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UNIVERSITY OF CALIFORNIA, SAN DIEGO

Essays on Investor and Mutual Fund Behavior

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy

in

Economics

by

Andrew John Caffrey

Committee in charge:

Professor Allan Timmermann, Chair Professor Richard Carson Professor Graham Elliot Professor Bruce N. Lehmann Professor Jun Liu

2006

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Chair

University of California, San Diego

2006

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ABSTRACT OF THE DISSERTATION

Essays on Investor and Mutual Fund Behavior

by

Andrew John Caffrey Doctor of Philosophy in Economics University of California, San Diego, 2006 Professor Allan Timmermann, Chair

This dissertation consists of three essays on the relations among investors, mutual funds, and fund families.

Chapter one presents a model of new fund openings as a function of the past performance of a family's existing funds. At the fund level, we model the relations among fund performance, investment flows, and the risk-taking behavior of the fund manager. Our model predicts that families dominated either by outperforming funds or by underperforming funds are more likely to open a new fund than are families composed of average performers. We predict that an asymmetric performance-fund flow relation combined with expected intra-family flows from existing underperformers to a new fund provide an incentive for families with severely under-performing funds to open a new fund in hopes of managing a 'star'.

Chapter two presents an empirical analysis of new fund openings. We study fund performance, investment flows, and risk level and examine the relation between the distribution of performance across funds within a family and new fund openings. We find that new fund openings are positively correlated with measures of both extreme underperformance and extreme outperformance of existing funds as well as measures of the number of 'dog' funds within a family. The evidence supports our predictions in Chapter 1.

Chapter three addresses the relation between advisory firm organization and mutual fund performance and expenses. Specifically, we hypothesize three relations. First, the ownership structure of a fund family–mutualized, privately held, or publicly owned–may impact fund manager behavior and be reflected in expenses and/or performance. Second, fund families may experience some net pecuniary benefit or harm as a result of subsidiary affiliation. Finally, we examine expense and performance differences across directly advised versus subadvised funds. We find evidence that publicly owned fund families provide investors with lower style-adjusted returns and α at higher cost than do privately owned or mutualized families. Similarly, we find that bank and insurance affiliates underperform their peers in both returns net of expenses and α net of expenses, and that diversified financial services affiliates outperform in these measures.

Research Overview

This dissertation is part of a broader research agenda addressing the relations between mutual fund investors and the entities which provide them with the services they demand. These entities fall into three primary categories.

First are the mutual funds themselves. Although marketed as members of fund families, typically sponsored by, and overseen by, an investment advisor, mutual funds are independent legal entities in which investors purchase shares, and which contract with outside entities to provide all services required in the operation of the fund. These include advisory services, underwriting, transfer agency services, distribution, etc. Each mutual fund has a board of directors whose responsibility it is to safeguard shareholders' interest and ensure that these entities fulfill their contractual obligations.¹

Second are the entities which provide services to the mutual fund. Chief among these are the investment advisors which make the day-to-day investment decisions in management of the portfolio. Other entities include a transfer agent, underwriter, and distributor, each of which provides services necessary to the operation of the fund.²

Third are the intermediaries through which investors obtain research and invest in mutual funds, and in many cases purchase other financial services. These include full service brokers, banks, independent investment advisors, fund super-

 $^{^{1}}$ As we will discuss in chapter 3, this independence is largely a facade as there is a great degree of capture of funds by investment advisors

 $^{^{2}}$ These services are often provided either by the same entity or by related subsidiaries of a larger entity.

markets, and in some cases direct access to the fund. Figure III.1 in chapter 3 provides a graphical representation of the relations among these entities, and provides a good departure point for addressing potential conflicts of interest among these entities.

The three chapters of this dissertation investigate several aspects of the relation between fund shareholders and the investment advisor. The first chapter expands an existing literature on the asymmetric relation between mutual fund performance and investment flows, where inflows are seen to be far more sensitive to fund performance than are outflows. I model the relation between the performance of a fund family's existing funds and new fund openings, and find that under simple parameterizations the shape of the performance-flow relation gives rise to an incentive on the part of both families composed of winning funds and those composed of losing funds to open new funds. The former case takes advantage of a spillover, or reputation, effect, while the latter takes advantage of what I term a 'cannibalization effect'. In chapter two, I empirically test for evidence of these relations and find some support for the hypotheses derived from the model.

The third chapter directly addresses the structure of the fund industry and tests for the existence of performance and expense differentials across fund family structures. Specifically, we note that the relations among entities which provide services to a fund vary systematically across families sponsored by investment advisors with different governance characteristics, and across those sponsored by investment advisors which are subsidiaries of different types of conglomerates. This paper expands an existing branch of research which focusses on the potential impact of the governance characteristics of the mutual fund itself by addressing the governance characteristics of the sponsoring entity, typically the investment advisor. We group fund families by ownership type (privately owned, publicly held, or mutualized) and by conglomerate affiliation.³ We find systematic and statistically significant differences in performance and expenses across these family types.

 $^{^{3}}$ Either as subsidiaries of diversified financial services conglomerates, banks, insurance companies, non-financial firms, or as non-subsidiaries.

Chapter I

How to Build a Better Family: The Effect of Family-Level Performance on Fund Creation

I.A Introduction

This paper seeks to characterize the mechanisms by which past relative performance of a mutual fund family's existing funds impacts the family's incentives to open a new fund. The underlying phenomena motivating this work are the asymmetric response of investors to mutual fund performance and the degree to which a new fund is expected to draw investment funds from a family's existing funds, which we term 'cannibalization'. There exists a rich empirical literature including Starks (1987), Sirri and Tufano (1998), Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), Nanda, Wang, and Zheng (2004), and Goriaev, Nijman, and Werker (2004), which has concluded that investment flows into a mutual fund pursuant to strong performance relative to a peer group are much stronger than are investment flows out of a relatively poorly performing fund. These empirical papers have generally studied the effects of this convex 'fund flow-relative performance relation' on fund manager behavior. We suggest that the fund manager and the fund family can be viewed as two separate agents, with the fund manager making day-to-day operational decisions and the fund family making overall strategic decisions. In our simple framework, the manager of each individual fund chooses the level of risk taken on by that fund, while the fund family chooses the basket of funds to be offered. Our contribution to the literature is to model the effect of the aforementioned convex performance-flow relation not only on the behavior of the fund manager, but also on that of the fund family.

We think of the opening of a new fund within a family as analogous to the purchase of a call option by the fund family. The family faces (known or estimable) fixed costs of opening a new fund, and expects some initial capitalization of the fund either through cannibalization of the family's existing funds, through new investment, or through merger/acquisition. If the fund is truly new,¹ then the expected future excess return to the fund is zero, and fund flows are expected to be close to zero. Should the new fund under-perform, the family faces little downside risk, since investors are expected to react sluggishly to such poor performance.² Thus, the family can still hope to cover its costs and, should the fund continue to perform poorly, will have the opportunity to close or merge the 'dog' fund. However, should the new fund out-perform, prior empirical studies suggest dramatic net inflows will follow, both to the 'star' fund as well as to other funds within the family.³

Our approach suggests that the expected net benefit to the family of opening a new fund is a function of the fixed costs of opening the fund, the sensitivity of fund flows to relative performance, the magnitude of initial capitalization of the fund and associated degree of cannibalization of sister funds, and the distribution of future returns to each fund. To weigh the potential net benefit of a new

¹That is, if investors have no prior beliefs on new fund performance resulting from, e.g., knowledge about the fund manager or perceived correlations between the performance of new and existing funds.

²See, for example, Starks (1987), Sirri and Tufano (1998), Chevalier and Ellison (1997), and Brown, Harlow, and Starks (1996).

 $^{^{3}}$ See Nanda, Wang, and Zheng (2004) for a discussion of the spillover effect.

fund, the fund family must estimate these relations, which requires knowledge of the shape of the relative performance-fund flow relation, the distribution of future excess returns, the cost of opening a new fund, and the impact of the new fund on existing funds.

We first specify a simple parametric form for the relation between mutual fund performance and investment flows, consistent with prior empirical studies. We assume the fund manager maximizes revenue, which is earned as a percentage of assets managed, and use this specification to derive an explicit solution for the manager's choice of idiosyncratic portfolio risk as a function of performance. We specify the fund opening decision faced by the fund family, consistent with our discussion above, and derive an associated first order condition. We then combine our fund- and family-level results to examine the relation between the distribution of performance across funds within a family and the fund opening decision.

The resulting theoretical model suggests the following;

- Families composed largely of underperforming funds will set the initial risk level of a new fund higher than would a fund manager with unknown 'ability' acting in isolation. This will result in maximizing the cannibalization effect of the new fund on the set of existing funds, thereby moving investment within the family toward a fund with a higher expected probability of being a 'star'. The converse is true for a family composed largely of outperforming funds.
- For fund families with a large number of underperforming funds: the higher is the sensitivity of cannibalization to, and/or the lower is the sensitivity of external investment flows to, changes in the initial risk level of a new fund, the higher is the likelihood that the optimal level of risk of the new fund is greater than that which would be set by a manager acting in isolation. The converse is true for a family composed largely of outperforming funds.
- There exists a level of underperformance on the part of existing funds above

which relative performance and fund openings are positively correlated and below which relative performance and fund openings are negatively correlated. This suggests that a family composed largely of severely underperforming funds will be more likely to open a new fund than a family of average performers.

Our paper proceeds as follows. Section I.B reviews the relevant literature. Section I.C presents a simple theoretical model of the relation between fund performance and the fund manager's risk taking decision. Section I.D presents a model of the fund family's fund opening decision. Section I.E discusses our results. Section I.F concludes.

I.B Literature Review

Our paper is directly related to two existing areas of research. The fundlevel analysis in Section I.C draws upon a rich empirical literature concerning the relation between fund performance, investment flows, and the behavior of mutual fund managers. Our main contribution stems from the family-level analysis in Section I.D, and contributes to a sparse literature on the proliferation of funds and fund categories.

I.B.1 Models of Fund Openings

While the dramatic growth in both the number of mutual funds available to investors and the level of assets managed by these funds has been well documented, there is a relative dearth of research directly focusing on the fund family as the fund-opening agent. Several largely theoretical studies exist which seek to explain the growth in funds offered as a brand proliferation strategy (Massa 1998) and (Massa 2003), wherein a family will seek to deter entry by rival families by occupying market share. Massa (1998) proposes a model from micro-foundations to argue that fund and category proliferation are marketing strategies on the part of the fund family, and are driven by investors' limited information and heterogeneity. He identifies three competing forces driving the decision to expand fund offerings in breadth or depth; a signalling externality, a risk-hedging externality, and a learning-by-doing externality. Massa concludes that these forces result in sub-optimality, specifically the over-segmentation of the mutual fund industry and the under-provision of funds within each category.

Massa (2003) observes that there exist many mutual funds in many categories, offered by a relatively small number of fund families. He suggests that funds are differentiated at both the fund level (performance, fees, etc.) and the family level (what he refers to as the 'free-switching' option, wherein fees for transfers between funds within a family are effectively waived). Building on his earlier paper, Massa develops a framework from micro-foundations to explain the segmentation of the mutual fund industry into ever more categories, as well as the proliferation of funds within categories He empirically tests a number of hypotheses relating fund and category proliferation to investor preferences, family structure, and performance, using monthly and annual data at the fund and fund family level from the CRSP Mutual Fund database.⁴

Massa concludes that market structure affects mutual fund performance. He finds that the degree of product differentiation within a category is negatively correlated with returns and positively correlated with turnover within that category. Additionally, he finds that product differentiation is positively related to fund proliferation, measured as either the number of fund offered by a family within a category or as the number of categories in which a family offers funds. His results lend support for the assertion that performance is only one of numerous dimensions across which funds are differentiated by showing that performance is negatively correlated with the degree of product differentiation in these dimensions.

 $^{^4}$ Specifically, Massa includes 1992-2000 data on all US mutual funds except those categorized as Index or Option Income funds.

Khorana and Servaes (1999) and Khorana and Servaes (2006) empirically address fund openings and family market share respectively. Khorana and Servaes (1999) find that fund openings are positively correlated with category size, capital gains overhang, overall family-level performance, the percentage of family assets in category (bonds), 'leader' family behavior, and the scale and scope of a family's portfolio of funds. They find that openings are negatively correlated with fees and the percentage of family assets in category (stocks). They find no evidence that families with poor performers within a category are more likely to open a new fund. Khorana and Servaes (2006) find that market share is positively correlated with performance, innovation, media attention, the number and size of distribution channels, and the breadth and depth of funds offered by the family. They find a negative correlation with expenses and the degree of 'crowdedness' of the given category.

More recently, Zhou and Chiang (2005) study the cross-family acquisition of mutual funds. They document that families acquire funds both to achieve synergies stemming from the cost structure of fund operation and to acquire talent in the form of star funds or reputable managers. While our model specifically addresses the opening of new funds, rather than the acquisition of existing funds, the cause and effect may be the same across the two forms of family growth. Although only tangentially related to our model, Guedj and Papastaikoudi (2004) find that fund families promote funds that are most profitable to the family more than less profitable funds. Evans (2004) finds evidence of the use of incubator funds as a strategy for enhancing the return histories of 'new' funds, an approach which is consistent with maximizing the cannibalization effect we discuss below. These studies provides some support for our approach.

I.B.2 Fund Flows and Fund Performance

The last decade has seen a dramatic rise in the amount of research devoted to studying the relation between the behavior of mutual fund investors and that of mutual fund managers. Numerous empirical studies have focused on the relation between fund flows and past performance, particularly the observed asymmetry in investor response to performance. Our approach draws upon work by Sirri and Tufano (1998), who document the asymmetric relation between fund flows and past performance and find a similar asymmetric response to fees, and Chevalier and Ellison (1997) who estimate a semi-parametric model of this relation and show that flows respond asymmetrically to past performance, with inflows in response to outperformance greater in magnitude than outflows following poor performance.

Nanda, Wang, and Zheng (2004) model the spillover effects of 'star' and 'dog' funds on investment flows into a fund family, and find strong evidence of correlation (positive in the case of a 'star' fund and negative in the case of a 'dog' fund). They expand upon the literature citing a convex flow-performance relation and suggest that under-performing fund families are likely to embark upon a starmaking strategy in an attempt to take advantage of the potential spillover effect.

Berk and Xu (2004) draws upon Berk and Green (2004), which develops a rational model of mutual fund investment in a world where there exist managers with skill to outperform passive benchmarks, with this skill declining in assets managed. In their model, assets flow into (out of) outperforming (underperforming) funds to the point where the funds' performance net of expenses matches the benchmark. Berk and Xu (2004) find that the observed persistence in performance of poorly pereforming funds is a result of the asymmetric flow-performance relation, in that funds with shareholders who are insensitive to poor performance will continue to perform poorly, given the breakdown in the mechanism to bring down assets.⁵

Recently, Johnson (2006) uses a unique trade-level dataset from one noload fund family to examine the behavior of fund shareholders. Consistent with an asymmetric flow-performance relation, he finds that new and old shareholders respond positively to periods of outperformance, but are unresponsive to periods

⁵Although, over time persistently poor performance may achieve the same effect.

of underperformance. He suggests that intra-family transfers are motivated by the performance of the destination fund, rather than by the origination fund.

We suggest that the convexity of the fund flow-relative performance relation not only affects the decisions of the individual fund manager, but also those of the fund family, in particular the decision to open a new fund. To model these effects, we specify a framework in which the fund manager's decisions are limited to the choice of idiosyncratic risk borne by the fund, while the fund family manages the family-level risk profile through the opening of new funds.⁶ We first specify a parsimonious functional form for the fund flow-relative performance relation, subsequently deriving the fund manager's optimal risk-setting decision. Drawing upon this fund level result, we state the fund family's new fund opening decision and derive conditions under which the fund family is likely to open a new fund.

I.C A Simple Model of the Fund Manager's Risk-Taking Decision

Let returns earned by the i^{th} fund be decomposed as follows;

$$r_i = \alpha_i + \beta'_i \mathbf{X} + \sigma_i \varepsilon_i, \tag{I.1}$$

where r_i denotes the raw return earned by the i^{th} fund, α_i is a measure of the 'ability' of the manager of the i^{th} fund, **X** is a vector of risk factors with β_i the associated loadings, σ_i is the level of idiosyncratic risk borne by the i^{th} fund, and $\varepsilon_i \sim N(0,1)$ is a standard normal disturbance term. We are purposely vague in defining **X**, so that the specification may nest a wide range of risk-adjusting approaches. As all variables are contemporaneous, we omit a time subscript. We define risk-adjusted or 'abnormal' performance as

$$o_i = \alpha_i + \sigma_i \varepsilon_i.$$

⁶Two obvious extensions to the current paper include jointly modeling fund openings and closings and incorporating incubator funds into the model.

We assume that the fund manager maximizes expected income, which given fees proportional to assets under management is equivalent to maximizing expected investment flows. Flows are defined as a function of relative performance, denoted $flow(\rho_i)$. Fund manager 'skill', α_i , is taken as given,⁷ and so the fund manager's choice variable is σ_i , the level of risk borne by the fund. Thus, the fund manager's maximization problem can be stated as follows;

$$MAX_{\sigma} \int_{-\infty}^{\infty} flow(\rho_i) \frac{1}{\sqrt{2\pi\sigma_i}} \exp\left(\frac{-(\rho_i - \alpha_i)^2}{2\sigma_i^2}\right) d\varepsilon.$$
(I.2)

In specifying a functional form for $flow(\rho_i)$, we wish to accommodate nonlinearities in the fund flow-relative performance relation as documented by Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997). In addition, we argue that there exists a point of underperformance below which investors will react strongly, and we limit the universe of candidate models to those which yield analytically tractable results. Below, we discuss using sigmoid, cubic polynomial and piecewise linear functions for $flow(\rho_i)$. Derivations for the cubic and piecewise linear case are presented in Appendix I.A and I.B, respectively.

Sigmoid

If we wish to explicitly accommodate the notion of limited liability, a sigmoid function may be the most intuitively appealing form for the flow-performance relation. However, such a form provides analytically intractable results. While it may be interesting to derive numerical results using a sigmoid, we opt to use the more analytically tractable cubic and piecewise linear forms discussed below.

Cubic Polynomial

An appropriately parameterized cubic polynomial can accommodate both the empirically observed asymmetry in flows around 'average' performance and the intuitively appealing idea that there exists some level of underperformance which will result in strong net outflows.⁸ We approximate the relative performance-

⁷Although it may be argued that the fund manager can manipulate α_i through, for instance, investment in information or education, we wish to focus on the manipulation of risk.

⁸This effect may not be apparent from in recent empirical studies for several reasons. First, such

investment flow relation as follows;

$$flow(\rho_i) = (a\rho_i + b)^3 + c,$$

where we assume a > 0, so that fund flows are increasing in relative performance.

Rewriting this function as;

$$flow(\rho_i) = a^3 \rho_i^3 + a^2 b \rho_i^2 + a b^2 \rho_i + b^3 + c,$$

the fund manager's maximization problem becomes;⁹

$$MAX_{\sigma} \int_{-\infty}^{\infty} (a^{3}\rho_{i}^{3} + a^{2}b\rho_{i}^{2} + ab^{2}\rho_{i} + b^{3} + c)\frac{1}{\sqrt{2\pi}\sigma_{i}} \exp\left(\frac{-(\rho_{i} - \alpha_{i})^{2}}{2\sigma_{i}^{2}}\right) d\varepsilon.$$

Noting that $\int_{-\infty}^{\infty} x^n \frac{1}{\sqrt{2\pi\sigma}} \exp\left(\frac{-(x-\mu)^2}{2\sigma^2}\right) d\varepsilon = E[x^n]$, it is clear that the objective function is a weighted sum of the first three noncentral moments of a Normal distribution, plus a constant;

$$MAX_{\sigma}\left[a^{3}\left(\alpha_{i}^{3}+\alpha_{i}\sigma_{i}^{2}\right)+a^{2}b\left(\alpha_{i}^{2}+\sigma_{i}^{2}\right)+ab^{2}\left(\alpha_{i}\right)+\left(b^{3}+c\right)\right],$$

which has no well-defined solution. As a result of the symmetry of the cubic, for any parametrization there exists a level of (under)performance below which the optimal level of sigma is zero, and above which it is infinite.¹⁰

Piecewise Linear

Alternatively, the relative performance-investment flow relation can be parameterized as a piecewise linear function with two kinks, as follows;

levels of underperformance may be extremely rare events. Second, flows estimated on monthly data as a percent of beginning of period assets may be a poor estimate of actual flows.

⁹See Appendix I.A for derivations.

¹⁰This result stems directly from our assumption that a > 0. Were a < 0, we would have the opposite result.

$$flow(\rho_i) = \begin{cases} b_1(\rho_i - L_1) + b_2 L_1 & if \quad \rho_i < L_1 \\ b_2 \rho_i & if \quad L_1 \le \rho_i < L_2 \\ b_3(\rho_i - L_2) + b_2 L_2 & if \quad L_2 \le \rho_i \end{cases}$$
(I.3)

where $flow(\rho_i)$ is defined as net asset flows as a proportion of assets currently managed by the i^{th} fund, $b_1 > b_3 > b_2 \ge 0$, and $L_1 < L_2$.¹¹

The fund manager's maximization problem becomes

$$MAX_{\sigma} \left\{ \int_{-\infty}^{\frac{L_{1}-\alpha}{\sigma}} \left[b_{1} \left(\alpha + \sigma \varepsilon \right) + L_{1} \left(b_{2} - b_{1} \right) \right] \exp\left(\frac{-\varepsilon^{2}}{2} \right) d\varepsilon + \int_{\frac{L_{1}-\alpha}{\sigma}}^{\frac{L_{2}-\alpha}{\sigma}} \left[b_{2} \left(\alpha + \sigma \varepsilon \right) \right] \exp\left(\frac{-\varepsilon^{2}}{2} \right) d\varepsilon + \int_{\frac{L_{2}-\alpha}{\sigma}}^{\infty} \left[b_{3} \left(\alpha + \sigma \varepsilon \right) + L_{2} \left(b_{2} - b_{3} \right) \right] \exp\left(\frac{-\varepsilon^{2}}{2} \right) d\varepsilon \right\},$$
(I.4)

with solution¹²

$$\sigma_{opt}^{2}(\alpha) = \frac{L_{2}^{2} - L_{1}^{2} + 2(L_{1} - L_{2})\alpha}{\ln\left(\frac{b_{3} - b_{2}}{b_{1} - b_{2}}\right)}.$$
(I.5)

As we have derived an expression for the optimal level of risk, it is appropriate to discuss the assumptions necessary to ensure non-negativity of $\sigma_{opt}^2(\alpha)$. Given our assumption that $b_1 > b_3 > b_2$, we have $\ln((b_3 - b_2) / (b_1 - b_2)) < 0$. Thus, we have that $\sigma_{opt}^2(\alpha) > 0$ when $L_2^2 - L_1^2 + 2(L_1 - L_2)\alpha < 0$, which is equivalent to $\alpha > (L_2^2 - L_1^2) / 2(L_2 - L_1)$. This implies that there exists a level of performance below which $\sigma_{opt}^2(\alpha)$ is negative, and necessitates the assumption of at least a lower bound on the fund manager's choice of portfolio risk. In fact, it is not uncommon for a fund's prospectus to specify a minimum percentage of equity holdings and to rule out hedging strategies, in which case the fund can never achieve zero portfolio risk. Similar rules place an upper bound on the level of risk the manager can assume, and so we define σ_{LB}^2 and σ_{UB}^2 as the minimum and maximum allowable risk exposures as set forth in the fund's prospectus, respectively.

¹¹We specify a piecewise linear function in order to ease derivation of a closed form expression for σ_i as a function of α_i . Two kinks are needed to represent both the empirically documented convexity and the idea that some level of underperformance becomes disastrous for the manager.

¹²See Appendix I.B for derivations.

While we have made no assumptions on the relative magnitudes of the kinks L_1 and L_2 , intuition suggests that L_1 , the point where performance becomes extremely poor, is far below zero, while L_2 , the point where fund flows react strongly to performance is close to zero. This implies $|L_1| > |L_2|$, in which case the α below which $\sigma_{opt}^2(\alpha)$ becomes negative is less than zero.

Our results suggest the following proposition.

Proposition 1 Assume that an expected revenue-maximizing fund manager faces the relative performance-investment flow relation given by equation I.3. The manager's optimal choice of idiosyncratic risk is given by;

$$\sigma_{fundopt}^{2}\left(\alpha\right) = \begin{cases} \sigma_{LB}^{2} \ if \ \sigma_{opt}^{2}\left(\alpha\right) < \sigma_{LB}^{2} \\ \sigma_{UB}^{2} \ if \ \sigma_{opt}^{2}\left(\alpha\right) > \sigma_{UB}^{2} \\ \sigma_{opt}^{2}\left(\alpha\right) \ otherwise \end{cases}$$
(I.6)

where

$$\sigma_{opt}^{2}(\alpha) = \frac{L_{2}^{2} - L_{1}^{2} + 2(L_{1} - L_{2})\alpha}{\ln\left(\frac{b_{3} - b_{2}}{b_{1} - b_{2}}\right)}.$$
(I.7)

The proof follows directly from the optimization problem solved above. The following corollary interprets this result.

Corollary 1 For parameterizations of equation I.3 such that flows respond most strongly to outperformance and least strongly to average performance, that is $b_1 > b_3 > b_2 \ge 0$, $L_1 \ll 0$, and $L_1 \ll L_2$, the fund manager's optimal risk strategy is (weakly);

- 1. increasing in managerial ability, α ;
- 2. increasing in L_1 , the point where performance becomes extremely poor, for $\alpha > -L_1$, else decreasing;
- 3. increasing in L_2 , the point where performance becomes 'good', for $\alpha < L_2$, else decreasing;

- 4. decreasing in b_1 , the sensitivity of net investment outflows in response to extreme underperformance, for $\alpha > (L_2^2 - L_1^2)/2(L_2 - L_1)$, else decreasing, and;
- 5. increasing in b_3 , the sensitivity of net investment inflows in response to extreme outperformance, for $\alpha > (L_2^2 - L_1^2)/2(L_2 - L_1)$, else decreasing.

Proof: See Appendix I.C.

The intuition behind Corollary 1 provides the central results of this section of our paper;

- 1. The more skilled a manager, the higher is the optimal level of risk.
- 2. The closer to 0 is the point below which flows respond negatively to underperformance, the higher is the optimal level of risk for very talented managers, and the lower is the optimal level of risk for those with average and low skills.
- 3. The lower the level of performance associated with the convexity in $flow(\rho)$ (i.e. the point above which flows respond positively to performance), the higher is the optimal level of risk for talented managers, and the lower is the optimal level of risk for those with below average skills.
- 4. The more sensitive are outflows in response to extreme underperformance, the lower is the optimal level of risk for managers of average and above average skills, and the higher is the optimal level of risk for managers of below average skills.
- 5. The more sensitive are inflows in response to extreme outperformance, the higher is the optimal level of risk for managers of average and below average skills, and the lower is the optimal level of risk for managers of above average skills.

I.D A Model of the Fund Family's Fund Opening Decision

We next examine how the fund flow-relative performance relation affects the family's fund opening decision. We suggest that a fund family with a disproportionate number of underperforming funds, each of which has a high probability of landing in the 'extreme underperformance' region of $flow(\rho)$, has an incentive to open a new fund in the hope that the new fund will outperform and land in the 'extreme outperformance' region of $flow(\rho)$. We formalize this assertion in the following sections.

I.D.1 Defining Family-Level Performance

We define family level returns as the asset-weighted average of fund-level returns;

$$r_j^{fam} = \frac{\sum_{i=1}^{I} A_i r_i}{\sum_{i=1}^{I} A_i}$$

where r_j^{fam} denotes the return earned by the j^{th} family, A_i is the level of assets managed by, and r_i is the return earned by, the i^{th} fund, and I is the number of funds managed by family j.

Similarly, we define family level relative performance as the asset-weighted average of fund level relative performance;

$$\rho_j^{fam} = \frac{\sum_{i=1}^{I} A_i \rho_i}{\sum_{i=1}^{I} A_i}$$

where ρ_j^{fam} denotes the relative performance of the j^{th} family and ρ_i is the relative performance of the i^{th} fund in family j.

Finally, we define family-level investment flows as the sum of fund-level flows, and thus as a function of fund-level relative performance;

$$flow(\rho_j^{fam}) = flow(\rho_{1,\dots,\rho_I}) = \sum_{i=1}^{I} flow(\rho_i)$$

I.D.2 Defining the Family's Payoff Schedule

We assume that family-level remuneration is given by the sum of fundlevel remuneration;

$$\Pi_j = \sum_{i=1}^I \pi_i$$

where Π_i denotes the income earned by the j^{th} family composed of I funds, and π_i is the income earned by the i^{th} member fund.

Remuneration is earned as a percentage of assets managed, denoted by δ .¹³ Thus;

$$\Pi_j = \sum_{i=1}^{I} \delta \left[A_i \left(1 + r_i + flow(\rho_i) \right) \right].$$

I.D.3 The Family's Decision

The fund family decides to open a new fund if and only if doing so increases expected remuneration net of fund opening costs and conditioned on expected cannibalization of assets from existing funds by the new fund. We write the first step in the family's maximization problem as follows;

$$MAX_{f_{I+1}\in F}E_{-1}\left\{\sum_{i=1}^{I}\delta\left[\left(1-c_{i}\left(f_{I+1}\right)\right)A_{i}\left(1+r_{i}+flow(\rho_{i})\right)\right]\right.\\\left.+\delta\left[\left(C\left(f_{I+1}\right)+\sum_{i=1}^{I}c_{i}\left(f_{I+1}\right)A_{i}\right)\left(1+r_{f_{I+1}}+flow(\rho_{f_{I+1}})\right)\right]\right.$$
(I.8)
$$\left.-Costs\left(f_{I+1}\right)\right\},$$

where E_{-1} {} is the expectation operator¹⁴, $c_i(f_{I+1})$ is defined as the proportional level of 'cannibalization' of the i^{th} existing fund by a new fund f_{I+1} , $C(f_{I+1})$ is defined as the initial external asset flow into a new fund f_{I+1} , and $Costs(f_{I+1})$ denotes the fixed cost of opening a new fund of type f_{I+1} . The functions $c_i(f_{I+1})$,

 $^{^{13}\}text{For simplicity, we assume }\delta$ constant across all funds within a family.

 $^{^{14}}$ To avoid becoming inundated with subscripts, and as we are deriving a fairly straightforward two period model, we refer to the two periods as -1 and 0, and omit the subscript 0. The family makes the period 0 fund opening decision on the basis of the period -1 information set.

 $C(f_{I+1})$, and $Costs(f_{I+1})$ are assumed to be nonnegative. The set F is composed of all potential new funds as well as the action 'no new fund'. The family maximizes iteratively, with the optimal strategy involving how many funds and of what type to open. The family subsequently opens a new fund f_{I+1}^* if and only if expected revenues with the new fund are greater than without, i.e. if and only if the following condition is satisfied;

$$E_{-1} \left\{ \sum_{i=1}^{I} \delta \left[\left(1 - c_i \left(f_{I+1}^* \right) \right) A_i \left(1 + r_i + flow(\rho_i) \right) \right] + \delta \left[\left(C \left(f_{I+1}^* \right) + \sum_{i=1}^{I} c_i \left(f_{I+1}^* \right) A_i \right) \left(1 + r_{f_{I+1}^*} + flow(\rho_{f_{I+1}^*}) \right) \right] - Costs \left(f_{I+1}^* \right) \right\}$$

$$> E_{-1} \left[\sum_{i=1}^{I} \delta \left[A_i \left(1 + r_i + flow(\rho_i) \right) \right] \right].$$
(I.9)

To proceed, we make the simplifying assumptions that there are only two fund characteristics of interest; the 'ability' of the fund manager (α_i) and the risk borne by the fund (σ_i^2),¹⁵ and that the cost of opening a new fund is constant for a given fund family. This implies

$$c_{i}(f_{I+1}) = c_{i}\left(\alpha_{f_{I+1}}, \sigma_{f_{I+1}}^{2} | \alpha_{1}, ..., \alpha_{I}, \sigma_{1}^{2}, ..., \sigma_{I}^{2}\right),$$
$$C(f_{I+1}) = C\left(\alpha_{f_{I+1}}, \sigma_{f_{I+1}}^{2} | \alpha_{1}, ..., \alpha_{I}, \sigma_{1}^{2}, ..., \sigma_{I}^{2}\right),$$

and

$$Costs(f_{I+1}) = Costs.$$

As for the shapes of $c_i(f_{I+1})$ and $C(f_{I+1})$, we assume that $c_i(f_{I+1})$ is decreasing in $\left(\sigma_i^2 - \sigma_{f_{I+1,0}}^2\right)^2$ and α_i and increasing in $\alpha_{f_{I+1,0}}$, while $C(f_{I+1})$ is increasing in $\left(\sigma_i^2 - \sigma_{f_{I+1,0}}^2\right)^2$, increasing and concave in both α_i and $\alpha_{f_{I+1,0}}$ for all *i*, and bounded below by zero. Effectively, the more similar the risk level of a

¹⁵This is clearly a great oversimplification, as there are numerous non-performance fund characteristics of interest to investors. However, we are primarily interested in the impact of performance on fund openings, and this assumption provides a needed degree of tractability. We will explicitly address this issue in future empirical work.

new fund is to that of an existing fund, the stronger is the cannibalization effect, and the lower is the level of initial external investment. Furthermore, we assume that $c_i(f_{I+1})$ approaches upper and lower bounds asymptotically,¹⁶ so that for extreme underperformance $c_i(f_{I+1})$ is concave, while for extreme outperformance, it is convex.

Additionally, we assume that the skill level (α) of the 'new' fund manager is unknown and the skills of the existing managers are approximated from historical data, so that initially;¹⁷

$$E\left[\rho_{f_{I+1}}\right] = 0,$$

$$E_{-1}\left[r_{f_{I+1}}\right] = E_{-1}\left[\beta'_{f_{I+1}}\mathbf{X}\right]$$

and

$$E_{-1}[r_i] = E_{-1}[\rho_i] + E_{-1}[\beta'_i \mathbf{X}] = \widehat{\alpha}_i + E_{-1}[\beta'_i \mathbf{X}]$$

Note that given our fund level results, we are dealing with a specific pair of funds in (α, σ^2) -space, specifically $(0, \sigma_{f_{I+1,0}}^2)$ for a new fund and $(\widehat{\alpha}_i, \sigma_{fundopt}^2(\widehat{\alpha}_i))$ for an existing fund.

The family's decision involves whether to open a new fund and where to set the new fund's initial risk level $\sigma_{f_{I+1},0}^2$, taking $\{\widehat{\alpha}_1...\widehat{\alpha}_I\}$ and $\{\sigma_1^2(\widehat{\alpha}_1)...\sigma_I^2(\widehat{\alpha}_I)\}$ as given. For existing funds, σ_i^2 is set by the fund family at time of fund inception, and subsequently evolves through time as the fund manager optimizes with respect to the fund's developing performance history, consistent with our fund-level results above. The set \digamma of available new funds is now composed of all funds with initial risk level $\sigma_{f_{I+1},0}^2 \in (\sigma_{MIN}^2, \sigma_{MAX}^2)$ where σ_{MIN}^2 and σ_{MAX}^2 are lower and upper bounds on the level of risk a fund may assume.¹⁸

¹⁶With cannibalization expressed as a percentage. these bounds must lie on the interval (0,1).

¹⁷A more detailed treatment might allow for expectations on new manager skill to be a function either of sister fund performance or of public perception based on a fund manager's historical performance in e.g. a different family. This would result in the family optimizing over both α and σ^2 .

¹⁸Imposed by God, nature, or the SEC.

We rewrite the family's optimization problem as

$$MAX_{f_{\sigma_{f_{I+1},0}^{2}}}\left\{\delta\sum_{i=1}^{I}A_{i}\left(1+E_{-1}\left[r_{i}\right]+E_{-1}\left[flow\left(\rho_{i}\right)\right]\right)\right)+\\\delta\sum_{i=1}^{I}c_{i}\left(f_{I+1}\right)A_{i}\left(E_{-1}\left[r_{f_{I+1}^{*}}\right]-E_{-1}\left[r_{i}\right]+E_{-1}\left[flow\left(\rho_{f_{I+1}^{*}}\right)\right]-E_{-1}\left[flow\left(\rho_{i}\right)\right]\right)\\+\delta C\left(f_{I+1}\right)\left(1+E_{-1}\left[r_{f_{I+1}^{*}}\right]+E_{-1}\left[flow\left(\rho_{f_{I+1}^{*}}\right)\right]\right)\\-Costs\left(f_{I+1}\right)\right\}.$$
(I.10)

Thus, the family opens a new fund f^*_{I+1} with initial risk exposure $\sigma^2_{f^*_{I+1}}$ satisfying the first order condition

$$\delta \sum_{i=1}^{I} \frac{\partial c_{i}(f_{I+1})}{\partial \sigma_{f_{I+1}^{*}}^{2}} A_{i} \left(E_{-1} \left[r_{f_{I+1}^{*}} \right] - E_{-1} \left[r_{i} \right] + E_{-1} \left[flow \left(\rho_{f_{I+1}^{*}} \right) \right] - E_{-1} \left[flow \left(\rho_{i} \right) \right] \right) \\ + \delta \sum_{i=1}^{I} c_{i} \left(f_{I+1} \right) A_{i} \left(\frac{\partial E_{-1} \left[flow \left(\rho_{f_{I+1}^{*}} \right) \right]}{\partial \sigma_{f_{I+1}^{*}}^{2}} \right) \\ + \delta \frac{\partial C(f_{I+1})}{\partial \sigma_{f_{I+1}^{*}}^{2}} \left(1 + E_{-1} \left[r_{f_{I+1}^{*}} \right] + E_{-1} \left[flow \left(\rho_{f_{I+1}^{*}} \right) \right] \right) \\ + \delta C \left(f_{I+1} \right) \left(\frac{\partial E_{-1} \left[flow \left(\rho_{f_{I+1}^{*}} \right) \right]}{\partial \sigma_{f_{I+1}^{*}}^{2}} \right) = 0 .$$
(I.11)

Rearranging yields;

$$\delta \sum_{i=1}^{I} \frac{\partial c_{i}(f_{I+1})}{\partial \sigma_{f_{I+1}^{*}}^{2}} A_{i} \left(E_{-1} \left[r_{f_{I+1}^{*}} \right] - E_{-1} \left[r_{i} \right] + E_{-1} \left[flow \left(\rho_{f_{I+1}^{*}} \right) \right] - E_{-1} \left[flow \left(\rho_{i} \right) \right] \right) \\ + \delta \frac{\partial C(f_{I+1})}{\partial \sigma_{f_{I+1}^{*}}^{2}} \left(1 + E_{-1} \left[r_{f_{I+1}^{*}} \right] + E_{-1} \left[flow \left(\rho_{f_{I+1}^{*}} \right) \right] \right) \\ + \delta \left(C \left(f_{I+1} \right) + \sum_{i=1}^{I} c_{i} \left(f_{I+1} \right) A \right)_{i} \left(\frac{\partial E_{-1} \left[flow \left(\rho_{f_{I+1}^{*}} \right) \right]}{\partial \sigma_{f_{I+1}^{*}}^{2}} \right) = 0 ,$$
(I.12)

which is insufficiently specified to yield a solution, so we ask: When does the fund family's optimal choice of initial fund risk, $\sigma_{f_{I+1,0}}^2$, differ from the flow-maximizing choice $\sigma_{fundopt}^2(0)$ made by a fund manager with $\alpha = 0$ acting in isolation?

Defining $R_i = r_i + flow(\rho_i)$ and setting I = 1 (equivalent to the case of a family with a single existing fund), equation I.12 becomes

$$\delta \frac{\partial c_{1}(f_{I+1})}{\partial \sigma_{f_{I+1}^{*}}^{2}} A_{1} \left(E_{-1} \left[R_{f_{I+1}^{*}} - R_{i} \right] \right) + \delta \frac{\partial C(f_{I+1})}{\partial \sigma_{f_{I+1}^{*}}^{2}} \left(1 + E_{-1} \left[R_{f_{I+1}^{*}} \right] \right) + \delta \left(C \left(f_{I+1} \right) + c_{1} \left(f_{I+1} \right) \right) A_{1} \left(\frac{\partial E_{-1} \left[flow \left(\rho_{f_{I+1}^{*}} \right) \right]}{\partial \sigma_{f_{I+1}^{*}}^{2}} \right) = 0 .$$
(I.13)

Since we have assumed $E_{-1}\left[\alpha_{f_{I+1}^*}\right] = 0$, it follows that $\sigma_{fundopt}^2(0)$ satis-

$$\left(\frac{\partial E_{-1}\left[flow\left(\rho_{f_{l+1}^*}\right)\right]}{\partial \sigma_{f_{l+1}^*}^2}\right) = 0 \tag{I.14}$$

and

$$\left(\frac{\partial^2 E_{-1}\left[flow\left(\rho_{f_{I+1}^*}\right)\right]}{\left(\partial\sigma_{f_{I+1}^*}^2\right)^2}\right) < 0, \tag{I.15}$$

and that

$$\delta \left(C \left(f_{I+1} \right) + c_1 \left(f_{I+1} \right) \right) A_1 > 0.$$
(I.16)

Given our assumptions about $\partial c_1(f_{I+1}) / \partial \sigma_{f_{I+1}^*}^2$ and $\partial C(f_{I+1}) / \partial \sigma_{f_{I+1}^*}^2$, we may be able to say something about the relative magnitudes of $\sigma_{f_{I+1,0}}^2$ and $\sigma_{fundopt}^2(0)$. Equation I.13 can be rewritten as follows;

$$\begin{pmatrix} \frac{\partial E_{-1} \left[flow\left(\rho_{f_{I+1}^{*}}\right) \right]}{\partial \sigma_{f_{I+1}^{*}}^{2}} \end{pmatrix} = \\ \delta \frac{\partial c_{1}(f_{I+1})}{\partial \sigma_{f_{I+1}^{*}}^{2}} A_{1} \left(\frac{E_{-1} \left[R_{f_{I+1}^{*}} - R_{1} \right]}{C(f_{I+1}) + c_{1}(f_{I+1})} \right) \\ - \delta \frac{\partial C(f_{I+1})}{\partial \sigma_{f_{I+1}^{*}}^{2}} \left(\frac{1 + E_{-1} \left[R_{f_{I+1}^{*}} \right]}{C(f_{I+1}) + c_{1}(f_{I+1})} \right). \quad (I.17)$$

If neither $C(f_{I+1})$ nor $c_i(f_{I+1})$ depend on $\sigma^2_{f^*_{I+1}}$, then¹⁹

¹⁹Recall that $E_{-1}[flow(\rho)]$ is maximized by $\sigma_{opt}^2(0)$ when $E_{-1}[\rho] = 0$.

$$\sigma_{f_{I+1,0}^{*}}^{2}=\sigma_{fundopt}^{2}\left(0\right)$$

However, we have assumed this is not the case. If the net performancerelated effects of a change in $\sigma_{f_{I+1,0}}^2$ are positive (negative) then $\sigma_{f_{I+1,0}}^2$ is greater than (less than) $\sigma_{fundopt}^2(0)$.

