Flows Our model generates a positive relationship between past performance and expected fund flows (size). As discussed in Section 3.4.2, the steep relationship between performance and expected fund flows is driven by the learning channel.

In the model with only Bayesian persuasion, fund flows are not responsive to past performance because marketing strategies are sufficient in telling the fund types. Investors chase marketing efforts instead of past performance. Although we believe Bayesian persuasion is crucial to understand the variation of marketing effort across funds and over time, our model also allows us to generate a realistic relationship between performance

Figure VII. Relation between expected size and the optimal marketing strategy

This figure reports the expected flow of mutual funds under the optimal marketing plans. Panel A shows the relation between the average number of marketing employees and the total fund flow if $r_0 = -0.15$. Panel B, C, and D report this relation when $r_0 = 0.05, 0.25$ and 0.45. Other parameters are $\gamma = 1, \lambda = 1, \beta = 1, \sigma_\epsilon = 0.2, \alpha_h = 0.25, \alpha_l = -0.07, q = 0.5$, where γ is the risk aversion of the CARA investor, and λ is the relative population weight of new investors. 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 wage w varies from 0.001 to 1. Hence we have the average number of marketing employees varies from 0 to 10.



and expected flows as observed in the data.

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 (i.e., Corollary 3.1). Then, we examine the predictions of optimal m^* on equilibrium, i.e., *MKT* that we observe on fund flow. The results provide additional support for 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. 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 (Figure V demonstrates this conjecture with model calibration).

Our primary measure of marketing persistence is the volatility of MKT, which is calculated as the standard deviation of MKT through the sample period of 2011 to 2019 (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. Since Form ADV only provides employment information at the annual level, $Vol(MKT)$ captures little high-frequent 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 conjecture, we run the following regression,

$$\text{Firm Return}_{i,t+1} = Vol(MKT)_i + \text{Firm Return}_{i,t} + Control_{i,t} + v_t + \epsilon_{i,t+1}. \tag{10}$$

Firm $\text{Return}_{i,t+1}$ refers to the value-weighted average returns of mutual funds that fund company i manages in year $t+1$. Since a fund company may manage mutual funds with a variety of styles and asset focuses, including domestic equity, fixed income, international, balanced, and so on, 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.[12] We also use CAPM-adjusted fund returns and raw returns (net of fee fund returns) as alternative measures. We control for Firm Return at year t and fund company characteristics, including size, age, and the expense ratio, as well as year-fixed effects. Standard errors are clustered at the firm level. Note that this is not a test of forecasting fund returns, as $Vol(MKT)_i$ is calculated using full sample information.

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

Table II reports the results. In column (1), we use 6-factor adjusted fund returns and find that the coefficient before $Vol(MKT)$ is significantly negative (t-stat = 3.5). In terms of economic magnitude, a one-standard-deviation increase in $Vol(MKT)$ is associated with 0.48% higher 6-factor alpha per year. This is sizeable given that the average annual 6-factor alpha of fund companies in our sample is -1.14%. 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 appears to be negatively correlated with fund performance, while the coefficients before firm age and size are insignificant.

In column (2), we use the level of $MKT_{i,t}$ instead of $Vol(MKT)$ in equation 10. 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 XI with model simulation). Consistent with the model prediction, the coefficient before MKT is not significantly different from zero. In column (3), we further include both MKT and $Vol(MKT)$ into the right-hand side of the regression, the coefficients before MKT and $Vol(MKT)$ are virtually unchanged compared with columns (1) and (2). In columns (4)-(6) and (7)-(9), we repeat the analysis with CAPM-adjusted and raw fund returns, respectively, and the results are robust.

We also test whether the relationship between $Vol(MKT)$ and firm returns is predictive. We estimate the $Vol(MKT)_{t-1}$ using past 3 years $\{MKT_{t-3}, ...MKT_{t-1}\}$, and regress firm return at t on the past $Vol(MKT)_{t-1}$. Table III reports the regression results. The results are similar to the regression results in Table II. The coefficient before $Vol(MKT)_{t-1}$ is significantly negative when predicting 6-factor adjusted fund returns in column (1), with a larger economic magnitude, a one-standard-deviation increase in $Vol(MKT)_{t-1}$ is associated with 0.91% decrease in the 6-factor adjusted Alpha. In column (4) and column (7), we report the regression results for CAPM Alpha and raw returns, and both are significantly predicted by $Vol(MKT)_{t-1}$.

In Table IV, we conduct several robustness tests. In Panel A, we use an alternative way to measure the variability of firm MKT, that is, the range of MKT over the sample period (denoted as $Range(MKT)$). We find the coefficients before $Range(MKT)$ remain significantly negative (with tt-stats between 2.6 to 3.4). In Panel B, we conduct the regression of equation 10 at the fund level. We use fund-level returns as the dependent variable and fund characteristics as the controls (including fund size, age, expense, and past performance). $Vol(MKT)$ is still measured at the company level. The results are consistent with what we find at the firm level, albeit lower statistical significance. The coefficients before $Vol(MKT)$ are all negative in the three specifications and significant at the 10% level when using 6-factor and CAPM adjusted fund returns.

Figure IX visualizes such a finding. Here, we sort all fund companies into quintiles based on $Vol(MKT)$ and plot the average firm returns on the y-axis. We use raw returns in the upper panel and 6-factor adjusted returns in the lower panel.[13] One can see that average fund returns decrease with $Vol(MKT)$, particularly Groups 4 and 5.

One may wonder how the above finding can be reconciled with 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. However, note that our model analyzes the alpha skill of fund companies, not individual mutual funds. The founders or CEOs of fund companies themselves may have superior investment skills, but more importantly, 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 show 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

[13]For all groups, the average 6-factor alpha is negative, consistent with the well-known fact of mutual fund underperformance (e.g., Carhart (1997) and Chen et al. (2004))

(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) find that fund family size predicts positive fund subsequent 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 data) does not necessarily reveal the funds' type. Nonetheless, our model suggests MKT be unambiguously associated with fund companies' subsequent fund flow and asset growth. As discussed in Section 3, such an effect arises through two channels. One, high-type funds, which adopt persistently high levels MKT to separate from low-type funds, tend to exhibit better performance and more inflow. The other channel is based on the learning effect that low-type funds may increase MKT upon good past performance and attract subsequent fund inflow. Thus, in the cross section, we expect MKT to be positively correlated with subsequent fund flow or asset growth (Figure VII shows these results with model simulations). Furthermore, since the former channel (i.e., Bayesian persuasion) 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:

$$Firm\ Flow_{j,t+1} = \alpha + \beta_1 MKT_{j,t} + Controls_{j,t} + \epsilon_{i,t+1}. \tag{11}$$

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.

Panel A in Table V reports the result. In Column (1), the coefficient of MKT is significantly positive, suggesting those fund companies with a high marketing employee shares tend to experience more subsequent fund flow. The coefficient of MKT equals 1.318 (with a t-statistic of 2.1) and is economically meaningful: A one standard deviation increase in MKT is associated with a 32.9% increase in fund flow, which equals 46.7% of the average growth rate 70.5% during our sample period.

