Why Do We Have So Many Funds?

The Organizational Structure of Mutual Fund Families

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Abstract

We develop a model of delegated portfolio management to explain why we have so many mutual funds in a fund family. We first design a setting in which performance-maximizing investors always prefer to have fewer funds, yet fund families always prefer to have more funds to maximize their own profits. In particular, we consider the incentives for fund families to offer “simple” team funds in which two fund managers run independent portfolios but report their combined performance to investors as a team fund. A simple team fund should have at least as good a risk-adjusted performance as the two single-manager funds, with weighted average expected returns and lower risk due to diversification. Thus, performance-maximizing investors should prefer this team structure to single-manager funds. Yet we show that fund families always design contracts to induce an interior mix of single-manager and team funds to maximize their own profits, generating too many funds in equilibrium. Moreover, families with more convex compensation (e.g., due to convex fund flows) optimally choose a lower fraction of team-managed funds and have a lower average performance. Finally, using mutual fund data, we empirically confirm our model’s predictions regarding flow convexity, fraction of team management, and fund performance.

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1 Introduction

The mutual fund industry is peculiar: There are too many choices, for investors who are totally incapable of making the choices. According to ICI 2013 factbook, there are over 13 trillion assets under management and 8,752 open-end mutual funds available to investors. In his AFA presidential address, Sharpe (1981) asks the question of whether and how investors could efficiently combine the portfolios formed by multiple fund managers, assuming they could identify superior managers. He shows that only under strong assumptions can investors efficiently combine portfolios from two managers. It’s certainly no trivia task for any investor to identify a set of superior managers from 8000+ funds and efficiently combine the portfolios constructed by these managers.

Mutual fund families compete by offering similar products. In 2016, Vanguard offers 127 funds, covering all investment styles and industries imaginable. Menu choices are similar across all major fund families. Presumably, investors do not care about investment styles per se. All they want is higher expected return and lower risk. Given that fund families have much better information about their managers’ abilities and the expected performance of various investment styles, why don’t families offer “all-in-one” products to simplify investors’ tough choices?

In many other industries, firms make clear and tough choices for consumers, and these choices can make or break a firm. Take iphone for an example. For each new release, Apple needs make thousands of choices among product designs and suppliers. Consumers are not able to make these choices and not required to. All they need to decide is whether they like the final product. Their preferences then drive the fierce competition among industry participants like Samsung and Nokia.

Why do mutual fund families compete in a totally different way? In this paper, to shed light on this issue, we explicitly model fund families’ contracts choices for managers that set the industry’s organizational structure. In particular, we design a setting in which performance-maximizing investors always prefer to have fewer funds, yet fund families always prefer to have more funds to maximize their own profits.

Our model of delegated portfolio management has two layers of agency problems between in-
vestors, fund families and managers. Investors delegate their assets to fund families, who then hire managers to make investment decisions. Neither fund families nor investors can observe managers’ ability levels, but managers know their own ability. Fund families design team and single-manager contracts to maximize family profit. Managers self-select into team or single-manager funds to maximize their own utility.

For simplicity, we do not model the optimization problem of investors. Instead, we assume an exogenous contract between investors and fund families. Investors invest in all funds offered by the family and compensate each fund based only on its performance. The compensation can be either linear or convex in performance. The convex compensation is meant to capture either implicit contracts like convex flow-performance relation (Chevalier and Ellison (1997), Sirri and Tufano (1998) and Huang, Wei, and Yan (2007)) or explicit contracts like the limited liability of funds, asymmetric mutual fund advisory contracts (Starks (1987) and Grinblatt and Titman (1989)) or option-like incentive fee contracts for hedge funds (Ross (2004) and Agarwal, Daniel, and Naik (2009)).

A key consideration in the model is the incentives for fund families to offer “simple” team funds in which two fund managers run independent portfolios but report their combined performance to investors as a team fund. This simple team fund is always feasible to implement and is effectively a “fund of funds” without the additional layer of management fees. In particular, each manager has full discretion over his “sub-fund”, maintains separate internal track records, and is compensated based only on his own performance. In this independent format, a team fund is merely a platform for the fund family to provide the combined performance to its investors. This team fund should have at least as good a risk-adjusted performance as the two sub-funds, with weighted average expected returns and lower risk due to diversification of investment risks and manager skills. Therefore, performance-maximizing investors should always prefer this team structure to single-manager funds.

Our first main result is that fund families always design contracts to induce an interior mix of single-manager and team funds. In the model, we simplify the analysis by endowing managers with information to avoid effort choices and eliminate the selection of manager pools by setting the reservation utility at a level that all managers participate in equilibrium. This simplified setting
provides a good benchmark to study the conflict between fund families and investors. The optimal organizational structure for investors who care only about fund performance is all team funds, because the risk-adjusted performance of a team fund is always better than the average of two single-manager funds due to diversification. Yet fund families’ incentive to maximize expected profit yields very different outcome from maximizing fund performance for investors. In particular, we find that fund families always prefer an interior mix of single-manager and team funds. Therefore, in equilibrium, there are always too many funds in the industry due to fund families’ incentive to maximize their own profit.

Our second result is on the design of team compensation contracts for fund families. Fund families can either provide risk sharing among team managers by basing compensation on the team performance and rewarding managers for their teammates’ superior performance, or encourage fierce competition by overcompensating winning managers at the expense of losing managers. We find that fund families always prefer risk sharing contracts. The reason is that risk averse managers enjoy the risk sharing benefit. As a result, they are willing to take lower average compensation when offered risk sharing contracts. Fund families are risk neutral and maximize total profit which is the difference between management fees paid by investors and compensations to managers. Fund families find it optimal to always provide risk sharing team contracts, even though these contracts can lead to poor performance for team funds in equilibrium.

Our third result is that better skilled managers prefer single-manager funds to team funds. Given risk sharing team contracts offered by fund families, managers trade off the gain of diversification and pooling with better skilled managers with the loss of pooling with worse managers. For better managers, they are more likely to pool with worse managers and hence benefit less from team contracts. We find a unique separating equilibrium in which managers with skills above the cutoff level prefer single-manager funds and managers with skills below prefer to team. This self-selection by fund managers explains the poorer performance of team funds. This result is not new. Bliss, Potter, and Schwarz (2008) and Bar, Kempf, and Ruenzi (2011) have established the poor performance of team funds and Massa, Reuter, and Zitzewitz (2010) and Han, Noe, and Rebello (2012) have
related the performance to the self-selection of better managers into single-manager funds. Our main contribution is to establish that fund families optimally choose to offer risk sharing contracts for their teams, anticipating the self-selection of managers and poor performance for team funds in equilibrium.

Our fourth result is that convex compensation for fund families leads to a preference for single-manager funds over team funds, and that families with more convex compensation choose a lower fraction of team-managed funds. When investors compensate fund families according to a convex schedule, fund families benefit more from two single-manager funds than from a team fund with the same two managers. The reason is that the team fund is likely to have mediocre realized performance after averaging two managers’ performances, and families benefit less from the convexity of the compensation contract. As a result, families with more convex compensation optimally choose a lower fraction of team-managed funds.

This result also points out a fundamental problem with team funds if investors do not recognize the benefit of lower risks and pay attention only to realized performances (Gruber (1996), Goetzmann and Peles (1997), Zheng (1999), and Huang, Wei, and Yan (2010)). With lower expected profit, a team fund can no longer replicate two independent single-manager funds regardless of whether families offer risk sharing contracts or not. It’s also harder to retain good managers as a result.

Before we turn to our empirical results, it is important to recognize that in our model, we consider only the independent team structure and ignore any interactions within the team including information sharing, cost sharing, or hierarchical costs. Thus, our model provides only a starting point to understand the benefits and costs of team contracts for fund families and investors. Our purpose for the empirical test is not to claim that our theory is the only determinant behind team funds. But rather, we show that data is consistent with our theory that families’ objective to maximize profit is an important consideration behind the decision to offer team vs. single-manager funds.

Figure 1 illustrates the explosive growth of team-managed funds in the last two decades, increasing from about 30% of total net assets in early nineties to about 70% recently. Figure 1 panel (c) shows
that during the twenty year period, team funds underperform single-manager funds for about two thirds of the time. Our paper provides a unified theory of why team funds underperform and when fund families prefer to adopt the team structure.

Our model yields several testable predictions for empirical study. First, fund families with more convex compensations have lower fractions of team funds. Second, within each family, team fund managers have worse skills than managers in single-manager funds. Third, across families, controlling for family performance, team fund (or stand-alone) managers in more convex-compensation families have worse skills than team fund (or stand-alone) managers in less convex-compensation families.\footnote{The last prediction follows directly from the first one. It is easier to illustrate the point with an example. Say top 20\% of managers in the less convex family choose to be stand-alone managers while the fraction is 40\% in the more convex family. Once we control for family performance, managers in the top 20\% (stand-alone managers for the less convex family) are necessarily better than those in the top 40\% (stand-alone managers for the more convex family). Similarly, managers in the bottom 80\% (team managers for the less convex family) are necessarily better than those in the bottom 60\% (team managers for the more convex family).}

Empirically, we use CRSP Survivorship Bias Free Mutual Fund Database from 1992-2012 to test our predictions. We focus our analysis on 3288 unique actively managed U.S. domestic equity funds. We consider convex compensation due to the convexity of flow-performance relation. The main proxy we rely on is family size, since small fund families have more convex fund flow reaction to past performance (Huang, Wei, and Yan (2007)). We also conduct subperiod analysis since Kim (2014) find that the flow-performance relation is more convex in earlier years than in recent years. Next, we identify measures of skills based both on outcome (i.e., fund performance) and actions (i.e., portfolio management activeness). Outcome variables include four-factor alpha (Jensen (1968) and Carhart (1997)), the volatility of alpha, and information ratios. Action variables include industry concentration (Kacperczyk, Sialm, and Zheng 2005), return gap (Kacperczyk, Sialm, and Zheng 2008), and active shares (Cremers and Petajisto 2009).

Our empirical findings are largely consistent with our theoretical predictions. First, we find strong evidence that small fund families (i.e., the ones with more convex flow compensation) have lower fractions of team funds. In the time series, the explosive growth in team funds in recent years coincides with a decrease in the convexity of the flow-performance relation. Second, within
each family, team funds have worse performance than single-manager funds, measured both by four-factor alpha or information ratio. Team funds are less active in managing their portfolios as measured by lower return gap, lower industry concentration, and a smaller fraction of active shares. Third, across families, after controlling for family performance, team (or single-manager) funds in smaller families have worse skills than team (or single-manager) funds in larger families, measured by both outcome and action variables.

Our paper is related to several strands of literatures. First, there is a theory literature on the benefits and costs of team-managed funds. Sharpe (1981) argues that team management can be beneficial for mutual fund investors due to specialization by fund managers and diversification across manager styles. Barry and Starks (1984) show that team management offers additional benefits by reducing agency problems between investors and managers. On the other hand, moral hazard in teams (Holmstrom (1982)) and hierarchical costs in organizations (Stein (2002)) can lead to poor performance of teams. The literature focuses on the interaction between team members in sharing and utilizing information and whether the team structure adds or subtracts value from their individual managers, which are clearly very important questions. We study the simplest possible team structure in which team members operate independently. Thus the team performance is by definition the sum of its members’ performance, and is necessarily better due to the diversification benefit. Our simple setting allows us to study the additional layer of agency conflict between fund families and investors and to understand its impact on the design of team contracts, which is complementary to the traditional principal and agent analysis in literature (Stoughton 1993). We find that fund families optimally choose risk sharing team contract even though it may lead to poor team performance, and they design contracts to induce a mix of team and single-manager funds to maximize their own compensation rather than fund performance.

Second, we contribute to the empirical literature on the performance of team-managed funds. Bliss, Potter, and Schwarz (2008), Bar, Kempf, and Ruenzi (2011), and Massa, Reuter, and Zitzewitz (2010) find inferior performance by team-managed fund despite their increasing popularity. Patel and Sarkissian (2014) attribute the inferior team performance to data error in which both CRSP
and Morningstar datasets have large discrepancies in reported managerial structures relative to SEC records. Adams, Nishikawa, and Rao (2015) find that a subset of team-managed funds, namely, those with highly independent boards, perform better. Han, Noe, and Rebello (2012) use the self-selection of better managers to single-manager funds to explain the poor performance of team funds. They show that once managers’ ability is properly controlled for, team funds perform better. We add to the literature by establishing the relation between the convexity of family’s compensation and the fraction of team funds. Our results on cross-family comparisons of team and single-manager fund performances are also new.

Third, our paper is related to the literature on the decreasing return to scale for mutual funds. Pastor and Stambaugh (2012) argue that there is decreasing return to scale at the industry level because it is harder for managers to outperform passive benchmarks when the industry’s size increases. Berk and Green (2004) show that the decreasing return to scale at the fund level is a natural outcome when funds flow to superior managers but managers face decreasing returns in deploying their superior ability. Chen, Hong, Huang, and Kubik (2004) document empirically the decreasing return to scale at the fund level and attribute it to hierarchical costs (Stein (2002)), assuming larger funds necessarily employ multiple managers. Our story is complementary to the literature. We show that fund families can offer independent team contracts, which are easily implementable and do not suffer from hierarchical costs. Therefore, decreasing return to scale at the manager level does not necessarily translate to decreasing return to scale at the fund level. However, we also find that agency problems at the family level and self-selection of fund managers can lead to lower performance of team funds and decreasing return to scale at the fund level. It is worth pointing out that transaction cost is not a viable explanation for decreasing return to scale at the fund level whenever team management is an option. An independent team fund with two managers should always have lower transaction costs than two separately run single-manager funds, because it’s always feasible to disregard any interactions between the two managers and form two independent portfolios.² Empirically, Busse,

²Whenever the two managers have opposite trades, the team fund can cross trades and save transaction costs both ways. If two managers have similar trades, they have the option to reduce trade sizes if the combined price impact would have been too large. They could supplement these trades using other second-best trading ideas with lower
Chordia, Jiang, and Tang (2015) find that larger funds have lower percentage transaction costs than smaller funds.

The remainder of this paper is structured as follows: Section 2 sets up the model. Section 3 derives empirical predictions of the model. Section 4 explains the data sources and empirical results. Section 5 concludes.

2 Model
2.1 Model Setup

We consider an economy with a representative mutual fund family and a continuum of fund managers $i \in \Omega$. Each manager has a unique trading strategy that generates risk-adjusted active return $\tilde{\alpha}_i$. When managers are uninformed, probability distribution of $\tilde{\alpha}_i$ is

$$\text{Pr}\{\tilde{\alpha}_i = \alpha\} = \text{Pr}\{\tilde{\alpha}_i = -\alpha\} = 0.5$$

(1)

Manager $i$ has private access to a binary signal $\tilde{s}_i$ about the outcome of her trading strategy. Conditional on a positive (negative) signal, $\tilde{\alpha}_i$ is distributed as

$$\text{Pr}\{\tilde{\alpha}_i = \alpha|\tilde{s}_i = +1\} = \text{Pr}\{\tilde{\alpha}_i = -\alpha|\tilde{s}_i = -1\} = 0.5 + \sqrt{\tau_i},$$

(2)

where $\tau_i$ is manager $i$’s signal precision. Positive and negative signals appear with equal probabilities.

All managers have a positive reservation utility $U$, below which no manager would participate. They are risk averse with coefficient $\gamma$, and derive mean-variance utility over their compensation $\hat{f}_i$. Given the private signal $\tilde{s}_i$, manager $i$ chooses trading amount $x_i$ to maximize her utility:

$$U_i = E(\hat{f}_i|\tilde{s}_i) - \frac{\gamma}{2} Var(\hat{f}_i|\tilde{s}_i).$$

(3)

Assumption 1 Managers are constrained in trading amount. In particular, manager $i$ chooses trading costs. This combined outcome for the team fund is necessarily better than the outcome when two managers cannot coordinate trades in the case of the two separately run funds.
whether fully or not to implement her trading strategy according to her signal:

\[ x_i = \begin{cases} 
1, & \text{if } \hat{s}_i = +1 \\
0, & \text{if } \hat{s}_i = -1 
\end{cases} \]  \hspace{1cm} (4)

A manager actively trades only when her signal indicates a good chance to implement her trading strategy. Otherwise, she forgoes the trading opportunity to avoid loss relative to the benchmark. Thus, at manager level (with subscript \(i\)), active return is defined as

\[ \tilde{R}_i = x_i \tilde{\alpha}_i. \]  \hspace{1cm} (5)

Signal precision is determined by managerial skill, which is exogenously endowed and heterogeneous across managers. Among all managers in the pool \(\Omega\), precision level \(\tau_i\) is uniformly distributed over \(\Phi = [\tau_L, \tau_H] \subseteq [0, 0.25]\). \(\Omega \mapsto \Phi\) is a point-wise mapping from the pool of managers to signal precision levels. Precision of each manager is privately known by herself, and is not observed by other managers or the fund family. For expository convenience, we have:

**Assumption 2** Private signals \(\hat{s}_{i_1}, \hat{s}_{i_2}\), and excess returns \(\tilde{\alpha}_{i_1}, \tilde{\alpha}_{i_2}\) are independently distributed for \(\forall i_1, i_2\) such that \(i_1 \neq i_2\).

There are two types of management structure within the mutual fund family: single-manager and team funds. A single-manager fund is solely managed by one manager, with \(W_0\) assets under management (AUM). For simplicity, we assume that each management team consists of two managers, each assigned with \(W_0\) initial AUM. The two managers operate independently, and their combined performance will be reported as fund level performance. When a team fund is set up, two managers from \(\Omega\) will be randomly paired to manage it. For a single-manager fund managed by manager \(i\), fund level active return (with subscript \(j\)) is the same as its manager level counterpart:

\[ \tilde{R}_{j,S} = \tilde{R}_i. \]  \hspace{1cm} (6)

For a team fund jointly managed by manager \(i\) and manager \(-i\), fund level active return is

\[ \tilde{R}_{j,T} = \frac{1}{2}(\tilde{R}_i + \tilde{R}_{-i}). \]  \hspace{1cm} (7)
Managerial performance is also measured with Information Ratio. At manager level (or for a single-manager fund managed by manager $i$),

$$IR_i = IR_{j,S} = E(\tilde{R}_i)Var(\tilde{R}_i)^{-\frac{1}{2}}.$$  

(8)

For a team-managed fund, Information Ratio is calculated as

$$IR_{j,T} = E(\tilde{R}_{j,T})Var(\tilde{R}_{j,T})^{-\frac{1}{2}}.$$  

(9)

The fund family contracts with managers from the manager pool. Its current period revenue comes exclusively from fixed management fees based on the size of assets under management. Nonetheless, there is an implicit performance-based incentive for the family: investors’ future money flows. When a sibling fund delivers good (bad) active returns, money flows into (out of) that fund. Moreover, the return-flow relationship is non-linear: a mutual fund with outstanding performance attracts much more money inflows than other funds. We capture the implicit contract in family revenue with the following assumption.