Now, the family opens a new fund characterized by $\sigma_{f_{I+1,0}}^2$ if and only if the expected net payoff to opening is positive, i.e. if;

$$E_{-1}\left\{\sum_{i=1}^{I} \delta\left[\left(1-c_{i}\left(f_{I+1}^{*}\right)\right) A_{i}\left(1+r_{i}+flow(\rho_{i})\right)\right]\right.$$

+ $\delta\left[\left(C\left(f_{I+1}^{*}\right)+\sum_{i=1}^{I} c_{i}\left(f_{I+1}^{*}\right) A_{i}\right)\left(1+r_{f_{I+1}^{*}}+flow(\rho_{f_{I+1}^{*}})\right)\right]$
- $Costs\left(f_{I+1}^{*}\right)\right\}-E_{-1}\left[\sum_{i=1}^{I} \delta\left[A_{i}\left(1+r_{i}+flow(\rho_{i})\right)\right]\right]>0.$ (I.18)

This is equivalent to

$$\delta \sum_{i=1}^{I} c_i \left(f_{I+1}^* \right) A_i \left(E_{-1} \left[R_{f_{I+1}^*} - R_i \right] \right) + \delta C \left(f_{I+1}^* \right) \left(1 + E_{-1} \left[R_{f_{I+1}^*} \right] \right) - Costs \left(f_{I+1}^* \right) > 0.$$
(I.19)

Defining the left hand side of equation I.19 above as $\Delta_{f_{I+1}^*}$, where

$$\Delta_{f_{I+1}^*} = \delta \sum_{i=1}^{I} c_i \left(f_{I+1}^* \right) A_i \left(E_{-1} \left[R_{f_{I+1}^*} - R_i \right] \right) + \delta C \left(f_{I+1}^* \right) \left(1 + E_{-1} \left[R_{f_{I+1}^*} \right] \right) - Costs \left(f_{I+1}^* \right) , \qquad (I.20)$$

we can restate equation I.19 as $\Delta_{f_{I+1}^*} > 0$. Thus, the greater is the value of $\Delta_{f_{I+1}^*}$, the higher is the probability that a family opens a new fund f_{I+1}^* .

$$\frac{d\Delta_{f_{I+1}^*}}{d\rho_i} = \delta \sum_{i=1}^{I} \frac{\partial c_i(f_{I+1}^*)}{d\rho_i} A_i \left(E_{-1} \left[R_{f_{I+1}^*} - R_i \right] \right) \\
+ \delta \sum_{i=1}^{I} c_i \left(f_{I+1}^* \right) A_i \left(1 + \frac{\partial E_{-1}[flow(\rho_i)]}{d\rho_i} \right) \\
+ \delta \frac{\partial C(f_{I+1}^*)}{d\rho_i} \left(1 + E_{-1} \left[R_{f_{I+1}^*} \right] \right).$$
(I.21)

We summarize our findings in the following propositions.

Proposition 2 Assuming a non-decreasing relation between α estimates based on past performance $(\widehat{\alpha}_i)$ and the subsequent optimal level of idiosyncratic risk from Section I.C $(\sigma_{fundopt}^2(\widehat{\alpha}_i))$ for all existing funds, and assuming the degree of cannibalization is strongest for funds most similar to a new fund (i.e. $(c_i(f_{I+1}))$ decreasing in $(\sigma_i^2 - \sigma_{f_{I+1,0}}^2)^2$), then;

1. For a family consisting of only existing underperformers, the cannibalization effect is maximized by setting the risk level of a new fund higher than that of an investment-flow maximizing manager acting in isolation;

$$\sigma_{f_{I+1}^{*}}^{2} > \sigma_{fundopt}^{2}\left(0\right).$$

2. For a family consisting of only existing outperformers, the cannibalization effect is minimized by setting the risk level of a new fund lower than that of an investment-flow maximizing manager acting in isolation;

$$\sigma_{f_{I+1}^*}^2 > \sigma_{fundopt}^2\left(0\right).$$

3. For a family consisting of some underperformers and some outperformers, the net cannibalization effect is indeterminate.

Proof: See Appendix I.C.

Proposition 3 For fund families with a large number of underperforming funds, assuming the degree of cannibalization is decreasing in the difference between the risk level of an existing fund and that of a new fund, we have the following;

- The higher is the sensitivity of cannibalization to the initial risk level of a new fund, σ²_{fi+1}, the higher is the likelihood that the optimal level of risk of the new fund is greater than that which would be set by a fund manager with α = 0 acting in isolation, σ²_{fundopt} (0).
- The lower is the sensitivity of external investment flows to σ²_{f^{*}_{t+1}}, the higher is the likelihood that the optimal level of risk of the new fund is greater than σ²_{fundopt} (0).

Conversely;

- 3. The higher is the sensitivity of cannibalization to $\sigma_{f_{I+1}}^2$, the higher is the likelihood that optimal level of risk of the new fund is less than $\sigma_{fundopt}^2(0)$.
- 4. The lower is the sensitivity of external investment flows to $\sigma_{f_{I+1}}^2$, the higher is the likelihood that optimal level of risk of the new fund is less than $\sigma_{fundopt}^2(0)$.

Proof: See Appendix I.C.

Proposition 4 There exists a level of underperformance on the part of existing funds, ρ' , above which relative performance and fund openings are positively correlated and below which relative performance and fund openings are negatively correlated.

Proof: See Appendix I.C.

I.E Discussion

I.E.1 Fund Level Results

We have assumed a simple piecewise linear functional form for the relation between relative performance and investment fund flows, and have derived the revenue-maximizing fund manager's optimal level of idiosyncratic risk as a function of past performance as a proxy for managerial ability. Our approach differs from that of Chevalier and Ellison (1997) in several key aspects. Chevalier and Ellison estimate a semi-parametric functional form for the flow-performance relation, and subsequently characterize the fund manager's incentive to manipulate risk by estimating the expected change in flows for a change in risk. Although it may provide a weaker fit than the semi-parametric approach of Chevalier and Ellison, specifying a piecewise linear flow-performance specification allows us to extend Chevalier and Ellison's work by analytically deriving the optimal level of risk borne by the manager as a function of past performance. In addition, while Chevalier and Ellison use deviations from the market return as their measure for performance, and limit the range of performance studied to (-0.15, +0.15), we employ a more flexible risk-adjustment approach and impose no such limitations on the range of performance addressed. In fact, when Chevalier and Ellison turn to the data, estimating two-kinked piecewise models of funds' actual risk changes in response to performance, their estimates of the kinks are largely statistically significant, while their slope estimates are largely not significantly different from zero, and at times are significant and positive. This calls into question their assertion that funds with fairly small negative returns have an incentive to increase portfolio risk.

We find that, if revenue-maximization is the fund's goal, and given appropriate parametrization of the flow-performance relation, the optimal level of idiosyncratic risk taken on by a fund is increasing in the fund's performance history, subject to upper and lower bounds imposed on the fund. The most contestable assumption we make is on the relative slopes of the left and right sections of $flow(\rho_i)$, specifically that $b_1/b_3 > 1$. If we allow $b_1/b_3 < 1$, our model suggests that past performance and optimal risk are negatively related. In the absence of strong empirical support that $b_1/b_3 < 1$, we will maintain that the left kink is intended to represent the point where performance becomes disastrous,²⁰ and assume $b_1/b_3 > 1$.

I.E.2 Family Level Results

We have defined a framework wherein the mutual fund family sets the initial risk level of a new fund, with the risk level in subsequent periods set by the fund manager according to an expected revenue maximizing rule, as in our fund level model discussed above. The fund family is assumed to allow the manager of an existing fund to manage the fund autonomously, subject to guidelines set forth in

²⁰Note that this point is likely far below -0.15, the limit of Chevalier and Ellison's empirical work. They suggest that this limitation was imposed to avoid the problems of survivorship bias inherent in their data. We will avoid this problem by using the CRSP Survivor Bias Free US Mutual Fund Database.

the fund's prospectus and following an agreed-upon expected revenue maximizing rule. We assume the family maximizes family-level expected revenue by deciding whether or not to open a new fund and where to set the initial risk level of the new fund, and derive the associated optimization problem.

Our results are summarized as follows;

- 1. Families composed largely of underperforming funds will set the initial risk level of a new fund higher than that set by a fund manager with unknown 'ability' acting in isolation. This will result in maximizing the cannibalization effect of the new fund on the set of existing funds, thereby moving investment within the family toward a fund with a higher ex ante probability of being a 'star'. The opposite is true for a family of outperforming funds.
- 2. For fund families with a large number of underperforming funds; the higher is the sensitivity of cannibalization and/or the lower is the sensitivity of external investment flows to changes in new fund initial risk level, the higher is the likelihood that the optimal level of risk of the new fund is greater than that which would be set by a manager acting in isolation. The opposite is true for a family composed largely of outperforming funds.
- 3. There exists a level of underperformance on the part of existing funds, ρ' , above which relative performance and fund openings are positively correlated and below which relative performance and fund openings are negatively correlated. Furthermore, the family will set the initial risk level of the new fund higher than would the associated fund manager acting in isolation.

Our paper is unique among existing studies of mutual fund proliferation in several ways. Khorana and Servaes (1999) and Khorana and Servaes (2006) are largely empirical in nature²¹, while our derivation of the family's fund opening decision differs from the approaches of Massa (1998) and Massa (2003), which

²¹The empirically testable implications stemming from Propositions 1-5 will be addressed in a separate paper, at which time direct comparison with Khorana and Servaes results will be more relevant.

model the overall degree of fund and category proliferation, rather than explicitly defining the family's decision process, as we do. Our results regarding the optimal level of risk of a new fund are similarly unique.

A central result of the previous literature is a positive relation between family-level performance and fund and category proliferation. We suggest that in addition to this positive relation for average and above average performance levels there is an incentive, through the cannibalization effect, for families with a high percentage of poorly performing funds to open a new fund.

I.F Conclusion and Extensions

Our paper supports the assertion that there exist incentives, stemming from investors' asymmetric response to mutual fund performance, for mutual fund managers to alter fund risk. Our main contribution to the literature on mutual funds results from combining this asymmetry with a mechanism by which a new fund draws investment dollars from a fund family's basket of existing funds, leading to an incentive for families with a large number of poorly performing funds to open a new fund.

There are a number of empirically testable implications arising from Propositions 1-5;

- 1. Asymmetries in the relation between performance and subsequent fund flows.
- 2. A nondecreasing relation between fund performance and subsequent fund risk.
- 3. A family composed largely of underperforming funds will set the risk level of a new fund higher than would a fund manager acting in isolation, and vice versa.
- 4. For a family composed largely of underperforming funds, there is a positive correlation between the risk level of a new fund and the sensitivity of

cannibalization to new fund risk, and vice versa.

- 5. For a family composed largely of underperforming funds, there is a positive correlation between the risk level of a new fund and the sensitivity of initial new fund capitalization to new fund risk, and vice versa.
- 6. Both families composed largely of outperforming funds and those composed largely of underperforming funds are more likely to open new funds, relative to families dominated by 'average' performers.

These empirical questions will be addressed in chapter 2.

There are a number of natural extensions to the current paper. These include modeling fund openings and closings jointly, allowing a more flexible specification for the expected performance of a new fund, and extending the model to address the issue of incubator funds.

I.G Appendix I.A: Optimal σ^2 Under a Cubic Flow - Performance Relation

We first approximate the relative performance-investment flow relation as a cubic polynomial, as follows;

$$flow(\rho_i) = (a\rho_i + b)^3 + c,$$

where we assume a > 0, so that fund flows are increasing in relative performance.

Rewriting this function as

$$flow(\rho_i) = a^3 \rho_i^3 + a^2 b \rho_i^2 + a b^2 \rho_i + b^3 + c_i$$

the fund manager's maximization problem becomes;

$$MAX_{\sigma} \int_{-\infty}^{\infty} \left[a^{3} \rho_{i}^{3} + a^{2} b \rho_{i}^{2} + a b^{2} \rho_{i}^{2} + b^{3} + c \right] \frac{1}{\sqrt{2\pi\sigma_{i}}} \exp\left(\frac{-\left(\rho_{i} - \alpha_{i}\right)^{2}}{2\sigma_{i}^{2}}\right) d\varepsilon.$$
(I.22)

Noting that $\int_{-\infty}^{\infty} x^n \frac{1}{\sqrt{2\pi\sigma}} \exp\left(\frac{-(x-\mu)^2}{2\sigma^2}\right) d\varepsilon = E[x^n]$, it is clear that the objective function is the sum of the first three noncentral moments of a Normal distribution plus a constant;

$$MAX_{\sigma} \left[a^3 \left(\alpha_i^3 + \alpha_i \sigma_i^2 \right) + a^2 b \left(\alpha_i^2 + \sigma_i^2 \right) + a b^2 \left(\alpha_i \right) + \left(b^3 + c \right) \right], \qquad (I.23)$$

with first order condition $6a^2b\sigma_i^2 + 6a^3\alpha_i\sigma_i = 0$, which has no well-defined solution.

That is, due to the symmetry of the cubic, for any parametrization there exists a level of (under)performance above which the optimal level of sigma is zero, and above which it is infinite.

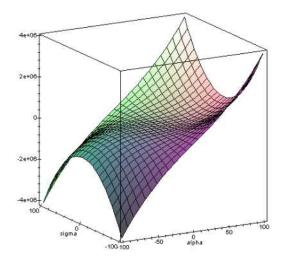


Figure I.1: Expected Fund Flows Under a Cubic Flow-Performance Relation: a=1, b=-1, c=-1

I.H Appendix I.B: Optimal σ^2 Under a Piecewise Linear Flow-Performance relation

Alternatively, the relative performance-investment flow relation be parameterized as a piecewise linear function with two kinks, as follows;

$$flow(\rho_i) = \begin{cases} b_1(\rho_i - L_1) + b_2L_1 & if \quad \rho_i < L_1 \\ b_2\rho_i & if \quad L_1 \le \rho_i < L_2 \\ b_3(\rho_i - L_2) + b_2L_2 & if \quad L_2 \le \rho_i \end{cases}$$
(I.24)

where $flow(\rho_i)$ is defined as net asset flows as a proportion of assets currently managed by the i^{th} fund, $b_1 > b_3 > b_2 \ge 0$, $L_1 < L_2$.²²

We assume that the fund manager maximizes expected income, which given fees proportional to assets under management is equivalent to maximizing

²²We specify a piecewise linear function in order to ease derivation of a closed form expression for σ_i as a function of α_i . Two kinks are needed to represent both the empirically documented convexity and the idea that some level of underperformance becomes disastrous for the manager.

expected investment flows. The fund manager's 'skill', α_i , is taken as given,²³ and so the fund manager's choice variable is σ_i , the level of risk borne by the fund. Thus, the fund manager's maximization problem can be stated as follows (we drop the subscript *i* and proportionality constant $1/\sqrt{2\pi}$ for clarity);

$$MAX_{\sigma} \left\{ \int_{-\infty}^{\frac{L_{1}-\alpha}{\sigma}} \left[b_{1} \left(\alpha + \sigma \varepsilon \right) + L_{1} \left(b_{2} - b_{1} \right) \right] \exp\left(\frac{-\varepsilon^{2}}{2} \right) d\varepsilon + \int_{\frac{L_{1}-\alpha}{\sigma}}^{\frac{L_{2}-\alpha}{\sigma}} \left[b_{2} \left(\alpha + \sigma \varepsilon \right) \right] \exp\left(\frac{-\varepsilon^{2}}{2} \right) d\varepsilon + \int_{\frac{L_{2}-\alpha}{\sigma}}^{\infty} \left[b_{3} \left(\alpha + \sigma \varepsilon \right) + L_{2} \left(b_{2} - b_{3} \right) \right] \exp\left(\frac{-\varepsilon^{2}}{2} \right) d\varepsilon \right\}.$$
(I.25)

The resulting first order condition becomes, after applying Liebniz's formula;

$$\begin{cases} -\frac{(b_{1}L_{1}+L_{1}(b_{2}-b_{1}))(L_{1}-\alpha)\exp\left(\frac{-(L_{1}-\alpha)^{2}}{2\sigma^{2}}\right)}{\sigma^{2}} - b_{1}\exp\left(\frac{-(L_{1}-\alpha)^{2}}{2\sigma^{2}}\right) \\ +\frac{(b_{2}L_{1})(L_{1}-\alpha)\exp\left(\frac{-(L_{1}-\alpha)^{2}}{2\sigma^{2}}\right)}{\sigma^{2}} - \frac{(b_{2}L_{2})(L_{2}-\alpha)\exp\left(\frac{-(L_{2}-\alpha)^{2}}{2\sigma^{2}}\right)}{\sigma^{2}} \\ -b_{2}\exp\left(\frac{-(L_{2}-\alpha)^{2}}{2\sigma^{2}}\right) + b_{2}\exp\left(\frac{-(L_{1}-\alpha)^{2}}{2\sigma^{2}}\right) + \frac{(b_{3}L_{2}+L_{2}(b_{2}-b_{3}))(L_{2}-\alpha)\exp\left(\frac{-(L_{2}-\alpha)^{2}}{2\sigma^{2}}\right)}{\sigma^{2}} \\ +b_{3}\exp\left(\frac{-(L_{2}-\alpha)^{2}}{2\sigma^{2}}\right) = 0 \end{cases}$$
(I.26)

This simplifies to;

$$(b_2 - b_1) \exp\left(-\frac{(L_1 - \alpha)^2}{2\sigma^2}\right) + (b_3 - b_2) \exp\left(-\frac{(L_2 - \alpha)^2}{2\sigma^2}\right) = 0.$$
(I.27)

Note that the second order condition,

$$\frac{1}{\sigma^3} \left[(b_2 - b_1) \left(L_1 - \alpha \right)^2 \exp\left(-\frac{\left(L_1 - \alpha \right)^2}{2\sigma^2} \right) + b_3 \exp\left(\frac{-\left(L_2 - \alpha \right)^2}{2\sigma^2} \right) \right] < 0 \quad (I.28)$$

is satisfied as $b_1 > b_3 > b_2$ by assumption.

Solving equation I.27 for the optimal σ^2 yields;

²³Although it may be argued that the fund manager can manipulate α_i through, for instance, investment in information or education, we wish to focus on the manipulation of risk.

$$\sigma_{opt}^{2}(\alpha) = \frac{L_{2}^{2} - L_{1}^{2} + 2(L_{1} - L_{2})\alpha}{\ln\left(\frac{b_{3} - b_{2}}{b_{1} - b_{2}}\right)}.$$
(I.29)

I.I Appendix I.C: Proofs

Proof of Corollary 1:

Recall we assumed $L_1 < L_2$ and $|L_1| > |L_2|$, so that $(L_2^2 - L_1^2)/2(L_2 - L_1)$ is negative. The proof stems directly from the following partial derivatives;

$$\frac{\partial \sigma_{fundopt}^{2}(\alpha)}{\partial \alpha} = \frac{2\left(L_{1}-L_{2}\right)}{\ln\left(\frac{b_{3}-b_{2}}{b_{1}-b_{2}}\right)},$$
$$\frac{\partial \sigma_{fundopt}^{2}(\alpha)}{\partial L_{1}} = \frac{2L_{1}+2\alpha}{\ln\left(\frac{b_{3}-b_{2}}{b_{1}-b_{2}}\right)},$$
$$\frac{\partial \sigma_{fundopt}^{2}(\alpha)}{\partial L_{2}} = \frac{2L_{2}-2\alpha}{\ln\left(\frac{b_{3}-b_{2}}{b_{1}-b_{2}}\right)},$$
$$\frac{\partial \sigma_{fundopt}^{2}(\alpha)}{\partial b_{1}} = \frac{L_{2}^{2}-L_{1}^{2}+2\left(L_{1}-L_{2}\right)\alpha}{\ln\left(\frac{b_{3}-b_{2}}{b_{1}-b_{2}}\right)^{2}\left(b_{1}-b_{2}\right)},$$
$$\frac{\partial \sigma_{fundopt}^{2}(\alpha)}{\partial b_{3}} = \frac{L_{2}^{2}-L_{1}^{2}+2\left(L_{1}-L_{2}\right)\alpha}{\ln\left(\frac{b_{3}-b_{2}}{b_{1}-b_{2}}\right)^{2}\left(b_{2}-b_{3}\right)},$$

Proof: of Proposition 2:

- 1. Assume $\hat{\alpha}_i \ll 0$ for all *i*. Thus, by Proposition 1 above, $\sigma_{fundopt}^2(\hat{\alpha}_i) < \sigma_{f_{I+1,0}}^2$ for $\sigma_{f_{I+1,0}}^2$ 'near' $\sigma_{fundopt}^2(0)$ for all *i*. It follows that $\frac{\partial c_i(f_{I+1})}{\partial \sigma_{f_{I+1,0}}^2} < 0$. \therefore by setting $\sigma_{f_{I+1,0}}^2 < \sigma_{fundopt}^2(\hat{\alpha}_i)$, the fund family can maximize the cannibalization effect, thereby moving investment funds from underperforming funds to a new fund with higher probability of being an outperformer, relative to the new fund.
- 2. Assume $\widehat{\alpha}_i \gg 0$ for all *i*. Thus, by Proposition 1 above, $\sigma_{fundopt}^2(\widehat{\alpha}_i) > \sigma_{f_{I+1,0}}^2$ for $\sigma_{f_{I+1,0}}^2$ 'near' $\sigma_{fundopt}^2(0)$ for all *i*. It follows that $\frac{\partial c_i(f_{I+1})}{\partial \sigma_{f_{I+1,0}}^2} > 0$. \therefore by setting $\sigma_{f_{I+1,0}}^2 > \sigma_{fundopt}^2(\widehat{\alpha}_i)$, the fund family can minimize the cannibalization effect, thereby keeping investment funds in existing outperforming funds. outperformer.

3. Assume a family is composed of two funds and considers opening a third. Further, assume $\hat{\alpha}_1 \ll 0$ and $\hat{\alpha}_2 \gg 0$.

By Proposition 1 above, $\sigma_{fundopt}^2(\widehat{\alpha}_1) < \sigma_{f_{3,0}}^2$ for $\sigma_{f_{3,0}}^2$ and $\sigma_{fundopt}^2(\widehat{\alpha}_2) > \sigma_{f_{3,0}}^2$ for $\sigma_{f_{3,0}}^2$ 'near' $\sigma_{fundopt}^2(0)$. It follows that $\frac{\partial c_1(f_{I+1})}{\partial \sigma_{f_{3,0}}^2} < 0$. and $\frac{\partial c_2(f_{I+1})}{\partial \sigma_{f_{3,0}}^2} > 0$.

 \therefore setting $\sigma_{f_{3,0}}^2 < \sigma_{fundopt}^2(\widehat{0}_i)$ will result in maximizing the cannibalization effect with respect to fund 1, thereby moving investment funds from an underperforming fund to a new fund with higher probability of being an outperformer, relative to the new fund. outperformer. However, this will also result in cannibalizing the existing outperforming fund 2. Thus, the net cannibalization effect is indeterminate.

Proof of Proposition 3:

Take the simplest example of a family with I = 1 and recall the family's first order condition;

$$\begin{pmatrix} \frac{\partial E_{-1} \left[flow \left(\rho_{f_{I+1}^*} \right) \right]}{\partial \sigma_{f_{I+1}^*}^2} \end{pmatrix} = \\ \delta \frac{\partial c_1(f_{I+1})}{\partial \sigma_{f_{I+1}^*}^2} A_1 \left(\frac{E_{-1} \left[R_{f_{I+1}^*} - R_1 \right]}{C(f_{I+1}) + c_1(f_{I+1})} \right) \\ - \delta \frac{\partial C(f_{I+1})}{\partial \sigma_{f_{I+1}^*}^2} \left(\frac{1 + E_{-1} \left[R_{f_{I+1}^*} \right]}{C(f_{I+1}) + c_1(f_{I+1})} \right).$$

Recall from our fund-level analysis above that $\sigma^2 = \sigma_{fundopt}^2(0)$ solves;

$$\left(\frac{\partial E_{-1}\left[flow\left(0\right)\right]}{\partial\sigma^{2}}\right) = 0,$$

so that

$$\begin{pmatrix} \frac{\partial E_{-1} \left[flow \left(\rho_{f_{I+1}^*} \right) \right]}{\partial \sigma_{f_{I+1}^*}^2} \end{pmatrix} = 0 \Rightarrow \sigma_{f_{I+1}^*}^2 = \sigma_{fundopt}^2 \left(0 \right) + \\ \begin{pmatrix} \frac{\partial E_{-1} \left[flow \left(\rho_{f_{I+1}^*} \right) \right]}{\partial \sigma_{f_{I+1}^*}^2} \end{pmatrix} < 0 \Rightarrow \sigma_{f_{I+1}^*}^2 > \sigma_{fundopt}^2 \left(0 \right) + \\ \end{pmatrix}$$

$$\left(\frac{\partial E_{-1}\left[flow\left(\rho_{f_{I+1}^{*}}\right)\right]}{\partial \sigma_{f_{I+1}^{*}}^{2}}\right) > 0 \Rightarrow \sigma_{f_{I+1}^{*}}^{2} < \sigma_{fundopt}^{2}\left(0\right)$$

Thus, the Proposition results from specifying conditions under which it is possible to sign

$$RHS = \delta \frac{\partial c_1(f_{I+1})}{\partial \sigma_{f_{I+1}^*}^2} A_1 \left(\frac{E_{-1} \left[R_{f_{I+1}^*} - R_1 \right]}{C(f_{I+1}) + c_1(f_{I+1})} \right) - \delta \frac{\partial C(f_{I+1})}{\partial \sigma_{f_{I+1}^*}^2} \left(\frac{1 + E_{-1} \left[R_{f_{I+1}^*} \right]}{C(f_{I+1}) + c_1(f_{I+1})} \right).$$

Specifically;

- 1. Assume $\widehat{\alpha}_1 \ll 0$, which implies $R_{f_{I+1}^*} R_1 > 0$, $\sigma_{fundopt}^2(\widehat{\alpha}_1) < \sigma_{f_{I+1,0}}^2$, $\partial c_1(f_{I+1}) / \partial \sigma_{f_{I+1}^*}^2 > 0$, and $\partial C(f_{I+1}) / \partial \sigma_{f_{I+1}^*}^2 < 0$. It follows that the higher is the sensitivity of cannibalization to $\sigma_{f_{I+1}^*}^2$, the greater is *RHS*.
- 2. Similarly, it follows that the lower is the sensitivity of initial investment flows to $\sigma_{f_{I+1}}^2$, the greater is *RHS*.
- 3. Assume $\widehat{\alpha}_1 \gg 0$, which implies $R_{f_{I+1}^*} R_1 > 0$, $\sigma_{fundopt}^2(\widehat{\alpha}_1) > \sigma_{f_{I+1,0}}^2$, $\partial c_1(f_{I+1}) / \partial \sigma_{f_{I+1}^*}^2 < 0$, and $\partial C(f_{I+1}) / \partial \sigma_{f_{I+1}^*}^2 > 0$. It follows that the higher is the sensitivity of cannibalization to $\sigma_{f_{I+1}^*}^2$, the lower is *RHS*.
- 4. Similarly, it follows that the lower is the sensitivity of initial investment flows to $\sigma_{f_{t+1}}^2$, the lower is *RHS*.

Proof of proposition 4:

Take the simplest example of a family with I = 1, and rewrite equation I.19 from above;

35

and

$$\Delta_{f_2^*} = \delta c_1(f_2^*) A_1 \left(E_{-1} \left[R_{f_2^*} - R_1 \right] \right) + \delta C \left(f_2^* \right) \left(1 + E_{-1} \left[R_{f_2^*} \right] \right) - Costs(f_2^*) .$$

We suggest that $\Delta_{f_2^*}$ is convex with respect to $\widehat{\alpha}_1$ so that $\Delta_{f_2^*} > 0$ (and the family will open f_2^*) either when $\widehat{\alpha}_1$ is high enough or low enough. Rewrite equation I.21 for I = 1;

$$\frac{d\Delta_{f_2^*}}{d\rho_1} = \delta \frac{\partial c_1(f_2^*)}{d\rho_1} A_1 \left(E_{-1} \left[\left(\beta_{f_2^*}' \mathbf{X} - \beta_1' \mathbf{X} \right) + \left(flow \left(\rho_{f_2^*} \right) - flow \left(\rho_1 \right) \right) \right] - \widehat{\alpha}_1 \right) \\
+ \delta c_1 \left(f_2^* \right) A_1 \left(1 + \frac{\partial E_{-1}[flow(\rho_1)]}{d\rho_1} \right) \\
+ \delta \frac{\partial C(f_2^*)}{d\rho_1} \left(1 + E_{-1} \left[\beta_{f_2^*}' \mathbf{X} + flow \left(\rho_{f_2^*} \right) \right] \right).$$
(I.30)

Given our assumptions on the shapes of $c_i()$ and C();

For ρ_1 high, each term in equation I.30 is positive, $\Delta_{f_2^*}$ is clearly increasing, and the likelihood of the family opening a new fund f_2^* is increasing in ρ_1 .

For ρ_1 low, the second and third terms of equation I.30 are nonnegative and increasing in ρ_1 , while the first term is negative and decreasing in ρ_1 . Thus, for ρ_1 sufficiently low the first term will dominate and below this level, the likelihood of the family opening new fund f_2^* is increases as ρ_1 grows worse.

For completeness, we sign the second derivative, $d^2 \Delta_{f_2^*} / (d\rho_1)^2$;

$$\frac{d^{2}\Delta_{f_{2}^{*}}}{(d\rho_{1})^{2}} = \delta \frac{\partial^{2}c_{1}(f_{2}^{*})}{(d\rho_{1})^{2}} A_{1} \left(E_{-1} \left[\beta_{f_{2}^{*}}^{\prime} \mathbf{X} + flow \left(\rho_{f_{2}^{*}} \right) - E_{-1} \left[\rho_{1} + \beta_{1}^{\prime} \mathbf{X} + flow \left(\rho_{1} \right) \right] \right)
+ \delta c_{1} \left(f_{2}^{*} \right) A_{1} \left(\frac{\partial^{2} E_{-1} [flow(\rho_{1})]}{(d\rho_{1})^{2}} \right)
+ \delta \frac{\partial^{2} C(f_{2}^{*})}{(d\rho_{1})^{2}} \left(1 + E_{-1} \left[\beta_{f_{2}^{*}}^{\prime} \mathbf{X} + flow \left(\rho_{f_{2}^{*}} \right) \right] \right).$$
(I.31)

Given

$$\partial^2 c_1 \left(f_2^* \right) / \left(d\rho_1 \right)^2 < 0$$

and

$$\partial^2 C\left(f_2^*\right) / \left(d\rho_1\right)^2 < 0,$$

$$\partial^{2} E_{-1} \left[flow(\rho_{1}) \right] / (d\rho_{1})^{2} < 0$$

then $d^2 \Delta_{f_2^*} / (d\rho_1)^2 < 0$ for $\rho_1 \ll 0$. The first two conditions are met by our assumptions on the shapes of $c_1(f_2^*)$ and $C(f_2^*)$, while the third comes from our fund level results.

Chapter II

Fund Flows, Family Performance, and New Fund Openings: An Empirical Examination

II.A Introduction

This paper empirically examines the relation between new fund openings by a fund family and the historical distribution of relative returns of the families' existing funds, given the expected behavior of investors with respect to the reallocation of investment dollars.

The underlying phenomena motivating our work are the asymmetric response of investors to mutual fund performance and the degree to which a new fund is expected to draw investment dollars from a family's existing funds, which we term 'cannibalization'. There exists a rich empirical literature including Starks (1987), Sirri and Tufano (1998), Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), Nanda, Wang, and Zheng (2004), and Goriaev, Nijman, and Werker (2004), which has concluded that investment flows into a mutual fund subsequent to strong performance relative to a peer group are much stronger than are investment flows out of a relatively poorly performing fund. These papers have generally studied the effects of this convex fund flow-relative performance relation on fund manager behavior.

In Chapter 1 we derived the fund manager's optimal risk taking decision as a function of past fund performance, given an asymmetric relation between fund performance and net investment flows. We leveraged this result to develop a simple theoretical model of the fund family's new fund opening decision, with a number of interesting results stemming primarily from the asymmetric flow-performance relation and a cannibalization function defining the effect on a family's existing funds of the introduction of a new fund(s). The following empirically testable implications arose from these results;

- 1. Asymmetries in the relation between performance and subsequent fund flows.
- 2. A nondecreasing relation between fund performance and subsequent fund risk.
- 3. A family composed largely of underperforming funds will set the risk level of a new fund higher than would a fund manager acting in isolation, and vice versa.
- 4. For a family composed largely of underperforming funds, there is a positive correlation between the risk level of a new fund and the sensitivity of cannibalization to new fund risk, and vice versa.
- 5. For a family composed largely of underperforming funds, there is a positive correlation between the risk level of a new fund and the sensitivity of initial new fund capitalization to new fund risk, and vice versa.
- 6. Both families composed largely of outperforming funds and those composed largely of underperforming funds are more likely to open new funds, relative to families dominated by 'average' performers.

Implications 1, 2, 3, and 6 are fairly straightforward to test empirically, given fund-level data including returns, assets managed, and family membership.

However, empirically testing implications 4 and 5 requires knowledge of investment transfers between funds of the same family, which we lack. Thus, we set out in the following sections to empirically test implications 1, 2, 3, and 6, with particular focus on the relation between family performance new fund openings.

Our paper proceeds as follows. Section II.B reviews the relevant literature and summarizes the results of our prior theoretical work. Section II.C describes the data used in our study and the derivations of variables used in the following empirical work. Section II.D presents our empirical results. Section II.E concludes.

II.B Literature Review

Our paper is directly related to two existing areas of research. The fundlevel analysis of implications 1 and 2 above draw upon a rich literature concerning the relation between fund performance, investment flows, and the behavior of mutual fund managers, while the family-level analysis of implications 5 and 6 contribute to a less developed literature on fund and fund category proliferation.

II.B.1 Models of Fund Opening

While the dramatic growth in both the number of mutual funds available to investors and the level of assets managed by these funds has been well documented, there is a relative dearth of research directly focusing on the fund family as the fund-opening agent.

Several theoretical studies exist which seek to model the proliferation of funds. Notably, Massa (1998) proposes a model from micro-foundations which suggests that fund and category proliferation are a marketing strategy on the part of the fund family, and are driven by investors' limited information and heterogeneity. He concludes that these forces result in sub-optimality, specifically the over-segmentation of the mutual fund industry and the under-provision of funds within each category.

Massa (2003) suggests that funds are differentiated at both the fund level (performance, fees, etc.) and the family level (what he refers to as the 'freeswitching' option, wherein fees for transfers between funds within a family are effectively waived). He develops a framework to explain the segmentation of the mutual fund industry into ever more categories and the proliferation of funds within categories, and empirically tests a number of hypotheses relating fund and category proliferation to investor preferences, family structure, and performance, using monthly and annual data at the fund and fund family level from the CRSP Mutual Fund database.¹ Massa finds that the degree of product differentiation within a category is negatively correlated with returns and positively correlated with turnover within that category. Additionally, he finds that product differentiation is positively related to fund proliferation, measured as either the number of funds offered by a family within a category or as the number of categories in which a family offers funds. His results lend support for the assertion that performance is only one of numerous dimensions across which funds are differentiated by showing that performance is negatively correlated with the degree of product differentiation in these dimensions.

In related empirical work, Khorana and Servaes (1999) model the factors determining mutual fund starts by a fund family, using a dataset pieced together from Lipper, Morningstar, Standard & Poor's and Weisenberger databases including a large subset of the funds deceased at the end of 1992.^{2,3} They estimate clustered logistic regressions on the probability of a family opening a fund in a given category during a given year, and Poisson regressions on the number of funds opened in a given category during the year on a set of fund- and family-level characteristics. Their results suggest that fund openings are positively correlated with category size, capital gains overhang, overall family-level performance, the

 $^{^1 \}rm Specifically,$ Massa includes 1992-2000 data on all US mutual funds except those categorized as Index or Option Income funds.

 $^{^{2}}$ Data covers 1979 through 1992 and includes 366 fund families operating in 13 bond and equity fund categories as defined by Lipper. Of the 13 total categories covered, there are 11 equity categories and 2 bond categories.

³To correct for survivorship bias.

percentage of family assets in category (for bonds funds), 'leader' family behavior, and the scale and scope of a family's portfolio of funds, and negatively correlated with fees and the percentage of family assets in category (for stock funds). Category performance (both aggregate and within-family), fund flows and category returns are not found to have significant explanatory power. The authors conclude that a fund family is more likely to open a new fund in a large fund category within which competing funds have large capital gains overhang, and that new funds are more likely to be opened by families with a large number of low-fee and/or star funds. Notably, they find no evidence that families with poor performers within a category are more likely to open a new fund.

Khorana and Servaes (2006) model the factors influencing the market share of mutual fund families, and explain the evolution of market share during the 1980s and 1990s' explosive growth in assets under management. They use the CRSP database, augmented with data from Morningstar and Lexis-Nexis. The authors perform a collection of clustered OLS regressions using both annualized overall and within-category market share as dependent variables.⁴ They find that market share is positively correlated with performance, innovation, media attention, the number and size of distribution channels, and the breadth and depth of funds offered by the family. They find a negative correlation with expenses and the degree of 'crowdedness' of the given category. The degree of active management (proxied for by turnover), 12b-1 fees, and customer composition (i.e. percentage of 401k assets and high minimum initial investment) are all found to be nonsignificant. It is notable that both past performance and a 'star' fund dummy are found to be positively related to market share.⁵ When the authors perform separate regressions on small and large families⁶, past returns are non-significant in the case of large funds while the 'star' fund dummy is significant and greater in magnitude for large families than for small. Khorana and Servaes conclude that

⁴Market share is defined as the percentage of total net assets managed by the family.

⁵This is endogenous, as high performance relative to a peer group by definition increases assets under management relative to the peer group.

⁶Small and large are defined as managing less or more than \$1 billion 1979 (in 1979 dollars).

high market share is positively related to lower fees, better performance, the degree of product differentiation both within and across categories, and the presence of one of more 'star' funds within a family.

More recently, Zhou and Chiang (2005) study the cross-family acquisition of mutual funds. They document that families acquire funds both to achieve synergies stemming from the cost structure of fund operation and to acquire talent in the form of star funds or reputable managers. While our model specifically addresses the opening of new funds, rather than the acquisition of existing funds, the cause and effect may be the same across the two forms of family growth. Although only tangentially related to our model, Guedj and Papastaikoudi (2004) find that fund families promote funds that are most profitable to the family more than less profitable funds. Evans (2004) finds evidence of the use of incubator funds as a strategy for enhancing the return histories of 'new' funds, an approach which is consistent with maximizing the cannibalization effect we discuss below. These studies provides some support for our approach.

II.B.2 Fund Flows and Fund Performance

The last decade has seen a dramatic rise in the amount of research devoted to studying the relation between the behavior of mutual fund investors and that of mutual fund managers. Numerous studies have focused on the relation between fund flows and past performance, particularly the observed asymmetry in investor response to performance.

Sirri and Tufano (1998) document an asymmetric relation between fund flows and past performance, and find a similar asymmetric response to fees. Chevalier and Ellison (1997) estimate a semi-parametric model of this relation and show that flows respond asymmetrically to past performance, with inflows in response to outperformance greater in magnitude than outflows following poor performance.

More recently, Goriaev, Nijman, and Werker (2004) study the impact of past performance on mutual fund flows, allowing for differences across age and size of funds by utilizing a polynomial lag structure, and allowing for asymmetric effects by modeling on performance quintiles. Using monthly data, they find that performance during the most recent quarter has the least impact on flows, while performance lagged three quarters has the strongest impact. They find support for the convexity of the flow-performance relation.

Lynch and Musto (2003) take as given the asymmetry of the flow - performance relation and seeks to study why it is observed to be convex. They suggest that underperformance results in changes in fund manager and/or strategy, while outperformance results in no change. Thus, they argue, the signal received by investors from an outperforming fund is significantly stronger than that received from a poor performer, and the response is correspondingly asymmetric. However, the authors' model is unable to explain the insensitivity of fund flows to poor performance in cases where there is evidence of a strategy shift but no direct change in manager. This is a particularly relevant case, given empirical evidence suggesting the persistence of poor performance.

A number of papers, including several of the aforementioned, examine the conflict between investors' and fund managers' interests resulting from a convex fund flow-relative performance relation.