The coefficient of $Firm\ Expense$ appears to be negative, with a t-statistics of 3.9. If $Firm\ Expense$ as 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 11, 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 = 1.2), 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 high growth of fund company in the pooled regression, but such 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.

5 Conclusion

We analyze the allocation of human capital toward marketing by U.S. mutual fund companies. Mutual fund companies adopt very distinct marketing strategies: a large heterogeneity in fund companies' marketing employment share. We uncover a significant relationship between the persistence of marketing employment strategy and fund performance in the U.S. mutual fund industry. Not only that the marketing employment share increases in family size and predicts subsequent fund flows, but it is also persistent across fund families.

We propose a framework based on Bayesian persuasion and costly learning 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 the good-enough 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 Proofs

A.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:

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

where $W_1^j = W_0 + X_0^j(1 + r_1), j = e, n$. Investors n update the posterior based on the Bayes rules:

$$q_1^n \equiv Pr(\alpha = \alpha_h|I_1^n) = \frac{q_0^n(z)}{q_0^n(z) + (1 - q_0^n(z))\exp(-\frac{(2r_1-\alpha_h-\alpha_l)(\alpha_h-\alpha_l)}{2\sigma^2})}, \tag{A.2}$$

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

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

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

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

$$\max_{X_1 \geq 0} \quad E(-e^{-\gamma W_2}|I_1^j) = \min_{X_1 \geq 0} e^{\frac{1}{2}\gamma^2\sigma_\epsilon^2 X_1^2}(q_1^j e^{-\gamma\alpha_h X_1} + (1 - q_1^j)e^{-\gamma\alpha_l X_1}) \tag{A.4}$$

the first-order conditions can be written as

$$\gamma\sigma_\epsilon^2 X_1(q_1^j e^{-\gamma\alpha_h X_1} + (1 - q_1^j)e^{-\gamma\alpha_l X_1}) - (q_1^j \alpha_h e^{-\gamma\alpha_h X_1} + (1 - q_1^j)\alpha_l e^{-\gamma\alpha_l X_1}) = 0 \tag{A.5}$$

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 (A.5) 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 (A.5).
  - 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 (A.5) as

$$f(X_1) - h(X_1) = (1 - q_1^j)e^{-\gamma\alpha_l X_1}(\gamma\sigma_\epsilon^2 X_1 - \alpha_h)p(X_1) = 0 \tag{A.6}$$

    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 an 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

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

Take 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.□

A.2 Proof of Proposition 1

Reformulation To solve the problem (5), we follow Kamenica and Gentzkow (2011) and perform the reformulation. First, whatever marketing plan $\pi(m)$ fund managers choose, the expected fund flow is fully determined by existing investors' posterior. When both the fund company and existing investors holds belief q_1^e at $t = 1$, the fund's expected utility is

$$\hat{v}(q_1^e) = E_{\alpha \sim \mu} v(X_1^{e*}(q_1^e), \alpha) \tag{A.7}$$

Second, when the fund company chooses some marketing plan $\pi(m)$, each employment realization m leads to some posterior $\mu_\pi(\cdot|m)$. We can think of the choice of $\pi(m)$ as inducing a distribution of posteriors. Use notation $\tau =< \pi >$ to indicate that a distribution of posteriors τ is induced by the signal $\pi(m)$. We says τ is Bayes plausible if $E_{q_1^e \sim \tau} q_1^e = \mu_0$. These two observations allow us to reformulate the fund company's problem (5) as

$$\max_{\tau} E_{q_1^e \sim \tau} \hat{v}(q_1^e) \quad s.t \quad E_{q_1^e \sim \tau} q_1^e = \mu_0 \tag{A.8}$$

where $\hat{v}(q_1^e)$ is defined by Equation (A.7).

From the definition of $\hat{v}$ in equation (A.7), and Lemma 1 above, the optimal choice X_1^{e*} is a nonlinear function of q_1^e and not zero if and only if $\mu \alpha_h + (1-\mu)\alpha_l > 0$.

The mutual fund's expected utility given the investor's belief q_1^e is:

$$\hat{v}(q_1^e) = \begin{cases} x(q_1^e) - X_0^e(1 + q_1^e\alpha_h + (1 - q_1^e)\alpha_l) & if \quad q_1^e\alpha_h + (1 - q_1^e)\alpha_l > 0 \\ \qquad -X_0^e(1 + q_1^e\alpha_h + (1 - q_1^e)\alpha_l) & if \quad q_1^e\alpha_h + (1 - q_1^e)\alpha_l \leq 0 \end{cases}$$

In this case, $\hat{v}$ is a convex function because $x(\cdot)$ is convex. Based on the Corollary 2 in Kamenica and Gentzkow (2011), the solution to Problem (A.8) is full disclosure. In other words, funds would choose two different numbers of marketing employees m_h and m_l, such that $\pi(m_h|\alpha_h) = 1$ and $\pi(m_l|\alpha_l) = 1$. $\square$

A.3 Proof of Lemma 2

For new investors, $X_0^n = 0, W_1^n = W_0$. 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

$$\begin{aligned} \max_{X_1 \geq 0} \quad E(-e^{-\gamma W_2}|cost\ paid) =& E(-e^{-\gamma(W_0 + X_1 r_2 - c_k)}|q_1^n) \\ =& -e^{-\gamma W_0} \cdot e^{\frac{1}{2}\gamma^2\sigma_\epsilon^2 X_1^2}(q_1^n e^{-\gamma(X_1\alpha_h - c_k)} + (1 - q_1^n)e^{-\gamma(X_1\alpha_l - c_k)}) \\ =& -e^{-\gamma W_0} \cdot e^{-\gamma\left[-\frac{1}{\gamma}\ln(q_1^n e^{-\gamma\alpha_h X_1} + (1 - q_1^n)e^{-\gamma\alpha_l X_1}) - \frac{\gamma}{2}\sigma_\epsilon^2 X_1^2 - c_k\right]} \end{aligned}$$

From the first order conditions of portfolio allocation problem 1, we can get the certainty equivalent wealth gain

$$g(r_1; r_0) = \begin{cases} -\dfrac{1}{\gamma}\ln(q_1^n e^{-\gamma\alpha_h X_1} + (1 - q_1^n)e^{-\gamma\alpha_l X_1}) - \dfrac{\gamma}{2}\sigma_\epsilon^2 X_1^2 & if \quad r_1 > \hat{r}_1 \\ 0 & if \quad r_1 \leq \hat{r}_1 \end{cases}$$

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

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

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

$$\begin{aligned}
\exp(-\gamma g(r_1; r_0)) &= \int_0^{+\infty} (q_1^n e^{-\gamma \alpha_h X_1} + (1-q_1^n) e^{-\gamma \alpha_l X_1}) e^{\frac{1}{2}\gamma^2 \sigma_\epsilon^2 X_1} \cdot f(z) dz \\
&= \int_0^{\hat{z}} (q_1^n e^{-\gamma \alpha_h x(q_1^n)} + (1-q_1^n) e^{-\gamma \alpha_l x(q_1^n)}) e^{\frac{1}{2}\gamma^2 \sigma_\epsilon^2 x(q_1^n)} \cdot f(z) dz + \int_{\hat{z}}^{\infty} f(z) dz \\
&= \int_0^{\hat{z}} (q_1^n e^{-\gamma \alpha_h x(q_1^n)} + (1-q_1^n) e^{-\gamma \alpha_l x(q_1^n)}) e^{\frac{1}{2}\gamma^2 \sigma_\epsilon^2 x(q_1^n)} \cdot f(z) dz + \frac{1}{1+\hat{z}}
\end{aligned}$$

where

$$q_1^n = \frac{q_0^n}{q_0^n + (1-q_0^n)\exp(-\frac{(2r_1-\alpha_h-\alpha_l)(\alpha_h-\alpha_l)}{2\sigma^2})}$$

and q_0^n is defined by equation (A.3). q_0^n is increasing in r_0. 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 (A.4). For the convenience, define $Fval(X_1^{n*}) \equiv (q_1^n e^{-\gamma\alpha_h X_1^{n*}} + (1-q_1^n) e^{-\gamma\alpha_l X_1^{n*}}) e^{\frac{1}{2}\gamma^2\sigma_\epsilon^2 X_1^{n*}}$.

$$\frac{\mathrm{d}\, Fval(X_1^{n*}(q_1^n))}{\mathrm{d}\, q_1^n} = \frac{\partial\, Fval(X_1^{n*}(q_1^n))}{\partial\, q_1^n} + \frac{\partial\, Fval(X_1^{n*}(q_1^n))}{\partial\, X_1^{n*}} X_1^{n*\prime}$$

From the first order conditions of solving the optimization problem (A.4), $\frac{\partial\, Fval(X_1^{n*}(q_1^n))}{\partial\, X_1^{n*}} = 0$. The integrated function $Fval(X_1^{n*}(q_1^n))$ is decreasing in q_1^n because

$$\frac{\mathrm{d}\, Fval(X_1^{n*}(q_1^n))}{\mathrm{d}\, q_1^n} = e^{-\gamma\alpha_h X_1^{n*}} - e^{-\gamma\alpha_l X_1^{n*}} \leq 0$$

Hence $\exp(-\gamma g(r_1; r_0))$ is decreasing in q_1^n which means $g(r_1; r_0)$ is increasing in q_1^n then increasing in both r_1 and r_0. □

A.4 Proof of Proposition 2

First, define the total fund flow from new investors who have paid the cost as

$$FN(r_1, m_j) = \min[1, \frac{g(r_1; r_0)}{c(m_j)}] X_1^{n*} = \begin{cases} X_1^{n*} & g(r_1; r_0) \geq c(m_j) \\ \frac{g(r_1; r_0)}{c(m_j)} X_1^{n*} & g(r_1; r_0) < c(m_j) \end{cases}$$

The maximization problem (8) for a fund with ability α_j can be written as

$$\max_{m_j \geq 0} \quad \beta\lambda \int_{-\infty}^{+\infty} FN(r_1, m_j)\phi(r_1|\alpha_j, \sigma_\epsilon)dr_1 - wm_j, \tag{A.9}$$

where $r_1 \sim N(\alpha_j, \sigma_\epsilon)$. To solve this maximization function, we introduce the Lagrangian function as

$$L(m_j, \mu) = \quad \beta\lambda \int_{-\infty}^{+\infty} FN(r_1, m_j)\phi(r_1|\alpha_j, \sigma_\epsilon)dr_1 - wm_j + \mu m_j, \tag{A.10}$$

Take the derivative with respect to m_j, we have

$$\frac{\partial L(m_j, \mu)}{\partial m_j} = \beta\lambda \int_{-\infty}^{\tilde{r_1}} -\frac{g(r_1; r_0)c'(m_j)}{c^2(m_j)} X_1^{n*}\phi(r_1|\alpha_j, \sigma_\epsilon)dr_1 - w + \mu$$

where $g(\tilde{r_1}; r_0) = c(m_j)$. $\tilde{r_1}$ can be written as $g^{-1}(c(m_j); r_0)$. The first order condition gives the optimal solution m_j^* as

$$m_j^* = \begin{cases} m^*(r_0, \alpha_j) & \mu > 0 \\ 0 & \mu = 0 \end{cases}$$

and $m^*(r_0, \alpha_j)$ is the solution to the equation

$$-\frac{c'(m_j^*)}{c^2(m_j^*)} = \frac{w}{\beta\lambda \int_{-\infty}^{g^{-1}(m_j^*; r_0)} g(r_1; r_0)\phi(r_1|\alpha_j, \sigma_\epsilon)X_1^{n*}dr_1} \tag{A.11}$$

Moreover, $\mu = 0$ if and only if $r_0 \leq \tilde{r}_0^j$ where

$$-\frac{c'(0)}{c^2(0)} = \frac{w}{\beta\lambda \int_{-\infty}^{g^{-1}(0; \tilde{r}_0^j)} g(r_1; \tilde{r}_0^j)\phi(r_1|\alpha_j, \sigma_\epsilon)X_1^{n*}dr_1} \tag{A.12}$$

Thus the optimal marketing level m_j^* is equivalent to

$$m_j^* = \begin{cases} m^*(r_0, \alpha_j) & r_0 > \tilde{r}_0^j \\ 0 & r_0 \leq \tilde{r}_0^j \end{cases}$$

Both high-type and low-type funds have the threshold of r_0 that satisfy the equation (A.12) above. Then we can find the relationship between different thresholds as

$$\int_{-\infty}^{g^{-1}(0;\tilde{r}_0^h)} g(r;\tilde{r}_0^h)\phi(r|\alpha_h,\sigma_\epsilon)X_1^{n*}(r)dr = \int_{-\infty}^{g^{-1}(0;\tilde{r}_0^l)} g(r_1;\tilde{r}_0^l)\phi(r_1|\alpha_l,\sigma_\epsilon)X_1^{n*}(r_1)dr_1 \quad \text{(A.13)}$$

Replace r with $r_1 + \Delta$, which is also distributed as $N(\alpha_h, \sigma_\epsilon)$ when $\Delta = \alpha_h - \alpha_l$. The equation above is equivalent to

$$\int_{-\infty}^{g^{-1}(0;\tilde{r}_0^h)-\Delta} g(r_1+\Delta;\tilde{r}_0^h)\phi(r_1|\alpha_l,\sigma_\epsilon)X_1^{n*}(r_1+\Delta)dr_1 = \int_{-\infty}^{g^{-1}(0;\tilde{r}_0^l)} g(r_1;\tilde{r}_0^l)\phi(r_1|\alpha_l,\sigma_\epsilon)X_1^{n*}(r_1)dr_1$$

Because $r_1 + \alpha_h - \alpha_l > r_1$, $X_1^{n*}(r_1)$ increases in r_1 and the gain function $g(r_1; r_0)$ increases in r_1 and r_0, to guarantee that the equation (A.13) holds, we know that $\tilde{r}_0^h < \tilde{r}_0^l$. □

B Data and Sample Construction

B.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. Besides employment, Form ADV also includes information about an advisory company's size, employment, ownership structure, contact information, and so on.