**Assumption 3** The fund family’s revenue from fund $j$ is a quadratic function of active returns. Specifically, given fund level active return $\tilde{R}_j$, revenue from fund $j$ is

$$\tilde{F}_j = AW_j + BW_j\tilde{R}_j + CW_j\tilde{R}_j^2,$$  

(10)

where the initial fund size $W_j$ is given by

$$W_j = \begin{cases} 
W_0, & \text{if } j \text{ is a single-manager fund} \\
2W_0, & \text{if } j \text{ is a team fund} 
\end{cases}$$  

(11)

Parameter $A > 0$ is the fixed management fee rate charged on the initial assets under management. $B$ is the linear slope of the fund family’s present value of future fees in response to fund level active return. The third term is the present value of future fees from the convex part of future inflows. Parameter $C$ is the flow-convexity coefficient.

After paying managers their compensation, the fund family keeps the rest of its revenue as profit. Compensation contracts specify how a manager will be paid in the end of the management period. The fund family offers different contracts to single-manager and team fund managers. We index the
two types of contracts with \( \{S, T\} \).

There are three dates: \( t = 0, 1 \) and 2. At \( t = 0 \), the fund family offers compensation contracts to managers, and each manager chooses one of the two contracts to maximize her ex ante expected utility \( E(U_i) \). At \( t = 1 \), managers receive private signals, and then choose whether to trade actively, in order to maximize their expected utility. All uncertainty is resolved at \( t = 2 \), and managers get compensated according to contracts.

In either contract, manager compensation is paid as the sum of two components: fixed salary, and a linear incentive based on the value of active trading profit. A single-management compensation contract is

\[
\tilde{f}_{i,S} = a_S + b W_0 \tilde{R}_i,
\]

where \( a_S \) is the fixed component of compensation, and exogenous constant \( b > 0 \) is an incentive slope that determines the proportion of trading profit \( W_0 \tilde{R}_i \) to be paid to manager \( i \).

Team compensation contract is an extension of the simple single-management contract. For manager \( i \), who works with manager \(-i\) in a team, her compensation is:

\[
\tilde{f}_{i,T} = a_T + b W_0 \tilde{R}_i + \phi W_0 (\tilde{R}_i - \tilde{R}_{-i}),
\]

where \( a_T \) is the fixed component of compensation. Parameter \( \phi \in [-\frac{b}{2}, \frac{b}{2}] \) captures the flexibility of incentive policy for team managers. When \( 0 < \phi \leq \frac{b}{2} \), incentive bonus will be additionally based on manager \( i \)'s active return relative to her teammate; when \( -\frac{b}{2} \leq \phi < 0 \), the two managers will share risk, as each other’s compensation increases in active return of the teammate’s; when \( \phi = 0 \), their compensation differs from single-management contract only in fixed salary.

All parameter values and unconditional distributions are common knowledge in the economy. Note that given active returns, total incentives paid to two single managers are always the same as that paid to a team of two managers. Thus, contract parameter \( \phi \) serves as a costless policy tool for the fund family to maximize its objective, which is stated in the following assumption.

**Assumption 4** The fund family is risk neutral. It hires any manager randomly drawn from the pool
\[ \Omega, \text{ and maximizes its } t = 0 \text{ expected profit from a new manager:} \]

\[ \max_{\{a_S, a_T, \phi\}} \Pi = E_0[\tilde{\pi}_i(a_S, a_T, \phi)], \]

subject to managers’ participation constraint:

\[ \text{for } \forall i \in \Omega, \max \left\{ E(U_{i,S}), E(U_{i,T}) \right\} \geq U \text{ regardless of the contract choice of } \forall i' \neq i \]

The participation condition implies that the fund family cannot select good managers by offering an unattractive compensation contract to drive mediocre managers out of the pool. Competition for scarce managerial skill dictates that the fund family must ensure any manager would at least accept one of the two contracts, or the family would lose its chance to draw new managers from the talent pool.

### 2.2 Manager Contract Choices

In this section, we examine managers’ contract choices at \( t = 0 \) given contract parameters \( \{a_S, a_T, \phi\} \).

Manager \( i \) makes a decision based on public information, and her only private information at \( t = 0 \): her own signal precision \( \tau_i \).

To analyze contract choices, we first calculate managers’ ex ante expected utility from choosing both contracts. Then, based on their rational choices, we show properties of such an equilibrium that are related to the fund family’s decision on contract parameters.

#### 2.2.1 Manager Welfare

Expected utility is calculated by averaging conditional expectations and conditional variances of compensation over realizations of the private signal. If a manager with signal precision \( \tau_i \) chooses the single-management contract, conditional on \( \tilde{s}_i = +1 \) (good time to implement the trading strategy), expected active return is

\[ E(\tilde{R}_i|\tilde{s}_i = +1) = 2\sqrt{\tau_i}\alpha, \quad (14) \]
and conditional variance is

$$Var(\tilde{R}_i|\tilde{s}_i = +1) = (1 - 4\tau_i)\alpha^2.$$  \hspace{1cm} (15)

When $\tilde{s}_i = -1$ (bad time to implement the trading strategy), they are both zero. Insert compensation $\tilde{f}_{i,S}$ in equation (12) into utility function (3), and average over two possible states of the signal $\tilde{s}_i$,

$$E(U_{i,S}) = a_S + bw_0\alpha\sqrt{\tau_i} - \frac{1}{2}\gamma b^2w_0^2\alpha^2(1 - 4\tau_i).$$  \hspace{1cm} (16)

Expected utility increases in fixed salary $a_S$, and the manager’s signal precision, as skill brings higher expected profit with smaller risk. Alternatively, if the manager chooses team-management contract and works with manager $-i$ with signal precision $\tilde{\tau}_{-i}$, her expected utility can be calculated in a similar way. The result is

$$E(U_{i,T}|\tilde{\tau}_{-i}) = a_T + (b + \phi)w_0\alpha\sqrt{\tau_i} - \phi w_0\alpha\sqrt{\tilde{\tau}_{-i}} - \frac{1}{4}\gamma w_0^2\alpha^2[(b + \phi)^2(1 - 4\tau_i) + \phi^2(1 - 4\tilde{\tau}_{-i})].$$  \hspace{1cm} (17)

Now, expected utility depends on not only her own, but also her teammate’s signal precision. The more skilled she is, the higher expected utility she obtains given the fixed salary $a_T$. However, relationship between the manager’s expected utility and her teammate’s signal precision relies on parameter $\phi$. When $\phi$ is positive, the more skilled her teammate is, the smaller her expectation of compensation will be. But higher $\tilde{\tau}_{-i}$ also reduces the uncertainty about her terminal compensation. In contrast, when $\phi$ is negative and managers share risk with each other’s strategy performance, expected utility increases monotonically in the teammate’s signal precision.

When managers are making their contract choices, they have no information on the teammate’s signal precision $\tilde{\tau}_{-i}$. Instead, they make the choice by comparing ex ante expectation of utility from team-management with single-management contract. Define the sub-pool of managers that prefer the team contract as $\Gamma$, where $\Gamma \subset \Omega$. Then ex-ante expected utility from the team contract is

$$E(U_{i,T}) = E[E(U_{i,T}|\tilde{\tau}_{-i})|\tilde{\tau}_{-i} \in \Gamma].$$  \hspace{1cm} (18)

Managers always choose the contract that makes them better off in terms of expected utility. For convenience, we define a useful function: ex ante utility gap for a manager with signal precision $\tau_{-i}$,
given contract parameters and sub-pool of team managers:

\[ G(\tau_i; a_S, a_T, \phi, \Gamma) = E(U_{i,T}) - E(U_{i,S}). \]  

When \( G(\tau_i; a_S, a_T, \phi, \Gamma) \) is positive for manager \( i \), she chooses the team-management contract, and vice versa.

### 2.2.2 Equilibrium

Since randomly drawn teammate’s signal precision is important for any team manager’s welfare, each manager’s contract choice has an externality on other managers. However, managers choose contracts simultaneous without coordination. They do not observe other managers’ choices. Instead, each manager forms a belief on what other managers would choose, based on their information set. Each manager has a believed probability distribution regarding her potential teammate’s skill if she chooses the team-management contract. Given her own information set and such a belief, she makes her choice. When every manager’s belief coincides with everyone’s ex post choice, and nobody has incentive to deviate from her choice, a Bayesian Nash Equilibrium is established.

As each manager’s prior belief is consistent with posterior outcome in equilibrium, the correct belief must be shared by all managers. The sub-pool of managers that choose the team contract is crucial in the comparison of ex ante utility from single- and team-management contracts. Besides, managers’ beliefs and choices are affected by a set of specific contract parameters \( \{a_S, a_T, \phi\} \). We define the equilibrium first.

**Definition 1 (Equilibrium)** A pure-strategy Perfect-Bayesian Nash Equilibrium in managers’ contract choice game at \( t = 0 \) involves

1) A common prior belief: any manager belongs to a subset of \( \Gamma \subset \Omega \) chooses the team-management contract and other managers choose the single-management contract;

2) Given a set of contract parameters \( \{a_S, a_T, \phi\} \) and other managers’ choices in her belief, man-
ager i’s contract choice is

\[
\text{Argmax}_{\{S,T\}} \{ E(U_{i,S}), E(U_{i,T}) \}.
\] (20)

3) Ex post, any manager belongs to \(\Gamma\) chooses the team contract, and the rest of managers choose the single-management contract.

Since the set of manager pool \(\Omega\) is continuous, one might conjecture that any continuous or discontinuous subset \(\Gamma\) would choose the team-management contract. The following lemma helps us focus on one special form of belief on \(\Gamma\) that is viable in equilibrium.

**Lemma 1 (Segmented Contract Choices)** Given an arbitrary non-zero \(\phi \in [-\frac{b}{2}, \frac{b}{2}]\), for any equilibrium defined above, there exists a threshold signal precision \(\tau_\ast \in [\tau_L, \tau_H]\). If \(\phi > 0\), \(\Gamma = [\tau_\ast, \tau_H]\); if \(\phi < 0\), \(\Gamma = [\tau_L, \tau_\ast]\).

**Proof.** See the Appendix. \(\blacksquare\)

Evidently, for any continuous distribution of manager skill over a convex support \(\Phi = [\tau_L, \tau_H]\), the only separating equilibrium we can possibly have must be of this form. This is because, the difference between a manager’s expected utility from choosing the two contracts changes monotonically as her skill level changes. If managers with both higher and lower signal precision than a certain manager choose the same contract, that manager would also choose that contract. Suppose that one of the two contracts is attractive enough, all managers would choose that contract and we will see 100% of single-manager or team funds.

The threshold manager’s signal precision is

\[
\tau_\ast = \text{Max} \{\tau_L, \text{Min}(\hat{\tau}, \tau_H)\},
\] (21)

where \(\hat{\tau}\) is defined as

\[
\hat{\tau} = \{\tau_i : G(\tau_i; a_S, a_T, \phi, \Gamma) = 0\}.
\] (22)

In equilibrium, contract choices imperfectly signal managers’ signal precision levels. When a risk sharing rule is offered to team managers (\(\phi < 0\)), only relatively less skilled managers prefer
the team contract, and better skilled managers all prefer the single-management contract. Given an equilibrium sub-pool \( \Gamma \), the more skilled a manager is, the less likely that she prefers the team-management contract. If a relative performance rule is offered, in contrast, the relationship reverses and only better skilled managers prefer to team. So the sub-pool of managers who prefer to join teams must take the form \([\tau_L, \tau_*]\) or \([\tau_*, \tau_H]\). When \( \phi \) is zero, everyone is indifferent between the single- and team-management contracts as long as the same fixed salary is offered. However, it does not make sense that the fund family creates team-management without any substantial difference for itself from traditional single-management structure.

In what follows in this section, we focus on the case where a risk sharing rule within teams is created by the fund family \( (\phi < 0) \). We will show why this is the only possible case in the next section.

**Proposition 1 (Uniqueness)** Suppose \( \phi < 0 \), given contract parameters \( \{a_S, a_T, \phi\} \), there exists a unique separating equilibrium. In particular,

1) When \( a_T + c_1 < a_S < a_T + c_2 \), \( \tau_* \in (\tau_L, \tau_H) \);

2) When \( a_S < a_T + c_1 \), \( \tau_* = \tau_H \);

3) When \( a_S > a_T + c_2 \), \( \tau_* = \tau_L \).

Where constants

\[
c_1 = \frac{1}{6} \phi W_0 \alpha \left\{ \frac{2(\tau_H + \sqrt{\tau_H \tau_L} - 2\tau_L)}{\sqrt{\tau_H} + \sqrt{\tau_L}} - 3\gamma W_0 \alpha \left[ b(1 - 4\tau_H) - \phi(1 - 3\tau_H - \tau_L) \right] \right\},
\]

and

\[
c_2 = -\frac{1}{2} \phi (b + \phi) \gamma W_0^2 \alpha^2 (1 - 4\tau_L).
\]

**Proof.** See the Appendix. ■
The uniqueness of the equilibrium indicates that only one belief regarding everyone’s choice is correct ex post. In equilibrium, the threshold manager’s signal precision makes her exactly indifferent between the two contracts. The gap between her expected information gains from team- and single-management contracts is just offset by the gap in fixed salary. Any manager with signal precision lower than the threshold manager would voluntarily choose the team contract, knowing her teammate also comes from such a subset of the manager pool. Any manager with better skill than the threshold manager would voluntarily choose the single-management contract, and knows other better managers would do the same. For each team fund within the fund family, two managers’ signal precision levels are randomly drawn from the lower sub-pool.

This separating equilibrium is stable. Suppose some managers with precision lower than \( \tau^* \) mistakenly believed that they should choose the single-management contract. Then among these managers, the one with lowest signal precision would find out that the team contract could make her better off, and turn to it. Subsequently, all of these managers, from low ability to high ability, would do the same until the equilibrium is established. Alternatively, if some managers with signal precision higher than \( \tau^* \) intended to choose the team contract, with similar reasoning, from the highest-skilled manager to the lowest-skilled manager within this group, they would sequentially realize that a deviation to the single-management contract is a rational choice.

A pair of fixed salaries \( \{a_S, a_T\} \) is of great importance. The difference between the two fixed salaries determines managers’ equilibrium choices. One the one hand, relative to \( a_T \), when \( a_S \) is large enough and go beyond the cutoff \( c_2 \), all managers will be attracted to choose the single-management contract. On the other hand, if \( a_S \) is smaller than \( a_T + c_1 \), all managers prefer to team. Both cutoffs \( c_1 \) and \( c_2 \) are dependent on the magnitude of risk sharing according to parameter \( \phi \).

Note that \( c_2 \) is always positive. It implies that when the same fixed salary is offered in both contracts, the manager with lowest signal precision always prefers the team-management contract. However, the sign of \( c_1 \) is unclear. If \( c_1 > 0 \), all managers choose the team-management contract when \( a_S = a_T \). Otherwise, there are both types of funds given the same fixed salary.
2.3 Fund Family: Mechanism Design and Separation Policy

The mutual fund family cannot dictate the management structure of a new fund that is going to start. Fund types are determined by managers’ contract choices. Nonetheless, as a mechanism designer, the fund family chooses contract parameter values to manipulate self-selections of managers. In this way, fund types and the fund family’s own prospective profits can be indirectly chosen. In this section, we analyze how rational mutual fund family makes decision on compensation contracts, and the implications on its organizational structure.

2.3.1 Fund Family’s Profit Accounting

As a commercial organization, the mutual fund family cares about expected profit from starting a new fund and hiring a new manager, rather than the performance of its sibling mutual funds. The expectation is calculated by averaging over multiple layers of partitions in the probability space. First, managers’ contract choices and fund types are dependent on the signal precision of new managers randomly drawn from the pool at \( t = 0 \). Second, given fund types and managerial skill, managers receive random signals at \( t = 1 \) and trade accordingly. Third, given signal realizations, excess return at \( t = 2 \) is also stochastic. We calculate such an ex ante expectation as follows.

For single-manager fund \( j \) managed by manager \( i \), the fund family’s profit \( \tilde{\pi}_{i,S} \) is the difference between its revenue and manager compensation:

\[
\tilde{\pi}_{i,S}(a_S, a_T, \phi; \tilde{\tau}_i) = \tilde{F}_{j,S} - \tilde{f}_{i,S}.
\]  

Insert fund family revenue (10) and manager compensation (12) into it, we have

\[
\tilde{\pi}_{i,S}(a_S, a_T, \phi; \tilde{\tau}_i) = AW_0 - a_S + (B - b)W_0\tilde{R}_i + CW_0^2\tilde{R}_{i}^2.
\]  

By law of iterated expectations, given \( \tilde{\tau}_i \), expected value of (25) over conditional returns and realization of signals is

\[
E[\tilde{\pi}_{i,S}(a_S, a_T, \phi; \tilde{\tau}_i)] = AW_0 - a_S + (B - b)W_0E[E(\tilde{R}_i|\tilde{s}_i)] + CW_0E[E(\tilde{R}_{i}^2|\tilde{s}_i)],
\]  

18
which can be reduced to

\[ E[\tilde{\pi}_{i,S}(a_S, a_T, \phi; \tilde{\tau}_i)] = AW_0 - a_S + (B - b)W_0\sqrt{\tilde{\tau}_i} + \frac{1}{2}CW_0\alpha^2. \]  

(28)

Expected profit per team manager is calculated in a similar way. For a fund \( j \) team-managed by manager \( i \) and manager \(-i\), profit per manager is

\[ \tilde{\pi}_{i,T}(a_S, a_T, \phi; \tilde{\tau}_i, \tilde{\tau}_{-i}) = \frac{1}{2} [\tilde{F}_i - (\tilde{f}_i + \tilde{f}_{-i})] \]  

(29)

Insert family revenue (10) and manager compensation (13) into it,

\[ \tilde{\pi}_{i,T}(a_S, a_T, \phi; \tilde{\tau}_i, \tilde{\tau}_{-i}) = AW_0 - a_T + \frac{1}{2}(B - b)W_0(\tilde{R}_i + \tilde{R}_{-i}) + \frac{1}{4}CW_0(\tilde{R}_i + \tilde{R}_{-i})^2 \]  

(30)

Given signal precision \( \tilde{\tau}_i \) and \( \tilde{\tau}_{-i} \), expected value is

\[ E[\tilde{\pi}_{i,T}(a_S, a_T, \phi; \tilde{\tau}_i, \tilde{\tau}_{-i})] = AW_0 - a_T + \frac{1}{2}(B - b)W_0\left\{E[E(\tilde{R}_i|\tilde{s}_i)] + E[E(\tilde{R}_{-i}|\tilde{s}_{-i})]\right\} \]

\[ + \frac{1}{4}CW_0E\left\{E[(\tilde{R}_i + \tilde{R}_{-i})^2|\tilde{s}_i, \tilde{s}_{-i}]\right\}, \]  

(31)

which can be reduced to

\[ E[\tilde{\pi}_{i,T}(a_S, a_T, \phi; \tilde{\tau}_i, \tilde{\tau}_{-i})] = AW_0 - a_T + \frac{1}{2}(B - b)W_0(\sqrt{\tilde{\tau}_i} + \sqrt{\tilde{\tau}_{-i}})\alpha + \frac{1}{4}CW_0(1 + 2\sqrt{\tilde{\tau}_i\tilde{\tau}_{-i}})\alpha^2. \]  

(32)

In expressions (28) and (32), the first terms are the fund family’s management fee from current AUM. The second terms are fixed salary paid to managers. Other terms are related to fund performance and future money inflows. The fund family keeps the rest of linear component of flow-benefits, after paying a fraction to managers. Moreover, all benefits from convex component of inflows are kept by the fund family.

**Lemma 2** Given two managers from \( \Omega \) with precision \( \tilde{\tau}_i, \tilde{\tau}_{-i} \), the fund family expects to attract more money inflows if they manage two single-manager funds, compared to one team fund.

**Proof.** See the Appendix.  

In terms of revenue, the mutual fund family prefers to set up single-manager funds instead of team funds. This is because two managers’ active returns of a team-managed fund will be diversified. Thus, team funds are less likely to deliver superior fund level performance. Therefore, single-manager
funds can better capture the convexity of investor flows. As a result, the fund family has no incentive to raise \( a_T \), given other contract parameters, to make the team contract more attractive for managers. This intuition will be useful in the fund family’s choice of \( \phi \).

### 2.3.2 Expected Profit Per Manager

When the fund family makes contract decisions, it does not know the skill of new managers. However, it knows the probability distribution of skill, given contract choice of a new manager. We have expected profit from a new manager given her skill in equations (28) and (32). Now we can compute ex ante expected profit per manager by taking expectations over subsets of \( \Omega \) where managers in single-manager and team-managed funds are drawn from, respectively.

Averaging over manager’s signal precision gives ex ante expected profit from a new manager. That is,

\[
E[\tilde{\pi}_{i,S}(a_S, a_T, \phi)] = \int_{\tilde{\tau}_i \in \Gamma} E[\tilde{\pi}_{i,S}(a_S, a_T, \phi; \tilde{\tau}_i)] pdf(\tilde{\tau}_i | \tilde{\tau}_i \in \Gamma) d\tilde{\tau}_i, \tag{33}
\]

and

\[
E[\tilde{\pi}_{i,T}(a_S, a_T, \phi)] = \int_{\tilde{\tau}_i, \tilde{\tau}_{-i} \in \Gamma^c} E[\tilde{\pi}_{i,T}(a_S, a_T, \phi; \tilde{\tau}_i, \tilde{\tau}_{-i})] pdf(\tilde{\tau}_i, \tilde{\tau}_{-i} | \tilde{\tau}_i, \tilde{\tau}_{-i} \in \Gamma^c) d\tilde{\tau}_i d\tilde{\tau}_{-i}, \tag{34}
\]

where \( \Gamma^c \) is the complement set of \( \Gamma \) in the manager pool: \( \Gamma^c = \{ i : i \in \Omega \& i \notin \Gamma \} \).

Finally, average expectation of profit per manager, weighted by probability of contract choices of a new manager, is the direct objective function for the fund family to maximize. Given an equilibrium in the manager pool where managers in \( \Gamma \) and \( \Gamma^c \) self-select into single-manager and team funds, the mutual fund family’s problem is

\[
\max_{\{a_S, a_T, \phi\}} \Pi = \Pr(i \in \Gamma) E[\tilde{\pi}_{i,S}(a_S, a_T, \phi)] + \Pr(i \in \Gamma^c) E[\tilde{\pi}_{i,T}(a_S, a_T, \phi)], \tag{35}
\]

where \( \Pr(\cdot) \) is probability of drawing a manager from either subset of \( \Omega \).
2.3.3 Fund Family’s Contract Choice

After paying managers’ compensation, the fund family keeps the rest of their management fees from investors as profits. In this sense, the decision is straightforward: the more revenue collected and the less compensation paid, the better. By assumption, management fees based on current assets under management is constant. When flow-performance relationship is linear, the fund family designs contracts simply to extract rents from managers’ skill. Besides, as we have shown in Lemma (2), single-manager funds on average attract more money inflows than team funds when the relationship is convex. This fact creates an incentive for the fund family to induce more single-manager funds. Moreover, as threshold \( \tau^*(a_S, a_T, \phi) \) varies with three parameters, the fund family’s costs also change in inducing different managers to choose its desired contracts. Unlike \( \phi \), fixed salary \( a_S \) and \( a_T \) are costly. As a result, the fund family’s equilibrium contract choice is based on the trade off among keeping rents from talents, capturing convex flows, and saving costs.

We define the fund family’s equilibrium contract choice as follows.

**Definition 2 (Optimal Contract)** An equilibrium of the contracting problem between the fund family and managers is a set of parameters \( \{a_S, a_T, \phi\} \), for single and team contracts, such that

1) Given \( \{a_S, a_T, \phi\} \), managers’ contract choices constitute a Bayesian Nash Equilibrium, with a threshold skill level \( \tau^*(a_S, a_T, \phi) \);

2) Parameters \( \{a_S, a_T, \phi\} \) satisfy managers’ incentive rationality condition:

\[
\forall i \in \Omega, \max \left\{ E(U_{i,S}), E(U_{i,T}) \right\} \geq U \text{ regardless of the contract choice of } \forall i' \neq i ;
\]

3) Given fund flow convexity coefficient \( C \), parameters \( \{a_S, a_T, \phi\} \) solve the fund family’s expected profit maximization problem (35):

\[
\max_{\{a_S, a_T, \phi\}} \Pi = \Pr(i \in \Gamma)E[\tilde{\pi}_{i,S}(a_S, a_T, \phi)] + \Pr(i \in \Gamma^c)E[\tilde{\pi}_{i,T}(a_S, a_T, \phi)].
\]

In the last section, we have shown the uniqueness of pure-strategy Bayesian Nash Equilibrium. However, Proposition 1 is based on a case \( \phi < 0 \), which means the fund family offers risk sharing for
teammates. Now we show that it is the only non-trivial case.

**Proposition 2** The fund family will always impose a risk sharing rule \((\phi < 0)\) for the team-management contract.

**Proof.** See the Appendix. ■

Risk sharing rule within teams improves welfare of risk-averse managers, and the fund family can pay less fixed salary to them while keeping their participation. In contrast, relative performance burns welfare in the economy. Given advantage of single-manager funds in attracting inflows, for the fund family, any choice of \(\phi > 0\) is (at least weakly) dominated by effectively offering only the single-management contract \((\phi = 0)\). Therefore, the fund family would always offer risk sharing to team managers, and consequently less skilled managers would choose the team contract.

**Corollary 2.1** In equilibrium, managers with signal precision \(\tau_i \in \Gamma = [\tau_L, \tau_*)\) choose the team contract, and managers with \(\tau_i \in \Gamma^c = [\tau_*, \tau_H]\) choose the single-management contract.

**Proof.** This is a ready result following Lemma 1 and Proposition 2. ■

To further characterize the fund family’s equilibrium choice of contract parameters, we establish three intuitive and useful lemmas.

**Lemma 3 (Monotonicity)** Threshold manager’s signal precision \(\tau_*\) is monotone in fixed salary \(a_S\) and \(a_T\) when \(\phi < 0\). Specifically, \(\tau_*\) decreases in \(a_S\), and increases in \(a_T\).

**Proof.** See the Appendix. ■

Values of the two fixed salaries, \(a_S\) and \(a_T\), serve as a policy tool for the fund family to induce desired separation of managers. Marginal changes in fixed salary correspond to marginal changes in managers’ contract choices. For example, when \(a_T\) increases relative to \(a_S\), the manager whose signal precision is marginally higher than the original \(\tau_*\) (used to choose the single-management contract) will turn to the team contract. In this way, the fund family can indirectly manipulate proportions of two contracts preferred by managers with the fixed salaries.
Corollary 2.2 Given $\phi$ and $a_T$, $a_S(\tau_*)$ is the inverse function of $\tau_*(a_S)$.

Proof. This is a ready result from Lemma 3. ■

Intuitively, when $\phi$ and $a_T$ are fixed, the fund family directly chooses $a_S$ to indirectly choose $\tau_*$. So we can interpret as that the family chooses $\tau_*$ in the optimization process, and each choice of $\tau_*$ corresponds to a unique value of $a_S$, which must be implemented in order to reach that target $\tau_*$. With the natural lower and upper bounds of $\tau_*$ ($\tau_L$ and $\tau_H$) we can prove results more conveniently.

Lemma 4 Given $\phi$, the fund family’s optimal choice of $a_T$ solves

$$a_T + bW_0\alpha\sqrt{\tau_L} - \frac{1}{4}\gamma\left[(b + \phi)^2 + \phi^2\right] W_0^2 \alpha^2 (1 - 4\tau_L) = U. \quad (36)$$

Proof. This result follows Corollary 2.1, managers’ participation constraint, and the fact that ex ante utility increases in a manager’s signal precision. ■

The fund family will set $a_T$ as low as possible, since no benefit is associated with a higher $a_T$ as implied by the combination of Lemma 2 and Lemma 3. Better managers always get more rents from their own skills, and they are always better off ex ante than worse managers. As we have shown in Proposition 1, when risk sharing is offered, the manager with the lowest signal precision is the most incentivized to team. In equilibrium, the fund family would set fixed salary $a_T$ such that the least skilled manager is exactly kept at reservation utility $U$. Given our assumption on the participation condition, a limiting condition is that two managers, both with signal precision $\tau_L$, can get reservation utility if they form a team.

The choice of $a_T$ above keeps the worst skilled manager exactly at reservation utility. This is the smallest value of $a_T$ that satisfies the participation condition for all managers. Such an $a_T$ is independent of $a_S$. When $a_S$ is raised, some managers deviate to the single-management contract. Remaining managers, who still prefer to team, are still paid with $a_T$, though they will have a lower expectation for their teammate’s skill.

Note that in equation (36), optimal choice of $a_T$ decreases in the value of parameter $\phi$ for any $\phi \in [-\frac{b}{2}, 0)$. This is because the worst manager’s welfare improves as the magnitude of risk sharing
Proposition 3  The fund family’s optimal choice is $\phi = -\frac{b}{2}$.

Proof. See the Appendix. □

Risk sharing policy is beneficial for both managers and the fund family. Additionally, more generous risk sharing saves more fixed salary paid out. In equilibrium, the fund family chooses to impose a risk sharing rule with largest magnitude: each team manager receives half of the combined incentive bonus. With this rule, the fund family can always induce any equilibrium separation of managers at a lower cost. Though different choices of $\phi$ induces different equilibrium profit expectations, any other equilibrium revenue prospect can be replicated in a cheaper way with $\phi = -\frac{b}{2}$.

The manager with precision $\tau_L$ can never team with a manager with skill inferior to her. However, the more skilled a manager is, the more concerned she might be about sharing risk with a worse skilled teammate, which may harm her own welfare.

Given Lemma 4, $a_T$ is fixed when $\phi = -\frac{b}{2}$. For convenience, from now on, we rewrite the threshold manager’s precision level and expected profit per manager as univariate functions of $a_S$:

$$\tau_s(a_S) = \tau_s(a_S, a_T, -\frac{b}{2}),$$

(37)

Meanwhile, expected profit from a single-manager and a team fund can also be rewrite as

$$E[\tilde{\pi}_{i,S}(a_S)] = E\left[\tilde{\pi}_{i,S}(a_S, a_T, -\frac{b}{2})\right],$$

(38)

and

$$E[\tilde{\pi}_{i,T}(a_S)] = E\left[\tilde{\pi}_{i,T}(a_S, a_T, -\frac{b}{2})\right].$$

(39)

The choice of $a_S$ is critical in the fund family’s optimization problem. On the one hand, it is the cost of fixed salary paid to any manager that chooses the single-management contract. On the other hand, it changes managers’ equilibrium choices of contract and organizational structure within the fund family. The following proposition identifies flow-convexity’s effect on the fund family’s contract
choice and organizational structures.

**Proposition 4**  1) When money inflows are linear in fund active returns, when $c_1 < 0$, optimal
\[ \tau_\ast \in (\tau_L, \tau_H); \text{ when } c_1 \geq 0, \text{ optimal } \tau_\ast = \tau_H. \]

2) When money inflows are convex in fund active returns, given a reasonable value of convexity, (i.e. $C < \frac{4b}{3\alpha}$), equilibrium threshold manager’s signal precision decreases in family convexity coefficient:
\[ \frac{\partial \tau_\ast}{\partial C} < 0. \]  
(40)

**Proof.** See the Appendix.  ■

When flows are linear in fund active returns, the fund family is indifferent between single-manager and team funds. Both types of fund generate the same expected revenue. Future money inflows depend only on the manager’s skill and luck. Thus, the fund family’s expected profit maximization problem is reduced to a simple cost minimization problem.

When some better skilled managers prefer to work alone, setting a lower fixed salary for the single-management contract reduces the cost of hiring them. By doing that, the fund family can extract more rents from these managers’ skill. As long as $c_1 < 0$, there are some managers that prefer the single-management contract when $a_S = a_T$. In this case, reducing $a_S$ simultaneously pushes some managers to choose the team contract, but total costs are lower. However, setting a very low $a_S$, such that all managers prefer to team, is unwise. If that happens, the fund family has to pay every manager $a_T$ and cannot extract any rent from managerial skill of better managers. As a result, the fund family optimally creates an internal mix of single-manager and team funds.

Adding flow convexity into the model complicates this decision. The team contract serves as a shelter for worse managers. With a risk sharing rule, they can be paid with less fixed salary. But the diversification effect within a team also partially compromises investors’ money inflows that reward mutual funds with superior active returns.

The fund family faces a trade off between lower costs and better future inflows when the convexity
term is of a reasonable scale, and \( C < \frac{3b}{\alpha} \) is a loose sufficient condition for that. As \( \tau_* \) increases, the subset of two team managers improves, and flow-benefits for the family increases very fast in speed if convexity is too large. However, absolute size of that cross-term is small compared with single-manager funds, and we need a sufficient condition simply to avoid exaggerating the benefit from multiple managers in team funds.

The more convex the relationship between active returns and future fund flows is, the fund family is more willing to induce managers for single-manager funds, despite larger costs associated with the separation policy. As a result, we expect to see a larger fraction of team management for a fund family with less convex inflows.

### 2.4 Fund Level Performance: Risk and Returns

The fund family chooses fixed salaries in their compensation contracts to separate managers with heterogeneous skill levels into single-manager and team funds. Although the same manager pool is assumed, such a separation policy affects results of performance evaluations within and across mutual fund families.

Before comparing fund performance, we highlight two features of a performance measure: Information Ratio. Firstly, when uncertainty in active returns is taken into account, Information Ratio is an univariate increasing function of manager ability.

**Lemma 5** At manager level, Information Ratio is independent of \( \alpha \). Given the manager’s signal precision \( \tau_i \),

\[
IR_i = \sqrt{\frac{2\tau_i}{1 - 2\tau_i}}.
\]  

**Proof.** See the Appendix. ■

When \( \alpha \) of a trading strategy increases, expectation and standard deviation of the active return of her portfolio increases with the same magnitude. As a result, activeness of the trading strategy itself does not affect manager level Information Ratio.
However, managerial skill is critical for a manager’s Information Ratio. As a manager’s signal precision improves, her portfolio expected active return increases and meanwhile conditional risk decreases. The more skilled a manager is, a higher Information Ratio we expect at manager level.

Secondly, team funds benefit from diversifications of team managers’ independent privates signals and active returns.

Lemma 6  *At fund level, if managers have the same signal precision $\tau_i$, we have*

\[
IR_{j,T} = \sqrt{2} \, IR_{j,S}.
\]  

(42)

**Proof.** See the Appendix. ■

Suppose managers are homogeneous in managerial skill, team management is more than a perfect remedy for decreasing return to scale at manager level. Team managers can deliver the same expected active returns, and uncorrelated signals and active returns further contribute to a reduction in fund level risk.

Nonetheless, in equilibrium, single-manager funds are managed by relatively better skilled managers. From Lemma 5, manager level performance is solely determined by the manager’s skill. In this sense, single-manager funds are advantageous at delivering better performance. From Lemma 6, team funds have better fund level performance when managers are equally skilled, due to diversification within teams. The resultant relative performance between single-manager and team funds is a result of the combination of these two effects. Threshold level of signal precision matters. When $\tau_s$ increases, average signal precision of managers in single-manager and team funds improves, and the probability of hiring a new team manager increases.

### 2.4.1 Within the Fund Family: Single v.s. Team

Within the fund family, which type of funds on average outperforms the other? As we have shown, only two factors should be considered: difference in managerial skill and team diversification.