An early paper by Starks (1987) introduced agency-theoretic methods to study the relation between the shape of the incentive schedule facing a portfolio manager and the manager's resulting investment decisions. Specifically, she compares a symmetric performance incentive fee schedule and an asymmetric bonus performance incentive fee schedule. Her result suggests that the symmetric schedule strictly dominates the asymmetric schedule in that the former results in the manager taking on the optimal amount of risk while expending a sub-optimal level of resources, relative to the interests of the investor. The asymmetric schedule results in a sub-optimal level of both risk and resource expenditure.

Following Starks (1987), Brown, Harlow, and Starks (1996) study the behavior of the portfolio manager in a tournament framework, wherein the asymmetric incentive is driven by the convex fund flow-relative performance relation. They find that when this is viewed as a multi-period, multi-game tournament, funds which perform poorly during the early period(s) have an incentive to increase the risk of the portfolio in later periods, while high performing funds have an incentive to decrease the riskiness of their portfolio to lock-in gains, and conclude that there is a potential moral hazard inherent in the structure of the mutual fund industry. Chevalier and Ellison (1997) similarly suggest that this relation may result in an incentive for the manager to increase or decrease portfolio risk during the last quarter of the year depending on performance over the first three quarters, a potential conflict between the interest of the manager and the investor.

Later work by Chen and Penacchi (2005) employs this tournament framework to test for the relation between mutual fund performance and risk-taking. They find that it is the volatility of the fund's tracking error that is inversely related to past performance not, as has been suggested, the fund's total return volatility.

Expanding upon the literature citing a convex flow-performance relation Nanda, Wang, and Zheng (2004) model the spillover effects of 'star' and 'dog' funds on investment flows into a fund family, and find a strong positive relation. They suggest that under-performing fund families are likely to embark upon a star-making strategy in an attempt to take advantage of the potential spillover effect.

Berk and Xu (2004) draws upon Berk and Green (2004), which develops a rational model of mutual fund investment in a world where there exist managers with skill to outperform passive benchmarks, with this skill decreasing in assets managed. In their model, assets flow into (out of) outperforming (underperforming) funds to the point where the funds' performance net of expenses matches the benchmark. Berk and Xu (2004) find that the observed persistence in performance of poorly pereforming funds is a result of the asymmetric flow-performance relation, in that funds with shareholders who are insensitive to poor performance will continue to perform poorly, given the breakdown in the mechanism to bring down assets.⁷

Recently, Johnson (2006) uses a unique trade-level dataset from one noload fund family to examine the behavior of fund shareholders. Consistent with an asymmetric low-performance relation, he finds that new and old shareholders respond positively to periods of outperformance, but are unresponsive to periods of underperformance. He suggests that intra-family transfers are motivated by the performance of the destination fund, rather than by the origination fund.

II.C Data

II.C.1 Data Source

We use data from the Center for Research in Security Prices' 'CRSP Survivor Bias Free US Mutual Fund Data Base' (CRSP).⁸ The CRSP database provides monthly fund-level returns, net asset value, total net assets, and distribution data for all open end mutual funds in existence from December 1961 through December 2004 for all investment objectives; equity funds, taxable and municipal bond funds, international funds and money market funds. Annual fund family data is available from 1992 through 2004, and includes management company name, individual manager name, and date manager took over. Mark Carhart, the database for whose dissertation (Carhart 1997) served as the kernel of the CRSP database, noted that the failure of current periodicals to report on, and the typical purging from current databases of, deceased funds results in a sizable sample selection bias. He reports that using only surviving funds to estimate performance of an equalweighted portfolio of mutual funds biases the resulting measure upward by about one percent per year. The CRSP database avoids this bias by including data on all US mutual funds, live or dead. As our intention is to study fund openings, a

⁷Although, over time persistently poor performance may achieve the same effect.

⁸Source: CRSP®, Center for Research in Security Prices. Graduate School of Business, The University of Chicago 2005. Used with permission. All rights reserved. www.crsp.uchicago.edu

natural extension to which is the study of fund closings, this characteristic of the CRSP database is valuable to us.

The nature of our study is such that we require fund family data, so that our database is limited to monthly fund-level data for all US equity funds⁹ from 1992.1 through 2004.12, with the associated family-level data appended. In addition, we limit our sample to those fund families comprised of no fewer than three funds.

Monthly data obtained directly from the CRSP database include fund ICDI number, fund name, raw returns, total net assets, and net asset value. Annual data include fund ICDI number, fund name, fund management company ICDI number, fund management company name, turnover ratio, maximum expense ratio during the year, maximum 12b-1 fee during the year, and maximum front-end load during the year.¹⁰

II.C.2 Derivations

Performance Measures

We are interested in studying the behavior of mutual fund investors in response to fund performance, and assume that investors judge mutual funds based on performance relative to some benchmark. Several candidate benchmarking strategies suggest themselves, including measuring performance in excess of a riskfree rate of return, performance in excess of the market return (or an appropriately chosen proxy), and performance risk-adjusted relative to a set of carefully chosen factors. We suggest that the former approaches are appropriate when the researcher's interest lie in studying a mutual fund's tracking error. For our purposes, we are interested in studying mutual fund manager ability, and so we adopt the latter approach. We estimate the following 4-factor model for each month using a rolling 36-month window;

⁹Specifically, we use funds defined by the Investment Company Data Institute as aggressive growth, growth and income, income, long-term growth, or total return.

¹⁰See CRSP documentation for variable definitions.

$$(r_{i,t} - r_{f,t}) = \alpha_i + \beta_0 \left(r_{m,t} - r_{f,t} \right) + \beta_1 H M L_t + \beta_2 S M B_t + \beta_3 U M D_t + \varepsilon_{i,t}, \quad (\text{II.1})$$

where $r_{i,t}$ is the month t return for the i^{th} fund, $r_{f,t}$ is the month t risk-free return, $r_{m,t}$, HML_t and SMB_t are the Fama-French benchmark factors, and MOM_t is a momentum factor.¹¹

An argument can be made that funds with different stated or inferred strategies should be benchmarked differently, and so in addition to estimating models using both raw and risk-adjusted performance measures, we use these measures net of category averages. Categories are defined as broad agglomerations of the detailed Strategic Insight objective codes included in the CRSP database. These broad categories include Growth, Growth & Income, Bond Income, Sector, International, and Money Market.

Furthermore, we convert both raw returns and 4-factor α measures to normalized ranking for each month in our sample as follows;

$$Rank_{i,t} = 10 * PerformanceRank_{i,t}/N_t,$$
(II.2)

where $PerformanceRank_{i,t}$ is the performance ranking of the i^{th} fund at time tand N_t is the total number of funds in our sample at time t. Thus, $Rank_{i,t}$ is defined on (0,10].¹²

Fund Flow Measures

We are interested in studying the flow of *new* assets into or out of a fund. This is calculated as either the dollar or percentage change in total net assets of the fund during a given period, net of returns, estimated as follows;

¹¹Specifically, $r_{m,t}$ is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks, HML_t (High Minus Low) is the average return on two value portfolios minus the average return on two growth portfolios, SMB_t (Small Minus Big) is the average return on three small portfolios minus the average return on three big portfolios, and UMD_t (Up Minus Down) is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. See Fama and French (1993) and http://mba.tuck.dartmouth.edu/pages/faculty/ken.french for details

¹²Note that we calculate *PerformanceRank* only for raw returns and 4-factor α , not for the net-ofcategory average measures, and that N_t refers to the size of the entire cross-section.

$$NewMoney_{i,t} = TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}$$

and

$$NewMoneyGrowth_{i,t} = NewMoney_{i,t}/TNA_{i,t-1}$$

where $TNA_{i,t}$ is the level of total net assets managed by the i^{th} fund during period t and $r_{i,t}$ is the return to the i^{th} fund over period t.

'Star' and 'Dog' Fund Identification

The ex-post definition of winning and losing mutual funds is somewhat open to interpretation. While Morningstar ranks funds from one to five stars based on three-, five-, and ten-year measures of risk-adjusted performance net of fees. Our approach mirrors the methodology of Nanda, Wang, and Zheng (2004). We define a 'star' fund as one whose trailing 12-month risk-adjusted performance falls in the top 5% of in-sample funds during the given month. Analogously, we define a 'dog' fund as one whose trailing 12-month risk-adjusted performance falls in the bottom 5% of in-sample funds during the given month.¹³

Aggregation to Family Level

In aggregating the data to the fund family level, all non-performancerelated characteristics are treated as either simple or asset-weighted averages across the funds within the family for each time period, with notable exceptions. Familylevel NewMoney is defined as the sum of fund-level NewMoney, while family-level NewMoneyGrowth is defined as the sum of fund-level NewMoney divided by the sum of fund-level total net assets. The derivation of family-level performance measures will be discussed below.

¹³These definitions are equivalent to $Rank_{i,t} \leq 0.05$ and $Rank_{i,t} \geq 0.95$, respectively.

Fund Openings

We choose to examine fund openings on a quarterly basis, and define both a dummy variable, *OpenDummy*, set to one in the event that a family opens a new fund during the given quarter, and a variable containing the count of funds opened by a family during the quarter, *OpenCount*. We define a fund as 'opened' based on the date CRSP reports data first available.¹⁴

Family-Level Performance Measures

We use fund-level returns and associated rankings to calculate a variety of family-level performance measures. To proxy for the distribution of quarterly performance across funds within families, we calculate the asset-weighted mean, standard deviation, skewness, and kurtosis across all funds in family j for each period.¹⁵ We calculate weighted moments using fund-level total net assets as the weighting variable, for each performance measure; raw returns, raw return net of category average, 4-factor α , and 4-factor α net of category average.

In addition to the moment estimates, we calculate the percentage of funds within a family whose returns fall in the bottom 20%, top 20%, or bottom 50% of all in-sample returns during the period, using each of the performance measures.

II.C.3 Overview of the Data

Table II.1 presents summary statistics on quarterly fund-level data taken from the CRSP database, and associated derived variables. Our data includes quarterly observations on all funds from the CRSP database for a total of 584,638 fund-quarters. The average quarterly raw return earned by a fund in our sample was 1.40%, while the average α was -1.87%, and the average annual expense ratio was 1.28%. Assets under management (total net assets) was broadly distributed,

¹⁴Thus, acquisitions of existing funds through e.g. fund family mergers are not treated as new fund openings.

¹⁵Calculating these moments over all funds within each family, over each month in the quarter, ensures that we have a sufficient number of observation even for 'small' families, as opposed to estimating moments separately for each category.

with the average fund managing roughly \$380 million and a number of funds managing tens of billions of dollars. Quarterly fund-level *NewMoneyGrowth* averaged 0.11%, with a cross-sectional standard deviation of 3.56%, consistent with the empirical wisdom that assets flow strongly into a select group of winning funds.

Table II.2 presents summary statistics on quarterly family-level non performance related characteristics resulting from aggregation of the fund-level variables. Though not included in the tables, a breakdown by year shows that the explosion in the number of funds offered over the sample period is reflected in the growth of the average number of funds within a family from 9.1 in 1992 to 32.6 in 2004 and the coincident growth in the number of families from 410 to 553. This suggests that the growth in fund offerings was driven largely by the introduction of new funds by existing families, rather than by growth in the number of fund families. Quarterly family-level *NewMoneyGrowth* averaged 0.10% over the period, while the average level of total net assets managed by a family grew from roughly \$3.2 billion in 1992 to \$13.3 billion in 2004.

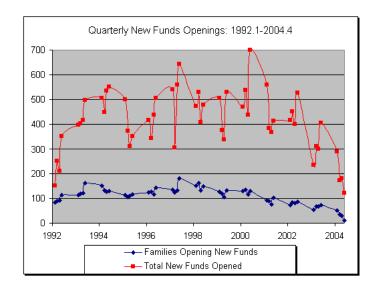


Figure II.1: Quarterly US Equity Fund Openings, 1992-2004

Table II.3 presents summary statistics on equity fund openings across our universe of 26,165 family-quarters for each of the full sample, the set of small families, and the set of large families. The data suggest that new funds are disproportionately opened by large families. Table II.4 presents summary statistics on fund openings from 1992 through 2004, with quarterly openings graphed in Figure II.1. We note that more than half of the fund families in our sample opened at most two funds during the sample period, and that 223 families opened none;

We suspect that a number of our family-level performance measures may be highly cross-correlated. Though omitted to conserve space, we estimate a series of correlation matrices, one for each of the eight categories of performance measures we calculate. We note that there are consistently high correlations between each of the % of Funds Below 20th % ile, % of Funds Above 20th % ile, and % of Funds Below Median variables and the Number of Star Funds and Number of Dog Funds variables, as well as between several of the Mean() variables, and the associated StDev() and Skew() variables. While this is not surprising, it is worth noting and we estimate models using either the % of Funds Below 20th % ile and % of Funds Above 20th %ile or the Number of Star Funds and Number of Dog Funds variables. and estimate models with and without the StDev() and Skew() variables. We similarly estimate correlations between our binomial and count variables describing quarterly fund openings, and each of the non-performance and performance-related variables in out dataset, lagged one quarter. Of the non-performance characteristics, fund openings are most highly correlated with lagged own values and with the number of funds in the family. Among the performance-related characteristics, the strongest correlations are between measures of kurtosis and skewness and the number of star and dog funds in the family.

II.D Empirical Work

II.D.1 Fund Flows and Fund-Level Past Performance

While there exists a rich empirical literature documenting the asymmetric investment flow-relative performance relation, past studies have largely focused on the convexity around zero in this relation. Our theoretical model assumes, in addition to this convexity around 'average' performance, concavity in the relation for some level of underperformance. That is, there exists some level of underperformance below which funds experience strong outflows. Our theoretical work therefore uses a two-kink piecewise linear functional form for this relation, with the left and right slopes assumed positive and greater than the middle slope.

To test for the validity of this relation, we estimate piecewise linear functions of *NewMoneyGrowth* on both lagged raw and net returns and 4-factor α . We estimate models for all pairs of kinks (L, H) such that $L \in [-50, -10]$, $H \in [-5, 40]$. Additionally, using performance rank (scaled from 0 to 100), we estimate models for all pairs of kinks (L, H) such that $L \in [0, 40]$, $H \in [45, 85]$.¹⁶

Specifically, we estimate

$$NewMoneyGrowth_{i,t} = \beta_0 + \beta_1 R_{i,t-1} + \beta_2 (R_{i,t-1}) D_{i,t-1}^L + \beta_3 (R_{i,t-1}) D_{i,t-1}^H + \varepsilon_{i,t},$$
(II.3)

where $D_{i,t-1}^L$ and $D_{i,t-1}^H$ represent dummy variables set to one if the observed excess return is greater that L and H, respectively. Thus, $\beta_{Left} = \beta_1$, $\beta_{Mid} = \beta_1 + \beta_2$, and $\beta_{Right} = \beta_1 + \beta_2 + \beta_3$ report the slopes of the left, middle, and right sections. For each of six performance measures, the squared error-minimizing model is presented in Figure II.2. We note that the reported significance level is that of a test of the null hypothesis that the incremental slope is different from zero.

Judging from the adjusted R^2 value, the models fit the data poorly. There are clearly a number of factors influencing investment flows which we have ignored. However, there are a number of interesting conclusions to be drawn from these results.

The hypothesized concavity at lower returns and convexity at higher returns are represented by $(\beta_{Left} > \beta_{Mid})$ and $(\beta_{Mid} < \beta_{Right})$, respectively. Fur-

¹⁶Using integer increments.

Model	L	Η	β_0	β_{Left}	β_{Mid}	β_{Right}	RMSE	Adj. \mathbb{R}^2
Alpha	-45	48	0.402	0.021 **	-0.010	0.012	0.502	0.012
Net Alpha	-29	50	0.365	0.026 **	-0.005 *	-0.021	0.502	0.004
Rank (Alpha)	29	54	0.527	0.014 *	-0.034	-0.048 **	0.518	0.006
Raw Return	-24	31	4.372	-0.051 **	0.100 **	0.228 **	1.031	0.017
Net Return	-43	27	3.869	0.051 **	-0.228 **	-0.156 **	1.031	0.011
Rank (Return)	7	52	9.210	-0.121 **	1.334 **	1.357 **	1.030	0.032
* indicates significance at the 1% level, $**$ at the 5% level.								

Figure II.2: Root Mean Squared Error-Minimizing Piecewise Linear Flow-Performance Results, 1992-2004

thermore we assumed in chapter 1 that the floe-performance relation is always positive and that while flows are less responsive to moderate underperformance than to outperformance, flows are more responsive to extremely poor performance than to outperformance. These assumptions imply that our prior on the signs and magnitudes of the coefficients can be summarized as $\beta_{Left} > \beta_{Right} > \beta_{Mid} > 0$.

This prior is most closely born out only in the α model, although β_{Right} is non-significant and β_{Mid} is non-significant and negative. However, there is evidence both of concavity at lower returns and convexity at higher returns, with each of $\beta_{Left} > \beta_{Mid}$ and $\beta_{Right} > \beta_{Mid}$ in four of the six models (although not the same four).

In light of out theoretical model, the relative magnitudes of the left and right slopes warrant discussion. Our model in Chapter 1 suggested that, given a piecewise linear fund flow-relative performance relation, the expected-revenuemaximizing fund manager's optimal level of portfolio risk as a function of manager ability (α) is given by

$$\sigma_{opt}^{2}\left(\alpha\right) = \frac{H^{2} - L^{2} + 2\left(L - H\right)\alpha}{\ln\left(\frac{\beta_{Right} - \beta_{Mid}}{\beta_{Left} - \beta_{Mid}}\right)}.$$
(II.4)

It follows that if flows are more responsive to outperformance than to severe underperformance (i.e. $\beta_{Left} > \beta_{Right}$), then optimal risk is increasing in ability, and vice versa. In four of the six models presented, $\beta_{Left} > \beta_{Right}$, however, the omitted variables problem and poor fit of the models presented in Figure II.2 suggests using caution in interpreting the results.

II.D.2 Realized Fund Risk and Fund-Level Past Performance

Our specification for the fund manager's optimal risk level, given by equation II.4 and derived from the fund-level analysis from Chapter 1, suggests several empirical exercises. Notably, we may seek to refine the functional form and parametrization of the flow-performance relation, and attempt to validate the resulting risk-setting rule. We will save the bulk of this effort for future work and present here, as we did above, a brief empirical analysis of this relation. We calculate the compounded net-of-category-average raw return and 4-factor α over the trailing 4 quarters for each fund-quarter in our sample, and place the resulting observations into performance bins each of width 1%. For each bin we calculate the average observed standard deviation of raw and 4-factor α for the following quarter. Figures II.3 and II.4 present plots of average standard deviation on lagged performance bins using returns net of category averages and 4-factor α net of category averages, respectively.

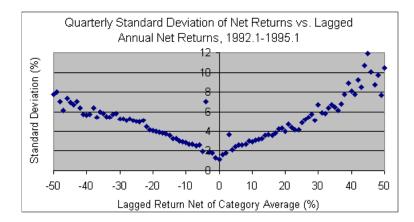


Figure II.3: Risk as a Function of Lagged Performance: Trailing 4-Quarter Net Returns, 1992-2004

These results do not appear to be consistent with equation II.4, which predicts that the fund manager's optimal risk is an increasing linear function of

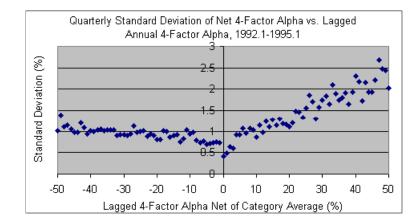


Figure II.4: Risk as a Function of Lagged Performance: Trailing 4-Quarter Net 4-Factor α , 1992-2004

past α . However, the 'V' shape evident in both the raw return and α cases may reflect persistence in portfolio risk through time. It is the asymmetry of the 'V', most noticeable in Figure II.4, which lends support to our hypothesis that winning fund manager's take on more risk than do underperformers.

II.D.3 Performance and Risk Level of New Versus Old Funds

To examine the performance and risk level of new versus old funds, we calculate cross-sectional averages for the quarterly average and standard deviation of raw returns net of category averages for each quarter in our sample, separately for new funds and old funds. We define new funds as those in their first year of existence, and old funds as those having been in existence at least two years. Figure II.5 presents the difference in mean performance between new and old funds for each year, while Figure II.6 presents the ratio of new fund standard deviation of performance to that of old funds. Figures II.5 and II.6 suggest that returns are not systematically different between new funds and old funds. However, new funds seem, ex post, to have borne more idiosyncratic risk during the early and late parts of the sample period (1992-93 and 2003-04), but less risk during the middle of the period (1994-2002). We hypothesize that this may have been driven in part by the types of new funds introduced during the relevant periods. These results suggest

that deeper study is warranted.

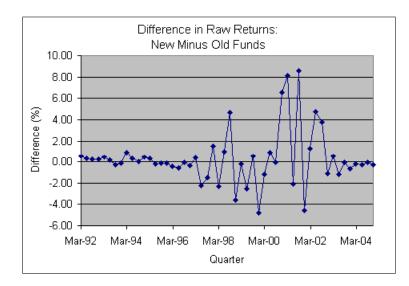


Figure II.5: Average Performance: New Minus Old Funds, 1992-1998

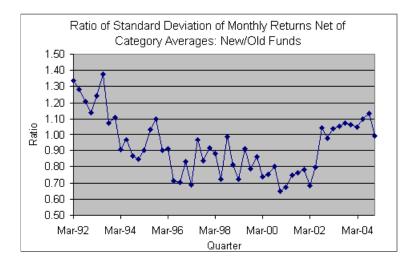


Figure II.6: Risk: Ratio of New to Old Funds, 1992-1998

II.D.4 Fund Openings and Family-Level Past Performance

Our primary empirical effort is focused on using the data described in Section II.C to model the factors influencing the opening of a new fund by a fund family, with particular emphasis on variables describing the distribution of returns across funds within the family. In this section, we test the proposition that families with a high number of underperforming funds have an incentive to open a new fund, leveraging the hypothesized cannibalization effect of a new fund on existing funds, in an attempt to manage a 'star' fund and reap the rewards stemming from investors' asymmetric response to fund performance.

Our theoretical model ignores the role played by non-performance related fund and family characteristics in both families' fund opening and investors' fund selection decisions, as we are mainly interested in modeling performance effects holding other fund and family characteristics constant. To correct for such affects in our empirical work, we include non-performance related characteristics in the models presented below. Specifically, we model the event of a fund family opening a new fund in a given quarter as a function of lagged family characteristics and variables describing the cross-sectional distribution of performance across funds within the family. We estimate similar models of the count of funds opened during a given quarter.

Econometric Issues

There are a number of econometric issues to be addressed before we present and discuss our results. These include the temporal aggregation of the data, the particular choice of event and count models, the specification of functional forms to address the cross sectional and time series characteristics of our data, and interpretation of the regression output.

Temporal Aggregation

We use as dependent variables binomial and count variables for the opening of a new fund and the number of new funds opened by a family during each quarter of our sample period. We suggest that historical performance and lagged family and fund characteristics may help explain fund openings. While the mutual fund industry typically presents one-, three-, and five-year returns as performance measures, the study of fund openings precludes this approach, and we use as predictors lagged quarterly data. We include year dummies to accommodate time effects.

Panel Data Issues

Our dataset is composed of time series observations on a large number of mutual fund families. Intuitively, we expect there to be a substantial familyspecific component to the fund opening decision, and so we treat each family as a panel. There are three basic approaches to dealing with differences across panels in binomial and count models; the fixed-effects model which takes panel-specific effects to be parametric shifts of the regression function, the random effects model which assumes panel-specific effects are randomly distributed across panels, and the population averaged model. We rule out the population averaged model, as the results of such models are interpreted as differences across average members of groups with different regressor values, while the results from fixed effects and random effects models are interpreted as the expected change for an individual given a change in the regressor. With respect to performance measures, we are interested in the latter interpretation.

For several baseline models, we perform Hausman tests for fixed effects versus random effects. In all cases, the null hypothesis of uncorf between the random effects and the regressors is rejected at better than the 1% level. We therefore estimate fixed effects models.

Modeling Approach: Fund Openings

We assume that the observed binomial variable $OpenDummy_{jt}$ is representative of some unobserved latent variable y_{jt}^* where

$$y_{jt}^* = \mathbf{x}_{jt}'\beta + \epsilon_{jt},$$

and that $OpenDummy_{jt} = 1$ if $y_{jt}^* > 0$ and 0 otherwise. The appropriate approach to modeling this problem is to estimate the binomial regression model of choice, depending on the modeler's beliefs about the distribution of the error term. The logistic model, given by

$$P(\mathbf{Y}_{jt} = 1 | \mathbf{x}_{jt}) = \frac{\exp(\mathbf{x}'_{jt}\beta^{LOGIT})}{1 + \exp(\mathbf{x}'_{jt}\beta^{LOGIT})}$$

where \mathbf{Y}_{jt} represents an observed outcome and \mathbf{x}_{jt} represents a vector of covariates, is a plausible choice for our data.¹⁷ The simplest approach to accommodating fixed-effects in such a model is to include a set of panel-specific dummy variables. However, estimation issues arise quickly as the number of panels grows large relative to the number of time periods per panel, as is the case in our sample. Similarly, the nonlinearity of the model prohibits the standard fixed-effects approach of dealing with this so-called 'incidental parameters' problem, the taking of differences or de-meaning of the data.

Chamberlain (1980) suggests a conditional maximum likelihood approach to this problem, where the set of observations for each panel are considered as a group, and the resulting likelihood function is conditional upon the sum of observations for each panel. The resulting conditional fixed effects logit can be represented as

$$\Pr\left(\mathbf{Y}_{jt} = 1 | \sum_{t=1}^{T_j} y_{jt}\right) = \left(\frac{\exp\left(\sum_{t=1}^{T_j} y_{jt} \mathbf{x}'_{jt} \beta^{LOGIT}\right)}{\sum_{\mathbf{d}_j \in S_j} \left(\sum_{t=1}^{T_j} d_{jt} \mathbf{x}'_{jt} \beta^{LOGIT}\right)}\right),$$

where y_{jt} equals one in the event a fund is opened by the j^{th} family during period t, \mathbf{x}_{jt} is our vector of independent variables, and \mathbf{d}_j is a possible set of outcomes over time 1 to T for the j^{th} family, the space of which is defined as S_j . It is worth noting that under this approach, panels with no variation in outcome across the sample fall out of the likelihood function, and so provide no explanatory power.

Specifically, we use conditional maximum likelihood to estimate a conditional logit regression with both family and time effects;

¹⁷While there are other candidate binomial models, most notably the probit, in practice it is difficult to justify one choice over another.

$$OpenDummy_{jt} = \alpha_j + \delta_y + \mathbf{x}'_{jt}\beta^{LOGIT} + \epsilon_{jt}, \qquad (II.5)$$

where $OpenDummy_{jt}$ is a binomial fund opening variable set to 1 if a family opened a fund during time t, \mathbf{x}_{jt-1} is a vector of explanatory variables consisting of both the performance measures defined above and a set of non-performance-related family characteristics, α_j accommodates family effects, and δ_y accommodates year effects. Since we have only thirteen years in our sample, we use a set of dummy variables to allow year effects. By comparison, Khorana & Servaes (1999) estimate logistic regressions of fund openings with year effects only.

Modeling Approach: Count of Fund Openings

A number of econometric issues arise in the estimation of count data models. The nature of our data as representative of an ordered, discrete process suggests using a simple Poisson model. However, the Poisson model assumes the data is equidispersed.¹⁸ This is unlikely to be the case in our data, as the unconditional variance is much greater than the unconditional mean in our sample (the ratio being roughly 6.2), and it is unlikely that our model could explain sufficient variation to induce equidispersion. We therefore perform a series of likelihood ratio tests per Cameron and Trivedi (1997), on a number of baseline models.¹⁹ In all cases the null hypothesis of equidispersion is overwhelmingly rejected, in support of the negative binomial.

As there are many family-quarters in our dataset during which there were no funds opened (more than half), we perform Vuong (1989) tests of zero-inflated negative binomial versus negative binomial on a number of baseline models. Large negative values (≤ 2) of the Vuong statistic favor the negative binomial while large positive values (> 2) favor the zero-inflated model. In each test we perform, the resulting test statistic lies well within (-2,2), and the test is inconclusive. We

¹⁸That is, the conditional mean and variance are equal

¹⁹Specifically, the Negative Binomial model permits overdispersion by allowing the specifying the variance as a function of the mean: $\varpi_i = \mu_i + k\mu_i$ or $\varpi_i = \mu_i + k\mu_i^2$. As the Poisson is therefore nested in the Negative Binomial, a LR test with $H_o: k = 0$ is appropriate.

therefore default to the simplest approach allowing for overdispersion, and estimate a series of fixed effects negative binomial models.

The estimation problems resulting from the number of panels in our data relative to the number of time periods reappear in the negative binomial. A conditional fixed effects negative binomial model, analogous to the conditional logit and using conditional maximum likelihood, was proposed by Hausman, Hall, and Griliches (1984), which can be stated as

$$\Pr(Y_{jt} = y_{jt}|\delta_i) = \frac{\Gamma(\lambda_{jt} + y_{jt})}{\Gamma(\lambda_{jt})\Gamma(y_{jt} + 1)} \left(\frac{1}{1 + \delta_i}\right)^{\lambda_{jt}} \left(\frac{\delta_i}{1 + \delta_i}\right)^{y_{jt}}$$

where y_{jt} is the number of fund openings by the j^{th} fund family during period t and

$$\lambda_{jt} = \exp(\mathbf{x}'_{jt}\beta^{NBREG} + c),$$

where y_{jt} is conditionally Poisson, dispersion is equal to $1 + \delta_i$, and \mathbf{x}_{jt} is a vector of covariates.

Specifically, we use the method outlined above to estimate conditional negative binomial regressions with both family and time effects;

$$OpenCount_{jt} = \alpha_j + \delta_y + \mathbf{x}'_{jt}\beta^{NBREG} + \epsilon_{jt}, \qquad (II.6)$$

where $OpenCount_{jt}$ is a count of the number of funds opened during period t, \mathbf{x}_{jt} is a vector of explanatory variables consisting of both the performance measures defined in Section II.C.2 above and a set of non-performance-related family characteristics, α_j accommodates family effects, and δ_y accommodates year effects. Since we have only thirteen years in our sample, we use a set of dummy variables to allow year effects. By comparison, Khorana and Servaes (1999) estimate Poisson regressions with year effects only.

Interpretation of the Results

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It is important to note that interpretation of the coefficients from logit and negative binomial models differs from the standard linear model. We choose to report exponentiated coefficients, which are interpreted as either an odds ratio (in the logit case) or as an incidence rate ratio (in the negative binomial case). The odds ratio reports the multiplicative change in $P(Y_{jt} = 1) / P(Y_{jt} = 0)$ for a one unit change in the regressor, while the incidence rate ratio reports the multiplicative change in the incidence rate, or predicted count, for a one unit change in the regressor. Accordingly, a coefficient less than one indicates a negative relation, while a coefficient greater than one indicates a positive relation.

Results

Univariate Panel Models

Tables II.5 and II.6 present results from a series of univariate conditional fixed effects logit and conditional fixed effects negative binomial models, respectively. While we estimate both one-way fixed effects models (family effects only) and two-way fixed effects models (both family and year effects), only two-way models are presented.

Among the non-performance characteristics, we find that fund openings are positively correlated with lagged openings, logs of the number of funds in family and total assets managed by the family, and *NewMoneyGrowth* (in the count models). Consistent with the results in Khorana and Servaes (1999) and Khorana and Servaes (2006), families with higher average expense ratios open fewer funds less often. However, families with higher average maximum load fees appear to open fewer new funds more often.

Among the performance-related characteristics, we find that fund openings are positively related to variables which capture the existence of extreme outperformers and underperformers within a family, both in the binomial and count models. These include the number of 'star' and 'dog' funds and percentage of funds in top and bottom quintiles (using both returns and α), and all kurtosis measures. There is also some evidence that openings are positively correlated with measures of variance and skewness of performance across existing funds.

However, the coefficient on mean raw returns across a family's funds is statistically significant and less than 1 in both the binomial and count models. This runs counter our prior that there exists a reputation effect, although these univariate models should be interpreted with caution as there is clearly substantial omitted variable bias.

Multivariate Panel Models

Drawing on the results discussed above, we estimate a series of multivariate conditional fixed effects logit and conditional fixed effects negative binomial models, for each of four specifications.

In each model we include lagged fund openings (Fund Opening Dummy or Count of Fund Openings), the log of the number of funds in the family (Log # Funds), the log of average total net assets across funds managed by the family (Log Avg. Total Net Assets), net new investment flows (NewMoneyGrowth), average expense ratio (Expenses), average maximum load (Maximum Load), average turnover ratio (Turnover), and a subset of our family-level performance measures.

For each model, we include mean and kurtosis measures as well as either 'star' and 'dog' counts (models i and iii in each panel) or the percentage of funds in the top and bottom performance quintiles (models ii and iv). We estimate models both with and without standard deviation and skewness measures.

We estimate each set of four models both with year effects (two-way models) and without (one-way models), separately using performance measures based on raw returns, returns net of category averages, 4-factor α , and 4-factor α net of category averages. We do not report results from models using the ranking-based measures from equation II.2, as these measures displayed inferior predictive ability. Furthermore, we include the square of lagged openings in each of the count models. Full sample results from the logit models are presented in Tables II.7 through II.10, with results from the negative binomial models in Tables II.11 through II.14. In both cases, the results are for the most part qualitatively consistent across specifications.

Tables II.7 and II.8 present results from conditional logit regressions using raw returns and net returns, respectively. Among the non-performance characteristics, the results indicate that fund openings are positively related to lagged openings, the log of the number of funds within family, and weighted average load fees. Fund openings are negatively related to the log of average fund size and weighted average expense ratios. Neither NewMoneyGrowth nor Turnover enter the models with significance. Notably, coefficients on Log Avg. Total Net Assets, *Expenses*, and *Maximum Load*, while statistically significant in the 1-way models, are non-significant once year effects are included. Among the performance measures, mean returns are negatively related to fund openings in both the raw and net return models, while kurtosis measures are positively related. The mean return results are counterintuitive, as we expect a positive relation, even conditional on star and dog fund measures. However, this result is somewhat contradicted by the α results discussed below. Also inconsistent with our hypotheses are the few statistically significant negative coefficients on Number of Star Funds and % Funds in Top Fifth.

Results from the corresponding α models presented in Tables II.9 and II.10 differ from the returns-based models in significant ways. Average fund size (negatively related in the return models) is positively related to fund openings in the α models, while the coefficients on *Turnover* are greater than 1 and statistically significant, suggesting that growth in funds conditional on α is correlated with the degree of active management for which *Turnover* is considered to be a proxy. Mean performance measures are positively related and statistically significant in several of the α models, while they were negatively related in the return models. Similarly, kurtosis measures (positively related in the return models) are negatively related in the α models (although statistically significant in only 2 of 16 specifications). Most strikingly, our measures of the presence of extreme underand outperforming funds are statistically significant in all of the α specifications. Results from the star/dog fund specifications appear to contradict those from the top/bottom quintile specifications. Consistent with past studies which find a positive relation between performance and new fund openings, coefficients on % Funds in Bottom Fifth are all statistically significant and substantially less than 1 in the α models (ranging from 0.32 to 0.49, suggesting that a family with all of its funds in the bottom performance quintile will open one third to one half as many new funds as a similar family with no funds in the bottom performance quintile), while the coefficients on % Funds in Top Fifth ranged from 4.9 to 11.3. However, coefficients on Number of Star Funds are all statistically significant and positive.²⁰ These results lend some support for our hypothesis that a family of underperforming funds has a stronger incentive to open new funds than an 'average' family, and suggests that there are differences in the sensitivity of the reputation and cannibalization effects to performance.

The results from the conditional negative binomial models presented in Tables II.11 through II.14 differ substantively from conditional logit results only in several points. Notably, *Maximum Load* is negatively related to fund openings in the count models (whereas the relation was positive in the binomial models). This is consistent with a pattern of growth in the industry wherein families offering load funds open fewer funds more often, relative to no-load families. This is sensible since our analysis treats the introduction of a new share class as a new fund.

Similar to the logit results, the negative binomial results using returns and net returns are fairly weak with respect to our measures of extreme underperformers and outperformers, while the α models are substantially stronger. Analogous to the logit case, the coefficients on % Funds in Top Fifth are all statistically significant and range from 0.47 to 0.51, while the coefficients on % Funds in Top Fifth ranged from 4.1 to 6.2. Similarly, coefficients on Number of Star Funds are

²⁰Note that the difference in units of measurement for the Star/Dog variables and the performance quintile variable makes direct comparison of the economic magnitude of these results difficult.

all statistically significant and less than one, while those on *Number of Dog Funds* are significant and positive.

We note that there is evidence of a positive and significant relation between current fund openings and lagged count of fund openings, and a negative relation with squared fund openings (although at 0.999, the coefficients are perhaps not economically significant).

Discussion

The most economically significant of our results suggest that new fund openings are best explained by variations in the following:

- Number of existing funds, with families managing more funds opening more new funds more often.
- 2. Average assets managed by existing funds, with families managing on average larger funds opening more new funds more often.
- 3. Costs, with low expense families opening more new funds more often and load families opening fewer new funds more often. The latter result is likely driven by the multi-class structure of load funds and may suggest that new share classes of the same portfolio are rolled out over different quarters as demand builds.²¹
- 4. Percentage of a family's funds in the top and bottom contemporaneous α quintiles, with families whose funds are concentrated in the bottom quintile opening far fewer funds less often and families whose funds are concentrated in the top quintile opening many more funds more often.
- 5. The number of star and dog funds managed by a family, with families managing more star funds opening fewer new funds less often and families managing more funds opening more new funds more often.

²¹This may be driven by the growth in types of share classes offered through the sample period, rather than by strategic decisions on the part of load families.

While the last two points appear contradictory, we suggest that this is indicative of an asymmetry in the relationship between the performance of existing funds and new fund openings, with the cannibalization effect stronger for families with extremely poor performing funds (i.e. dogs) and the reputation effect stronger for families with more moderately outperforming performing funds (i.e. those in the top 20%).

In fact, these results are consistent with the parametrization of the flow-performance relation described in chapter 1 and represented in equation II.3. Recall we assumed, consistent with existing empirical evidence, that net new flows are convex around average performance, with strong inflows in response to outperformance and relatively weak outflows in response to underperformance. In addition, we assumed that there exists some level of underperformance below which outflows will respond strongly. Since the cannibalization effect is dependent on investors fleeing an underperforming fund, we see this effect only in families where the level of underperformance is sufficient to spur such behavior.

These results lend support for our hypothesis that, in addition to the reputation (or spillover) effect identified by Nanda, Wang, and Zheng (2004) and others, there exists a cannibalization effect which families composed largely of underperforming funds may attempt to capitalize on by opening new funds.

The results suggest that while new fund openings may be positively related to both measures of extreme outperformance and underperformance of a family's existing funds, (using α measures, in particular) the relation is certainly asymmetric, with the reputation effect appearing to be substantially stronger than the cannibalization effect.

II.E Conclusions and Extension

Chapter 1 proposed a theoretical framework for modeling fund openings which yielded the following implications:

- 1. Families composed largely of underperforming funds will set the initial risk level of a new fund higher than that set by a fund manager with unknown 'ability' acting in isolation. This will result in maximizing the cannibalization effect of the new fund on the set of existing funds, thereby moving investment within the family toward a fund with a higher ex ante probability of being a 'star'. The opposite is true for a family of outperforming funds.
- 2. For fund families with a large number of underperforming funds, the higher is the sensitivity of cannibalization and the lower is the sensitivity of external investment flows to changes in new fund initial risk level, the higher is the likelihood that the optimal level of risk of the new fund is greater than that which would be set by a manager acting in isolation. The opposite is true for a family composed largely of outperforming funds.
- 3. There exists a level of underperformance on the part of existing funds, ρ' , above which relative performance and fund openings are positively correlated and below which relative performance and fund openings are negatively correlated. Furthermore, the family will set the initial risk level of the new fund higher than would the associated fund manager acting in isolation.

While we have not yet developed a framework to empirically test all of these implications, the results of our empirical analysis thus far are consistent with the predictions made by our theoretical model. While we observe a positive relation between fund openings and strong family performance (measured using 4-factor α) across funds within a family, fund openings appear also to be positively correlated with both measures of extreme underperformance and extreme outperformance, albeit asymmetrically. Both of these results are consistent with the implications of our theoretical model.

Our results are largely consistent with those of previous studies. Direct comparison of our empirical results with those of Massa (1998) and Massa (2003) is made difficult by differences in approach, since Massa models the growth of aggregate fund offerings while we model the underlying fund family decision driving that growth. Khorana and Servaes (1999) and Khorana and Servaes (2006) are closer in approach to our paper. Khorana and Servaes (1999) is the most similar to our own, estimating logistic and Poisson models on annual data from 1979 to 1992 by fund category. Our results support their findings that fund openings are positively related to family performance (measured using α and 'scale and scope' of family offerings, and negatively related to fee levels.

Our paper improves upon prior studies in more thoroughly modeling the effect of the distribution of performance across funds within a family on the family's fund opening decision. We have hypothesized that, in addition to the positive effect of strong average family performance on the likelihood of opening a new fund, other characteristics of family level performance create similar incentives. We suggest that asymmetries in investor response to fund performance may create a winwin situation for fund families considering the opening of a new fund or funds, conditional on the distribution of returns of existing funds. Specifically, a family with extremely poorly performing funds expects a new fund to cannibalize existing funds. Assuming that expected excess returns to a new fund are zero, while the expected excess return to an existing 'dog' funds is expected to be negative, we view the opening of a new fund as similar to the purchase of a call option by the family-if the new fund should outperform, the family will see strong inflows and increased fee income, whereas if the new fund underperforms the family has lost little since the cannibalized funds are expected to underperform and outflows are expected to be unresponsive to poor performance in either case.

Our results offer some support for this theory. Although our estimates of the first four moments of the distribution of performance across families' existing funds have little predictive strength, the statistically significant results on our α -based measures of extreme underperformance and outperformance (% funds in top/bottom performance quintile and counts of star/dog funds) suggest that families with a high fraction of funds on the extreme ends of the relative performance spectrum are more likely to open new funds. These results lend support for the reputation and cannibalization effect, and suggest that these effects are asymmetric with respect to α .

A number of potential improvements and extensions to the current paper present themselves. These include modeling fund openings and closings jointly, accounting for the effects of incubator funds on reported fund openings, and designing a more econometrically sophisticated test for the existence and extent of the cannibalization effect.

II.F Appendix II.A: Tables

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Data include 603,247 class-quarter observations from 1992.1 through 2004.4. Star Flag and Dog Flag are defined as 1 if the fund is in the top or bottom 5% of contemporaneous returns (or α), respectively, otherwise 0. Return Rank and Alpha This table presents summary statistics on quarterly class-level performance variables derived from the monthly CRSP data. Rank are normalized contemporaneous ranking variables scaled to range on (0,10].

Variable	Raw Return (%)	Net Return (%)	Return Rank	Dog Flag (Return)	Star Flag (Return)
Z	584,638	584,638	584,638	584,638	584,638
Mean	1.40	-0.07	5.00	0.05	0.05
Std Dev	8.10	4.47	2.88	0.21	0.22
$\operatorname{Skewness}$	-0.67	-0.32	0.00	4.21	4.16
Kurtosis	5.26	12.82	-1.20	15.76	15.31
	4-Factor Alpha (%)	Net Alpha (%)	Alpha Rank	Dog Flag (Alpha)	Star Flag (Alpha)
Z	393,089	393,089	393,089	393,089	393,089
Mean	-1.87	0.09	5.01	0.05	0.05
Std Dev	7.52	6.17	2.87	0.21	0.22
Skewness	-0.23	-0.03	0.00	4.29	4.15
Kurtosis	6.53	12.32	-1.20	16.43	15.25
	Expense Ratio (%)	Max. Load (%)	Total Net Assets (\$mil)	Turnover Ratio	New Money Growth (%)
Z	574,465	584,620	576,964	511,678	562,904
Mean	1.28	1.13	381.50	0.98	0.11
Std Dev	0.76	2.04	1892.01	3.25	3.56
$\mathbf{Skewness}$	7.42	1.40	19.04	170.65	78.05
Kurtosis	283.30	0.21	565.28	44935.25	7592.56

Univariate Statistics Across Equity Funds: 1992-2004 Quarterly Data

Table II.2: Summary Statistics: Quarterly Family Data, 1992-2004

This table presents summary statistics on quarterly family-level variables used in our analysis. Statistics are presented both for the cross-section of 553 families in our sample as of the end of 2004, as well as for the universe of 26,165 family-quarters from 1992.1 through 2004.4 for all US fund families composed of a minimum of three funds. *Star Flag* and *Dog Flag* are defined as 1 if the fund is in the top or bottom 5% of contemporaneous returns (or α), respectively, otherwise 0. *New Money Growth, Max. Load, Expenses*, and *Turnover* are defined as asset-weighted averages of class-level values.

	20	004.4	1992.1	- 2004.4
Variable	Mean	Std Dev	Mean	Std Dev
# Stars (Return)	1.34	3.92	0.81	2.40
# Dogs (Return)	1.34	4.55	0.81	2.36
# Stars (Alpha)	1.64	4.64	1.09	3.08
# Dogs (Alpha)	1.64	4.92	1.08	3.03
# Funds	32.63	74.44	21.71	49.76
Total Net Assets (Sum)	$13,\!345$	62,332	8,214	39,095
Total Net Assets (Avg)	397	1,644	249	865
New Money Growth	-0.04	0.26	0.10	6.36
Max. Load (%)	0.73	1.45	0.96	1.70
Expenses (%)	1.35	1.14	1.32	1.17
Turnover Ratio	0.84	1.21	0.92	3.82
# Observations		553	26	5,165

Table 2A: Univariate Family-Level Statistics, Quarterly Data

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This table presents summary statistics on quarterly fund openings from 1992.1 through 2004.4. OpenDummy is defined as 1 if a family opened a new fund during the quarter. OpenCount is defined as the number of new funds opened by a family large families. Small families are defined as those offering fewer than 7 funds in a given quarter, while large families are during the quarter. The data include 26,165 family-quarters covering 749 unique families over the sample period, with 553 families in existence as of the fourth quarter 2004. Statistics are presented separately for the full sample, small families and those offering 7 or more.

		All Families		Small	Small Families (NumFunds<7)	unds < 7	Large]	Large Families (NumFunds>6)	unds>6
Variable	# Classes	OpenDummy	OpenCount	# Classes	Classes OpenDummy	OpenCount	# Classes	OpenDummy OpenCount	OpenCount
Count		26,071	26,071		15,136	15,136		10,935	10,935
Sum		4,242	21,369		744	1,392		3,498	19,977
Minimum	1	0	0	1	0	0	2	0	0
Maximum	738	1	142	9	1	40	738	1	142
Mean	22.21	0.16	0.82	2.44	0.05	0.09	49.73	0.32	1.83
Std Dev	50.48	0.37	3.80	1.61	0.22	0.66	69.20	0.47	5.67
$\mathbf{Skewness}$	4.51	1.83	13.12	0.84	4.17	24.13	2.96	0.77	8.86
Kurtosis	26.76	1.34	302.92	-0.55	15.40	1075.82	11.45	-1.40	138.08

Univariate Statistics Across Quarterly Fund Openings, 1992-2004

Table II.4: Summary Statistics: Fund Openings by Quarter, 1992-2004 This table presents summary statistics across quarters on fund openings from 1992.1 through 2004.4. The data include 26,165 family-quarters covering 749 unique families over the sample period, with 553 families in existence as of the fourth quarter 2004. # Families Opening New Funds is defined as the sum of OpenDummy across all families for each quarter, while # Funds Opened is defined as the sum of OpenCount across all families for each quarter, with OpenDummy defined as 1 if a family opened a new fund during the quarter and OpenCount defined as the number of new funds opened by a family during the quarter.

	# Families Opening New Funds $ $	# Funds Opened
Count	52	52
Sum	4,242	21,369
Minimum	10	121
Maximum	130	700
Mean	81.58	410.94
Std Dev	24.26	124.51
Skewness	-0.71	-0.32
Kurtosis	0.69	0.004

Univariate Statistics on Fund Openings by Quarter, 1992-2004

Table II.5:Univariate Conditional Logit Models of Quarterly FundOpenings, 1992-2004

This table presents results of univariate conditional logit models from quarterly fund openings on family-level performance- and non-performance-related characteristics, lagged one quarter. The dependent variable is *OpenDummy*, defined as 1 if a family opened a new fund during the quarter. Predictor variables are defined as asset-weighted averages of class-level values where appropriate. Both family and time effects are included, and performance measures using returns and 4-factor α , both raw and net of category averages, are included. Families with fewer than 3 funds were excluded from the analysis, leaving 13,403 observations on families with variation in *OpenDummy*. Exponentiated coefficients are presented, which in the logit model are interpreted as odds ratios (P(y=1)/P(y=0)). That is, the reported coefficient indicates the expected change in the probability of a fund opening for a one unit change in the regressor.

2-Way Logit Regressions with Family and Year Fixed Effects

Non-Performance Characteristics	Odds Ratio	P>z	Pseudo-R2
Fund Opening Dummy (t-1)	1.367	0.00	0.04
Count of Fund Opening (t-1)	1.022	0.00	0.03
Log # Funds (t-1)	2.281	0.00	0.07
New Money Growth (%) (t-1)	1.003	0.23	0.04
Log Avg. Total net Assets (t-1)	0.960	0.11	0.03
Log Sum Total net Assets (t-1)	1.276	0.00	0.04
Expenses $(\%)$ (t-1)	0.794	0.00	0.04
Maximum Load (%) (t-1)	1.015	0.60	0.03
Turnover (%) (t-1)	0.993	0.76	0.07
Performance Characteristics	Odds Ratio	P>z	Pseudo-R2
Number of Star Funds (Ret) (t-1)	1.010	0.00	0.05
Number of Dog Funds (Ret) (t-1)	1.078	0.00	0.03
Number of Star Funds (Alpha) (t-1)	1.010	0.00	0.05
Number of Dog Funds (Alpha) (t-1)	1.024	0.00	0.06
Mean(Raw Returns) (t-1)	0.991	0.00	0.03
Var(Raw Returns) (t-1)	1.000	0.08	0.11
Skew(Raw Returns) (t-1)	1.012	0.36	0.17
Kurt(Raw Returns) (t-1)	1.033	0.00	0.21
Mean(Returns Net of Cat. Avg.) (t-1)	0.994	0.17	0.03
Var(Returns Net of Cat. Avg.) (t-1)	1.000	0.17	0.11
Skew(Returns Net of Cat. Avg.) (t-1)	1.002	0.89	0.17
Kurt(Returns Net of Cat. Avg.) (t-1)	1.030	0.00	0.21
% Funds in Bottom Fifth (Ret) (t-1)	0.955	0.75	0.03
% Funds in Top Fifth (Ret) (t-1)	0.957	0.76	0.03
% Funds in Top Half (Ret) (t-1)	1.089	0.31	0.03
Mean(Alpha) (t-1)	0.995	0.22	0.17
Var(Alpha) (t-1)	1.000	0.15	0.25
Skew(Alpha) (t-1)	1.034	0.05	0.30
Kurt(Alpha) (t-1)	1.009	0.08	0.35
Mean(Alpha Net of Cat. Avg.) (t-1)	0.997	0.49	0.17
Var(Alpha Net of Cat. Avg.) (t-1)	1.000	0.32	0.25
Skew(Alpha Net of Cat. Avg.) (t-1)	1.016	0.30	0.30
Kurt(Alpha Net of Cat. Avg.) (t-1)	1.006	0.19	0.35
% Funds in Bottom Fifth (Alpha) (t-1)	2.822	0.00	0.04
% Funds in Top Fifth (Alpha) (t-1)	3.683	0.00	0.05
% Funds in Top Half (Alpha) (t-1)	3.416	0.00	0.04

Table II.6:Univariate Conditional Negative Binomial Models of Quar-
terly Fund Openings, 1992-2004

This table presents results from univariate conditional negative binomial models of quarterly fund openings on family-level performance- and non-performance-related characteristics, lagged one quarter. The dependent variable is *OpenCount*, defined as the number of new funds opened by a family during the quarter. Predictor variables are defined as asset-weighted averages of class-level values where appropriate. Both family and time effects are included, and performance measures using returns and 4-factor α , both raw and net of category averages, are included. Families with fewer than 3 funds were excluded from the analysis, leaving 13,403 observations on families with variation in *OpenCount*. Exponentiated coefficients are presented, which in the negative binomial model are interpreted as incidence rate ratios, that is, the proportional change in the incidence rate for a one unit change in the regressor.

2-Way Negative Binomial Regressions with Family and Year Fixed Effects

Non-Performance Characteristics (t-1)	IRR	P>z	Pseudo-R2
Fund Opening Dummy (t-1)	1.517	0.00	0.03
Count of Fund Opening (t-1)	1.016	0.00	0.01
Log # Funds (t-1)	1.744	0.00	0.05
New Money Growth (%) (t-1)	1.002	0.08	0.02
Log Avg. Total Net Assets (t-1)	1.135	0.00	0.02
Log Sum Total net Assets (t-1)	1.278	0.00	0.03
Expenses (%) (t-1)	0.690	0.00	0.02
Maximum Load (%) (t-1)	0.945	0.00	0.01
Turnover $(\%)$ (t-1)	0.985	0.39	0.04
Performance Characteristics	IRR	P>z	Pseudo-R2
Number of Star Funds (Ret) (t-1)	1.006	0.00	0.03
Number of Dog Funds (Ret) (t-1)	1.012	0.00	0.03
Number of Star Funds (Alpha) (t-1)	1.006	0.00	0.03
Number of Dog Funds (Alpha) (t-1)	1.012	0.00	0.03
Mean(Raw Returns) (t-1)	0.992	0.00	0.01
Var(Raw Returns) (t-1)	1.000	0.00	0.06
Skew(Raw Returns) (t-1)	1.013	0.17	0.09
Kurt(Raw Returns) (t-1)	1.022	0.00	0.12
Mean(Returns Net of Cat. Avg.) (t-1)	0.996	0.25	0.01
Var(Returns Net of Cat. Avg.) (t-1)	1.000	0.00	0.06
Skew(Returns Net of Cat. Avg.) (t-1)	0.995	0.55	0.09
Kurt(Returns Net of Cat. Avg.) (t-1)	1.020	0.00	0.12
% Funds in Bottom Fifth (Ret) (t-1)	0.986	0.91	0.01
% Funds in Top Fifth (Ret) (t-1)	0.853	0.17	0.01
% Funds in Top Half (Ret) (t-1)	1.043	0.52	0.01
Mean(Alpha) (t-1)	0.998	0.61	0.11
Var(Alpha) (t-1)	1.000	0.12	0.17
Skew(Alpha) (t-1)	1.007	0.56	0.20
Kurt(Alpha) (t-1)	1.021	0.00	0.23
Mean(Alpha Net of Cat. Avg.) (t-1)	0.999	0.70	0.11
Var(Alpha Net of Cat. Avg.) (t-1)	1.000	0.14	0.17
Skew(Alpha Net of Cat. Avg.) (t-1)	0.999	0.96	0.20
Kurt(Alpha Net of Cat. Avg.) (t-1)	1.021	0.00	0.23
% Funds in Bottom Fifth (Alpha) (t-1)	2.426	0.00	0.01
% Funds in Top Fifth (Alpha) (t-1)	2.316	0.00	0.02
% Funds in Top Half (Alpha) (t-1)	2.310	0.00	0.02

Table II.7:Multivariate Conditional Logit Models of Quarterly FundOpenings Using Raw Returns, 1992-2004

This table presents results from multivariate conditional logit models of quarterly fund openings on family-level performance- and non-performance-related characteristics, lagged one quarter. The dependent variable is *OpenDummy*, defined as 1 if a family opened a new fund during the quarter. Predictor variables are defined as asset-weighted averages of class-level values where appropriate. Performance measures are based on raw returns, with Panel A presenting result from models with family effects only, while Panel B includes both family and year effects. Families with fewer than 3 funds were excluded from the analysis, leaving 13,245 observations on families with variation in *OpenDummy*. Exponentiated coefficients are presented, which in the logit model are interpreted as odds ratios (P(y=1)/P(y=0)). That is, the reported coefficient indicates the expected change in the probability of a fund opening for a one unit change in the regressor.

	i		ii		ii	i	iv	
Lagged (t-1) Predictors:	OR	P>z	OR	P>z	OR	P>z	OR	P>z
Fund Opening Dummy	1.416	0.00	1.435	0.00	1.417	0.00	1.435	0.00
Log # Funds	1.570	0.00	1.317	0.00	1.576	0.00	1.321	0.00
Log Avg. Total Net Assets	0.849	0.00	0.855	0.00	0.858	0.00	0.866	0.00
New Money Growth (%)	1.002	0.36	1.002	0.37	1.002	0.36	1.002	0.37
Expenses (%)	0.614	0.00	0.623	0.00	0.619	0.00	0.628	0.00
Maximum Load	1.173	0.00	1.178	0.00	1.173	0.00	1.178	0.00
Turnover (%)	1.024	0.41	1.024	0.41	1.024	0.40	1.024	0.40
Mean(Raw Returns)	0.992	0.02	0.992	0.02	0.992	0.01	0.991	0.01
Var(Raw Returns)	1.000	0.09	1.000	0.06				
Skew(Raw Returns)	0.997	0.84	0.997	0.81				
Kurt(Raw Returns)	1.017	0.00	1.015	0.00	1.017	0.00	1.015	0.00
% Funds in Bottom Fifth			1.121	0.63			1.071	0.77
% Funds in Top Fifth			0.809	0.37			0.840	0.46
Number of Star Funds	0.996	0.00			0.996	0.00		
Number of Dog Funds	1.007	0.71			1.009	0.62		
Year Effects	No		No		No		No	
					1	I		
Number of Observations	$13,\!245$		13,245		13,245		13,245	
Pseudo-R2	0.21		0.21		0.21		0.21	

Panel A: 1-Way Models Using Raw Returns

Panel B:	2-Way	Models	Using	Raw	Returns

U U	i		ii		ii	i	iv	
Lagged (t-1) Predictors:	OR	P>z	OR	P>z	OR	P>z	OR	P>z
Fund Opening Dummy	1.180	0.00	1.183	0.00	1.180	0.00	1.183	0.00
Log # Funds	2.728	0.00	2.634	0.00	2.722	0.00	2.630	0.00
Log Avg. Total net Assets	0.963	0.41	0.962	0.39	0.975	0.57	0.974	0.56
New Money Growth (%)	1.002	0.36	1.002	0.36	1.002	0.37	1.002	0.37
Expenses (%)	0.875	0.35	0.884	0.38	0.878	0.36	0.887	0.40
Maximum Load (%)	1.027	0.51	1.028	0.49	1.029	0.48	1.030	0.46
Turnover (%)	1.025	0.39	1.025	0.39	1.025	0.39	1.025	0.39
Mean(Raw Returns)	0.987	0.00	0.986	0.00	0.987	0.00	0.985	0.00
Var(Raw Returns)	1.000	0.04	1.000	0.04				
Skew(Raw Returns)	1.000	0.98	0.999	0.92				
Kurt(Raw Returns)	1.007	0.10	1.007	0.12	1.007	0.09	1.007	0.11
% Funds in Bottom Fifth			0.956	0.85			0.913	0.71
% Funds in Top Fifth			0.658	0.09			0.680	0.12
Number of Star Funds	0.999	0.36			0.999	0.36		
Number of Dog Funds	1.000	0.99			1.002	0.90		
Year Effects	Yes		Yes		Yes		Yes	
				I				
Number of Observations	$13,\!245$		13,245		13,245		13,245	
Pseudo-R2	0.25		0.25		0.25		0.25	

Table II.8:Multivariate Conditional Logit Models of Quarterly FundOpenings Using Returns Net of Category Averages, 1992-2004

This table presents results from multivariate conditional logit models of quarterly fund openings on family-level performance- and non-performance-related characteristics, lagged one quarter. The dependent variable is *OpenDummy*, defined as 1 if a family opened a new fund during the quarter. Predictor variables are defined as asset-weighted averages of class-level values where appropriate. Performance measures are based on returns net of broad category averages derived from detailed Strategic Insight categories. Panel A presents result from models with family effects only, while Panel B includes both family and year effects. Families with fewer than 3 funds were excluded from the analysis, leaving 13,245 observations on families with variation in *OpenDummy*. Exponentiated coefficients are presented, which in the logit model are interpreted as odds ratios (P(y=1)/P(y=0)). That is, the reported coefficient indicates the expected change in the probability of a fund opening for a one unit change in the regressor.

0	i		ii	v	ii	i	iv	
Lagged (t-1) Predictors:	OR	P>z	OR	P>z	OR	P>z	OR	P>z
			•					
Fund Opening Dummy	1.414	0.00	1.432	0.00	1.415	0.00	1.433	0.00
Log # Funds	1.575	0.00	1.319	0.00	1.578	0.00	1.317	0.00
Log Avg. Total net Assets	0.843	0.00	0.846	0.00	0.855	0.00	0.862	0.00
New Money Growth $(\%)$	1.002	0.34	1.002	0.35	1.002	0.34	1.002	0.35
Expenses $(\%)$	0.612	0.00	0.618	0.00	0.620	0.00	0.626	0.00
Maximum Load (%)	1.168	0.00	1.173	0.00	1.167	0.00	1.172	0.00
Turnover (%)	1.024	0.40	1.024	0.40	1.024	0.40	1.024	0.39
Mean(Net Returns)	0.986	0.05	0.982	0.03	0.985	0.03	0.980	0.02
Var(Net Returns)	1.000	0.04	1.000	0.02				
Skew(Net Returns)	0.997	0.80	0.994	0.66				
Kurt(Net Returns)	1.015	0.00	1.013	0.00	1.015	0.00	1.013	0.00
% Funds in Bottom Fifth			0.996	0.99			0.927	0.76
% Funds in Top Fifth			0.707	0.18			0.757	0.27
Number of Star Funds	0.996	0.00			0.996	0.00		
Number of Dog Funds	1.006	0.73			1.010	0.59		
Year Effects	No		No		No		No	
Number of Observations	$13,\!245$		13,245		$13,\!245$		13,245	
Pseudo-R2	0.21		0.21		0.21		0.21	

Panel A: 1-Way Models Using Returns Net of Category Averages

Panel B: 2-Way M	odels Using Raw Retu	rns Net of Category Averages

v	i		ii		ii	iii		iv	
Lagged (t-1) Predictors:	OR	P>z	OR	P>z	OR	P>z	OR	P>z	
Fund Opening Dummy	1.178	0.00	1.181	0.00	1.179	0.00	1.182	0.00	
Log # Funds	2.727	0.00	2.628	0.00	2.718	0.00	2.616	0.00	
Log Avg. Total net Assets	0.958	0.35	0.956	0.32	0.970	0.50	0.969	0.48	
New Money Growth (%)	1.002	0.35	1.002	0.35	1.002	0.36	1.002	0.36	
Expenses $(\%)$	0.865	0.31	0.871	0.33	0.872	0.34	0.878	0.36	
Maximum Load (%)	1.026	0.53	1.027	0.51	1.027	0.52	1.028	0.50	
Turnover (%)	1.025	0.38	1.025	0.39	1.025	0.39	1.025	0.39	
Mean(Net Returns)	0.987	0.06	0.979	0.01	0.986	0.04	0.977	0.01	
Var(Net Returns)	1.000	0.07	1.000	0.05					
Skew(Net Returns)	1.000	1.00	0.996	0.75					
Kurt(Net Returns)	1.007	0.07	1.006	0.10	1.008	0.05	1.007	0.07	
% Funds in Bottom Fifth			0.862	0.57			0.812	0.42	
% Funds in Top Fifth			0.616	0.07			0.647	0.10	
Number of Star Funds	0.999	0.31			0.999	0.30			
Number of Dog Funds	1.003	0.85			1.006	0.74			
Year Effects	Yes		Yes		Yes		Yes		
	10.015								
Number of Observations	13,245		13,245		13,245		13,245		
Pseudo-R2	0.25		0.25		0.25		0.25		

Table II.9: Multivariate Conditional Logit Models of Quarterly Fund Openings Using 4-Factor α , 1992-2004

This table presents results from multivariate conditional logit models of quarterly fund openings on family-level performance- and non-performance-related characteristics, lagged one quarter. The dependent variable is *OpenDummy*, defined as 1 if a family opened a new fund during the quarter. Predictor variables are defined as asset-weighted averages of class-level values where appropriate. Performance measures are based on 4-factor α , with Panel A presenting result from models with family effects only, while Panel B includes both family and year effects. Families with fewer than 3 funds were excluded from the analysis, leaving 10,544 observations on families with variation in *OpenDummy*. Exponentiated coefficients are presented, which in the logit model are interpreted as odds ratios (P(y=1)/P(y=0)). That is, the reported coefficient indicates the expected change in the probability of a fund opening for a one unit change in the regressor.

,	i		ii	ii		iii		iv	
Lagged (t-1) Predictors:	OR	P>z	OR	P>z	OR	P>z	OR	P>z	
Fund Opening Dummy	1.298	0.00	1.300	0.00	1.310	0.00	1.313	0.00	
Log # Funds	1.807	0.00	1.438	0.00	1.834	0.00	1.415	0.00	
Log Avg. Total net Assets	1.096	0.12	1.220	0.00	1.142	0.02	1.269	0.00	
New Money Growth (%)	1.000	0.99	1.000	0.94	1.000	0.99	1.000	0.95	
Expenses (%)	0.589	0.00	0.638	0.01	0.619	0.01	0.669	0.02	
Maximum Load (%)	1.320	0.00	1.244	0.00	1.323	0.00	1.247	0.00	
Turnover (%)	0.986	0.74	0.989	0.79	0.987	0.76	0.989	0.80	
Mean(Alpha)	1.001	0.93	1.006	0.39	1.000	0.95	1.006	0.36	
Var(Alpha)	1.000	0.00	1.000	0.00					
Skew(Alpha)	1.053	0.00	1.057	0.00					
Kurt(Alpha)	0.995	0.33	0.994	0.26	0.996	0.47	0.996	0.40	
% Funds in Bottom Fifth			0.357	0.00			0.322	0.00	
% Funds in Top Fifth			11.289	0.00			12.210	0.00	
Number of Star Funds	0.988	0.00			0.988	0.00			
Number of Dog Funds	1.022	0.00			1.023	0.00			
Year Effects	No		No		No		No		
Number of Observations	$10,\!544$		10,544	1	10,544	I	10,544		
Pseudo-R2	0.37		10,344 0.37		0.37		0.37		
r seuuo-n2	0.57		0.57	I	0.57		0.57		

Panel	A: 1	1-Way	Models	Using	4-Factor	α

Panel B: 2-Way Models Using 4-Factor α

1 aller 21 2 ((a) 100 acto 001	i		ii		ii	i	iv	
Lagged $(t-1)$ Predictors:	OR	P>z	OR	P>z	OR	P>z	OR	P>z
Fund Opening Dummy	1.129	0.00	1.136	0.00	1.131	0.00	1.138	0.00
Log # Funds	3.073	0.00	2.631	0.00	3.101	0.00	2.644	0.00
Log Avg. Total net Assets	1.225	0.00	1.304	0.00	1.243	0.00	1.318	0.00
New Money Growth $(\%)$	1.000	0.98	1.000	0.98	1.000	0.99	1.000	0.97
Expenses $(\%)$	0.735	0.09	0.756	0.13	0.751	0.12	0.772	0.16
Maximum Load (%)	1.184	0.00	1.155	0.01	1.183	0.00	1.152	0.01
Turnover (%)	0.986	0.74	0.988	0.76	0.986	0.73	0.987	0.75
Mean(Alpha)	1.007	0.29	1.012	0.08	1.007	0.29	1.012	0.08
Var(Alpha)	1.000	0.21	1.000	0.39				
$\mathrm{Skew}(\mathrm{Alpha})$	1.028	0.15	1.040	0.04				
Kurt(Alpha)	0.995	0.41	0.996	0.47	0.996	0.45	0.996	0.49
% Funds in Bottom Fifth			0.487	0.02			0.457	0.01
% Funds in Top Fifth			4.978	0.00			5.025	0.00
Number of Star Funds	0.993	0.00			0.993	0.00		
Number of Dog Funds	1.014	0.00			1.014	0.00		
Year Effects	Yes		Yes		Yes		Yes	
	10 544	I	10 544	1	10 544	1	10 544	
Number of Observations	10,544		10,544		10,544		10,544	
Pseudo-R2	0.39		0.39		0.39		0.39	

Table II.10: Multivariate Conditional Logit Models of Quarterly Fund Openings Using 4-Factor α Net of Category Averages, 1992-2004

This table presents results from multivariate conditional logit models of quarterly fund openings on family-level performance- and non-performance-related characteristics, lagged one quarter. The dependent variable is *OpenDummy*, defined as 1 if a family opened a new fund during the quarter. Predictor variables are defined as asset-weighted averages of class-level values where appropriate. Performance measures are based on 4-factor α net of broad category averages derived from detailed Strategic Insight categories. Panel A presents result from models with family effects only, while Panel B includes both family and year effects. Families with fewer than 3 funds were excluded from the analysis, leaving 10,544 observations on families with variation in *OpenDummy*. Exponentiated coefficients are presented, which in the logit model are interpreted as odds ratios (P(y=1)/P(y=0)). That is, the reported coefficient indicates the expected change in the probability of a fund opening for a one unit change in the regressor.

v	i i		ii		ii	i	iv	
Lagged (t-1) Predictors:	OR	P>z	OR	P>z	OR	P>z	OR	P>z
Fund Opening Dummy	1.302	0.00	1.306	0.00	1.310	0.00	1.313	0.00
Log # Funds	1.788	0.00	1.408	0.00	1.839	0.00	1.417	0.00
Log Avg. Total net Assets	1.098	0.12	1.222	0.00	1.146	0.02	1.272	0.00
New Money Growth (%)	1.000	0.98	1.000	0.95	1.000	0.99	1.000	0.94
Expenses (%)	0.593	0.00	0.648	0.01	0.621	0.01	0.673	0.02
Maximum Load (%)	1.321	0.00	1.243	0.00	1.324	0.00	1.247	0.00
Turnover (%)	0.984	0.70	0.987	0.75	0.987	0.75	0.989	0.79
Mean(Net Alpha)	1.001	0.87	1.006	0.33	1.000	0.95	1.006	0.36
Var(Net Alpha)	1.000	0.00	1.000	0.01				
Skew(Net Alpha)	1.030	0.08	1.038	0.03				
Kurt(Net Alpha)	0.992	0.14	0.995	0.35	0.993	0.20	0.996	0.41
% Funds in Bottom Fifth			0.363	0.00			0.325	0.00
% Funds in Top Fifth			11.907	0.00			12.151	0.00
Number of Star Funds	0.988	0.00			0.988	0.00		
Number of Dog Funds	1.023	0.00			1.023	0.00		
Year Effects	No		No		No		No	
		1		1	1	1		
Number of Observations	$10,\!544$		10,544		10,544		10,544	
Pseudo-R2	0.37		0.37		0.37		0.37	

Panel A: 1-Way Models Using 4-Factor α Net of Category Averages

Panel B: 2-Way Model	s Using 4-Factor α Net of	f Category Averages

	i		ii	0 0	ii	i	iv	
Lagged (t-1) Predictors:	OR	P>z	OR	P>z	OR	P>z	OR	P>z
i								
Fund Opening Dummy	1.129	0.00	1.137	0.00	1.130	0.00	1.137	0.00
Log # Funds	3.083	0.00	2.665	0.00	3.116	0.00	2.677	0.00
Log Avg. Total net Assets	1.230	0.00	1.304	0.00	1.249	0.00	1.320	0.00
New Money Growth (%)	1.000	0.98	1.000	0.98	1.000	0.99	1.000	0.97
Expenses $(\%)$	0.736	0.09	0.761	0.14	0.751	0.12	0.772	0.16
Maximum Load (%)	1.182	0.00	1.151	0.01	1.184	0.00	1.153	0.01
Turnover (%)	0.985	0.71	0.986	0.73	0.986	0.73	0.986	0.75
Mean(Net Alpha)	1.006	0.34	1.011	0.10	1.007	0.27	1.012	0.08
Var(Net Alpha)	1.000	0.23	1.000	0.46				
Skew(Net Alpha)	1.022	0.21	1.025	0.15				
Kurt(Net Alpha)	0.990	0.06	0.993	0.18	0.990	0.07	0.993	0.17
% Funds in Bottom Fifth			0.492	0.02			0.467	0.02
% Funds in Top Fifth			4.880	0.00			4.891	0.00
Number of Star Funds	0.993	0.00			0.993	0.00		
Number of Dog Funds	1.014	0.00			1.014	0.00		
Year Effects	Yes		Yes		Yes		Yes	
Number of Observations	$10,\!544$		10,544		$10,\!544$		10,544	
Pseudo-R2	0.39		0.39		0.39		0.39	

Table II.11: Multivariate Conditional Negative Binomial Models of Quarterly Fund Openings Using Raw Returns, 1992-2004

This table presents results from multivariate conditional logit models of quarterly fund openings on family-level performance- and non-performance-related characteristics, lagged one quarter. The dependent variable is *OpenCount*, defined as the number of new funds opened by a family during the quarter. Predictor variables are defined as asset-weighted averages of class-level values where appropriate. Performance measures are based on raw returns, with Panel A presenting result from models with family effects only, while Panel B includes both family and year effects. Families with fewer than 3 funds were excluded from the analysis, leaving 10,544 observations on families with variation in *OpenCount*. Exponentiated coefficients are presented, which in the logit model are interpreted as incidence rate ratios, that is, the proportional change in the incidence rate for a one unit change in the regressor.

v	i i		ii	ii		iii		
Lagged (t-1) Predictors:	IRR	P>z	IRR	P>z	IRR	P>z	IRR	P>z
Count of Fund Openings	1.027	0.00	1.027	0.00	1.027	0.00	1.027	0.00
Count of Fund $Openings^2$	0.999	0.00	0.999	0.00	0.999	0.00	0.999	0.00
Log # Funds	1.533	0.00	1.384	0.00	1.535	0.00	1.385	0.00
Log Avg. Total Net Assets	1.016	0.45	1.015	0.49	1.020	0.33	1.019	0.37
New Money Growth $(\%)$	1.001	0.33	1.001	0.31	1.001	0.33	1.001	0.32
Expenses $(\%)$	0.807	0.00	0.812	0.00	0.808	0.00	0.812	0.00
Maximum Load (%)	0.942	0.00	0.946	0.00	0.943	0.00	0.946	0.00
Turnover (%)	1.043	0.02	1.044	0.01	1.044	0.01	1.044	0.01
Mean(Raw Return)	0.994	0.02	0.993	0.01	0.994	0.02	0.993	0.01
Var(Raw Return)	1.000	0.40	1.000	0.40				
Skew(Raw Return)	1.004	0.63	1.005	0.58				
Kurt(Raw Return)	1.009	0.00	1.008	0.00	1.009	0.00	1.008	0.00
% Funds in Bottom Fifth			0.831	0.32			0.819	0.28
% Funds in Top Fifth			1.038	0.85			1.048	0.81
Number of Star Funds	0.998	0.00			0.998	0.00		
Number of Dog Funds	1.008	0.42			1.008	0.40		
Year Effects	No		No		No		No	
				I		1		
Number of Observations	$13,\!245$		13,245		13,245		13,245	
Pseudo-R2	0.13		0.13		0.13		0.13	

Panel A: Models 1-Way Using Raw Returns

Panel B:	Models	2-Way	Using	Raw	Returns

v	i		ii	ii		iii		
Lagged (t-1) Predictors:	IRR	P>z	IRR	P>z	IRR	P>z	IRR	P>z
Count of Fund Openings	1.010	0.00	1.010	0.01	1.010	0.00	1.010	0.00
Count of Fund $Openings^2$	0.999	0.03	0.999	0.03	0.999	0.03	0.999	0.03
Log # Funds	1.844	0.00	1.831	0.00	1.841	0.00	1.829	0.00
Log Avg. Total net Assets	0.947	0.01	0.947	0.01	0.956	0.03	0.955	0.03
New Money Growth (%)	1.001	0.27	1.001	0.27	1.001	0.28	1.001	0.27
Expenses $(\%)$	0.910	0.16	0.903	0.13	0.912	0.17	0.903	0.13
Maximum Load (%)	0.883	0.00	0.884	0.00	0.884	0.00	0.885	0.00
Turnover (%)	1.050	0.00	1.050	0.00	1.051	0.00	1.051	0.00
Mean(Raw Return)	0.989	0.00	0.988	0.00	0.989	0.00	0.988	0.00
Var(Raw Return)	1.000	0.02	1.000	0.04				
Skew(Raw Return)	1.001	0.87	1.002	0.85				
Kurt(Raw Return)	1.003	0.11	1.003	0.11	1.003	0.11	1.003	0.11
% Funds in Bottom Fifth			0.693	0.06			0.670	0.04
% Funds in Top Fifth			0.950	0.80			0.971	0.88
Number of Star Funds	1.000	0.71			1.000	0.70		
Number of Dog Funds	1.001	0.88			1.003	0.79		
Year Effects	Yes		Yes		Yes		Yes	
			-		•			
Number of Observations	$13,\!245$		$13,\!245$		13,245		13,245	
Pseudo-R2	0.15		0.15		0.15		0.15	

Table II.12: Multivariate Conditional Negative Binomial Models of Quar-terly Fund Openings Using Returns Net of Category Averages, 1992-2004

This table presents results from multivariate conditional logit models of quarterly fund openings on family-level performance- and non-performance-related characteristics, lagged one quarter. The dependent variable is *OpenCount*, defined as the number of new funds opened by a family during the quarter. Predictor variables are defined as asset-weighted averages of class-level values where appropriate. Performance measures are based on returns net of broad category averages derived from detailed Strategic Insight categories. Panel A presents result from models with family effects only, while Panel B includes both family and year effects. Families with fewer than 3 funds were excluded from the analysis, leaving 10,544 observations on families with variation in *OpenCount*. Exponentiated coefficients are presented, which in the logit model are interpreted as incidence rate ratios, that is, the proportional change in the incidence rate for a one unit change in the regressor.

	i		ii	ii		iii		
Lagged (t-1) Predictors:	IRR	P>z	IRR	P>z	IRR	P>z	IRR	P>z
Count of Fund Openings	1.027	0.00	1.027	0.00	1.027	0.00	1.027	0.00
Count of Fund Openings ²	0.999	0.00 0.00	0.999	0.00	0.999	0.00 0.00	0.999	0.00
Log $\#$ Funds	1.541	0.00	1.388	0.00	1.541	0.00	1.386	0.00
Log π rands Log Avg. Total net Assets	1.016	$0.00 \\ 0.45$	1.014	0.52	1.020	0.35	1.017	0.00 0.41
New Money Growth (%)	1.010	0.33	1.014	0.31	1.020	0.33	1.001	0.31
Expenses (%)	0.806	0.00	0.809	0.00	0.809	0.00	0.810	0.01
Maximum Load (%)	0.942	0.00	0.946	0.00	0.942	0.00	0.946	0.00
Turnover (%)	1.043	0.02	1.043	0.02	1.043	0.02	1.043	0.02
Mean(Net Returns)	0.989	0.06	0.985	0.03	0.988	0.04	0.983	0.01
Var(Net Returns)	1.000	0.07	1.000	0.09	0.000	0.01	0.000	0.01
Skew(Net Returns)	1.000	0.96	0.998	0.86				
Kurt(Net Returns)	1.007	0.00	1.006	0.00	1.007	0.00	1.006	0.00
% Funds in Bottom Fifth		0.00	0.746	0.15		0.00	0.721	0.10
% Funds in Top Fifth			0.960	0.84			0.960	0.84
Number of Star Funds	0.998	0.00			0.998	0.00		
Number of Dog Funds	1.009	0.34			1.010	0.32		
Year Effects	No		No		No		No	
Noushan of Observerstiens	12.045	I	12.045	1	12.045	1	12.045	
Number of Observations Pseudo-R2	13,245		$13,245 \\ 0.13$		13,245		$ \begin{array}{c c} 13,245 \\ 0.13 \end{array} $	
r seudo-rt2	0.13		0.15		0.13		0.15	
Panel B: Models 2-Way Usi	ng Net R	eturns						
	i		ii		ii	i	iv	
Lagged (t-1) Predictors:	IRR	P>z	IRR	P>z	IRR	P>z	IRR	P>z
Count of Fund Openings	1.010	0.00	1.010	0.00	1.010	0.00	1.010	0.00
Count of Fund Openings ²	0.999	0.00 0.03	0.999	0.00	0.999	0.00 0.03	0.999	$0.00 \\ 0.03$
Log $\#$ Funds	1.851	0.00	1.842	0.00	1.850	0.00	1.840	0.00
Log Avg. Total net Assets	0.949	0.02	0.948	0.01	0.953	0.00	0.951	0.00 0.02
New Money Growth (%)	1.001	0.02 0.27	1.001	0.01	1.001	0.28	1.001	0.02 0.27
Expenses (%)	0.904	0.13	0.893	0.10	0.906	0.14	0.894	0.10
Maximum Load (%)	0.883	0.00	0.884	0.00	0.884	0.00	0.884	0.00
Turnover (%)	1.050	0.00	1.049	0.00	1.050	0.00	1.050	0.00
Mean(Net Returns)	0.986	0.02	0.979	0.00	0.985	0.01	0.977	0.00
· /	1				1		1	

Panel A: Models 1-Way Using Net Returns

Lagged (t-1) I redictors.	mn	1 > 2	min	1 > z	mn	1 >Z	Inn	1 > 2
Count of Fund Openings	1.010	0.00	1.010	0.00	1.010	0.00	1.010	0.00
Count of Fund $Openings^2$	0.999	0.03	0.999	0.03	0.999	0.03	0.999	0.03
Log # Funds	1.851	0.00	1.842	0.00	1.850	0.00	1.840	0.00
Log Avg. Total net Assets	0.949	0.02	0.948	0.01	0.953	0.03	0.951	0.02
New Money Growth $(\%)$	1.001	0.27	1.001	0.27	1.001	0.28	1.001	0.27
Expenses (%)	0.904	0.13	0.893	0.10	0.906	0.14	0.894	0.10
Maximum Load (%)	0.883	0.00	0.884	0.00	0.884	0.00	0.884	0.00
Turnover (%)	1.050	0.00	1.049	0.00	1.050	0.00	1.050	0.00
Mean(Net Returns)	0.986	0.02	0.979	0.00	0.985	0.01	0.977	0.00
Var(Net Returns)	1.000	0.02	1.000	0.07				
Skew(Net Returns)	1.002	0.81	0.999	0.93				
Kurt(Net Returns)	1.002	0.39	1.002	0.39	1.002	0.37	1.002	0.35
% Funds in Bottom Fifth			0.612	0.02			0.590	0.01
% Funds in Top Fifth			0.887	0.58			0.880	0.55
Number of Star Funds	1.000	0.73			1.000	0.71		
Number of Dog Funds	1.005	0.64			1.005	0.62		
Year Effects	Yes		Yes		Yes		Yes	
Number of Observations	$13,\!245$		13,245		13,245		13,245	
Pseudo-R2	0.15		0.15		0.15		0.15	
		ľ				1		

Table II.13: Multivariate Conditional Negative Binomial Models of Quarterly Fund Openings Using 4-Factor α , 1992-2004

This table presents results from multivariate conditional logit models of quarterly fund openings on family-level performance- and non-performance-related characteristics, lagged one quarter. The dependent variable is *OpenCount*, defined as the number of new funds opened by a family during the quarter. Predictor variables are defined as asset-weighted averages of class-level values where appropriate. Performance measures are based on 4-factor α , with Panel A presenting result from models with family effects only, while Panel B includes both family and year effects. Families with fewer than 3 funds were excluded from the analysis, leaving 10,544 observations on families with variation in *OpenCount*. Exponentiated coefficients are presented, which in the logit model are interpreted as incidence rate ratios, that is, the proportional change in the incidence rate for a one unit change in the regressor.

i		ii		iii		iv	
IRR	P>z	IRR	P>z	IRR	P>z	IRR	P>z
1.020	0.00	1.016	0.00	1.021	0.00	1.017	0.00
0.999	0.00	0.999	0.01	0.999	0.00	0.999	0.01
1.701	0.00	1.449	0.00	1.698	0.00	1.431	0.00
1.076	0.00	1.150	0.00	1.098	0.00	1.170	0.00
1.000	0.89	1.000	0.85	1.000	0.88	1.000	0.84
0.818	0.01	0.815	0.01	0.835	0.02	0.825	0.01
0.921	0.00	0.920	0.00	0.924	0.00	0.922	0.00
1.036	0.16	1.010	0.72	1.038	0.15	1.011	0.68
1.005	0.27	1.009	0.05	1.007	0.18	1.010	0.03
1.000	0.01	1.000	0.02				
1.033	0.00	1.034	0.00				
0.997	0.26	0.999	0.71	0.998	0.54	1.000	0.98
		0.513	0.00			0.485	0.00
		5.883	0.00			6.195	0.00
0.995	0.00			0.995	0.00		
1.008	0.00			1.008	0.00		
No		No		No		No	
10 551		10 551	1	10 551	I	10 551	
0.25		0.25		0.25		0.25	
	IRR 1.020 0.999 1.701 1.076 1.000 0.818 0.921 1.036 1.005 1.000 1.033 0.997 0.995 1.008	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c c c c c c c c c c c c c c c c c c c $

Panel A: Models 1-Way Using 4-Factor α

Panel B: Models 2-Way Using 4-Factor α

•	i		ii	ii		iii		
Lagged (t-1) Predictors:	IRR	P>z	IRR	P>z	IRR	P>z	IRR	P>z
Count of Fund Openings	1.007	0.04	1.006	0.08	1.007	0.04	1.006	0.08
Count of Fund Openings ²	0.999	0.06	0.999	0.11	0.999	0.06	0.999	0.11
Log # Funds	1.967	0.00	1.822	0.00	1.964	0.00	1.823	0.00
Log Avg. Total net Assets	0.987	0.62	1.051	0.08	0.994	0.80	1.049	0.07
New Money Growth (%)	1.000	0.89	1.000	0.90	1.000	0.90	1.000	0.89
Expenses (%)	0.861	0.05	0.825	0.02	0.863	0.06	0.826	0.02
Maximum Load (%)	0.883	0.00	0.887	0.00	0.884	0.00	0.887	0.00
Turnover (%)	1.054	0.03	1.034	0.18	1.056	0.03	1.034	0.19
Mean(Alpha)	1.015	0.01	1.018	0.00	1.014	0.01	1.018	0.00
Var(Alpha)	1.000	0.44	1.000	0.97				
Skew(Alpha)	0.997	0.80	1.009	0.44				
Kurt(Alpha)	0.998	0.39	1.000	0.85	0.998	0.41	1.001	0.83
% Funds in Bottom Fifth			0.479	0.00			0.472	0.00
% Funds in Top Fifth			4.083	0.00			4.084	0.00
Number of Star Funds	0.997	0.00			0.997	0.00		
Number of Dog Funds	1.006	0.00			1.006	0.00		
Year Effects	Yes		Yes		Yes		Yes	
Number of Observations	$10,\!551$		10,551		$10,\!551$		10,551	
Pseudo-R2	0.264		0.266		0.264		0.266	

Table II.14: Multivariate Conditional Negative Binomial Models of Quarterly Fund Openings Using 4-Factor α Net of Category Averages, 1992-2004

This table presents results from multivariate conditional logit models of quarterly fund openings on family-level performance- and non-performance-related characteristics, lagged one quarter. The dependent variable is *OpenCount*, defined as the number of new funds opened by a family during the quarter. Predictor variables are defined as asset-weighted averages of class-level values where appropriate. Performance measures are based on 4-factor α net of broad category averages derived from detailed Strategic Insight categories. Panel A presents result from models with family effects only, while Panel B includes both family and year effects. Families with fewer than 3 funds were excluded from the analysis, leaving 10,544 observations on families with variation in *OpenCount*. Exponentiated coefficients are presented, which in the logit model are interpreted as incidence rate ratios, that is, the proportional change in the incidence rate for a one unit change in the regressor.

	i i			ii		iii		
Lagged (t-1) Predictors:	IRR	P>z	IRR	P>z	IRR	P>z	IRR	P>z
			•				•	
Count of Fund Openings	1.020	0.00	1.016	0.00	1.021	0.00	1.017	0.00
Count of Fund $Openings^2$	0.999	0.00	0.999	0.01	0.999	0.00	0.999	0.01
Log # Funds	1.690	0.00	1.422	0.00	1.692	0.00	1.418	0.00
Log Avg. Total net Assets	1.080	0.00	1.160	0.00	1.095	0.00	1.170	0.00
New Money Growth (%)	1.000	0.89	1.000	0.85	1.000	0.88	1.000	0.82
Expenses (%)	0.816	0.01	0.819	0.01	0.825	0.01	0.822	0.01
Maximum Load (%)	0.923	0.00	0.922	0.00	0.924	0.00	0.923	0.00
Turnover (%)	1.037	0.16	1.015	0.57	1.040	0.13	1.018	0.51
Mean(Net Alpha)	1.014	0.03	1.028	0.00	1.016	0.01	1.031	0.00
$Var(Net \alpha)$	1.000	0.07	1.000	0.23				
Skew(Net α)	1.012	0.26	1.019	0.07				
$\operatorname{Kurt}(\operatorname{Net} \alpha)$	0.998	0.34	1.001	0.70	0.998	0.42	1.001	0.64
% Funds in Bottom Fifth			0.637	0.05			0.620	0.04
% Funds in Top Fifth			6.279	0.00			6.307	0.00
Number of Star Funds	0.995	0.00			0.995	0.00		
Number of Dog Funds	1.008	0.00			1.008	0.00		
Year Effects	No		No		No		No	
	10 551		10 551		10 551		10 221	
Number of Observations	10,551		10,551		10,551		10,551	
Pseudo-R2	0.25		0.25		0.25		0.25	

Panel A: Models 1-Way Using Net 4-Factor α

Panel B:	Models	2-Way	Using	Net	4-Factor	α

	i		ii	ii		i	iv	
Lagged (t-1) Predictors:	IRR	P>z	IRR	P>z	IRR	P>z	IRR	P>z
					1			
Count of Fund Openings	1.007	0.05	1.006	0.09	1.007	0.05	1.006	0.09
Count of Fund Openings ²	0.999	0.07	0.999	0.12	0.999	0.06	0.999	0.12
Log # Funds	1.960	0.00	1.827	0.00	1.959	0.00	1.827	0.00
Log Avg. Total net Assets	0.991	0.73	1.055	0.05	0.997	0.92	1.053	0.05
New Money Growth (%)	1.000	0.92	1.000	0.93	1.000	0.90	1.000	0.90
Expenses (%)	0.858	0.05	0.822	0.01	0.862	0.05	0.822	0.01
Maximum Load (%)	0.881	0.00	0.885	0.00	0.881	0.00	0.885	0.00
Turnover (%)	1.051	0.04	1.032	0.21	1.052	0.04	1.032	0.22
Mean(Net Alpha)	1.012	0.06	1.018	0.01	1.013	0.03	1.019	0.00
Var(Net Alpha)	1.000	0.46	1.000	0.79				
Skew(Net Alpha)	1.013	0.21	1.018	0.08				
Kurt(Net Alpha)	0.994	0.03	0.999	0.74	0.995	0.04	0.999	0.70
% Funds in Bottom Fifth			0.504	0.00			0.496	0.00
% Funds in Top Fifth			4.066	0.00			4.018	0.00
Number of Star Funds	0.998	0.00			0.998	0.00		
Number of Dog Funds	1.006	0.00			1.006	0.00		
Year Effects	Yes		Yes		Yes		Yes	
Number of Observations	$10,\!551$		10,551		$10,\!551$		10,551	
Pseudo-R2	0.26		0.27		0.26		0.27	

Chapter III

Mutual Fund Performance and Advisory Firm Organization

III.A Introduction

As the mutual fund industry has grown in size and importance in U.S. financial markets, practitioners, regulators, and academics have become increasingly aware of potential agency conflicts in these entities. Academic studies have tended to focus on agency conflicts arising from the interactions between investors and fund managers. Notably, the shape of the compensation contract and the responsiveness of investors to fund performance have received a great deal of attention, primarily with respect to their ramifications for fund manager behavior.¹

Recently, several mutual fund industry leaders have suggested that the mutual fund industry is not necessarily organized to align fund managers' interests with those of shareholders. Swensen (2005) suggests the ownership structure of the investment advisor has a substantial impact on the returns investors can expect to receive. Indeed, he suggests the investment advisor's profit motive is important enough to ensure the advisor's investment decisions will tend to favor the profits of the firm at the expense of the investor.

... When the fiduciary responsibility to produce high risk-adjusted re-

¹See, for example, Chevalier and Ellison (1997) and Sirri and Tufano (1998).

turns for investors inevitably comes into conflict with the profit motivation to provide substantial revenue for fund management companies, investor returns lose and company profits win.

Mutual-fund investors consistently fail to achieve investment objectives, because the balance of power in the investment management world skews dramatically in favor of the profit-seeking investment manager ...

... Investors increase the odds for success by avoiding purely profitmotivated firms and engaging organizations that reduce or eliminate the conflict between seekers of profit and seekers of return. Not-forprofit organizational structures allow investment management companies to focus solely on fulfilling fiduciary responsibilities. Moreover in the not-for-profit world, the absence of profit-margins leads to lower cost for mutual-fund shareholders.²

In his most recent book, mutual fund industry icon John Bogle (Bogle 2005) rails against the transition of the US economy from one of *owners' capitalism* to one of *managers' capitalism*. On the mutual fund industry, he laments the trends which have changed mutual fund management "...from a profession to a business", and suggests this has been detrimental to investors.

... As 1958 ended, the regulatory wall that had prevented public ownership of management companies since the industry began thirty-four years earlier came tumbling down. A rush of initial public offerings followed, with the shares of a dozen management companies quickly brought to market.

... Indeed, it is possible to envision circumstances in which the pressure for earnings and earnings growth engendered by public ownership is antithetical to the responsible operation of a professional organization.

... The third major force in the industry's transformation, and a rather unrecognized one at that, was the growing control of mutual fund management companies by large financial conglomerates.

... The change in the mutual fund industry from profession to business was clearly accelerated by the shift in control of a major portion of the industry, first from private to public hands, then from independent firms to subsidiaries of financial conglomerates. The staggering aggregations of managed assets that resulted from these combinations - often billions of dollars under a single roof - surely serve the interests of the fund manager. With size came burgeoning fees that helped support

 $^{^2 \}mathrm{Swensen}$ (2005) page 341.

the costly battle to build market share, and the ability to market the "brand name" of the fund complex across the nation.

... Nor has the change improved investor returns. In fact, the reverse is true. The record shows that funds operated under the aegis of financial conglomerates have provided distinctly inferior returns compared to the returns achieved by funds managed by privately held firms.³

Swenson and Bogle are suggesting that the governance characteristics of the *investment advisor* have real effects on investors' interests. This implies a different focus than that of the current state of academic literature, which has focused on governance characteristics of the *investment company* (i.e. the mutual fund).⁴ While there exists anecdotal evidence in support of Swenson's and Bogle's arguments that the ownership structure of investment advisors affects performance and expenses, a broad empirical analysis of these effects has not previously been carried out. The primary contribution of our paper is to carry out just such an analysis.

In this paper we analyze the mutual fund industry with respect to the ownership structure of the investment advisor (i.e. fund family). We address this issue from two perspectives. First, we examine the effects on fund investors (in terms of performance and fees) of different investment advisor ownership structures. In particular we compare privately held, publicly owned, and mutualized firms. Second, we examine whether mutual fund investors are better served by a fund family that is independent or a subsidiary of a larger concern, and whether fund families that are subsidiaries (of, for example, banks, insurance companies, or financial services conglomerates) outperform their non-subsidiary peers. The rise of the fund family as subsidiary resulted, in no small part, from conglomeration in the mutual fund industry following the Gramm-Leach-Bliley Act of 1999 (GLBA).⁵

 $^{^{3}}$ Bogle (2005) page 177-9.

⁴Relevant studies of mutual fund governance include Ferris and Yan (2005), Tufano and Sevick (1997), Khorana, Tufano, and Wedge (2006)and Meschke (2005).

⁵The GLBA formally removed many of the legal constraints on affiliations between banks, securities firms, and insurance companies put in place by the Glass-Steagall Act of 1933. In particular GLBA repealed the restrictions on banks affiliating with securities firms. In addition, GLBA created a new "financial holding company" engaging in a broad range of financial activities including insurance company

Notable in the subsequent industry changes was the entrance of large banking and insurance conglomerates into the mutual fund business. In 2004, 196 of 547 fund families were subsidiaries of larger concerns: 59 fund families had insurance parents, 82 fund families had banking parents, 44 fund families were subsidiaries of financial services conglomerates, and 10 families were subsidiaries of non-financial firms.⁶

We hypothesize that the performance of funds belonging to subsidiary families differs from non-subsidiary family funds for several reasons. First, ownership by a conglomerate may provide access to skills and services unavailable to independent fund families and translate into increased fund performance and decreased fund fees. For example, a financial services conglomerate may be able to provide its subsidiary funds with better research and cheaper execution services. Access to these services could translate into benefits to investors in terms of higher returns or lower expenses.⁷

Alternatively, investors in fund families affiliated with diversified conglomerates realize benefits not measured in performance or expenses. These may include lower search costs, faster and more efficient transfers and coordinated reporting among other financial service entities within the conglomerate, and better/coordinated advice across multiple dimensions of investors' financial needs. For example, investors in bank or insurance company affiliated mutual funds may realize some benefit from investing in mutual funds where they consume other financial services. If investors value these services in aggregate, this could explain an equilibrium that results in some degree of investor capture reflected in lower

portfolio investment. Passage of GLBA permitted substantial conglomeration in the financial services sector. For full text of the act and it's provisions see http://banking.senate.gov/conf/. GLBA also contained provisions that made the regulation of bank holding companies that are mutually held consistent with the regulation of other bank holding companies. Potential conflicts of interest in the mutual fund business were addressed in amendments to the Investment Advisors Act of 1940 to require banks that advise mutual funds to register as investment advisors.

⁶Of course, there is substantial overlap across banks, insurance companies, and financial services conglomerates. We have characterized parent firms according to their core business. For example, Banc of America is characterized as a bank, although its operations include broader financial services.

⁷Of course, such savings may or may not be passed along to investors in the form of lower expenses.

performance and/or higher fees.⁸

A related issue involves the question of who is actually managing the mutual fund portfolio. That is, are the day-to-day operations of the fund being carried out by an employee of the investment advisor, or has the investment advisor contracted with an outside entity to act as subadvisor for the fund? If we make the argument that characteristics of the investment advisor may play a role in fund management decisions because the portfolio manager is an employee of the advisor, then we may be interested in knowing whether or not the manager is directly employed by the advisor. Thus, we examine performance and expense differences between directly advised and subadvised funds.⁹

The remainder of our paper is organized as follows. In section III.B we briefly discuss the relevant literature. Section III.C discusses the structure of the mutual fund industry and the interaction of industry participants. Section III.D.1 discusses investment advisor ownership structure and the implications of different ownership structures for investors. Section III.D.2 addresses the relevance of the mutual fund subsidiary relation to shareholders. Section III.D.3 describes the interaction between investment advisors and sub-advisors. Section III.E describes our data, defines variables used, and address a number of econometric issues. Section III.F presents our empirical models, Section III.G discusses our empirical results in light of our hypotheses, and section III.H concludes.

III.B Literature

The focus of this paper is on the ownership structure of the investment advisor and the incentive effects this structure has with respect to the advisor's responsibility to fund shareholders. Several papers have examined the role of the fund complex in the mutual fund industry, notably Khorana, Tufano, and Wedge (2006) and Gervais, Lynch, and Musto (2005). Abstracting from the mutual fund

⁸See, for instance, Sirri and Tufano (1993).

⁹For a survey of the literature relevant to delegated monitoring issues, see Stracca (2005).

industry, problems associated with the distribution of resources in internal capital markets have been examined in the corporate governance literature in the context of other types of firms. For example, Rajan, Servaes, and Zingales (2000) and Scharfstein and Stein (2000) both develop models of internal power struggles and rent-seeking behavior within diversified firms.¹⁰

The fund family literature has focused on other aspects of the relation of individual funds to the fund complex. Guedj and Papastaikoudi (2004) examine whether fund families promote funds that are most profitable to the family more than less profitable funds. They find evidence that funds belonging to larger families exhibit more performance persistence than funds belonging to smaller families. They explain the persistence by suggesting that larger fund families have more latitude to promote their most successful funds over other funds in the family. They also find evidence of within-family performance persistence.

A problem similar to ours was studied by Siggelkow (2005), who identifies the issue of competing incentives faced by mutual fund providers. He focuses on the ability of fund managers to shift expenses they would normally pay themselves onto investors. In particular, he examines the impact of 12b-1 fees and soft dollars on fund shareholders. He finds evidence that funds pass through 12b-1 fees to shareholders. He also documents evidence that competition among fund providers does not moderate the two agency relations managers find themselves in.¹¹ In our paper we suggest the ownership of the investment advisor is a mechanism through which investment advisor incentives may be closely aligned with fund shareholders.

Kempf and Ruenzi (2004) study competition for resources by funds within the same fund family using a tournament framework.¹² They argue that funds in

 $^{^{10}}$ The problem of allocating authority within a firm's hierarchy and the associated organizational design issues has been studied by Harris and Raviv (2005) and Aghion and Tirole (1997) in the context of other types of diversified firms.

¹¹Other studies of agency issues in mutual funds include Tufano and Sevick (1997), who study fund board incentives and Chevalier and Ellison (1997) who examine the incentives of the fund manager. Zitzewitz (2003) also studies agency issues at the level of the fund provider, but focuses on mechanisms for protecting investors from dilution.

¹²Kempf and Ruenzi (2004) build on a broader mutual fund tournament literature including Chevalier and Ellison (1997), Brown, Harlow, and Starks (1996) and more recently Goriaev, Nijman, and Werker (2005)

small families, in response to stricter competition, show risk-taking behavior that is distinct from larger fund families. The authors find evidence that fund rank within investment category and within family determine the risk-taking behavior of the fund. How a fund reacts to midyear rank depends on the number of competitors within the family and the segment. Our results suggest an alternative explanation for the relation between fund risk taking behavior and the size of the fund family.

Models of optimal fund family structure are developed in Gervais, Lynch, and Musto (2005). They examine the impact of ownership structure on the information transmitted by fund families about the degree of talent of their manager pool.^{13,14}

To our knowledge, the present paper is the first to conduct a broad empirical examination of the impact of the ownership structure of the advisor on the performance and expenses of the fund.

III.C Industry Structure

We are careful to distinguish between fund shareholders, who are owners of the mutual portfolio, and the shareholders in the investment advisor. Investment advisor shareholders have a claim on the profits of the advisor. We would expect the management incentives of the advisory firm to conform to the well established corporate governance literature. In particular, management incentives of the investment advisory firms themselves should not differ substantially from management incentives of firms in other industries. Shareholders in the advisory firm expect management to undertake profitable projects and generate positive returns to their investment of capital.¹⁵

¹³Other models of fund family interaction include Dybvig, Farnsworth, and Carpenter (2004), Garcia (2001), Garcia (2004), Garcia and Vanden (2005)

¹⁴Deli (2002) examines marginal compensation rates for mutual fund advisory contracts. He finds marginal compensation is greater for equity advisors than for debt advisors. He also finds that marginal compensation rates for advisors of foreign firms are greater than for domestic firms. The focus of his study differs from ours. We empirically examine the impact of organizational structure on advisor incentives.

¹⁵Related to this topic, there exists a broad and deep literature on the question of optimal industry structure applied to other industries. See, for example, Fama and Jensen (1985).

An investment advisor is charged with generating positive returns to the investment portfolio for the fund's shareholders. The fund's board of directors is responsible for oversight of the investment advisor and represents the interests of fund shareholders. Shareholders in the fund do not purchase shares of the investment advisor, they purchase advisory services with the expectation that the advisor makes investment decisions that generate positive returns to their portfolio, and the board of directors monitors the advisor throughout the process. The investment advisor's responsibility to fund shareholders is, among other things, to generate positive returns to the fund's portfolio. However, the advisor is also responsible to the advisory shareholders for generating positive returns to *their* investment of capital in the advisory firm.

For example, the shareholders of Bank X have expectations about the future profits of Bank X. If Bank X owns the investment advisor to Fund Y, the investment advisor to Fund Y must satisfy both her responsibilities to the fund shareholders and generate sufficient return to capital for Bank X to satisfy Bank X shareholders. In addition, the investment advisor has a fiduciary responsibility to Fund Y shareholders. While we assume the advisor does not necessarily violate her fiduciary duties, it is clear that she faces the added responsibility of maximizing the profitability of the advisory division of Bank X. If these responsibilities are at odds, the additional incentive to ensure the profitability of advisory services provided to the fund (and the return to capital for Bank X shareholders) may result in lower performance and higher expenses for Fund Y shareholders, relative to a comparable fund managed by an investment advisor with no such dual allegiance. Alternatively, if we believe that manager skill is decreasing in assets managed and that assets will flow in response to performance net of fees, into outperforming funds and out of underperforming funds to the point that managers capture any rents earned through their skill (as in Berk and Green (2004)), this may simply suggest that Fund Y will be smaller than a hypothetical comparable fund.¹⁶ The

¹⁶Other possible explanations include the existence of sophisticated and unsophisticated cohorts among investors, high and low search cost investors, and benefits which accrue to investors in Bank Y funds

board of directors of the fund are charged with the responsibility of monitoring the investment advisor and ensuring that the decisions of the advisor are in the best interest of shareholders.

As discussed above, we do not assume that the tradeoffs faced by investment advisors imply direct violations of their fiduciary duties. However, the investment advisor may, for example, employ trading services affiliated with the holding company and in so doing not receive best execution, thereby increasing associated trading fees. Alternatively, the tradeoffs may simply be reflected in the packaging of advisory services as part of a larger package of financial services available to fund investors. For example, the profitability of advisory service provision may increase if investors also purchase other financial services from the firm. Direct competition between subsidiary funds and non-subsidiary funds may be diminished by the fact that subsidiary funds are part of a package of financial services not limited to mutual funds alone.

The competing incentives faced by the investment advisor in this simple example illustrate the complexity of interactions among market participants in the mutual fund industry. As we add market participants, the interaction of their incentives becomes more complicated and the associated incentive impacts become progressively more difficult to measure. In the next section we provide a detailed description of the typical fund complex to identify the incentive interactions among market participants.

III.D Fund Complex Structure

The terms *investment company* and *investment advisor* have distinct legal definitions. An investment company is " \cdots a company (corporation, business trust, partnership, or limited liability company) that issues securities and is primarily engaged in the business of investing in securities."¹⁷ An investment company

that are not measured in performance and fees.

¹⁷For further details see http://www.sec.gov/info/advisers.shtml.

invests the money it receives from investors on a collective basis, and each investor shares in the profits and losses in proportion to each investor's interest in the investment company. The performance of the investment company will be based on (but will not be identical to) the performance of the securities and other assets that the investment company owns".¹⁸ This includes mutual funds (technically, open-end companies), closed-end funds, and unit investment trusts. Investment companies are regulated by the Investment Company Act of 1940, as well as the Securities Act of 1933 and the Securities Exchange Act of 1934. As the management, governance, and marketing structures differ across these three entities, the focus of the present paper is on open-end mutual funds.

A mutual fund is a legal entity with no employees. The fund is overseen by a board of directors (or trustees), that contracts with outside parties to act as investment advisor, underwriter, transfer agent, independent accountant, etc.¹⁹ The fund's independent directors are the only agents whose sole duty is to the fund's investors, hence the recent focus among regulators and academic researchers on the responsibilities and independence of such directors.²⁰

The assets of a mutual fund are typically managed by an investment advisor. An *investment advisor* is a person or organization employed by an individual, institution, or mutual fund to manage assets or provide investment advice. Such a person or organization registered with the SEC is referred to as a *registered investment advisor* and is regulated by the Investment Advisers Act of 1940 and related rules.²¹

A key characteristic of this structure is that the fund's directors have a fiduciary duty to ensure that the terms of the advisory contract are in the best interests of the fund's investors. This responsibility includes both selection of the investment advisor and approval of the form of the advisory contract (notably, the

¹⁸http://www.law.uc.edu/CCL/InvCoAct/index.html.

¹⁹For a detailed discussion of mutual fund board responsibilities, see Tufano and Sevick (1997)

²⁰For recent regulatory activities and rules see http://www.sec.gov.

²¹More detailed definitions and links to the text of the 1940 Act and related rules can be found at www.sec.gov/info/advisers.shtml.

advisory fee contract). The reality is somewhat more complicated.

Figure III.1 shows the typical fund complex structure, with particular emphasis on the agents involved and the relations among them. A mutual fund is organized as a legally independent entity, overseen by a board of directors.²² The board of directors chooses the investment advisor, who employs, either directly or by subcontracting with a third party, the fund manager(s). The fund's board of directors is comprised of independent directors, who are unrelated to the investment advisor or any of its entities, and interested directors, who are often employees of the investment advisor.²³ Recent SEC rule-making has endeavored to strengthen the independent oversight of fund managers by, among other things, requiring that at least 75% of directors be independent and requiring that the chairman (or lead director) be independent.

Several facets of this structure call into question the extent to which a mutual fund's legally independent status is reflected in its day-to-day operations. First, a fund is brought into existence by a *sponsor*, which in most cases is also the investment advisor.^{24,25} The typical process of fund creation involves an investment advisor acting as sponsor for a new fund and appointing the board of directors - typically composed of directors from the sponsor/advisor's other funds. The board of directors then contracts with the sponsor to act as investment advisor for the new fund. The group of funds sponsored and managed by a given investment advisor become known as a *fund family*. Thus, a broad strain of the academic literature examines fund proliferation as a multi-product branding strategy, an approach which is consistent with the de facto structure of the industry, but is at odds with funds' independent legal status.²⁶

 $^{^{22}}$ By *legally independent*, we mean that the fund is neither owned nor controlled by, in particular, the investment advisor.

 $^{^{23}}$ See Tufano and Sevick (1997) for a study of the role and responsibilities of the fund board.

²⁴A ramification of this is that changes of investment advisor typically occur through advisor-initiated merger or acquisition of the advisor, rather than through board-initiated actions.

 $^{^{25}}$ For more detail about the establishment of funds see the discussions in Tufano and Sevick (1997) and Sirri and Tufano (1993).

²⁶For example, Hortacsu and Syverson (2004) examine product differentiation in the mutual fund industry.

A related issue involves the extent to which directors play an active monitoring role on the fund board. A fund board typically oversees many funds within the same family. In fact, most fund families have a single board overseeing all funds, with the average number of boards per family less than two.²⁷ One might question how any board which oversees multiple funds can put the interests of each fund overseen first and foremost. In addition, this structure leads to questions about the degree of capture of the board by the investment advisor, particularly when interested board members hold sway over the board.

A result of this is that the independent legal structure of a mutual fund industry is not immediately transparent to the investing public, who identify funds as part of a larger fund family, such as Fidelity or Vanguard. Fund families can be viewed as marketing entities and are composed of one or more registered investment advisors. For example, Fidelity Investments (FMR Corporation), is one of the strongest brand names in the mutual fund industry. Fidelity is in fact composed of multiple registered investment advisors, among them Fidelity Management and Research Inc., Fidelity Management and Research (Far East) Inc., Fidelity Management and Research (UK) Inc., and Fidelity Investments Money Management Inc, each of which acts as advisor or subadvisor to one or more investment companies.²⁸

While a registered investment advisor is a clearly defined entity (owing to SEC regulatory requirements), the definition of a fund family is less clear. Empirical work at the family-level requires specifying this definition and a mapping data from funds to fund family. Commercial mutual fund data vendors such as Lipper, Morningstar and CRSP have each created this mapping. We rely on the CRSP definitions in this paper, a result of which is that combining data from, for example, the CRSP database with data culled from publicly available SEC filings

 $^{^{27}\}mathrm{See},$ for example, Meschke (2005). As of 2004 fund families managed on average 12 portfolios (32 classes) per family.

 $^{^{28} {\}rm Information}$ registered related to investment advisors is electronically obtainable from the SEC's Investment Adviser Public Disclosure website atwww.adviserinfo.sec.gov/IAPD/Content/IapdMain/iapd_SiteMap.aspx.

is nontrivial.

As Figure III.1 suggests, there are a number of other actors in the mutual fund industry, including the underwriter and transfer agent. These entities may or may not be affiliated with the investment advisor, which may introduce additional conflicts of interest. The focus of this paper is limited to the relation between the investment advisor and associated parent firm, that between the investment advisor and the subadvisor, and the effects these relations have on fund expenses and performance.²⁹

III.D.1 Investment Advisor Ownership

In this paper, we examine the ownership characteristics of the fund family. For example, Fidelity (FMR Corp.) is a privately held firm, while Nations Funds is a subsidiary of publicly-owned Banc of America, and Vanguard is mutualized. We suggest that the ownership structure of the investment advisor plays a crucial role in determining how fund managers balance the (at times contradictory) interests of the investment advisor and fund shareholders. We argue that fund managers' actions in balancing these dual interests may directly affect performance and/or expenses. Several recent speeches, interviews, and books (in particular Bogle (2005) and Swensen (2005)) have echoed this idea.

We note that privately owned investment advisors are typically employeeowned. This may result in a greater percentage of advisor profits going to the investment manager, which should serve to attract the most skilled managers to these types of families. In this case, we would expect to see directly privately held families outperform mutualized and publicly-owned families. However, the empirical evidence on performance persistence calls into question this hypothesis.

We suggest that the primary difference across ownership types is in the degree of concentration of ownership. We define three categories of ownership of investment advisors: mutualized entities, publicly held entities and privately held

²⁹Figure III.1 also provides a framework for discussing potential conflicts arising from such issues as pay-for-play, soft dollars, and 12b-1 fees.

entities. At one end of the spectrum, directly mutualized entities avoid many conflicts of interest since the owners of the investment advisor and the fund shareholders overlap perfectly. Publicly held investment advisors, where ownership is diffuse and the owners may be primarily interested in the short-term profitability of the investment advisory firm, lie at the other end of the spectrum. Between these two organizational structures are privately held investment advisors, where ownership is more highly concentrated than in the publicly held case, but does not necessarily reside with the shareholders of the fund. We suggest that more concentrated ownership of the investment advisor may lead to a longer investment horizon on the part of the firm's owners, which may be reflected in quality of governance. This, in turn, may be reflected in fund managers' attitudes towards shareholder interests and thus result in lower expenses and/or higher performance.

This leads to the following testable hypotheses.

- H1 Mutualized fund families outperform privately held families, gross of fees, which in turn outperform publicly held families.
- H2 Mutualized fund families charge lower fees than privately held families, which in turn charge lower fees than publicly held families.

III.D.2 Subsidiary Type

Roughly half of investment advisors in the mutual fund industry are subsidiaries of larger concerns. We suggest that the other businesses within which a parent entity operates may affect the levels of performance achieved and fees incurred by a subsidiary family. To illustrate this effect, we present the mutual fund value chain (Sirri and Tufano 1993) in Figure III.2. Sirri and Tufano (1993) posit two views of the mutual fund industry: the activity based (or institutional based) view and the functional view. The activity based view of mutual funds defines funds according to the activities the fund performs.³⁰ Figure III.2 depicts

 $^{^{30}}$ Sirri and Tufano (1993) describe the functional view of mutual funds in which the fund is defined according to its most basic economic functions. For example, a fund can function as a payments system

the activities performed by a fund within the typical fund complex. These activities equate to ways in which the complex can affect performance, lower costs, and/or differentiate products. Both economies of scale and economies of scope (i.e. synergies) can be derived from each of the activities performed by the fund.

Figure III.2 motivates our hypotheses that subsidiary type may impact fund expenses and performance. The benefits of economies of scale may come in the form of greater expertise in investment selection (alternatively, more investment in research efforts), lower trading and execution costs, or more efficient record keeping and reporting.³¹ Our hypothesis is that economies of scale may result in higher returns or lower expenses to larger conglomerates.³²

Similarly, economies of scope may be realized across multiple steps in the value chain. Subsidiaries of diversified financial services conglomerates (typically brokerages) may have access to better investment selection and lower trading and execution costs through the parent firm.

Alternatively, benefits from economies of scope may arise from 'one-stop shopping'. That is, investors seek to minimize the total costs of managing their portfolio of financial services, including asset management, banking, mortgage and insurance. Investors may value coordinated record keeping and reporting resulting from having their mutual fund investments through their bank, broker, or insurance provider. Similarly, investors may face high search costs and thus realize substantial saving by 'one-stop shopping'. To the extent that investors value the consolidation of their investments in this fashion, they may be willing to sacrifice some of their returns, pay higher expenses, or both. Finally, firms may provide discounts across funds or other financial products in order to retain customers within

the firm.³³

for exchange, a mechanism for pooling funds in order to undertake large indivisible projects, a way of managing risk through selling, hedging and diversifying, and a way of dealing with the agency problems created by asymmetric information. The mutual fund industry accomplishes many of these economic functions.

 $^{^{31}}$ Baumol, Goldfeld, Gordon, and Koehn (1990) and Collins and Mack (1997) have documented evidence of economies of scale in the mutual fund industry.

 $^{^{32}}$ This is not to say that there is not a point at which diseconomies of scale may occur.

³³For a detailed discussion of investor capture by mutual fund complexes and financial conglomerates

Notably, these benefits are not expected to be realized in the form of higher performance or lower fees. This implies that performance and fees are only two of numerous dimensions across which mutual funds compete, and conglomerate affiliation may provide subsidiary funds with opportunities to trade off between performance, fees, and these other dimensions. This suggests that there may exist an equilibrium in which performance and fees vary systematically across subsidiary types. Thus, while we posit that economies of scale are related to higher performance and lower expenses (at least within some range), economies of scope may be related to higher or lower performance and expenses.

We categorize parent conglomerates according to their core business as follows:

- 1. Bank (eg: TD Waterhouse is a subsidiary of Toronto Dominion Bank),
- 2. Insurance Company (eg: Russell Investment Group is a subsidiary of Northwestern Mutual),
- 3. Diversified Financial Services Company (eg: Smith Barney Asset Management is a subsidiary of Citigroup),
- 4. Dedicated Mutual Fund Company (eg: Tweedy Browne is a subsidiary of Affiliated Managers Group),
- 5. Other (eg: AMR Investment Services and General Electric Investment Corp are subsidiaries of American Airlines and GE, respectively).³⁴

Each of these conglomerate types varies in potential scale and scope efficiencies. This suggests the following hypotheses with respect to performance and fee differences across subsidiary types.

H3 Families affiliated with diversified financial services conglomerates outperform dedicated mutual funds, gross of fees, which in turn outperform bank and insurance affiliates.

see Sirri and Tufano (1993).

³⁴There are 11 families defined subsidiaries as 'other' in our sample

H4 Families affiliated with diversified financial services conglomerates charge lower fees than dedicated mutual funds, which in turn charge lower fees than bank and insurance affiliates.

III.D.3 Sub-Advisory Services

Most mutual fund portfolios are managed by employees of the investment advisor. However, a non-trivial proportion of funds, roughly 13% at year-end 2004, are subadvised in part or in whole. That is, the investment advisor has contracted externally for some or all fund management services. An investment advisor may even act both as advisor to to it's own family of funds as well subadvisor to one or more funds offered by another family. Haslem (2003) describes three forms of subadvisory relations. In the first form, the subadvisor has complete management responsibility for a specific fund. For example, a fund family may hire a subadvisor to manage an international fund, where the subadvisor has responsibility for all aspects of managing the entire portfolio. The fund is marketed under the banner of the fund family, but is actually managed by the subadvisor, which may or may not manage and market its own funds. In the second form of the advisory relation, the fund family employs (directly) a lead advisor (who may manage part of the portfolio) and contracts with one or more subadvisors to manage specified part(s) of the portfolio. In the third form, the investment advisor may provide active portfolio guidance, while contracting with (one or more) subadvisors for direct portfolio management.

It bears noting that in many cases the advisor and subadvisor share a common owner. Empirical investigators using a data source which only flags the existence of a subadvisor without providing the subadvisor's identity, such as ours, must be aware of this. In this case it may be difficult to identify systematic differences between directly-advised and subadvised funds, even if such differences exist.³⁵

³⁵At present, we are building a database which will include subadvisor name for each subadvisor managing part of all of a fund, allowing us to correct for affiliated subadvisors.

One popular example of the second form discussed above is the use of *multimanagers*, where the portfolio diversifies management by investment style using separate managers for each style. The fund may periodically re-allocate capital among multimanagers to preserve the aggregate investment style of the portfolio If re-allocation occurs frequently, the overall portfolio strategy indirectly becomes one of timing subadvisor performance.

Given these subadvisory relations, we identify the following possible motivations to subadvise.

- 1. To take advantage of economies of scale in investment management.
- 2. To purchase general investment skill not held by the nominal advisor.
- 3. To purchase category-specific investment skill not held by the nominal advisor.
- 4. To capture reputation effects of a well-known subadvisor.
- 5. To avoid the return-damping effects of large funds by farming out management of some portion of the portfolio.

Thus, we form the following empirically testable hypotheses related to subadvising.

H5 Small fund families are more likely to hire subadvisors for funds not in their core specialization.

H6 Large funds are more likely to hire a subadvisor for part of the fund.

H7 'Star' families are less likely to hire subadvisors.

Furthermore, each of the motives to subadvise above suggest that the goal is either to increase performance or to decrease expenses. In the former case, it may be naturally expected that investors will realize higher returns. In the latter case, it is unclear whether lower expenses will be passed along to investors, or whether the nominal advisor will absorb any such benefits.³⁶ We therefore posit the following hypotheses.

H8 Subadvised funds outperform directly advised funds, gross of fees.

H9 Subadvised funds charge lower fees than directly advised funds

III.D.4 Equilibrium Models of the Mutual Fund Industry

Our hypotheses appear to contradict recent theoretical work. In particular, Berk and Green (2004) develop an equilibrium model which explains a number of stylized facts in the mutual fund industry by assuming managerial skills are decreasing in the level of assets managed.³⁷ Investment dollars flow from unskilled to skilled managers to the point that returns net of fees are constant across all funds and, in equilibrium, investors earn zero (economic) profits as managers capture all rents generated by their skill.

There are several reasons we expect to find deviations from Berk and Green's theoretical predictions in the data. Most importantly, Berk and Green (2004) do not model the benefits accruing to, and costs faced by, investors not captured in returns and expenses. We argue that such costs and benefits may derive from characteristics of the fund family, as discussed in sections III.D.1 and III.D.2 above. If these hidden, potentially non-pecuniary, costs and benefits vary systematically across fund family ownership and subsidiary types, then an equilibrium may exist in which returns and expenses (and especially returns net of expenses) vary systematically across these family types. This suggests that a finding that one family type provides investors with higher performance net of fees than another type does not unequivocally imply that such families are better than

³⁶This effect may make it difficult to empirically identify motives to subadvise. We are currently working on building a database which will include both the nominal investment advisor and the name of the subadvisor. This will allows us to compare directly advised funds with those which are subadvised.

³⁷These stylized facts include returns-chasing behavior on the part of investors, lack of persistence in performance, and the dearth of evidence that active managers outperform passive benchmarks in the face of overwhelming evidence that market participants believe such skill exists

others. Rather, it may be the case that other family types provide investors with greater non-pecuniary benefits.

Second, it is unclear how quickly the industry will return to a steady state subsequent to a 'shock'. In the mutual fund industry, such a shock may arise from a structural shift in the securities markets resulting in a redistribution of investment skill across managers (for example, the internet boom). Alternatively, the entry and exit of firms may temporarily move the system away from a steady state equilibrium. Empirical evidence suggests that investment flows respond to performance over subsequent quarters. Thus, broad historical studies may find evidence of persistent deviations in net performance as the industry returns to the steady state.

Finally, Berk and Green (2004) assume no asymmetric information, and endow both investors and managers with identical mechanisms for updating expectations on managerial skill. The assumption of symmetric initial information is not unreasonable, however assuming investors and managers update their priors identically is a much stronger assumption. Specifically, we suggest that there are similarities between the process of choosing investments and the process of choosing managers. Thus, if we assume that agents (managers) with investment skill exist, it is not unreasonable to assume agents with skills to identify good managers should also exist. In fact, we would argue that these skill sets are related and that skilled managers will more efficiently update their priors on manager skill than will unskilled managers (or investors). A number of papers have specifically addressed this issue in the context of fund families as delegated monitors of investment managers.³⁸

³⁸For an example, see Gervais, Lynch, and Musto (2005).

III.E Data Description and Variable Derivations

III.E.1 Data Sources

Our dataset is derived from three distinct sources. The primary source is the Center for Research in Securities Prices' Survivor-Bias Free US Mutual Fund Database (CRSP), which contains monthly price and asset data, and annual characteristics, for the entire US open-end mutual fund universe from 1962 to the present.³⁹ We augment CRSP with data from the Strategic Insight Simfund database (SI).⁴⁰ The SI data include a wide range of portfolio- and class-level variables, notably primary distribution channel, a flag indicating whether the portfolio is subadvised, and a wealth of fund flow and investment strategy information. While the Simfund database includes some historical data, the bulk of the information covers 2004. Of particular note is the SI mapping from class to portfolio.⁴¹

We augment these commercially available data sources with fund family ownership data manually collected from fund family web sites, fund prospectuses and SAIs, form ADV, and Hoovers.com. For each fund family in the CRSP database from 1995 through 2004, we characterize the ownership structure of the family in terms of whether the family is a subsidiary of a larger entity, what the primary business of that entity is, and whether it (or the fund family, if not a subsidiary) is privately held, publicly held, or mutualized.⁴² We categorize the primary business of a parent entity as either banking, insurance, diversified financial

³⁹Source: CRSP®, Center for Research in Security Prices. Graduate School of Business, The University of Chicago 2005. Used with permission. All rights reserved. www.crsp.uchicago.edu

⁴⁰Source: Simfund, Strategic Insight, Inc. 2005 www.sionline.com. All analysis and commentary based on the Simfund data are the products of the authors only.

⁴¹Difficulties arise in creating a mapping between the CRSP and Simfund databases. Although both databases include CUSIP and ticker symbol at the class level, the degree of completeness in these identifying variables varies across the two sources. Ticker is especially difficult to match on, as tickers symbols are routinely reused. The format of fund names also varies between the two data sources, making matching difficult. Where possible we match on CUSIP. Otherwise, we match on ticker symbols. All ticker and CUSIP matches were verified by fund name, with remaining unmatched funds matched manually by fund name. The CRSP database includes data at the class and family levels, the Simfund data at class and portfolio levels, and our hand-collected ownership data is at the CRSP family level. Having matched the CRSP and Simfund data at the class level allows us to include the full complement of variables in class, portfolio or family level analysis, aggregated appropriately.

⁴²We group non-profit entities with mutualized

services, mutual fund, or other.⁴³ In addition, we identify whether the family is foreign-owned, and whether a subsidiary is 'buried', defined as the parent entity not being obvious to the casual investor.⁴⁴ For families that changed ownership during the period through, e.g., merger, acquisition, public offering, mutualization, or de-mutualization, we identify the date of such change as well as the 'new' and 'old' ownership structure. These changes were identified through SEC filings, form ADV, and historical news sources.⁴⁵ Our final sample consists of 1,002 familyownership pairs covering 1995-2004. At the end of 2004 our sample includes 547 families managing roughly \$7.8 trillion, including 176 publicly held fund families, 336 privately held families and 35 mutualized or non-profit fund families.

Choice of unit of measurement

It is beneficial to discuss the question of the appropriate unit(s) of measurement, in terms of the analysis we undertake in the present paper and the relation to our data. A mutual fund family is composed of a number of portfolios, each offering one or more share classes which vary primarily in expenses and distribution channel. Accordingly, mutual fund data is collected at a variety of levels. For example, family ownership characteristics are observed at the family level, investment policy characteristics are observed at the portfolio level, and expenses and reported returns are observed at the class level.⁴⁶

The appropriate unit of measurement depends on the question being asked. Expense models may be best structured at the class level, although the researcher may wish to use an asset-weighted average of class-level expenses in a portfolio-level or family-level model. Similarly, an analysis of family ownership is most appropriate at the family-level, using asset-weighted averages of class- and

 $^{^{43}\}mbox{`Other'}$ nests a variety of non-financial entities, including General Electric, American Airlines, and several religious orders

⁴⁴We define 'obvious' as having a similar name. This is, admittedly, somewhat ad hoc.

⁴⁵As our data is in annual series, we assign the ownership structure under which a family operated for the greater part of the year for any family-year in which the structure changed.

⁴⁶Not to mention fund governance characteristics, which are observed at the board level. While smaller fund families typically have a single board overseeing all funds in that family, many of the larger fund families are composed of multiple boards, each overseeing a subset of funds.

portfolio-level covariates. However, family-level studies of limited cross-sectional and time series dimensions may face substantial power issues. We attempt to avoid these issues by estimating models at both the class-level and family-level, using asset-weighted averages of variables which vary across classes.

SI-derived fund styles and distribution channel measures

The CRSP database provides several fund categorization schemes. For consistency, we use the Strategic Insight Fund Objective codes. We map the SI objectives into 6 broad fund classes: Growth, Growth & Income, Bond Income, Sector, International, and Money Market. In addition, a novel aspect of the Simfund data is the inclusion of the primary distribution channel.

III.E.2 Variable Definitions

Performance and Expense Measures

Several issues arise in estimating annual α . Direct estimation using annual return data is hampered by data availability, primarily as a result of the vast number of new funds with an insufficient history to permit estimation. Estimation using annual returns is also made difficult by the extent to which funds change investment strategy, and thus factor loadings, either directly through changes in stated investment strategy or indirectly through manager changes. Although estimation of monthly α is relatively straightforward, temporal aggregation to annual α raises other issues. Unlike raw returns, α is not by definition constrained to be greater than -1, and compounding may, in extreme cases, lead to misleading results. We choose to estimate monthly α and use the average of these monthly values as an estimate of annual alpha,

Specifically, we estimate the monthly 4-factor α (Carhart 1997), α_{it} , as follows:

$$r_{it} - r_{ft} = \alpha_{it} + \beta_{1i} \left(r_{mt} - r_{ft} \right) + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} MOM_t + \epsilon_{it},$$
(III.1)

where, r_{it} denotes the return to fund *i* in month *t*, r_{mt} denotes the market return in month *t*, and SMB_t , HML_t , and MOM_t are the small minus big, high minus low, and momentum factors.⁴⁷

The costs of mutual fund ownership borne by investors include the fund's stated expense ratio, 12b-1 sales and marketing fees, sales loads, and redemption fees. Load fees are charged either as front-end loads or contingent deferred sales loads, commonly referred to as CDSLs or 'back-end' loads. Front-end loads are payable upon entering the fund and subject to discount depending on amount invested (referred to as *breakpoints* and typically decreasing step-wise to zero for investments of \$1 million or more).⁴⁸ CDSLs typically decrease by one point per year invested in the fund. While no standard rule exists for annualizing loads, a common approach is to divide the maximum total load by 7 years, the approach we use here.⁴⁹ In addition, many funds charge a redemption fee on withdrawals within a set period from purchase, typically ranging from a few weeks to one year. We treat redemption fees separately from expense and load fees.

We expect that funds with different investment strategies may face different cost structures in terms of research and execution costs. We therefore define all performance and expense variables as net of category averages using broad fund categories derived from SI objective codes. For example, the (asset-weighted) average α across all classes in category S at time t, $\overline{\alpha}_{St}$ is given by

$$\overline{\alpha}_{St} = \frac{\sum\limits_{s \in S} \alpha_{st} T N A_{st}}{\sum\limits_{s \in S} T N A_{st}},$$
(III.2)

where TNA_{st} denotes the total net assets of the s^{th} fund in category S at time t.

⁴⁷We thank Ken French for making these factors readily available on his web site.

 $^{^{48}\}mathrm{In}$ the absence of investor-level purchase and redemption data, we are unable to correct for breakpoints.

⁴⁹This differs from Bergstresser, Chalmers, and Tufano (2006), who annualize over five years.

We define asset-weighted category averages for returns, annualized loads, 12b-1 fees, and non-12b-1 expenses analogously. For each class in our sample, net-of-category-average measures are calculated by subtracting the corresponding category average from the class-level value:

$$\alpha_{it}^{NetCatAvg} = \alpha_{it} - \overline{\alpha}_{St} \tag{III.3}$$

for class i in category S. Portfolio- and family-level net-of-category-average measures are calculated as asset weighted averages of the component class-level values.

Fund families are heterogeneous in the types of costs captured in reported expense ratios, and those costs paid directly out of fund assets. Similarly, funds that charge neither load fees nor 12b-1 fees nevertheless bear some cost of attracting and servicing new clients, which must either be paid out of fund assets or be (implicitly) included in the expense ratio. This makes comparisons of expenses across funds with different cost structures difficult. In an attempt to circumvent these issues, we calculate both gross performance measures (before expenses are taken into account) and performance measures net of expenses. In the latter case, we use both performance net of expenses only, and performance net of expenses including annualized loads.⁵⁰ These measures are calculated as follows (using netof-category-average values).⁵¹

$$GrossPerformance_{it} = Return_{it},$$
 (III.4)

$$NetPerformance_{it}^{1} = Return_{it} - Expenses_{it},$$
(III.5)

$$NetPerformance_{it}^{2} = Return_{i,t} - Expenses_{it} - (1/7) TotalLoad_{it}.$$
 (III.6)

Net α measures are calculated in a similar fashion.

⁵⁰Here, expenses equals non-12b-1 expenses plus 12b-1 expenses.

 $^{^{51}}$ Note that since CRSP returns are calculated from dividend-adjusted changes in NAV, and expenses are deducted from fund assets on an ongoing basis, the reported CRSP return is equivalent to $NetPerformance^{1}$.

Fund Flows

We define the flow of new assets into or out of a fund as the percentage change in total net assets of the fund during a given period, net of returns. Following the methodology in Nanda, Wang, and Zheng (2004) we call this *New-MoneyGrowth* (*NMG*) and estimate it as follows:

$$NewMoneyGrowth_{it} = (TNA_{it} - (1 + r_{it})TNA_{it-1})/TNA_{it-1}, \qquad (III.7)$$

where r_{it} is the raw return to, and TNA_{it} is the level of total net assets managed by, the i^{th} fund during period t.

A number of issues arise when estimating net flows in this manner, chief among them the degree to which the estimate is dependent on comovements in daily returns and flows over the period. Broad empirical mutual fund analysis almost universally rely on monthly data, and to our knowledge no studies have addressed the potential biases of doing so.⁵² It can be shown that NMG as defined above is a biased estimate of actual net new investment in the case where actual daily flows are correlated with returns. While this may be inconsequential for broadly diversified funds dominated by buy-and-hold investors, the recent market timing and late trading scandals have come about as a result of exactly the kind of behavior which will result in biased estimates of NMG. Researchers, particularly those studying the causes and effects of market timing and late trading, would be advised to keep this in mind.

These issues may be exaggerated when estimating annual flows. The naive approach of using beginning of year and end of year total net assets and the return over the year is of course even more path dependent than the monthly case. Alternatively, summing monthly estimates of net dollar flows and dividing by lagged (i.e. end of prior year) total net assets will still result in potentially problematic estimates of NMG in extreme cases. A fund that is tiny at the

⁵²Several authors have obtained access to daily flows through, for example, TrimTabs, but for only a subset of funds.

beginning of the year and grows dramatically during the year will result in an enormous estimate of annual NMG which, while accurate, will impact the analysis unless scale issues are addressed.

Measures of Family Level Category Concentration

Following the method in Khorana and Servaes (2006) and Siggelkow (2003), we estimate measures of category concentration and investment focus for each category within a family and for each family as follows. For each category C in which family j offers one or more funds at time t, we calculate the percentage of family assets in that category, *relatedness*_{Cjt}:

$$Relatedness_{Cjt} = \frac{\sum_{i \in C} TNA_{it}}{\sum_{i} TNA_{it}},$$
(III.8)

where TNA denotes total net assets in the i^{th} fund of family j, and $i \in C$ denotes that fund i is in category $C.^{53}$

We subsequently define the following Herfindahl-like measures of fund style concentration for each family;

$$Focus_{jt} = \sum_{C} \left(\frac{\sum_{i \in C} TNA_{it}}{\sum_{i} TNA_{it}} \right)^2,$$
(III.9)

where C specifies the set of categories in which family j manages funds. Thus, $focus \in (0, 1]$, with $focus_{it} = 1$ indicating a family with all funds in a single category.

Each class and portfolio will have associated *relatedness* and *focus* measures, while each family will have an associated *focus* measure only.

⁵³Throughout our empirical work, we assign each fund to one of the following 6 broad categories: growth, growth and income, bond income, international, sector, or money market. These are an aggregation of the Strategic Insight objective code from the CRSP database.

III.E.3 Univariate Statistics

Tables III.1, III.2, and III.3 summarize our fund family ownership data. Table III.1 includes counts, average assets managed per family, and total assets managed by ownership and subsidiary type categories as of the end of 2004. Our sample covers virtually the entire mutual fund universe, including 547 US mutual fund families at year end 2004, which managed some \$7.8 trillion. Of these, 176 were publicly owned managing \$4.3 trillion, 336 were privately held managing \$2.3 trillion, and 35 were mutualized managing \$1.2 trillion. Of the mutualized families, only two are directly mutualized (Vanguard and ICMA, which is in fact non-profit), and accounted for \$870 billion in assets. We note that 64% of assets were managed by 351 families that were either non-subsidiaries or subsidiaries of larger fund complexes (as opposed to subsidiaries of diversified conglomerates), and that sizeable proportions of the total industry are managed by each of bank-, insurance-, and diversified financial services conglomerates.⁵⁴ It bears noting that the industry is dominated, in terms of assets managed and number of fund offerings, by a handful of large families. The top three families–Fidelity, Vanguard, and American Funds (managed by Capital Research and Management), each manage the lion's share of assets within their category (directly privately held, mutualized, and subsidiary of privately held, respectively). Conversely, the population of fund families is dominated by directly privately held mutual fund companies which are (with the exception of Fidelity), smaller than average in terms of assets under management. This characteristic of the industry may result in marked differences between class-level and family-level analyses.

Table III.2 includes two-way sorts of class-level performance measures net of category averages across ownership and subsidiary types, using 1995-2004 data. The data suggest a consistent pattern in unconditional category-adjusted performance both gross and net of expenses across subsidiary type, with 'other', dedi-

⁵⁴The current sample differs markedly from that in the prior draft of this paper, which covered only the largest 128 fund families. The smaller families are predominantly directly privately held. This has ramifications for the results of our empirical analyses.

cated mutual fund, diversified financial services, bank, and insurance subsidiaries ranked highest to lowest in three of the four measures. However, using gross returns, insurance and diversified services switch rankings. Furthermore, in 10 of 12 cases, funds managed by directly owned families outperform their subsidiary counterparts. Finally, there is evidence, again in 10 of 12 cases, that publicly owned families underperform privately held and mutualized families. Depending on performance measure used, the difference ranges from a few basis points to as high as 147 basis points annually (directly mutualized relative to directly publicly owned using returns net of all expenses).

In Table III.3 we present 3-way sorts of class-level performance measures across ownership type, subsidiary type, and the subadvised/non-subadvised flag using 2004 data. Panels A and B include gross α and gross returns net of category averages, while panels C and D include these measures net of expenses including 12b-1 fees and annualized load.

In each of the four cases (gross α , net α , gross returns and net returns), subadvised funds underperform non-subadvised funds overall by approximately 1 basis point annually in gross measures, and 11 and 28 basis points annually in α and returns net of expenses, respectively. These differences are statistically significant, although the economic significance of a 1 basis point difference is debatable. Interestingly, subadvised funds offered by dedicated mutual fund families and 'other' subsidiaries outperform their non-subadvised peers in each of the four measures, while subadvised funds offered by insurance subsidiaries underperform. Subadvised funds offered by either diversified financial services- or bank-affiliates earned higher gross α and returns, but lower performance net of expenses. In terms of ownership type, subadvised funds offered by publicly owned families and those offered by privately held subsidiary families underperform their non-subadvised peers, while those offered by mutualized families and those offered by directly privately held families outperform.

We include in Table III.4 a series of summary statistics at the class- and

family-level. Panels A and B include class-level data for 1995-2004, by ownership type and subsidiary type respectively. Panels C and D include the corresponding family-level statistics.

Across our sample, the average class managed approximately \$422 million, had average annual net inflows of \$15 million, and achieved average annual returns of 6.53% with an average 4-factor α of -0.09.⁵⁵ At the family level, the average family managed \$10.7 billion in 25 classes, had net annual inflows of \$89.9 million, and achieved asset weighted average returns and α of 8.62% and -.05%, respectively. These average performance numbers are consistent with previous studies of the mutual fund industry, which suggest that funds on average earn positive returns but negative α .

From panel A of Table III.4 we note that, in the mutualized and privately owned cases, funds managed by directly owned funds tend to charge lower fees and achieve higher performance than those managed by subsidiaries. However, this is not apparent in the publicly owned case. This result is reflected at the family level in Table III.5. Average performance measures by subsidiary type (in panel D) are mixed at both the class level and panel level, although there is evidence that non-subsidiaries and subsidiaries of 'other' provide investor with both higher returns and α at lower cost than do subsidiaries of banks, insurance companies, and financial services conglomerates.

We hesitate to draw conclusions based on these (unconditional) results, since fund offerings may vary systematically across ownership and subsidiary type, particularly in size, investment style, and distribution. However, our empirical results in section III.F below will address these issues.

Other characteristics of the data warrant comment. The reader will note that in both the class- and family-level tables, the minimum observed values of Stocks(%), Bonds(%), and Cash(%), are negative, while the maximum values are

 $^{^{55}}$ Note that these summary statistics were calculated across the universe of funds, and the outliers indicated by -96.80% and 977.04% *return(%)* (among others) were dropped in estimating the models due to missing data.

greater than 100%. While it is commonly believed that mutual funds are prohibited from holding short positions, this is not the case. Rather, the nature of IRS rules and the wording of the Investment Company Act have historically served to discourage this practice.⁵⁶ However, there are a handful of funds which characterize themselves as *long-short* or *market neutral*, and which hold both long and short positions.⁵⁷

III.E.4 Econometric Issues

Heteroscedasticity

For each of the linear models presented below, we report t-statistics from heteroscedasticity-consistent covariance matrices using the jackknife approach.⁵⁸

Power

Equity returns are, by their very nature, noisy. It follows that mutual fund returns are also by nature noisy. A result of this is that standard econometric techniques typically suffer from low power in models of returns. This is an issue of direct concern for this project, since our variables of interest (ownership and subsidiary type) are observed at the family level and the number of families in the industry is small relative to the number of funds and classes offered. We have attempted to mitigate this issue by collecting data on nearly the entire universe of fund families over ten years, and by estimating models at both the family- and class-level.⁵⁹

The current data covers all CRSP families from 1995-2004 and corrects for mergers, acquisition and other ownership-changing events, Thus, our dataset

 $^{^{56}}$ Until its repeal in 1996, IRS Code section 851(b)(3) indirectly limited short selling by mutual funds, limiting the fraction of gross income which could be generated by the sale of securities held for less than three months.

⁵⁷In fact, effective March 1, 2006, Morningstar has introduced a long-short category including 30 funds. ⁵⁸For details, see Davidson and Mackinnon (1993).

⁵⁹In a previous version of this paper, which included data on only the largest 128 fund families at 2004, we also estimated models at the portfolio-level. These models have been dropped in the current draft as we have access to a class-portfolio mapping only for 2004, and such results were largely uninformative.

is free of both survivorship bias and look back bias.

Strong statistical evidence of a relation is a necessary but by no means sufficient condition for success in empirical research. One must also weigh the magnitude of such results and assess their economic significance. Where possible, we have stated all flow variables in annual percentage terms in order to enable the reader to better judge the economic significance of our results.

Endogeneity

An important issue which arises in our analysis is the choice of specification relating to the timing of dependent and independent variables. A key question relates to the timing of expenses relative to returns. Most of a fund's stated expense ratio is the management fee, which is set (or at a minimum, approved) *ex ante* by the fund's board of directors or trustees on an annual basis. 12b-1 fees and sales loads are similarly set in advance. Accordingly, models with expenses on the left hand side should be specified with lagged covariates. We make a similar argument for the lagged specification of our logit and generalized logit models of subadvising and subsidiary type. Conversely, since expenses are paid contemporaneously with returns (at least in annual series), we argue that performance should be a function of contemporaneous expenses and specify our annual return and α models accordingly.

However, it has been noted that not all of a funds stated expenses are predetermined. This may arise from a lack of consistency in the components of stated expense ratios across the industry, as well as from the existence of performance-fee schedules in determining management fees.⁶⁰

If we specify expenses as a function of contemporaneous covariates, we are faced with a system of two simultaneous equations in two endogenous variables (performance and expenses). As a robustness check we estimated this system of equations using ordinary least squares as the baseline model, and two-stage least

⁶⁰Such incentive performance-fee schedules are the exception in the mutual fund industry and must be, by regulatory requirement, symmetric.

squares, three-stage least squares, and seemingly unrelated regression techniques to address the simultaneity.⁶¹ In addition, we performed Hausman's test across these specifications. While we have omitted these results in the interests of space, the results are qualitatively similar to the lagged specification employed below, and Hausman's test favored the OLS specification. Similarly, we employed a Heckman approach to estimate logit models of subadvised and subsidiary flags with contemporaneous covariates, with results qualitatively similar to the lagged specification used below.

III.F Empirical Results

III.F.1 The Relation Between Performance, Expenses and Industry Structure

In order to empirically test for relations among performance, expenses, and industry structure, we estimate a series of linear regressions of the following general form:

$$\begin{aligned} PerfMeasure_{it} &= \beta_0 + \beta_1^{'} OwnSubsidTypes_{it} \\ &+ \beta_2^{'} ExpMeasure_{it}^{'} + \beta_3^{'} \Phi_{it} + \epsilon_{it}, \end{aligned}$$

where $PerfMeasure_{it}$ denotes one of 6 performance measures; $ExpMeasure_{it}$ denotes one of three expense measures; $OwnSubsidTypes_{it}$ denotes a vector of fund family ownership and subsidiary characteristics; and Φ_{it} denotes a vector of characteristics of the i^{th} class, portfolio, or family.⁶²

Specifically, we use as expense measures either (1) expenses net of 12b-1 fees, (2) expenses including 12b-1 fees, or (3) expenses including 12b-1 fees and one

⁶¹We note that 2SLS and 3SLS approaches are highly sensitive to poor fit in the first stage. Notably, models of α and returns tend to exhibit poor fit. In this case, any decrease in bias resulting from addressing the simultaneity may come at the cost of a substantial decrease in efficiency, and these approaches are suspect.

 $^{^{62}}$ We also estimates a series of similarly specified models of expenses on lagged performance, Own-SubsidTypes, and Φ . These regressions are omitted in part in the interest of space and in part because similar intuition is captured in modeling performance net of expenses. However, we refer to these results below.

seventh of the maximum total load. All are calculated as net of category averages. Performance measures are also calculated as net of category averages and include (1) gross returns and gross 4-factor α , (2) returns and α net of expenses including 12b-1 fees, and (3) returns and α net of expenses including 12b-1 fees and one seventh of the maximum total load. We employ such a broad menu of expense and performance measures in an effort to both nest a wide range of expectations with respect to investors' objective function, and enable fair comparisons across load and no-load fund families.⁶³

We group variables into three categories. Performance and expense measures are as discussed in section III.E.2 above. $OwnSubsidTypes_{it}$ includes the following fund family ownership and subsidiary type flags:⁶⁴

- 1. Ownership Type: Mutualized, Privately Held or Publicly Owned;
- 2. Subsidiary Type: Bank Affiliate, Insurance Affiliate, Diversified Financial Services Affiliate, Other Affiliate, or Non-Subsidiary;
- 3. Buried Subsidiary Flag: Dummy variable set to 1 if the fund family subsidiary relation is not obvious;
- 4. Foreign Owned Flag: Dummy variable set to 1 if the fund family is a subsidiary of a non-US owned conglomerate.

 Φ_{it} is comprised of the following fund, portfolio, and/or family characteristics thought to impact fund performance and expenses:

- 1. Age: Maximum age across share classes;
- 2. Turnover: Annual asset purchases as a fraction of average total net assets;
- 3. Log of Total Net Assets;

⁶³There is some variation as to specifically what costs are included in a fund's reported expense ratio and which costs are paid directly out of fund assets and thus indistinguishable from returns. Using performance net of returns avoids this issue.

⁶⁴Note that dedicated mutual fund company and mutualized flags were omitted from the models to avoid multicollinearity among the subsidiary type and ownership type variables, respectively.

- 4. Log of Family Total Net Assets: Log of the sum of total net assets across all funds in the same family;
- 5. NewMoneyGrowth: Estimated % net new investment;
- 6. Log of Number of Shareholder Accounts;
- Redemption Fee Flag: Dummy variable set to 1 if fund charges a redemption fee;
- 8. Percent Assets Invested in Cash (from CSRP);
- 9. Percent Assets Invested in Stocks (from CSRP);
- 10. Investment Category: Growth, Growth-Income, Bond-Income, Sector, International, Money Market (derived from Strategic Insight objective codes);
- 11. Distribution Channel: Primary distribution channel (from SI);
- 12. Year Dummies.

Each model is estimated at the class- and family-level, where class level covariates are as described in Section III.E. In family-level models, quantitative class-level variables are replaced with the appropriate sum (total net assets, number of shareholder accounts), maximum (age), or asset-weighted average (turnover, all expense and performance measures). Qualitative variables are replaced with the corresponding proportion of classes. Flows are estimated separately for families using the sum of class-level dollar inflows and beginning of period assets.⁶⁵

Table III.5 presents results from OLS regressions of performance measures on ownership and subsidiary type flags, and other fund characteristics. As above, we present results using both class-level and family-level data. In each case, we estimate models separately for gross performance, performance net of expenses including 12b-1 fees, and performance net of expenses including 12b-1 fees and one seventh of the maximum total load (performance models). Models are estimated

 $^{^{65}\}mathrm{See}$ III.E.2 for a discussion of estimating flows.

using both raw returns and 4-factor α , and all expense and performance measures are net of category averages as discussed in section III.E.2.

Consistent with prior empirical evidence, we find that performance is negatively related to age and turnover (in the class-level α models). There is evidence at the class level of a positive relation between size and α , but a negative relation with returns. The coefficients on lagged flows are non-significant in all cases, suggesting that investors are unsuccessful at predicting future performance. The class-level results suggest higher non-12b-1 fees are related to higher gross returns. However, the coefficient is 0.55, suggesting that investors receive less in performance than they pay in expenses. Furthermore, the corresponding coefficient in the α model is non-significant, and there is evidence that higher 12b-1 fees and higher loads are related to lower performance. The only statistically significant performance-fee relation in the family-level models is between load fees and gross α , and again suggests that investor receive less in return than they pay in fees (coefficient of 0.07).

In both the class- and family-level models, subadvising is related to lower returns but higher α . Both subadvised funds and families which employ subadvisors for one or more funds are seen to earn roughly 24 basis points higher α . The results are similar using net performance measures.

At the family-level, there is strong evidence that publicly owned families underperform their privately held and mutualized peers, ranging from 22 to 37 basis points. A similar result is seen in the class-level models, with mutualized outperforming privately held, which outperform publicly held in each of the six regressions of panel A.

At the class level, there is evidence that insurance and bank affiliates underperform dedicated mutual fund families in gross performance measures (21 and 79 basis points for insurance-affiliates and 9 and 33 basis points for bankaffiliates in α and returns, respectively) although only the effect for insurance remains significant in the net-of-expense α and return regressions. At the familylevel, coefficients on the subsidiary type flags are largely non-significant, although there is some evidence that bank-affiliates underperform in α measures, and that 'other' subsidiaries outperform in return measures.

Although not presented, results from class- and family-level expense models are consistent with a number of previously identified empirical relations. Expenses are negatively related to fund and family size, and positively related to age, turnover, and log of number of shareholder accounts, at both the class- and family-level. Interestingly, contemporaneous flows are non-significant in each of the models.

In the class-level models, subadvised funds are seen to charge higher expenses conditional on returns, but lower expenses conditional on α . This suggests that subadvised funds generate lower raw returns but higher α for each unit of fees than do directly advised funds. This result is consistent with class-level performance results in panel A of Table III.7 (discussed below), which indicate that subadvised funds earn higher α on lower raw returns than do their counterparts, suggesting that subadvisors are both more skilled and more conservative. At the family level, families which employ subadvisors for one or more funds are seen to charge lower fees, ranging from 15 to 22 basis points depending on expense measure used.

There is some evidence that funds in highly specialized families charge higher expenses, given the negative and statistically significant coefficients on *focus*. However, this effect is not seen in the family-level models, as the coefficients on *focus* in these models are non-significant. The class-level results suggest that funds in categories within which their families have a higher proportion of assets under management (high *relatedness*) charge lower non-12b-1 expenses but higher 12b-1 and load fees. In both the class- and family-level models, the coefficients on α are non-significant while those on return are significant and negative, albeit small in magnitude (a fraction of a basis point in each case).

The class-level models suggest that mutualized families charge lower fees

than those which are privately held, which in turn charge lower fees than publicly owned families. In the family models, mutualized and privately held families switch places in this ordering. This may be due to the different weights given to Vanguard, a provider of notoriously low expense funds, under the two units of measurement.⁶⁶ We will address this, and other effects of the industry dominance of the largest families below. The results suggest that share classes offered by publicly held families range from 5 to 19 basis points more expensive than their privately held and mutualized counterparts, depending on expense measure used. At the family level, the difference is 2 to 14 basis points.

In terms of subsidiary type, at the class-level we see that the coefficients on *Parent=Other* are lower than those on *Parent=Financial Svs*, which in turn are lower than those on *Parent=Bank* and *Parent=Insurance*. All coefficients are negative and statistically significant, suggesting that dedicated mutual fund companies and their subsidiaries charge higher fees than each of the other subsidiary types. these differences range from 24 basis points for 'other' affiliates to 3 basis points for insurance affiliates. The family-level models in panel B tell a somewhat different story. Diversified financial services affiliates are 11 to 14 basis points more expensive than dedicated mutual fund companies and their subsidiaries. The coefficients on *Parent=Bank* are statistically non-significant, as are those on *Parent=Other* in the non-12b-1 and expenses including 12b-1 regressions. Interestingly, insurance affiliates appear to be 13-14 basis points less costly in these two models than dedicated mutual fund firms. These differences between the class-and family-level results may again be driven by the relative weights given to a small group of large families (in terms of assets managed and number of funds offered) in class-level models versus those at the family level.⁶⁷

It bears noting that the expense models achieved substantially higher fit than the performance models. The former had \bar{R}^2 values ranging from 0.16 to

⁶⁶Vanguard offers far more funds than any of the other 34 mutualized fund families. Thus, while Vanguard comprises less than three percent of the mutualized family sub-sample, its funds make up the lions's share of the mutualized class sample.

⁶⁷Each of three largest fund families–American, Fidelity, and Vanguard–fall into the MF category.

0.39, while the latter had \overline{R}^2 values from 0.01 to 0.09.

III.F.2 Models of Subsidiary Type

Family-Level Generalized Logit Models of Subsidiary Type

As an alternative approach to the subsidiary type hypothesis, we estimate generalized logit models of the following form:

$$\begin{aligned} Subsidiary Type_{jt} &= \beta_0 + \beta_1' Own Types_{jt-1} + \beta_2 PerfMeasure_{jt-1} \\ &+ \beta_3' ExpMeasure_{jt-1} + \beta_4' \Phi_{jt-1} + \epsilon_{jt}, \end{aligned}$$

where again $ExpMeasure_{jt}$ denotes one of three expense measures; $PerfMeasure_{jt}$ denotes one of 6 performance measures; $OwnTypes_{jt}$ denotes a vector of fund family ownership characteristics; and Φ_{jt} denotes a vector of characteristics of the j^{th} family. $SubsidiaryType_{jt}$ denotes the subsidiary type of the j^{th} family–bank affiliate, insurance affiliate, financial services affiliate, dedicated mutual fund company, or 'other'.

We present estimation results from family-level generalized logit models of subsidiary type on expense, performance and fund characteristics in Table III.6. Panel A presents results using gross 4-factor α and return measures, while those in panel B use α and returns net of total expenses including 12b-1 fees and one seventh of the maximum total load. As throughout our empirical analysis, all expense and return measures are net of category averages. With *Dedicated Mutual Fund* the omitted category, the reported odds ratio indicates the proportional change in the value of P(Subsidiary Type)/P(Dedicated Mutual Fund) for a one unit change in the regressor. Thus, values greater than one indicate a positive relation while values less than one indicate a negative relation. Comparing any two pairs of odds ratios gives an idea of the relative difference in sensitivity to the regressor across a pair of (included) categories, although we are have not computed significance levels for these implied differences. The results in panel A suggest that underperforming funds, and funds charging low non-12b-1 expense ratios, are most likely to be insurance-affiliates. Furthermore, there is evidence that funds charging higher 12b-1 fees are more likely to be either bank- or financial services-affiliates, while those charging higher sales loads are more likely to be bank-affiliates. This relation holds across both α and returns models. In panel B, there is evidence that funds with lower α net of expenses are more likely to be insurance-affiliates.

Not surprisingly, considering that the models differ only in right-handside performance measures, the non-performance results are fairly consistent across the four model specifications. Funds from highly specialized families (high *focus* value) are least likely to be bank- or insurance-affiliates, relative to dedicated mutual fund companies. Interestingly, subadvised funds are also more likely to be managed by insurance affiliates, and are less likely to be part of bank or financial services affiliates.

Family-Level Logit Models of Subsidiary Flag

While the generalized logit models presented above are interesting, the results are difficult to interpret. Furthermore, we may be interested in asking broader questions related to differences between subsidiaries and non-subsidiaries. To that end, we estimate a series of logit models of the following form:

$$\begin{split} SubsidiaryFlag_{jt} &= \beta_0 + \beta_1' Own Types_{jt-1} + \beta_2 PerfMeasure_{jt-1} \\ &+ \beta_3' ExpMeasure_{jt-1} + \beta_4' \Phi_{jt-1} + \epsilon_{jt}, \end{split}$$

where $ExpMeasure_{jt-1}$ denotes one of three expense measures; $PerfMeasure_{jt-1}$ denotes one of 6 performance measures; $OwnTypes_{jt-1-1}$ denotes a vector of fund family ownership; and Φ_{jt-1} denotes a vector of characteristics of the j^{th} family. $SubsidiaryFlag_{jt}$ is set equal to 1 if the family is a subsidiary of a larger conglomerate at time t, 0 if the family is directly owned.

Table III.7 presents the results of these models estimated at the family

level using 1995-2004 data. In each of the models the coefficient on performance is negative but statistically non-significant. However, there is statistically significant evidence that funds which charge lower non-12b-1 expenses and those that charge higher sales loads are more likely to be managed by subsidiary families. Furthermore, there is evidence across the four specifications that specialized families (high *focus*) are more likely to be directly owned.

III.F.3 Models of Subadvising

Logit Models of Subadvised Flag

During 2004, 13 percent of classes were subadvised, with 29 percent of fund families offering at least one subadvised fund. Table III.8 reports estimation results from logit models of subadvising on expense measures, performance measures and a number of class- and family-level characteristics;

$$\begin{aligned} Subadvised_{it} &= \beta_0 + \beta_1^{'} OwnSubsidTypes_{it-1} + \beta_2 PerfMeasure_{it-1} \\ &+ \beta_3^{'} ExpMeasure_{it-1} + \beta_4^{'} \Phi_{it-1} + \epsilon_{it}, \end{aligned}$$

where $ExpMeasure_{it-1}$ denotes one of three expense measures; $PerfMeasure_{it-1}$ denotes one of 6 performance measures; $OwnSubsidTypes_{it-1}$ denotes a vector of fund family ownership and subsidiary characteristics; and Φ_{it-1} denotes a vector of characteristics of the i^{th} class or family. $Subadvised_{jt}$ is set equal to 1 if the fund is subadvised at time t (in the class-level models) or the family has at least one subadvised fund (in the family-level models), 0 otherwise.

Panel A presents the results of class-level models using 2004 data, with the dependent variable a dummy variable equal to one if the fund is subadvised. Panel B reports the results of family-level models using 2004 data, where the dependent variable is a dummy variable equal to one if the given family has *at least one* subadvised fund. Models are estimated using either returns or α , both gross and net of all expenses including 12b-1 fees and one seventh of the maximum total load. All expense and performance measures are net of category averages. The class-level results in panel A indicate that funds which outperform their peers are more likely to be subadvised. The coefficients on performance in the return models are each roughly 7 basis points, while those in the α models are an economically significant 55 and 35 basis points on gross α and α net of expenses, respectively. However, there is no statistically significant evidence of a relation between subadvising and the expense components in the first two models. These results are consistent with a hypothesis that families are buying skill, rather than low cost, when they employ subadvisors. Interestingly, redemption fee funds are shown to be less likely to be subadvised. Consistent with our priors, funds in categories in which family-level assets are more highly concentrated (high *relatedness*) are less likely to be subadvised, although there is no evidence of a statistically significant relation between *focus* and subadvising.

Conversely, the family-level results suggest that subadvising by families is related to weaker performance (in return measures), higher 12b-1 fees and higher redemption fees. This disconnect between class-level and family-level performance results may be consistent with a management-skill driven decision to subadvise.

The results suggest than insurance-affiliated funds are more likely to use subadvisors, while financial services-affiliates are less likely to do so, relative to portfolios managed by dedicated mutual fund companies. Funds managed by families identified as buried subsidiaries are less likely to be subadvised, while those managed by families that are subsidiaries of foreign firms are more likely to be subadvised. Finally, there is some evidence (in the class-level models) that funds managed by mutualized families are more likely to be subadvised than their publicly owned peers.

Family-Level Linear Models of Percent of Classes Subadvised

Table III.9 presents the results of family-level OLS regressions modeling the proportion of subadvised classes within the family on expense and performance measures and a collection of family-level characteristics;

$$\begin{aligned} PctSubadvised_{jt} &= \beta_0 + \beta_1' OwnSubsidTypes_{jt-1} + \beta_2 PerfMeasure_{jt-1} \\ &+ \beta_3' ExpMeasure_{jt-1} + \beta_4' \Phi_{jt-1} + \epsilon_{jt}, \end{aligned}$$

where $ExpMeasure_{jt-1}$ denotes one of three expense measures; $PerfMeasure_{jt-1}$ denotes one of 6 performance measures; $OwnSubsidTypes_{jt-1}$ denotes a vector of fund family ownership and subsidiary characteristics; and Φ_{jt-1} denotes a vector of characteristics of the j^{th} family. $PctSubadvised_{jt}$ the percentage of classes offered by a fund family which are subadvised in part or in whole at time t.

Models are estimated separately using gross α and gross returns, as well as α and returns net of all expenses including 12b-1 fees and one seventh of the maximum total load. Again, all expense and performance measures are net of category averages.

The results indicate that families with lower returns and higher α , as well as those charging lower non-12b-1 fees, tend to subadvise a higher proportion of funds. Consistent with our prior beliefs, specialized families (high *focus*), older families, and larger families tend to subadvise a lower proportion of their funds. Bank- and financial services-affiliates employ fewer subadvisors than do dedicated mutual fund companies, while the opposite holds for 'other'- and insurance-affiliates.

III.F.4 The Impact of Dominant Industry Participants

As we have noted several times, the mutual fund industry is dominated, both in terms of assets under management and sheer number of funds offered, by a small number of very large families. As a test of the sensitivity of our results to these large families, we re-estimate our linear expense and performance models from section III.F on a trimmed sample, dropping the largest 5% of families.^{68,69}

⁶⁸We used the time series average of end-of-year total net assets for each family in our ten year sample as our metric.

⁶⁹In the interests of minimizing output, we have omitted these results.

We observe little change qualitatively between the full population models and those estimated on the trimmed sample, suggesting that our full-sample results are not driven by the largest fund families. Notably, privately held families charge lower expenses than mutualized, which in turn charge lower fees than publicly owned families (both at the class- and family-level). Also, mutualized families outperform privately held, which outperform publicly held at the family-level. At the class level, publicly owned underperform both mutualized and privately held.

Arguably, investors are most concerned with performance net of expenses. The class-level models of performance net of total expenses suggest that funds offered by mutualized families outperform those offered by publicly owned families by 88 basis points in returns and 13 basis points in α . The corresponding results for privately held families are 6 basis points in both returns and α . These results are enlightening, as it may have been suspected that our full-sample results, which were favorable to mutualization, were largely driven by the dominance of Vanguard in the mutualized subsample. Clearly, this was not the case.

III.G Discussion

In this section we discuss in turn each of the empirically testable hypotheses laid out in section III.D, in light of the results presented above.

III.G.1 Industry Structure

The empirical results discussed in section III.F provide strong evidence in support of our hypotheses that performance and expense differences are related to differences in investment advisor ownership structure.

H1 Mutualized fund families outperform privately held families, gross of fees, which in turn outperform publicly held families.

The linear performance models in Table III.5 suggest that funds managed by publicly owned families underperform both their mutualized and privately owned counterparts. The class-level model using gross α (from panel A) indicates that publicly owned underperformed mutualized and privately held by 5 and 15 basis points, respectively, while the coefficients on the *Privately Owned* and *Mutualized* flags in the gross return model are roughly 14 and 71 basis points, respectively, although the coefficient on *Privately Owned* is non-significant. These results are mirrored in the net performance models, where the coefficients on the *Privately Owned* dummies are significant at the 10% level. Generally, the evidence is convincing that funds managed by publicly held families underperform those offered by mutualized and privately owned families. However, the evidence relating performance across privately held and mutualized is less clear.

At the family level (panel B), mutualized and privately held families outperformed publicly held by 26 and 22 basis points in gross α . In the gross return model, the coefficient on *Privately Owned* (96 basis points) is significant at the 10% level, while the coefficient on the *Mutualized* flag is non-significant. As in the class-level models, the net performance models are qualitatively consistent with the gross performance models.

Notably, these results are robust to trimming the largest fund families from the sample, as Table III.12 indicates. This suggests that our results are not driven by the largest fund families.

H2 Mutualized fund families charge lower fees than privately held families, which in turn charge lower fees than publicly held families.

The linear expense models (not presented) suggest that both privately owned and mutualized fund families charge lower fees than their publicly owned peers.

At the class level, this difference ranges from 5 to 15 basis points annually (depending on whether distribution fees are included and whether the model conditions on returns or α). At the family level, this difference ranges from 13 to 21 basis points for privately held families. The coefficients on *Mutualized* in the Non-12b-1 and Expenses including 12b-1 models are nonsignificant, although in the total expense models they are 14 and 12 basis points (and statistically significant) in α - and return-conditional models, respectively.

As in the performance models, the difference between privately owned and mutualized is less clear. In the family-level models, the coefficients on the *Privately Owned* flags are substantially lower than those on the *Mutualized* flags, the latter of which are at any rate non-significant in four of the six models. At the class-level, the coefficients on *Mutualized* are lower than those on *Privately Owned* in the Non-12b-1 and Total Expense models.

The trimmed-sample results (not presented) are somewhat more consistent, and suggest that, absent the largest 5% of families, privately held families are less expensive than mutualized, which are less expensive than publicly owned at both the class- and family-level. A natural conclusion is that our results in favor of mutualized and privately owned families are robust to the effects of the dominant industry participants, but that the results suggesting mutualized families charge overall lower fees than those which are privately held may be attributable by a 'Vanguard effect'.

H3 Families affiliated with diversified financial services conglomerates outperform dedicated mutual fund families, gross of fees, which in turn outperform bank and insurance affiliates.

Table III.5 presents evidence that bank- and insurance-affiliated fund families underperform dedicated mutual fund families, diversified financial services- and 'other'-affiliates The class-level models of panel A suggest that this underperformance is roughly 21 and 9 basis points in gross α and 79 and 33 basis points in gross returns for insurance- and bank-affiliates, respectively.

At the family-level, the only statistically significant evidence is that insurance affiliates underperform (by 33 basis points) in the gross α model, and 'other'-affiliates outperform (by 175 basis points in gross returns). These results are mirrored in the models of performance net of all expenses. Interestingly, while they are non-significant in the gross performance models, both diversified financial services- and 'other'-affiliates show statistically significant outperformance in the net α models (17 and 34 basis points in α net of expenses including 12b-1 fees, and 10 and 11 basis point in α net of all expenses). The results using the trimmed sample in Table III.12 are qualitatively consistent in every case with those of the full sample, suggesting that differences in performance across subsidiary type are not driven by the dominant industry participants.

These results are partially validated in the generalized logit models of Table III.6, where insurance-affiliates are seen to be associated with lower lagged α , relative to dedicated mutual fund families (13 basis points in gross α and 11 basis points in α net of all expenses).

Overall, the results are consistent with our assertion that funds managed by bank- and insurance-affiliates underperform those offered by dedicated mutual fund families, and provide some statistically significant evidence of outperformance on the part of diversified financial services-affiliates and subsidiaries of 'other' types of conglomerates.

H4 Families affiliated with diversified financial services conglomerates charge lower fees than dedicated mutual funds, which in turn charge lower fees than bank and insurance affiliates.

The results from our linear expense models are mixed with respect to H4. At the class level, we see consistent evidence that dedicated mutual fund families charge higher fees than do subsidiaries of diversified conglomerates (ranging from 3 to 23 basis points, depending on expense measure and whether expenses are conditioned on α or returns). The coefficients on *Parent=Other* are consistently lower than on the other subsidiary type dummies (at both the class- and family-level), suggesting that families affiliated with non-financial conglomerates charge lower fees than their peers. The coefficients on *Parent=Bank* and *Parent=Insurance* are consistently smaller in magnitude than those on *Parent=Financial Svs*, suggesting that bank-and insurance-affiliates charge higher fees than their peers.

At the family-level, diversified financial services-affiliates are seen to charge higher expenses than all other groups (coefficients on *Parent=Financial Svs* range from 12 to 14 basis points depending on specification), while there is evidence that insurance affiliates charge lower expenses (coefficients on the *Parent=Insurance* flags are roughly -14 basis points in the non-12b-1 and expenses including 12b-1 models, and non-significant in the total expense models. This directly contradicts our assertion in H4.

Likewise, both the results using the trimmed sample and the generalized logit results in Table III.6 suggest that dedicated mutual fund families and subsidiaries of diversified financial services firms charge higher expenses than other types of conglomerate affiliates.

Our results suggest that if diversified financial services affiliates and dedicated mutual fund families face cost savings in mutual fund operation expenses relative to bank, insurance, and 'other' affiliates, these savings are not passed along to investors. Quite the contrary, investors in these funds pay more in expenses than their counterparts. Possible reasons for this finding include the nonexistence of such savings, systematic fund size differences across subsidiary types interacting with scale economies (or possibly *diseconomies*), or systematic expense differences driven by systematic performance differences. That is, on average investors get what they pay for.

This last reason suggests something we have touched on several times, and motivates our inclusion of performance net of expenses as a dependent variable in each of our models. That is, while there may be an open and active debate as to the appropriate performance measure on which investors base their decisions (raw, net of category average, risk-adjusted in some way), it may be far easier to justify that investors use this measure *net of expenses* as an input to their decisionmaking process. Our linear class-level model of α net of total expenses in panel A of Table III.5 suggests that diversified financial services-affiliate funds outperform funds managed by dedicated mutual fund families by 10 basis points annually, while bank- and insurance-affiliates underperform dedicated mutual funds by 25 and 8 basis points respectively. These results are consistent with a joint hypothesis combining H3 and H4.

III.G.2 Subadvising

The key limitation in our subadvising analysis is that our data is limited to a flag indicating whether or not a portfolio is subadvised. Ideally, we would include the name of the subadvisor so that we could more accurately study potential differences across directly advised and subadvised funds. However, our empirical results can provide some insight into the types of funds that are subadvised, and the types of firms which employ subadvisors. We will discuss each of the hypotheses described in section III.D.3, and note a course of future study to remedy these issues.

H5 Fund families are more likely to hire subadvisors for funds not in their core specialization.

The negative and statistically significant coefficients on *relatedness* in each of the class-level logit models in Table III.8 suggest that the higher is the percentage of assets managed by a family in a given category, the less likely is the family to employ a subadvisor for a fund within that category. At the familylevel, the coefficients on *focus* in each of the logit (Table III.8, panel A) and linear (Table III.9) models are statistically significant and negative, suggesting that highly specialized families are less likely to employ a subadvisor for any fund, and that the more specialized is the family the fewer funds will be subadvised. These results provide strong support for hypothesis H5.

H6 Large funds are more likely to hire a subadvisor for part of the fund.

Our subadvising data does not include the percentage of fund assets managed by the subadvisor, versus that (if any) managed in house, although we know that this type of management structure exists within the industry. However, from panel A of Table III.8, we see that the log of total net assets is strongly positively related to the probability of subadvising. This provides support for hypothesis H6. We note also that the log of family total net assets is consistently negatively related to the incidence (in class- and family-level logit models) and rate (in the family-level linear models) of subadvising.

H7 'Star' families are less likely to hire subadvisors.

Our results are mixed with respect to H7. Our family-level results in Tables III.8 and III.9 suggest that families with higher weighted average α measures, or lower weighted average return measures, are more likely to employ subadvisors. However, we have not defined 'star' families in a rigorous way, as we did at the fund level, and weighted average α and returns may be a poor indicator of a 'star' family.⁷⁰

H8 Subadvised funds outperform directly advised funds, gross of fees.

H9 Subadvised funds charge lower fees than directly advised funds.

The linear performance models in panel A of Table III.5 suggest that subadvised funds outperform non-subadvised funds by 24 basis points in gross α , but underperform in gross returns by 55 basis points. Consistent with this result, the expense models (not presented) suggest that subadvised funds are more expensive conditional on α , but less expensive conditional on returns. However, the statistically significant coefficients on *subadvised flag* in the expense models range from 2 to 5 basis points, an effect which is dominated by the performance results.

These results may suggest that while subadvised funds earn lower returns than their non-subadvised counterparts, they do so while taking on much less risk. This may be related to differences in the shape of the management contracts between the fund and the investment advisor and that between the investment advisor and the subadvisor.

 $^{^{70}{\}rm For}$ example, Nanda, Wang, and Zheng (2004) identify a 'star' fund as being in the top 5% of contemporaneous risk-adjusted returns.

III.H Conclusions and Future Research

Our study of the mutual fund industry describes the structure of the industry, particularly the ownership structure of the advisory firm. We hypothesize that differences in economies of scale and scope across different types of investment advisors may have real effects on performance and expenses. We consider the degree of concentration in ownership of the investment advisor. Specifically, whether the investment advisor is mutualized, privately owned, or publicly held, and whether or not the advisor is a subsidiary of a larger entity. If a subsidiary relation exists, we consider whether the parent entity is engaged in other businesses such as diversified financial services, banking, insurance, or 'other' non-financial activities. In addition, we examine the motivations to subadvise by mutual fund families and empirically test for differences in performance and expenses across directly advised versus subadvised funds.

Using both raw returns and 4-factor α net of category averages, and conditioning on a variety of fund- and family-level characteristics, we find evidence of the following:

- Publicly owned fund families provide lower performance at higher cost to investors than do privately owned or mutualized families. Our results suggest that this difference is as great as -71 basis per year in returns, -15 basis points in α, and roughly +19 basis points in total expenses.
- 2. Bank- and insurance-affiliated funds provide lower performance net of expenses than do dedicated mutual fund families, while diversified financial services affiliates provide higher performance net of expenses than do funds offered by dedicated mutual fund families. The difference is as high as -25 and -8 basis points annually for insurance- and bank-affiliates, and as high as +10 basis points for diversified financial services.
- 3. The foregoing results are not driven by the dominant fund families, as they

are robust to trimming the data of the largest 5% of families by assets managed.

- 4. Highly specialized families are less likely to employ subadvisors, and funds outside of a family's core specialization(s) are more likely to be subadvised.
- 5. Subadvised funds provide investors with lower returns, but higher α , relative to non-subadvised funds. This may be explained by subadvisors both having more skill and taking on substantially less market risk (i.e. lower β) relative to other advisors.

Our analysis suggests several other interesting empirical observations. Foreign owned fund families are more likely to use subadvisors than U.S. owned families; insurance-affiliates and affiliates of non-financial conglomerates are more likely to use subadvisors than are dedicated fund families or bank-affiliates, which are in turn more likely to do so than are diversified financial services affiliates. These observations in combination with point 5 above suggest that fund families employ subadvisors largely as a way to gain access to investment skills not held in-house, particularly in niche markets.

There is also evidence that specialized families, and funds within a family's category of specialization, provide investors with higher α , and that funds offered by specialized families earn higher raw returns. Interestingly, specialized families appear to charge higher non-12b-1 expenses, while funds within a family's category of specialization charge lower non-12b-1 expenses.

A key weakness with our subadvising analysis lies in having only a flag indicating that a portfolio is subadvised. We intend to rectify this weakness by utilizing a new dataset which includes subadvisor name for each subadvisor managing any part of a fund. This dataset will allow us to (1) identify cases where the subadvisor is an affiliate or subsidiary of the advisory firm, (2) perform comparisons between funds directly advised and those subadvised by an advisor, and(3) identify cases where a multi-manager type of subadvisory approach is employed.

III.I Appendix III.A: Figures

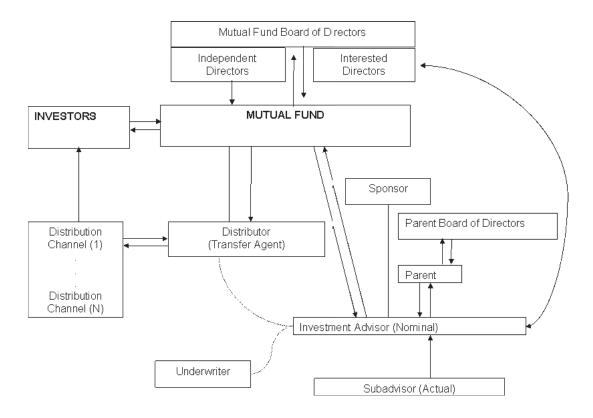


Figure III.1: Typical Relations Among Entities in the Mutual Fund Industry

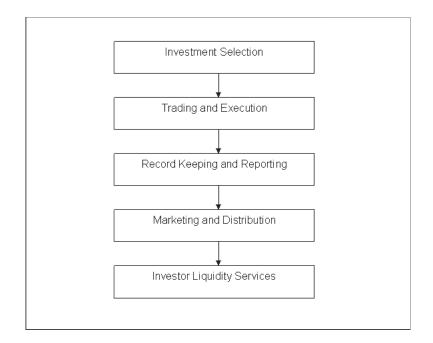


Figure III.2: The Mutual Fund Value Chain

III.J Appendix III.B: Tables

iation, fund family out consulting, e.g. es and subsidiaries	Totals % of Total.	/0 OI TOUGHT	8.4% 53.0% 29.4%	2.7% 6.0% 0.4%	100%		10tals % of Total:	8.8%	47.6%	4.3% 11.1%	100%	Totale	Ratio to Overall Avg	1.05	0.40 1.62 2.60	0.71 3043.80	1.00
aonal inform estor (withc m-subsidiari	Sum	IIIInG	$\begin{array}{c} 46\\290\\161\\161\end{array}$	$\begin{array}{c} 15\\33\\2\end{array}$	$\begin{array}{c}547\\100\%\end{array}$	L	Sum	690,894	3,721,786	333,512 870,207	$7,819,197\\100\%$	-	Row Avg R	15,019	23,117	10,106 435104	14,295 1.00
ts of addit casual inv es both nc	MF II		$25 \\ 21 \\ 21 \\ 21 \\ 21 \\ 21 \\ 21 \\ 21 \\ $	$\begin{bmatrix} 13\\ 2 \end{bmatrix}$	$\left\ \begin{smallmatrix} 351 \\ 64.2\% \end{smallmatrix} \right\ $		MF	661,949	1,020,201 595,645 561 540	301,340 870,207	$\left. \begin{array}{c} 4,314,608 \\ 55.2\% \end{array} \right\ $		MF	26,478	28,364 12,105	$435,10\dot{4}$	$12,292 \\ 0.86 \\ \ $
atement to the includues ustries.	Other	COLLET	m. 7	6	$\overset{11}{2.0\%}$		Other	102	33,934	$2,96\dot{7}$.	${37,004 \atop 0.5\%}$		Other	51	$11,31\dot{1}$	$49\dot{4}$.	$3,364 \\ 0.23$
im ADV, fund prospectuses and/or statemen- licates that the parent is not obvious to the te that 'MF' (<i>Dedicated Mutual Fund</i>) inclu- ter nests a variety of non-financial industries.	Parent Type Insurance	anna martt	38.2	19	$\begin{array}{c} 59\\ 10.8\%\end{array}$	E	rarent 1ype Insurance	6,196	$497, 32\dot{4}$	281, 129.	$784,650\ 10.0\%$	er Family	Insurance	3,098	$1308\dot{7}$	$14,79\dot{6}$.	$13,299\\0.93$
spectuses rent is no icated Mu_{i} of non-fin	Fin Sve	TILL D'VO	35. 7 35.	2	$\overset{44}{8.0\%}$		Svs.	3,901	1,463,553		$^{1,483,444}_{19.0\%}$	\$Millions per Family Denote Tune	Fin. Svs.	557	$\substack{41,816\\7,005}$	· · ·	33,715 2.35
, fund pro at the pay MF' (Ded' a variety	S Rank	TIM	10 64	· ∞ ·	$^{82}_{15.0\%}$	cteristics, \$N	Bank	18,746	1,131,329	49,415.	$ \begin{array}{c}1,199,490\\15.3\%\end{array}$	aracteristics,	Bank	1,874	$17,67\dot{7}$	$6,17\dot{6}$.	14,628 1.02
orm ADV, dicates th ote that 'I <i>her</i> nests	haracteristic ags Buried II	nating	$\begin{bmatrix} 4\\1\\76 \end{bmatrix}$	18	18.1%	rship Chara	ags Buried	$7,098 \\ 67 \\ 67 \\ 67 \\ 67 \\ 67 \\ 67 \\ 67 \\ 6$	1,174,641	$24,46\dot{5}$.	$\left. {{1,426,460}\atop{18.2\%}} \right\ $	vnership Cha	Buried	$1,774 \\ 67 \\ 67$	15,456	13,592.	$\left. \begin{array}{c} 14,409\\ 1.01 \end{array} \right\ $
lucing to <i>suried</i> in SAI). No while <i>Ot</i>	wnership C Fl	TOTOR	$\frac{1}{49}$.	. 7	$\begin{array}{c} 57\\10.4\%\end{array}$	ed by Owne	rı Foreign	81	857,382	$49,09\dot{2}$.	$\begin{array}{c} 906,556 \\ 11.6\% \end{array}$	aged by Ov	Foreign	81	$17,49\dot{8}$	$7,01\dot{3}$.	$15,905 \\ 1.11$
from a range of sources including form ADV, fund prospectuses and/or statements of additional information, fund family web sites, and Hoovers. <i>Buried</i> indicates that the parent is not obvious to the casual investor (without consulting, e.g. Hoovers, form ADV, or an SAI). Note that 'MF' (<i>Dedicated Mutual Fund</i>) includes both non-subsidiaries and subsidiaries of mutual fund companies, while <i>Other</i> nests a variety of non-financial industries.	Panel A: Family Counts by Ownership Characteristics Plags Ownershin Buried II	Omiterative	Subsidiary of Privately Held Directly Privately Owned Subsidiary of Publicly Held	Directly Publicly Owned Subsidiary of Mutualized Directly Mutualized	Sum: % of Total:	Panel B: Total Assets Managed by Ownership Characteristics, \$Millions	Ownership	Subsidiary of Privately Held	Subsidiary of Publicly Held	Subsidiary of Mutualized Directly Mutualized	Sum: % of Total:	Panel C: Average Assets Managed by Ownership Characteristics,	Ownership	Subsidiary of Privately Held	Subsidiary of Publicly Held Directly Publicly Meld	Subsidiary of Mutualized Directly Mutualized	Column Avg: Ratio to Overall Average:

istics of 547 US mutual fund families, which collectively managed approximately \$7.8 trillion at the end of 2004. Family counts, end-of-year average assets per family and total assets managed are presented. Family ownership data were gathered from a range of sources including form ADV, fund prospectuses and/or statements of additional information. fund family Table III.1: Fund Family Counts by Ownership Characteristics, 2004 This table summarizes ownership characterTable III.2: Two-Way Sort of Class-Level Performance Measures Net of Category Averages by Family Ownership, 1995-2004, Annual %: This table presents performance measures across all mutual fund classes managed by our sample of 547 fund families from 1995-2004. Counts, averages and standard deviations of performance measures by ownership type and parent type are included for both 4-factor α and raw returns, both gross and net of all expenses including 12b-1 fees and one seventh of the maximum total load. In each case, the data are net of the contemporaneous average across all funds within the same broad SI-derived investment category. Note that *Mutual Fund* includes both non-subsidiaries and subsidiaries of mutual fund companies, and *Other* nests several non-financial industries. Row and column totals are calculated across all observations in the given row or column.

Parent Type:			Fin'l			Mutual	Row
		Bank	Svs	Insurance	Other	Fund	Total
	Ν			•		949	949
Directly Mutualized	μ					-0.0517	-0.0517
	σ					0.0706	0.0706
	Ν	891		5006	94		5991
Subsidiary of Mutualized	μ	0.1005		-0.0202	0.2773		0.0024
	σ	0.0681	•	0.0375	0.1707		0.0331
	Ν			•		15159	15159
Directly Private	μ					0.2097	0.2097
	σ		•			0.0261	0.0261
	Ν	622	192	409	155	1297	2675
Subsidiary of Private	μ	-0.1502	-0.2539	-0.1727	0.0809	0.0734	-0.0393
	σ	0.0689	0.2008	0.0989	0.0587	0.0671	0.042
	Ν		1120	•		6554	7674
Directly Public	μ		0.0574			-0.0235	-0.0117
	σ		0.0215			0.033	0.0284
	Ν	20341	15689	14699	890	10757	62376
Subsidiary of Public	μ	-0.0919	0.0078	-0.1297	0.2619	0.0248	-0.0505
	σ	0.0133	0.0201	0.0213	0.0749	0.0282	0.0097
	Ν	21854	17001	20114	1139	34993	95101
Column Total	μ	-0.0857	0.0081	-0.1033	0.2386	0.0934	-0.0028
	σ	0.0128	0.0187	0.0183	0.0607	0.0159	0.0083

Panel A: Gross Alpha, Annual % Net of Category Average

Panel B: Gross Returns, Annual % Net of Category Average

Parent Type:			Fin'l			Mutual	Row
		Bank	Svs	Insurance	Other	Fund	Total
	Ν					1313	1313
Directly Mutualized	μ					0.8484	0.8484
	σ					0.2385	0.2385
	Ν	1073		8217	118		9408
Subsidiary of Mutualized	μ	1.3587		0.1232	0.2423		0.2656
	σ	0.4335		0.131	0.9982		0.1253
	Ν					22333	22333
Directly Private	μ					0.619	0.619
	σ					0.1172	0.1172
	Ν	864	280	560	243	2204	4151
Subsidiary of Private	μ	0.2541	0.4282	-0.2482	1.6707	0.5101	0.4169
	σ	0.3402	0.8961	0.4529	0.3568	0.1969	0.1542
	Ν		1486			8476	9962
Directly Public	μ		-0.4498			0.7356	0.5588
	σ		0.1628			0.1282	0.1118
	Ν	28182	21025	21092	1212	15487	86998
Subsidiary of Public	μ	-0.3496	-0.1881	-0.2683	0.4149	-0.3618	-0.2824
	σ	0.0636	0.0874	0.0808	0.3604	0.1129	0.041
	Ν	30119	22791	29869	1573	50308	134660
Column Total	μ	-0.2715	-0.1976	-0.1602	0.596	0.3239	-0.0017
	σ	0.0623	0.0821	0.068	0.2929	0.0673	0.0355

Parent Type:			Fin'l			Mutual	Row
		Bank	Svs	Insurance	Other	Fund	Total
	Ν			•		949	949
Directly Mutualized	μ					0.21	0.21
	σ	•	•		•	0.0707	0.0707
	Ν	891		5005	94		5990
Subsidiary of Mutualized	μ	0.2081		-0.0862	0.5578		-0.0323
	σ	0.068		0.0378	0.1717	•	0.0333
	Ν	•				15159	15159
Directly Private	μ	•	•	•		0.3159	0.3159
	σ	•	•	•	•	0.0262	0.0262
	Ν	622	192	409	155	1297	2675
Subsidiary of Private	μ	-0.2489	-0.1285	-0.2705	-0.0428	-0.106	-0.1623
	σ	0.0704	0.2037	0.101	0.0629	0.0691	0.0431
	Ν		1120			6554	7674
Directly Public	μ		0.0423			-0.0184	-0.0095
	σ	•	0.0233			0.0333	0.0287
	Ν	20324	15689	14281	890	10757	61941
Subsidiary of Public	μ	-0.0903	-0.0107	-0.2274	0.3968	-0.0229	-0.0831
	σ	0.0135	0.0203	0.0213	0.0753	0.0284	0.0098
	Ν	21837	17001	19695	1139	34993	94665
Column Total	μ	-0.0827	-0.0085	-0.1924	0.3503	0.1234	-0.0108
	σ	0.013	0.019	0.0183	0.0613	0.016	0.0084

Table III.2 continued Panel C: Alpha Minus Expenses and Annualized Load, Annual % Net of Category Average

Panel D: Returns Minus Expenses and Annualized Load, Annual % Net of Category Average

Parent Type:			Fin'l			Mutual	Row
		Bank	Svs	Insurance	Other	Fund	Total
	Ν					1412	1412
Directly Mutualized	μ					1.9327	1.9327
	σ					0.2292	0.2292
	Ν	1099		8618	118		9835
Subsidiary of Mutualized	μ	1.4085		0.0623	0.5732		0.2188
	σ	0.4287		0.127	0.9939		0.1218
	Ν			•	•	22984	22984
Directly Private	μ					0.6297	0.6297
	σ				•	0.1153	0.1153
	Ν	931	293	579	243	2301	4347
Subsidiary of Private	μ	-0.431	0.1958	-0.6843	1.267	0.5641	0.1992
	σ	0.3314	0.8565	0.4415	0.3539	0.1943	0.1512
	Ν	•	1492	•	•	8699	10191
Directly Public	μ		-0.4899			0.6259	0.4626
	σ		0.1643			0.128	0.112
	Ν	28984	21594	21856	1227	15871	89532
Subsidiary of Public	μ	-0.3652	-0.2326	-0.639	0.7717	-0.5291	-0.4135
	σ	0.0629	0.0866	0.0798	0.3601	0.1117	0.0406
	Ν	31014	23379	31053	1588	51769	138803
Column Total	μ	-0.3043	-0.2436	-0.4452	0.8327	0.2849	-0.0929
	σ	0.0615	0.0814	0.0669	0.2929	0.0664	0.035

Table III.3: Three-Way Sort of Class-Level Performance Measures Relative to Category Averages by Family Ownership, 2004 %: This table presents 2004 averages and standard deviations of performance measures by ownership type and parent type, for both subadvised and non-subadvised funds. Note that *Dedicated Mutual Fund* includes both non-subsidiaries and subsidiaries of mutual fund companies, and *Other* nests a range of non-financial industries. 4-factor α measures are presented. Row and column totals are calculated across all observations in the given row or column. Results from two-sample difference in means tests between subadvised and non-subadvised classes are reported, with * indicating significant at the 5% level, ** at the 1% level.

	_		vised	പ	Ç		Ē
rarent 1ype:	N	bank ·	FINT SVS	Insurance .	Otner .		
Directly Mutualized	πρ					$\begin{array}{c} 0.1284 & ** \\ 0.0635 \end{array}$	$0.1284 \ ^{**}$
Subsidiary of Mutualized	ZΖρ	$\begin{array}{c} 15 \\ 0.0673 \\ 0.2058 \end{array}$		$\begin{array}{c} 261 \\ 0.019 \\ 0.0382 \end{array}$	$^{+0.1915}_{-0.1372}$		$\begin{array}{c} 282 \\ 0.0171 \\ 0.037 \end{array}$
Directly Private	Nπρ					$\begin{array}{c} 242 \\ 0.0334 \\ 0.0413 \end{array}$	$\begin{array}{c} 242 \\ 0.0334 \\ 0.0413 \end{array}$
Subsidiary of Private	Nμρ	$\left \begin{smallmatrix} 30 \\ -0.1406 \\ 0.0606 \end{smallmatrix} \right $	$^{5}_{-0.1508}_{-0.0789}$	$\begin{array}{c} 7\\ 0.2398\\ 0.2372\end{array}$	$^{3}_{-0.3996} ** \\ 0.0415$	$^{-0.125}_{-0.085}$ **	$^{76}_{-0.1101}$ ** 0.0488
Directly Public	ZΖρ		$\begin{array}{c} 12 \\ 0.1373 \\ 0.0689 \end{array}$			$\begin{array}{c} 96 \\ 0.0104 \\ 0.0564 \end{array}$	$\begin{array}{c} 108 \\ 0.0245 \\ 0.0508 \end{array}$
Subsidiary of Public	Z Z D	$\begin{array}{c} 255 \\ 0.0177 \\ 0.0376 \end{array}$	$^{180}_{-0.121}$ ** $^{0.0353}_{-0.0353}$	$^{488}_{-0.0455 \ **}_{0.0271}$	$^{-0.1093}_{-0.0698}$ **	-0.0002 ** 0.0645	$\begin{array}{c} 1023 \\ -0.0418 \\ 0.0178 \end{array}$
Column Total	N ZP	$\begin{array}{c} 300 \\ 0.0043 \\ 0.0341 \end{array}$	$\begin{array}{c} 197 \\ -0.106 \\ 0.0329 \end{array}$	$^{756}_{-0.0206}$ ** 0.022	$^{39}_{-0.1443}$ ** $^{0.0584}_{-0.0584}$	$519 \\ 0.0298 \\ 0.0256$	$\begin{array}{c} 1811 \\ -0.014 \\ 0.0136 \end{array}$
		Z	Non-Subadvised Portfolios	ed Portfolios			
Parent Type:		Bank	Fin'l Svs	Insurance	Other	Mutual Fund	Row Total
Directly Mutualized	ZΖρ					$\begin{array}{c} 118 \\ 0.0821 \\ 0.0342 \end{array}$	$\begin{array}{c} 118 \\ 0.0821 \\ 0.0342 \end{array}$
Subsidiary of Mutualized	NΙρ	$\begin{array}{c} 127 \\ 0.0188 \\ 0.0562 \end{array}$		$\begin{array}{c} 597 \\ 0.0922 \\ 0.0246 \end{array}$	$^{-0.32}_{0.1471}$		$\begin{array}{c} 731 \\ 0.0755 \\ 0.0224 \end{array}$
Directly Private	ZΖρ					-0.0184 0.0195	-0.0184 0.0195
Subsidiary of Private	Nβρ	$\left. \begin{array}{c} 111 \\ -0.0624 \\ 0.0312 \end{array} \right $		$\begin{bmatrix} 37\\-0.2259\\0.0961 \end{bmatrix}$	$\begin{array}{c} 1 \\ -0.2233 \\ 0 \end{array} * *$	$\begin{array}{c} 223 \\ 0.0204 \\ 0.0177 \end{array}$	$^{384}_{-0.0316}$ ** $^{0.0174}$
Directly Public	Nμρ					$\begin{array}{c} 824 \\ 0.0725 \\ 0.0196 \end{array}$	$\begin{array}{c} 963 \\ 0.0777 \\ 0.017 \end{array}$
Subsidiary of Public	NΙρ	$\begin{array}{c} 2617 \\ -0.0417 \\ 0.0078 \end{array}$	$\begin{array}{c} 2397 & ** \\ 0.0005 \\ 0.0107 \end{array}$	*	$^{77}_{-0.2048}$ ** 0.0258	$\begin{array}{c} 902 \\ -0.0234 \\ 0.045 \end{array}$	$\begin{array}{c} 7455 \\ -0.0131 \\ 0.0074 \end{array}$
Column Total	ZZP	$\begin{array}{c} 2855 \\ -0.0398 \\ 0.0076 \end{array} $	$\begin{array}{c} 2548 & ** \\ 0.0059 \\ 0.0101 \end{array}$	$\begin{array}{c} 2096 \\ 0.0445 \\ 0.0114 \end{array}$	$^{85}_{-0.2145}$ ** 0.0262	$\begin{array}{c} 4039 \\ 0.004 \\ 0.0144 \end{array}$	$11623 \\ -0.0006 \\ 0.0062$

Panel A: Gross Alpha, Annual % Net of Category Average

Fanel D: Gross Returns, Annual 70 Net of Category Average Subscheided Doubled	Annual 70 INET O	I Category Average Subadwised Portfolios	.verage Portfolios			
Parent Type:	Bank	Fin'l Svs	Insurance	Other	Mutual Fund	Row Total
Directly Mutualized	N 30				$\begin{array}{c} 67 \\ 1.7534 \\ 0.6574 \end{array}$	$\begin{array}{c} 67 \\ 1.7534 \\ 0.6574 \end{array}$
Subsidiary of Mutualized	$ \begin{array}{c} \mathrm{N} & 15 \\ \mu & -1.7744 \\ \sigma & 0.9937 \end{array} $		$\begin{array}{c} 305 \\ 1.75 \\ 1.114 \end{array}$	$^{8}_{-1.2956}_{-1.7004}$		$\begin{array}{c} 328 \\ 1.5146 \\ 1.0385 \end{array}$
Directly Private	ν				$\begin{array}{c} 280 \\ 0.912 \\ 0.4261 \end{array}$	$\begin{array}{c} 280 \\ 0.912 \\ 0.4261 \end{array}$
Subsidiary of Private	$ \begin{bmatrix} N & 14 \\ \mu & 1.7323 \\ \sigma & 1.3449 \end{bmatrix} $	$\begin{array}{c} 5 \\ 0.0658 \\ 1.2452 \end{array}$	$^{10}_{-1.976}$ ** $^{0.9036}_{-1.976}$	$^3_{-2.3935}$ -3.1962	$^{32}_{-0.953}$ ** 1.1212	$^{64}_{-0.5134}$ ** $^{6778}_{-0.6778}$
Directly Public		$^{12}_{-1.3647}$ ** $^{0.6886}$			$^{107}_{-0.5675 \ **}$ 0.6105	$^{119}_{-0.6479 \ **}$
Subsidiary of Public		$egin{array}{c} 204 \ 1.3463 \ 0.3534 \ \end{array}$	$^{562}_{-1.3371}$ ** $^{0.2692}$	$\begin{smallmatrix} 32\\ 3.7735\\ 0.7706 \end{smallmatrix}$	$\begin{array}{c} 72 \\ 1.3366 \\ 0.8686 \end{array}$	$^{1164}_{-0.2438}$ ** $^{0.1853}_{-0.1853}$
Column Total	$ \begin{matrix} \mathrm{N} & 323 \\ \mu & -0.0816 \\ \sigma & 0.3501 \end{matrix} \end{matrix} $	$\left \begin{array}{c} 221 \\ 1.1702 \\ 0.3318 \end{array} \right $	$\begin{bmatrix} 877\\-0.2707\\0.4267\end{bmatrix}$	$ \begin{bmatrix} 43\\ 2.4002\\ 0.7628 \end{bmatrix} $	$ \begin{bmatrix} 575 \\ 0.712 \\ 0.2806 \end{bmatrix} $	$\begin{array}{c} 2039 \\ 0.2489 \\ 0.2115 \end{array}$
	Z	Non-Subadvised Portfolios	ed Portfolios			
Parent Type:	Bank	Fin'l Svs	Insurance	Other	Mutual Fund	Row Total
Directly Mutualized					$\begin{array}{c} 121 \\ 0.8023 \\ 0.364 \end{array}$	$\begin{array}{c} 121 \\ 0.8023 \\ 0.364 \end{array}$
Subsidiary of Mutualized	$ \begin{bmatrix} N & 139 \\ \mu & 1.3185 \\ \sigma & 0.5448 \end{bmatrix} $		$\begin{array}{c} 639\\ 0.8807\\ 0.2377\end{array} \ast \ast$	$^{7}_{-0.9875}_{1.3854}$		$\begin{array}{c} 785 \\ 0.9415 \\ 0.2165 \end{array}$
Directly Private					$\begin{array}{c} 2174 \\ 0.2311 \\ 0.183 \end{array}$	$\begin{array}{c} 2174 \\ 0.2311 \\ 0.183 \end{array}$
Subsidiary of Private	$ \begin{bmatrix} N & 68 \\ \mu & -0.0471 \\ \sigma & 0.5277 \end{bmatrix} $	$^{14}_{-1.2311}$ -1.2311 $^{1.9993}$	$\begin{array}{c} 28\\ 0.2399\\ 0.5655\end{array} * \end{array}$	-0.8234	$egin{array}{c} 403 \ 0.61 \ ** \ 0.1461 \end{array}$	$\begin{array}{c} 514 \\ 0.45 \\ 0.1479 \end{array}$
Directly Public		$egin{array}{c} 142 \\ 0.6322 & ** \\ 0.3091 \end{array}$			$\begin{array}{c} 895 \\ 0.5793 & ** \\ 0.1843 \end{array}$	$\begin{array}{c} 1037 \\ 0.5865 & ** \\ 0.1645 \end{array}$
Subsidiary of Public	N 2974 μ -0.2716 ** σ 0.0868	$\begin{array}{c} 2567 \\ 0.5292 \\ 0.1255 \end{array}$	$\begin{array}{c} 1671 \\ 0.7434 \\ 0.1484 \end{array}$	$^{77}_{-3.1833}$ ** $^{0.3701}_{-0.3701}$	$\begin{array}{c} 989 \\ 0.4944 \\ 0.1921 \end{array}$	$\begin{array}{c} 8278 \\ 0.2461 \\ 0.0629 \end{array}$
Column Total	N 3181 μ -0.1973 ** σ 0.0855	$\begin{array}{c} 2723 \\ 0.5255 \\ 0.1198 \end{array}$	$\begin{array}{c} 2338 \\ 0.7749 \\ 0.1245 \end{array}$	$^{85}_{-2.9747}$ ** 0.3585	$\begin{array}{c} 4609 \\ 0.3974 \\ 0.1037 \end{array}$	$\begin{array}{c} 12936 \\ 0.3242 \\ 0.0545 \end{array}$

Table III.3 continued Panel B: Gross Returns, Annual % Net of Category Average

Table III.3 continued Panel C: Alpha Minus Expenses and Annualized Load, Annual % Net of Category Average Curbadwised Portfolios

r Mutual Fund Row Total		0.0	$\begin{array}{c ccccc} ** & 222 & 222 \\ & 0.1112 & 0.1112 & ** \\ & 0.0183 & 0.0183 \end{array}$	**	$\left \begin{array}{c c} 96 \\ 0.1123 \\ 0.0886 \\ 0.0251 \\ 0.0259 \\ 0.025$	* *	$\begin{array}{c c c c c c c c c c c c c c c c c c c $		r Mutual Fund Row Total	$\begin{array}{c c c c c c c c c c c c c c c c c c c $. 729 0.0528 ** 0.013	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c cccccccccccc} ** & & 223 \\ & & 223 \\ & & 0.0723 \\ & & 0.017 \\ & & 0.017 \\ \end{array} \\ \end{array} \\ \begin{array}{c} 384 \\ & & 384 \\ & & 384 \\ & & 384 \\ & & 384 \\ & & 384 \\ & & 384 \\ & & & 384 \\ & & & 384 \\ & & & & 384 \\ & & & & & 384 \\ & & & & & & & & & \\ \end{array}$	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	** 4006 11208 $**$ 10094 $**$
Other	•••	$\begin{array}{c} 6\\ 0.1862\\ 0.0962 \end{array}$		$\begin{array}{c} 3\\ 0.2589\\ 0.0077 \end{array}$		$\begin{array}{c} 30\\ 0.2414\\ 0.0396\end{array}$	$\begin{array}{c} 39\\ 0.2343\\ 0.0335\end{array}$		Other		$\begin{array}{c} 7\\ 0.2292\\ 0.0367\end{array}$		0.3189		$\begin{array}{c} 77 \\ 0.1112 \\ 0.0311 \end{array}$	0.1234
Portfolios Insurance		$\begin{array}{c} 261 \\ 0.0294 \\ 0.0232 \end{array}$		$^{7}_{-0.2646}$ 0.1163		$^{484}_{-0.1014}$ ** $^{0.016}_{-0.016}$	$\begin{array}{c} 752\\ -0.0575 & **\\ 0.0133 \end{array}$	ed Portfolios	Insurance		$595 \\ -0.0749 \\ 0.0147$		$\begin{array}{c} 37 \\ 0.0314 \\ 0.046 \end{array}$		$\begin{array}{c} 1438 \\ -0.0443 \\ 0.0088 \end{array}$	$2070 \\ -0.0517 **$
Subadvised Portfolios Fin'l Svs Insuran				$\begin{array}{c} 5 \\ 0.2885 \\ 0.0073 \end{array}$	$^{-0.1009}_{-0.1073}$	$124 \\ -0.0316 \\ 0.0302$	$\begin{array}{c} 141 \\ -0.0262 \\ 0.0285 \end{array}$	Non-Subadvised Portfolios	Fin'l Svs				$\begin{array}{c} 12 \\ 0.1702 \\ 0.0896 \end{array}$	$^{139}_{-0.0207}$	$\begin{array}{c} 2056 \\ 0.0054 \\ 0.0071 \end{array}$	2207 0.0046 **
Bank		$\begin{array}{c c} N & 15 \\ \mu & -0.1712 \\ \sigma & 0.1081 \end{array}$	 	$\begin{array}{ccc} N & 30 \\ \mu & 0.0739 \\ \sigma & 0.0557 \end{array}$		$\begin{array}{ccc} { m N} & 255 \ \mu & -0.1067 & ** \ \sigma & 0.0244 \end{array}$		Z	Bank	 N 36	$egin{array}{ccc} { m N} & 127 \ \mu & 0.0351 & * \ \sigma & 0.027 \end{array}$		$\begin{array}{cccc} 111 & 111 \\ 1 & 0.0407 & ** \\ 7 & 0.0313 \end{array}$		N $2602 \\ \mu -0.041 \\ \sigma 0.0065$	N 2840 μ -0 0344 **
Parent Tvpe:	ized	Subsidiary of Mutualized \int_{0}^{1}	Directly Private $\frac{1}{c}$	Subsidiary of Private $\frac{1}{c}$	Directly Public $\frac{1}{6}$	Subsidiary of Public $\frac{1}{6}$	Column Total $\frac{N}{\sigma}$		Parent Type:	Directly Mutualized $\frac{1}{6}$	Subsidiary of Mutualized $\frac{1}{d}$	Directly Private $\frac{1}{c}$	Subsidiary of Private $\frac{1}{6}$	Directly Public $\frac{1}{6}$	Subsidiary of Public 1	Column Total

Table III.3 continued Panel D Returns Minus Expenses and Annualized Load, Annual % Net of Category Average دىنامىلىنايەم Portfolios

Parent Type:		Bank	Subadvised Portfolios Fin'l Svs Insuranc	Portfolios Insurance	Other	Mutual Fund	Row Total
Directly Mutualized	Z Z D					$\begin{array}{c} 67\\ 2.9628\\ 0.6597\end{array}$	2.9628 ** 0.6597 0.6577 0.6777 0
Subsidiary of Mutualized		$^{15}_{-2.4918}$ ** $^{0.9002}_{-1.4912}$		$\begin{array}{c} 315 \\ 1.6654 \\ 1.0876 \end{array}$	$^{8}_{-1.1474}_{-1.7806}$		$\begin{smallmatrix} & 338 \\ 1.4143 \\ 1.0163 \end{smallmatrix}$
Directly Private						$\begin{array}{c} 292 \\ 0.6459 \\ 0.4227 \end{array}$	$\left\ \begin{array}{c} 292\\ 0.6459\\ 0.4227\end{array}\right.$
Subsidiary of Private	Z Z D	$^{31}_{-6.2648}$ ** $^{1.6437}_{-1.6437}$	$\begin{array}{c} 5 \\ 0.307 \\ 1.1924 \end{array}$	$^{10}_{-2.8187}$ ** $^{10}_{0.9963}$	$^3_{-1.8169}_{-3.1992}$	$^{32}_{-1.8348} ** \\ 1.126$	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$
Directly Public	ZΞb		$^{-1.8156}_{-0.6889}$ **			$^{107}_{-0.4184}$ ** $^{0.6486}$	$\left\ \begin{array}{c}1119\\-0.5593\\0.588\end{array}\right $
Subsidiary of Public	Z Zb	$^{318}_{-0.8034}$ ** $^{0.3726}$	$ \begin{smallmatrix} 214 \\ 0.4507 \\ 0.417 \end{smallmatrix} $	$\begin{array}{c} 585 \\ -2.0948 \\ 0.2802 \end{array}$	$\begin{array}{c} 32 \\ 4.5084 \\ 0.7895 \end{array}$	$\begin{array}{c} 72 \\ 1.0032 \\ 0.8608 \end{array}$	$\begin{array}{ c c c c } 1221 & & \\ -0.9566 & ** & \\ 0.1931 & & \\ \end{array}$
Column Total	Z Z D	$\left. \begin{array}{c} 364 \\ -1.3381 \\ 0.3644 \end{array} \right * *$	$\begin{array}{c} 231 \\ 0.3298 \\ 0.3898 \end{array}$	$\left \begin{array}{c} 910\\ -0.8012\\ 0.4213 \end{array} \right $	$\begin{array}{c} 43\\ 3.0149\\ 0.7936 \end{array}$	$\begin{array}{c} 587 \\ 0.6202 \\ 0.2841 \end{array}$	$\left\ \begin{array}{c} 2135\\ -0.3027 \\ 0.2111 \end{array}\right.$
		Z	Non-Subadvised Portfolios	ed Portfolios			
Parent Type:		Bank	Fin'l Svs	Insurance	Other	Mutual Fund	Row Total
Directly Mutualized	Z Z b					$\begin{array}{c} 127 \\ 2.1138 \\ 0.3684 \end{array}$	$\begin{array}{ c c c } & 127 \\ & 2.1138 \\ & 0.3684 \end{array}$
Subsidiary of Mutualized	Z Zb	$\begin{array}{c} 139 \\ 1.3014 \\ 0.5479 \end{array}$		$\begin{array}{c} 720 \\ 0.3294 \\ 0.2239 \end{array}$	$^{7}_{-0.5836}_{1.3864}$		$\begin{smallmatrix} 866\\ 0.4781\\ 0.2064 \end{smallmatrix}$
Directly Private	N I P					$\begin{array}{c} 2225 \\ 0.1379 \\ 0.1856 \end{array}$	$\left\ \begin{array}{c} 2225\\ 0.1379\\ 0.1856\end{array}\right.$
Subsidiary of Private		$^{111}_{-3.4818}$ ** $^{0.6107}$	$^{16}_{-1.4862} * ^{16}_{1.8957}$	$^{39}_{-1.4596}$ ** $^{0.5644}$	-0.1701	$\begin{array}{c} 435 \\ 0.1587 \\ 0.1828 \end{array}$	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$
Directly Public	N IP		$\begin{smallmatrix} 143\\ 0.5619\\ 0.3057 \end{smallmatrix}$			$\begin{array}{c} 920 \\ 0.1666 \\ 0.1956 \end{array}$	$\left\ \begin{array}{c} 1063\\ 0.2198\\ 0.1742\end{array}\right.$
Subsidiary of Public	Z Z D	$\begin{array}{c} 3068 \\ -0.4954 \\ 0.0881 \end{array}$	$\begin{smallmatrix} 2681 \\ 0.1809 \\ 0.1319 \end{smallmatrix}$	$\begin{array}{c} 1756 \\ 0.2701 \\ 0.1535 \end{array}$	$^{77}_{-2.6923}$ ** $^{0.3862}$	$^{+0.2751}_{-0.2008}$ **	$\begin{array}{ c c c c c c c c c c c c c c c c c c $
Column Total	ZΖρ	$3318 \\ -0.52 \\ 0.0878$	$\begin{array}{c} 2840 \\ 0.1907 \\ 0.1259 \end{array}$	$\begin{array}{c} 2515\\ 0.2603 \\ 0.1252 \end{array} \\ \ast \ast$	$\begin{bmatrix} 85\\ -2.489\\ 0.3719 \end{bmatrix}$	$\begin{array}{c} 4784 \\ 0.0968 \\ 0.1061 \end{array}$	$\left\ \begin{array}{c}13542\\-0.0205\\0.0559\end{array}\right $

and family-level annual performance and expense measures for 1995-2004. Panels A and B include class-level performance and expense measures by ownership type and subsidiary type, respectively. Panels C and D include family-level performance and expense measures by ownership type and subsidiary type, respectively. 4-factor α are presented throughout and all Table III.4: Summary Statistics, All Variables 1995-2004: This table presents summary statistics on the set of classvariables are annual % values.

			Dire	ctly					Subsi	idiary		
	Mutu	alized	Pu	Public	\mathbf{Pr}	ivate	Mutı	alized	Pu	Public	Pri	vate
	N=1	N=1,494	N=1(0,750	N	N=23,760	N=1	N=10,060	N=9	1,058	ľ N	N=4,606
Variable	μ	α	μ	α	μ	α	μ	σ	μ	σ	μ	α
Return (%)	7.71	15.46	6.56	16.97	7.92	22.32	6.61	18.31	6.12	18.03	6.88	16.08
α (%)	-0.09	0.38	-0.11	0.39	-0.07	0.41	-0.09	0.37	-0.09	0.33	-0.08	0.32
Expense Ratio (%)	0.32	0.51	1.37	0.77	1.35	1.11	1.36	0.68	1.31	0.67	1.30	0.70
12b-1 Fees (%)	0.00	0.00	0.40	0.41	0.24	0.34	0.40	0.41	0.37	0.39	0.40	0.39
Front End Load $(\%)$	0.00	0.00	0.97	1.90	0.83	1.77	1.10	2.06	1.15	2.05	1.75	2.50
Maximum CDSL (%)	0.00	0.00	0.98	1.71	0.45	1.25	1.02	1.83	0.96	1.76	0.80	1.69
Maximum Total Load $(\%)$	0.21	0.54	2.00	2.16	1.40	2.02	2.18	2.36	2.15	2.28	2.58	2.52
Expense Ratio (% Net of Cat. Avg)	-0.99	0.56	0.09	0.68	-0.02	1.05	0.03	0.61	0.01	0.56	-0.01	0.64
Non-12b-1 Exp (% Net of Cat. Avg)	-0.63	0.54	0.04	0.49	0.10	0.99	-0.02	0.39	-0.02	0.38	-0.05	0.53
12b-1 Fees (% Net of Cat. Avg)	-0.36	0.08	0.05	0.41	-0.12	0.34	0.04	0.41	0.02	0.38	0.04	0.38
Total Load (% Net of Cat. Avg)	-1.87	0.73	-0.06	2.09	-0.68	1.98	0.10	2.30	0.16	2.15	0.47	2.43
Total Expenses (% Net of Cat. Avg)	-1.25	0.58	0.08	0.81	-0.12	1.13	0.05	0.78	0.03	0.71	0.06	0.76
Return - Gross (% Net of Cat. Avg)	0.83	8.43	0.49	10.94	0.68	17.11	0.27	12.00	-0.22	11.85	0.40	9.66
Ret. Net of Exp (% Net of Cat. Avg)	1.65	8.41	0.39	11.07	0.60	17.08	0.24	11.93	-0.31	11.90	0.25	9.71
Ret. Net of Exp, Load/7 (% Net of Cat. Avg)	1.92	8.41	0.40	11.08	0.70	17.09	0.23	11.93	-0.34	11.91	0.18	9.71
α (% Net of Cat. Avg)	-0.01	0.29	0.00	0.31	0.02	0.38	0.00	0.30	0.00	0.28	-0.01	0.26
α Net of Exp (% Net of Cat. Avg)	0.97	0.44	-0.04	0.69	0.09	1.25	0.00	0.63	0.02	0.60	0.02	0.64
α Net of Exp, Load/7 (% Net of Cat. Avg)	0.25	0.31	0.00	0.44	0.13	0.47	-0.04	0.45	-0.04	0.42	-0.14	0.45

Panel A: Performance Measures by Ownership Type (Class-Level Variables, 1995-2004, Annual %)

	s-Level Variables, 1995-2004, Annual %)
	asures by Subsidiary Type (Class-
Table III.4 continued	Panel B: Performance Mea

	Non-Si $N = N$	Non-Subsidiary $N = 52.740$	$\operatorname{Bank}_{N=5}$	Bank Sub. $N = 31.837$	Fin'l S N =	Fin'l Svs Sub. $N = 22.559$	Insura N =	Insurance Sub. $N = 30.722$	Othen N =	Other Sub. $N = 1.797$
Variable	μ	α	π	σ	π	σ	μ	Q	μ	α
Return $(\%)$	7.35	20.12	5.62	16.49	5.93	18.47	6.41	18.48	7.30	15.73
α (%)	-0.08	0.40	-0.09	0.27	-0.08	0.32	-0.11	0.38	-0.05	0.21
Expense Ratio $(\%)$	1.32	0.93	1.18	0.62	1.28	0.66	1.48	0.68	1.09	0.64
12b-1 Fees (%)	0.30	0.38	0.29	0.36	0.37	0.39	0.48	0.41	0.30	0.39
Front End Load $(\%)$	1.04	1.97	0.98	1.93	1.09	2.02	1.31	2.16	0.69	1.73
Maximum CDSL (%)	0.68	1.51	0.79	1.66	0.95	1.72	1.24	1.93	0.61	1.35
Maximum Total Load $(\%)$	1.79	2.20	1.83	2.24	2.09	2.25	2.59	2.31	1.30	2.00
Expense Ratio (% Net of Cat. Avg)	-0.01	0.85	-0.06	0.49	-0.04	0.57	0.12	0.61	-0.19	0.62
Non-12b-1 Exp (% Net of Cat. Avg)	0.04	0.75	-0.01	0.33	-0.06	0.38	0.00	0.42	-0.15	0.40
12b-1 Fees (% Net of Cat. Avg)	-0.05	0.37	-0.05	0.35	0.01	0.38	0.12	0.40	-0.05	0.39
Total Load (% Net of Cat. Avg)	-0.25	2.12	-0.05	2.11	0.04	2.15	0.45	2.24	-0.73	1.93
Total Expenses (% Net of Cat. Avg)	-0.04	0.96	-0.06	0.67	-0.04	0.72	0.20	0.75	-0.30	0.77
Return - Gross (% Net of Cat. Avg)	0.36	14.68	-0.23	10.61	-0.09	12.20	-0.12	11.57	0.39	10.85
Ret. Net of Exp (% Net of Cat. Avg)	0.30	14.70	-0.26	10.63	-0.12	12.28	-0.34	11.60	0.53	10.87
2 (% N	0.34	14.70	-0.26	10.64	-0.13	12.29	-0.41	11.61	0.63	10.89
α (% Net of Cat. Avg)	0.01	0.35	-0.01	0.22	0.01	0.27	-0.01	0.32	0.01	0.17
α Net of Exp (% Net of Cat. Avg)	0.06	0.97	0.08	0.52	0.06	0.61	-0.10	0.63	0.30	0.61
α Net of Exp, Load/7 (% Net of Cat. Avg)	0.04	0.47	0.00	0.37	-0.01	0.41	-0.10	0.45	0.12	0.32

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	Mutualized N=17	alized :17	Pu N=2	Public N=2,775	Pri N=	Private N=171	Mutu N=	Mutualized N=338	Public N=412	olic 412	Priv N=1	Private N=1,742
Variable	π	σ	μ	α	μ	α	μ	α	μ	α	μ	α
Return (%)		13.85	9.73	24.41	9.47	15.54	7.14	13.42	7.39	15.79	7.44	14.64
α (%)		0.06	-0.04	0.35	-0.06	0.22	-0.05	0.14	-0.08	0.24	-0.04	0.23
Expense Ratio $(\%)$	0.45	0.25	1.57	1.65	1.11	0.34	1.02	0.42	1.41	0.81	1.04	0.49
12b-1 Fees $(\%)$		0.00	0.11	0.17	0.19	0.21	0.17	0.20	0.17	0.24	0.16	0.20
Front End Load $(\%)$		0.00	0.69	1.58	1.24	1.81	1.02	1.51	1.51	2.10	0.92	1.44
Maximum CDSL (%)		0.00	0.10	0.43	0.39	0.88	0.35	0.75	0.12	0.41	0.30	0.66
Maximum Total Load $(\%)$		0.06	0.95	1.71	1.70	2.08	1.43	1.93	1.72	2.16	1.28	1.74
Expense Ratio (% Net of Cat. Avg)		0.14	0.13	1.62	-0.19	0.34	-0.23	0.40	0.05	0.73	-0.19	0.38
Non-12b-1 Exp (% Net of Cat. Avg)		0.17	0.38	1.61	-0.05	0.22	-0.07	0.32	0.23	0.65	-0.04	0.31
12b-1 Fees (% Net of Cat. Avg)		0.04	-0.25	0.18	-0.14	0.21	-0.16	0.20	-0.18	0.24	-0.15	0.20
Total Load (% Net of Cat. Avg)		0.20	-1.19	1.70	-0.23	1.94	-0.46	1.88	-0.36	2.15	-0.41	1.64
Total Expenses (% Net of Cat. Avg)		0.12	-0.04	1.69	-0.22	0.54	-0.30	0.55	0.00	0.78	-0.24	0.52
Return - Gross (% Net of Cat. Avg)		2.52	1.55	18.84	2.26	9.44	0.41	7.33	0.18	10.86	0.75	9.07
Ret. Net of Exp (% Net of Cat. Avg)		2.59	1.36	19.01	2.61	9.62	0.67	7.33	0.09	10.97	0.93	9.17
Ret. Net of Exp, Load/7 (% Net of Cat. Avg)		2.57	1.53	19.02	2.64	9.63	0.73	7.34	0.14	10.96	0.99	9.18
α (% Net of Cat. Avg)		0.02	0.04	0.35	0.03	0.16	0.02	0.13	0.00	0.21	0.01	0.20
α Net of Exp (% Net of Cat. Avg)		0.10	-0.09	1.79	0.22	0.38	0.25	0.44	-0.03	0.77	0.20	0.43
α Net of Exp, Load/7 (% Net of Cat. Avg)		0.03	0.21	0.42	0.06	0.33	0.09	0.29	0.03	0.39	0.06	0.30

atinued	ormance Measures by Subsidiary Type (Family-Level Variables, 1995-2004, Annual $\%)$
	Panel D: Performance Mea

	Non-S1	Non-Subsidiary	Bank	Sub.	Fin'l S	bys Sub.	Insura	Insurance Sub.	Other	Sub.
	= N	N = 3,432	N =	835	= N	N = 470	Z	N = 642	$\mathbb{N} = \mathbb{N}$	111
Variable	μ	α	μ	σ	μ	α	μ	σ	μ	α
	0		0						1	
Return $(\%)$	9.36	23.08	6.84	12.75	7.73	15.26	7.92	14.89	7.11	17.57
α (%)	-0.04	0.34	-0.04	0.19	-0.06	0.26	-0.07	0.18	-0.05	0.20
Expense Ratio $(\%)$	1.52	1.51	0.91	0.37	1.17	0.69	1.11	0.43	1.01	0.70
12b-1 Fees $(\%)$	0.13	0.19	0.09	0.13	0.17	0.18	0.23	0.24	0.09	0.17
Front End Load $(\%)$	0.84	1.70	0.61	1.17	0.88	1.46	1.53	1.68	0.14	0.58
Maximum CDSL $(\%)$	0.13	0.48	0.10	0.33	0.29	0.61	0.56	0.90	0.16	0.79
Maximum Total Load $(\%)$	1.11	1.84	0.79	1.33	1.25	1.68	2.12	2.07	0.30	1.08
Expense Ratio (% Net of Cat. Avg)	0.09	1.48	-0.23	0.25	-0.08	0.57	-0.19	0.38	-0.28	0.65
Non-12b-1 Exp (% Net of Cat. Avg)	0.32	1.47	-0.03	0.22	0.06	0.55	-0.09	0.25	-0.01	0.60
12b-1 Fees (% Net of Cat. Avg)	-0.23	0.19	-0.20	0.15	-0.15	0.19	-0.11	0.24	-0.26	0.18
Total Load (% Net of Cat. Avg)	-1.00	1.82	-0.73	1.30	-0.53	1.68	0.17	1.98	-1.74	1.08
Total Expenses (% Net of Cat. Avg)	-0.05	1.55	-0.33	0.36	-0.16	0.68	-0.17	0.59	-0.52	0.69
Return - Gross (% Net of Cat. Avg)	1.33	17.53	0.86	7.94	1.04	10.47	0.66	7.67	-1.01	13.91
Ret. Net of Exp (% Net of Cat. Avg)	1.20	17.69	1.06	7.93	1.11	10.71	0.85	7.67	-0.74	14.24
Ret. Net of Exp, Load/7 (% Net of Cat. Avg)	1.34	17.70	1.17	7.94	1.19	10.71	0.82	7.68	-0.49	14.23
α (% Net of Cat. Avg)	0.03	0.33	0.01	0.16	0.00	0.21	0.00	0.16	0.01	0.18
α Net of Exp (% Net of Cat. Avg)	-0.06	1.63	0.23	0.30	0.12	0.56	0.20	0.41	0.27	0.69
α Net of Exp, Load/7 (% Net of Cat. Avg)	0.17	0.42	0.11	0.25	0.07	0.31	-0.03	0.33	0.26	0.25

Table III.5: Linear Models of Performance Measures, 1995-2004 Annual: This table presents the results of a series of linear models of mutual fund performance measures. Models in panel A were estimated at the class level, while those in panel B were estimated at the family level. Dependent variables are performance measures net of category averages. Gross Alpha and Gross Return refer to pre-expense measures, Net Alpha^{*} and Net Return^{*} refer to 4-factor α and return net of expenses (including non-12b-1 and 12b-1 fees) and Net Alpha^{**} and Net Return^{**} refer to 4-factor α and return net of expenses (including non-12b-1 and 12b-1 fees) and total load annualized over seven years. Heteroscedasticity consistent standard errors are used to calculate all p-values. All performance and expense measures are net of broad SI-derived category averages.

Panel A: Class-Level, 1995-2004 Annual	Luata		ζ				14	_				
	Alpha (t)	ass a (t)	$\begin{array}{c} \operatorname{Gross} \\ \operatorname{Return} (t) \end{array}$	u (t)	$\operatorname{Alpha}^{\operatorname{Net}}($	(t)	Return [*] (t)	t l* (t) 	$\operatorname{Alpha^{**}}($	* (t)	Return ^{**} ($\mathbf{t}^{t}(\mathbf{t})$
	β	d	β	d	β	d	β	d	β	d	β	d
Parent = Other (t)	0.085	0.16	-0.086	0.74	0.342	0.00	-0.061	$0.81 \parallel$	0.108	0.08	-0.027	0.92
Parent = Financial Svs (t)	0.051	0.13	-0.101	0.49	0.170	0.00	-0.001	1.00	0.102	0.00	0.033	0.82
Parent = Insurance (t)	-0.212	0.00	-0.785	0.00	-0.124	0.00	-0.776	0.00	-0.247	0.00	-0.807	0.00
Parent = Bank(t)	-0.085	0.01	-0.325	0.02	0.039	0.23	-0.231	0.10	-0.079	0.01	-0.228	0.11
Privately Owned (t)	0.151	0.00	0.141	0.31	0.255	0.00	0.250	0.07	0.146	0.00	0.246	0.07
Mutualized (t)	0.051	0.23	0.705	0.00	0.168	0.00	0.840	0.00	0.091	0.03	0.868	0.00
Buried Flag (t)	0.090	0.00	0.269	0.01	0.022	0.37	0.215	0.04	0.089	0.00	0.215	0.04
ForeignOwned Flag (t)	-0.198	0.00	-0.314	0.03	-0.215	0.00	-0.289	0.05	-0.181	0.00	-0.272	0.06
Non-12B1 Expenses (Cat. Adj. %) (t)	-0.059	0.31	0.516	0.01								
12b-1 Fees (Cat. Adj. $\%$) (t)	-0.104	0.00	-0.504	0.00								
Total Load/7 (Cat. Adj. %) (t)	0.008	0.18	0.046	0.05	-0.024	0.00	0.023	0.32				
Redemption Fee Flag (t)	0.092	0.00	0.577	0.00	0.131	0.00	0.605	0.00	0.047	0.15	0.563	0.00
Subadvised Flag (t)	0.237	0.00	-0.554	0.00	0.246	0.00	-0.552	0.00	0.253	0.00	-0.549	0.00
Relatedness (t)	0.248	0.00	-0.087	0.69	0.214	0.00	-0.136	0.52	0.229	0.00	-0.133	0.53
Focus (t)	0.306	0.00	1.312	0.00	0.245	0.00	1.336	0.00	0.340	0.00	1.351	0.00
Log of Age (Years) (t)	-0.299	0.00	-0.161	0.08	-0.177	0.00	0.009	0.92	-0.350	0.00	-0.030	0.73
Turnover (t)	-0.046	0.00	0.009	0.84	-0.082	0.00	-0.002	0.97	-0.047	0.00	-0.001	0.99
Log of Total Net Assets (t)	0.070	0.00	-0.131	0.00	0.182	0.00	-0.059	0.01	0.075	0.00	-0.062	0.01
Log of Family Total Net Assets (t)	0.005	0.58	-0.106	0.00	0.066	0.00	-0.074	0.01	0.005	0.53	-0.074	0.01
Flows $(\%)$ (t)	0.000	0.93	0.000	0.39	0.000	0.89	0.000	0.37	0.000	0.84	0.000	0.37
Log of $\#$ Accounts (t)	0.016	0.00	0.330	0.00	-0.043	0.00	0.273	0.00	0.007	0.17	0.268	0.00
Stocks $(Avg \%) (t)$	0.005	0.00	0.011	0.00	0.002	0.00	0.010	0.00	0.005	0.00	0.010	0.00
$\operatorname{Cash}\left(\operatorname{Avg}\%\right)(t)$	0.003	0.02	-0.005	0.59	-0.001	0.54	-0.007	0.49	0.003	0.01	-0.007	0.51
Money Market (t)	0.110	0.33	0.543	0.16	0.169	0.14	0.561	0.14	0.089	0.43	0.554	0.15
Sector (t)	0.097	0.54	0.706	0.49	-0.244	0.19	0.272	0.79	0.027	0.86	0.223	0.83
International (t)	0.022	0.72	0.348	0.08	0.009	0.88	0.352	0.08	0.033	0.58	0.366	0.07
Bond-Income(t)	0.612	0.00	0.344	0.22	0.293	0.00	0.100	0.71	0.647	0.00	0.150	0.58
Growth-Income (t)	0.085	0.00	-0.159	0.22	-0.069	0.02	-0.284	0.03	0.072	0.01	-0.282	0.03
Dist = Affinity Group (t)	-0.037	0.71	0.899	0.08	0.494	0.00	1.543	0.00	0.381	0.00	1.829	0.00
Dist = Bank Proprietary (t)	0.021	0.51	0.238	0.10	0.344	0.00	0.601	0.00	0.198	0.00	0.728	0.00
Dist = Direct (t)	-0.024	0.58	0.484	0.01	0.272	0.00	0.978	0.00	0.433	0.00	1.337	0.00
Dist = Institutional (t)	0.022	0.54	0.747	0.00	0.585	0.00	1.418	0.00	0.472	0.00	1.764	0.00
Dist = Insurance (t)	0.072	0.21	-0.588	0.01	0.172	0.00	-0.486	0.04	0.101	0.08	-0.495	0.03
Dist = Proprietary (t)	-0.205	0.00	-0.278	0.05	-0.136	0.00	-0.265	0.06	-0.243	0.00	-0.302	0.03
Intercept	-0.498	0.00	-1.616	0.00	-1.178	0.00	-2.124	0.00	-0.524	0.00	-2.153	0.00
Year Dummes	Inclu	aea	Inclue	lea	Incluc	lea	Inclu	ded	Incluc	lea	Included	lea
Adjusted R-Squared N	$\left \begin{array}{c} 0.01\\ 64,885 \end{array} \right $		$0.01\\86,866$		$0.04 \\ 64,885$		$\begin{array}{c} 0.01 \\ 87,313 \end{array}$		$\begin{array}{c} 0.02 \\ 64,889 \end{array}$		$0.01 \\ 87,313$	

Panel A: Class-Level, 1995-2004 Annual Data

Table III.5 continued Double D. Frankly, Loude 1006 2004 Ammed	D_{o+o}											
I allel D. Fallily-Devel, 1999-2004 Allilla	$\left \begin{array}{c} \text{Data} \\ \text{Alpha} \\ \beta \end{array} \right _{\beta} $	$\mathbf{D} \begin{pmatrix} \mathbf{x} \\ \mathbf{x} \\ \mathbf{x} \end{pmatrix}$	$\begin{array}{c} \operatorname{Gross} \\ \operatorname{Return} (\mathrm{t}) \\ \beta & \mathrm{D} \end{array}$	${\operatorname{ss}\atop{{\operatorname{D}}}}_{{\operatorname{D}}}^{{\operatorname{ss}}}(t)$	$\substack{ \substack{ \text{Net} \\ \text{Alpha}^* (t) \\ \beta } }_{D} $	b b b	$\substack{\operatorname{Net}\\\operatorname{Return}^{*}(t)\\ \beta \mathbf{p}\end{array}$	$\mathbf{p}_{\mathbf{n}^{*}(t)}^{\mathrm{et}}$	$\substack{ \text{Alpha}^{**}(t) \\ \beta \text{p} }$	$\mathbf{b}_{\mathbf{D}}^{\mathbf{t}}$	$\substack{\text{Net}\\\text{Return}^{**}(t)\\ \beta \mathbf{D} \\ }$	b b
Parent = Other (t)	-0.103	0.51	1.753	0.06	-0.042	0.81	1.841	0.05	-0.051	0.75	1.917	0.04
Parent = Financial Svs (t)	-0.182	0.13	0.234	0.73	-0.314	0.02	0.075	0.91	-0.198	0.10	0.078	0.91
Parent = Insurance (t)	-0.328	0.01	0.010	0.99	-0.194	0.18	0.158	0.82	-0.368	0.00	0.056	0.93
Parent = Bank(t)	-0.002	0.99	1.150	0.10	-0.042	0.75	1.069	0.12	0.035	0.78	1.136	0.10
Privately Owned (t)	0.217	0.03	0.965	0.09	0.373	0.00	1.140	0.04	0.239	0.02	1.155	0.04
Mutualized (t)	0.264	0.01	-0.469	0.45	0.337	0.00	-0.370	0.55	0.311	0.00	-0.321	0.60
Buried Flag (t)	0.044	0.61	-0.298	0.53	0.115	0.22	-0.180	0.70	0.042	0.63	-0.179	0.70
ForeignOwned Flag (t)	0.078	0.51	0.141	0.83	0.174	0.17	0.211	0.75	0.114	0.34	0.267	0.69
Non-12B1 Expenses (Cat. Adj. %) (t) 13b 1 $\overline{\text{P202}}$ (Cat. Adj. %) (t)	-0.050	0.72	-0.423	0.22								
Total Load /7 (Cat. Adj. %) (t)	0.075	0.03	$-0.00\pm$ 0168	0.00	-0.088	0.09	-0.051	0 79				
% Classes w/ Redemption Fee (t)	-0.366	0.00	1.364	0.08	-0.100	0.43	1.662	0.03	-0.352	0.00	1.648	0.03
Subadvised $(\%)$ (t)	0.241	0.01	-2.537	0.00	0.431	0.00	-2.329	0.00	0.231	0.02	-2.346	0.00
Focus	0.580	0.00	0.871	0.33	0.669	0.00	1.001	0.26	0.578	0.00	0.996	0.26
Log of Age (Years) (t)	-0.171	0.05	-1.438	0.00	-0.370	0.00	-1.745	0.00	-0.173	0.04	-1.748	0.00
Turnover (t)	-0.023	0.57	-0.128	0.64	-0.071	0.08	-0.190	0.49	-0.029	0.47	-0.193	0.48
Log of Total Net Assets (t)	0.088	0.02	-0.097	0.58	0.397	0.00	0.275	0.11	0.124	0.00	0.313	0.08
Flows (%) (t)	0.000	0.71	0.000	0.40	0.000	0.58	0.000	0.33	0.000	0.80	0.000	0.30
Log of $\#$ Accounts (t)	0.011	0.64	0.449	0.00	-0.086	0.00	0.343	0.00	-0.022	0.28	0.299	0.01
Stocks $(Avg \%)$ (t)	0.006	0.02	0.025	0.09	0.007	0.04	0.027	0.06	0.006	0.02	0.027	0.07
Cash (Avg %) (t)	0.000	0.86	-0.019	0.25	-0.004	0.23	-0.022	0.18	0.000	0.85	-0.022	0.18
Money Market (% Classes) (t)	1.800	0.00	1.553	0.60	2.173	0.00	1.958	0.50	1.819	0.00	1.942	0.51
Sector (% Classes) (t)	0.287	0.38	3.747	000	0.245	0.52	3.783	000	101.U	0.59	3.044	0.00
$\frac{1}{1}$	0.394	0.03	-U.034	0.00	1.040	70.0	-0.00/	01.0	0.900	0.04	-0.044	71.0
DUIU-IIICOIIIE (70 Classes) (1) Current Innouno (02 Classes) (1)	0.004 0.976	0.10	1 984	0.40	1.040 0.045	0.00	401.7 1 584	01.0	100.0	0.0	2.000 1 572	0.20
Dist = Affinity Groun (% Classes) (t)	0.504	0.17	-3 014	0.19	0.720	0.05	-2,775	0.22	0.628	0 11	-2,450	0.10
Dist = Bank Proprietary (% Classes) (t)	-0.069	0.53	-1.031	0.19	0.085	0.46	-0.793	0.31	0.001	1.00	-0.702	0.37
Dist = Direct (% Classes) (t)	0.145	0.26	0.363	0.64	0.198	0.13	0.449	0.55	0.356	0.01	0.847	0.24
Dist = Institutional (% Classes) (t)	-0.014	0.91	1.554	0.03	0.081	0.54	1.741	0.01	0.111	0.32	1.972	0.00
Dist = Insurance (% Classes) (t)	0.008	0.96	-1.262	0.12	0.467	0.01	-0.665	0.41	0.070	0.66	-0.583	0.47
Dist = Proprietary (% Classes) (t)	-0.054	0.69	-0.974	0.23	0.219	0.17	-0.643	0.42	-0.031	0.82	-0.673	0.40
Intercept Year Dummies	-1.309 includ	0.00 ed	-2.543 inclue	0.25 Jed	-2.152 inclue	$_{ m ded}^{ m 0.00}$	-3.624 inclu	0.10 ded	-1.220 inclue	0.01 led	-3.433 incluc	$_{ m led}^{ m 0.11}$
Adjusted R-Squared	0.04		0.02		0.09		0.02		0.05		0.02	
N1	0,904		4,400	_	0,904		4,402		0,904		4,402	

Table III.5 continued

Measures
Performance
Gross
Annual
using
Models
Level
Family
Panel A:

,		Ŭ	Gross Alpha (t)	ıa (t)				5	Gross Return (t)	ırn (t		
	Bank		Financia	al	Insurance	ıce	Bank	Ş	Financia	ial	Insurance	ce
Performance (Cat. Adj. %) (t-1)	-0.013		-0.021		-0.127	*	0.000		0.000		-0.006	
Non-12B1 Expenses (Čat. Adj. %) (t-1)	-0.001		0.023		-1.888	* *	0.009		0.056		-1.802	* *
12b-1 Fees (Cat. Adj. %) (t-1)	-1.687	* *	0.945	*	0.839		-1.549	* *	1.055	*	0.959	*
Total Load/7 (Cat. Ådj. %) (t-1)	-0.151	*	-0.087		0.113		-0.172	* *	-0.072		0.101	
Privately Held Flag (t-1)	-3.592	* *	-3.048	* *	-4.221	* *	-3.546	* *	-3.208	* *	-4.085	*
Mutualized Flag $(t-1)$	2.618	* *	-0.432		3.179	* *	1.997	* *	-1.070		2.627	* *
% Subadvised $(t-1)$	-0.422		-1.138	* *	0.946	* *	-0.649	*	-1.328	* *	0.785	*
Focus $(t-1)$	-1.583	* *	-0.461		-1.223	* *	-1.342	* *	-0.415		-1.499	*
Log of Agé (Years) (t-1)	-0.959	* *	-1.155	* *	-0.697	* *	-0.842	* *	-1.139	* *	-0.582	* *
Turnover $(t-1)$	-0.118		-0.048		-0.054		-0.081		0.000		-0.038	
Log of Total Net Assets (t-1)	-0.176	* *	0.102		-0.224	* *	-0.138	* *	0.058		-0.279	* *
Flows (%) (t-1)	0.002		0.002		0.002		0.000		0.000		0.000	
Log of $\#$ Accounts (t-1)	-0.018		-0.023		0.056		-0.018		0.002		0.097	*
$\operatorname{Cash}\left(\operatorname{Avg}\%\right)(\operatorname{t-1})$	0.026	* *	0.015	*	0.009		0.022	* *	0.015	* *	0.010	
Stocks $(Avg \%)$ (t-1)	0.005		-0.001		0.004		0.004		-0.001		0.003	
% Money Market Funds (t-1)	-3.759	* *	0.312		-3.963	* *	-3.978	* *	0.287		-4.043	* *
% Sector Funds (t-1)	0.732		-2.426	*	-1.945		1.138		-2.254	*	-1.956	*
% International Funds (t-1)	0.631		-1.128		-1.222	*	0.628		-0.986		-1.072	*
% Bind/Income Funds (t-1)	2.102	* *	0.450		-1.446	*	2.367	* *	0.782		-1.236	*
-	1.233	* *	0.278		1.063	*	1.247	* *	0.378		0.601	
Dist = Bank Proprietary (% Classes) (t-1)	2.623	* *	1.378	* *	-0.643		2.891	* *	1.503	* *	-0.606	
Ξ	-1.634	* *	-1.084	*	-1.640	* *	-1.350	* *	-0.869	* *	-1.371	* *
Dist = Institutional (% Classes) (t-1)	0.115		0.681	*	0.730	* *	-0.094		0.670	* *	0.516	*
Dist = Insurance (% Classes) $(t-1)$	0.673	*	1.540	* *	-1.313	* *	0.780	*	1.533	* *	-1.454	* *
			included	g			_		included	ğ		
Intercept	3.465	*	3.114	*	4.234	*	2.648	*	2.954	*	3.948	*
Likelihood Ratio p-value Pseudo R-Squared N	$\begin{array}{c} 0.00\\ 0.63\\ 3.396\end{array}$						0.00 0.62 3.806					
-	00010					_	0000					

Panel B: Family Level Models using Annual Net Performance Measures	Net Perfe	orma	nce Meas	ures								
		Z	Net Alpha $(t)^{**}$	(t)*	*			Ż	Net Return (t)**	n (t)*	*	
	Bank		Financial	ial	Insurance	JCe	Bank	×	Financial	ial	Insurance	ce
Performance (Cat. Adi. %) (t-1)	0.024		-0.024		-0.108	*	0.002		0.000		-0.006	
Privately Held Flag (t-1)	-3.575	* *	-3.040	* *	-4.122	*	-3.556	* *	-3.242	* *	-4.005	*
Mutualized Flag $(t-1)$	2.849	* *	-0.431		3.375	* *	2.201	* *	-1.105		2.767	*
% Subadvised $(t-1)$	-0.506		-1.103	* *	1.073	*	-0.676	*	-1.313	* *	0.857	*
Focus $(t-1)$	-1.599	* *	-0.501		-1.222	* *	-1.311	* *	-0.478		-1.605	*
Log of Age (Years) (t-1)	-1.036	* *	-1.187	* *	-0.710	*	-0.904	* *	-1.156	* *	-0.654	*
Turnover $(t-1)$	-0.108		-0.039		-0.110		-0.083		0.006		-0.116	
Log of Total Net Assets (t-1)	-0.122	*	0.102		-0.075		-0.095		0.037		-0.145	* *
Flows (%) (t-1)	0.002		0.002		0.002		0.000		0.000		0.000	
Log of $\#$ Accounts (t-1)	-0.082	*	-0.015		0.057		-0.080	*	0.021		0.106	* *
Cash (Avg %) (t-1)	0.028	* *	0.016	* *	0.006		0.023	* *	0.015	* *	0.007	
Stocks (Avg %) (t-1)	0.008		-0.001		0.004		0.007		-0.003		0.003	
% Money Market Funds (t-1)	-4.437	* *	0.309		-3.395	*	-4.322	* *	0.250		-3.561	*
% Sector Funds (t-1)	0.159		-2.419	*	-1.916		0.676		-2.350	* *	-1.871	
% International Funds (t-1)	0.512		-1.191	*	-1.122	*	0.521		-1.105	*	-1.096	*
% Bind/Income Funds (t-1)	2.096	* *	0.502		-1.125		2.382	* *	0.679		-1.002	
% Growth/Income Funds (t-1)	1.101	*	0.322		1.147	*	1.083	* *	0.362		0.829	
Dist = Bank Proprietary ($\%$ Classes) (t-1)	2.722	* *	1.269	* *	-0.903	*	2.967	* *	1.333	* *	-0.929	*
Dist = Direct (% Classes) (t-1)	-1.165	* *	-1.053	* *	-2.23	* *	-0.917	* *	-0.897	* *	-1.882	* *
Dist = Institutional (% \dot{C} lasses) (t-1)	0.406		0.663	×	0.699	* *	0.251		0.612	*	0.480	*
Dist = Insurance (% Classes) $(t-1)$	0.643	*	1.494	* *	-1.399	* *	0.759	*	1.466	* *	-1.519	*
Intercept	4.130	* *	2.971	* *	3.081	*	3.270	* *	3.016	* *	3.183	*
Year Dummies			included	ed		-	_		included	ed		
Likelihood Ratio p-value Pseudo R-Squared	$\begin{array}{c} 0.00\\ 0.62\\ 0.62\end{array}$						$0.00 \\ 0.61 \\ 0.61 \\ 0.62 \\ 0.62 \\ 0.61 \\ $					
** Net of Non-12h-1 expenses. 12h-1 fees. and total load/7	nd total lo	7/ Dad				_	0,000					
		. /										

Table III.6 continued Panel B: Family Level Models using Annual Net Performance Measures

Table III.7: Logit Models of Subsidiary Flag, 1995-2004 Family Level: This table presents the results of a series of logit models of conglomerate affiliation in the mutual fund industry. The dependent variable is a dummy variable set to one if the family is a subsidiary of a larger corporate entity. Results are based on annual 1995-2004 family level data. <i>Gross Alpha</i> and <i>Gross Return</i> refer to pre-expense measures. <i>Net Alpha</i> ^{**} and <i>Net Return</i> ^{**} refer to 4-factor α and return net of expenses (including non-12b-1 and 12b-1 fees) and total load annualized over 7 years. All performance and expense measures are net of broad SI-derived category averages.

	Exp
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Family-Level, 1995-2004 Annual Data with Perf and Exp vars	Perf and	Exp vars:	Ę			(1) ** 1		(1) **
	β	β p-value	β	β p-value	β	$\beta \beta$ p-value	β	β p-value
Privately Owned (t-1)	-3.771	0.00	-3.755	0.00	-3.720	0.00	-3.717	0.00
Mutualized $(t-1)$	1.615	0.00	1.188	0.00	1.586	0.00	1.141	0.00
dj. %) (t-1	-0.040	0.12	-0.001	0.76	-0.045	0.06	-0.001	0.85
Non-12B1 Expenses (Cat. Adj. %) (t-1)	-0.259	0.05	-0.236	0.04				
	-0.277	0.45	0.086	0.80				
Total Load/7 (Cat. Adj. %) (t-1)	0.173	0.00	0.146	0.00				
% Classes w/ Redemption Fee (t-1)	-0.106	0.52	0.171	0.25	-0.097	0.56	0.161	0.28
Focus	-1.302	0.00	-1.099	0.00	-1.238	0.00	-1.066	0.00
Age (Years) $(t-1)$	-0.461	0.00	-0.333	0.00	-0.463	0.00	-0.349	0.00
Turnover $(t-1)$	0.026	0.44	0.021	0.43	0.025	0.45	0.021	0.42
Log of Total Net Assets (t-1)	-0.050	0.28	-0.047	0.25	-0.031	0.44	-0.036	0.32
Flows $(\%)$ (t-1)	0.000	0.66	0.000	0.85	0.000	0.69	0.000	0.84
Log of $\#$ Accounts (t-1)	-0.107	0.00	-0.115	0.00	-0.082	0.00	-0.085	0.00
$\operatorname{Cash}\left(\operatorname{Avg}\%\right)(\operatorname{t-1})$	0.007	0.09	0.005	0.19	0.007	0.13	0.004	0.28
Stocks ($Avg \%$) (t-1)	-0.008	0.01	-0.009	0.00	-0.007	0.02	-0.008	0.00
Money Market (% Classes) (t-1)	-0.747	0.09	-0.731	0.06	-0.645	0.15	-0.663	0.08
Sector ($\%$ Classes) (t-1)	-0.210	0.76	0.233	0.71	-0.109	0.87	0.409	0.51
International (% Classes) (t-1)	0.570	0.09	0.453	0.11	0.607	0.07	0.500	0.08
Bond-Income ($\%$ Classes) (t-1)	-0.836	0.02	-0.524	0.11	-0.605	0.09	-0.370	0.25
.) (S	0.728	0.00	0.666	0.00	0.745	0.00	0.677	0.00
Dist = Bank Proprietary (% Classes) (t-1)	1.743	0.00	1.947	0.00	1.746	0.00	1.950	0.00
= Direct (% Cl ²	-1.141	0.00	-0.991	0.00	-1.414	0.00	-1.265	0.00
Dist = