The London School of Economics and Political Science

Essays on Communication and Trading in Financial Markets

Jane Jingxuan Chen

A thesis submitted to the Department of Finance of the London School of Economics and Political Science for the degree of Doctor of Philosophy, London, June 2023

Declaration

I certify that the thesis I have presented for examination for the Ph.D. degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

I declare that the thesis consists of 23,497 words excluding appendices.

Statement of co-authored work

I confirm that Chapter 3 is jointly co-authored with Wenxi Jiang and Mindy Z.Xiaolan and I contributed 33% of this work.

Acknowledgement

I am deeply grateful to my main advisor, Péter Kondor, for his invaluable guidance, knowledge, inspiration, encouragement, and patience throughout my PhD journey. His expertise and mentorship have set a remarkable example for me as an academic.

I would also like to express my sincere appreciation to the other members of my job market committee, Cameron Peng and Mindy Z.Xiaolan, for their continuous support and insightful inputs. I am truly thankful for their exceptional contributions to my research.

I am indebted to my co-authors, Wenxi Jiang and Mindy Z.Xiaolan, with whom I have had the privilege of working on the third chapter of this thesis. I have learned an immense amount from our collaboration.

I am grateful for the meaningful discussions and interactions with many other individuals who have influenced and enriched this thesis, including Ulf Axelson, Cynthia Balloch, Georgy Chabakauri, J.Anthony Cookson, Kim Fe Cramer, Daniel Ferreira, Dirk Jenter, Christian Julliard, Dong Lou, Ian Martin, Igor Makarov, Stavros Panageas, Daniel Paravisini, Pedro Saffi, Dimitri Vayanos, Michela Verardo, Kathy Yuan and Hongda Zhong.

I would like to extend my appreciation to the faculty and staff at LSE who have provided support at various stages, particularly Ashwini Agrawal, Mike Burkart, Thummim Cho, Mary Comben, Ricardo Reis, Huan Tang and Simon Tuck. I am also grateful for the financial support received from the London School of Economics and the Paul Woolley Centre.

I feel fortunate to have shared my PhD years with a supportive cohort and colleagues Fabrizio Core, Juan Chen, Chris Greiner, James Guo, Brandon Han, Jiantao Huang, Zhongchen Hu, Dimitris Papadimitriou, Alberto Pellicioli, Amir Salarkia, Jiahong Shi, Ran Shi, Arthur Taburet, Bo Tang, Yanhuan Tang, Jiaxing Tian, Karamfil Todorov, Song Xiao, Yun Xue and Xiang Yin.

Lastly, I want to express my gratitude to my parents for their unwavering love and support throughout my journey.

Abstract

This thesis studies information transmission via communication and trading in financial markets.

In the first chapter, to understand strategic interaction among short sellers, I develop a model to explain how size affects a short seller's incentive and behaviour in trading and disclosing. The model rationalizes the strategic complementarity between small and large funds in short-selling campaigns. Namely, the delayed entry of the large fund helps the small fund avoid margin calls, while the large fund free-rides on the small fund's disclosed information. I discuss the ambiguous effect of announcements on market efficiency and provide further predictions.

In the second chapter, I empirically study how hedge funds strategically disclose their private information during short-selling campaigns. Using data on hedge funds' voluntary announcements and daily short positions in the EU market, I document the existence of two groups of funds: Announcers and Followers. Announcers, typically small and young, (1) establish short positions, (2) publish research reports about short targets, and (3) realise profits from the falling price within a short time frame. Followers, usually large, enter at the release of reports and increase their short positions even after announcers exit. I also test two unique predictions. Stocks with lower borrowing costs and wider mispricing are more likely to be publicly attacked by hedge funds.

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

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Chapter 1

A Theory of Strategic Announcements in Short-Selling Campaigns

Jane Chen [1]

To understand strategic interaction among short sellers, I develop a model to explain how size affects a short seller's incentive and behaviour in trading and disclosing. The model rationalizes the strategic complementarity between small and large funds in short-selling campaigns. Namely, the delayed entry of the large fund helps the small fund avoid margin calls, while the large fund free-rides on the small fund's disclosed information. I discuss the ambiguous effect of announcements on market efficiency and provide further predictions.

[1] I am extremely grateful to my advisors Péter Kondor and Cameron Peng for invaluable guidance and support. I also thank Ulf Axelson, Cynthia Balloch, Georgy Chabakauri, J.Anthony Cookson, Kim Fe Cramer, Daniel Ferreira, Dirk Jenter, Wenxi Jiang, Christian Julliard, Dong Lou, Ian Martin, Igor Makarov, Stavros Panageas, Daniel Paravisini, Dimitri Vayanos, Michela Verardo, Mindy Z. Xiaolan, Kathy Yuan, Hongda Zhong and seminar participants at the London School of Economics for helpful comments. All errors are my own.

1.1 Introduction

In a frictionless market, informed traders are typically incentivized to keep information private. They trade cautiously so that any private information is incorporated into prices gradually and not easily inferred by other investors in the market (Kyle, 1985). In reality, however, we sometimes observe hedge fund managers, the prototype of informed traders, deviate from this conventional wisdom. As evidenced in Chapter 2, while some hedge funds remain silent about their targets, a significant number of them have recently engaged in very public short-selling campaigns. In particular, smaller funds tend to be more active in announcing their short targets but also cover their positions more rapidly. On the other hand, larger funds tend to follow the entry and announcements of smaller funds and maintain their short positions for longer periods. Such contrasting behaviours across hedge funds raise the following questions: What are the strategic considerations among short sellers of different sizes, and why do some announce their private information while others do not? Furthermore, how does this strategic interaction affect market efficiency?

I address these questions by examining hedge funds' disclosure behaviour and short-selling activities when they face leverage constraints. I propose a limits-to-arbitrage model where each strategic hedge fund decides when to short-sell and whether to release her information to the other funds. Funds may have different sizes and are subject to leverage constraints. I show that funds naturally gravitate towards an equilibrium where their strategies complement each other. The small fund is willing to do a costly search for overpriced targets, short and announce their investment. The large fund tends to wait for the announcement, save on research costs, and follow the lead. This is beneficial for both parties: the small one avoids costly liquidation when the noise traders move against them, while large funds save on the cost of information acquisition. With the help of my model, I discuss the ambiguous effect of announcements on market efficiency and provide further testable predictions.

In this chapter, hedge funds make decisions on trading, information acquisition, and disclosure. Inspired by Shleifer and Vishny (1997), I build a game theoretic model where two strategic hedge funds with limited capital trade against non-strategic noise traders in three periods. In the initial period, a subset of risky assets in the market is overpriced due to noise traders. In the interim period, mispricing could worsen, that is, the noise trader shock might push the price further away from the fundamentals. However, it is also possible that mispricing might disappear. In the final period, the price exogenously returns to its fundamental value for sure. Funds can take short positions subject to a leverage constraint. The novel element of my model is that hedge funds do not initially know which assets are mispriced. A fund can search for the mispriced asset at a cost. After it has established its position, it can decide to reveal this information to other hedge funds. Alternatively, a hedge fund can wait for the information revelation from the other fund and jump into the fray only then.

There are two interconnected layers of trade-offs in this model. First, just as in Shleifer and Vishny (1997), funds in my model have to decide whether to enter early, risking being wiped out if the mispricing worsens, or to wait until the interim period, risking missing out on the opportunity. However, I show that the possibility of learning and communication can change this trade-off. Funds which enter early can limit the adverse effects of noise trader shocks by attracting the entry of other funds via announcements. In the meanwhile, the opportunity of free-riding on information from others' announcements increases the funds' incentive to wait until the interim period.

In particular, I show that there is a Nash equilibrium where one fund (called fund A to denote *Announcer*) chooses to pay the information cost, holds short positions of the overpriced asset, and reveals its information, while the other fund (called fund F to denote *Follower*) decides to wait, to not pay the cost of learning, and enters only after A's announcement. I prove that this equilibrium exists only when fund A is sufficiently small and fund F is sufficiently large. If fund A is small, its price effect is limited. Therefore, the arbitrage trade remains sufficiently profitable for fund F even if fund A has already established its position. On the other hand, to avoid costly liquidation when mispricing deepens, fund A wants to share its information and attract extra capital from fund F to drive down the price. In this sense, the size of fund F should be large enough to be able to provide this protection for fund A. To summarise, small funds voluntarily publish their information to avoid potential loss from fire sales. Large funds save the search cost by waiting for others' information and make profits from being able to trade against noise traders until the price incorporates all the information.

An important implication of the model is that the effect of announcements on market efficiency is ambiguous. With announcements, small funds are more likely to short once they find a mispriced asset because they are more protected against fire sales. This increases market efficiency. However, if large funds can free-ride on the information of the announcers, their incentive to search for other mispriced assets decreases. This decreases market efficiency. I show that the overall effect depends on the size distribution of announcers and followers. In particular, when announcers are better capitalized, the first effect can dominate. The idea is that in this case, they can significantly improve market efficiency even in the periods when the followers are still inactive.

As further testable predictions, my model suggests that we should observe more short-selling campaigns with announcements targeting stocks with lower margin requirements and lower surprises in mispricing. Significant increases in mispricing in the interim period discourage small funds to search for information and enter early. At the same time, very large margin requirements imply that even large hedge funds can only have small price effects. This limits the followers' capability to provide protections against temporarily deepened mispricing for the announcers.

My analysis suggests that if regulators were to validate the credibility of the disclosed information in a timely manner, this would help the market to incorporate the information in prices faster. It would not only encourage the announcers to discover and announce new evidence on more targets but would also decrease the free-riding incentives of followers.

Literature review There is a growing empirical literature studying the effects of arbitrageurs' announcements (e.g., Ljungqvist and Qian (2016), Gillet and Renault (2018), van Binsbergen, Han and Lopez-Lira (2021)). Furthermore, several papers document evidence of the informativeness of short-seller announcements (e.g., Appel and Fos (2019), Kartapanis (2019)). These papers offer evidence to support the mechanism in my model. They demonstrate that hedge funds hold true information about their targets when make announcements. These announcements introduce new information to others, leading to a significant impact on prices.

This chapter is also related to recent theoretical work on arbitrageurs' disclosing behaviours. Pagano and Kovbasyuk (2022) argue that hedge funds with short investment horizons will concentrate their disclosures on a few assets because of the limited attention of rational investors. Pasquariello and Wang (2021) propose a model to explain why information disclosure is optimal for mutual funds with short-term incentives. Liu (2017) develops a two-period Kyle-type model (Kyle, 1985), where it is optimal to disclose the information when the informed shorthorizon investor has a higher reputation. These papers focus on the optimal choice of information disclosures of an informed short seller. Instead, I focus on the strategic game where any of the participating hedge funds can decide whether to be an announcer or follower.

The remainder of the chapter is organised as follows. Section 1.2 describes the model setup and equilibrium concept. Section 1.3 demonstrates the existence of equilibrium both under a simplified setup and in a general setting. Section 1.4 discusses market efficiency and comparative statistics. Section 1.6 concludes. The Appendix includes proofs of all lemmas and propositions and additional figures.

1.2 The Model

1.2.1 The Model Setup

In this section, I develop a model based on Shleifer and Vishny (1997), who study how informed funds optimally exploit mispricings when facing constraints on equity capital. My model departs from theirs principally by introducing the choice of being informed and the possibility of announcements. Under this setting, I examine how funds strategically exploit arbitrage opportunities against noise traders. Consider an economy with two types of market participants: two hedge funds specialised in short selling and a mass of noise traders with a downward-sloping demand curve. All agents live for three dates: 0, 1, and 2. There are one risk-free bond and N risky assets on the market. Assume that there is no discounting. Each unit of risky asset n gives a payoff of $V_{n,2}$ at date 2, which is independent across all assets with uniform distribution $V_{n,2} \sim U[V-\epsilon, V+\epsilon]$. The price of asset n at date t is $p_{n,t}$. At date 2, the price is equal to the realised value of $V_{n,2}$.

To model the mispriced assets, I assume that noise traders' demand shocks distort a subset of risky assets at date $t = 0, 1$. In particular, these assets face the shock U_t at date t. This generates noise traders' aggregate demand of asset n as

$$QL(n,t) = (V + U_t)/p_{n,t}, \tag{1.1}$$

where asset n belongs to the mispriced subset. At date 1, misperception might deepen ($U_1 = U > U_0$) with probability q, or noise traders' demand recovers ($U_1 = 0$) with probability $1 - q$. These shocks might drive prices away from fundamental values.

Two hedge funds, denoted by A and F, can take short positions of assets subject to the leverage constraint at date 0 and 1. Without loss of generality, I assume that each fund can only short one asset with its full capacity or hold zero position at each date.[2] The initial wealth of fund j at date 0 is given as W_j, $j = A, F$. If hedge fund j decides to short $x^j_{n,t}$ units of asset n at date t, the total margin on its position cannot exceed its total wealth W^j_t,

$$W^j_t \geq \frac{1}{\phi} x^j_{n,t} p_{n,t}, \qquad j = A, F, \tag{1.2}$$

where $\frac{1}{\phi}$ is the margin requirement, exogenously given by financiers. ϕ stands for the maximum leverage that funds can take. At date $t+1$, the total wealth of fund j would be

$$W^j_{t+1} = W^j_t + x^j_{n,t}(p_{n,t} - p_{n,t+1}). \tag{1.3}$$

The maximum leverage is not too large, that is, $\phi \leq \min(\frac{V}{U-U_0}, \frac{U-U_0}{W_F})$. And hedge funds' initial wealth is limited, $\phi W_j < \min(U_0, \frac{U}{2})$. Thus, hedge funds' resources are insufficient to bring prices back to their fundamental values. Funds' demand for asset n is $QS(n,t) = x^A_{n,t} + x^F_{n,t}$. Given one unit supply of the asset, the market

[2] If funds are allowed to short with fractional capital, they can spread out the effect of a deeper shock in the interim period by holding more capital at date 0. However, with limited capital, funds still suffer from the liquidation cost when facing larger noise trader shocks. The arguments in the model also hold.

clearing condition is

$$(V + U_t)/p_{n,t} - x^A_{n,t} - x^F_{n,t} = 1. \tag{1.4}$$

At date 0, hedge funds can pay a cost, denoted by κ, to find one mispriced asset n_j, $j = A, F$. I assume that funds never find the same mispriced asset ($n_A \neq n_F$). This assumption is realistic because many risky assets might be on the market or funds have different technologies to identify mispricing.

Each fund can decide whether to announce the mispriced asset n_j to another fund at the end of date 0. Announcements are verifiable, so only funds that have identified the mispricing might announce their findings.[3] If fund j pays the searching cost and decides to keep silent, fund j would be the only informed trader of asset n_j. In contrast, if fund j announces, another fund also realises that asset n_j is mispriced. As only hedge funds can verify the information, noise traders might still trade against the hedge fund after the announcement.

Given the risk-neutral assumption, hedge funds make decisions on trading, information acquisition, and disclosure to maximize their wealth W_2^j at date 2. The decision-making process is illustrated in Figure 3.3.1.

1.2.2 Equilibrium Concept

To summarise, the environment described above represents a two-player game

$$\Gamma = (2, \{S_A, S_F\}, \{u_A, u_F\}),$$

which is defined by (1) the set of strategies of hedge fund j,

$$S_j = \Big\{ s_j | s_j \in (\{\kappa,\, 0\},\ \{Announce(A),\ Not\, Announce(NA)\},\ \{(0,1)\times(0,1)\}) \Big\},$$

[3] In the literature of strategic communication (e.g., Crawford and Sobel (1982), Sobel (1985)), privately informed agents choose to fully reveal their information in the equilibrium if their utility is aligned with uninformed agents.

Figure 1.1. Decision Process

t=0	t=1	t=2
Noise traders: Demand $(V+U_0)/p_0$ unit of risky assets.	Noise traders: Demand $(V+U_1)/p_1$ unit of risky assets.	Fundamental value realised, V_2
HF with initial wealth W_j: Pay cost κ or not; Choose the optimal short position x_0^j and receive $D_0^j = x_0^j p_0$; Decide whether to announce.	HF : Choose the optimal short position x_1^j and receive $D_1^j = x_1^j p_1$. $W_1^j = W_0^j + D_0^j(1 - p_1/p_0)$	HF : Accumulated wealth is $W_2^j = W_1^j + D_1^j(1 - V_2/p_1)$
Leverage constraint: $\phi W_0^j \geq D_0^j$	Leverage constraint: $\phi W_1^j \geq D_1^j$	
Market clearing: $p_0 = V + U_0 - D_0^A - D_0^F$	Market clearing: $p_1 = V + U_1 - D_1^A - D_1^F$	

where $\{(0,1)\times(0,1)\}$ represents the set of decisions of trading (0 for zero position, and 1 for shorting with full capacity) at date 0 and 1; and (2) the payoff $u_j(s_j, s_{-j})$, the expected terminal wealth of fund j at date 0 when fund j chooses action s_j and the counterparty chooses action s_{-j}. Hedge funds optimally choose their strategies to maximize their wealth at date 2.

Definition 1.2.1. *A Nash equilibrium of this two-fund game is a vector* (s_A^*, s_F^*) *such that* s_j^* *solves the problem*

$$\max_{s_j \in S_j} E(u_j(s_j, s_{-j}^*))$$

for each fund j.

1.3 Equilibrium with Announcements

In this section, I examine the equilibrium strategy of the game described above in three steps. First, I explain what would happen without announcements. This is my version of the Shleifer and Vishny (1997) benchmark. Next, I introduce the possibility of announcements but assuming fund F has unlimited capital. Under this simplified setting, the optimal strategy of fund F is trivial since fund F always has the capital to follow another's investments when observing the announcement. Therefore, I can separate fund A's incentive to announce. After paying the cost, funds which enter early can limit the adverse effects of noise trader shocks by attracting the entry of other funds via announcements. I show that the region of fund A choosing to announce is decreasing in the fund size.

Finally, in the general setup, I demonstrate why and when the equilibrium with Announcers and Followers exists when each has limited capital. Small fund A prefers to announce, and large fund F waits to learn A's information to exploit the mispricing.

1.3.1 Strategy without Announcements: SV Benchmark

Consider the case without announcements, wherein each fund optimally chooses short positions after paying the cost. For concreteness, I study fund A's optimal choice in this subsection. Fund F's problem is independently identical to A's problem since each of them would be the only informed trader once paying the cost.

To begin, I examine the choice of fund A given it has paid the cost and learns asset n_A is mispriced. Let D_t denote the amount that fund A receives from short sales at date t. At date 1, when the optimistic belief of noise traders disappears $U_1 = 0$, fund A would liquidate its position and hold cash ($D_1 = 0$, $W_2^A = W_1^A$). In contrast, when the misperceptions of noise traders deepen $U_1 = U$, fund A would fully invest $D_1 = \phi W_1^A$ because the price p_1 is above the fundamental value.[4] If fund A fully invests from date 0, p_0^A represents the asset price at date 0

[4] Although fund A is a monopolist here, it would choose to short with the full capacity as long as shorting is profitable by assumption. Another explanation is that fund A's capital is limited, so the profits from short selling always increase in the shorting amount and fund A would reach the corner solution.

and p_1^{AA} is the price when the demand shock is worse at date 1. If fund A chooses to wait and begin to short at date 1, the asset price is $V + U_0$ at date 0 and p_1^A at date 1. The following Lemma 1.3.1 demonstrates the optimal choice of shorting for fund A.

Lemma 1.3.1. *If fund A has paid the cost and no announcements were made, for given W_A, U_0, U, V, and ϕ, there is a threshold q^{na} such that, for $q > q^{na}$, fund A would wait $D_0 = 0$ and for $q \le q^{na}$, fund A would fully invest $D_0 = \phi(W_A - \kappa)$. q^{na} is written as*

$$q^{na} = \begin{cases} \dfrac{\phi(1-\frac{V}{p_0^A})}{1+\phi(1-\frac{V}{p_0^A})+\phi(1-\frac{V}{p_1^A})} & W_A > W^* \\ \dfrac{1-\frac{V}{p_0^A}}{1-\frac{V}{p_1^A}-(1+\phi)(1-\frac{p_1^{AA}}{p_0^A})(1-\frac{V}{p_1^{AA}})} & W_A \le W^* \end{cases},$$

where $W^* = \kappa + \frac{1}{\phi(1+\phi)}(V + U_0 - \phi(U - U_0))$. q^{na} decreases in W_A.

Lemma 1.3.1 is parallel to the results in Shleifer and Vishny (1997). The leverage constraint gives rise to the amplification of mispricing via a mechanism similar to that for capital constraints. Suppose fund A has identified the overpriced asset and takes short positions with full capacity at date 0. Fund A then has exposure to the risk of worsening mispricing at date 1. If noise traders continue to be confused and demand more shares at date 1, the increasing price triggers the margin calls. Consequently, fund A is forced to reduce short positions when the arbitrage opportunities are the best. Instead of shorting at the beginning, fund A could also wait to short sell at a higher price and avoid the potential loss from margin calls. Therefore, in cases where noise trader misperceptions are very likely to deepen—that is, the noise trader risk q is large than the threshold q^{na}—fund A would refrain from shorting early and choose to enter during the interim period instead.

The threshold q^{na} is determined differently when fund A is wealthier. Given other parameters fixed, fund A could take more short positions with larger initial wealth. The asset price at date 0, p_0^A, is smaller because of the larger price impact. If fund A has taken large short positions and mispricing worsens, there is a possibility that the increasing price would drive the fund's wealth below zero. In the extreme case, fund A is forced to buy back stocks and go bankrupt. Fund A has no capital to correct the price $D_1 = 0$ even if the asset is overpriced. More formally, when fund A holds short positions with full capacity at date 0 and 1,

$$W_1^A < 0 \quad \textit{iff} \quad p_1^{AA} > (1 + \frac{1}{\phi})p_0^A. \tag{1.5}$$

Based on condition (1.5) and market clearing condition, when $W_A > W^*$, fund A is required to close short positions $W_1^A \equiv 0$ if $U_1 = U$. In contrast, when $W_A \leq W^*$, fund A can keep shorting the asset. Lemma 1.3.1 shows threshold q^{na} for fund A in each situation.

Moreover, q^{na} is decreasing in W_A. When fund A is wealthier, it has more exposure to the noise trader risks if shorting early. If the probability of deeper shock is considerable, wealthier funds choose to delay shorting and wait until date 1. More detailed proof could be found in the appendix.

Based on Lemma 1.3.1, next, I compare the expected profit of shorting with the learning cost. Lemma 1.3.1 shows when funds decide to learn.

Lemma 1.3.2. *When $W_A > \underline{W}$, the benefits of gaining the information and shorting are more significant relative to the cost κ, and fund A would always pay to learn.*

Intuitively, as long as fund A's remaining capital after paying the learning cost is not too small, fund A could take enough short positions and receive positive net profits. In the Appendix, I provide the proof of lemma 1.3.2.

1.3.2 Announcements when One Fund Has Unlimited Capital

In this subsection, I investigate the optimal strategy of funds on announcements. Assume that the initial wealth of hedge fund F is unlimited. Note that whenever fund F observes an announcement about another mispriced asset, fund F would engage in shorting since it has no shorting constraint. Only hedge fund A's decision matters in the equilibrium. In this modified setting, I can focus on the incentive of fund A to announce. Now fund A's problem is to maximize the expected assets under management $E(W_2^A)$ at date 2.

Fund A makes decisions on shorting, announcing and information acquisition. First, if fund A does not pay the learning cost, fund A would hold risk-free bonds because shorting is costly without any information. Second, consider the case when fund A has paid the cost and identified that asset n_A is mispriced. At date 1, fund A always hold short position with its full capacity if the misperception is worse. If fund A decides to keep silent, its optimal choice is determined by the noise trader shock based on Lemma 1.3.1. If fund A makes an announcement, fund F realises that the asset is mispriced. Both funds are informed and choose their optimal short positions simultaneously.[5] Compared with shorting silently, the asset price at date 1 is lower because of the entry of fund F. Hence if and only if fund A decides to short from date 0, A would announce to avoid costly liquidation. Fund A solves the maximization problem:

$$\max_{s_A} E(W_2^A) = (1-q)W_1^A(V) + q(1+\phi(1-\frac{V}{p_1^u}))W_1^A(p_1^u)$$
$$s.t. \quad W_1^A(p_1) = W_A - I_{s_A}k + D_0(1-p_1/p_0),$$

where the feasible set of strategies $s_A \in \{(0, NA, 0\times 0),\ (\kappa, NA, 0\times 1),\ (\kappa, A, 1\times$

[5] In the duopoly model where fund F has unlimited capital, fund A would short at its full capacity and fund F's profit is at the monopoly level.

1)} and p_1^u is the asset price when noise traders experience a deeper shock at date 1. The following proposition 1.3.3 illustrates the optimal strategy of fund A.

Proposition 1.3.3. *For given $W_A > \underline{W}$, U_0, U, V, κ and ϕ, there is a threshold q^a such that, fund A chooses to wait $(\kappa, NA, 0 \times 1)$ if $q > q^a$ and chooses to fully invest and announce $(\kappa, A, 1 \times 1)$ if $q \leq q^a$.*

From Lemma 1.3.2, fund A prefers to learn the mispriced asset when $W_A > \underline{W}$. If the mispricing of noise traders worsens with a large probability, it is optimal for fund A to wait and silently invest from date 1 because fund A could short when the overpricing is the most extreme and prevent costly liquidation. However, if it is very likely that the mispricing disappears at date 1, $q \leq q^a$, fully investing and announcing is the best strategy for fund A to gain profits from correcting prices at date 0 and reduce the loss from the potential margin calls. Fully investing and keeping silent is a dominated strategy in this setting because (1) the shorting return is the same when the demand shock of noise traders disappears at date 1, and (2) fund A is forced to reduce more positions since the asset price is higher when keeping silent. This explains why some hedge fund managers might reveal information about their shorting targets to the public.

The region of q in which fund A chooses to fully invest and announce at date 0 is determined by the given parameters. Given other parameters constant, I further check the role of the fund size in funds' announcing decisions.

Proposition 1.3.4. *q^a decreases in W_A. The area of shorting early is larger compared with the SV benchmark, $q^a > q^{na}$.*

Proposition 1.3.4 shows that small funds are more likely to reveal their shorting information. When the initial wealth is larger, fund A is less willing to invest fully at date 0 because of the potential margin calls or forced liquidation. Instead, waiting for larger mispricing is safer for a given q. Although announcements help to control the price, the benefits of announcing are less attractive when fund A is wealthier and can take more prominent positions. Large funds can wait to hold large short positions when the mispricing is deepened. It is less profitable for them to establish positions early and make announcements. This predicts it is more common to observe small funds instead of large funds sharing their information.

Moreover, announcements encourage short sellers to take positions once they find mispricing assets. Prices are more efficient with announcements. From Proposition 1.3.4, the threshold of shorting early is higher than the benchmark, $q^a > q^{na}$. This implies that if funds have the option to announce their shorting targets, they are more willing to start shorting whenever they identify an overpriced asset. Information is incorporated into prices faster than in the benchmark case.

1.3.3 Equilibrium when Two Funds Interact

In the simplified setup above, fund A's decision-making purely depends on its own profits. Fund F would always add short positions when fund A makes announcements. When fund F has limited capital and plays a non-trivial strategy, how would funds change their decisions? To address this question, I further explore the equilibrium in the general setting, where arbitrage resources are insufficient to bring prices back to the expected fundamental values. The asset price at date 1, $p_{n,1}$, is always above the fundamental value V if noise traders continue to be confused. Uninformed funds could still benefit from shorting after observing announcements at date 1. In particular, I focus on an equilibrium where fund A announces and fund F waits to invest later. I prove that the equilibrium holds under certain conditions.

First, I narrow down the feasible strategies of hedge funds in the general setting.

To maximize their wealth, funds' decisions on learning, announcing, and shorting at date 0 are closely related. If the fund manager decides not to pay the cost at date 0, she would only take a short position after observing announcements at date 1. Otherwise, she would hold bonds until date 2. If the manager of fund j chooses to learn, she might announce her information to the public only when she starts shorting at date 0. Otherwise, keeping silent is preferred when she decides to enter at date 1 because she wants to sell at a higher price. Hence, there are in total four feasible strategies for each hedge fund to play, $(0, NA, 0 \times \cdot)$ (No cost paid, no announcements, and no shorting at date 0), $(\kappa, NA, 1 \times \cdot)$, $(\kappa, NA, 0 \times \cdot)$, and $(\kappa, A, 1 \times \cdot)$ (pay the cost, announce, and fully invest at date 0).

The trading decisions at date 1 is fully determined by the realization of noise trader shock. When noise traders are more optimistic $U_1 = U > U_0$ at date 1, the asset price is higher than the fundamental value because funds' capital is limited. In this case, hedge funds would always short with total capacity if they know the asset is overpriced from learning or announcements. When noise traders realise the true value $U_1 = 0$ and $p_{n,1} = V$, funds liquidate their positions and hold risk-free bonds until date 2.

Second, I pin down the expected wealth of each fund j given its strategy. Let $p_t = p_{n_j,t}$, $V_2 = V_{n_j,2}$ for notational simplicity, where asset n_j is an arbitrary mispriced asset that fund j learns by paying the cost or seeing announcements. p_1^u is the asset price when $U_1 = U$. D_t^j is the shorting value that fund j decides to take on the mispriced asset n_j at date t. The asset index is negligible here because funds can take short positions in only one asset. The expected terminal wealth of fund j can be written as

$$u_j = (1-q)[W_j - I_{s_j}\kappa + D_0^j(1 - \frac{V}{p_0})] + q(1 + \phi(1 - \frac{V}{p_1^u}))W_1^j(s_j, s_{-j}, W_j). \quad (1.6)$$

I restrict the attention to the specific equilibrium where $s_A^* = (\kappa, A, 1 \times 1)$ and

$s_F^* = (0, NA, 0 \times 1)$ and verify that it is a Nash equilibrium. In the equilibrium, fund A pays the cost, makes an announcement, and fully invests at date 0; Fund F does not pay the cost and waits to hold a short position silently at date 1; Each fund j maximizes the expected terminal wealth u_j. This equilibrium is beneficial to both funds. By fully investing at date 0, fund A gains profits from correcting the price. It also shares the mispricing information to fund F to reduce the potential loss from margin calls. Fund F chooses to save the cost of learning by waiting for the announcement. If there is an announcement and the demand shock deepens, fund F profits from absorbing the demand of noise traders.

The equilibrium exists if and only if each fund maximizes its expected wealth and no one deviates. To verify the equilibrium, I proceed in two steps. First, I derive conditions when s_F^* is the best response for fund F. Second, I find conditions that s_A^* is the best response for fund A. Combining all conditions, I present the existence of the equilibrium.

Fund F's best response is s_F^* Fund F will not deviate from the equilibrium. Given the strategy of fund A, the payoff of fund F in the equilibrium, $u_F(s_A^*, s_F^*)$, should be larger than payoffs when fund F chooses any other strategy. Suppose that fund F decides to learn and gain the information of another asset n_F. If fund F also chooses to short early and announce, neither F nor A wants to change their existing shorting targets at date 1. This is because the demand shocks are the same for both assets and the shorting return is lower at date 1 if they bet against the same asset. In addition, if they switch targets, funds have to close their previous positions at higher prices. Thus, the payoff for fund F to playing the strategy $(\kappa, A, 1 \times 1)$ is the same as with $(\kappa, NA, 1 \times 1)$. On the other hand, if fund F chooses to keep silent and starts shorting at date 1, define p_0^F and p_1^{FF} as prices of the asset that fund F finds and fully invests at dates 0 and 1. p_1^F represents the asset price when fund F chooses to wait and short only at date 1.

p_1^{u*} is the asset price in the equilibrium when $U_1 = U$. Thus, the fact that s_F^* is the best response of fund F if and only if

$$\kappa \geq \frac{\phi \bar{R}_F + q\phi(V/p_1^{u*} - V/p_1^{FF})}{(1 + \phi \bar{R}_F + q\phi(1 - V/p_1^{FF}))} W_F \tag{1.7}$$

$$\kappa \geq \frac{q\phi(V/p_1^{u*} - V/p_1^{F})}{1 + q\phi(1 - V/p_1^{F})} W_F, \tag{1.8}$$

where $\bar{R}_F = (1-q)(1 - V/p_0^F) + q(1 - p_1^{FF}/p_0^F)(1 + \phi(1 - V/p_1^{FF}))$ represents fund F's expected return when choosing to short silently from date 0. Intuitively, Fund F would stay in equilibrium when the information cost is higher than the marginal benefits of learning and silently shorting overpriced assets. Condition (1.7) guarantees that it's not profitable for fund F learning and shorting from date 0. Condition (1.8) represents that the marginal benefit of changing to learning and shorting at date 1 is less than the information cost saved in the equilibrium. These conditions imply that the equilibrium price p_1^{u*} is the only channel that fund A has a impact on fund F's choice.

Rearranging conditions (1.7) and (1.8), fund F's best response is s_F^* if the equilibrium price satisfies

$$p_1^{u*} \geq \frac{V}{1 - \frac{1}{q\phi}(\frac{u_F^{na}}{W_F} - 1)}, \tag{1.9}$$

where u_F^{na} is the maximum wealth if fund F holds short positions silently. Fund F profits from shorting after learning about mispriced assets in others' announcements. The higher the equilibrium price, the higher the return fund F would gain. This means that the equilibrium price should be large enough that it is more valuable for fund F to wait for announcements and sell at the equilibrium price. Given the information cost κ and other parameters constant, from the market clearing condition, I derive the equilibrium price as a function of W_A and W_F:

$$p_1^{u*} = (1 + \frac{U - U_0 - \phi W_F}{V + U_0 - \phi(1+\phi)(W_A - \kappa)})(V + U_0 - \phi(W_A - \kappa)). \tag{1.10}$$

Thus, condition (1.9) for the equilibrium price characterizes the relations between

W_A and W_F in the equilibrium. Lemma 1.3.5 demonstrate the conditions when Fund F won't deviate from the equilibrium.

Lemma 1.3.5. *The equilibrium price p_1^{u*}, is decreasing in W_A. There exists an upper bound $g(W_F)$ such that condition (1.9) is satisfied if and only if $W_A < g(W_F)$. In other words, given fund A's strategy s_A^*, $s_F^* = (0, NA, 0 \times 1)$ is the best response of fund F if and only if $W_A < g(W_F)$. This upper bound is decreasing in W_F, $g'(\cdot) < 0$.*

The dotted line in Figure 1.2 represents the function $g(W_F)$ for the upper bound of fund A size. For given parameters, V, U_0, U, ϕ, κ, and q, fund F has no incentive to deviate if the size of fund A is below the dotted line. Fund F would like to wait for A's information when it receives high shorting benefits at date 1. When fund A is small, its price effect is limited. Therefore it remains profitable for fund F to trade even if fund A has established its position. It is a good deal for fund F to save searching costs and benefit from shorting.

The upper bound decreases when fund F gets larger. In other words, the richer fund F is less likely to wait and not pay the learning cost. This is because when fund F has more capital, the learning cost is relatively lower than the profit of actively shorting. The opportunity cost of foregoing the arbitrage opportunity at date 0 increases as fund F is able to take larger positions. On the other hand, when the mispricing deepens at date 1, fund F gains a higher selling price if it remains silent compared to the price it would obtain from sharing information with fund A. Thus, fund A has to be much smaller when fund F is large in the equilibrium. This explains why the announcers we observe are tiny on average among other short sellers.

Fund A's best response is s_A^* Second, Fund A won't deviate in the equilibrium when the payoff $u_A(s_A^*, s_F^*)$ of fund A in the equilibrium is larger than the outcome of other strategies. Specifically, when fund A does not pay the cost, it would hold cash and the expected utility is W_A, which should be lower than $u_A(s_A^*, s_F^*)$. In addition, when fund A chooses to learn and silently short, fund A should also receive a payoff that is below $u_A(s_A^*, s_F^*)$.

To pin down the payoff, it is important to first check whether fund A would be forced to liquidate its position at date 1 if fund A chooses to short early. As with the definition under the simplified setup, p_0^A and p_1^{AA} stand for asset prices at date 0 and 1 when fund A starts shorting silently from date 0. p_1^A represents the asset price when fund A chooses to wait and silently short from date 1. In equilibrium, fund A takes short positions from the beginning. The equilibrium price p_0^* is equivalent to p_0^A because fund A is the only informed trader at date 0. Similar to the previous discussion, suppose that fund A has to liquidate because the equilibrium price is too high, that is, $p_1^{u*} > (1+\frac{1}{\phi})p_0^*$ from equation (1.5). The asset price when fund A silently shorts for two periods, p_1^{AA}, is always higher than the price in the equilibrium with announcements p_1^{u*}. When fund A is forced to liquidate in the equilibrium, fund A must also liquidate when choosing to silently short from date 0. In this case, the profit of shorting silently is the same as that of shorting loudly from date 0, and fund A will not deviate from s_A^*. When fund A can take non-zero short positions at date 1, it gives the relation between W_A and W_F in the equilibrium:

$$W_A \leq \kappa + \frac{1}{\phi(1+\phi)}(V + U_0 - \phi(U - U_0 - \phi W_F)). \tag{1.11}$$

The equilibrium payoff of fund A when announcing can be written as

$$u_A(s_A^*, s_F^*) = \left[(1-q)(1+\phi(1-\frac{V}{p_0^*})) + q(1+\phi(1-\frac{p_1^{u*}}{p_0^*}))(1+\phi(1-\frac{V}{p_1^{u*}}))\right](W_A - \kappa). \tag{1.12}$$

Again from the equation (1.3.3), fund F affects fund A's decision only through the equilibrium price p_1^{u*}. Note that based on equation (1.10), the equilibrium price p_1^{u*} is decreasing in the fund F size. When fund F has more capital, it can take more positions in mispriced assets and drive the price more towards the expected fundamental value. Under the assumption that ϕ is not too large, the expected wealth $u_A(s_A^*, s_F^*)$ is decreasing in p_1^{u*}. Thus, fund A profits more in the equilibrium when fund F is larger. In the appendix, I prove the following lemma that shows the second relation between W_A and W_F for the equilibrium to hold.

Lemma 1.3.6. *The payoff of fund A in the equilibrium, $u_A(s_A^*, s_F^*)$, is decreasing in p_1^{u*} and increasing in W_F. There exists a lower bound $h(W_A)$ such that given fund F's strategy s_F^* and $W_A > \underline{W}$, $s_A^* = \{\kappa, A, 1 \times 1\}$ is the best response of fund A if and only if $W_F > h(W_A)$. This lower bound is increasing in W_A, $h'(\cdot) > 0$.*

The dashed line in Figure 1.2 plots the lower bound $h(W_A)$ for the size of fund F. Any points on the right-hand side of the dashed line stand for a combination of fund size such that it is optimal for fund A to announce and fully invest at date 0. When fund A is not tiny, the manager prefers to learn the overpriced asset since she can benefit from shorting after paying the information cost. To avoid the potential cost of liquidation, fund A is willing to share the information only if the asset price after announcements is low enough. Because the asset price with announcements is decreasing in the size of fund F, W_F, fund A will not deviate from the equilibrium as long as fund F is large enough.

When the size of fund A increases, this lower bound of fund F size in the equilibrium increases. When fund A is larger, fund A will sell assets at a lower price at date 0, and the performance is poorer at date 1. In this case, fund A suffers more from margin calls, and the asset price at date 1 increases because of fund A's buying back. Thus, fund A needs to attract more capital to drive down the price at date 1 by announcements. In this sense, the lower bound of the size of fund F is higher to provide protection to fund A when fund A is rich.

In the Nash equilibrium, neither fund A nor F will deviate from their strategies.

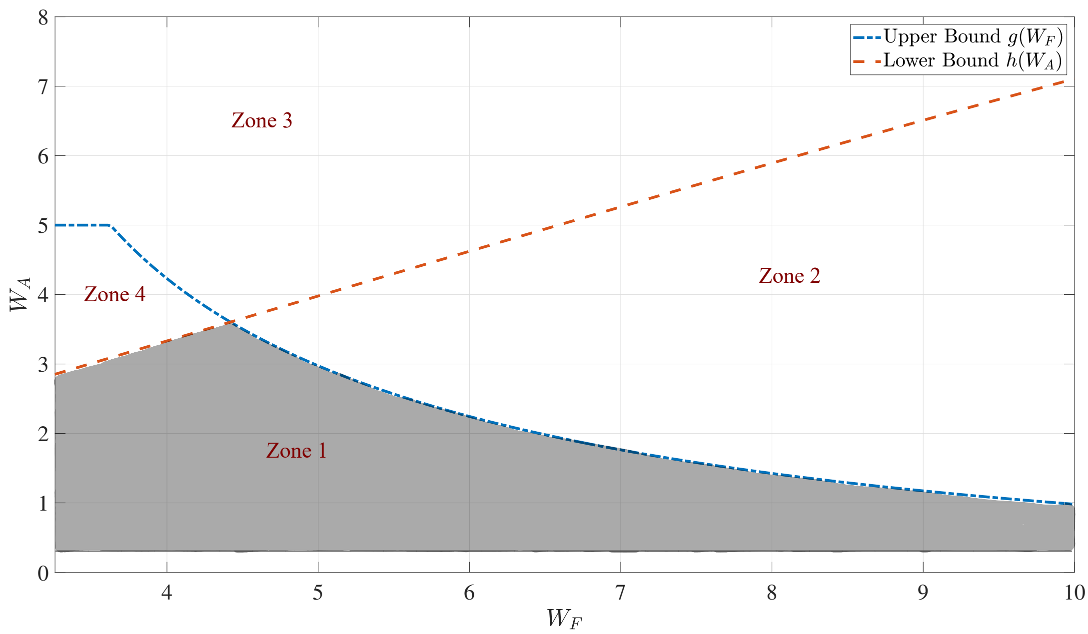
Combining Lemmas (1.3.6) and (1.3.5) together, I provide sufficient conditions of the existence of the equilibrium as follows.

Proposition 1.3.7. *There exists an equilibrium* $s_A^* = \{\kappa, A, \phi(W_A - \kappa)\}$ *and* $s_F^* = \{0, NA, 0\}$ *in the area where* $W_A < g(W_F)$ *and* $W_F > h(W_A)$.

The shaded area (marked as "Zone 1") in Figure 1.2 illustrates the region where the equilibrium exists. There is a lower bound for the size of fund F and an upper bound for the size of fund A. As previously discussed, the upper bound of fund A decreases when fund F is wealthier. And the equilibrium price is falling in the size of funds A and F. The feasible region would be situated in a scenario where fund A has a small size while fund F has a large size. In the appendix, I also show that $W_A < \min(h^{-1}(W_F), g(W_F)) < W_F$. This result implies that the size of funds that announce their information is usually small compared with the size of funds that passively wait for trading.

Figure 1.2. Theoretical relation between fund A and fund F

This figure reports the relation between fund A and fund F given the following parameters that satisfy all assumptions: $V = 100, U_0 = 30, U = 60, \kappa = 0.05, \phi = 2, q = 0.35$. The dashed line gives the lower bound of fund F, and the dotted line gives the upper bound of fund A. The shaded area is the validated zone for the equilibrium to hold.



To summarise, in this two-player game, the equilibrium with Announcers and Followers exists only if fund A is small enough and fund F is large enough. Fund F benefits less from the announcements (the price impact of additional capital is weaker), which leads fund F to wait and then free-ride on fund A's information. Meanwhile, fund A faces the potential costs of liquidation and benefits more from the price drop at date 1. Size plays an important role in hedge funds' decisions on trading and disclosing.

1.4 Model Implication

In this section, I further explore the impact of announcements on market efficiency and other elements that affect funds' disclosing behaviour. First, I find that the effect of announcements on market efficiency is dependent on the size distribution of announcers and followers. Announcements improve market efficiency if announcers are better capitalized, while if announcers are tiny, the effect of announcements discouraging followers from searching for other arbitrage opportunities dominates. Second, for a given distribution of fund size, small funds make more announcements if they can take larger leverage. Last, the more volatile the noise trader shock is, the less likely the small funds will announce.

1.4.1 Market Efficiency

In the previous section, I discuss that in the simplified version, where fund F has unlimited capital, asset prices are more efficient when announcements are allowed. However, in the general setup, there are two competing forces affecting market efficiency. On the one hand, small funds are willing to short immediately since they can reduce liquidation costs by making announcements. Asset prices are corrected faster. This helps market efficiency. On the other hand, large funds lose their incentive to search by themselves and choose to wait for others' information instead. Fewer mispriced assets are identified. This hurts market efficiency. In combination, it is ambiguous whether the market is more efficient because of funds' announcements.

To study the aggregate effects formally, I build the following measure of market efficiency:

$$\text{Market Efficiency} = E_0 \sum_{n=1}^{N} (\frac{p_{n,0} + p_{n,1}}{2} - V)^2. \tag{1.13}$$

This is the squared sum of the price difference from the fundamental value for all assets on the market. The higher the value, the less efficient the market is. There are two main determinants of market efficiency captured by this measure. First, if asset prices keep deviating from the fundamental value in date 0 and 1, the value is higher. Second, if there are more unidentified mispriced assets, the market is less efficient.

Next, I compare the market efficiency of the equilibrium with that of the SV benchmark. Each fund would identify one overpriced asset in the benchmark with no announcements. In contrast, only one asset is found by fund A in the equilibrium. So the difference in the market efficiency comes from two assets. If an asset is not found by funds, the asset price is $V + U_t$ at date t. Figure 1.3 illustrates how the market efficiency changes in the equilibrium and in the benchmark case when one fund has a fixed size and the other fund's size varies. Given a fixed size of fund A, the market is always more efficient with announcements compared with the benchmark case. The bottom graph shows that the impact of announcements on market efficiency does not vary too much when the size of fund F increases.

However, when the fund F size is fixed, the market could be less or more efficient depending on the size of fund A. When fund A is larger and can hold some short positions, the prices at dates 0 and 1 are closer to the fundamentals. Compared with the benchmark, the benefits of announcements to avoid margin calls also increase when A is wealthier. Thus, the market is more efficient. When fund A is tiny, the effect of correcting the price early is limited and sharing information hurts fund F's incentive to search. As a result, the market is less efficient, although the magnitude is negligible. In summary, the relative size of announcers to followers determines the aggregate effects of announcements on market efficiency. When announcers manage more assets, the effect of announcers' early entry dominates and their announcements improve market efficiency.

An important implication for the regulator here is to help timely verify the announced mispricing information so that it is quickly incorporated into the price, which further encourages more funds to announce. When a group of small funds begin to short and share their information, more mispriced assets are found, and the capital can be allocated to other arbitrage opportunities.

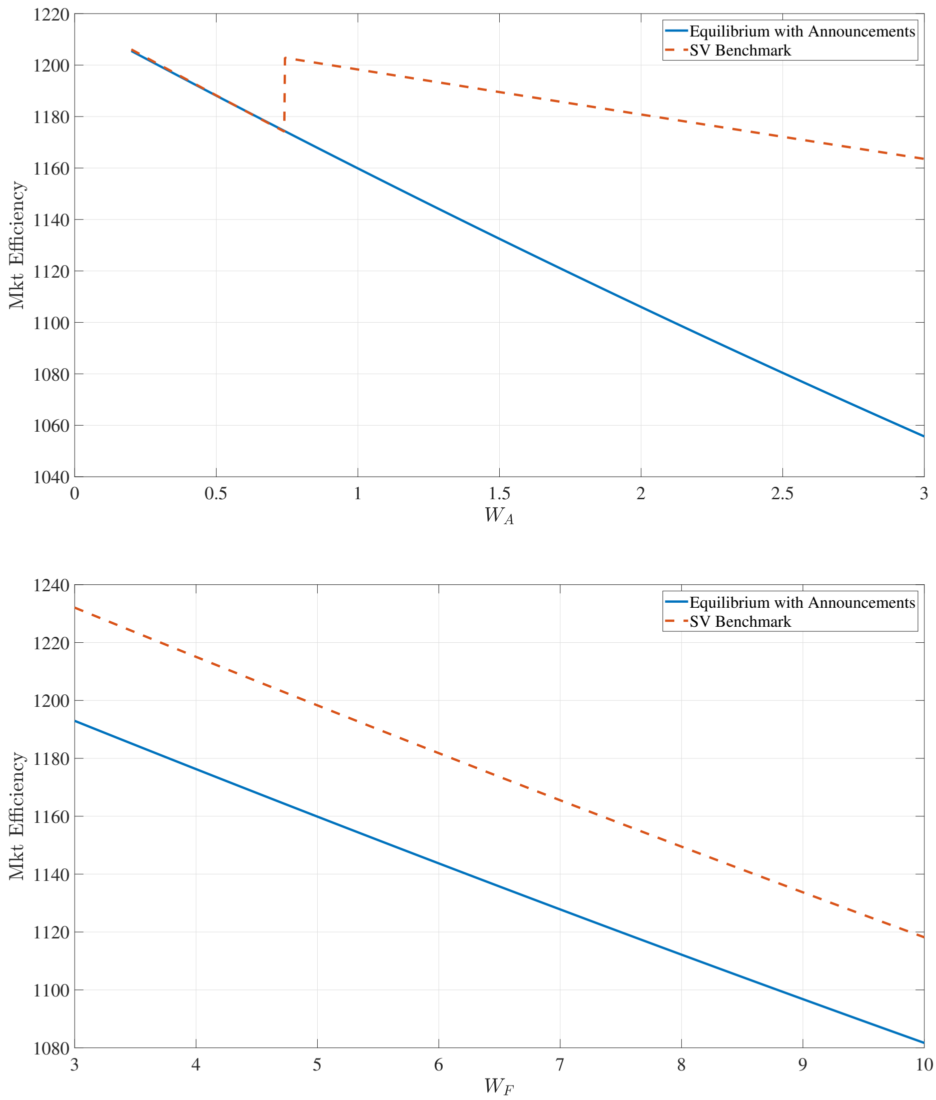
1.4.2 The Effect of the Maximum Leverage ϕ

The probability q of mispricing worsening at date 1 plays a critical role in the existence of the equilibrium. Given the distribution of fund sizes, there is a range of q where the equilibrium exists. When it is more likely that the noise trader will meet an increased optimistic shock, fund A prefers to wait and short from date 1 instead. When q is small, fund F is less willing to passively wait for others' information. As shown in Figure 1.B.1, the area where the equilibrium exists widens when funds can take higher leverage.

Intuitively, the impact of increasing leverage is more substantial on fund F. If the margin requirement is lower, large fund F is able to take larger short positions. Fund F would like to wait since it will gain more from exploiting the mispricing

Figure 1.3. Market efficiency under different fund sizes

This figure reports the market efficiency of the equilibrium and the benchmark. $V = 100, U_0 = 30, U = 60, \kappa = 0.05, \phi = 2, q = 0.35$. The upper graph plots the market efficiency when the size of fund F is fixed, $W_F = 5$, and the bottom graph plots the market efficiency when the size of fund F is fixed, $W_A = 1$.



at date 1, which means the lower bound of q decreases. In contrast, the increase in fund A's capacity to short is relatively minor. The upper bound of q will not differ much. Therefore, the range of q for the equilibrium to exist is larger. This generates the unique implication that we should observe more announcements from small funds when hedge funds can borrow stocks with higher leverage.

1.4.3 The Effect of Surprise in Mispricing $U - U_0$

Funds would also vary their decisions based on the targets' characteristics. In the model, the magnitude of potential demand U is directly related to funds' shorting profits at date 1. When the distribution of fund size is fixed, the equilibrium exists within a range of q. If the change in the misperceptions is larger, both funds would like to wait and short from date 1. Controlling the size of fund F, when it is more costly to short early and the impact of announcements is limited, fund A would prefer to short silently from date 1. As Figure 1.B.2 indicated, small funds are less likely to reveal their information when the surprise in mispricing is very large. Moreover, the relative growth in shorting profits for large fund F is small when the scale of misperceptions increases. Hence the changes in the lower bound of q for fund F to follow A's information are small. In total, the area where the equilibrium exists is shrinking when the potential demand shock increases. It implies that more announcements would be made on stocks with lower surprise in mispricing.

1.5 Further Discussions

1.5.1 The Existence of Other Equilibriums

In contrast to the equilibrium with announcements that I have discussed so far, it is important to note that there are other equilibriums within this game. Holding other parameters constant, my focus lies in exploring the equilibrium in the space of fund size (W_A, W_F). Without the loss of generality, I confine the analysis to the region where $W_F > W_A$, as equilibriums are symmetric in the region where $W_F < W_A$.

First, an equilibrium where both funds announce their information does not exist. When both funds make announcements after shorting, no one will change the existing target. In that sense, announcements attract zero capital. Funds' payoffs are indifferent from shorting silently. Second, an equilibrium where both funds pay the cost and only one fund chooses to announce doesn't exist either. Suppose fund A chooses to announce and fund F short silently in the equilibrium. Fund F would always short early otherwise it has incentives to deviate to not paying the cost. But if fund F has already taken short positions at date 0, fund A can't attract extra capital from F by announcing. Fund A would deviate and the equilibrium does not exist. As a result, the only region where we can observe the equilibrium with announcements is when $W_A < g(W_F)$ and $W_F > h(W_A)$.

In a specific parameter space, an equilibrium without announcements exists. Each fund acts as the sole informed trader of the identified asset, resulting in independent decision-making for each fund. The strategy in the equilibrium is uniquely determined by the fund size according to Lemma 1.3.1. As shown in Zone 2 of Figure 1.2, characterized by the presence of two large funds, both funds would pay the cost and silently trade. In particular, the larger fund would silently short from the interim period. In Zone 3, even if both funds have sizeable capital and identified the mispricing, neither of them would announce their information. In this case, whether funds are shorting from date 0 or the interim period in the equilibrium is determined by the probability of deeper demand shock. In Zone 4, both funds have very limited capital and choose to short silently. Fund A would wait to short silently when the mispricing gets worse.