Item 5 of 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 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 they key information for our study: it asks "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 her customers (as a broker), for her own account (as a dealer), or for both. In a brokerage or fund company, the sales personnel (or 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.[14] 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. Also, registered representatives often called account executives, who are responsible of providing custom 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,

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

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 2019. The key variable of our paper, *MKT*, is defined as the fraction of registered representatives to total employees, i.e., the number in Item 5.B(2) divided by the number in Item 5.A.[15]

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 arrangement 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, operation, and compliance for all funds. In nature, measures on marketing efforts must refer to the company level. In the literature, some 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, Odean and Zheng (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, pension fund, and so on. 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.

B.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

[15]We drop obvious data errors here, such as when *MKT* is not smaller than one. The dropped observations account for less than 2% of the whole sample.

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.[16]

We further categorize all funds into seven groups based on Lipper Objectives (crsp_obj_name). [17] 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 0.5% and 99.5% 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 is 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. Besides, we also 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 CAPM beta to adjust risk exposure when making investment decisions. For robustness, we also consider raw returns as a simple measure of fund performance that an investor may use.

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.

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

[17] 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.

The identifier of the fund company that we use in CRSP is adv_name. Note that this is different 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.[18] As a result, the analysis in this paper speaks to advisory firms. We also conduct our analysis at the fund company level and found similar results.

$Vol(MKT)$ is the standard deviation of MKT during the sample years. $Rang(MKT)$ 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: *N_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 funds' TNA at each month end and sum up all fund-month revenue 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, i.e., 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 0.5% and 99.5% 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 0.5% and 99.5% 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 two names to be the same. We allow only trivial variations in the 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 in Form ADV. Also, we require a minimum fund size of $1 million.

[18] 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 portfolio of the fund. 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.

C Marketing and Performance

Marketing and Past Performance fund companies' marketing strategy is not necessarily monotonic in past performance. Signaling through marketing strategy is not crucial when a mutual fund's past performance is superior. When the return in time $t = 0$ is large enough, the learning effect dominates. Investors, based on a past good performance, are more likely to form their posterior of the fund being a good type and invest. Thus the number of marketing employees decreases in r_0 if the performance is good enough.

This is a key result that connects the fund's past performance to its marketing plans. Although marketing can potentially bring fund flows for all types of funds, these plans are costly. Funds strategically choose to signal their types and attract flows using the marketing tool. Figure IV shows these non-monotonic patterns between past performance and fund flows.

Marketing Plan and Future Performance The non-monotonic relationship between past performance and expected fund flows indicates that a fund company's marketing plan can not necessarily predict future returns. Since either a high-type fund or a low-type fund with good past returns would choose to do more marketing, the return in the next period does not have a clear relation with the marketing plan, which is plotted in Figure V.

D Figures and Tables

Figure VIII. The Relation of MKT and Expense Ratio to Firm Size

The upper panel plots the median *MKT* by fund companies' size quintiles, which are sorted on a fund company's total assets under management. The lower panel plots the median of the Expense Ratio, which is the average expense ratio of funds in a fund company, value weighted by funds' assets.

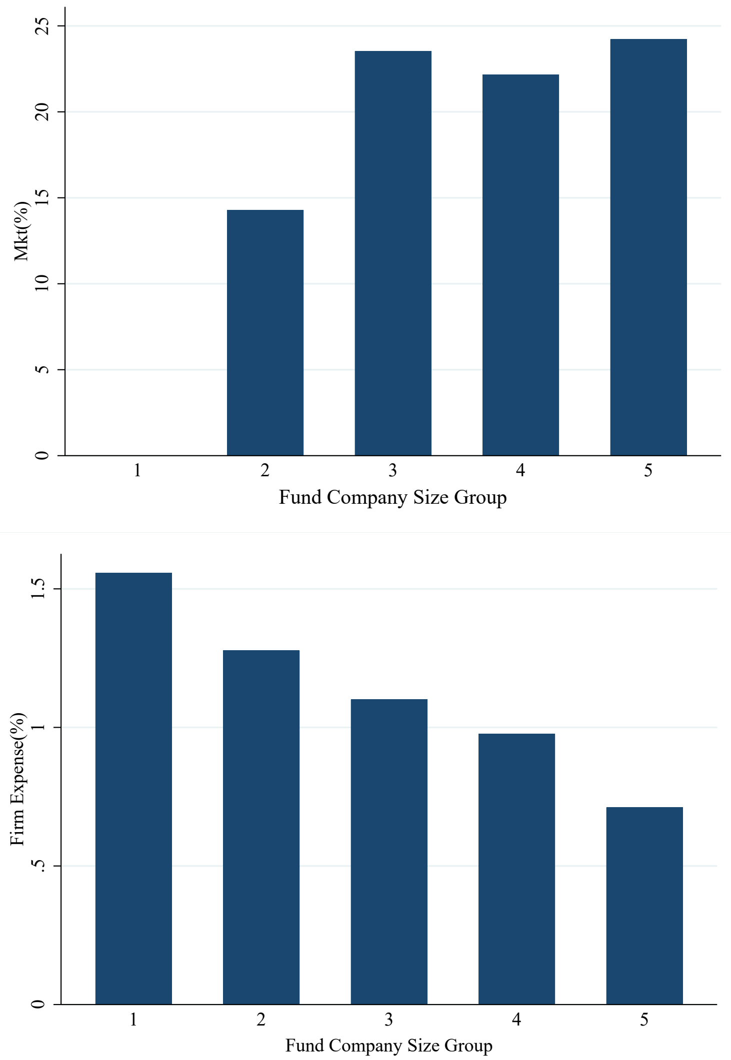


Figure IX. The Relation of Firm return and MKT-to-Performance Sensitivity

Fund companies are sorted into quintiles based on *MKT*-to-Performance sensitivity. *MKT*-to-Performance sensitivity is measured by the volatility of the marketing ratio, *Vol(MKT)*, where we require that firms must have a 3-year record of marketing and ignore firms with zero marketing along the sample period. *Firm Return* is the average past year net return of mutual funds of an advisory firm, value-weighted by each fund's total assets. *6-factor Alpha* is the average return of funds of an advisory firm, where the fund return is adjusted by the 6-factor model. Fund companies in the top quintile are categorized as firms with the most sensitive marketing strategies, and the rest are firms with the least sensitive marketing strategies. The y-axis plots the average firm return for each quintile.