On the one hand, single-manager funds are managed by better skilled managers. This means,
single-manager funds have advantage on expected active returns, which is linear and solely dependent on signal precision. To see this, consider one single-manager fund and one team fund randomly drawn from the mutual fund family. Ex ante expected active returns are

\[ E(\tilde{R}_{j,S}) = E\left[ E(\tilde{R}_{j,S}|\tilde{\tau}_i)|\tilde{\tau}_i \in [\tau_s, \tau_H]\right], \quad (43) \]

and

\[ E(\tilde{R}_{j,T}) = E\left[ E(\tilde{R}_{j,T}|\tilde{\tau}_i, \tilde{\tau}_{-i})|\tilde{\tau}_i, \tilde{\tau}_{-i} \in [\tau_L, \tau_*]\right]. \quad (44) \]

Their difference can be reduced to

\[ E(\tilde{R}_{j,S}) - E(\tilde{R}_{j,T}) = \sqrt{\tau_H \tau_L}(\sqrt{\tau_H} - \sqrt{\tau_L}) + \sqrt{\tau_*} (\tau_H - \tau_L) \]
\[ \left(\sqrt{\tau_H} + \sqrt{\tau_*}\right)^2, \quad (45) \]

which is always positive.

On the other hand, team funds benefit from diversification of managers’ independent signals and strategy active returns. Even though managed by less skilled managers, it is possible that team funds have lower fund level active risk.

Comparison of fund level risk between two fund management structures depends on which factor dominates. If team diversification dominates effect of difference in skill levels, team funds are less risky, and vice versa.

Moreover, if team funds are less risky such that fund level active risk is small enough to overwhelm single-manager funds’ advantage in expected active returns, then team funds can possibly outperform single-managed funds on average. In our model, the result is unclear and sensitive to parameter values.

2.4.2 Performance Across Fund Families

If fund families have different convexity in the relation between mutual fund performance and investors’ money inflows, as Proposition 4 shows, they will have different optimal threshold in the separation of single and team managers. The following proposition gives implications of different thresholds on fund level performance across fund families.
**Proposition 5** Across mutual fund families, a fund family with higher equilibrium threshold skill level has

1) Higher expected active returns, lower active risk and higher Information Ratio for its single-manager funds;

2) Higher expected active returns, lower active risk and higher Information Ratio for its team funds.

**Proof.** See the Appendix. ■

The difference in relative performance of mutual funds is driven by difference in organizational structure optimally chosen by different mutual fund families. When more managers in the given pool prefer the team contract, average skill levels of both team and single managers increase. We have shown that when mutual funds with the same management structure are compared, the only determinant of performance is managerial skill. Thus, sibling funds belonging to a fund family with larger fraction of team managers tend to have higher expected active return, lower active risk and of course higher Information Ratio.

**3 Empirical Predictions**

Our model yields the following testable predictions.

**Hypothesis 1 (H1)** Fund families with more convex flows have smaller fractions of team funds.

**Hypothesis 2 (H2)** Within each family, team fund managers have worse skills than managers in single-manager funds.

**Hypothesis 3 (H3)** Across families, controlling for family performance, team fund managers in more convex families have worse skills than team fund managers in less convex families; and stand-alone managers in more convex families have worse skills than stand-alone managers in less convex families.
4 Empirical Results

We test these hypotheses in this section using a sample of actively managed U.S. domestic equity funds from the Center for Research in Security Prices (CRSP) Mutual Fund Database.

4.1 Data

We obtain our data from several sources. We take fund names, returns, total net assets (TNA), expense ratios, investment objectives, and other fund characteristics from CRSP Survivorship Bias Free Mutual Fund Database. The CRSP mutual fund database lists multiple share classes separately. We obtain mutual fund portfolio holdings from the Thomson Reuters Mutual Fund Holdings (formerly CDA/Spectrum S12) database. The database contains quarterly portfolio holdings for all U.S. equity mutual funds. We merge the CRSP Mutual Fund database and the Thomson Reuters Mutual Fund Holdings database using the MFLINKS table available on WRDS (see Wermers (2000)).

We examine actively-managed U.S. equity mutual funds from January 1992 to December 2012. Our sample period starts in January 1992 as information about fund family is available in CRSP Mutual Fund data since then. We exclude balanced, bond, sector, index, and international funds. We identify and exclude index funds using their names and CRSP index fund identifier. To be included in the sample, a fund’s average percentage of stocks in the portfolio as reported by CRSP must be at least 70 percent or missing. Following Elton, Gruber, and Blake (2001), Chen, Hong, Huang, and Kubik (2004), and Yan (2008), we exclude funds with less than $15 million in TNA. We further eliminate observations before the fund’s starting date reported by CRSP to address

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3Similar to prior studies (e.g., Kacperczyk, Sialm, and Zheng (2008)), we base our selection criteria on objective codes and on disclosed asset compositions. First, we select funds with the following Lipper classification codes: EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, or SCVE. If a fund does not have a Lipper Classification code, we select funds with Strategic Insight objectives AGG, GMC, GRI, GRO, ING, or SCG. If neither the Strategic Insight nor the Lipper objective is available, we use the Wiesenberger Fund Type Code and select funds with objectives G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, or SCG. If none of these objectives is available, we keep a fund if it has a CS policy (i.e., the fund holds mainly common stocks). Further, we exclude funds that have the following Investment Objective Codes in the Thomson Reuters Mutual Fund Holdings database: International, Municipal Bonds, Bond and Preferred, Balanced, and Metals.

4Similar to Busse and Tong (2012) and Ferson and Lin (2014), we exclude from our sample funds whose names contain any of the following text strings: Index, Ind, Idx, Index, Mkt, Market, Composite, S&P, SP, Russell, Nasdaq, DJ, Dow, Jones, Wilshire, NYSE, iShares, SPDR, HOLDRs, ETF, Exchange-Traded Fund, PowerShares, StreetTRACKS, 100, 400, 500, 600, 1000, 1500, 2000, 3000, 5000. We also remove funds with CRSP index fund flag equal to D (pure index fund) or E (enhanced index fund).
incubation bias (Evans (2010)). Our final sample consists of 3,288 unique actively-managed U.S. equity mutual funds and 422,831 fund-month observations.

4.2 Variable Construction

To measure performance, we compute alphas using the Carhart (1997) four-factor model, which adjusts for excess market return (Mktrf), size (SMB), book-to-market (HML), and momentum (UMD) factors. Specifically, we first estimate the factor loadings using the preceding 24 monthly fund net returns. We require a minimum of 12 monthly observations in our estimation. We then calculate monthly out-of-sample alpha as the difference between a fund’s net return in a given month and the sum of the product of the estimated factor loadings and the factor returns during that month.

In addition to the four-factor alpha measure, we employ several variables to capture the activeness of fund managers’ portfolio management: (i) active share (Cremers and Petajisto (2009)), (ii) return gap (Kacperczyk, Sialm, and Zheng (2008)), and (iii) industry concentration (Kacperczyk, Sialm, and Zheng (2005)). First, active share captures the percentage of a manager’s portfolio that differs from its benchmark index. It is calculated by aggregating the absolute differences between the weight of a portfolio’s actual holdings and the weight of its closest matching index. Second, return gap measures the difference between fund gross returns and holdings-based returns. We compute gross fund returns by adding one-twelfth of the year-end expense ratio to the monthly net fund returns during the year. We calculate the holdings-based gross portfolio return each month as the return of the disclosed portfolio by assuming constant fund portfolio holdings from the end of the previous quarter. Finally, we compute industry concentration index as the sum of the squared deviations of the value weights for each industry held by the mutual fund, relative to the industry weights of the total stock market.

Team fund is an indicator variable that equals to one if the fund is managed by a team of portfolio managers based on CRSP mutual fund data and zero otherwise. Fund TNA is the sum of portfolio assets across all share classes of a fund. Fund Age is the age of the oldest share class in the fund. Family TNA is the aggregate total assets under management of each fund in a fund family.
Expense Ratio is the average expense ratio value-weighted across all fund share classes. Turnover ratio is defined as the minimum of sales or purchases divided by total net assets of the fund. Fund flow is calculated as the average monthly net growth in fund assets beyond capital gains and dividends (e.g., Sirri and Tufano (1998)). We report the summary statistics of all variables discussed above in Table 1.

### 4.3 Empirical Results

#### 4.3.1 Fraction of Team Funds and Flow Convexity

In this section, we test our model's prediction (H1) regarding the relation between family flow convexity and percentage of team funds. Following the insight from Huang, Wei, and Yan (2007) that small fund families have a more convex flow-performance relation compared to large families, we use fund family size as our main proxy for flow convexity. We then test hypothesis H1 that families with more convex flow compensation (i.e., small size families) have lower percentage of team funds.

We first use our sample to verify the previous finding that small fund families have higher flow convexity. Following Huang, Wei, and Yan (2007), we use a piecewise linear regression to analyze flow convexity. In particular, each month, we assign funds’ fractional performance ranks from zero to one based on their past 12-month net returns relative to other funds with similar investment objectives, or based on their four-factor alphas during the past 24 months. The fractional rank for funds in the bottom performance quintile (Low) is defined as \( \min(Rank, 0.2) \). Funds in the three medium performance quintiles (Mid) are grouped together and receive ranks that are defined as \( \min(0.6, Rank - Low) \). The rank for the top performance quintile (High) is defined as \( \text{Rank} - \text{Mid} - \text{Low} \). Each month a piecewise linear regression is performed by regressing monthly flows on lagged funds’ fractional performance rankings over the low, medium, and high performance ranges, their interaction terms with an indicator variable (Large Family) that equals one if the fund belongs to a family whose size is above median value and zero otherwise. The control variables include aggregate flow into the fund objective category, fund size, fund age, team fund dummy, expense ratio, turnover ratio, volatility of monthly returns during past 12 month.
Table 2 reports the time series average of the monthly coefficient estimates and Fama and MacBeth (1973) t-statistics adjusting standard errors using the Newey and West (1987) correction with 12 lags. Fractional performance ranks are based on past 12-month net returns in columns (1) and (2) and based on four-factor alphas in columns (3) and (4). First, the coefficient estimate of High is significantly larger compared to the coefficient of Low or Mid in columns (1) and (3). It suggests that the flow-performance relation is convex, consistent with prior studies such as Chevalier and Ellison (1997) and Sirri and Tufano (1998). Second, like in Huang, Wei, and Yan (2007), we find that the flow-performance relation is more convex for smaller size families. In particular, in columns (2) and (4), the coefficients of the interaction term between High and Large Family are both significantly negative, while the coefficients of the interaction term between Mid and Large Family are positive. With the above evidence, we use fund family size as the proxy for family flow convexity.

Next, we test hypothesis H1 by analyzing the percentage of team funds across families with difference flow convexity proxied by family size. In particular, in a given month, we calculate for each fund family the percentage of team funds based on the number of funds or fund TNA. Then, we sort fund families into quintiles each month based on lagged family size and calculate the time series average of the percentage of team funds for each of the family size quintiles. We also test the difference in team fund percentage between the smallest and largest family size quintiles and adjust standard errors using the Newey and West (1987) correction with 12 lags. Table 3 presents the results. Consistent with hypothesis H1, we find that small families (i.e., the ones with more convex flow compensation) have lower percentage of team funds compared to large families. In particular, the average percentage of team funds is 54% based on number of funds for largest family size quintile (Q5). In contrast, the corresponding percentage of team funds for smallest family size quintile is 40.7%, with a difference of 13.3% being both statically and economically significant. We find similar evidence if we compute the percentage of team funds based on fund TNA, rather than number of funds.

In Figure 2, we plot the yearly averages of the percentage of team funds in the smallest and largest family size quintiles (Q1 and Q5) over the entire sample period. The percentage of team
funds is calculated using the number of funds in Panel (a) and fund TNA in Panel (b). In both panels, we find that small families of Q1 have lower percentage of team funds compared to large families of Q5 in 20 out of the 21 years.

We further plot the time series of the convexity of the flow-performance relation in Figure 3. In particular, Panels (a) and (b) plot the 2-year moving averages of the monthly coefficient estimates of Low, Mid, and High based on the results in Table 2 columns (1) and (3), respectively. Similar to Kim (2014), we find a clear decreasing trend over time in the convexity of the flow-performance relation over the period from 1992 to 2012 in the U.S. mutual fund industry. This decreasing trend in convexity coincides with the increasing trend in the percentage of team funds as shown in Figure 1 Panels (a) and (b), which is also broadly consistent with the hypothesis H1 that associates less flow convexity with higher percentage of team funds.

4.3.2 Team vs. Single-Manager Funds within Family

In this section, we test our model’s prediction (H2) that, within each family, team fund managers have worse skills than managers in single-manager funds. In particular, we run Fama-MacBeth regressions of monthly fund performance or portfolio activeness measure on the team fund dummy with family fixed effects:

\[ Y_{i,j,t} = \alpha + \beta \text{TeamFund}_{i,j,t-1} + \gamma X_{i,j,t-1} + f_j + \epsilon_{i,j,t}, \]  

(46)

where \( Y_{i,j,t} \) refers to fund i’s performance or portfolio management activeness as measured by active share, return gap, or industry concentration index; TeamFund_{i,j,t-1} is a dummy variable that takes the value of one if the fund is a team fund and zero otherwise; \( f_j \) refers to family fixed effects. The control variables \( X_{i,j,t-1} \) include lagged family size dummies, fund size, fund age, expense ratio, fund flow, turnover ratio, and fund net return. Table 4 reports the estimation results on fund performance. We analyze fund net return in columns (1) and (2) and four-factor alpha in columns (3) and (4). Consistent with our model’s prediction H2, we find that team funds underperform single-manager funds within family. In columns (2) and (4) that include control variables, the coefficient estimates of
team fund dummy are both negative and significant at the 5% level. In terms of economic significance, based on the results in column (4), team funds underperform single-manager funds within family by 30.1 basis points per annum as measured by four-factor alpha.

Table 5 reports the estimation results on active share, return gap, and industry concentration. Consistent with our model’s prediction H2, we find that within family team funds are less active in managing their portfolios compared to single-manager funds. The coefficient estimates of team fund dummy are all negative, significant in four of six specifications. It suggests that team fund managers are less active in deviating from benchmarks and holding concentrated portfolios. In summary, the evidence in Tables 4 and 5 supports to our model’s prediction that, within family, team fund managers have worse skills than managers in single-manager funds.

We further examine the difference in volatility of alpha and information ratio for team vs. single-manager funds. Each year we calculate the average of monthly four-factor alphas, volatility (i.e., standard deviation) of alpha, and information ratio (i.e., alpha mean over its standard deviation). We then run yearly Fama-MacBeth regressions of these three variables on team fund dummy and other controls with family fixed effects. Table 6 reports the estimation results. First, consistent with Table 4, the results in columns (1) and (2) show that team funds underperform single-manager funds within family. Second, we find that team funds exhibit lower risk compared to single-manager funds as measured by volatility of alpha as shown in columns (3) and (4). Third, team funds also have lower information ratio compared to single-manager funds within family as shown in columns (5) and (6), which suggests that the effect of team management on alpha dominates the effect on volatility of alpha.

4.3.3 Fund Performance and Activeness across families

In this section, we test our model’s prediction (H3) that, across families, team fund and stand-alone managers in families with more convex flows have worse skills than their counterparts in less convex families, respectively. To conduct an across-family analysis, we run Fama-MacBeth regressions of monthly fund performance or portfolio activeness measure on the family flow convexity proxy (i.e.,
two family size dummies). We include control variables such as lagged family size dummies, fund size, fund age, expense ratio, fund flow, turnover ratio, and fund net return. To alleviate the potential concern that certain families (e.g., larger size ones) attract more talented managers, we further control for the average performance or portfolio activeness of all funds in the family excluding the fund itself in our main regressions. Table 7 reports the estimation results. We analyze single-manager funds in columns (1) and (4), team funds in columns (2) and (5), and all funds in columns (3) and (6). We add family average alpha as an additional control in columns (3) to (6). Consistent with our model’s prediction H3, we find that team fund and stand-alone managers in small families (i.e., with more convex flows) underperform their counterparts in large families (i.e., with less convex flows), respectively, after controlling for family performance. In particular, the coefficient estimates of Middle Family and Large Family are positive and significant at the 10% or better in all six specifications. Moreover, the differences between Large Family and Middle Family are all positive, significant in four out of six specifications as shown in the bottom of Table 7.

Next, we examine the activeness of fund managers’ portfolio management across families and present the estimation results in Table 8. Our results shows that team fund and stand-alone managers in small families are less active in managing their portfolios compared to their counterparts in large families, respectively, after controlling for the family average of portfolio management activeness. In particular, the coefficient estimates of Middle Family and Large Family are all positive, significant in most specifications. Moreover, the coefficient estimate of Large Family is significantly larger than the one of Middle Family in seven out of nine specifications. This evidence provides further support to our hypothesis H3.

Finally, we examine the across-family difference in volatility of alpha and information ratio for team fund and stand-alone managers, respectively. We report the Fama-MacBeth estimation results in Table 9. Consistent with Table 6, the results in columns (1) to (3) show that team fund and stand-alone managers in small families underperform their counterparts in large families, respectively. We also find that funds in larger families also have higher volatility of alpha. Furthermore, we find that team fund and stand-alone managers in small families have lower information ratio compared their
counterparts in large families, respectively, which is also consistent with our model’s prediction (H3).

5 Conclusion

We develop a model of delegated portfolio management with two layers of agency problems between investors, fund families and managers. We consider an independent team structure in which each manager has full discretion over their own sub portfolio. Given any two managers, a team fund provides at least as good a performance as the weighted average of two separately-run single-manager funds, with similar mean return and lower variance due to diversification of investment risks and manager skills. However, team funds on average can still underperform single-manager funds.

The reason is that fund families always choose to offer risk sharing contracts within their team funds. Their objective is to maximize their own profit by reducing expected compensation to risk averse managers. As a result, better skilled managers prefer single-manager fund over team fund structure, leading to underperformance of team funds. Thus, fund families’ incentive to maximize expected profit yields very different outcome from maximizing fund performance for investors.