1.5.2 Cost of Announcements

In the present model, I assume that the announcements are verifiable by hedge funds. Funds have accurate information about the mispriced asset. This assumption implies that the cost of spreading false information is infinitely high. Consequently, funds would only announce their information after incurring the learning cost and identifying the overpriced asset. Once the other fund observes the announcement, she would short as long as there is available capital.

However, in reality, the situation is more complex as hedge funds might obtain noisy information about the fundamental value. This leaves room for potential disparities between the realized value and the fund's expectations. Verifying the announcements directly becomes challenging. In such cases, we can assume there is a cost associated with making announcements. When the asset value in the final period significantly deviates from the announced value, the funds face penalties ex-post. For instance, this cost could be legal fees if the target company fight against the announcer aggressively, or it could be modeled as a reputation cost.

In particular, consider a variation in which there exists a legal cost c of making announcements. If the realized value $V_{i,2}$ at date 2 exceeds the expected value V announced by the funds at date 1, they would incur a punishment of L. Here, L represents the legal fee, which is typically much larger compared with regular investment sizes. As a result, the legal cost c of making announcements is defined as the minimum between the assets that could be forcibly sold and the legal fee. This can be expressed as follows:

$$c = \min\{fW_2^j, L\}, \quad j = A, F.$$

where f denotes the portion of the fund's overall wealth that is eligible for potential forced sale.

Considering the impact of legal costs, funds exercise greater caution in announcing their information to the public. The benefits of sharing the information are reduced due to potential legal expenses. Hedge funds face a similar trade-off: announcements decrease the profitability of shorting but help avoid margin calls if the mispricing widens. The key findings presented in Proposition 1.3.7 remain valid, albeit with a lower threshold for the size of fund A and a higher threshold for the size of fund F. In other words, when incorporating the legal costs of making announcements, the region of fund sizes (W_A, W_F) in which the equilibrium with announcements exists becomes more limited, holding all parameters constant. However, for the equilibrium with announcements to exist, we still need fund A to be small enough and fund F to be large enough.

This chapter primarily focuses on the role of size in hedge funds' decisions on trading and disclosing. I examine this aspect using the main framework, without incorporating assumptions about legal costs. This variation of the model provides a foundation for future studies investigating how the heterogeneous precision of information affects funds' decision-making.

1.6 Conclusion

Hedge funds are often viewed as mysterious investment pools with a high capital base. In practice, however, they strategically give away information to the public. This chapter proposes a model to explain to what extent the fund size plays a role in the strategies of hedge funds' trading and disclosing. Small funds benefit from announcing because of the threat from margin calls caused by the leverage constraint. At the same time, large funds save the information cost and absorb the noise trader shocks. It is beneficial for both funds. The results under the simplified setup show that there are more mispricing opportunities that funds would like to share when funds are small. More importantly, the general model claims that in the equilibrium where one fund shorts early and announces and another fund waits and shorts after observing the announcements, the announcer is small in size and the follower is larger. That is because the benefits of pushing down the price for small funds are relatively higher, while waiting is more attractive to large funds since they could still profit by taking prominent short positions without paying any information cost.

I have also studied the effects of the announcement on market efficiency. On the one hand, small funds are willing to reveal the information to the public. Information is incorporated into prices faster, which helps to increase market efficiency. On the other hand, larger funds lose their incentive to search for other arbitrage opportunities because of announcements. The aggregate effect of these two aspects is ambiguous. My model suggests that the regulators should validate the information quickly so that they will encourage more hedge fund managers to reveal the information to increase market efficiency.

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Appendices

1.A Proofs

Proof of Lemma 1.3.1

When there are no announcements, only fund A know that asset n_A is overpriced. The expected utility of fund A when choosing the strategy s_A is denoted as $u(s_A)$. If fund A chooses to short from date 1, the expected utility is

$$u(\kappa, NA, 0\times 1) = (1-q)(W_A-\kappa) + q(1+\phi(1-\frac{V}{p_1^A}))(W_A-\kappa). \tag{1..14}$$

If fund A chooses to short early, it may face a risk of liquidation at date 1. Because the function of expected terminal wealth $u(\kappa, NA, 1\times 1)$ is different when funds are forced to liquidate at date 1, I will first discuss the case when the interim wealth is below zero and funds are forced to liquidate. At date 0, fund A shorts with full capacity, from the market clearing condition $p_0^A = V + U_0 - \phi(W_A-\kappa)$. At date 1, if the mispricing worsens and fund A continues to short fully:

$$W_1^A = W_A - \kappa + \phi(W_A-\kappa)(1-\frac{p_1^{AA}}{p_0^A}) \tag{1..15}$$

$$p_1^{AA} = V + U - \phi W_1^A. \tag{1..16}$$

Combining these two equations, we get the price at date 1 when funds continue to short silently:

$$p_1^{AA} = \left(\frac{V+U-\phi(1+\phi)(W_A-\kappa)}{V+U_0-\phi(1+\phi)(W_A-\kappa)}\right)p_0^A. \tag{1..17}$$

From the equation (1..15), the theoretical wealth at date 1 is larger than 0, $W_1^A \geq 0$, if and only if $p_1^{AA} \leq (1+\frac{1}{\phi})p_0^A$. Based on the expression of p_1^{AA} in (1..17), this is also equivalent to

$$W_A \leq W^* \doteq \kappa + \frac{1}{\phi(1+\phi)}(V+U_0-\phi(U-U_0)). \tag{1..18}$$

Otherwise, when $W_A > W^*$, the fund is forced to liquidate $D_1 = 0$, $p_1^{AA} = V+U$, and $W_1^A = 0$. Fund A chooses to short from date 0 only if $u(\kappa, NA, 1\times 1) \geq$

$u(\kappa, NA, 0 \times 1)$. When $W_A \le W^*$,

$$u(k, NA, 1 \times 1) = \Big((1-q)(1+\phi(1-\frac{V}{p_0^A})) + q(1+\phi(1-\frac{V}{p_1^{AA}}))(1+\phi(1-\frac{p_1^{AA}}{p_0^A}))\Big)(W_A-\kappa). \tag{1..19}$$

Replacing the utilities with equation (1..14) and (1..19) and rearranging the inequality, I get

$$q\Big(1-\frac{V}{p_1^A}-(1-\frac{V}{p_1^{AA}})(1-\frac{p_1^{AA}}{p_0^A})(1+\phi)\Big) \le 1-\frac{V}{p_0^A}. \tag{1..20}$$

When $W_A > W^*$,

$$u(k, NA, 1 \times 1) = (1-q)(1+\phi(1-\frac{V}{p_0^A}))(W_A-\kappa). \tag{1..21}$$

Plugging equation (1..14) and (1..21) into condition $u(\kappa, NA, 1\times1) \ge u(\kappa, NA, 0\times 1)$, I get

$$q\Big(1+\phi(1-\frac{V}{p_0^A})+\phi(1-\frac{V}{p_1^A})\Big) \le \phi(1-\frac{V}{p_0^A}). \tag{1..22}$$

Combining the conditions (1..20) and (1..22), fund A would start to short from date 0 if $q \le q^{na}$, where q^{na} can be written as

$$q^{na} = \begin{cases} \dfrac{\phi(1-\frac{V}{p_0^A})}{1+\phi(1-\frac{V}{p_0^A})+\phi(1-\frac{V}{p_1^A})} & W_A > W^* \\ \dfrac{1-\frac{V}{p_0^A}}{1-\frac{V}{p_1^A}-(1+\phi)(1-\frac{p_1^{AA}}{p_0^A})(1-\frac{V}{p_1^{AA}})} & W_A \le W^* \end{cases},$$

where $p_0^A = V + U_0 - \phi(W_A-\kappa)$, $p_1^A = V + U - \phi(W_A - \kappa)$ and p_1^{AA} is calculated as (1..17). q^{na} is fully determined by W_A, U, U_0, V, κ and ϕ.

Now I show that q^{na} is decreasing in W_A. First, when $W_A > W^*$, the partial derivative of q^{na} with respect to W_A is

$$\frac{\partial q^{na}}{\partial W_A} = \frac{\phi^2 V}{(1+\phi(1-\frac{V}{p_0})+\phi(1-\frac{V}{p_1}))^2}\Big[\frac{\phi}{p_1^2}(1-\frac{V}{p_0})-\frac{\phi}{p_0^2}(1-\frac{V}{p_1})-\frac{1}{p_0^2}\Big],$$

where $p_0 \doteq p_0^A$ and $p_1 \doteq p_1^A$ for notational simplicity. Since $U > U_0$, $p_1 > p_0$,

$$\frac{\phi}{p_1^2}(1-\frac{V}{p_0}) < \frac{\phi}{p_0^2}(1-\frac{V}{p_1}).$$

Therefore, $\frac{\partial q^{na}}{\partial W_A} < 0$. q^{na} is decreasing in W_A when $W_A > W^*$.

Second, when $W_A \leq W^*$, p_0 and p_1 are defined the same as above,

$$\frac{1}{q^{na}} = \underbrace{\frac{1-\frac{V}{p_1}}{1-\frac{V}{p_0}}}_{PART1} + (1+\phi)\underbrace{(\frac{p_1^{AA}}{p_0}-1)}_{PART2}\underbrace{\frac{1-\frac{V}{p_1^{AA}}}{1-\frac{V}{p_0}}}_{PART3}. \quad (1..23)$$

Plugging in the expressions of p_0, p_1, and p_1^{AA} gives

$$\frac{\partial PART1}{\partial W_A} \propto \frac{V}{p_0^2}(1-\frac{V}{p_1}) - \frac{V}{p_1^2}(1-\frac{V}{p_0}) > 0$$
$$\frac{\partial PART3}{\partial W_A} \propto V + U - \phi(1+\phi)(W_A-\kappa) + (1+\phi)(U_0 - \phi(W_A-\kappa)) > 0$$

and

$$PART2 = \frac{U-U_0}{V+U_0-\phi(1+\phi)(W_A-\kappa)},$$

which is also increasing in W_A. Therefore, $\frac{1}{q^{na}}$ is increasing in W_A. q^{na} is decreasing in W_A when $W_A \leq W^*$.

In summary, when $q \leq q^{na}$, fund A would short early. Otherwise, fund A would like to wait and start shorting at date 1. q^{na} is decreasing in the size of fund A. □

Proof of Lemma 1.3.2

Based on Lemma 1.3.1, we know that fund A would choose to wait when $q > q^{na}$. The expected wealth equal to

$$u(\kappa, NA, 0\times 1) = (1 + q\phi(1-\frac{V}{p_1^A}))(W_A-\kappa)$$

Because $u(\kappa, NA, 0\times 1)$ is increasing in q, for all $q > q^{na}$,

$$u(\kappa, NA, 0\times 1) \geq (1 + q^{na}\phi(1-\frac{V}{p_1^A}))(W_A-\kappa)$$

When $q \leq q^{na}$, fund A chooses to fully invest at date 0. From the expected utility (1..19) and (1..21) with different initial wealth, I have

$$\frac{\partial\, u(\kappa, NA, 1\times 1)}{\partial\, q} = \begin{cases} -(1+\phi(1-\frac{V}{p_0^A}))(W_A-\kappa) \leq 0, & W_A > W^* \\ -\phi(1+\phi)(1-\frac{V}{p_1^{AA}})(\frac{p_1^{AA}}{p_0^A}-1)(W_A-\kappa) \leq 0, & W_A \leq W^* \end{cases}.$$

The expected utility is decreasing in q, for all $q \leq q^{na}$,

$$u(\kappa, NA, 1\times 1) \geq (1+q^{na}\phi(1-\frac{V}{p_1^A}))(W_A-\kappa).$$

Hence if the expected utility of fund A when $q = q^{na}$ is larger than its initial wealth W_A, which means

$$(1+q^{na}\phi(1-\frac{V}{p_1^A}))(W_A-\kappa) \geq W_A, \tag{1..24}$$

then it's always better for the fund to pay the learning cost for all $0 \leq q \leq 1$. To study when the condition is satisfied, I define

$$h(W_A) \doteq \frac{1}{q^{na}\phi(1-\frac{V}{p_1^A})} - \frac{W_A-\kappa}{\kappa}.$$

The condition (1..24) is held if and only if $h(W_A) \leq 0$. Plugging q^{na} into the function and taking the derivative with respect to W_A, I get $h'(W_A) \leq 0$. Therefore there exists $\underline{W}$ such that, for any $W_A \geq \underline{W}$, $h(W_A) \leq h(\underline{W}) = 0$. □

Proof of Proposition 1.3.3

Fund A chooses the optimal strategy from $\{(0, NA, 0\times 0), (\kappa, NA, 0\times 1), (\kappa, NA, 1\times 1), (\kappa, A, 1\times 1)\}$. The expected utility of fund A when choosing the strategy s_A is denoted as $u(s_A)$ for simplicity. First, when $W_A > \underline{W}$, not learning $(0, NA, 0\times 0)$ is always a dominated strategy according to Lemma 1.3.2. Second, compared with shorting early, the expected wealth of waiting and shorting at date 1, $u(\kappa, NA, 0\times 1)$, is larger if $q > q^{na}$. Now consider the case when fund A starts shorting early and announcing. After announcements, fund F finds that asset n_A is overpriced and wants to short. Funds A and F simultaneously trade against a mass of noise traders. In the duopoly model where fund A has limited capacity to short, fund A would short with its full capacity and fund F choose the optimal level of shorting.[6] The expected shorting profits of fund F is

$$\pi_F = D_1^F(1 - \frac{V}{p_1^{ad}}),$$

where D_1^F is the amount of asset n_A that fund F decides to short, p_1^{ad} is the asset price after announcements when noise trader risks worsen. Note that the market clearing condition gives

$$p_1^{ad} = V + U - \phi W_1^A - D_1^F.$$

From the first-order condition, I have that

$$p_1^{ad} = \sqrt{V(V + U - \phi W_1^A)} \tag{1..25}$$

$$W_1^A = (W_A - \kappa) + \phi(W_A - \kappa)(1 - \frac{p_1^{ad}}{p_0^A}). \tag{1..26}$$

Rearranging, I get

$$p_1^{ad} = \frac{\phi^2 V(W_A - \kappa)}{2p_0^A} + \frac{1}{2}\sqrt{\left(\frac{\phi^2 V(W_A - \kappa)}{p_0^A}\right)^2 + 4V\Big(V + U - \phi(1+\phi)(W_A - \kappa)\Big)}, \tag{1..27}$$

where $p_0^A = V + U_0 - \phi(W_A - \kappa)$, the same as in the silent case. Equations (1..25) and (1..16) imply that $p_1^{ad} < p_1^{AA}$. When $W_A < W^*$,

$$u(\kappa, A, 1\times 1) - u(\kappa, NA, 1\times 1) = q(W_A - \kappa)\phi(1+\phi)(p_1^{AA} - p_1^{ad})(\frac{1}{p_0^A} - \frac{V}{p_1^{AA}p_1^{ad}}) > 0.$$

When $W_A \geq W^*$, fund A is forced to liquidate all of its positions if A keeps silent. While if fund A chooses to announce, the price is lower than in the silent case and A may not have to liquidate. Thus, shorting and announcing $(\kappa, A, 1\times 1)$ is always better for fund A compared with shorting and keeping silent $(\kappa, NA, 1\times 1)$. Shorting and announcing is the optimal strategy if

$$u(\kappa, A, 1\times 1) \geq u(\kappa, NA, 0\times 1).$$

[6]See Osborne and Pitchik (1986) for more detailed discussions in a capacity-constrained duopoly.

Plugging the utility of waiting and shorting, (1..14), and the utility of shorting and announcing into the condition gives

$$\begin{cases} q \le \dfrac{\phi(1-\frac{V}{p_0^A})}{1+\phi(1-\frac{V}{p_0^A})+\phi(1-\frac{V}{p_1^A})} & W_A > W_{ad}^* \\ q \le \dfrac{1-\frac{V}{p_0^A}}{1-\frac{V}{p_1^A}-(1+\phi)(1-\frac{p_1^{ad}}{p_0^A})(1-\frac{V}{p_1^{ad}})} & W_A \le W_{ad}^*, \end{cases}$$

where

$$W_{ad}^* = \kappa + \frac{1}{1+\phi}\Big((1+\frac{1}{\phi})(V+U_0) - \sqrt{V(V+u)}\Big). \qquad (1..28)$$

W_{ad}^* is the threshold of the fund A size when A needs to liquidate all its positions even with announcements. To summarise, fund A's optimal strategy is shorting and announcing when $q \le q^a$; otherwise, fund A would choose to wait if $q > q^a$. q^a can be written as

$$q^a = \begin{cases} \dfrac{\phi(1-\frac{V}{p_0^A})}{1+\phi(1-\frac{V}{p_0^A})+\phi(1-\frac{V}{p_1^A})} & W_A > W_{ad}^* \\ \dfrac{1-\frac{V}{p_0^A}}{1-\frac{V}{p_1^A}-(1+\phi)(1-\frac{p_1^{ad}}{p_0^A})(1-\frac{V}{p_1^{ad}})} & W_A \le W_{ad}^* \end{cases},$$

From previous definitions of p_0^A, p_1^A, p_1^{ad}, we know that q^a can be expressed in terms of W_A, U, U_0, V, κ and ϕ. □

Proof of Proposition 1.3.4

First, I show that q^a is decreasing in W_A. Comparing the thresholds of full liquidation (1..18) and (1..28), we know that $W_{ad}^* > W^*$. When $W_A > W_{ad}^*$, q^a is equal to q^{na}, which is decreasing in W_A. When $W_A \le W_{ad}^*$, let $p_0 \doteq p_0^A$ and $p_1 \doteq p_1^A$ for notational simplicity.

$$\frac{1}{q^a} = \underbrace{\frac{1-\frac{V}{p_1}}{1-\frac{V}{p_0}}}_{PART1} + (1+\phi)\underbrace{(\frac{p_1^{ad}}{p_0}-1)\frac{1-\frac{V}{p_1^{ad}}}{1-\frac{V}{p_0}}}_{PART4}. \qquad (1..29)$$

From the previous discussion in Proof 1.A, we know that $\frac{\partial PART1}{\partial W_A} > 0$. $PART1$ is increasing in W_A. Plugging the expressions of p_0, p_1, and p_1^{ad} into $PART4$ gives

$$\frac{\partial PART4}{\partial W_A} \quad \propto \quad \Big(\frac{p_1^{ad}}{p_0} - \frac{V}{p_1^{ad}}\Big)\Big(\frac{p_1^{ad}}{p_0} - (1+\frac{1}{\phi})\Big).$$

Since $p_1^{ad} \leq (1+\frac{1}{\phi})p_0$, when $W_A \leq W_{ad}^*$:

$$\begin{aligned}\frac{p_1^{ad}}{p_0} - \frac{V}{p_1^{ad}} &= \frac{p_1^{ad^2} - Vp_0}{p_0 p_1^{ad}} \\ &= \frac{p_1^{ad} + D_1^F - p_0^A}{p_0 p_1^{ad}} \leq 0.\end{aligned}$$

Therefore $PART4$ is also increasing in W_A. $\frac{1}{q^a}$ is increasing in W_A. q^a is decreasing in W_A when $W_A \leq W_{ad}^*$. In summary, q^a is decreasing in the size of fund A.

Moreover, when $W_A \leq W_{ad}^*$:

$$\begin{aligned}\frac{1}{q^a} - \frac{1}{q^{na}} &= \frac{1+\phi}{1-\frac{V}{p_0^A}}\Big(\frac{V}{p_1^{ad}} + \frac{p_1^{ad}}{p_0^A} - \frac{V}{p_1^{AA}} - \frac{p_1^{AA}}{p_0^A}\Big) \\ &= \frac{1+\phi}{1-\frac{V}{p_0^A}}(p_1^{ad} - p_1^{AA})\Big(\frac{1}{p_0^A} - \frac{V}{p_1^{ad}p_1^{AA}}\Big) < 0.\end{aligned}$$

Thus $q^a > q^{na}$. $\square$

Proof of Lemma 1.3.5

To verify it is a Bayesian-Nash Equilibrium, first fund F will not deviate from the equilibrium. Given the strategy of fund A, the payoff of fund F is equal to

$$u_F(s_A^*, s_F^*) = [1 + q\phi(1 - V/p_1^{u*})]W_F, \tag{1..30}$$

where $p_1^{u*} = V + U - \phi W_1^A - \phi W_F$, $p_0^* = V + U_0 - \phi(W_A - \kappa)$, $W_1^A = (1 + a\phi(1 - \frac{p_1^{u*}}{p_0^*}))(W_A - \kappa)$. From the previous discussion, if fund F decided to learn and gained the information of another asset n, neither fund would switch their target at date 1 when fund F also announces because the size of the optimistic shock is the same to both assets. Thus strategy $(\kappa, A, 1\times 1)$ is identical to $(\kappa, NA, 1\times 1)$. The payoff of the latter strategy, $u_F(s_A^*, (\kappa, NA, 1\times 1))$, would be

$$[(1-q)(1+\phi(1-\frac{V}{p_0^F}))+q(1+\phi(1-\frac{p_1^{FF}}{p_0^F}))(1+\phi(1-\frac{V}{p_1^{FF}}))](W_F-\kappa). \quad (1..31)$$

where $p_0^F = V + U_0 - \phi(W_F - \kappa), \quad p_1^{FF} = V + U - \phi(1 + \phi(1 - \frac{p_1^{FF}}{p_0^F}))(W_F - \kappa)$. If fund F chose to wait and fully invest at date 1 when keeping silent, the payoff would be

$$u_F(s_A^*, (\kappa, NA, 0\times 1)) = [1+q\phi(1-V/p_1^F)](W_F-\kappa), \qquad p_1^F = V+U-\phi(W_F-\kappa). \quad (1..32)$$

Thus, to guarantee that fund F will not deviate from s_F^*, the following conditions must hold:

$$u_F(s_A^*, (\kappa, NA, 1 \times 1)) \leq u_F(s_A^*, s_F^*) \quad (1..33)$$
$$u_F(s_A^*, (\kappa, NA, 0 \times 1)) \leq u_F(s_A^*, s_F^*). \quad (1..34)$$

Plug in the previous expressions of payoffs (1..30), (1..31), and (1..32) and get the following conditions that κ must satisfy,

$$\kappa \geq \frac{\phi \bar{R}_F + q\phi(V/p_1^{u*} - V/p_1^{FF})}{(1 + \phi \bar{R}_F + q\phi(1 - V/p_1^{FF}))} W_F$$
$$\kappa \geq \frac{q\phi(V/p_1^{u*} - V/p_1^F)}{1 + q\phi(1 - V/p_1^F)} W_F.$$

where $\bar{R}_F = (1-q)(1 - V/p_0^F) + q(1 - p_1^{FF}/p_0^F)(1 + \phi(1 - V/p_1^{FF}))$. Intuitively, the information cost should be higher than the marginal cost of switching assets for fund F.

Since the payoffs of fund F are not related to fund A's size when F chooses to pay the cost and trade silently, these payoffs are determined by $W_F, V, U, U_0, \phi, \kappa$ and q. Therefore, define

$$MAXF \doteq \max\Big\{u_F(s_A^*, (\kappa, NA, 1 \times 1)), u_F(s_A^*, (\kappa, NA, 0 \times 1))\Big\}.$$

Condition (1..33) and (1..34) can be combined together. Plugging equation (1..30) into the equilibrium price p_1^{u*} gives

$$p_1^{u*} \geq \frac{1}{1 - \frac{1}{q\phi}(\frac{MAXF}{W_F} - 1)}. \quad (1..35)$$

Since

$$\frac{\partial p_1^{u*}}{\partial W_A} = \frac{\phi p_1^{u*}}{p_0^*}\Big(\frac{p_1^{u*}(1+\phi)}{U - U_0 - \phi W_F} - 1\Big) < 0 \tag{1..36}$$

according to the assumption that $\phi \leq \frac{U-U_0}{W_F}$, p_1^{u*} is decreasing in the size of fund A. Therefore, there exists an upper bound $g(W_F)$ such that when $W_F \leq g(W_F)$, condition (1..35) is satisfied, and fund F will not deviate from the equilibrium. □

Proof of Lemma 1.3.6

Given the strategy s_F^* of fund F, the payoff of fund A in the equilibrium is equal to

$$u_A(s_A^*, s_F^*) = (1-q)(1+\phi(1-\frac{V}{p_0^*}))(W_A - \kappa) + q(1+\phi(1-\frac{V}{p_1^{u*}}))W_1^A, \tag{1..37}$$

where p_0^*, p_1^{u*}, W_1^A are defined in equation (1..30). If fund A does not pay the cost, it would hold cash and the expected utility is W_A. If fund A has paid the cost and decides not to announce, the payoff of investing at date 0, $u_A((\kappa, NA, 1\times 1), s_F^*)$, would be

$$[(1-q)(1+\phi(1-\frac{V}{p_0^*})) + q(1+\phi(1-\frac{p_1^{AA}}{p_0^*}))(1+\phi(1-\frac{V}{p_1^{AA}}))](W_A - \kappa), \tag{1..38}$$

where $p_1^{AA} = V + U - \phi(1 + a\phi(1 - \frac{p_1^{AA}}{p_0^*}))(W_A - \kappa)$. The payoff of waiting would be

$$u_A((\kappa, NA, 0\times 1), s_F^*) = [1+q\phi(1-V/p_1^A)](W_A-\kappa), \qquad p_1^A = V+U-\phi(W_A-\kappa). \tag{1..39}$$

To summarise, the payoff of fund A in the equilibrium should satisfy that

$$u_A((\kappa, NA, 1\times 1), s_F^*) \leq u_A(s_A^*, s_F^*) \tag{1..40}$$

$$u_A((\kappa, NA, 0\times 1), s_F^*) \leq u_A(s_A^*, s_F^*) \tag{1..41}$$

$$u_A((0, NA, 0), s_F^*) = W_A \leq u_A(s_A^*, s_F^*). \tag{1..42}$$

The payoffs of fund A when it keeps silent, given by (1..38) and (1..39), are not correlated with the size of fund F. Define

$$MAXA \doteq \min\Big\{u_A((\kappa, NA, 1\times 1), s_F^*), u_A((\kappa, NA, 0\times 1)\Big\}.$$

When $W_A > \underline{W}$, it is always good to pay the cost and identify the overpriced assets, $MAXA > W_A$. Therefore, combining conditions (1..40)(1..41)(1..42), I get

$$u_A(s_A^*, s_F^*) \geq MAXA, \tag{1..43}$$

where $MAXA$ is a function of W_A, V, U, U_0, ϕ and q.

Since

$$\frac{\partial u_A^*}{\partial W_F} = \frac{\partial u_A^*}{\partial p_1^{u*}} \frac{\partial p_1^{u*}}{\partial W_F}, \qquad \frac{\partial p_1^{u*}}{\partial W_F} < 0,$$

note that

$$\frac{\partial u_A^*}{\partial p_1^{u*}} = q(W_A - \kappa)\phi(1+\phi)\Big(\frac{V}{p_1^{u*2}} - \frac{1}{p_0^*}\Big) < 0. \tag{1..44}$$

based on the assumption that $\phi W_F < U - U_0$ and $\phi W_A \leq \frac{U}{2}$. Therefore, $\frac{\partial u_A^*}{\partial W_F} > 0$, the payoff of fund A in the equilibrium is increasing in the size of fund F. From condition 1..43, there exists a lower bound $h(W_A)$, such that fund A won't deviate if $W_A \leq h(W_A)$. $\square$

1.B Additional Figures

Figure 1.B.1. Thresholds for the equilibrium to hold under different leverage ϕ

This figure reports the thresholds of noise trader risk q under different ϕ given following parameters that satisfy all assumptions: $V = 100, U_0 = 30, U = 60, \kappa = 0.05, W_A = 0.5, W_F = 6$. The solid line plots the upper bound and the dashed line plots the lower bound of q in the equilibrium.

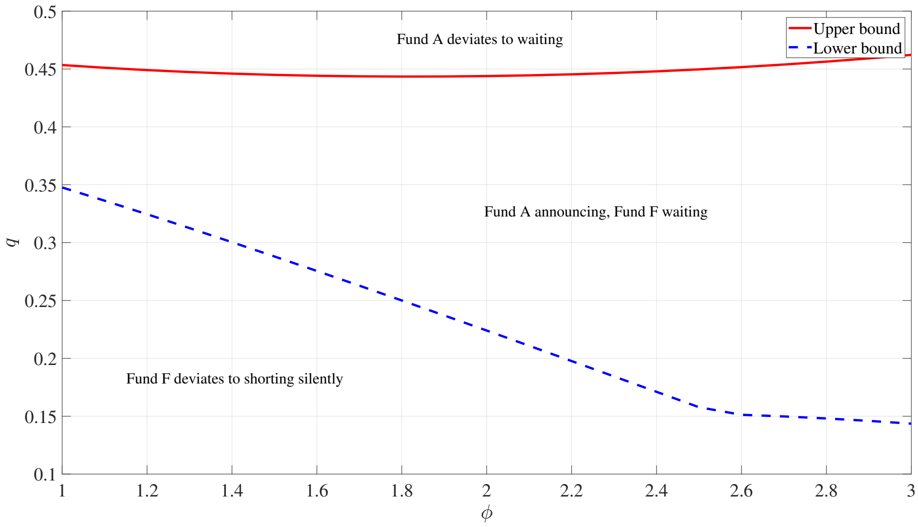
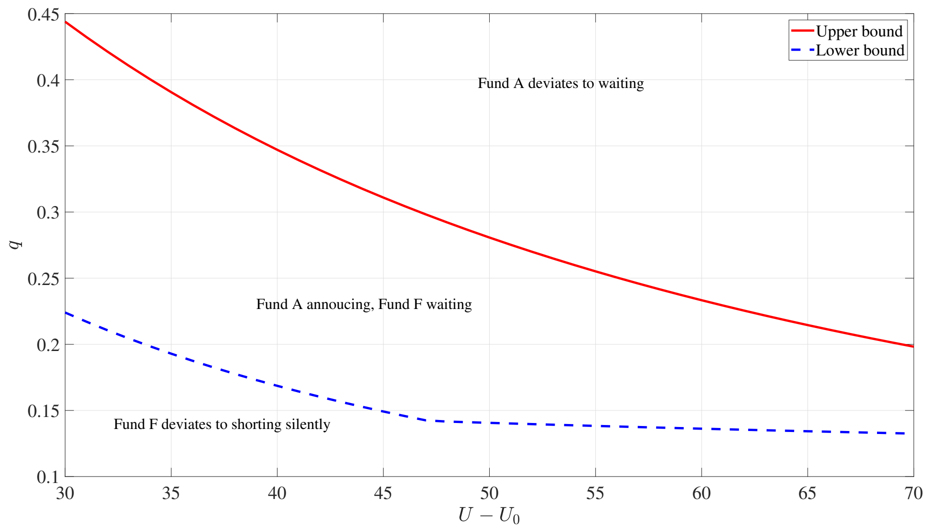


Figure 1.B.2. Thresholds for the equilibrium to hold under different surprise in mispricing $U - U_0$

This figure reports the thresholds of noise trader risk q under different U given following parameters that satisfy all assumptions: $V = 100, U_0 = 30, \phi = 2, W_A = 0.5, W_F = 6$. The solid line plots the upper bound and the dashed line plots the lower bound of q in the equilibrium.



Chapter 2

Empirical Study on Strategic Announcements in Short-Selling Campaigns

Jane Chen [1]

I empirically study how hedge funds strategically disclose their private information during short-selling campaigns. Using data on hedge funds' voluntary announcements and daily short positions in the EU market, I document the existence of two groups of funds: Announcers and Followers. Announcers, typically small and young, (1) establish short positions, (2) publish research reports about short targets, and (3) realise profits from the falling price within a short time frame. Followers, usually large, enter at the release of reports and increase their short positions even after announcers exit. I also test two unique predictions. Stocks with lower borrowing costs and wider mispricing are more likely to be publicly attacked by hedge funds.

[1] I am extremely grateful to my advisors Péter Kondor and Cameron Peng for invaluable guidance and support. I also thank Ulf Axelson, Cynthia Balloch, Georgy Chabakauri, J.Anthony Cookson, Kim Fe Cramer, Daniel Ferreira, Dirk Jenter, Wenxi Jiang, Christian Julliard, Dong Lou, Ian Martin, Igor Makarov, Stavros Panageas, Daniel Paravisini, Dimitri Vayanos, Michela Verardo, Mindy Z. Xiaolan, Kathy Yuan, Hongda Zhong and seminar participants at the London School of Economics for helpful comments. All errors are my own.

2.1 Introduction

On Dec 17, 2015, US hedge fund Muddy Waters accused French retailer Casino of overstating its EBITDA to disguise its deterioration in a detailed research report and an interview with Bloomberg.[2] The price of Casino dropped by 11.5% on the announcement date and a rough estimate of Muddy Waters' short profits is around 615 million euros. While existing studies have explored the impact of these announcements (e.g., Ljungqvist and Qian (2016), Luo (2018), Appel and Fos (2019)), important questions regarding the strategic considerations among short sellers and the factors influencing their decision to disclose private information still remain unanswered. Understanding these motivations is crucial for a comprehensive understanding of the dynamics and decision-making processes of hedge funds on disclosing and shorting.

In this chapter, I address these questions empirically by examining hedge funds' disclosure behaviour and trading activities around short-selling campaigns. I hand-collect data on hedge funds' announcements and individual short positions, and, using an event study framework, I establish the existence of two types of short sellers in short-selling campaigns. In particular, funds smaller in size tend to be more active in announcing their short targets, but also exit short positions more quickly. In contrast, larger funds tend to follow the smaller funds' entry and announcement but then stay in the market for a longer period. In addition, I empirically test two unique predictions derived from the model in Chapter 1. Stocks with lower borrowing costs and wider mispricing in the current period are more likely to be targeted by hedge funds with announcements.

To study information disclosure around short campaigns, one needs data containing hedge funds' short positions in each target, along with the information

[2] See details in Stothard (2015) published on Financial Times.

releases of these hedge funds. Neither is readily available. Most importantly, disclosure requirements on hedge funds' short positions are limited.[3] For instance, only aggregated short interests at the stock level are released in the US. To address these issues, I exploit public notifications from short-selling campaigns in the European Union (EU) required by regulation. From November 2012, short sellers with a net short position of more than 0.5% of the target's issued stock are required to notify regulators in the EU.[4] After matching position holders with hedge funds, I construct the sample of the daily net short position at the fund-target level. The sample period is from 1 November 2012 to 30 November 2021. Then, I go through all fund-target shorting events in the net short position sample and hand-collect announcements that are voluntarily made by hedge funds on their shorting targets. In total, fifty-eight announcements were made by twenty-seven hedge funds in the net short position sample. Finally, I merge the announcement data with the daily position sample, combined with hedge funds' characteristics, and stocks' trading and price information.

I demonstrate large and sudden stock market reactions to hedge fund announcements. On the announcement date, the price drops around 6% on average and trading volume increases. As a control test, I show that the market reaction to public notifications of short positions is insignificant. I then define the fund of a shorting event as an *Announcer* when the fund has made announcements about the target during the shorting period. *Followers* are hedge funds that keep silent and start to add short positions after others have released information about the targets. I find that *Announcers* first increase their investments sharply. The short

[3]Regulators worry that more precise and timely reporting of short selling would facilitate copycat and order anticipation strategies that discourage hedge funds' short-selling activities (SEC, 2014).

[4]These data are also used by several recent papers to study different topics. Della Corte et al. (2021) examine the predictability of the positions on stocks' future returns. Li et al. (2021) study how the presence of large short positions positively influences activists' targeting decisions. Jank et al. (2021) and Jones et al. (2016) study the effects of this public disclosure requirement on trading and stock prices.

position reaches its peak four days before the announcements. Within 2–3 trading days after the announcements, they cover the position and realise profits from correcting the overpricing in the short term. In contrast, a growing number of *Followers* entering into short positions even after announcers exit. The aggregate short positions of *Followers* keep increasing and remain at approximately 1.4% even one year after the announcement. Following the announcements, the short seller who takes dominating positions n the market switches from *Announcers* to *Followers*. Moreover, *Announcers* are usually younger and smaller in asset size than *Followers*.

Moreover, I investigate which characteristics of target stocks are related to hedge funds' decisions on trading and disclosing. Specifically, I examine how borrowing constraints and surprise in mispricing are associated with the likelihood of short sellers publicly announcing their positions, which is derived from the model in Chapter 1. I first construct the sample by focusing on short events held by identified announcers and followers in months when announcements are made. For example, in month t, announcer A made an announcement on stock i and fund F is the follower. The testing sample contains all targets including stock i that are shorted by fund A and F in month t.

The findings from analyzing the stocks in the shorting portfolios of *Announcers* and *Followers* within the same months of announcements provide empirical support for the model in Chapter 1. Combining with characteristics of stocks and funds, I then estimate a Probit regression model. The dependent variable is a dummy for each shorting event, equal to one if the short seller made an announcement against the target in month t, zero otherwise. In the first test, the key independent variable is the borrowing costs of stocks in month $t-1$, measured by the daily cost of borrow score in Markit. In the second test, the key independent variable is the magnitude of mispricing in month $t-1$, which is measured by the percentage of upward revisions of analyst forecasts for stocks' EPS. Controlling other stock and fund characteristics, the results indicate that stocks with lower borrowing costs and wider mispricing have a significantly higher likelihood of being publicly announced by hedge funds.

Literature review There is a growing empirical literature studying the effects of arbitrageurs' announcements. Using 124 disclosures of short-sale campaigns in the US, Ljungqvist and Qian (2016) document that investors respond strongly to small arbitrageurs' announcements. Gillet and Renault (2018) find evidence of large market reactions to negative tweets by short sellers at intraday frequency. Wong and Zhao (2017) and van Binsbergen et al. (2021) also examine the impact of short sellers' announcements on real economic activities. They find that target firms significantly reduce their real investment, stock issuance, and payout after announcements. Brendel and Ryans (2021) provide descriptive evidence on how target firms respond to short-seller reports and highlight the material outcomes associated with firm responses. Furthermore, several papers document evidence of the informativeness of short-seller announcements.[5] Luo (2018) and Appel and Fos (2019) show that target stocks earn a cumulative abnormal return after the announcements. Chen (2016) finds that short sellers tend to target firms that have financial reporting red flags and exhibit good reported operating performance. Kartapanis (2019) find that short sellers' allegations in their voluntary reports are a strong predictor of accounting fraud.

My main departure from this literature is that I combine announcement data with the list of short targets at the hedge fund level. Therefore, I can analyse the decisions of shorting with or without the revelation of information. This chapter fills the gap in discussions about the subjects who make announcements. Using

[5] A number of papers suggest that short sellers indeed have valuable information since their aggregate shorting can predict stocks' future returns. (e.g., Akbas et al. (2017), Wang et al. (2020), Hu et al. (2021), Chen et al. (2022))

the novel dataset, I empirically test predictions uniquely generated from Chapter 1. In addition, my empirical results in Europe also complement the work on the impact of short-seller announcements on the US equity market.

The remainder of the paper is organised as follows. Section 2.2 presents the data. Section 2.3 describes the strong market reaction to hedge funds' announcements. Section 2.4 describes hedge funds' shorting activities around announcements. Section 2.6 provides details of the sample construction and the results of testing. Section 2.7 concludes. The Appendix includes additional tables and figures for robustness.

2.2 Data

In this chapter, I use four types of data to study hedge funds' announcing strategies and trading behaviours: hedge funds' short positions of their targets, voluntary announcements about their shorting strategies, institutional information of hedge funds, and stock-level characteristics. The sample period is from 1 November 2012 to 30 November 2021.

2.2.1 Net Short Position of Hedge Funds

Disclosure requirements on hedge funds' short positions are limited. To address the data issue, I find information on individual short positions by regulation in the EU. According to Regulation (EU) No 236, starting on 1 November 2012, all EU members have introduced public-notification requirements for short sellers. The regulation requires holders of net short positions to notify the relevant authorities when their net short positions of shares reach 0.5% of the issued shares and then at each 0.1% above 0.5%. Notifications must be disclosed no later than the day following the trading day when the positions are held. Regulators in each country publish the latest net short positions on their official websites.[6] For example, the Financial Conduct Authority (FCA) in the UK updates short positions daily on its website.

I download and combine all historical records of net short positions from national regulators' websites in the UK, France, Germany, Netherlands, and Italy. The combined net short position dataset consists of the name of position holders, net short position, position date, and the shorting targets' name and identifier (the International Securities Identification Number, ISIN). In total, there are 1,632 stocks shorted by 722 holders in the net short position dataset from 1 November 2012 to 30 November 2021.

Since the paper focuses on hedge funds' announcements and trading activities, I exclude other types of holders: non-financial corporate firms, pension funds, banks, etc. I manually match the name of position holders in the net short position data with the name of hedge fund companies in Form ADV fillings and the Morningstar Direct global hedge fund database.[7] If matched, I identify the holder as a hedge fund company and keep it.[8] Moreover, I require the shorting targets to be common stocks that are exchange-traded using the stock information from Datastream. After applying all these procedures, I end up with a sample of 428 hedge fund companies' daily short positions in 1,314 stocks. I use NSP to stand for net short positions and call this daily position sample as *Sample NSP*.

[6]Links to the national websites where procedures for notifications of net short positions are explained: https://www.esma.europa.eu/regulation/trading/short-selling

[7]Based on Griffin and Xu (2009) and Jiang (2021), I identify hedge fund advisers from Form ADV fillings by requiring that an adviser's master fund is a hedge fund or it has more than 80% of AUM from its hedge funds.

[8]Net short position notifications are generally submitted by hedge fund companies. In a few cases, the holder's name is the fund name instead of its company name. For these, I change the holder's name to the company name. It is also consistent with the fact that the fund manager, who represents the whole fund company, usually makes announcements.

2.2.2 Voluntary Announcements of Hedge Funds

Next, I obtain hedge funds' announcement data by checking whether hedge funds have voluntarily posted any private information about their short targets contained in Sample NSP. If a report contains additional information about target stocks beyond the size of short positions, I identify it as an announcement. This information could be regarding hedge funds' expectations about falling earnings, allegations of accounting fraud, questions about high valuation multiples, etc.

To simplify the search process, I first define a short-selling link as a unique link between one hedge fund and one of its shorting targets in Sample NSP, regardless of position date. For example, Marshall Wace LLP, a London-based hedge fund, held short positions in Sky PLC from December 2014 to November 2016. This is identified as one link between Marshall Wace and Sky. There are 7,642 such links placed in Sample NSP. Then I search each link in a news database, Factiva, within the sample period.[9] If a shorting link appears in the news and the contents show short sellers' voluntary information about their targets, I take down the earliest announcement date and a summary of such news.

I also complement the announcement data from Factiva with campaigns from Activist Insight Shorts (AiS). AiS is a service module of the data provider Activist Insight. It follows and keeps records of every shorting announcement from all countries. Shorting announcements are short sellers' voluntary disclosures like their research reports or personal opinions from short sellers' websites, Seeking Alpha, Twitter, and press releases. If the target stocks of short-selling campaigns in AiS also appear in *Sample NSP*, I add these campaigns to the announcement data. The announcement sample includes 117 announcements attacking short targets in Sample NSP. Fifty-eight of them are made by 27 hedge funds. And

[9]Factiva is a global news dataset with more than 28,000 sources, including US and international newspapers, continuously updated newswires, trade journals, websites, blogs, and multimedia.

only 12 hedge funds show up both in the announcement sample and Sample NSP.

2.2.3 Other Data

To understand which funds are more likely to make announcements, I analyze fund characteristics using Form ADV filings and Morningstar Direct data. Considering that hedge funds holding short positions in the EU market originate from various countries, I collect my dataset in two steps. First, I obtain the quarterly holdings from Thomson-Reuters 13F S34 data to generate the fund size and quarterly returns of hedge funds matched with Form ADV fillings.[10] Additional characteristics like fund age and style are also sourced from Form ADV. This initial step ensures the inclusion of all US hedge funds in *Sample NSP*. Second, for the remaining hedge funds in *Sample NSP*, I aggregate the monthly fund information in Morningstar Direct to the quarterly fund-company level.

Another crucial aspect in analyzing hedge funds' decisions is to explore the relevance of stock characteristics. I obtain daily price and trading data from Datastream and accounting data for the target stocks from Worldscope. I also construct proxy variables for measuring hedge funds' borrowing cost and noise trader demand shock from Markit and IBES. More information variables can be found in Section 2.6.

2.3 Stock Market Reaction to Announcements

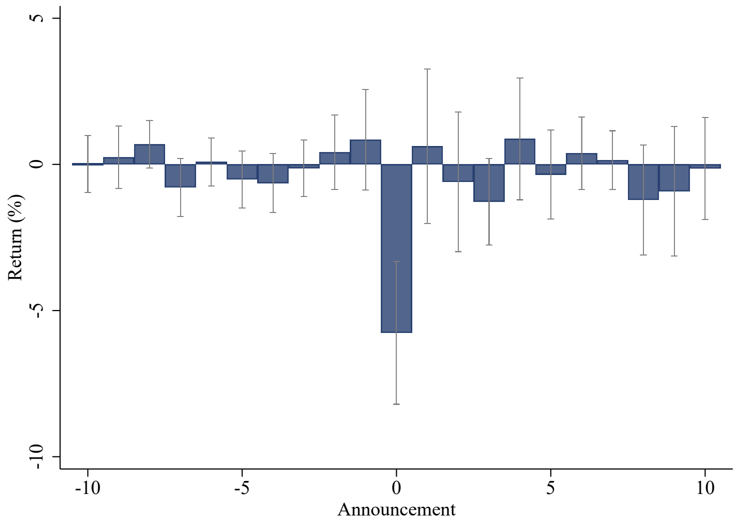
In this section, I show that the stock market reacts strongly to hedge funds' announcements. If there are multiple announcements associated with the same stock in the same month, I consider only the earliest one. Figure 2.3.1 shows the

[10]The link table of investment advisers between Form ADV and 13F is from Dimmock et al. (2018).

average return on each trading day around the release of an announcement. On the announcement date, the price drops around 6%. Figure 2.A.1 in Appendix shows that the cumulative excess return reaches 9.76% if investors start shorting ten trading days before the announcement and buy back ten days later. Figure 2.A.2 plots the daily trading volume around the announcement and shows large trading volumes between days -1 and 4. These figures all reveal investors' strong and rapid reactions to hedge fund announcements.

Figure 2.3.1. Average daily return around the announcement

This figure plots the average return of the target stocks on each trading day around the announcement. Announcement date = 0. The error bars show the 95% confidence interval for the average return.



This strong reaction indicates hedge funds' announcements contain new information for market participants. As a control test, I show that the market reaction to public notifications of short positions is insignificant in Appendix. I identify the first notification as the earliest published position of the target stock or the subsequent position when there are no existing position holders during the past year. The daily return on the notification date and cumulative return around the events are both negative. The daily trading volume reaches its peak on the first notification day. However, the magnitude is much smaller than the reactions to announcements. Markets value the information in voluntary reports more than in mandatory disclosed positions.

2.4 Shorting Activities around Announcements

In what follows I examine how hedge funds trade around announcements. I begin by constructing the sample and then proceed to analyze the trading behaviour of two distinct groups of funds.

2.4.1 Sample Selection

First, I define short seller/target shorting events in *Sample NSP* considering that a fund might bet against a stock multiple times in the sample period. For each shorting event, I identify the first shorting date as the day when the net short position first exceeds 0.5% and the last shorting date as the first subsequent day when the notified net short position falls below 0.5%. In total, there are 15,516 shorting events identified in *Sample NSP*. Because short sellers only need to notify the regulators every 0.1% change of positions, the position dates reported in *Sample NSP* are discontinuous. Assuming that the number of positions is constant between two reported dates within each event, I construct the daily net short positions of hedge funds for all shorting events.

Then, I analyse the hedge funds' roles in each shorting event. I merge the announcement data with the daily short position sample. In this section, my primary focus is to analyze the shorting activities around announcements. To achieve this, I exclude stocks that have never been targeted by any announcements throughout the sample period. The announcement date of each shorting event is when an announcement is published against the stock. If there are multiple announcements, I keep the announcement which is closest to the position date. For each shorting event, I identify the role of short sellers as follows. If a hedge fund made announcements about its target stock, I define the fund as an *Announcer* of this stock. If the fund made no announcements and started to hold short positions after the announcement date, I call it a *Follower*. For instance, fund Y held a short position in stock X on 12 December 2013. There are two announcements about stock X; one was published on 1 November 2013, and another was posted on 5 March 2014. The announcement date of stock X shorted by fund Y on 12 December 2013 is 1 November 2013. If fund Y made the announcement, Y is an *Announcer* of stock X. If not, Y is a *Follower* of stock X. This left us with a total sample of 394 shorting events, where 48 stocks are announced by their short sellers. I call this sample as *Sample A*.

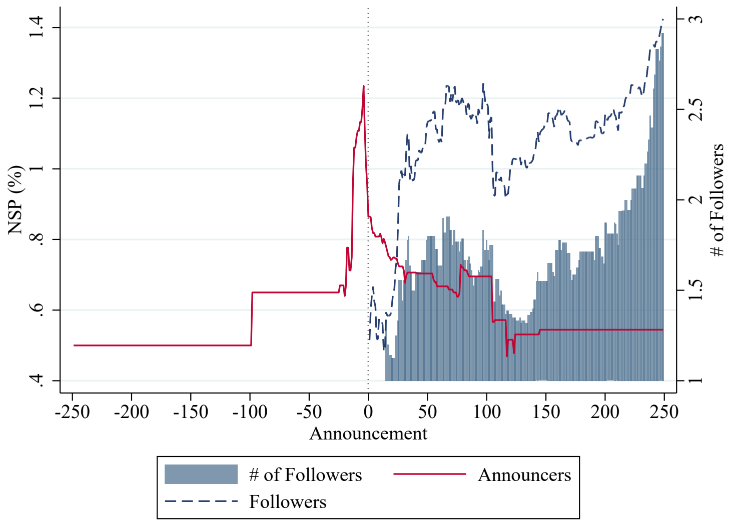
2.4.2 Different Shorting Activities

Next, I examine the shorting activities of *Followers* versus *Announcers* using *Sample A* constructed above. Figure 2.4.1 plots their average shorting activities on each trading day around the release of the announcement.[11] Note that there are no position records if the short position drops below 0.5%. I assume the short position as zero when there is no record. Thus the accurate short positions might be higher than in the figure, but the trend should be similar. The solid line in Figure 2.4.1 shows the average daily position of *Announcers*. They first increase their short position sharply around 3–4 trading days before the announcement. The average position of *Announcers* reaches a peak of 1.24% of the stock's total shares four days before the announcement. Immediately after the announcements, *Announcers* liquidate their position and realize profits rapidly. In contrast, as shown by the dashed line, *Followers* start to add in short positions after the announcement and trade in the opposite direction to *Announcers* and stay much

[11] Note that different countries have different trading calendars. I exclude each stock's non-trading days based on its exchange's trading calendar.

Figure 2.4.1. Hedge Funds' Daily Short Positions Around Announcements

This figure reports shorting activities of *Announcers* and *Followers* around the announcement. For every announcement on each trading day, there are one *Announcer* and multiple *Followers*. This graph shows average net short positions (NSP) of *Announcers* and *Followers* 250 trading days before and after the announcement. The solid line plots the average *Announcers'* positions per announcement. The dashed line plots the average short positions of all *Followers* per announcement. The grey bar stands for the average number of *Followers* with short positions larger than 0.5% for each announcement.



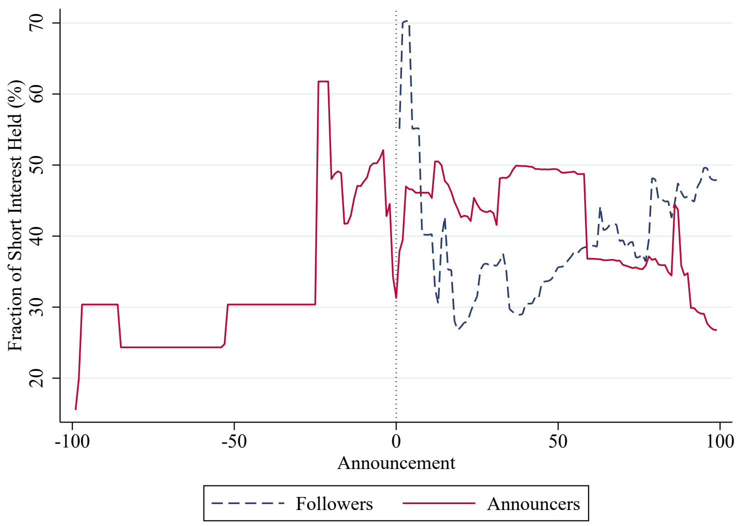
longer. As shown in the bar chart of Figure 2.4.1, there is a growing number of followers entering into short positions even after announcers exit. The aggregate short positions of *Followers* keep increasing and remain at approximately 1.4% even one year (250 trading days) after the announcement.

In terms of the impact on the market's short selling, both *Announcers* and *Followers* show distinct patterns. Figure 2.4.2 reveals that, in comparison to the overall short interest by short sellers, *Followers* rapidly take dominant positions after observing the announcements. Following the announcements, the role of the main short seller of the target switches from *Announcers* to *Followers*.

Besides the contrasting trading activities observed in the two primary groups of short sellers, I also identify a final group referred to as the Existing Short Sellers. These are short sellers who do not make announcements regarding their

Figure 2.4.2. Average Fraction of Short Interest Around Announcements

This figure reports the average fraction of short interest of *Announcers* and *Followers* around the announcement. The stock's short interest is the total net short positions held by all short sellers in the daily short position sample. For each shorting event, the fraction of each group is calculated as the individual short position divided by the short interest on each trading day. For every announcement on each trading day, there are one *Announcer* and multiple *Followers*. The solid line plots the average fraction of *Announcers* positions per announcement. The dashed line plots the average fraction of all *Followers* per announcement.



targets and engage in short selling prior to the announcements made by others. Figure 2.A.5 illustrates that their positions remain relatively stable before and after announcements. For the purpose of this Chapter, the main focus will be on the two primary groups, namely the *Announcers* and *Followers*, given their distinct trading activities.

2.5 Fund Characteristics and Short-Selling

In this section, I investigate which fund characteristics are related to funds' decisions on shorting and disclosing. First, I extract *Announcers* and *Followers* with their shorting targets and corresponding announcement dates from *Sample A*. I then merge it with hedge funds' fundamental information that corresponds to the same month as the announcement date.

Table 2.5.1 summarises the average size of an *Announcer* in the dataset is around 3.04 billion dollars. In contrast, on average, a *Follower* manages 28.43 billion dollars, about ten times the size of announcers. Beyond that, the average age of announcers is 4.53 years, roughly half the age of followers. Each announcer, on average, manages 4.04 funds, and each follower manages 29.4 funds. The last column in Table 2.5.1 confirms that for hedge funds shorting the same group of stocks, announcers are significantly younger and smaller than *Followers*.[12]

I further explore the profits of hedge funds with different shorting strategies. Specifically, I construct the measure of the shorting return of fund j holding short positions in stock i as

$$\text{Shorting Return}_{i,j} = \frac{p_{i,1}}{p_{i,T}} - 1, \tag{2.5.1}$$

[12]Existing Short Sellers are typically larger than *Announcers*. Table 2.A.1 shows that they exhibit similar characteristics to the *Followers*. In practice, these short sellers hold a diverse range of targets in their portfolios to hedge risks.

Table 2.5.1. Summary statistics of hedge funds in two groups

This table shows summary statistics of fund-company-level variables. The sample period is from November 2012 to November 2021. *Announcers* and *Followers* are defined for each fund/target shorting event through the sample period. Target stocks that have never been announced by any hedge funds are removed from the full sample. This left 394 shorting events, where short sellers made 48 announcements. If the fund has made announcements on its target, it is an announcer in this shorting event. In contrast, *Followers* are funds which have not made any announcements and started to short the target after announcements. The table presents the summary statistics of *Announcers'* and *Followers'* characteristics in the month of shorting events when the target stocks were attacked by *Announcers*. *Size* is the total net assets (in billions of USD) under management in the fund company. *Age* equals the number of years since the inception of the company's first fund. *Number of funds* is the number of hedge funds in the company.

	Announcers			Followers				
	Mean	Std. errs.	Obs.	Mean	Std. errs.	Obs.	Diff	t-stat
Size ($B)	3.038	2.203	46	28.429	5.15	198	-25.39	-2.361
Age	4.532	0.688	48	9.407	0.479	187	-4.875	-4.835
Number of funds	4.037	0.65	27	29.446	7.134	56	-25.409	-2.463

where $p_{i,1}$ is the price of stock i on the first shorting date and $p_{i,T}$ is the stock price on the last shorting date. T represents the total holding period of this shorting event.

The shorting return stands for the return when funds sell on the first shorting day and buy back on the last shorting day. It captures the return on the net change of positions during the reporting period. The benefit of this measure is to better detect the return of announcements by assuming that funds keep holding the remaining positions. Table 2.A.2 reports the summary statistics of this measure. Announcers' average return during the reporting period is around 19.07%, and followers' return is around 1.76%. The announcers' return is higher than that of the followers', which implies that when announcers can time the market well, they can earn superior profits on their targets.

Empirical results indicate that small funds prefer to short and reveal their information to the public, then make profits from liquidating after announcing. On the other hand, large funds usually add short positions silently after observing the announcements. Henceforth, I label the former group of hedge funds (*An-*

nouncers) as Group A and the latter group (*Followers*) as Group F. Chapter 1 provide one possible explanation for why Group A funds want to disclose their private information is that they face tighter leverage constraints. Large hedge funds have built relationships with prime brokers at investment banks willing to lend them shares. Small funds, which could not form a relationship in their early days, usually find it hard to borrow from institutional primes. Thus, funds in Group A might prefer to drive down the price in the short run by sharing their information when mispricing widens. Funds in Group F save information acquisition costs and benefit from offering protection to small funds.

2.6 Tests of Model Predictions

This section presents empirical tests of the unique predictions derived from the model discussed in Chapter 1. The first set of tests focuses on the hypothesis regarding the relationship between borrowing constraints and hedge funds' disclosure behavior. Then, I examine the relationship between the surprise in mispricing and the probability of announcements. The findings offer empirical support for the model as a valuable framework for understanding hedge funds' decision-making in real-world scenarios.

2.6.1 Sample Selection

I use a two-stage process to identify the disclosing decision of short sellers within their shorting portfolio. First, I extract *Announcers* and *Followers* with their corresponding announcement date from *Sample A*, which is constructed in Section 2.4. These short sellers were betting against the same stock that was announced by one of them. Then, for each announcement, I select all shorting events in

Sample NSP and keep month-end information where the short seller is either an identified announcer or follower in the same month as the announcement was made. Therefore, in the month when an announcement about stock i was made, the sample includes all stocks held in the shorting portfolios of hedge funds that were shorting i. Combining with characteristics of stocks and funds, this gives me a total sample of 1,362 shorting events, which I call it *Sample B*. Table 2.A.3 shows the mean value for all variables used in regression analyses. Using this sample, I can examine which characteristics are related to a fund's decision on announcing her information.

2.6.2 Borrowing Constraints and Announcements

The first unique prediction from Chapter 1 suggests that hedge funds are more inclined to disclose their information publicly when they face lower margin requirements. The rationale behind this is that when it's easier for funds to short upon identifying mispricing opportunities, larger funds can take substantial positions to protect small funds from incurring costly liquidation. One testable implication arising from this model prediction is that stocks with lower borrowing costs are more likely to be targeted by hedge funds with announcements.

Measuring Borrowing Costs Markit provides data on global equity lending flow daily back to 2006.[13] Following Jones, Reed and Waller (2016), I use *Daily Cost of Borrow Score* as a key measure of shorting cost. It is a number from 1 to 10 indicating the cost of borrowing the security reported by securities lenders, where 1 is the cheapest and 10 is the most expensive. *Lender Concentration* is the Herfindahl index that measures the distribution of lender value on loan, where zero indicates many lenders with small loans and 1 indicates a single lender

[13]This database has been widely used to study global short selling in a number of papers, such as Berkman and McKenzie (2012), Saffi and Sigurdsson (2011), and Jones et al. (2016).

with all the value on loan. When loans are concentrated among a few lenders, it becomes more difficult for investors to increase short positions. *Percentage of Lendable Value* is the value of stock inventory which is actively made available for lending divided by the market value of the stock. The borrowing costs are lower when there are more inventories available to borrow.

To investigate the impact of borrowing constraints on hedge funds' decisions, I analyze each shorting event at the monthly level. By combining this data with *Sample B* described above, I estimate a Probit regression model with the following specifications:

$$\text{DAnnounced}_{i,j,t} = f(Borrowing\ Costs_{i,t-1},\ Fund\ Size_{j,t-1},\ Control_{i,t-1}) \quad (2.6.1)$$

The dependent variable $\text{DAnnounced}_{i,j,t}$ is equal to one if hedge fund j made announcements against stock i in month t, zero otherwise. $Borrowing\ Costs_{i,t-1}$ can be measured by *Daily Cost of Borrow Score*, *Lender Concentration* and *Percentage of Lendable Value*. Since large funds are more likely to wait for others' information and keep silent, I add *Fund Size* as a control for hedge funds' characteristics. Additionally, I also control for various stock characteristics including the stock size, turnover, CAPM-adjusted stock returns, and idiosyncratic volatility calculated over the past three months. Standard errors are clustered by stock and year-month.

Table 2.6.1 reports the results for the Probit model. I use *Daily Cost of Borrow Score* as a proxy for borrowing costs. The coefficient before *Daily Cost of Borrow Score* is significantly negative. The findings indicate that stocks with lower borrowing costs, as reflected by lower scores, are more likely to be publicly attacked by hedge funds. Moreover, the marginal effects suggest that stocks with small units decrease in the *Daily Cost of Borrow Score* have roughly 0.05% higher probability of being announced by hedge funds.

Table 2.6.1. Borrowing Constraints and Announcements

This table presents the results of Probit regressions. The dependent variable is one if hedge fund j made announcements against stock i in month t. It is equal to zero if hedge fund j kept silent on stock i. *Daily Cost of Borrow Score* is a number from 1 to 10 indicating the cost of borrowing stock i at the end of month $t-1$. It is based on Markit proprietary benchmark rate, where 1 is the cheapest and 10 is the most expensive. *Fund Size* is the total asset under management, measured in billions of dollars, within the fund company at the end of the previous quarter. *Stock Size* is the month-end market capitalization of each stock, measured in billions of dollars. *CAPM Alpha* is the adjusted monthly return using CAPM model. *Log Turnover* is the average log of turnover of each stock in month $t-1$. *IVOL* is the standard deviation of residuals from the regression of daily returns on market factor in the past three months. The columns report coefficients from the Probit regression, associated z-values, and marginal effects on announcing probability (evaluated at the average value of the other regressors). Observations are from November 2012 to November 2021. Standard errors are clustered by stock and year-month.

	Coefficient	z-value	Marginal Effects
Daily Cost of Borrow Score	-0.105	-2.33**	-0.000486
Fund Size	-0.0241	-2.08**	-0.000112
Stock Size	0.0179	3.52***	0.000083
CAPM Alpha	-0.0091	-1.5	-0.000042
Log Turnover	0.0580	0.57	0.000268
IVOL	0.0576	0.88	0.000267
Obs.	1,306		
Pseudo R^2	0.188		

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

The result presented in Table 2.A.4, which includes various measures for borrowing costs, is also consistent with the prediction of the model. In Panel A of Table 2.A.4, the coefficient before *Lender Concentration* is significantly negative at 5% level. As the concentration of loans increases, there is a higher probability that funds would prefer to silently trade. The coefficient for *Percentage of Lendable Value* is negative though not statistically significant in Panel B. The ability to borrow stocks is positively related to the likelihood of being publicly announced by hedge funds. This observation supports the view that funds with lower borrowing costs are more likely to reveal their information.

The coefficients for *Fund Size* in all three tests are significantly negative, which is consistent with the observation in Section 2.5. An interesting finding is the significant positive relationship between the market size of stocks and the likelihood of being announced. One possible explanation is that the firm size may capture the underlying factors that influence borrowing costs, which in turn affect the probability of being announced.

2.6.3 Surprise in Mispricing and Announcements

The second unique prediction derived from my model in Chapter 1 is that when there is a larger change in mispricing driven by noise trader demand, hedge funds are less likely to reveal their information. Assuming the expected mispricing is constant in the next period, the model indicates a positive relationship between the mispricing in the current period and the probability of hedge funds making announcements.

Analyst Forecast Revisions

The noise trader demand is typically reflected in greater trading volume, which is strongly associated with investor disagreement.[14] In particular, as a common proxy for investor disagreement, I employ positive revisions in analysts' forecasts to measure the noise trader demand. For each stock i in each month t, the summary statistics of analyst forecasts of the earnings-per-share (EPS) are obtained from I/B/E/S summary database. *Percentage of Up* is the ratio of the number of upward revisions to the total number of analyst forecasts for stock i's EPS in month $t-1$. When there are more analysts revising their forecast upward, it indicates higher demand and leads to an increase in mispricing.

Next, I examine the impact of demand shock on hedge funds' disclosing behaviours by running the following Probit model.

$$\text{DAnnounced}_{i,j,t} = f(Mispricing_{i,t-1}, Fund\ Size_{j,t-1}, Control_{i,t-1}) \qquad (2.6.2)$$

Both the dependent variable and control variables are the same as the previous test (2.6.1). $Mispricing_{i,t-1}$ is measuring by *Percentage of Up* in Columns(1)(2) of Table 2.6.2. The coefficient for *Percentage of Up* is significantly positive. This result suggests that stocks facing high demand in the current period are more likely to be publicly announced by hedge funds. The marginal effects indicate that small units increase in the percentage of upward revisions is related to approximately 0.76% higher probability of announcing. This is consistent with the model prediction. When the mispricing is greater in the current period, funds are more willing to short immediately and disclose their information in the next period.

As placebo tests, I also regress on *Analyst Dispersion* and *Percentage of Down* in

[14] Cookson and Niessner (2020) document robust relation between investor disagreement and trading volume and daily changes in disagreement can explain up to a third of the increase in trading volume after earnings announcements.

Table 2.6.2. Noise Trader Risk and Announcements

This table presents the results of Probit regressions. The dependent variable is one if hedge fund j made announcements against stock i in month t. It is equal to zero if hedge fund j kept silent on stock i. *Percentage of Up* is the ratio of the number of upward revisions to the total number of analyst forecasts for stock i's EPS in month $t-1$. *Percentage of Down* is the ratio of the number of downward revisions to the total number of analyst forecasts for stock i's EPS in month $t-1$. *Analyst Dispersion* is the standard deviation of analyst forecasts divided by the mean in month $t-1$. *Fund Size* is the total asset under management, measured in billions of dollars, within the fund company at the end of the previous quarter. *Stock Size* is the month-end market capitalization of each stock, measured in billions of dollars. *CAPM Alpha* is the adjusted monthly return using CAPM model. *Log Turnover* is the average log of turnover of each stock in month $t-1$. *IVOL* is the standard deviation of residuals from the regression of daily returns on market factor in the past three months. Columns(1)(3)(4) report coefficients from the Probit regression, and the corresponding associated z-values are reported in parentheses. Columns(2)(4)(6) represents the marginal effects on announcing probability (evaluated at the average value of the other regressors). Observations are from November 2012 to November 2021. Standard errors are clustered by stock and year-month.

	(1)	(2)	(3)	(4)	(5)	(6)
	Coefficients	Marginal Effects	Coefficients	Marginal Effects	Coefficients	Marginal Effects
Percentage of Up	1.668***	0.007590				
	(4.42)					
Percentage of Down			0.507	0.002720		
			(1.43)			
Analyst Dispersion					0.0225	0.000131
					(0.87)	
Fund Size	-0.0188*	-0.000086	-0.0198*	-0.000106	-0.0194*	-0.000113
	(-1.67)		(-1.81)		(-1.74)	
Stock Size	0.0220***	0.000100	0.0192***	0.000103	0.0216***	0.000125
	(3.55)		(3.48)		(3.79)	
CAPM Alpha	-0.0201**	-0.000091	-0.0132*	-0.000071	-0.0150**	-0.000087
	(-2.06)		(-1.81)		(-1.99)	
Log Turnover	0.156	0.000708	0.145	0.000778	0.183	0.001060
	(0.90)		(0.87)		(1.16)	
IVOL	-0.0311	-0.000142	-0.0260	-0.000139	-0.0241	-0.000140
	(-0.44)		(-0.38)		(-0.35)	
Obs.	1,014		1,014		1,003	
Pseudo R^2	0.242		0.200		0.193	

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Columns (3)-(6) where *Percentage of Down* is the ratio of the number of downward revisions to the total number of analyst forecasts for stock i's EPS in month $t-1$. *Analyst Dispersion* is the standard deviation of analyst forecasts divided by the mean in month $t-1$. Both of them are alternative measures of investor disagreement but are not related to the surprise in mispricing. The coefficients are positive but not statistically significant. This suggests that these two measures may not adequately capture the noise trader demand, as short sellers are primarily exposed to upward risk.

2.7 Conclusion

A number of hedge funds have recently engaged in very public short-selling campaigns. To examine hedge funds' incentive of engaging in disclosing, I construct a novel data set to study such short-selling campaigns. Using the data on short sellers' voluntary announcements and their real-time short positions at the stock level, I found that a group of specialised hedge funds, which are small in asset size, first increase their short positions by full capacity and publish research reports attacking the short targets. After the announcements, they quickly liquidate and realise profits from correcting the overpricing in the short term. Another group of larger hedge funds follows and keeps adding positions even after announcers leave. Consistent with the model in Chapter 1, size plays an important role in hedge funds' trading and disclosing.

Furthermore, I test two unique predictions derived from the model by measuring borrowing costs and surprises in mispricing. First, stocks with lower borrowing costs are more likely to be publicly attacked by hedge funds. Second, stocks with wider mispricing in the current period are more likely to be announced by hedge funds. The results provide support for the validity of my model as a framework for understanding hedge funds' behaviour.

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Appendices

2.A Additional Tables and Figures

Market Reactions to Hedge Funds' Announcements

Figure 2.A.1. Average cumulative return around the announcement

This figure plots the average cumulative excess return on each trading day around the announcement. The excess return is measured by the daily return minus the market return, which is the daily return of the EURO STOXX 50.

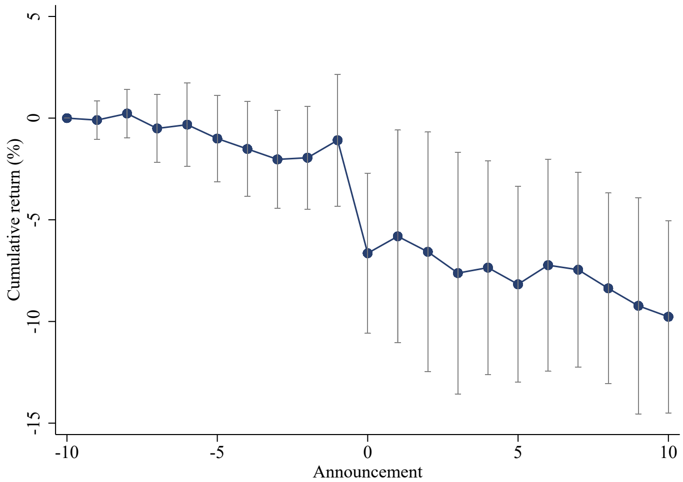
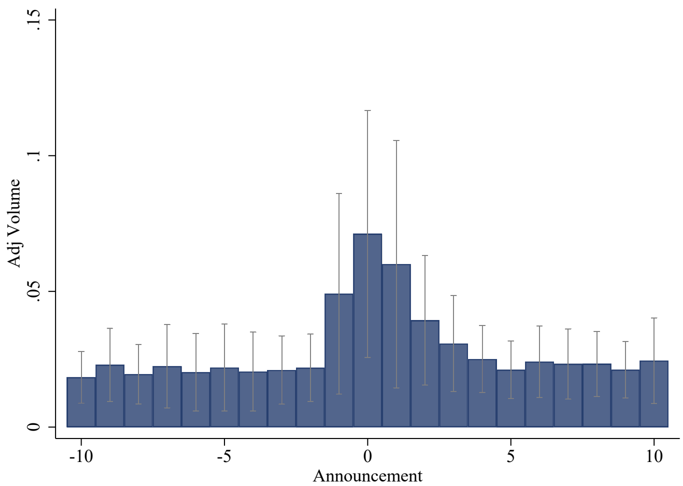


Figure 2.A.2. Average trading volume around the announcement

This figure plots the average adjusted trading volume on each trading day around the announcement. The adjusted trading volume is measured by the daily trading volume in shares divided by the stock's total outstanding shares.



Market Reaction to Notifications of Short Positions

Figure 2.A.3. Average return around the first notification of short positions

This upper graph plots the average daily return on each trading day around the first notification of short positions. The bottom graph plots the average cumulative excess return. The excess return is measured by the daily return minus the market return, which is the daily return of the EURO STOXX 50. The event date is identified when the regulator published the first record of positions in each target stock within the past one year.

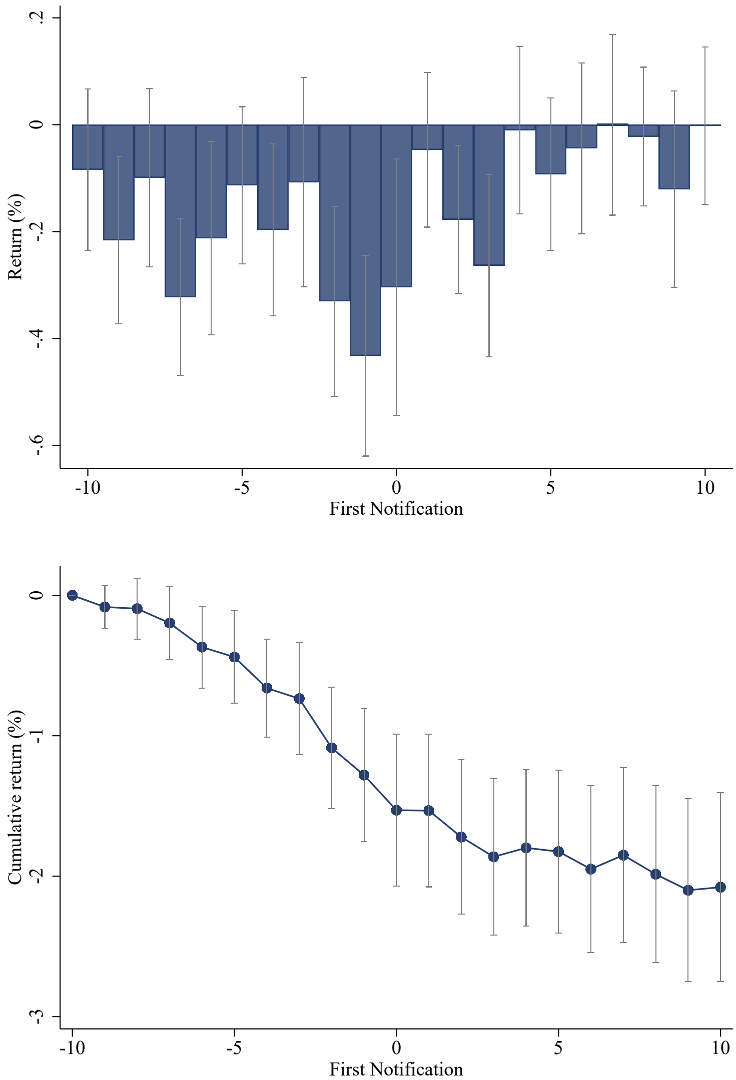
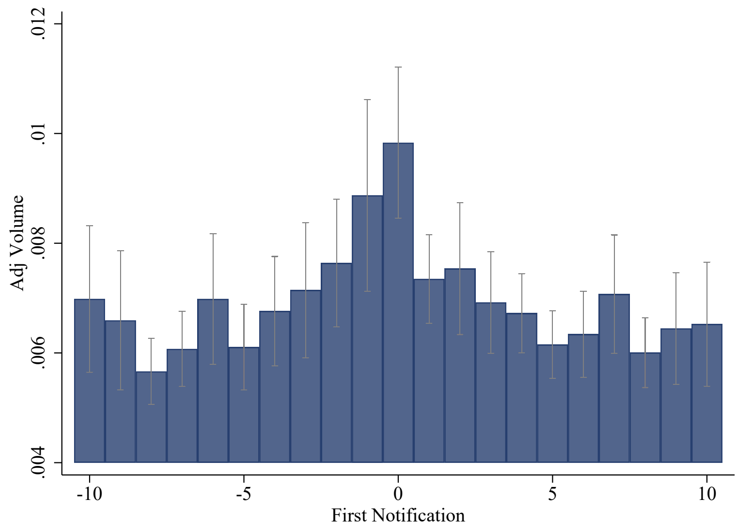


Figure 2.A.4. Average trading volume around the first notification of short positions

This figure plots the average adjusted trading volume on each trading day around the first notification of short positions. The adjusted trading volume (Adj Volume) is measured by the daily trading volume in shares divided by the stock's total outstanding shares.



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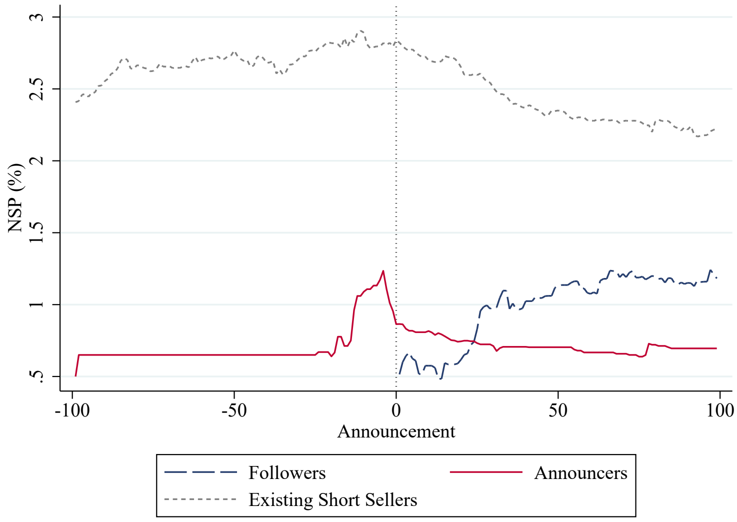
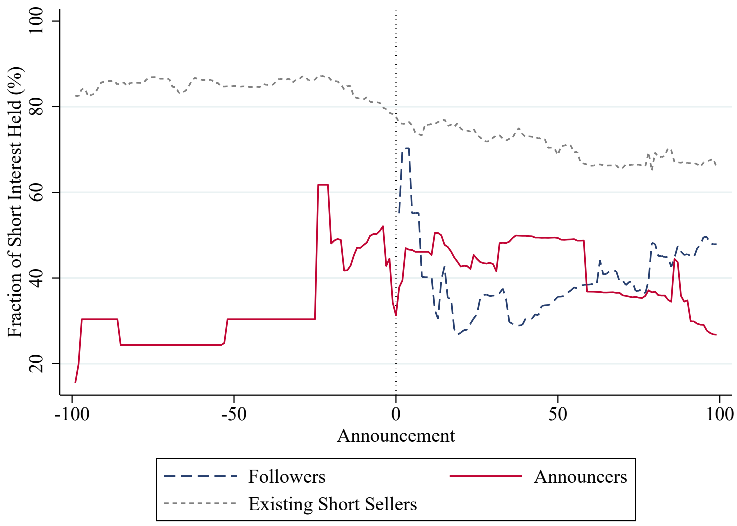
Shorting Activities of Existing Short Sellers

Figure 2.A.5. Average shorting activities around the announcement

This upper graph plots the average net short position on each trading day around the announcement. The bottom graph plots the average fraction of short positions of each group to the total short interest. The solid line represents the shorting of *Announcers*, the long-dashed line represents the shorting of *Followers* and the short-dashed line represents the shorting of *Existing Short Sellers*.





Fund Characteristics

Table 2.A.1. Summary statistics of Existing Short Sellers

This table shows summary statistics of fund-company-level variables. The sample period is from November 2012 to November 2021. *Existing Short Sellers* and *Followers* are defined for each fund/target shorting event through the sample period. Target stocks that have never been announced by any hedge funds are removed from the sample. *Followers* are funds which have not made any announcements and started to short the target after announcements. If funds who never made announcements and held short positions before the announcements, it is a *Existing Short Seller*. The table presents the summary statistics of *Existing Short Sellers'* and *Followers'* characteristics in the shorting events when the target stocks were attacked by *Announcers*. *Size* is the total net assets (in billions of USD) under management in the fund company. *Age* equals the number of years since the inception of the company's first fund. *Number of funds* is the number of hedge funds in the company.

	Existing Short Sellers			Followers				
	Mean	Std. errs.	Obs.	Mean	Std. errs.	Obs.	Diff	t-stat
Size ($B)	38.936	6.01	187	28.429	5.15	198	10.508	1.333
Age	10.551	0.480	184	9.407	0.479	187	1.144	1.6878
Number of funds	45.167	8.496	60	29.446	7.134	56	15.72	1.4068

Table 2.A.2. Summary statistics of shorting profits in two groups

This table shows summary statistics of shorting returns of hedge funds. The sample period is from November 2012 to November 2021. *Announcers* and *Followers* are defined for each fund-target shorting event through the sample period. If the fund has made announcements on its target, it is an announcer in this shorting event. In contrast, *Followers* are funds which have not made any announcements and started to short the target after announcements. *Shorting Return* is the period return measured by the stock price on the last position reporting date divided by the price on the first position reporting date minus one. The table presents the summary statistics of *Announcers'* and *Followers'* shorting returns on stocks that were attacked publicly by *Announcers*.

	Announcers			Followers				
	Mean	Std. errs.	Obs.	Mean	Std. errs.	Obs.	Diff	t-stat
Shorting Return (%)	19.07	18.84	12	1.76	1.38	356	17.304	2.102

Table 2.A.3. Summary statistics of regression sample

This table presents the mean value for variables used in regression analyses. *Daily Cost of Borrow Score* is a number from 1 to 10 indicating the cost of borrowing the target stock at the end of the month. It is based on Markit proprietary benchmark rate, where 1 is the cheapest and 10 is the most expensive. *Lender Concentration* is the Herfindahl index that measures the distribution of lender value on loan, where zero indicates many lenders with small loans and 1 indicates a single lender with all the value on loan. *Percentage of Lendable Value* is the value of stock inventory which is actively made available for lending divided by the market value of the stock. *Percentage of Up* is the ratio of the number of upward revisions to the total number of analyst forecasts for the stock's EPS. *Percentage of Down* is the ratio of the number of downward revisions to the total number of analyst forecasts for the stock's EPS. *Analyst Dispersion* is the standard deviation of analyst forecasts divided by the mean in month $t-1$. *Fund Size* is the total asset under management, measured in billions of dollars, within the fund company at the end of the previous quarter. *Stock Size* is the month-end market capitalization of each stock, measured in billions of dollars. *CAPM Alpha* is the adjusted monthly return using CAPM model. *Log Turnover* is the average log of turnover of each stock in month $t-1$. *IVOL* is the standard deviation of residuals from the regression of daily returns on market factor in the past three months. The columns report coefficients from the Probit regression, associated z-values, and marginal effects on announcing probability (evaluated at the average value of the other regressors). Observations are monthly-level shorting events from November 2012 to November 2021.

	All	Target is announced	Target is not announced
Daily Cost of Borrow Score	2.09	1.71	2.10
Lender Concentration	0.24	0.20	0.24
Percentage of Lendable Value	14.70	17.00	14.70
Percentage of Up	0.12	0.25	0.11
Percentage of Down	0.22	0.35	0.22
Analyst Dispersion	0.11	0.32	0.11
Fund Size	52.80	4.11	53.90
Stock Size	4.16	6.95	4.10
CAPM Alpha	-0.16	-2.99	-0.10
Log Turnover	-5.69	-4.97	-5.70
IVOL	2.30	2.98	2.29
Obs.	1362	29	1333

Table 2.A.4. Borrowing Constraints and Announcements: Robustness

This table presents the results of Probit regressions. The dependent variable is one if hedge fund j made announcements against stock i in month t. It is equal to zero if hedge fund j kept silent on stock i. *Lender Concentration* is the Herfindahl index that measures the distribution of lender value on loan, where zero indicates many lenders with small loans and 1 indicates a single lender with all the value on loan. *Percentage of Lendable Value* is the value of stock inventory which is actively made available for lending divided by the market value of the stock. *Fund Size* is the total asset under management, measured in billions of dollars, within the fund company at the end of the previous quarter. *Stock Size* is the month-end market capitalization of each stock, measured in billions of dollars. *CAPM Alpha* is the adjusted monthly return using CAPM model. *Log Turnover* is the average log of turnover of each stock in month $t-1$. *IVOL* is the standard deviation of residuals from the regression of daily returns on market factor in the past 3 months. The columns report coefficients from the Probit regression, associated z-values, and marginal effects on announcing probability (evaluated at the average value of the other regressors). Observations are from November 2012 to November 2021. Standard errors are clustered by stock and year-month.

Panel A: Borrowing Costs Measured by Lender Concentration

	Coefficient	z-value	Marginal Effects
Lender Concentration	-1.754	-2.18**	-0.00734
Fund Size	-0.0244	-2.09**	-0.000102
Stock Size	0.0216	3.71***	0.000090
CAPM Alpha	-0.0104	-1.79*	-0.000044
Log Turnover	0.002	0.02	0.000008
IVOL	0.0382	0.58	0.000160
Obs.	1,309		
Pseudo R^2	0.193		

Panel B: Borrowing Costs Measured by Percentage of Lendable Value

	Coefficient	z-value	Marginal Effects
Percentage of Lendable Value	0.0114	1.29	0.000060
Fund Size	-0.0232	-2.04**	-0.000122
Stock Size	0.0189	3.55***	0.000099
CAPM Alpha	-0.0094	-1.6	-0.000049
Log Turnover	0.0402	0.43	0.000211
IVOL	0.0367	0.61	0.000193
Obs.	1,308		
Pseudo R^2	0.181		

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Chapter 3

The Economics of Mutual Fund Marketing

Jane Chen, Wenxi Jiang and Mindy Z. Xiaolan [1]

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

[1]The authors thank Ulf Axelson, Si Cheng (discussant), Will Goetzmann, William Fuchs, Jennifer Huang, Dirk Jenter, Peter Kondor, Ron Kaniel, Andrey Ordin, Cameron Peng, Veronika Pool, Clemens Sialm, Michael Sockin, Denis Sosyura, Sheridan Titman, Kelsey Wei (discussant), Max Wei (discussant), and Yao Zeng (discussant) for their helpful comments as well as the seminar participants at the Chinese University of Hong Kong, Cheung Kong Graduate School of Business, UT Austin, University of Hong Kong, UT Dallas, London School of Economics, Arizona State University, the 2023 AFA meeting, the 2023 SFS Calvacade NA, and the ABFER 10th Annual Conference. We thank Hulai Zhang and Nicole Liu for their excellent research assistance.

3.1 Introduction

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

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

Our data are from the SEC's Form ADV filings, through which fund companies have been required to report information on their employees' profiles since 2011.

The key variable that we examine, *MKT*, equals the fraction of employees who have the legal qualification of sales, and MKT is measured at the fund company level.[2] The new data on mutual funds' marketing efforts reveal several interesting stylized facts.

First, marketing efforts are substantially different across fund companies. On average, 24% of fund companies' employees are marketing-oriented, but the cross-sectional standard deviation is significant at 25%. Conventional wisdom typically views marketing as "gloss[ing] over the fact."[3] That is, marketing could influence and convenience investors in a psychological way (naive persuasion). However, this naive persuasion can hardly explain the cross-sectional heterogeneity; otherwise, one would expect all fund companies to hire a sizeable marketing force. Furthermore, the level of *MKT* does not signal funds' performance, which aligns with previous studies using other measures of marketing (e.g., Jain and Wu (2000)).

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

To reconcile the puzzling facts on fund companies' marketing, we propose an eco-

[2] This is natural given the typical organizational structure of mutual fund companies, in which services such as marketing, operations, and compliance are shared among the funds within the company. For a more detailed discussion, see Gallaher et al. (2006).

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

nomic framework to understand fund companies' strategic allocation of human capital to marketing. Our framework also produces novel and testable implications on the relationships among marketing, fund flows, and fund performance. In our model, marketing matters for the following two reasons. First, in a world with information frictions and performance-chasing investors, marketing helps lower the information acquisition cost for investors (*learning*). This is a common view of marketing in the mutual fund industry (e.g., Roussanov et al. (2021); Huang et al. (2007)). Second, the marketing effort is a costly signal. Fund companies persuade fund flows through marketing strategies that affect investors' allocation by only changing their beliefs (*costly signaling*). The joint force of learning and signaling is novel to the literature and key to the non-monotonicity of the marketing–performance relationship. Instead of the level of marketing, the persistent effort of marketing indicates the skill type. Depending on the realized past performance and the skill of fund managers, either learning or signaling can be the dominating mechanism that drives fund companies' optimal allocation on marketing.

We see our paper's broad contribution as twofold. The literature on mutual funds finds little support for the existence of persistent superior performance. Regardless of the tremendous effort that fund companies devote to marketing, not surprisingly, we have not identified a significant relationship between marketing effort and fund performance (Jain and Wu, 2000; Bergstresser et al., 2009).[4] We partially fill this gap by recognizing the importance of the persistence of this strategic decision and its link to information available only to the fund company. The persistence of marketing strategy robustly predicts future performance. Our labor-based measure also highlights the company-level marketing policy, which complements the fee-based measures (e.g., broker distribution expense or 12b-1

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

fee). Second, we theoretically analyze the interaction of the learning and signaling mechanisms and characterize the equilibrium marketing strategy as a non-monotonic function of past performance. Our particular insight can be extended to other industries where the learning of product quality is not perfect.[5]

In our model, fund companies have heterogeneous investment skills (high versus low).[6] There are three periods. At date 0, the fund company observes its type and chooses a marketing strategy, a policy that maps each skill type into a marketing employment ratio (the signal). The optimal marketing strategy maximizes the fund company's expected profits, which is the fee from the investors' flow minus the cost of the marketing force. There are two types of investors: performance chasers and sophisticated investors. Both investors do not observe the skill type. They face different information sets and make portfolio allocation decisions at date 1. Sophisticated investors start with more precise prior information sets than the performance chasers. Performance chasers only update their prior beliefs about this unknown type based on past performance. Sophisticated investors can update their beliefs based on past performance and the additional signal of the marketing employment strategy chosen by the fund company. We show a separating equilibrium exists that strictly benefits the fund company.

Performance chasers learn from past performances. At date 0, performance chasers obtain a noisier prior about the skill type than sophisticated investors. However, at date 1, they can pay a participation cost to obtain more precise information about the skill level—the same as sophisticated investors have. Hiring

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

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

more marketing employees can lower the participation cost, but it is more costly given marketing employees' fixed wages. With a participation cost, the classic result from learning indicates that performance chasers only allocate capital (positive flows) when past performance surpasses a specific threshold. As a result, fund companies only choose to build up a marketing labor force when the past performance is good enough.

Sophisticated investors observe fund companies' marketing strategies in addition to past performance. They update their beliefs about the fund company's skill type after observing the realization of past performances and the marketing employment strategy at date 1. The marketing employment strategy, optimally chosen by the fund companies, then contains information about fund type beyond past performance. In this way, companies use their overall marketing effort as a costly signal to shape investors' beliefs and persuade flows. The signaling mechanism is the foundation of the persistence of marketing strategies.

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

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

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

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

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

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

Our theoretical implication is not restricted to the company's hiring decision of marketing force. We show that the results are robust using the fee-based measure for marketing intensity, such as 12b-1 fees. Also, a natural auxiliary prediction is that $Vol(MKT)$ should be correlated with more value-added, which proxies for skills (Berk and Van Binsbergen, 2015). Our evidence supports this conjecture.

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

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

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

Although costly signaling is a workhorse in the theoretical marketing literature, it has not been used to study fund companies' non-investment-related decisions. A classic costly signaling framework tends to conclude that the marketing effort conveys the direct and indirect product quality information (Kihlstrom and Riordan, 1984; Milgrom and Roberts, 1986). Unlike those classic settings, the quality of mutual funds is not verifiable, and marketing as a signal is costly and productive. The imperfect learning then allows the optimal marketing policy to depend on the observed past performance, which is key to understanding the heterogeneity of the marketing effort across fund companies. Consistent with Jain and Wu (2000), who showed no performance-related signal in advertisements, our theory predicts that it is the persistence of the marketing effort, instead of the level of marketing effort, that contains information about management skills. More generally, our results can be extended to other dimensions of fund companies' strategic decisions beyond investment management.[7]

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

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

markets, which focus on whether the broker or advertising helps investors find better financial products due to the potential conflicts of interest (Christoffersen et al. (2005), Bergstresser et al. (2009), Gurun et al. (2016)).

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

3.2 Data and Stylized Facts

In this section, we describe the main stylized facts of mutual fund marketing using the new dataset we constructed based on the SEC's Form ADV filings. Investment companies that manage more than $100 million in assets must file Form ADV annually. Item 5 in Part 1A of Form ADV requires investment companies to report employment information, including the total number of employees (Item 5.A) and the breakdown by functions. We are interested in Item 5.B(2), which reports the number of employees who are registered representatives of a broker-dealer. Legally conducting trading and sales of mutual fund shares in the U.S. requires being a registered representative.[8] The key variable of our paper, marketing employment share (MKT), is defined as the fraction of registered representatives to total employees.[9] Given that the asset management industry is

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

[9]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.

human capital intensive (its production function features various types of human capital or skills as the inputs), our labor-based measure MKT captures how much human resources the fund allocates toward marketing and sales versus other key functions, such as investment, research, and operations. In Item 5.B(1), companies report their number of employees who perform investment advisory functions (including research).[10]

MKT can potentially better capture funds' marketing efforts at the company level, where most of the meaningful marketing strategy is determined. In fund companies, portfolio management and investment decisions are typically made at the fund level, while the company is responsible for marketing, operations, and compliance for all funds. Based on this distinction, measures of marketing efforts should refer to the company level (Gallaher et al., 2006). In comparison, fee- or expenditure-based measures, such as 12b-1 or advertisement spending, capture the marketing cost that individual funds pay to external partners. For example, 12b-1 fees refer to the fund's expenses on distribution channels and advertisements. In addition, the 12b-1 fee is a cost of fund flows, so fund companies compete by charging lower fees to attract flows. Hence, a higher 12b-1 fee is likely to capture lower marketing strength (Barber et al., 2005).[11]

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

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

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

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

on mutual fund advisers, we manually merge Form ADV data with the CRSP Survivor-Bias-Free US Mutual Fund Database to implement our empirical tests. The merge is conducted using the names of fund advisory companies.[12] More details on Form ADV, the variable MKT, and our sample construction are in Appendix 3.C. Finally, our sample includes 711 unique fund companies and 3,776 company–year observations from 2011 to 2020.

Next, we document several stylized facts regarding mutual funds' marketing efforts, measured by both MKT and 12b-1 fees. The first is the sizeable cross-sectional variation of *MKT*. Panel A of Table 3.D.1 reports the summary statistics of MKT. *MKT* is on average 23.7% with a substantial cross-sectional variation, standard deviation of 24.4%. This suggests that fund companies adopt different strategies in allocating human capital to marketing. The fund company level 12b-1 fee as a ratio of AUM also exhibits a significant cross-sectional variation: The mean of *Firm 12b-1* is 0.33% with a standard deviation of 0.17%.

The second stylized fact is the persistence of *MKT*. Following the procedure of Carhart (1997), we sort fund companies into quintiles based on MKT at each year and track the average MKT of each quintile over the next five years in the upper panel of Figure 3.D.1. One can find that high MKT companies continue to have high MKT over the following years. The lower panel replicates the finding of Carhart (1997) at the fund company level, using gross returns to measure performance. We find that there is weak persistence in performance. The empirical facts shown in both panels of Figure 3.D.1 suggest that mutual fund companies exhibit persistent marketing in the lack of persistent performance.

More importantly, there is substantial heterogeneity in the persistence of *MKT*. That is, although some fund companies tend to make persistent marketing efforts,

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

others choose to adjust MKT frequently over time. To measure the persistence of MKT, we calculate the standard deviation of MKT over time for each company, labeled as $Vol(MKT)$. In the upper panel of Figure 3.D.2, we sort fund companies into quintiles based on $Vol(MKT)$, and the y-axis plots the distribution (i.e., the minimum, maximum, median, and the first and third quartiles) within each quintile. One can see that Group 1, the most persistent one, exhibits little variation in MKT, while Group 5 shows high variation of MKT over time. In the lower panel, we repeat the same analysis using the 12b-1 fee ratio: the pattern is similar, while there is little heterogeneity in the low $Vol(12b1)$ groups in the sample.

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

3.3 Model of Mutual Fund Marketing

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

3.3.1 Environment

Consider an economy with three periods: $t = 0, 1, 2$. Investors allocate their wealth between a risk-free bond and an array of active mutual funds managed by fund companies. For simplicity, we assume that each fund company manages the portfolio of a mutual fund with one manager, and henceforth the fund company and mutual fund and its manager are all indexed by i.[13] The return on the risk-free bond r_f is normalized to zero for each period. Mutual funds differ according to their manager's ability to generate returns. The mutual fund i produces a risky return of r_{it} at time $t = 0, 1, 2$ according to the following process:

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

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

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

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

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

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

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

Marketing Fund companies maximize revenues generated from choosing different marketing strategies by hiring a certain number of marketing employees.[14] Marketing can increase fund flow through two channels. First, marketing facilitates learning. Marketing can lower the information acquisition cost c_i of fund i for performance chasers. Let M be some sufficiently large set of marketing employment realizations, and the participation cost is a function of the number of marketing employees $m_i \in \mathbb{M}$. We assume that the participation cost function $c_i = c(m_i)$ is decreasing and concave in m_i—that is,

$$c(\cdot) > 0, \quad c'(\cdot) < 0, \quad c''(\cdot) < 0 \tag{3.3.1}$$

This assumption is made in many economic analyses. The more marketing employees hired, the lower the participation cost. The marginal benefit of hiring one more marketing employee decreases when the fund company already has a large

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

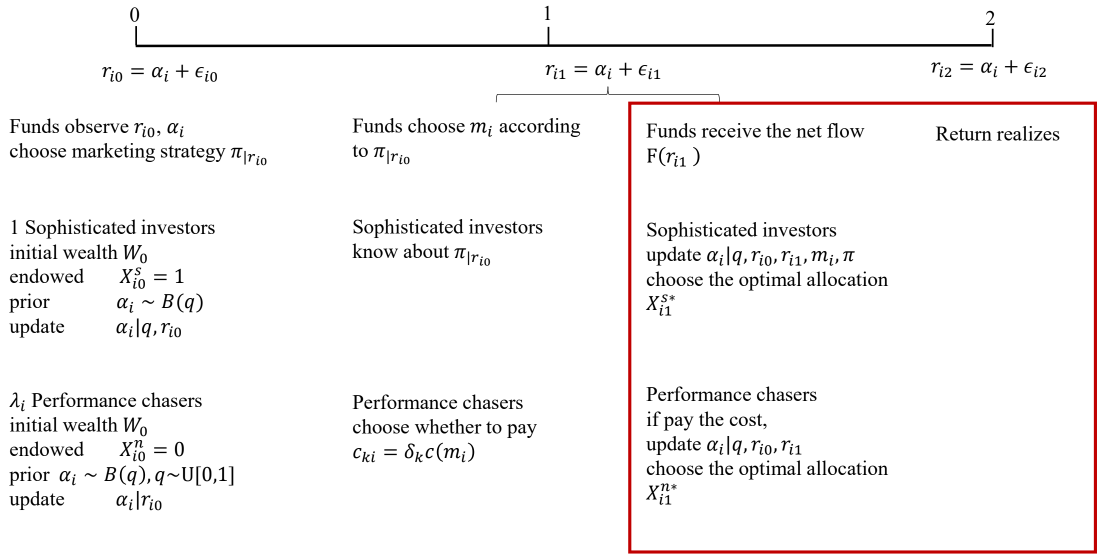
marketing group. This property is also consistent with the assumption made in the literature on information acquisition that investors' objective function is usually convex in signal precision. The more marketing employees the fund hires, the lower the participation cost and the more precise the signal investors are likely to gain.

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

In our setting, the fund company observes r_0 and its type, and then determines a marketing strategy at date $t = 0$. A marketing strategy is a function $\pi : \Omega \times \mathbb{M} \rightarrow [0, 1]$ such that $\sum_{m \in \mathbb{M}} \pi(\alpha, m) = 1$. $\pi(\alpha, m)$ stands for the probability that the fund i hires m marketing employees when it observes its type α. The marketing employment m is the costly signal. In other words, π is a density function that specifies the statistical relationship between truth ($\alpha \in \Omega$) and the fund company's choice ($m \in M$). The fund company's choice $m(\cdot)$ is allowed to be the policy as a function of other state variables. We will discuss in detail in Section 3.3.2 how fund companies strategically choose the marketing strategy to reveal their types and attract flows.

Timing Figure 3.3.1 summarizes the timing of the model. At $t = 0$, mutual fund companies choose the marketing strategy π *after* observing r_{i0} and their types. After the realization of r_{i0}, both the sophisticated investors and perfor-

Figure 3.3.1. 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 $1 - q$).

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

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

3.3.2 Marketing Strategy in the Equilibrium

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

Portfolio Allocation

At date 1, performance chasers choose to pay the cost, and sophisticated investors allocate their capital to the fund based on their information set. As previously mentioned, the performance chasers who pay the cost have the information set as $I_1^n = \{q, r_{i0}, r_{i1}\}$. Meanwhile, sophisticated investors' information set is $I_1^s = \{q, r_{i0}, r_{i1}, m_i, \pi\}$. For simplicity, we assume that each investor only invests in one fund. Henceforth, we abstract the subscript i in the investor's problem. Problem (3.3.2) solves for the optimal portfolio allocation:

$$\max_{X_1^j \geq 0} \quad E(-e^{-\gamma W_2^j} | I_1^j) \qquad\qquad s.t \quad W_2^j = W_1^j + X_1^j r_2, \tag{3.3.2}$$

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

Lemma 3.3.1. *At date* $t = 1$*, the optimal allocation of any investors who have a posterior belief that the fund manager has a higher ability with probability* $q_1^j := Prob(\alpha_i = \alpha_h | I_1^j), j = s, n$ *is*

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

where $x(q_1^j) > 0$ *and strictly increases in* q_1^j*.*[15]

Lemma 3.3.1 indicates that there exists a threshold of $\hat{r}_1^j, j = s, n$ such that the optimal allocation $X_1^{j*} = x(q_1^j)$ is positive only if $r_1 > \hat{r}_1^j$. Intuitively, only when the expected return of the fund is positive, $q_1^j\alpha_h + (1 - q_1^j)\alpha_l > 0$, indicating that the return at date 1 is higher than a certain threshold, investors would like to hold the fund.

Participation Decision

Performance chasers make the optimal decision by comparing the expected benefit with the participation cost if they pay. At date 0, performance chasers observe the risky return r_0 and update their belief on the distribution of the manager's ability q_0^n based on equation (3..6). Investors then observe fund return r_1 and update their beliefs based on the available information. They would learn about the prior q as sophisticated investors if they pay the cost. The updated belief is q_1^n defined in equation (3..7). Note that the participating performance chasers do not observe the company's marketing strategies, so their posterior is not based on the marketing plan $\mathcal{M}$.

We allow each performance chaser to have different levels of financial sophistication and different learning costs. To capture the heterogeneity, we follow Huang et al. (2007) and assume that performance chaser, indexed by k, has the par-

[15] See appendix 3.B for detailed proof and properties of $x(q_1^j)$.

ticipation 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 3.3.1, we can calculate the certainty-equivalent wealth gain from investing in new funds:

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

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

Lemma 3.3.2. *Given r_0, the certainty-equivalent wealth gain $g(r_1; r_0)$ satisfies*

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

where

$$\tilde{q}_1^n \equiv Pr(\alpha = \alpha_h | r_0, r_1) = \frac{q_0^n(z)}{q_0^n(z) + (1 - q_0^n(z)) \exp(-\frac{(2r_1 - \alpha_h - \alpha_l)(\alpha_h - \alpha_l)}{2\sigma^2})} \qquad (3.3.3)$$

$q_0^n, f(z)$ *are defined by equation* (3..6), X_1^{n*} *by lemma 3.3.1.*

Performance chasers base their participation decision only on the fund's past performance $\{r_1; r_0\}$. We obtain the certainty-equivalent wealth gain $g(r_1; r_0)$ as a function of q_0^n and r_1. q_0^n is monotonically increasing in r_0. $g(r_1; r_0)$ is increasing in both r_1 and r_0, as plotted in Figure 3.3.2.[16] For performance chaser k with the participation cost $c_k = \delta_k c(m)$, there exists a unique cutoff return $\hat{r}(c_k)$ such that the investor chooses to participate if and only if $r_1 \geq \hat{r}(c_k)$.

Separating Equilibrium

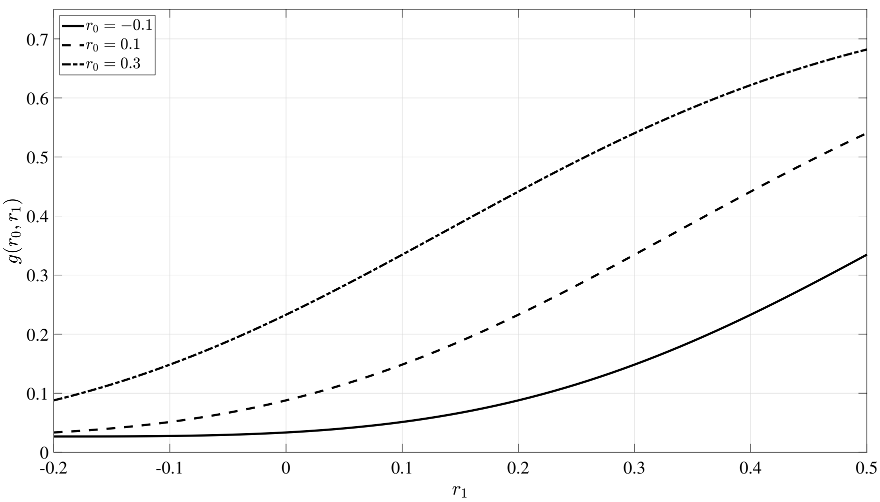
Given the optimal portfolio allocation in Section 3.3.2 and participation decision in Section 3.3.2, we now determine the optimal marketing strategy at date 0.

At date 0, the type of ability is revealed to fund managers. Given their abilities and date 0 performance r_0, fund companies choose the optimal marketing strategy

[16] See Appendix 3.B for the proof.

Figure 3.3.2. Relation Between the Gain Function and Fund Returns

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



$\pi^*(\alpha, m)$, and marketing employment m^* to maximize the net profits, equal to the expected flow of sophisticated investors and performance chasers minus the salary paid to marketing employees. As participation cost is a function of the level of marketing force m given the observed past return r_0, m directly impacts the expected net profits by altering the flow of performance chasers and wage costs. At date 0, fund companies maximize the *expected net profits* $U^F(\alpha_i, m, X_1^s)$ in equation (3.3.4) for a given ability type α_i and r_0,

$$U^F(\alpha_i, m, X_1^s) = f \int_{-\infty}^{\infty} \left[X_1^s + \lambda \min(1, \frac{g(r_1; r_0)}{c(m)}) X_1^{n*} \right] \phi(r_1|\alpha_i, \sigma_\epsilon) dr_1 - wm, \tag{3.3.4}$$

where $r_1 \sim N(\alpha_i, \sigma_\epsilon)$, $\phi(r_1|\alpha_i, \sigma_\epsilon)$ is the corresponding probability density function, $i = h, l$. f is the management fee charged by the fund, and w is the wage per marketing employee. The optimal allocation rule for sophisticated investors X_1^s follows Lemma 3.3.1. We assume that the cost of hiring managers and other skilled employees is fixed in this context for simplicity.[17] The overall expected revenue consists of two parts: (1) the expected revenue from the sophisticated investors and (2) the expected revenue from the performance chasers. Based on the insight of Lemma 3.3.1, improved revenue from sophisticated investors can be achieved through either a stronger past performance, denoted as r_0, or an increased belief among investors that the likelihood of being a high-type investment is high. The second component is the income generated from the information acquisition channel. Based on Lemma 3.3.2, both the participation decision and the strength of past performance play a key role to increase this part of income.

We focus on pure strategies. We define the Nash Equilibrium in Appendix 3.A. The equilibrium is characterized by the schedule of marketing profits, the sophisticated investor's portfolio allocation X_1^s, and optimized employment choice given the portfolio allocation of sophisticated investors. The following proposition shows the conditions of the existence of the separating equilibrium in the space of pure strategy.

Proposition 3.3.3. *Given $r_0 \geq \hat{r}$, the single crossing property is satisfied. A separating equilibrium exists and satisfies the intuitive criterion. A mutual fund company's optimal marketing strategy is heterogeneous conditional on its types.*

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

Proposition 3.3.3 shows that a separating equilibrium exists when past performance r_0 is not too weak, $r_0 \geq \hat{r}$. The proof is in Appendix 3.B.

Figure 3.3.3 illustrates the intuition behind Proposition 3.3.3. We plot the expected profits as a function of the marketing employment m given different levels

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

of past performances, r_0. The expected profit function is non-convex in m. First, the equilibrium is pooling when the past performance is weak, $r_0 < \hat{r}$. When the historical performance is poor, performance chasers are unlikely to invest even if marketing employees can lower information acquisition cost $c(m)$. The information-acquisition channel of marketing is insignificant. The weak performance also deters the flow from sophisticated investors. Hence, the expected profit U^F strictly decreases in m given the cost of marketing employees as in Panel A of Figure 3.3.3. This scenario is close to a classic costly signaling setting (Spence, 1973), where signals do not directly affect the output. Given that the marginal cost of signal, w, is identical for both high and low types, the single crossing property is not satisfied, and the separating equilibrium doesn't exit. The optimal marketing employment $m_h^* = m_l^* = 0$ (i.e., the m that maximizes expected profits) is zero for both high and low types. If the high type chooses to hire $m_h^* > 0$ in the equilibrium, the low type would always deviate. When mimicking the high type, the expected profit for the low type is improved by paying a marketing cost and getting the expected flow from sophisticated investors. Choosing $m > 0$ is costly and not profitable for the high type.

However, the benefits of the separating equilibrium are more pronounced when past performance is relatively strong ($r_0 > \hat{r}$). Facing a high r_0, the potential profits from new flows can be large if fund companies lower the participation cost $c(m)$. In this case, the signaling directly contributes to the return of the fund, and the profit function is concave in m. For a concave objective, the high type can achieve a larger inflow by hiring $m > 0$ and separating them from the low type. However, it is not a dominant strategy for the low type to mimic because maintaining a large marketing force is costly. Depending on how strong the past performance is, the low type might choose not to hire or hire a positive number of marketing employees to lower the participation cost for its performance chasers. Panels B and C of Figure 3.3.3 concern the two different scenarios, which we will discuss in Section 3.3.2.

Optimal Marketing Employment Policy

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

Proposition 3.3.4. *In any separating equilibrium $r_0 \geq \hat{r}$, a high-type manager always chooses to hire marketing employees, $m_h^* = m^*(\alpha_h; r_0) > 0$, while a low-type manager's policy is the following:*

$$m_l^* = \begin{cases} m^*(\alpha_l; r_0) & if \quad r_0 > \tilde{r} \\ 0 & if \quad r_0 \leq \tilde{r} \end{cases} \tag{3.3.5}$$

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

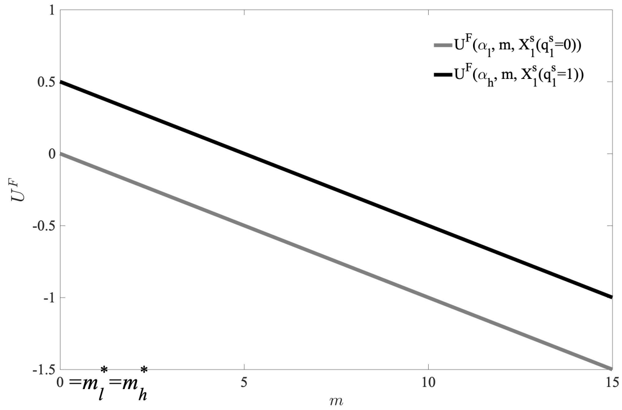
From Proposition 3.3.3, the optimal number of marketing employees for both ability types is zero when the return is lower than the threshold $r_0 < \hat{r}$ at time $t = 0$, and the equilibrium is pooling. When the past performance r_0 is stronger than the threshold return $\hat{r}$, high-type funds start building their marketing force $m_h^* > 0$. However, for the low-type funds to have a positive marketing force, it requires a much higher return threshold $\tilde{r} > \hat{r}$. Proof of Proposition is in Appendix 3.B. We discuss two scenarios of this proposition and illustrate the separating equilibrium in Figure 3.3.4.

Scenario I: $\tilde{r} > r_0 > \hat{r}$. When the past performance is moderately strong ($\tilde{r} > r_0 > \hat{r}$), the high type will hire $m_h^* > 0$, while the low type stays away from marketing $m_l^* = 0$. Intuitively, fund companies will attract little flows

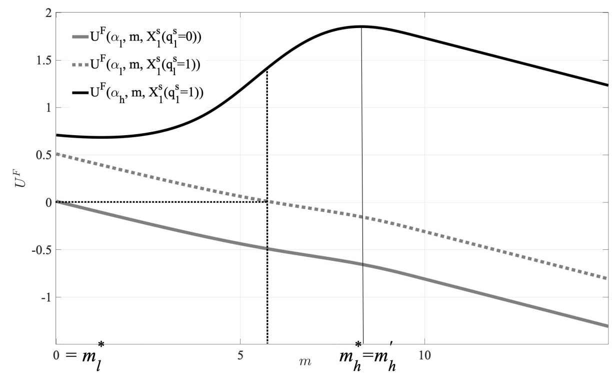
Figure 3.3.3. Expected Profits When Signaling is Costly and Productive

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

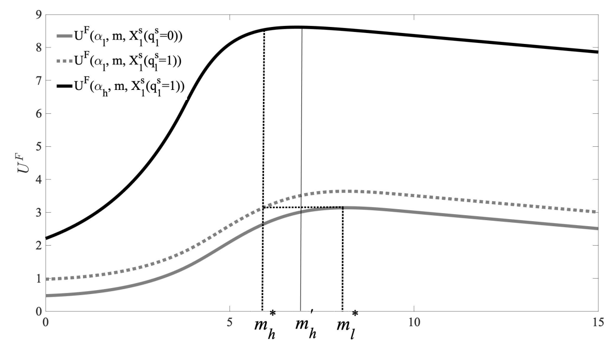
Panel A: $r_0 < \hat{r}$ Pooling



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



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



from performance chasers when past performance r_0 is not strong, even with the substantial marketing effort. Both the expected return at date $t = 1$ and signaling costs matter for the expected profits. High-type funds are more confident in signaling themselves even if the realized past return is not outstanding because their expected return at date 1 is good. The low-type funds could mimic the high-type funds to hire the same number of marketing employees. However, once the low-type funds deviate from the separating equilibrium, they are still unlikely to profit, given their low expected return and costly marketing. There exists a threshold $\tilde{r}$ so that a low-type is indifferent in mimicking or not—that is the IC constraint is binding in Equation (3.3.6).

$$U^F(\alpha_l, m_h^*, X_1^{s^*}(q_1^s = 1)) \leq U^F(\alpha_l, m_l^*, X_1^{s^*}(q_1^s = 0)) \tag{3.3.6}$$

This scenario is shown in Panel B of Figure 3.3.3. The dotted line plots the left side of the IC constraint, i.e. the expected profits of low-type funds, when the low type mimics the high type and sophisticated investors, allocate given they observed m_h^* and believe the manager as the high-type ($q_1^s = 1$). The right side of the IC constraint is the expected profits of the low type in the separating equilibrium. Since $U^F(\alpha_l, m_h^*, X_1^s(q_1^s = 1))$ is increasing in r_0, so $\tilde{r}$ is the threshold performance level that the IC constraint is binding. When $\tilde{r} > r_0 > \hat{r}$, the high type will hire m_h^* to maximize the expected profits. Given the costly signaling, the best response of low-type funds is to not hire any marketing employees $m_l^* = 0$.

Scenario II: $r_0 > \tilde{r}$. Low-type funds will only hire to lower the participation costs and attract inflows from performance chasers when the past performance is strong enough $r_0 > \tilde{r}$. To ensure a separating equilibrium, the high-type fund now deviates from its optimal marketing employment level (the m_h' that maximizes the expected profits for the high-type fund) to the equilibrium m_h^* in Panel C of Figure 3.3.3, so that it becomes too costly for the low-type fund to mimic.

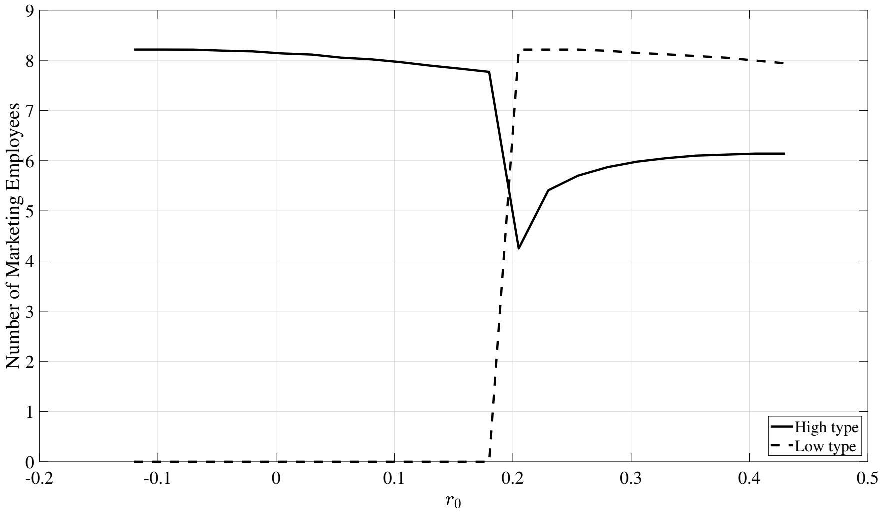
The dotted line in the figure shows the expected profits for the low-type fund if it mimics such efforts. Hiring m_h^* makes it indifferent for the low-type fund to mimic. Optimally and efficiently, the high type should hire any number less than m_h^* to ensure that the benefit of pooling equilibrium is smaller than the separating equilibrium. As a result, the low-type fund stays at m_l^* to enjoy the maximized flow from the performance chasers.

We next discuss the equilibrium uniqueness. Note that, in the case of Panel C of Figure 3.3.3, there exists one more separating equilibrium given the concave profit function. In signaling games with two types, we use the intuitive criterion proposed in Cho and Kreps (1987) to get the unique equilibrium: the best separating equilibrium. This refinement is particularly relevant when $r_0 > \tilde{r}$. Given the concave profit function, the high-type fund faces two options to achieve separation. The first is what is shown in Panel C, an equilibrium $m_h^* < m_h'$ on the left of the profit-maximizing marketing level m_h'. The second is a $m_h^* > m_h'$ on the right of the profit-maximizing marketing level. That is, the high-type funds may be better off choosing a slighter higher or lower number of marketing employees than m_h'. Given the intuitive criterion, the separating equilibrium with the most efficient m_h^* would be the unique equilibrium in this signaling game where $m_h^* < m_h'$ as long as $m_h^* > 0$. Under specific choices of the parameter set, $m_h^* > m_h'$ can be the only available equilibrium if choosing a lower amount of marketing force is not feasible.

Figure 3.3.4 summarizes the marketing employment policy of both high type and low type within the reasonable regime of the realized returns. The high-type fund keeps the size of its marketing force relatively persistent. A high-type fund maintains its marketing force even if it experiences negative past returns because it knows that the low return is a small probability event. A low-type fund chooses to enhance its marketing force after the realization of a strong past performance.

Figure 3.3.4. Optimal Marketing Plans for Two Types of Abilities

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



In the separating equilibrium, it could even build up a larger marketing force than the high-type fund to attract flows from the performance-chasing investors. This implication shares a similar insight as in Roussanov et al. (2021)—namely, that the low-skilled funds over-market themselves, leading to misallocation between capital and skill.

3.3.3 Testable Model Implications

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

Persistence of Marketing Strategy and Fund Manager Skill

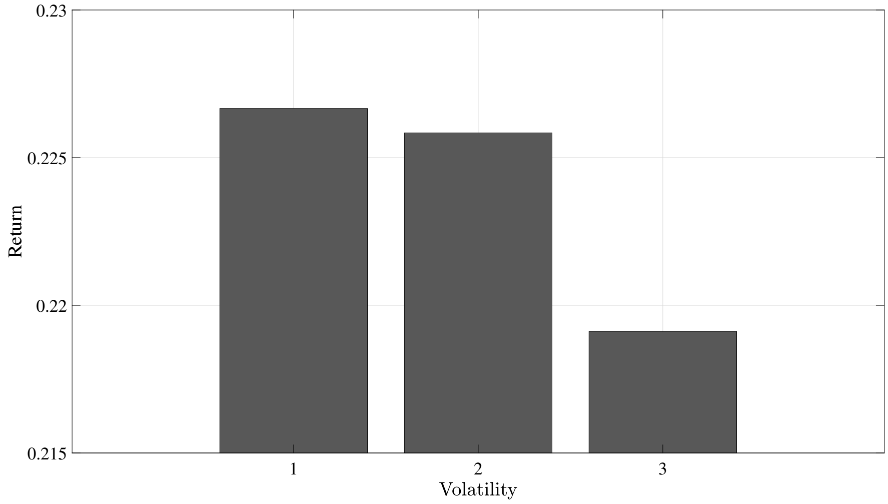
As our Proposition 3.3.3 indicates, fund companies optimally fully reveal their types via the optimal marketing strategy when past performance is not too weak. In Figure 3.3.4, high-type fund companies signal themselves by hiring a large marketing force even when the past performance was poor. As long as the performance is higher than the threshold return for the separating equilibrium, high-type funds enhance their marketing force. This is because they are confident in their future performance after observing their type at date 0. However, this is not the case for low-type fund companies. The optimal marketing effort is zero if the return at time 0 is lower than the threshold, and this threshold is much higher for the low-type fund companies to maintain a positive scale of the marketing labor force. Suppose the average performance for the high-type fund is superior enough. In that case, its optimal marketing employment policy will not experience a non-marketing regime over the observed realized past returns, making them much more persistent than the strategies adopted by the low-type funds. This insight from the model yields the following testable implication:

Remark 3.3.5. ***Persistent Marketing Strategies.*** *Given that $\alpha_l \leq \alpha_h$ and ϵ_{it} is normally distributed, there is a smaller variation in the marketing labor force $\sigma(m_h^*)$ in the high-type fund companies than that in the low-type fund companies.*

Figure 3.3.5 shows that the volatility of marketing employment level m in our calibrated numerical example is correlated with the fund performance. There is more volatility in marketing labor forces/actions in the low-type mutual funds. The persistence of marketing strategy, instead of past performance, then reveals the fund company's average skill. The Remark 3.3.5 stands as the unique implication of costly signaling and learning, and we test this result in our next section. Note that in Remark 3.3.5, it is essential for α_l not to be significantly smaller than α_h. If there is a substantial difference, investors can reasonably infer the

Figure 3.3.5. Return Predictability of Marketing Strategy Volatility

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



fund's type based on past performance alone, leading the low-type fund to consistently choose $m_l^* = 0$ in equilibrium. In our calibrated numerical example, we set α_l and α_h as one standard deviation below and above the mean of net return in the sample. We argue that a broad range of reasonable choices of mean and standard deviation for the return distribution would yield results exhibiting a similar pattern as in Figure 3.3.5. In our empirical test, we exclude funds with a marketing employment share of zero throughout the sample.

Marketing Strategies and Fund Flow

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

Remark 3.3.6. ***Expected flow under optimal choices.*** *The fund flow* $F(r_1)$

at time $t = 1$ *is written as*

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

where X_1^{s*} *and* X_1^{n*} *are defined in Lemma 3.3.1, and the gain function* $g(r_1; r_0)$ *is from Lemma 3.3.2.*

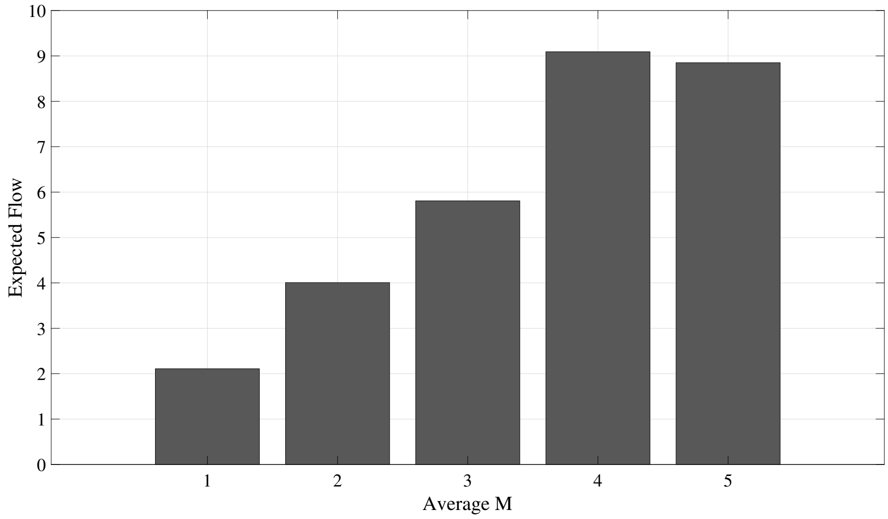
Figure 3.3.6 describes the total expected flow of mutual funds given their past performance and optimal marketing employment policy. Noticeably, the expected fund flow is increasing in the number of marketing employees given the fund's past performance r_0. The average number of marketing employees is the expected number weighted by the probability of ability types of mutual funds. The learning channel drives this positive correlation between the expected fund flow and marketing policy. The more marketing employees are hired, the lower the participation costs for performance chasers and, hence, larger new inflows on average. Given X_0^s, the relative comparative statics for fund flow is equivalent to that for the fund size.

3.4 Tests of Model Predictions

In this section, we test several unique predictions from our model. We first test the hypothesis about the relationship between marketing persistence and fund company performance. Then, we examine the predictions of optimal m^* on equilibrium (i.e., MKT) that we observe on fund flow. The results support our model as a relevant economic force in the real world.

Figure 3.3.6. Relationship between Expected Flow and the Optimal Marketing Employment

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



3.4.1 Marketing Persistence and Fund Performance

Our model implies a full disclosure of marketing strategies by high- and low-type mutual funds if past performance is not too weak. That is, high alpha funds should exhibit persistent marketing efforts with respect to fund performance, while low-type funds' marketing input tends to change with past performance. A testable implication from this model prediction is that funds with more persistent MKT should exhibit better long-term fund performance as shown in Figure 3.3.5.

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

$$\text{Firm Return}_{i,t+1} = Vol(MKT)_i + \text{Firm Return}_{i,t} + Control_{i,t} + v_t + \epsilon_{i,t+1}. \quad (3.4.1)$$

Firm $\text{Return}_{i,t+1}$ refers to the value-weighted average returns of mutual funds that fund company i manages in month $t+1$. As a fund company may manage mutual funds with different styles and asset focuses, including domestic equity, fixed income, international, and balanced, we adjust fund return with a 6-factor model, which augments Carhart's 4-factor model with an international market factor and a bond market factor, as our baseline measure.[18] We also use CAPM-adjusted fund returns and raw returns as alternative measures. We control for Firm Return at year t and fund company characteristics, including size, age, the number of managed funds, and the expense ratio. We show the Fama and MacBeth (1973) estimates of monthly fund firms' performance regressed on firm characteristics lagged one month. The t-statistics are adjusted for serial correlation using Newey and West (1987) lags of order 12. Note that this is not a test of forecasting fund returns, as $Vol(MKT)_i$ is calculated using full sample information.

Table 3.D.2 reports the results. In Panel A, gross fund returns are used, as the before-fee returns presumably better measure fund skills. In column (1), we use 6-factor adjusted fund returns and find that the coefficient before $Vol(MKT)$ is significantly negative (t-stat = 4). In terms of economic magnitude, a one-standard-deviation decrease in $Vol(MKT)$ is associated with a 3.75 bps higher 6-factor gross alpha per month. This is sizeable given that the average monthly 6-factor gross alpha of fund companies in our sample is -2 bps. The coefficient before past firm return (6-factor Alpha_t) is significantly positive, consistent with

[18] 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.

the smart money effect (e.g., Zheng (1999)). The firm expense ratio is not correlated with higher gross fund returns, and firm size is positively correlated with performance; the two patterns are consistent with the findings in the literature (e.g., Chen et al. (2004)). The coefficient of firm age is insignificant.

In column (2), we use the level of $MKT_{i,t}$ instead of $Vol(MKT)$ in regression (3.4.1). 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 3.3.4 with model simulation). Consistent with the model prediction, the coefficient of MKT is not significantly different from zero. This finding also echoes the results of Jain and Wu (2000) and Bergstresser et al. (2009), who showed the level of marketing efforts is not correlated with performance. In column (3), we further include both MKT and $Vol(MKT)$ into the right-hand side of the regression, and the coefficients of MKT and $Vol(MKT)$ are virtually unchanged compared with columns (1) and (2). In columns (4)–(6) and (7)–(9), we repeat the analysis with CAPM-adjusted gross returns and raw fund gross returns, respectively, and the results are robust. In Panel B, we repeat the regressions using net-of-fee fund returns; the results are virtually the same.

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

B the results using net fund returns; in all specifications, fund performance is significantly predicted by $Vol(MKT)_t$.

Next, we conduct several robustness tests. In Panel A of Table 3.D.4, we use an alternative way to measure the variability of firm MKT: the range of MKT over the past 3-year rolling window (denoted as $Range(MKT)_t$). We find that the coefficients of $Range(MKT)_t$ remain significantly negative (with t-stats between 4.5 to 5.9). In Panel B, we replace the left-hand side variable with the adjusted return of the fund company's flagship fund. Flagship fund is defined as the largest fund that the company manages based on AUM. The results are also robust: the coefficients before $Vol(MKT)_t$ are significantly negative (with t-stats between 3.05 to 6.02).

In Table 3.D.5, we examine whether the volatility of total employment ($Vol(EMP)$) or the volatility of investment-oriented employment share ($Vol(INV)$) exhibits a similar predictability of fund performance. We define EMP as the number of total employees and INV as the fraction of investment-oriented employees to total employment. This is to address the concern that the volatility of marketing employment share may capture funds' labor adjustment cost or turnover rate of the general labor force, which might be related to fund investment skills. Our results show this is not the case; neither $Vol(EMP)$ nor $Vol(INV)$ exhibits significant predictability of fund returns. This finding highlights the uniqueness of marketing-oriented employees, who can lower the participation cost and be used as a signaling device of fund type.

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

The coefficients of $Vol(12b1)$ are all negative in both panels and significant at the 10% level when using 6-factor gross and net returns.

Figure 3.D.3 visualizes our baseline finding in Table 3.D.2. We sort all fund companies into quintiles based on $Vol(MKT)$ and plot the average firm returns on the y-axis. We use gross returns in the upper panel and 6-factor adjusted returns in the lower panel. Average fund returns decrease with $Vol(MKT)$, particularly Groups 4 and 5.

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

For month t, we define fund-level *Value Added*$_t$, as a fund's 6-factor alpha (based on gross returns) times the fund's AUM at the beginning of the month. We take the value-weighted average of value added of all funds in the fund company. Then, we re-estimate the regressions (3.4.1) by replacing the dependent variable with *Value Added*$_t$. Table 3.D.7 shows that the results are consistent with our conjecture. The coefficient of $Vol(MKT)$ is negative with a t-statistic around 5, while MKT itself is insignificant. In columns (4)–(6), the rolling $Vol(MKT)_t$ is used, and the results are similar, albeit at a noisier point estimation.

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

3.4.2 Optimal *MKT* and Fund Flows

The previous subsection shows that the optimal m^* (or, empirically, the level MKT that we observe in the data) does not necessarily reveal the funds' type. Nonetheless, our model suggests that MKT is unambiguously associated with fund companies' subsequent fund flow and asset growth. As discussed in Section 3.3, such an effect arises through two channels. First, high-type funds, which adopt persistently high levels of MKT to separate from low-type funds, tend to exhibit better performance and more inflow. Second, due to costly learning, low-type funds may increase MKT upon good past performance to attract subsequent inflow. Thus, in the cross section, we expect MKT to be positively correlated with subsequent fund flow or asset growth (Figure 3.3.6 shows these results with model simulations). Furthermore, as the former channel (i.e., signaling) is driven by fund companies' type, which is likely time-invariant, the cross-sectional effect should be significantly attenuated after controlling for firm fixed effects.

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

$$Firm\ Flow_{j,t+1} = \alpha + \beta_1 MKT_{j,t} + Controls_{j,t} + \epsilon_{i,t+1}. \tag{3.4.2}$$

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

Table 3.D.8 reports the results. In column (1), the coefficient of MKT is significantly positive, suggesting that those fund companies with high marketing employee shares tend to experience more subsequent fund flow. The coefficient of MKT equals 1.319 (with a t-statistic of 2.4) and is economically meaningful: A one-standard-deviation increase in MKT is associated with a 32.2% increase in fund flow, which equals 53% of the average growth rate (i.e., 60.7%) during our sample period.

The coefficient of $Firm\ Expense$ appears to be negative, with a t-statistics of 4.5. If $Firm\ Expense$ is a proxy for the company's spending on advertising and distribution, then it is hard to interpret this result. Nonetheless, this pattern is likely driven by investors' preference for funds with lower fees. The difference in the effect on future asset growth between MKT and $Firm\ Expense$ highlights the importance of measuring marketing efforts by human capital. In column (2), we add firm fixed effects into equation (3.4.2), which can rule out unobservable and time-invariant firm characteristics, such as firms' skill level. The point estimate of the coefficient of MKT remains positive but becomes insignificant (t-stat = 0.9), consistent with our conjecture.

Next, we examine alternative measures of firm growth. First, in columns (3) and (4), we use the growth rate of total assets under management of the fund company, denoted as $\Delta Firm\ Assets_{j,t+1}$. We find similar results that MKT forecasts the high growth of the fund company in the pooled regression, but such an effect becomes weaker and insignificant after controlling for firm effects. Second, in columns (5) and (6), we construct the growth rate of total firm revenue (assets times expense ratio), $\Delta Firm\ Revenue_{j,t+1}$ as the dependent variable. We find a highly similar pattern that hiring more marketing employees is associated with higher revenue. Overall, the evidence shown in Table 3.D.8 provides additional support to our model.

3.5 Conclusion

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

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

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Appendices

3.A Equilibrium

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

Definition 3..1. *Behavior strategies (π^*, μ^*) form a Nash Equilibrium if and only if*

1) for $i = l, h$

$$\pi^*(\alpha_i, m') > 0 \quad \textit{implies} \quad \sum_{X_1^s} U^F(\alpha_i, m', X_1^s)\mu^*(m', X_1^s) = \max_m \sum_{X_1^s} U^F(\alpha_i, m, X_1^s)\mu^*(m, X_1^s) \tag{3..1}$$

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

$$\mu^*(m', X_1^{s'}) > 0 \quad \textit{implies} \quad \sum_{\alpha_l, \alpha_h} U^s(\alpha_i, m, X_1^{s'})q_1^{s^*}(\alpha_i, X_1^{s'}) = \max_{X_1^s} \sum_{\alpha_l, \alpha_h} U^s(\alpha_i, m, X_1^s)q_1^{s*}(\alpha_i, X_1^s) \tag{3..2}$$

where

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

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

3.B Proofs

Proof of Lemma 3.3.1

At date 1, investors who have a posterior belief that $\alpha = \alpha_h$ with probability q_1^j solve Problem (3.3.2):

$$\max_{X_1^j \geq 0} \quad E(-e^{-\gamma W_2^j}|I_1^j) \qquad\qquad s.t \quad W_2^j = W_1^j + X_1^j r_2, \tag{3..4}$$

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

$$\tilde{q}_1^n \equiv Pr(\alpha = \alpha_h | r_0, r_1) = \frac{q_0^n(z)}{q_0^n(z) + (1 - q_0^n(z)) \exp(-\frac{(2r_1 - \alpha_h - \alpha_l)(\alpha_h - \alpha_l)}{2\sigma^2})}, \tag{3..5}$$

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

$$q_0^n \equiv Pr(\alpha = \alpha_h | r_0) = \frac{1}{1 + \exp(-\frac{(2r_0 - \alpha_h - \alpha_l)(\alpha_h - \alpha_l)}{2\sigma^2})z}, \tag{3..6}$$

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

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

$$q_1^n \equiv Pr(\alpha_i = \alpha_h | q, r_0, r_1) = \frac{q_0^s}{q_0^s + (1 - q_0^s) \exp(-\frac{(2r_1 - \alpha_h - \alpha_l)(\alpha_h - \alpha_l)}{2\sigma^2})}. \tag{3..7}$$

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

$$q_0^s \equiv Pr(\alpha_i = \alpha_h | q, r_0) = \frac{q}{q + (1 - q) \exp(-\frac{(2r_0 - \alpha_h - \alpha_l)(\alpha_h - \alpha_l)}{2\sigma^2})}. \tag{3..8}$$

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 3.3.2 is equivalent to

$$\max_{X_1 \geq 0} \quad E(-e^{-\gamma W_2}|I_1^j) = \min_{X_1 \geq 0} e^{\frac{1}{2}\gamma^2 \sigma_\epsilon^2 X_1^2}(q_1^j e^{-\gamma \alpha_h X_1} + (1 - q_1^j) e^{-\gamma \alpha_l X_1}) \tag{3..9}$$

the first-order conditions can be written as

$$\gamma\sigma_\epsilon^2 X_1(q_1^j e^{-\gamma\alpha_h X_1} + (1-q_1^j)e^{-\gamma\alpha_l X_1}) - (q_1^j\alpha_h e^{-\gamma\alpha_h X_1} + (1-q_1^j)\alpha_l e^{-\gamma\alpha_l X_1}) = 0 \quad (3..10)$$

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 (3..10) 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 (3..10).
  - 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 (3..10) as

$$f(X_1) - h(X_1) = (1-q_1^j)e^{-\gamma\alpha_l X_1}(\gamma\sigma_\epsilon^2 X_1 - \alpha_h)p(X_1) = 0 \quad (3..11)$$

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

    X_1^* is an optimal allocation if and only if $X_1^* < \frac{\alpha_h}{\gamma\sigma_\epsilon^2}$ and $p(X_1^*) =$

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

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

To summarize, the solution to Problem (3.3.2) is

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

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

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

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

Proof of Lemma 3.3.2

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

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

From the solution to the portfolio allocation problem (3.3.2), we can define the gain function as

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

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

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

and $f(z) = \frac{1}{(z+1)^2}$, $z \in [0, +\infty)$ by equation (3..6). Hence the certainty equivalent wealth gain is equal to

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

where $\tilde{q}_1^n$ is defined by equation (3..5) and q_0^n is defined by equation (3..6). q_0^n is increasing in r_0. $\tilde{q}_1^n$ is increasing in r_1 and q_0^n. Notice that the integrated part is the minimum of the objective function as (3..9). For the convenience, define $Fval(X_1^{n*}) \equiv (\tilde{q}_1^n e^{-\gamma\alpha_h X_1^{n*}} + (1-\tilde{q}_1^n)e^{-\gamma\alpha_l X_1^{n*}})e^{\frac{1}{2}\gamma^2\sigma_\epsilon^2 X_1^{n*}}$.

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

From the first order conditions of solving the optimization problem (3..9), $\frac{\partial\, Fval(X_1^{n*}(\tilde{q}_1^n))}{\partial\, X_1^{n*}} = 0$. The integrated function $Fval(X_1^{n*}(\tilde{q}_1^n))$ is decreasing in $\tilde{q}_1^n$ because

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

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

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

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

Proof of Proposition 3.3.3

First, we discuss the utility of funds when selecting m, which equals the fee charged for the assets of sophisticated investors and performance chasers minus the salary paid to marketing employees. Only performance chasers who choose to pay the cost would have investments in funds. Given the posterior belief of performance chasers after paying the cost, q_1^n in equation (3..7), Lemma 3.3.1 indicates that there exists a threshold of $\hat{r}_1$ such that the optimal allocation of performance chasers $X_1^{n*} = x(q_1^n)$ is positive only if $r_1 > \hat{r}_1$. $\hat{r}_1$ satisfies the equation

$$\frac{1}{1+(\frac{1}{q}-1)\exp(-\frac{(\hat{r}_1+r_0-\alpha_h-\alpha_l)(\alpha_h-\alpha_l)}{\sigma^2})} = \frac{-\alpha_l}{\alpha_h-\alpha_l} \tag{3..12}$$

Intuitively, only when the expected return of the fund is positive, $q_1^n\alpha_h + (1-q_1^n)\alpha_l > 0$, indicating that the return at date 1 is higher than a certain threshold, investors would like to hold the fund. Equation (3..13) restates Lemma 3.3.1 for the performance chasers:

$$X_1^{n*} = \begin{cases} x(q_1^n) & if \quad r_1 > \hat{r}_1 \\ 0 & if \quad r_1 \leq \hat{r}_1 \end{cases} \tag{3..13}$$

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

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

For the simplicity of notation, let U_i^F denote the utility of funds with type α_i. At any separating equilibrium, the skill type is fully revealed by the marketing level m. Sophisticated investors believe they know the true type by observing m. The optimal allocation is $X_1^{s^*}(1)$ if the manager is perceived to be high type and $X_1^{s^*}(0) = 0$ if it's low type. In such cases, it's convenient to define $U_i^F(m,1) = U^F(\alpha_i, m, X_1^{s^*}(1))$ and $U_i^F(m,0) = U^F(\alpha_i, m, X_1^{s^*}(0))$. Given the definition of $FN(r_1, m)$, the expected profits (3.3.4) of a fund with ability α_i can be written as

$$U_i^F(m, X_1^{s^*}(I)) = fX_1^{s^*}(I) + f\lambda\int_{\hat{r}_1}^{\infty} FN(r_1,m)\phi_i(r_1)dr_1 - wm,\ I = 0\,or\,1, \tag{3..14}$$

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

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

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

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

where $\hat{r}_1(\hat{r})$ is the solution to equation (3..12) given $r_0 = \hat{r}$. When $r_0 < \hat{r}$, $g(r_1; r_0) \geq c(m)$ for all $r_1 > \hat{r}_1$. In that case, the utility function (3..14) is equal to

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

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

Case II: $r_0 \geq \hat{r}$**.** Second, when $r_0 \geq \hat{r}$, the strict single crossing property is satisfied. There exists a threshold $\bar{r}_1 > \hat{r}_1$ of returns at date 1 such that $g(\bar{r}_1; r_0) = c(m)$. The utility function (3..14) is equal to

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

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

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

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

$$\begin{aligned} &\max U_h^F(m, X_1^{s^*}(1)) \\ &\text{subject to } U_l^F(m, X_1^{s^*}(1)) \leq U_l^{F^*}. \end{aligned} \tag{3..15}$$

When the optimization problems in Steps 1 and 2 have solutions, we know it is a separating equilibrium. The low-type manager won't deviate from the equilibrium given that m_h^* is selected in Step 2 to satisfy the constraint in Problem (3..15). Because m_h^* is the solution to Problem (3..15) and the utility is strictly increasing in X_1^s,

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

The high-type manager won't deviate.

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

$$\frac{\partial U_i^F(m, X_1^{s^*}(I))}{\partial m} = -f\lambda \frac{c'(m)}{c^2(m)} \int_{\hat{r}_1}^{\bar{r}_1} g(r_1; r_0) x(q_1^n) \phi_i(r_1) dr_1 - w \qquad (3..16)$$

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

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

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

Proof of Proposition 3.3.4

First, we discuss the curvature of funds' expected utility with respect to the marketing level m. From the previous equation (3..16), the second-order derivative of the utility function is equal to

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

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

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

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

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

$$-\frac{c'(m_i')}{c^2(m_i')} = \frac{w}{f\lambda \int_{\hat{r}_1}^{\tilde{r}_1} g(r_1; r_0)\phi(r_1|\alpha_i, \sigma_\epsilon) X_1^{n*} dr_1} \qquad (3..17)$$

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

$$-\frac{c'(0)}{c^2(0)} = \frac{w}{f\lambda \int_{\hat{r}_1}^{g^{-1}(c(0);\tilde{r}_{i,0})} g(r_1; \tilde{r}_{i,0})\phi(r_1|\alpha_i, \sigma_\epsilon) X_1^{n*} dr_1} \qquad (3..18)$$

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

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

there exists a positive solution to equation (3..17). Thus for the low-type fund, the optimal marketing level m_l^* in the equilibrium is equivalent to

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

From the equation (3..18), we know that $\tilde{r}_{h,0} < \tilde{r}_{l,0}$.

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

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

As long as

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

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

When $r_0 \geq \tilde{r}_{l,0} > \tilde{r}_{h,0}$, from the equation (3..17), we know that $m_h' < m_l' = m_l^*$

because $\phi(r_1|\alpha_h,\sigma_\epsilon) > \phi(r_1|\alpha_l,\sigma_\epsilon)$ and $-\frac{c'(m)}{c^2(m)}$ is increasing in m. In this case, to guarantee that funds would not deviate from the equilibrium, the optimal marketing level m_h^* satisfies the following

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

Rewriting the inequalities, we get

$$\begin{cases} w(m_h^* - m_l^*) \leq fX_1^s(1) + f\lambda \int_{-\infty}^{+\infty} (FN(r_1, m_h^*) - FN(r_1, m_l^*))\phi(r_1|\alpha_h, \sigma_\epsilon)dr_1 \\ w(m_h^* - m_l^*) \geq fX_1^s(1) + f\lambda \int_{-\infty}^{+\infty} (FN(r_1, m_h^*) - FN(r_1, m_l^*))\phi(r_1|\alpha_l, \sigma_\epsilon)dr_1 \end{cases} \tag{3..19}$$

Thus if

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

then there exists the optimal marketing level $m_h^* \leq m_h'$ such that $U^F(\alpha_l, m_h^*, X_1^s(1)) = U^F(\alpha_l, m_l^*, X_1^s(0))$. m_h^* is the solution to the equation (3..20),

$$w = \frac{f}{(m_h^* - m_l^*)}(X_1^s(1) + \lambda \int_{-\infty}^{+\infty} (FN(r_1, m_h^*) - FN(r_1, m_l^*))\phi(r_1|\alpha_l, \sigma_\epsilon)dr_1). \tag{3..20}$$

In this case, the inequalities (3..19) hold. (m_l^*, m_h^*) is the marketing strategy in the equilibrium and $m_h^* \leq m_h' < m_l^*$. The high-type fund would hire less than the low-type.□

3.C Data and Sample Construction

Form ADV data

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

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

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

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

In response to the Dodd–Frank Act, the SEC has made substantial changes to

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

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

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

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

Sample construction and variable definitions

We start by constructing a monthly file of mutual funds from CRSP. We download data on monthly net returns (*Fund_Return*), total net assets (TNA, *Fund Assets*), and *Expense Ratio* for each share class of a mutual fund and then collapse the share class level variables into fund level by taking the average value weighted by the previous month-end TNA. To identify a fund's different share classes, we use CRSP Class Group (crsp_cl_grp), which is available to all funds in CRSP. By comparison, the literature typically uses Mutual Fund Links (MFlinks), which only covers domestic equity mutual funds. Because our analysis is conducted at the company level, we must include *all* mutual funds in a company.[19]

We further categorize all funds into seven groups based on Lipper Objectives (crsp_obj_name).[20] Funds with TNA less than $1 million are dropped. We calculate each mutual fund's monthly flow (*Flow*) as the percentage of new funds that flow into the mutual fund over a month. *Flow* is winsorized at both the 1% and 99% levels at each month. *Fund Age* is the number of years since the inception of the fund.

To adjust fund performance for different risk exposures, we use a 6-factor model, which augments the Fama–French three-factor model (MKTRF, SMB, HML) with a momentum factor (MOM), a bond market factor, and a factor for international stock markets. This approach aims to better adjust risk exposures for international, balanced, and fixed-income mutual funds in our sample. We use the Bloomberg Barclays US Aggregate Bond Index (BABI) return as our bond factor and the Morgan Stanley Capital International index (MSCI) return to proxy the performance of international markets. In addition, we use CAPM-adjusted return as an alternative measure. This is motivated by the finding in Berk and van Binsbergen (2016) and in Barber et al. (2016): Investors use the CAPM-beta

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

[20] Following Chen et al. (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.

to adjust risk exposure when making investment decisions. For robustness, we also consider raw returns a simple measure of fund performance that an investor may use. In the regression, we adjust gross returns (the sum of the net return and the 1/12 expense ratio) and net returns of funds.

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

Next, we construct several company-level variables based on fund-level information. The identifier of the fund company that we use in CRSP is *adv_name*. Note that this differs from the management company name normally used in the literature to identify fund families. We use the adviser name because Form ADVs are filed by advisory firms, not by a fund family.[21] We also conduct our analysis at the fund company level and find similar results.

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

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

$TNA_{k,t} = \sum_{i=1}^{N} TNA_{i,t}$ and TNA refers to the total net asset value. *Firm Flow* is winsorized at the 1% and 99% levels by year. The variables *Firm Expense* and *Firm Return* equal the value-weighted average of the expense ratio and the

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

previous year's return or alpha of all funds in the company, respectively. The expense ratio is also winsorized at the 1% and 99% levels by year.

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

3.D Figures and Tables

Figure 3.D.1. Persistence of Fund Performance and Marketing

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

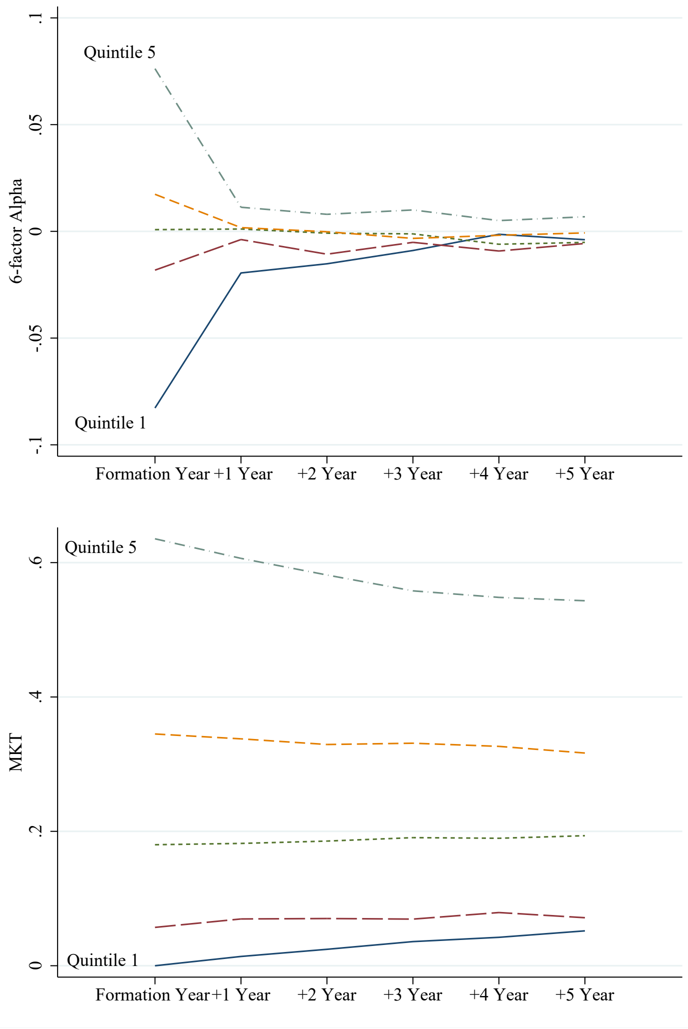

Figure 3.D.2. Heterogeneous Persistence of Fund Marketing

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

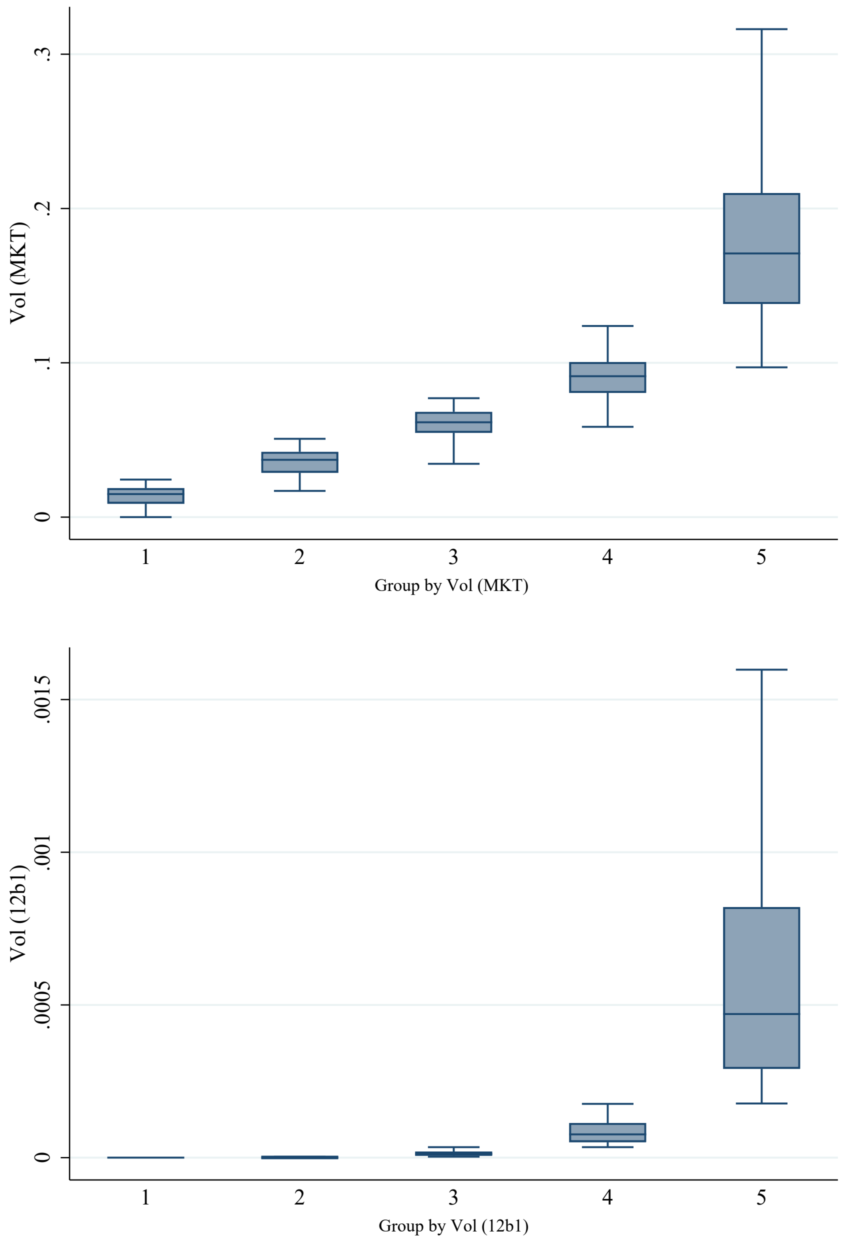

Figure 3.D.3. The Relationship between Firm Return and Marketing Persistence

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

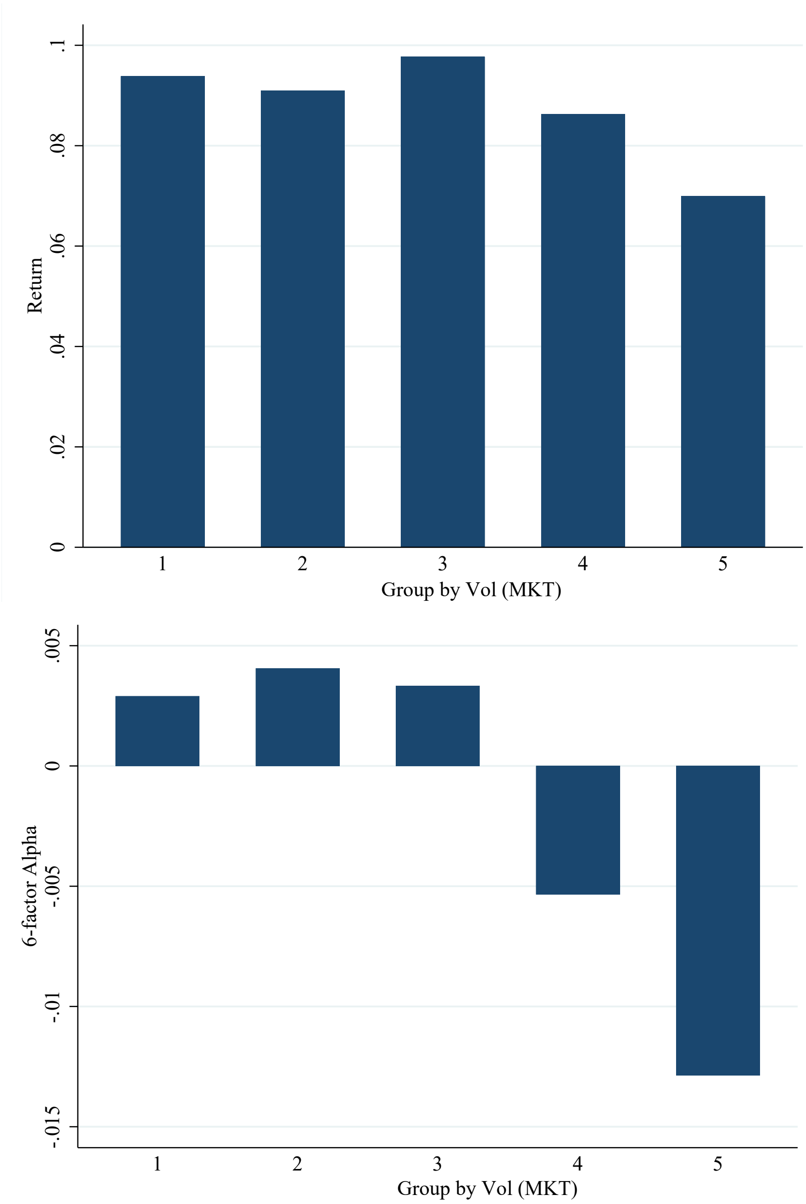

Table 3.D.1. Summary Statistics

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

Panel A: Annual Variables

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

Panel B: Monthly Variables

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

Table 3.D.2. Marketing Persistence and Fund Performance

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

Panel A: Performance Measured by Gross Return

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

Panel B: Performance Measured by Net Return

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

Table 3.D.3. Marketing Persistence and Fund Performance: Predictive Regressions

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

Panel A: Performance Measured by Gross Return

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

Panel B: Performance Measured by Net Return

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

Table 3.D.4. Marketing Persistence and Fund Performance: Robustness Tests

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

Panel A: Alternative Measure of Marketing Persistence

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

Panel B: Flagship Fund Performance

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

Table 3.D.5. Employment Persistence and Fund Performance

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

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

Table 3.D.6. Marketing Persistence and Fund Performance: 12b1 Fee

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

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

Table 3.D.7. Marketing Persistence and Fund Performance: Value Added

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

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

Table 3.D.8. Regressions of Future Firm Revenue on MKT

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

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