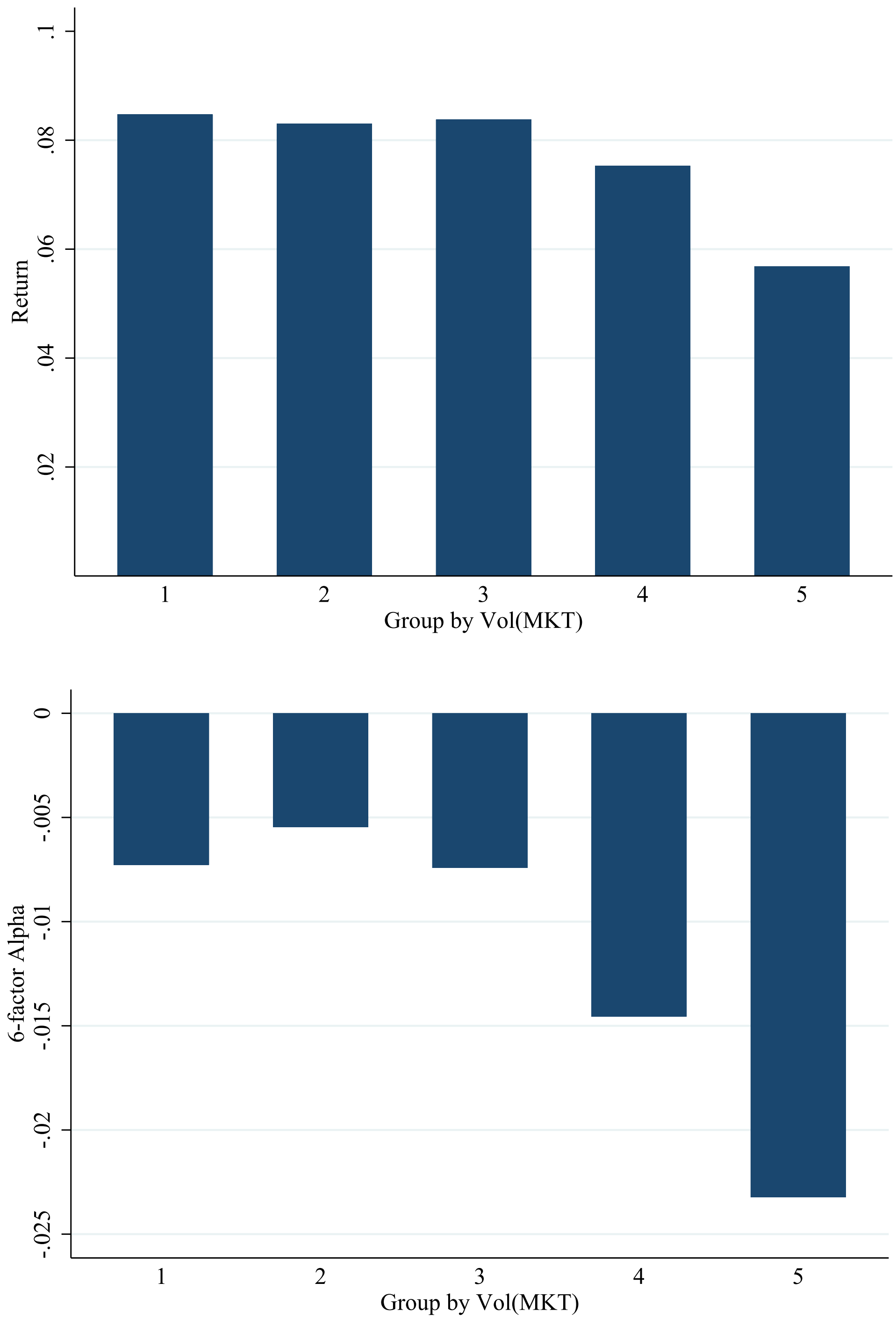
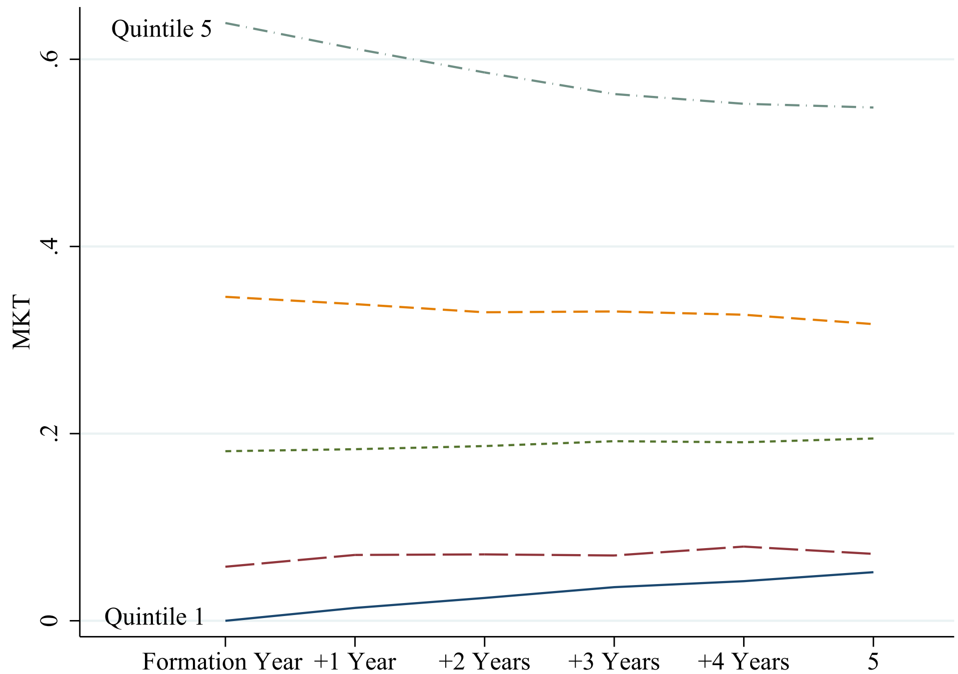


Figure X. Persistence of Fund Performance and Marketing

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 past year net return of mutual funds in the fund company, value-weighted by each fund's total assets; The net return here is adjusted by the 6-factor model. *MKT* is the fraction of marketing employees (i.e., registered brokers) to total employees.



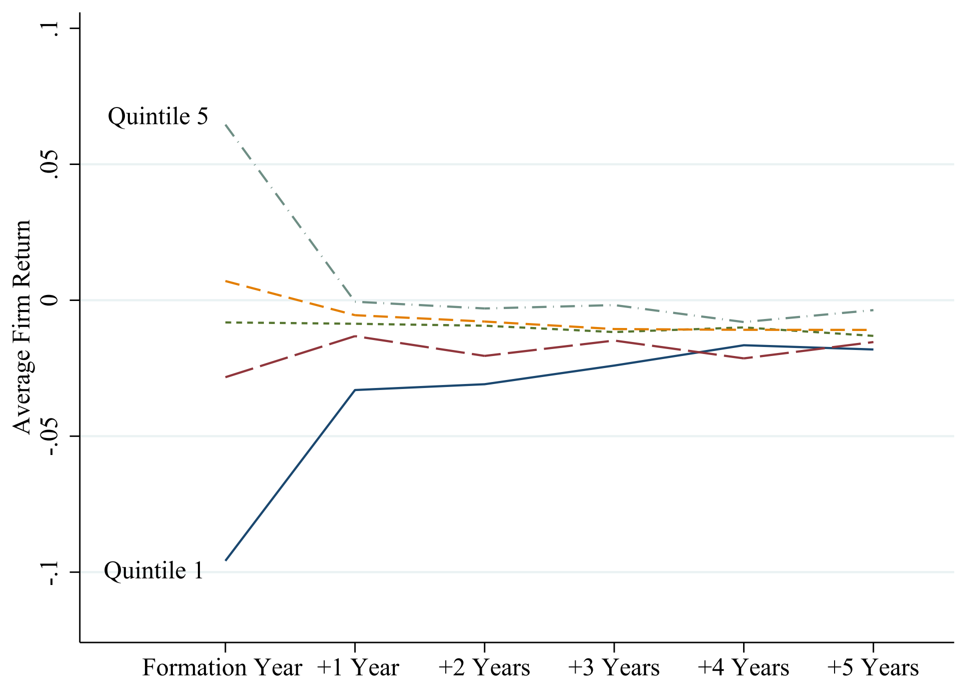


Figure XI. Return Predictability of Optimal Market Plans

This figure reports the relation between optimal marketing plans and the expected return r_1 at time 1. Other parameters are $\gamma = 1, \lambda = 1, \beta = 1, \sigma_\epsilon = 0.2, \alpha_h = 0.25, \alpha_l = -0.07, q = 0.5, w = 0.1$, where γ is the risk aversion of the CARA investor, and λ is the relative population weight of new investors. 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 $c(m) = \exp(1 - 0.3m - 0.01m^2)$.

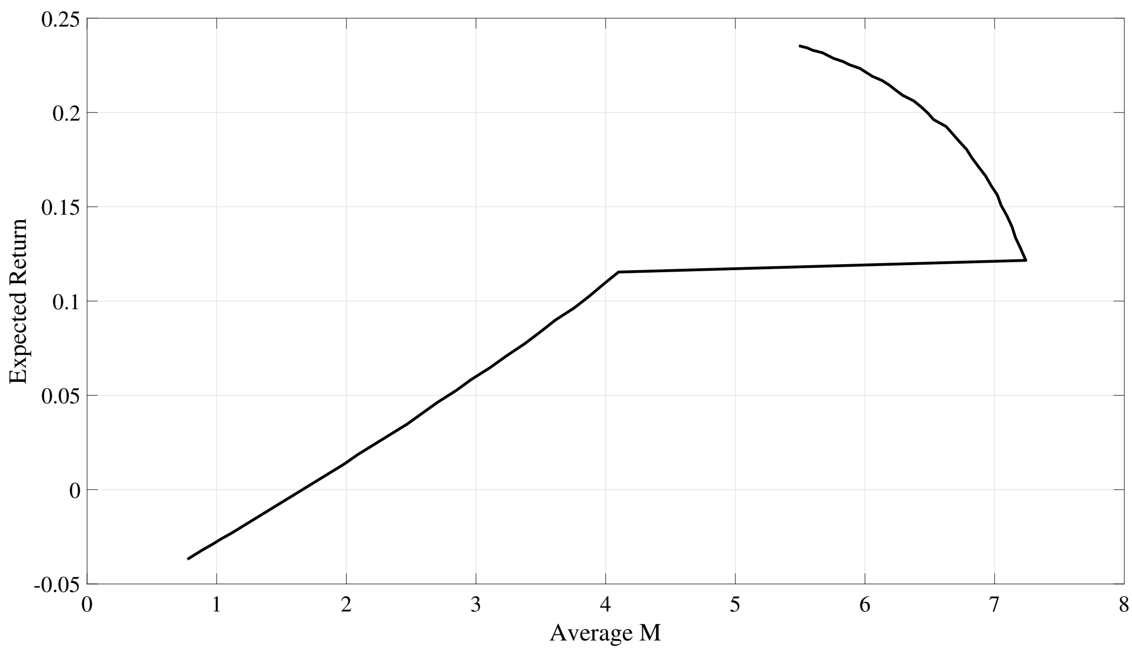


Table I. Summary Statistics

The sample period is from 2011 to 2019. Panel A shows summary statistics of fund company-level variables. *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* through the sample period when fund companies have at least 3-year record of *MKT*. *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*. *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. and *Log Firm Revenue* is the log of *Firm Revenue*. *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*. Δ*Firm Assets* is the (annual) log change of *Firm Assets*. *Firm Flow* is the percentage of total new fund flows into the company's funds over a year and is winsorzied at the 0.5% and 99.5% levels. *Firm Expense* is the average expense ratio of mutual funds in the firm, value-weighted by each fund's total assets. Δ*Firm Expense* is the (annual) change of *Firm Expense*. *Firm Return* is the average past year net return of mutual funds in the fund company, value-weighted by each fund's total assets; it is calculated with raw returns, CAPM-adjusted returns, and 6-factor adjusted returns, respectively. Panel B shows summary statistics of annual variables at the fund level. *Fund Assets* is the month-end total net assets. *Log Fund Assets* is the log of *Fund Assets*, and *Fund Age* equals the number of years since inception. *Log Fund Age* is the log of *Fund Age*. *Fund Expense* refers to the expense ratio and is winsorized at both the 0.5% and 99.5% levels by month. *Return* is a fund's monthly return net of fee. *CAPM Alpha* and 6-factor Alpha are adjusted returns using CAPM or 6-factor model, respectively. Panel C presents the result of regression of an advisory firm's MKT_Ratio and *Firm Expense* on its size and age in Columns (1) to (3) and in Columns (4) to (6), respectively. Year fixed effects are included. Observations are at the firm level annually from 2011 to 2019. Standard errors are clustered by firm, and the corresponding *t*-statistics are reported in parentheses.

Panel A: Advisory firm variables (annually)

Variable	Obs	Mean	Std. Dev.	P10	P25	P50	P75	P90
MKT	3426	0.24	0.25	0.00	0.00	0.18	0.39	0.62
Vol(MKT)	2656	0.08	0.07	0.02	0.03	0.06	0.10	0.17
Range(MKT)	2656	0.21	0.17	0.04	0.08	0.17	0.29	0.44
Firm Assets	3426	37819	205858	37.7	171	1191	10977	66956
Log Firm Assets	3426	7.22	2.79	3.66	5.15	7.08	9.30	11.10
Firm Revenue	3426	109.00	319.00	0.52	2.06	11.70	61.00	280.00
Log Firm Revenue	3426	2.79	1.92	0.42	1.12	2.54	4.13	5.64
ΔFirm Revenue	2828	6.32%	34.90%	-22.20%	-7.94%	3.66%	16.60%	35.70%
Firm Age	3426	20.20	17.10	3.00	6.79	17.40	27.60	38.90
Log Firm Age	3426	2.71	0.88	1.39	2.05	2.91	3.35	3.69
Firm Flow	3426	70.50%	536.00%	-196.00%	-53.70%	-2.93%	71.60%	324.00%
Firm Expense	3426	1.14%	0.52%	0.51%	0.79%	1.09%	1.40%	1.87%
ΔFirm Expense	2823	-0.02%	0.12%	-0.10%	-0.04%	-0.01%	0.01%	0.05%
Firm Return(Raw Return)	3426	6.81%	13.20%	-7.86%	-1.60%	5.59%	14.70%	23.90%
Firm Return(CAPM Alpha)	2909	-2.92%	7.34%	-11.30%	-5.84%	-1.89%	0.61%	3.35%
Firm Return(6-factor Alpha)	2909	-1.14%	6.35%	-6.96%	-3.29%	-0.61%	1.27%	4.18%

Panel B: Fund-level variables (annually)

Variable	Obs	Mean	Std. Dev.	P10	P25	P50	P75	P90
Fund Assets	78485	1950	10297	12.8	52.3	251	1029	3410
Log Fund Assets	78485	5.44	2.15	2.55	3.96	5.53	6.94	8.13
Age	78467	11.80	9.46	1.83	4.50	9.83	17.20	23.80
Log Age	78467	2.25	0.83	1.04	1.70	2.38	2.90	3.21
Fund Expense	60781	0.82%	0.49%	0.17%	0.45%	0.80%	1.13%	1.44%
Raw Return	78201	-0.09%	5.80%	-4.25%	-1.10%	0.30%	1.66%	2.95%
CAPM Alpha	78485	-1.53%	10.50%	-9.38%	-3.48%	0.00%	0.48%	4.52%
6-factor Alpha	78485	-0.46%	11.10%	-5.24%	-1.58%	0.00%	0.60%	3.93%

Panel C: Regression of *MKT* and Expense Ratio on Firm Size and Age

	(1)	(2)	(3)	(4)	(5)	(6)
	MKT_t			Firm Expense_t		
Log Firm Assets_t	0.014		0.017	-0.001		-0.001
	(4.51)		(3.67)	(-21.21)		(-16.29)
Log Firm Age_t		0.022	-0.012		-0.002	0.000
		(2.14)	(-0.84)		(-10.38)	(1.89)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3426	3426	3426	3426	3426	3426
Adj. R^2	0.026	0.005	0.027	0.411	0.135	0.415

Table II. Marketing Persistence and Fund Performance

The table presents the result of regressions of advisory firms' subsequent performance on *Vol(MKT)*. *Vol(MKT)* is the standard deviation of *MKT* through the sample period when fund companies have at least 3-year record of *MKT* and ignore observations which have zero marketing employees along the whole sample. *Log Firm Assets* is the log of one plus the total net assets (in millions USD) under management in the advisory firm. *Log Firm Age* is the log of *Firm Age*. *Firm Expense* is the average expense ratio of mutual funds in an advisory firm, value-weighted by each fund's total assets. Δ*Firm Expense* is the change of *Firm Expense* over a year. *Firm Return* is the average past year return of mutual funds of an advisory firm, value-weighted by each fund's total assets. All observations are at the firm-year level and firm performance is measured by 6-factor alpha in column (1)(2)(3), CAPM alpha in column (4)(5)(6) and raw return in column (7)(8)(9). *CAPM Alpha* and *6-factor Alpha* are adjusted returns using CAPM or 6-factor model, respectively. All dependent variables are at year $t + 1$, while independent variables are at year t. Year fixed effects are included in all columns. Observations are from 2011 to 2019. Standard errors are clustered by firm, and the corresponding t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	6-factor Alpha$_{t+1}$			CAPM Alpha$_{t+1}$			Raw Return$_{t+1}$		
Vol(MKT)	-0.068		-0.068	-0.076		-0.078	-0.114		-0.107
	(-3.50)		(-3.31)	(-3.23)		(-3.25)	(-3.37)		(-3.11)
MKT$_t$		-0.004	0.001		-0.004	0.004		-0.017	-0.013
		(-0.74)	(0.20)		(-0.67)	(0.50)		(-1.88)	(-1.31)
Log Firm Assets$_t$	-0.001	0.000	-0.001	-0.001	-0.000	-0.001	-0.002	-0.001	-0.002
	(-0.59)	(0.34)	(-0.59)	(-0.91)	(-0.18)	(-0.91)	(-1.31)	(-0.82)	(-1.31)
Log Firm Age$_t$	0.003	0.003	0.003	0.004	0.004	0.004	0.007	0.007	0.007
	(0.94)	(1.14)	(0.94)	(1.47)	(1.28)	(1.46)	(1.86)	(1.88)	(1.89)
Firm Expense$_t$	-1.151	-0.677	-1.155	-1.743	-1.136	-1.755	0.018	0.257	0.054
	(-2.74)	(-1.61)	(-2.77)	(-3.73)	(-2.07)	(-3.77)	(0.03)	(0.41)	(0.08)
6-factor Alpha$_t$	0.281	0.266	0.281						
	(5.02)	(6.00)	(5.03)						
CAPM Alpha$_t$				0.183	0.192	0.184			
				(3.74)	(4.57)	(3.74)			
Raw Return$_t$							0.159	0.156	0.157
							(3.62)	(4.19)	(3.54)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2176	2596	2176	2176	2596	2176	2418	3000	2418
Adj. R^2	0.121	0.085	0.120	0.116	0.088	0.116	0.494	0.447	0.494

Table III. Marketing Persistence and Fund Performance: Predictive Regressions

The table presents the result of regressions of advisory firms' subsequent performance on *Vol(MKT)* in the rolling window. *Vol(MKT)* is the standard deviation of *MKT* in the last 3 years and we drop observations which have zero marketing employees along the past 3 years. *Log Firm Assets* is the log of one plus the total net assets (in millions USD) under management in the advisory firm. *Log Firm Age* is the log of *Firm Age*. *Firm Expense* is the average expense ratio of mutual funds in an advisory firm, value-weighted by each fund's total assets. Δ*Firm Expense* is the change of *Firm Expense* over a year. *Firm Return* is the average past year return of mutual funds of an advisory firm, value-weighted by each fund's total assets. All observations are at the firm-year level and firm performance is measured by 6-factor alpha in column (1)(2)(3), CAPM alpha in column (4)(5)(6) and raw return in column (7)(8)(9). *CAPM Alpha* and *6-factor Alpha* are adjusted returns using CAPM or 6-factor model, respectively. All dependent variables are at year $t+1$, while independent variables are at year t. Year fixed effects are included in all columns. Observations are from 2011 to 2019. Standard errors are clustered by firm, and the corresponding t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	6-factor Alpha$_{t+1}$			CAPM Alpha$_{t+1}$			Raw Return$_{t+1}$		
Vol(MKT)$_t$	-0.091		-0.092	-0.074		-0.077	-0.073		-0.070
	(-3.47)		(-3.42)	(-2.63)		(-2.68)	(-2.05)		(-1.97)
MKT$_t$		-0.004	0.003		-0.004	0.007		-0.017	-0.012
		(-0.74)	(0.46)		(-0.67)	(0.81)		(-1.88)	(-1.05)
Log Firm Assets$_t$	-0.001	0.000	-0.001	-0.000	-0.000	-0.000	-0.001	-0.001	-0.001
	(-0.55)	(0.34)	(-0.54)	(-0.16)	(-0.18)	(-0.13)	(-0.68)	(-0.82)	(-0.70)
Log Firm Age$_t$	0.003	0.003	0.003	0.007	0.004	0.007	0.009	0.007	0.009
	(1.01)	(1.14)	(1.01)	(1.94)	(1.28)	(1.93)	(2.16)	(1.88)	(2.18)
Firm Expense$_t$	-1.359	-0.677	-1.369	-1.552	-1.136	-1.575	-0.650	0.257	-0.604
	(-2.70)	(-1.61)	(-2.72)	(-2.64)	(-2.07)	(-2.68)	(-0.83)	(0.41)	(-0.76)
6-factor Alpha$_t$	0.215	0.266	0.216						
	(5.02)	(6.00)	(5.04)						
CAPM Alpha$_t$				0.144	0.192	0.144			
				(3.33)	(4.57)	(3.35)			
Raw Return$_t$							0.082	0.156	0.081
							(1.79)	(4.19)	(1.76)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1537	2596	1537	1537	2596	1537	1608	3000	1608
Adj. R^2	0.095	0.085	0.094	0.102	0.088	0.101	0.534	0.447	0.534

Table IV. Marketing Persistence and Fund Performance: Robustness tests

The table presents the results of the robustness check for the relation between marketing persistence and subsequent performance. Panel A shows regressions of advisory firms' subsequent performance on an alternative measure of marketing persistence, *Range(MKT)*. Panel B shows regressions of funds' subsequent performance on *Vol(MKT)*. All observations are at the annual level. *Range(MKT)* is the range of *MKT* through the sample period when fund companies have at least 3-year record of *MKT*. *Log Firm (Fund) Assets* is the log of *Firm (Fund) Assets*. *Log Firm (Fund) Age* is the log of *Firm (Fund) Age*. *Fund Expense* is the expense ratio of the mutual fund each year. *Firm Expense* is the average expense ratio of mutual funds in an advisory firm, value-weighted by each fund's total assets. In Panel A, the firm performance is measured by 6-factor alpha in column (1), CAPM alpha in column (2) and raw return in column (3). In Panel B, the dependent variables are fund-level return and alphas. *CAPM Alpha* and *6-factor Alpha* are adjusted returns using CAPM or 6-factor model, respectively. *Firm Return* is the average past year net return and alphas of mutual funds of an advisory firm, value-weighted by each fund's total assets. All dependent variables are at year $t+1$, while independent variables are at year t. Year fixed effects are included in all columns of Panel A, and Year$\times$ Style fixed effects are added in all columns of Panel B. Observations are at the company/fund level annually from 2011 to 2019. Standard errors are clustered by firm, and the corresponding t-statistics are reported in parentheses.

Panel A: Alternative Measure

	(1)	(2)	(3)
	6-factor Alpha$_{t+1}$	CAPM Alpha$_{t+1}$	Raw Return$_{t+1}$
Range(MKT)	-0.025	-0.027	-0.034
	(-3.41)	(-3.23)	(-2.57)
MKT$_t$	0.002	0.004	-0.013
	(0.29)	(0.56)	(-1.29)
Log Firm Assets$_t$	-0.000	-0.001	-0.002
	(-0.50)	(-0.80)	(-1.19)
Log Firm Age$_t$	0.003	0.004	0.007
	(0.93)	(1.46)	(1.93)
Firm Expense$_t$	-1.172	-1.771	0.046
	(-2.81)	(-3.78)	(0.07)
6-factor Alpha$_t$	0.281		
	(5.01)		
CAPM Alpha$_t$		0.185	
		(3.73)	
Raw Return$_t$			0.158
			(3.55)
Year FE	Yes	Yes	Yes
Obs.	2176	2176	2418
Adj. R^2	0.120	0.115	0.493

Panel B: Fund Level Performance

	(1)	(2)	(3)
	6-factor Alpha_{t+1}	CAPM Alpha_{t+1}	Raw Return_{t+1}
Vol(MKT)	-0.017	-0.022	-0.002
	(-1.82)	(-1.68)	(-0.98)
MKT_t	-0.001	-0.004	0.001
	(-0.68)	(-1.84)	(2.44)
Log Fund Assets_t	-0.001	-0.001	-0.000
	(-2.99)	(-3.98)	(-3.61)
Log Firm Assets_t	0.001	0.001	0.000
	(5.35)	(5.07)	(3.40)
Log Fund Age_t	-0.001	-0.003	0.000
	(-2.57)	(-6.55)	(2.11)
Fund Expense_t	-0.301	-0.263	0.001
	(-3.30)	(-2.16)	(0.04)
6-factor Alpha_t	0.195		
	(8.42)		
CAPM Alpha_t		0.234	
		(8.56)	
Raw Return_t			-0.021
			(-0.85)
Year×Style FE	Yes	Yes	Yes
Obs.	53298	53298	53127
Adj. R^2	0.084	0.151	0.485

Table V. Regressions of Future Firm Revenue on MKT

The table presents the result of regressions of advisory firms' changes in size, flow, 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 0.5% and 99.5% 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 an advisory firm, value-weighted by each fund's total assets. Δ*Firm Expense* is the change of *Firm Expense* over a year. *Firm Return* is the average past year net return of mutual funds of an advisory firm, value-weighted by each fund's total assets. 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 2019. 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$_t$	1.318	1.646	0.090	-0.019	0.073	0.042
	(2.07)	(1.18)	(2.66)	(-0.23)	(2.91)	(0.59)
Log Firm Assets$_t$	0.120	-2.215	-0.003	-0.244	-0.002	-0.159
	(0.96)	(-2.65)	(-0.61)	(-9.02)	(-0.57)	(-9.27)
Log Firm Age$_t$	-1.272	0.267	-0.110	-0.180	-0.067	-0.089
	(-5.15)	(0.48)	(-8.52)	(-3.36)	(-6.71)	(-2.48)
Firm Expense$_t$	-157.311	-295.106	-12.302	-17.522	-10.131	-28.249
	(-3.87)	(-2.64)	(-5.33)	(-1.81)	(-6.02)	(-3.71)
Firm Return$_t$	0.889	2.860	0.691	0.353	0.489	0.324
	(0.70)	(1.98)	(8.02)	(4.88)	(7.82)	(5.48)
Firm FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3000	2912	3000	2912	3000	2912
Adj. R^2	0.055	0.287	0.163	0.408	0.144	0.326