We also find that convex compensation for fund families leads to a preference for single-manager funds over team funds, because their expected revenue is higher from two single-manager funds than from a team fund. Therefore, families with more convex compensation optimally choose a lower fraction of team-managed funds and have a lower risk-adjusted performance. An interesting application of this result is the overwhelming popularity of single-manager single-strategy funds for hedge funds, which arguably has the most convex, incentive fee compensation contracts. Hedge fund investors often hold several funds (sometimes issued by the same fund family or even the same fund manager), each focusing on a different strategy and charging a separate option-like compensation. While this payment scheme appears overly expensive for investors, it may not be in the best interest of investors to switch to multi-strategy hedge funds which charge incentive fees only when the combined performance of all strategies is sufficiently high. The reason is that the multi-strategy fund may not generate sufficient revenue to retain the best hedge fund managers in each of the strategies.

Our model yields several testable predictions for empirical study. We use the well-documented
fact that small families have more convex fund flows to test our theory and find consistent evidence: First, small fund families have lower fractions of team funds; Second, within each family, team funds have worse performance than single-manager funds; Third, across families, controlling for family performance, team (or single-manager) funds in smaller family perform worse than team (or single-manager) funds in large families.

There are interesting developments in the money management industry recently. Some fund families take the team logic further and roll out funds of mutual funds, which offer investors a diversified portfolio of managers in a single fund. Through team funds and funds of funds, investors can delegate the job of choosing fund managers and forming efficient portfolios to the fund families. At the opposite end of the spectrum, we observe fund families (especially hedge funds) offering multiple funds managed by the same fund manager, expanding and also complicating the choice set for investors. Our model is able to explain both the consolidation trend of team funds and funds of funds and the expansion trend of busy managers who manage multiple funds, based on the incentives of fund families to maximize their own profits. For future research, it is important to ask how to best align the incentives of fund families and investors so that the industry will develop in a direction that is socially optimal.

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5 See for example, an “all-in-one” fund, like Vanguard target retirement fund, which is “designed to help you simplify the way you manage your portfolio and reduce your investment risk” (https://investor.vanguard.com/mutual-funds/all-in-one-funds). Fund of funds is actually one of the fastest growing market segments in the mutual fund industry, with 1,156 funds of funds and 1.3 trillion TNA in 2012, according to ICI factbook.

6 An extreme example of this team approach is Berkshire Hathaway, in which Warren Buffett, Charlie Munger and all their employees combine their talents and offer one fund only, simplifying the task for their investors.
References


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Huang, J., K. D. Wei, and H. Yan (2010). Volatility of performance and mutual fund flows. Cheung Kong Graduate School of Business, University of Texas at Dallas, and Shanghai Advanced Institute of Finance.


Appendix: Proofs

Proof of Lemma 1

Given a common prior belief, where an arbitrary subset \( \Gamma \subset \Omega \) would choose the team-management contract, manager \( i \)'s ex ante expected utility from that contract can be calculated with equations (17) and (18):

\[
E(U_{i,T}) = a_T + W_0\alpha \left[ (b + \phi)\sqrt{\tau_i} - \phi E(\sqrt{\tau_i} | \tilde{\tau}_i \in \Gamma) \right] - \frac{\gamma W_0^2\alpha^2}{4} \left\{ (b + \phi)^2(1 - 4\tau_i) + \phi^2 \left[ 1 - 4E(\tilde{\tau}_i | \tilde{\tau}_i \in \Gamma) \right] \right\}.
\] (A1)

Subtract (16) from it, we have ex ante utility gap between the two contracts for the manager with \( \tau_i \),

\[
G(\tau_i; a_S, a_T, \phi, \Gamma) = a_T - a_S + \phi W_0\alpha \sqrt{\tau_i} - \frac{\gamma W_0^2\alpha^2}{4} \phi(\phi + 2b)(1 - 4\tau_i)
- \left[ \phi E(\sqrt{\tilde{\tau}_i} | \tilde{\tau}_i \in \Gamma) + \phi^2 \left( 1 - 4E(\tilde{\tau}_i | \tilde{\tau}_i \in \Gamma) \right) \right]
\] (A2)

where the last term is a constant given \( \Gamma \). Differentiate \( G(\tau_i; a_S, a_T, \phi, \Gamma) \) with respect to \( \tau_i \) and collect terms,

\[
\frac{\partial G(\tau_i; a_S, a_T, \phi, \Gamma)}{\partial \tau_i} = \phi W_0\alpha \left[ \frac{1}{2} \tau_i^{\frac{1}{2}} + \gamma W_0\alpha(\phi + 2b) \right].
\] (A3)

Since \( \phi \in [-\frac{2b}{\phi}, \frac{b}{2}] \), we have

\[
\text{sign} \left[ \frac{\partial G(\tau_i; a_S, a_T, \phi, \Gamma)}{\partial \tau_i} \right] = \text{sign}(\phi).
\] (A4)

It implies that given any equilibrium subset \( \Gamma \), utility gap \( G(\tau_i; a_S, a_T, \Gamma) \) changes in the manager’s signal precision monotonically. This completes the proof.

Proof of Proposition 1

(Uniqueness) Following Lemma 1, subset of team managers, \( \Gamma \), is endogenous in equilibrium and dependent on the threshold signal precision \( \tau_\ast \). When \( \phi < 0 \), we have \( \Gamma = [\tau_L, \tau_\ast] \). Insert it into the utility gap function, and for the threshold manager:

\[
G(\tau_\ast; a_S, a_T, \phi, [\tau_L, \tau_\ast]) = a_T - a_S + \phi W_0\alpha \sqrt{\tau_\ast} - E(\sqrt{\tau_i} | \tilde{\tau}_i \in [\tau_L, \tau_\ast])
- \frac{\gamma W_0^2\alpha^2}{4} \left\{ (\phi^2 + 2b\phi)(1 - 4\tau_\ast) + \phi^2 \left[ 1 - 4E(\tilde{\tau}_i | \tilde{\tau}_i \in [\tau_L, \tau_\ast]) \right] \right\}.
\] (A5)
With the uniform distribution assumption,
\[
\text{pdf}(\tilde{\tau}_{-i}|\tilde{\tau}_{-i} \in \Gamma = [\tau_L, \tau_*]) = \frac{1}{\tau_* - \tau_L}.
\] (A6)

Apply the probability density function (A6) in (A5), differentiate the utility gap with respect to \( \tau_* \), and collect terms,
\[
\frac{\partial G(\tau_*; a_S, a_T, \phi, [\tau_L, \tau_*])}{\partial \tau_*} = \frac{1}{6} \phi W_0 \alpha \left[ \frac{\tau_* + 2 \sqrt{\tau_0 \tau_L} + 3 \tau_L}{\sqrt{\tau_*} (\sqrt{\tau_*} + \sqrt{\tau_L})^2} + 3 \gamma W_0 \alpha (4b + 3\phi) \right],
\] (A7)
which is negative for any \( \phi \in [-\frac{b}{2}, 0) \). The monotonicity of \( G(\tau_*; a_S, a_T, \phi, [\tau_L, \tau_*]) \) dictates that there is at most one interior solution for equation (22), and we will always have a unique \( \tau_* \) in equilibrium.

(\text{Constant Values}) Since \( G(\tau_*; a_S, a_T, [\tau_L, \tau_*]) \) is a continuous and decreasing function of \( \tau_* \), with Intermediate Value Theorem, a sufficient and necessary condition for \( \tau_* \in (\tau_L, \tau_H) \) is
\[
\begin{cases}
\lim_{{\tau_* \to \tau_L}} G(\tau_*; a_S, a_T, \phi, [\tau_L, \tau_*]) > 0 \\
\lim_{{\tau_* \to \tau_H}} G(\tau_*; a_S, a_T, \phi, [\tau_L, \tau_*]) < 0.
\end{cases}
\]
This is equivalent to
\[
\begin{cases}
a_T - a_S - \frac{1}{2} \phi (b + \phi) \gamma W_0^2 \alpha^2 (1 - 4\tau_L) > 0 \\
a_T - a_S + \frac{1}{6} \phi W_0 \alpha \left\{ \frac{2(\tau_H + \sqrt{\tau_H \tau_L} - 2\tau_L)}{\sqrt{\tau_H} + \sqrt{\tau_L}} - 3 \gamma W_0 \alpha [b (1 - 4\tau_H) - \phi (1 - 3\tau_H - \tau_L)] \right\} < 0.
\end{cases}
\]
Match them to conditions in Proposition 1 yields constant term values.

\textbf{Proof of Lemma 2}

From equation (28), two single-manager funds are expected to deliver flow-benefits to fund family equal to
\[
(B - b) W_0 (\sqrt{\bar{\tau}_i} + \sqrt{\bar{\tau}_{-i}}) \alpha + CW_0 \alpha^2.
\] (A8)
If the same two managers work in a team-managed fund, from equation (32), expected flow-benefits are
\[
(B - b) W_0 (\sqrt{\bar{\tau}_i} + \sqrt{\bar{\tau}_{-i}}) \alpha + CW_0 \left( \frac{1}{2} + \sqrt{\bar{\tau}_i \bar{\tau}_{-i}} \right) \alpha^2.
\] (A9)
Compare (A8) and (A9), we can see that linear flows are the same across different types of funds, but differ in convex terms. Since \( \bar{\tau}_i, \bar{\tau}_{-i} \in \Phi \subset (0, \frac{1}{4}) \), we have \( \sqrt{\bar{\tau}_i \bar{\tau}_{-i}} < \frac{1}{4} \).

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Proof of Proposition 2

We start from a special case where $a_T = a_S$. Suppose instead $\phi > 0$, for an arbitrary threshold skill level $\tau_* \in [\tau_L, \tau_H]$, the subset of managers who choose team-management contract is $\Gamma = [\tau_*, \tau_H]$ according to Lemma 1. Insert $a_T$ and $\Gamma$ into the utility gap function 19. For the threshold manager:

$$
G(\tau_*; a_S, a_T, \phi, [\tau_L, \tau_*]) = \phi W_0 \alpha \left\{ \frac{2(\tau_* + \sqrt{\tau_* \tau_L} - 2\tau_L)}{\sqrt{\tau_*} + \sqrt{\tau_L}} - 3\gamma W_0 \alpha \left[ b(1 - 4\tau_*) - \phi(1 - 3\tau_* - \tau_L) \right] \right\},
$$

which is always negative for any $\tau_*$. A negative utility gap implies that the threshold manager has incentive to deviate and choose the single-management contract. If she deviates, then the next manager with marginally better skill faces the same problem. Repeat such a deviation argument and we can show that no manager would choose the team-management contract in equilibrium. That is to say, if the fund family offers the same fixed salary in two contracts, it is equivalent to offering only the single-management contract.

Then what if $a_T \neq a_S$? From Lemma 2, we see that it is optimal for the fund family’s revenue if all managers choose the single-management contract. Therefore, there is no incentive for the fund family to change fixed salary in order to induce any other equilibrium given a positive $\phi$. So $\phi < 0$ is the only non-trivial choice for the fund family.

Proof of Lemma 3

For an interior case in (22), threshold manager’s indifferent condition is

$$
G(\tau_*; a_S, a_T, \phi, [\tau_L, \tau_*]) = 0.
$$

(A11)

It can be simplified to

$$
a_T - a_S + \frac{1}{6} \phi W_0 \alpha \left\{ \frac{2(\tau_* + \sqrt{\tau_* \tau_L} - 2\tau_L)}{\sqrt{\tau_*} + \sqrt{\tau_L}} - 3\gamma W_0 \alpha \left[ b(1 - 4\tau_*) - \phi(1 - 3\tau_* - \tau_L) \right] \right\} = 0.
$$

(A12)

If we differentiate with respect to $a_S$ and $a_T$ at both sides of the equation, respectively, we get

$$
\frac{\partial \tau_* (a_S, a_T)}{\partial a_S} = \frac{1}{\partial G(\tau_*; a_S, a_T, \phi, [\tau_L, \tau_*]) / \partial \tau_*},
$$

(A13)

and

$$
\frac{\partial \tau_* (a_S, a_T)}{\partial a_T} = -\frac{1}{\partial G(\tau_*; a_S, a_T, \phi, [\tau_L, \tau_*]) / \partial \tau_*}.
$$

(A14)
Since we have
\[
\frac{\partial G(\tau^*_s; a_S, a_T, \phi, [\tau_L, \tau_s])}{\partial \tau_s} < 0,
\]
from (A7), this completes the proof.

**Proof of Proposition 3**

We prove it by showing that, with \( \phi = -\frac{b}{2} \) and smaller fixed salary \( \{\bar{a}_S, \bar{a}_T\} \), we can always construct a new equilibrium with the same threshold \( \tau_s \) to an equilibrium induced by any \( \bar{\phi} \in (-\frac{b}{2}, 0) \). Since only \( \tau_s \) and fixed salary affect the fund family’s profit, the new equilibrium dominates the original one.

To begin the proof, we show the effect of a marginal change of \( \phi \) on equilibrium \( \tau_s \). Take first and second order derivatives of \( G(\tau^*_s; a_S, a_T, \phi, [\tau_L, \tau_s]) \) with respect to \( \phi \):
\[
\frac{\partial G(\tau^*_s; a_S, a_T, \phi, [\tau_L, \tau_s])}{\partial \phi} = \frac{1}{6} W_0\alpha \left[ \frac{2(\tau_s + \sqrt{\tau_s \tau_L} - 2\tau_L)}{\sqrt{\tau_s} + \sqrt{\tau_L}} - 3\gamma b W_0\alpha (1 - 4\tau_s) - 6\gamma \phi W_0\alpha (1 - 3\tau_s - \tau_L) \right],
\]
(A15)

and
\[
\frac{\partial^2 G(\tau^*_s; a_S, a_T, \phi, [\tau_L, \tau_s])}{\partial \phi^2} = -\gamma W_0^2\alpha^2 (1 - 3\tau_s - \tau_L).
\]
(A16)
The sign of the first derivative is undetermined. But for the second, it is negative for any \( \tau_s \in [\tau_L, \tau_H] \), which means \( G(\tau^*_s; a_S, a_T, \phi, [\tau_L, \tau_s]) \) is a strictly concave function of \( \phi \). As \( \phi \) decreases, given the same \( \tau^*_s \), \( a_S \), and \( a_T \), \( G \) may increase or decrease. We analyze these two cases separately and start with an arbitrary feasible set of parameters: \( \{\bar{a}_S, \bar{a}_T, \bar{\phi}\} \).

1) If \( G(\tau^*_s; \bar{a}_S, \bar{a}_T, \bar{\phi}, [\tau_L, \tau_s]) \) decreases when \( \bar{\phi} \) shifts to \( -\frac{b}{2} \) from a larger negative value, we can easily construct a new equilibrium by reducing fixed salary for single-management contract \( \bar{a}_S \) while keeping \( \bar{a}_T = \bar{a}_T \). Since \( G \) decreases linearly in \( a_S \), such a reduction in \( \bar{a}_S \) leads to an increase in \( G \). There is no lower bound for \( a_S \), so there must exist an \( \bar{a}_S < \bar{a}_S \) such that
\[
G(\tau^*_s; \bar{a}_S, \bar{a}_T, -\frac{b}{2}, [\tau_L, \tau_s]) = G(\tau^*_s; \bar{a}_S, \bar{a}_T, \bar{\phi}, [\tau_L, \tau_s]),
\]
(A17)
and equilibrium \( \tau_s \) is brought back to the value before we change \( \phi \).

2) If \( G(\tau^*_s; \bar{a}_S, \bar{a}_T, \bar{\phi}, [\tau_L, \tau_s]) \) increases when \( \bar{\phi} \) shifts to \( -\frac{b}{2} \) from a larger negative value, we can similarly reduce \( \bar{a}_T \) while keeping \( \bar{a}_S = \bar{a}_S \) to replicate the old equilibrium. However, given managers’ participation constraint, there exists an effective lower bound for \( a_T \). Define function \( \bar{a}_T(\phi) \) as the optimal (smallest) choice of \( a_T \) for the fund family as a function of parameter \( \phi \). According to
Lemma 4, it is
\[
\hat{a}_T(\phi) = U + \frac{1}{4} \gamma \left[(b + \phi)^2 + \phi^2\right] W_0^2 \alpha^2 (1 - 4\tau_L) - b W_0 \alpha \sqrt{\tau_L}. \quad (A18)
\]
Note that this lower bound will be smaller as \( \phi \) decreases. Replace \( \hat{a}_T \) and \( \bar{\phi} \) with \( \hat{a}_T(\phi) \) and \( \phi \), we get \( G(\tau_s; \tilde{a}_S, \hat{a}_T(\phi), \phi, [\tau_L, \tau_s]) \). Differentiate it with respect to \( \phi \),
\[
\frac{\partial G(\tau_s; \tilde{a}_S, \hat{a}_T(\phi), \phi, [\tau_L, \tau_s])}{\partial \phi} = \frac{1}{3} W_0 \alpha \left[ \frac{\tau_s + \sqrt{\tau_s \tau_L} - 2\tau_L}{\sqrt{\tau_s} + \sqrt{\tau_L}} + 3\gamma(2b + 3\phi)W_0 \alpha (\tau_s - \tau_L) \right], \quad (A19)
\]
which is positive. It implies that when optimal fixed salary for team managers is imposed, utility gap monotonically increases in \( \phi \) for any \( \tau_s \). Then we have
\[
G(\tau_s; \tilde{a}_S, \hat{a}_T(-b/2), [\tau_L, \tau_s]) < G(\tau_s; \tilde{a}_S, \hat{a}_T(\bar{\phi}), [\tau_L, \tau_s]) \leq G(\tau_s; \tilde{a}_S, \hat{a}_T, [\tau_L, \tau_s])
\]
for \( \forall \tau_s \in [\tau_L, \tau_H] \). So there must exists an \( \bar{a}_T \in (\hat{a}_T(-b/2), \hat{a}_T) \), such that
\[
G(\tau_s; \tilde{a}_S, \bar{a}_T, [\tau_L, \tau_s]) = G(\tau_s; \tilde{a}_S, \hat{a}_T, [\tau_L, \tau_s]). \quad (A20)
\]
This completes the proof.

**Proof of Proposition 4**

Integrate over equilibrium \( \Gamma = [\tau_L, \tau_s] \) and \( \Gamma^c = [\tau_s, \tau_H] \) for single and team managers, the fund family’s expected profit per manager are:
\[
E[\pi_{i,S}(a_S)] = \int_{\tau_s(a_S)}^{\tau_H} \frac{E[\pi_S(a_S); \bar{\tau}_i]}{\tau_H - \tau_s(a_S)} d\bar{\tau}_i, \quad (A21)
\]
which is
\[
E[\pi_{i,S}(a_S)] = AW_0 - a_S + \frac{2}{3}(B - b)W_0 \alpha \frac{\frac{\tau_s}{2} - \frac{\tau_L}{2}}{\tau_H - \tau_s} + \frac{1}{2} CW_0 \alpha^2. \quad (A22)
\]
and
\[
E[\pi_{i,T}(a_S)] = \int_{\tau_L}^{\tau_s(a_S)} \int_{\tau_L}^{\tau_s(a_S)} \frac{E[\pi_T(a_S; \bar{\tau}_i, \tilde{\tau}_-i)]}{(\tau_s(a_S) - \tau_L)^2} d\bar{\tau}_i d\tilde{\tau}_-i, \quad (A23)
\]
which is
\[
E[\pi_{i,T}(a_S)] = AW_0 - a_T + \frac{2}{3}(B - b)W_0 \alpha \frac{\frac{\tau_s}{2} - \frac{\tau_L}{2}}{\tau_s - \tau_L} + \frac{1}{4} CW_0 \alpha^2 + \frac{2}{9} CW_0 \alpha^2 \left( \frac{\frac{\tau_s}{2} - \frac{\tau_L}{2}}{\tau_s - \tau_L} \right)^2. \quad (A24)
\]
Insert (A22) and (A24) into the objective function of the fund family’s expected profit maximization problem (35) and collect terms, we have

\[
\Pi = AW_0 + \frac{1}{4} CW_0 \alpha^2 + \frac{2}{3} (B - b) W_0 \alpha \frac{\tau_H^3 - \tau_L^3}{\tau_H - \tau_L} - \left( \frac{\tau_H - \tau_s}{\tau_H - \tau_L} \right) a_S (\tau_s - \tau_L) a_T + CW_0 \alpha^2 \left[ \frac{\tau_H - \tau_s}{4} + \frac{2}{9} \left( \frac{\tau_s^3 - \tau_L^3}{\tau_s - \tau_L} \right)^2 \right].
\]  

(A25)

For convenience, we define terms related to fixed salary \(a_S\) as functions of \(\tau_s\):

\[
K(\tau_s) = \frac{(\tau_H - \tau_s) a_S(\tau_s) + (\tau_s - \tau_L) a_T}{\tau_H - \tau_L},
\]

(A26)

and

\[
L(\tau_s) = \frac{\tau_H - \tau_s}{4} + \frac{2}{9} \left( \frac{\tau_s^3 - \tau_L^3}{\tau_s - \tau_L} \right)^2.
\]

(A27)

Then the objective function can be written as

\[
\Pi = AW_0 + \frac{1}{4} CW_0 \alpha^2 + \frac{2}{3} (B - b) W_0 \alpha \frac{\tau_H^3 - \tau_L^3}{\tau_H - \tau_L} - K(\tau_s) + CW_0 \alpha^2 \frac{\tau_H - \tau_s}{\tau_H - \tau_L} L(\tau_s).
\]

(A28)

1) When \(C = 0\), maximization problem (35) is equivalent to

\[
\min_{\tau_s \in [\tau_H, \tau_L]} K(\tau_s).
\]

Twice differentiate \(K(\tau_s)\) with respect to \(\tau_s\):

\[
K''(\tau_s) = \frac{(\tau_H - \tau_s) a''_S(\tau_s) - 2a'_S(\tau_s)}{\tau_H - \tau_L}.
\]

(A29)

We have

\[
a'_S(\tau_s) = \frac{1}{\partial \tau_s(a_S)/\partial a_S} < 0
\]

(A30)

from the proof of Lemma 3. To find out \(a''_S(\tau_s)\), twice differentiate with respect to \(\tau_s\) at both sides of equation (A12):

\[
a''_S(\tau_s) = -\phi W_0 \alpha \frac{\tau_s^3 + 3\tau_s \sqrt{\tau_L} + 9 \sqrt{\tau_L} \tau_s + 3 \tau_L^3}{12 \sqrt{\tau_s} + \sqrt{\tau_L} \tau_s} > 0.
\]

(A31)
Then we have

\[ K''(\tau_s) > 0, \]

which means that \( K(\tau_s) \) is a strictly convex function of \( \tau_s \). So the optimal choice of \( \tau_s \) solves the first order condition:

\[ K'(\tau_s) = a_T - a_S(\tau_s) + (\tau_H - \tau_s)a_S'(\tau_s) = 0. \tag{A32} \]

Since \( c_2 > 0, a_S(\tau_L) > a_T \). Then if we insert \( \tau_s = \tau_L \) into \( K'(\tau_s) \), we have

\[ K'(\tau_L) = a_T - a_S(\tau_L) + (\tau_H - \tau_L)a_S'(\tau_L) < 0. \tag{A33} \]

In addition, if \( c_1 < 0 \), then

\[ K'(\tau_H) = a_T - a_S(\tau_H) > 0. \tag{A34} \]

With (A33) and (A34), the optimal choice of \( \tau_s \) must satisfy \( \tau_s \in (\tau_L, \tau_H) \).

2) When \( C > 0 \), twice differentiate \( \Pi \) with respect to \( \tau_s \), we have

\[ \frac{\partial^2 \Pi}{\partial \tau_s^2} = \frac{CW_0\alpha^2}{\tau_H - \tau_L} L''(\tau_s) - K''(\tau_s), \tag{A35} \]

Insert full expressions of \( L''(\tau_s) \), \( K''(\tau_s) \) and \( \phi = -\frac{b}{2} \) into it, and with some tedious calculations, we get

\[ L''(\tau_s) = -\frac{W_0r}{72(\tau_H - \tau_L)(\sqrt{\tau_L} + \sqrt{\tau_s})^3\tau_s^3} \Upsilon, \tag{A36} \]

where

\[ \Upsilon = 90\gamma b^2 W_0 \alpha (\sqrt{\tau_L} + \sqrt{\tau_s})^3 \tau_s^3 - 8C\alpha \tau_s (3\tau_L^3 + 5\tau_L^3\sqrt{\tau_s} + 12\tau_L\tau_s + 12\sqrt{\tau_L}\tau_s^3 + 4\tau_s^3) \]

\[ + 3b \left[ \tau_H (3\tau_L^3 + 9\tau_L\sqrt{\tau_s} + 3\sqrt{\tau_L}\tau_s + \tau_s^3) + \tau_s (9\tau_L^3 + 11\tau_L\sqrt{\tau_s} + 9\sqrt{\tau_L}\tau_s + 3\tau_s^3) \right]. \tag{A37} \]

Since \( \tau_s \leq \tau_H < \frac{1}{4} \), we can shrink (A37) by multiplying the second term with \( \frac{1}{\tau_H} \), and simultaneously replacing \( \tau_H \) in the third term with \( \tau_s \):

\[ \Upsilon > 90\gamma b^2 W_0 \alpha (\sqrt{\tau_L} + \sqrt{\tau_s})^3 \tau_s^3 - 4C\alpha \tau_s \left( \frac{3\tau_L^3}{\sqrt{\tau_s}} + 5\tau_L^3 + 12\tau_L\sqrt{\tau_s} + 12\sqrt{\tau_L}\tau_s + 4\tau_s^3 \right) \]

\[ + 3b\tau_s \left( 12\tau_L^3 + 20\tau_L\sqrt{\tau_s} + 12\sqrt{\tau_L}\tau_s + 4\tau_s^3 \right). \tag{A38} \]
When
\[ C < \frac{3b}{4\alpha} \]
with the transitive property of inequalities, we can readily have
\[
\frac{\partial^2 \Pi}{\partial \tau_+^2} < -\frac{bW_0\alpha}{24(\tau_H - \tau_L)(\sqrt{\tau_L} + \sqrt{\tau_+})^3\tau_+} \left[ 30\gamma bW_0\alpha(\sqrt{\tau_L} + \sqrt{\tau_+})^3\tau_+ + \left( 7\tau_L^2\sqrt{\tau_L} + \tau_L(20\tau_+ - 3\tau_L) \right) \right] < 0,
\]
(A39)
which means \( \Pi \) is a concave function for any \( \tau^\ast \in [\tau_L, \tau_H] \). Thus, optimal choice of \( \tau^\ast \) can be characterized by the first order condition:
\[
\frac{\partial \Pi}{\partial \tau_+} = 0,
\]
(A40)
which is
\[
\frac{CW_0\alpha^2}{\tau_H - \tau_L} L'(\tau_+) = K'(\tau_+). \quad \text{(A41)}
\]
Notice that
\[
L'(\tau_+) = -\frac{1}{36} \left[ 9 - 16\tau_+ - \frac{8\tau_L(\tau_L - \sqrt{\tau_L\tau_+} - \tau_+)}{(\sqrt{\tau_L} + \sqrt{\tau_+})^2} \right].
\]
(A42)
We can enlarge it by replacing one \( \tau_+ \) and one \( \tau_L \) with \( \frac{1}{4} \),
\[
L'(\tau_+) < -\frac{1}{36} \left[ 5 - \frac{2(\tau_L - \sqrt{\tau_L\tau_+} - \tau_+)}{(\sqrt{\tau_L} + \sqrt{\tau_+})^2} \right]
\]
(A43)
\[
= -\frac{1}{36(\sqrt{\tau_L} + \sqrt{\tau_+})^2} (3\tau_L + 3\tau_+ + 8\sqrt{\tau_L\tau_+}) < 0.
\]
Then given a \( \tau_+ \), a marginal increase in \( C \) causes Left Hand Side of (A41) to be smaller. To ensure that the first order condition holds, a smaller \( \tau_+ \) is needed. The result follows as all functions are continuous and differentiable.

**Proof of Lemma 5**

Given signal precision \( \tau_i \), expected excess return of manager \( i \)'s (sub)portfolio is
\[
E(\hat{R}_i|\tau_i) = \sqrt{\tau_i}\alpha.
\]
(A44)
By law of total variance, unconditional variance of the portfolio is
\[
Var(\hat{R}_i|\tau_i) = E[Var(\hat{R}_i|\tilde{s}_i)] + Var[E(\hat{R}_i|\tilde{s}_i)],
\]
(A45)
where

$$\text{Var}(\tilde{R}_i | \tilde{s}_i) = \begin{cases} 
(1 - 4 \tau_i) \alpha^2, & \text{if } s_i = +1 \\
0, & \text{if } s_i = -1 
\end{cases},$$

and

$$E(\tilde{R}_i | \tilde{s}_i) = \begin{cases} 
2 \sqrt{\tau_i} \alpha, & \text{if } s_i = +1 \\
0, & \text{if } s_i = -1 
\end{cases}.$$ 

So

$$E[\text{Var}(\tilde{R}_i | \tilde{s}_i)] = \frac{1}{2} (1 - 4 \tau_i) \alpha^2, \quad (A46)$$

and

$$\text{Var}[E(\tilde{R}_i | \tilde{s}_i)] = \tau_i \alpha^2. \quad (A47)$$

Then

$$\text{Var}(\tilde{R}_i | \tau_i) = \frac{1}{2} (1 - 2 \tau_i) \alpha^2. \quad (A48)$$

Given \(\tau_i\), Information Ratio of the manager i’s portfolio is

$$IR_i = \frac{E(\tilde{R}_i | \tau_i)}{\sqrt{\text{Var}(\tilde{R}_i | \tau_i)}}, \quad (A49)$$

which can be reduced to equation (5). Note that excess return volatility \(\alpha\) are canceled out.

**Proof of Lemma 6**

By law of iterated expectations, team-managed fund j’s unconditional expected return is

$$E(\tilde{R}_j^T | \tau_i, \tau_{-i}) = E[E(\tilde{R}_j^T | \tilde{s}_i, \tilde{s}_{-i})]. \quad (A50)$$

Insert (4) and (5) into (7), and average over realizations of signals, we have

$$E(\tilde{R}_j^T | \tau_i, \tau_{-i}) = \frac{1}{2} (\sqrt{\tau_i} + \sqrt{\tau_{-i}}) \alpha. \quad (A51)$$

By law of total variance, unconditional variance given signal precision levels is

$$\text{Var}(\tilde{R}_j^T | \tau_i, \tau_{-i}) = E[\text{Var}(\tilde{R}_j^T | \tilde{s}_i, \tilde{s}_{-i})] + \text{Var}[E(\tilde{R}_j^T | \tilde{s}_i, \tilde{s}_{-i})] \quad (A52)$$

$$= \frac{1}{4} [(1 - \tau_i - \tau_{-i})] \alpha^2. \quad (A53)$$
Then given managers, Information Ratio of such a team-managed fund is

\[
IR^T_j = \frac{E(\tilde{R}^T_j | \tau_i, \tau_{-i})}{\sqrt{\text{Var}(\tilde{R}^T_j | \tau_i, \tau_{-i})}}
\]

\[
= \frac{\sqrt{\tau_i} + \sqrt{\tau_{-i}}}{\sqrt{1 - \tau_i - \tau_{-i}}}
\]

(A54)

If \(\tau_{-i} = \tau_i\),

\[
IR^T_j = \frac{2\sqrt{\tau_i}}{\sqrt{1 - 2\tau_i}}
\]

(A55)

which is \(\sqrt{2}\) times of \(IR^S_j\):

\[
IR^S_j = IR_i.
\]

(A56)

**Proof of Proposition 5**

Differentiate expected excess returns in (43) and (44) with respect to \(\tau^*_s\), we have

\[
\frac{\partial E(\tilde{R}^S_j)}{\partial \tau^*_s} = \frac{\alpha(2\sqrt{\tau_H} + \sqrt{\tau_s})}{3(\sqrt{\tau_H} + \sqrt{\tau_s})^2}
\]

(A57)

and

\[
\frac{\partial E(\tilde{R}^T_j)}{\partial \tau^*_s} = \frac{\alpha(2\sqrt{\tau_L} + \sqrt{\tau_s})}{3(\sqrt{\tau_L} + \sqrt{\tau_s})^2}
\]

(A58)

both of which are always positive. It implies average excess return increases in \(\tau^*_s\) for both types of funds.

Ex ante variances for single-manager and team funds can be calculated with law of total variances:

\[
\text{Var} (\tilde{R}^S_j) = E[\text{Var}(\tilde{R}^S_j | \tilde{\tau}_i) | \tilde{\tau}_i \in [\tau_s, \tau_H]] + \text{Var}[E(\tilde{R}^S_j | \tilde{\tau}_i) | \tilde{\tau}_i \in [\tau_s, \tau_H]]
\]

(A59)

and

\[
\text{Var}(\tilde{R}^T_j) = E[\text{Var}(\tilde{R}^T_j | \tilde{\tau}_i, \tilde{\tau}_{-i}) | \tilde{\tau}_i, \tilde{\tau}_{-i} \in [\tau_L, \tau_s]] + \text{Var}[E(\tilde{R}^T_j | \tilde{\tau}_i, \tilde{\tau}_{-i}) | \tilde{\tau}_i, \tilde{\tau}_{-i} \in [\tau_L, \tau_s]].
\]

(A60)

Insert (A44), (A48) into (A59), and (A50), (A51) into (A60), and calculate first and second order moments conditional on corresponding subsets of managers, we have

\[
\text{Var}(\tilde{R}^S_j) = \left[ \frac{1}{2} - \frac{4}{9} \left( \frac{\tau_H^{3/2} - \tau_s^{3/2}}{\tau_H - \tau_s} \right)^2 \right] \alpha^2,
\]

(A61)
and
\[ \text{Var}(\tilde{R}_j^T) = \left[ \frac{1}{4} - \frac{2}{9} \left( \frac{\tau^2}{\tau_s - \tau_L} \right)^2 \right] \alpha^2. \]  
(A62)

Both of the two variances decrease in \( \tau_s \):
\[ \frac{\partial \text{Var}(\tilde{R}_j^S)}{\partial \tau_s} = -\frac{4}{9} \left[ 1 + \frac{\tau^2}{(\sqrt{\tau_H} + \sqrt{\tau_s})^3} \right] \alpha^2, \]  
(A63)
and
\[ \frac{\partial \text{Var}(\tilde{R}_j^T)}{\partial \tau_s} = -\frac{2}{9} \left[ 1 + \frac{\tau^2}{(\sqrt{\tau_L} + \sqrt{\tau_s})^3} \right] \alpha^2. \]  
(A64)

Expected Information Ratio of single-manager fund \( j \) solely managed by manager \( i \) is
\[ E \left[ IR_j^S (\tilde{\tau}_i) \right] = \int_{\tau_s}^{\tau_H} \frac{IR_j^S (\tilde{\tau}_i)}{\tau_H - \tau_s} d\tilde{\tau}_i. \]  
(A65)

Differentiate \( E \left[ IR_j^S (\tilde{\tau}_i) \right] \) with respect to \( \tau_s \),
\[ \frac{dE \left[ IR_j^S (\tilde{\tau}_i) \right]}{d\tau_s} = \int_{\tau_s}^{\tau_H} \frac{IR_j^S (\tilde{\tau}_i)}{\tau_H - \tau_s} d\tilde{\tau}_i - \int_{\tau_s}^{\tau_H} \frac{IR_j^S (\tau_s)}{\tau_H - \tau_s} d\tilde{\tau}_i \]
\[ \frac{E \left[ IR_j^S (\tilde{\tau}_i) \right] - IR_j^S (\tau_s)}{\tau_H - \tau_s}. \]  
(A66)

In Lemma 5, we have shown manager level Information Ratio increases in signal precision. So for any \( \tau_s < \tau_H \), (A66) is positive.

Expected Information Ratio of a team-managed fund is
\[ E \left[ IR_j^T (\tilde{\tau}_i, \tilde{\tau}_{-i}) \right] = \int_{\tau_L}^{\tau_s} \int_{\tau_L}^{\tau_s} \frac{IR_j^T (\tilde{\tau}_i, \tilde{\tau}_{-i})}{(\tau_s - \tau_L)^2} d\tilde{\tau}_i d\tilde{\tau}_{-i}. \]  
(A67)

Differentiate it with respect to \( \tau_s \) gives
\[ \frac{dE \left[ IR_j^T (\tilde{\tau}_i, \tilde{\tau}_{-i}) \right]}{d\tau_s} = \int_{\tau_L}^{\tau_s} \frac{IR_j^T (\tilde{\tau}_i, \tau_s)}{(\tau_s - \tau_L)^2} d\tilde{\tau}_i + \int_{\tau_L}^{\tau_s} \frac{IR_j^T (\tau_s, \tilde{\tau}_{-i})}{(\tau_s - \tau_L)^2} d\tilde{\tau}_{-i} - 2 \int_{\tau_L}^{\tau_s} \int_{\tau_s}^{\tau_H} \frac{IR_j^T (\tau_s, \tau_{-i})}{(\tau_s - \tau_L)^3} d\tilde{\tau}_i d\tilde{\tau}_{-i} \]
\[ \frac{E \left[ IR_j^T (\tilde{\tau}_i, \tau_s) \right] + E \left[ IR_j^T (\tau_s, \tilde{\tau}_{-i}) \right] - 2E \left[ IR_j^T (\tilde{\tau}_i, \tilde{\tau}_{-i}) \right]}{\tau_s - \tau_L}. \]  
(A68)

From equation (A52) in proof of Lemma 6, a team-managed fund’s Information Ratio increases in signal precision of both managers. Then for any \( \tau_s > \tau_L \), (A68) is positive.
B Appendix: Figures and Tables
Figure 1: The growth and performance of team funds. Panel (a) reports the Total Net Assets (TNA) for single-manager and team funds. The red line reports the fraction of total TNA managed by team funds. Panel (b) reports the number of funds. Panel (c) is the performance difference between team and single-manager funds. The sample is actively managed U.S. domestic equity funds from CRSP Survivorship Bias Free Mutual Fund Database, from 1992 to 2012.
Figure 2: Fraction of team funds for small vs. large families. This figure plots the yearly averages of the percentage of team funds in the smallest and largest family size quintiles (Q1 and Q5) over the sample period from 1992 to 2012. The percentage of team funds is calculated using funds’ total net assets in Panel (a) and the number of funds in Panel (b).
Figure 3: Time series trend in flow-performance convexity. Panels (a) and (b) plot the 2-year moving averages of the monthly coefficient estimates of the Low, Mid, and High groups based the results in columns (1) and (3) of Table 2, respectively.
Table 1: Summary Statistics
This table summarizes the characteristics of the mutual funds in our sample over the period between 1992 and 2012. There are 3288 unique actively managed U.S. equity funds. Four-Factor Alpha is estimated using monthly fund net returns with Carhart (1997) four-factor model. We first estimate the factor loadings using the preceding 24 monthly returns. We then calculate monthly out-of-sample alpha as the difference between a funds return in a given month and the sum of the product of the estimated factor loadings and the factor returns during that month. Active share is calculated by aggregating the absolute differences between the weight of a portfolios actual holdings and the weight of its closest matching index. Return gap measures the difference between fund gross returns and holdings-based returns. Industry concentration index is calculated as the sum of the squared deviations of the value weights for each industry held by the mutual fund, relative to the industry weights of the total stock market. Team fund is an indicator variable that equals to one if the fund is managed by a team of portfolio managers based on CRSP mutual fund data and zero otherwise. Fund TNA is the sum of assets under management across all share classes of the fund; Fund Age is the age of the oldest share class in the fund; Expense Ratio is computed by dividing the funds annual operating expenses by the average dollar value of its assets under management; Net Flows is constructed as the net growth in fund assets beyond reinvested dividends (Sirri and Tufano, 1998); Turnover Ratio is defined as the minimum of sales or purchases divided by the total net assets of the fund; Family Size is the sum of total net assets of all equity funds in a fund family.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>p1</th>
<th>p99</th>
<th>N</th>
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<td>Net Return (in % per year)</td>
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<td>-45.62</td>
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<td>Industry Concentration Index</td>
<td>0.10</td>
<td>0.04</td>
<td>0.16</td>
<td>0.00</td>
<td>0.79</td>
<td>357,989</td>
</tr>
<tr>
<td>Team Fund</td>
<td>0.546</td>
<td>1.000</td>
<td>0.498</td>
<td>0.000</td>
<td>1.000</td>
<td>422,831</td>
</tr>
<tr>
<td>Fund TNA (in Millions)</td>
<td>1,175.8</td>
<td>231.4</td>
<td>4,479.6</td>
<td>16.4</td>
<td>16,946.4</td>
<td>422,831</td>
</tr>
<tr>
<td>Fund Age (in Months)</td>
<td>160.0</td>
<td>114.0</td>
<td>157.3</td>
<td>10.0</td>
<td>818.0</td>
<td>422,831</td>
</tr>
<tr>
<td>Expense Ratio (%)</td>
<td>1.266</td>
<td>1.230</td>
<td>0.451</td>
<td>0.100</td>
<td>2.540</td>
<td>414,456</td>
</tr>
<tr>
<td>Fund Flow (%)</td>
<td>0.590</td>
<td>-0.228</td>
<td>5.295</td>
<td>-14.249</td>
<td>28.930</td>
<td>422,721</td>
</tr>
<tr>
<td>Turnover Ratio</td>
<td>0.850</td>
<td>0.650</td>
<td>0.744</td>
<td>0.020</td>
<td>4.200</td>
<td>416,302</td>
</tr>
<tr>
<td>Family TNA (in Millions)</td>
<td>35,522</td>
<td>5,473</td>
<td>90,883</td>
<td>20</td>
<td>477,679</td>
<td>422,831</td>
</tr>
<tr>
<td>Family Fund Numbers</td>
<td>17.1</td>
<td>10.0</td>
<td>22.9</td>
<td>1.0</td>
<td>114.0</td>
<td>422,831</td>
</tr>
</tbody>
</table>
Table 2: *Family Size and the Flow-Performance Relationship*

This table reports Fama-MacBeth piecewise linear regression results of monthly fund flows on lagged funds fractional performance rankings. Each month, funds are assigned fractional performance ranks from zero to one based on their past 12-month net returns relative to other funds with similar investment objectives (columns (1) and (2)), or based on their four-factor alphas during the past 24 months (columns (3) and (4)). The fractional rank for funds in the bottom performance quintile (Low) is defined as Min (Rank, 0.2). Funds in the three medium performance quintiles (Mid) are grouped together and receive ranks that are defined as Min (0.6, Rank - Low). The rank for the top performance quintile (High) is defined as Rank - Mid - Low. Large family is an indicator variable that equals one if the fund belongs to a family whose size is above median value and zero otherwise. Category flow measures the aggregate monthly flow into each fund objective category. All other variables are defined in Table 1. Standard errors are adjusted using the Newey and West (1987) correction with 12 lags and t-statistics are reported in parentheses. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Past 12m Net Return</th>
<th>Four-Factor Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Low</td>
<td>0.046***</td>
<td>0.053***</td>
</tr>
<tr>
<td></td>
<td>(10.55)</td>
<td>(10.33)</td>
</tr>
<tr>
<td>Mid</td>
<td>0.029***</td>
<td>0.028***</td>
</tr>
<tr>
<td></td>
<td>(14.33)</td>
<td>(13.66)</td>
</tr>
<tr>
<td>High</td>
<td>0.134***</td>
<td>0.147***</td>
</tr>
<tr>
<td></td>
<td>(17.22)</td>
<td>(16.44)</td>
</tr>
<tr>
<td>Low * Large Family</td>
<td>-0.016***</td>
<td>-0.012*</td>
</tr>
<tr>
<td></td>
<td>(-2.79)</td>
<td>(-1.73)</td>
</tr>
<tr>
<td>Mid * Large Family</td>
<td>0.002</td>
<td>0.003***</td>
</tr>
<tr>
<td></td>
<td>(1.53)</td>
<td>(2.17)</td>
</tr>
<tr>
<td>High * Large Family</td>
<td>-0.024***</td>
<td>-0.050***</td>
</tr>
<tr>
<td></td>
<td>(-2.40)</td>
<td>(-4.37)</td>
</tr>
<tr>
<td>Category Flow</td>
<td>0.302***</td>
<td>0.303***</td>
</tr>
<tr>
<td></td>
<td>(5.94)</td>
<td>(5.95)</td>
</tr>
<tr>
<td>Log Family Size</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(1.31)</td>
<td>(1.42)</td>
</tr>
<tr>
<td>Large Family</td>
<td>0.004***</td>
<td>0.004***</td>
</tr>
<tr>
<td></td>
<td>(3.22)</td>
<td>(3.24)</td>
</tr>
<tr>
<td>Team Fund</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.79)</td>
<td>(0.87)</td>
</tr>
<tr>
<td>Log Fund TNA</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(1.54)</td>
<td>(1.13)</td>
</tr>
<tr>
<td>Log Fund Age</td>
<td>-0.007***</td>
<td>-0.007***</td>
</tr>
<tr>
<td></td>
<td>(-14.87)</td>
<td>(-14.90)</td>
</tr>
<tr>
<td>Expense Ratio</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.43)</td>
<td>(0.48)</td>
</tr>
<tr>
<td>Turnover Ratio</td>
<td>-0.000</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(-0.89)</td>
<td>(-0.92)</td>
</tr>
<tr>
<td>Volatility</td>
<td>-0.141***</td>
<td>-0.140***</td>
</tr>
<tr>
<td></td>
<td>(-3.38)</td>
<td>(-3.30)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.018***</td>
<td>0.018***</td>
</tr>
<tr>
<td></td>
<td>(5.04)</td>
<td>(4.97)</td>
</tr>
<tr>
<td>Observations</td>
<td>403,665</td>
<td>403,665</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.115</td>
<td>0.118</td>
</tr>
<tr>
<td>Number of months</td>
<td>252</td>
<td>252</td>
</tr>
</tbody>
</table>
Table 3: Fractions of Team Funds across Family Size Quintiles

This table reports the portfolio sorting results of percentage of team funds across different family size quintiles. Each month, we sort fund families into quintiles each month based on lagged family size and calculate the time series average of the percentage of team funds for each of the family size quintiles. We calculate for each fund family the percentage of team funds based on the number of funds or fund TNA. We test the difference in team fund percentage between the smallest and largest family size quintiles and adjust standard errors using the Newey-West (1987) correction with 12 lags.

<table>
<thead>
<tr>
<th>Family Size Quintile</th>
<th>No. of Months</th>
<th>Family TNA</th>
<th>% of Team Funds - No. of Funds</th>
<th>% of Team Funds - Fund TNA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1 (small family)</td>
<td>252</td>
<td>33.8</td>
<td>40.7%</td>
<td>40.7%</td>
</tr>
<tr>
<td>Q2</td>
<td>252</td>
<td>121.2</td>
<td>44.8%</td>
<td>44.2%</td>
</tr>
<tr>
<td>Q3</td>
<td>252</td>
<td>407.1</td>
<td>51.9%</td>
<td>52.3%</td>
</tr>
<tr>
<td>Q4</td>
<td>252</td>
<td>1,722.3</td>
<td>53.5%</td>
<td>53.7%</td>
</tr>
<tr>
<td>Q5 (large family)</td>
<td>252</td>
<td>23,360.1</td>
<td>54.0%</td>
<td>55.1%</td>
</tr>
</tbody>
</table>

**Diff**: Q5-Q1

<table>
<thead>
<tr>
<th>No. of Months</th>
<th>% of Team Funds - No. of Funds</th>
<th>% of Team Funds - Fund TNA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>13.3%</td>
<td>14.3%</td>
</tr>
<tr>
<td>t-stat.</td>
<td>9.98</td>
<td>8.25</td>
</tr>
</tbody>
</table>
Table 4: Performance of Team vs. Single-Manager Funds - Within Family
This table reports Fama-MacBeth regression results of fund performance on a team fund dummy and other control variables with family fixed effects. We measure fund performance using net return in columns (1) and (2) and four-factor alpha in columns (3) and (4). Team Fund is an indicator variable that equals to one if the fund is managed by a team of portfolio managers based on CRSP mutual fund data and zero otherwise. All other variables are defined in Table 1. Standard errors are computed using the time series of monthly estimates as in Fama-MacBeth (1973) and t-statistics are reported in parentheses. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Net Return (1)</th>
<th>Net Return (2)</th>
<th>Four-Factor Alpha (3)</th>
<th>Four-Factor Alpha (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Team Fund</td>
<td>-0.350*</td>
<td>-0.332**</td>
<td>-0.279*</td>
<td>-0.301**</td>
</tr>
<tr>
<td></td>
<td>(-1.73)</td>
<td>(-2.03)</td>
<td>(-1.85)</td>
<td>(-2.09)</td>
</tr>
<tr>
<td>Middle Family</td>
<td>2.889</td>
<td></td>
<td>-0.992</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.13)</td>
<td></td>
<td>(-0.46)</td>
<td></td>
</tr>
<tr>
<td>Large Family</td>
<td>1.993</td>
<td></td>
<td>2.120</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.96)</td>
<td></td>
<td>(1.13)</td>
<td></td>
</tr>
<tr>
<td>Log Fund TNA</td>
<td>-0.482***</td>
<td></td>
<td>-0.330***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.20)</td>
<td></td>
<td>(-3.61)</td>
<td></td>
</tr>
<tr>
<td>Log Fund Age</td>
<td>0.362**</td>
<td></td>
<td>0.073</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.31)</td>
<td></td>
<td>(0.63)</td>
<td></td>
</tr>
<tr>
<td>Expense Ratio</td>
<td>-0.032</td>
<td></td>
<td>-0.426</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.05)</td>
<td></td>
<td>(-1.12)</td>
<td></td>
</tr>
<tr>
<td>Fund Flow</td>
<td>0.089***</td>
<td></td>
<td>0.067***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.05)</td>
<td></td>
<td>(3.52)</td>
<td></td>
</tr>
<tr>
<td>Turnover Ratio</td>
<td>0.213</td>
<td></td>
<td>0.049</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.51)</td>
<td></td>
<td>(0.20)</td>
<td></td>
</tr>
<tr>
<td>Lagged Fund Return</td>
<td>0.084***</td>
<td></td>
<td>0.011</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.07)</td>
<td></td>
<td>(0.89)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>6.168*</td>
<td>7.366**</td>
<td>-5.062***</td>
<td>0.581</td>
</tr>
<tr>
<td></td>
<td>(1.71)</td>
<td>(2.10)</td>
<td>(-2.65)</td>
<td>(0.22)</td>
</tr>
</tbody>
</table>

Family Fixed Effects | Yes | Yes | Yes | Yes
Observations        | 420,019 | 407,357 | 412,765 | 405,363
R-squared            | 0.307 | 0.411 | 0.306 | 0.356
Number of Months     | 252 | 252 | 252 | 252
Table 5: Portfolio Management Activeness of Team vs. Single-Manager Funds - Within Family.
This table reports Fama-MacBeth regression results of fund portfolio management activeness measures on a team fund dummy and other control variables with family fixed effects. We measure fund portfolio management activeness using Active Share in columns (1) and (2), Return Gap in columns (3) and (4), and Industry Concentration in columns (5) and (6). Team Fund is an indicator variable that equals to one if the fund is managed by a team of portfolio managers based on CRSP mutual fund data and zero otherwise. All other variables are defined in Table 1. Standard errors are computed using the time series of monthly estimates as in Fama-MacBeth (1973) and t-statistics are reported in parentheses. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Active Share (1)</th>
<th>Active Share (2)</th>
<th>Return Gap (3)</th>
<th>Return Gap (4)</th>
<th>Industry Concentration (5)</th>
<th>Industry Concentration (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Team Fund</td>
<td>-0.008***</td>
<td>-0.003***</td>
<td>-0.085</td>
<td>-0.162</td>
<td>-0.017***</td>
<td>-0.011***</td>
</tr>
<tr>
<td></td>
<td>(-10.51)</td>
<td>(-3.56)</td>
<td>(-0.95)</td>
<td>(-0.68)</td>
<td>(-17.23)</td>
<td>(-10.98)</td>
</tr>
<tr>
<td>Middle Family</td>
<td>0.040***</td>
<td>1.148</td>
<td>2.166</td>
<td>0.027***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.18)</td>
<td>(0.47)</td>
<td>(0.98)</td>
<td>(2.89)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Large Family</td>
<td>0.058***</td>
<td>2.166</td>
<td>0.047***</td>
<td>0.047***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.99)</td>
<td>(0.98)</td>
<td></td>
<td>(5.68)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Fund TNA</td>
<td>-0.009***</td>
<td>-0.299***</td>
<td>-0.017***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-14.06)</td>
<td>(-4.49)</td>
<td>(-59.55)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Fund Age</td>
<td>0.000</td>
<td>-0.055</td>
<td>0.020***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.26)</td>
<td>(-0.59)</td>
<td>(12.27)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expense Ratio</td>
<td>0.126***</td>
<td>-0.163</td>
<td>0.074***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(40.97)</td>
<td>(-0.31)</td>
<td>(46.24)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fund Flow</td>
<td>0.000**</td>
<td>-0.010</td>
<td>-0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.09)</td>
<td>(-0.31)</td>
<td>(55.8)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Turnover Ratio</td>
<td>0.017***</td>
<td>-0.135</td>
<td>-0.013***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(21.82)</td>
<td>(-0.76)</td>
<td>(12.09)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged Fund Return</td>
<td>0.000***</td>
<td>0.036***</td>
<td>0.000***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.43)</td>
<td>(7.46)</td>
<td>(2.95)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.844***</td>
<td>0.660***</td>
<td>-1.054</td>
<td>-6.427**</td>
<td>0.091***</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>(90.83)</td>
<td>(54.46)</td>
<td>(-1.02)</td>
<td>(-2.05)</td>
<td>(14.18)</td>
<td>(0.91)</td>
</tr>
<tr>
<td>Family Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>392,216</td>
<td>381,179</td>
<td>359,008</td>
<td>348,869</td>
<td>357,989</td>
<td>348,121</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.326</td>
<td>0.457</td>
<td>0.348</td>
<td>0.381</td>
<td>0.301</td>
<td>0.359</td>
</tr>
<tr>
<td>Number of Months</td>
<td>252</td>
<td>252</td>
<td>249</td>
<td>249</td>
<td>247</td>
<td>247</td>
</tr>
</tbody>
</table>
Table 6: Information Ratio of Team vs. Single-Manager Funds - Within Family.

This table reports Fama-MacBeth regression results of information ratio on a team fund dummy and other control variables with family fixed effects. Each year we calculate the average of monthly four-factor alphas, volatility (i.e., standard deviation) of alpha, and information ratio (i.e., alpha mean over its standard deviation). We use average alpha as the dependent variable in columns (1) and (2), volatility of alpha in columns (3) and (4), and information ratio in columns (5) and (6). Team Fund is an indicator variable that equals to one if the fund is managed by a team of portfolio managers based on CRSP mutual fund data and zero otherwise. All other variables are defined in Table 1. Standard errors are computed using the time series of yearly estimates as in Fama-MacBeth (1973) and t-statistics are reported in parentheses. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Four-Factor Alpha Mean</th>
<th>Four-Factor Alpha STD</th>
<th>Information Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Team Fund</td>
<td>-0.338**</td>
<td>-0.304*</td>
<td>-0.425***</td>
</tr>
<tr>
<td></td>
<td>(-2.19)</td>
<td>(-2.03)</td>
<td>(-4.60)</td>
</tr>
<tr>
<td>Middle Family</td>
<td>-0.522</td>
<td>1.300</td>
<td>-0.020</td>
</tr>
<tr>
<td></td>
<td>(-0.56)</td>
<td>(1.29)</td>
<td></td>
</tr>
<tr>
<td>Large Family</td>
<td>-1.256</td>
<td>0.836</td>
<td>-0.012</td>
</tr>
<tr>
<td></td>
<td>(-1.25)</td>
<td>(0.88)</td>
<td></td>
</tr>
<tr>
<td>Log Fund TNA</td>
<td>-0.350***</td>
<td>-0.261***</td>
<td>-0.045***</td>
</tr>
<tr>
<td></td>
<td>(-3.30)</td>
<td>(-4.70)</td>
<td>(-2.93)</td>
</tr>
<tr>
<td>Log Fund Age</td>
<td>0.171</td>
<td>0.161</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>(1.30)</td>
<td>(1.68)</td>
<td>(0.97)</td>
</tr>
<tr>
<td>Expense Ratio</td>
<td>-0.373</td>
<td>2.688***</td>
<td>0.038</td>
</tr>
<tr>
<td></td>
<td>(-0.83)</td>
<td>(13.86)</td>
<td>(0.77)</td>
</tr>
<tr>
<td>Fund Flow</td>
<td>0.020</td>
<td>-0.021**</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
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<td>(1.23)</td>
</tr>
<tr>
<td>Turnover Ratio</td>
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<td>0.413***</td>
<td>0.028</td>
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<td>(0.96)</td>
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<td>(0.92)</td>
</tr>
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<td>Lagged Fund Return</td>
<td>-0.016</td>
<td>0.007</td>
<td>-0.001</td>
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<tr>
<td></td>
<td>(-1.51)</td>
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<td>(0.69)</td>
</tr>
<tr>
<td>Constant</td>
<td>-3.845*</td>
<td>-1.098</td>
<td>7.076***</td>
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<tr>
<td></td>
<td>(-1.83)</td>
<td>(-0.38)</td>
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<tr>
<td>Family Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
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<td>35,897</td>
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<td>0.355</td>
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<td>Number of Years</td>
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Table 7: **Fund Performance across Families**

This table reports Fama-MacBeth regression results of fund four-factor alpha on two family size dummies (i.e., Middle Family and Large Family) and other control variables. We analyze single-manager funds in columns (1) and (4), team funds in columns (2) and (5), and all funds in columns (3) and (6). We add as an additional control variable the average performance of all funds in the family excluding the fund itself in columns (4) to (6). All other variables are defined in Table 1. Standard errors are computed using the time series of monthly estimates as in Fama-MacBeth (1973) and t-statistics are reported in parentheses. The superscripts ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
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<tr>
<th>VARIABLES</th>
<th>Single (1)</th>
<th>Team (2)</th>
<th>All (3)</th>
<th>Single (4)</th>
<th>Team (5)</th>
<th>All (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Middle Family</td>
<td>0.498**</td>
<td>0.464**</td>
<td>0.362**</td>
<td>0.370**</td>
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<td>0.303**</td>
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<tr>
<td></td>
<td>(2.53)</td>
<td>(1.97)</td>
<td>(2.46)</td>
<td>(2.26)</td>
<td>(1.91)</td>
<td>(2.54)</td>
</tr>
<tr>
<td>Large Family</td>
<td>1.300***</td>
<td>0.778**</td>
<td>0.967***</td>
<td>0.964***</td>
<td>0.713**</td>
<td>0.777***</td>
</tr>
<tr>
<td></td>
<td>(4.48)</td>
<td>(2.35)</td>
<td>(3.94)</td>
<td>(4.19)</td>
<td>(2.42)</td>
<td>(4.00)</td>
</tr>
<tr>
<td>Log Fund TNA</td>
<td>-0.238**</td>
<td>-0.372***</td>
<td>-0.286***</td>
<td>-0.252***</td>
<td>-0.367***</td>
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</tr>
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<td>Log Fund Age</td>
<td>0.026</td>
<td>0.228*</td>
<td>0.061</td>
<td>0.039</td>
<td>0.219*</td>
<td>0.062</td>
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<td>(0.34)</td>
<td>(1.84)</td>
<td>(0.66)</td>
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<td>-0.743***</td>
<td>-0.778***</td>
<td>-0.544**</td>
<td>-0.575*</td>
<td>-0.623**</td>
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<td></td>
<td>(-2.39)</td>
<td>(-2.23)</td>
<td>(-2.79)</td>
<td>(-2.11)</td>
<td>(-1.89)</td>
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</tr>
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<td>Fund Flow</td>
<td>0.056**</td>
<td>0.103***</td>
<td>0.075***</td>
<td>0.049**</td>
<td>0.102***</td>
<td>0.072***</td>
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<td>(2.31)</td>
<td>(4.00)</td>
<td>(4.14)</td>
<td>(2.15)</td>
<td>(4.10)</td>
<td>(4.10)</td>
</tr>
<tr>
<td>Turnover Ratio</td>
<td>-0.094</td>
<td>-0.158</td>
<td>-0.027</td>
<td>-0.080</td>
<td>-0.079</td>
<td>-0.001</td>
</tr>
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<td></td>
<td>(-0.40)</td>
<td>(-0.59)</td>
<td>(-0.12)</td>
<td>(-0.37)</td>
<td>(-0.32)</td>
<td>(-0.01)</td>
</tr>
<tr>
<td>Lagged Fund Return</td>
<td>0.011</td>
<td>0.019</td>
<td>0.014</td>
<td>0.009</td>
<td>0.017</td>
<td>0.013</td>
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<td></td>
<td>(0.90)</td>
<td>(1.49)</td>
<td>(1.20)</td>
<td>(0.75)</td>
<td>(1.39)</td>
<td>(1.09)</td>
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<td>Team Fund</td>
<td>-0.303**</td>
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<td></td>
<td>0.336***</td>
<td>0.315**</td>
<td>0.332***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(38.61)</td>
<td>(36.70)</td>
<td>(55.90)</td>
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<tr>
<td>Constant</td>
<td>1.087</td>
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<td>1.334</td>
<td>0.923</td>
<td>1.631**</td>
</tr>
<tr>
<td></td>
<td>(1.04)</td>
<td>(0.91)</td>
<td>(1.67)</td>
<td>(1.40)</td>
<td>(1.03)</td>
<td>(2.03)</td>
</tr>
<tr>
<td>Observations</td>
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<td>205,965</td>
<td>369,356</td>
<td>163,391</td>
<td>205,965</td>
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<td>0.098</td>
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<td>0.111</td>
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<tr>
<td>F-tests (p-value)</td>
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</tr>
<tr>
<td>Middle=Large</td>
<td>0.000</td>
<td>0.189</td>
<td>0.001</td>
<td>0.000</td>
<td>0.118</td>
<td>0.000</td>
</tr>
</tbody>
</table>
Table 8: Fund Active Share, Return Gap, and Industry Concentration - Across Families

This table reports Fama-MacBeth regression results of fund portfolio management activeness measures on two family size dummies (i.e., Middle Family and Large Family) and other control variables. We measure fund activeness using Active Share in columns (1) to (3), Return Gap in columns (4) to (6), and Industry Concentration in columns (7) to (9). We analyze single-manager funds in columns (1), (4), and (7), team funds in columns (2), (5), and (8), and all funds in columns (3), (6), and (9). We add as an additional control variable the average activeness of all funds in the family excluding the fund itself in all columns. All other variables are defined in Table 1. Standard errors are computed using the time series of monthly estimates as in Fama-MacBeth (1973) and t-statistics are reported in parentheses. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Single</th>
<th>Team</th>
<th>All</th>
<th>Single</th>
<th>Team</th>
<th>All</th>
<th>Single</th>
<th>Team</th>
<th>All</th>
<th>Middle=Large</th>
</tr>
</thead>
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<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
<td>(9)</td>
<td>(7)</td>
</tr>
<tr>
<td>Middle Family</td>
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<td>0.009***</td>
<td>0.002***</td>
<td>0.250**</td>
<td>0.188</td>
<td>0.307***</td>
<td>0.017***</td>
<td>0.019***</td>
<td>0.018***</td>
<td>(16.13)</td>
</tr>
<tr>
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<td>(4.71)</td>
<td>(3.23)</td>
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<td>(1.26)</td>
<td>(3.04)</td>
<td>(4.40)</td>
<td>(3.80)</td>
<td>(4.00)</td>
<td>(27.84)</td>
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<td>0.007***</td>
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<td>0.896***</td>
<td>0.072***</td>
<td>0.026***</td>
<td>0.051***</td>
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<td>(5.15)</td>
<td>(0.01)</td>
<td>(3.65)</td>
<td>(20.13)</td>
<td>(14.07)</td>
<td>(20.55)</td>
<td>(44.08)</td>
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<td>Log Fund TNA</td>
<td>-0.011***</td>
<td>-0.008***</td>
<td>-0.010***</td>
<td>-0.190***</td>
<td>-0.217***</td>
<td>-0.249***</td>
<td>-0.022***</td>
<td>-0.006***</td>
<td>-0.014***</td>
<td>(12.93)</td>
</tr>
<tr>
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<td>(-11.97)</td>
<td>(-15.36)</td>
<td>(-3.65)</td>
<td>(-2.90)</td>
<td>(-4.19)</td>
<td>(-6.70)</td>
<td>(-15.75)</td>
<td>(-46.68)</td>
<td>(12.93)</td>
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<td>Log Fund Age</td>
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<td>-0.001***</td>
<td>-0.180*</td>
<td>-0.026</td>
<td>-0.075</td>
<td>0.025***</td>
<td>0.002**</td>
<td>0.012***</td>
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</tr>
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<td>(2.19)</td>
<td>(11.44)</td>
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<td>0.084***</td>
<td>0.176</td>
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<td>0.042***</td>
<td>0.043***</td>
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<tr>
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<td>(40.02)</td>
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<td>(48.25)</td>
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<td>0.001***</td>
<td>0.000***</td>
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<td>-0.026</td>
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<td>0.000</td>
<td>-0.000*</td>
<td>0.000</td>
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</tr>
<tr>
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<td>(3.86)</td>
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<td>(4.12)</td>
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<td>(1.00)</td>
<td>(-1.95)</td>
<td>(0.80)</td>
<td>(3.86)</td>
</tr>
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<td>0.012***</td>
<td>0.010***</td>
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<td>-0.007***</td>
<td>-0.001*</td>
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<td>(10.13)</td>
<td>(14.02)</td>
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<td>(-6.02)</td>
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<td>(19.99)</td>
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<td>0.000***</td>
<td>0.000***</td>
<td>0.048***</td>
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<td>0.032***</td>
<td>0.000***</td>
<td>0.000*</td>
<td>0.000***</td>
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<td>(2.59)</td>
<td>(3.97)</td>
<td>(2.95)</td>
<td>(1.78)</td>
<td>(3.02)</td>
<td>(3.37)</td>
</tr>
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<td>-0.015***</td>
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<td>(0.85)</td>
<td>(21.34)</td>
<td>(3.34)</td>
<td>(0.85)</td>
<td>(21.34)</td>
<td>(-7.97)</td>
</tr>
<tr>
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<td>(3.34)</td>
<td>(0.85)</td>
<td>(21.34)</td>
<td>(3.34)</td>
<td>(0.85)</td>
<td>(21.34)</td>
<td>(3.34)</td>
<td>(0.85)</td>
<td>(21.34)</td>
<td>(-7.97)</td>
</tr>
<tr>
<td>Family Average</td>
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<td>0.310***</td>
<td>0.331***</td>
<td>0.284***</td>
<td>0.223***</td>
<td>0.272***</td>
<td>0.588***</td>
<td>0.464***</td>
<td>0.565***</td>
<td>(48.01)</td>
</tr>
<tr>
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<td>(48.01)</td>
<td>(32.11)</td>
<td>(47.72)</td>
<td>(22.26)</td>
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<td>(21.25)</td>
<td>(59.59)</td>
<td>(47.12)</td>
<td>(74.88)</td>
<td>(48.01)</td>
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<td>0.476***</td>
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<td>0.360</td>
<td>-0.026***</td>
<td>0.012*</td>
<td>0.009</td>
<td>(48.34)</td>
</tr>
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<td>(37.37)</td>
<td>(49.72)</td>
<td>(-0.72)</td>
<td>(0.71)</td>
<td>(-3.26)</td>
<td>(1.73)</td>
<td>(1.37)</td>
<td>(48.34)</td>
<td>(37.37)</td>
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<td>175,771</td>
<td>315,445</td>
<td>143,221</td>
<td>171,757</td>
<td>314,978</td>
<td>(153,604)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.201</td>
<td>0.233</td>
<td>0.204</td>
<td>0.086</td>
<td>0.103</td>
<td>0.076</td>
<td>0.207</td>
<td>0.138</td>
<td>0.171</td>
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</tr>
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<td>Number of Years</td>
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<td>252</td>
<td>249</td>
<td>249</td>
<td>249</td>
<td>247</td>
<td>247</td>
<td>247</td>
<td>(252)</td>
</tr>
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<td>F-tests (p-value)</td>
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<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>(0.000)</td>
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</table>
Table 9: Fund Information Ratio - Across Families

This table reports Fama-MacBeth regression results of fund information ratio on two family size dummies (i.e., Middle Family and Large Family) and other control variables. Each year we calculate the average of monthly four-factor alphas, volatility (i.e., standard deviation) of alpha, and information ratio (i.e., alpha mean over its standard deviation). We use average alpha as the dependent variable in columns (1) to (3), volatility of alpha in columns (4) to (6), and information ratio in columns (7) to (9). We analyze single-manager funds in columns (1), (4), and (7), team funds in columns (2), (5), and (8), and all funds in columns (3), (6), and (9). We add as an additional control variable the average dependent variable of all funds in the family excluding the fund itself in all specifications. All other variables are defined in Table 1. Standard errors are computed using the time series of yearly estimates as in Fama-MacBeth (1973) and t-statistics are reported in parentheses. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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<th>Information Ratio</th>
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<td>All</td>
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<tr>
<td>Middle Family</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.561**</td>
<td>0.468</td>
<td>0.412**</td>
<td>0.090</td>
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<td>(2.74)</td>
<td>(1.43)</td>
<td>(2.78)</td>
<td>(0.94)</td>
</tr>
<tr>
<td>Large Family</td>
<td>1.131***</td>
<td>1.106*</td>
<td>0.913***</td>
</tr>
<tr>
<td>(4.45)</td>
<td>(2.00)</td>
<td>(3.28)</td>
<td>(7.45)</td>
</tr>
<tr>
<td>Log Fund TNA</td>
<td>-0.285***</td>
<td>-0.475***</td>
<td>-0.335***</td>
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<td>(-3.20)</td>
<td>(-3.52)</td>
<td>(-3.89)</td>
<td>(-5.79)</td>
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<td>Log Fund Age</td>
<td>0.074</td>
<td>0.317**</td>
<td>0.136</td>
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<td>(0.62)</td>
<td>(2.32)</td>
<td>(1.35)</td>
<td>(3.06)</td>
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<td>Expense Ratio</td>
<td>-0.449</td>
<td>-0.643*</td>
<td>-0.574*</td>
</tr>
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<td>(-1.40)</td>
<td>(-1.75)</td>
<td>(-1.89)</td>
<td>(11.07)</td>
</tr>
<tr>
<td>Fund Flow</td>
<td>-0.006</td>
<td>-0.019</td>
<td>-0.012</td>
</tr>
<tr>
<td>(-0.25)</td>
<td>(-0.64)</td>
<td>(-0.60)</td>
<td>(0.40)</td>
</tr>
<tr>
<td>Turnover Ratio</td>
<td>-0.025</td>
<td>0.174</td>
<td>0.056</td>
</tr>
<tr>
<td>(-0.12)</td>
<td>(0.57)</td>
<td>(0.25)</td>
<td>(5.71)</td>
</tr>
<tr>
<td>Logged Fund Return</td>
<td>0.014</td>
<td>0.027</td>
<td>0.018</td>
</tr>
<tr>
<td>(0.42)</td>
<td>(0.85)</td>
<td>(0.58)</td>
<td>(0.80)</td>
</tr>
<tr>
<td>Team Fund</td>
<td>-0.232*</td>
<td>-0.359***</td>
<td>-0.042*</td>
</tr>
<tr>
<td>(-1.74)</td>
<td>(-4.76)</td>
<td>(-2.02)</td>
<td></td>
</tr>
<tr>
<td>Family Average</td>
<td>0.386***</td>
<td>0.287***</td>
<td>0.351***</td>
</tr>
<tr>
<td>(11.81)</td>
<td>(8.40)</td>
<td>(15.88)</td>
<td>(13.76)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.155</td>
<td>-0.245*</td>
<td>0.130</td>
</tr>
<tr>
<td>(-0.13)</td>
<td>(-0.23)</td>
<td>(0.12)</td>
<td>(0.89)</td>
</tr>
<tr>
<td>Observations</td>
<td>13,514</td>
<td>17,456</td>
<td>30,970</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.107</td>
<td>0.113</td>
<td>0.096</td>
</tr>
<tr>
<td>Number of Years</td>
<td>21</td>
<td>21</td>
<td>21</td>
</tr>
<tr>
<td>F-tests (p-value)</td>
<td>0.009</td>
<td>0.043</td>
<td>0.013</td>
</tr>
<tr>
<td>Middle=Large</td>
<td>0.000</td>
<td>0.043</td>
<td>0.013</td>
</tr>
</tbody>
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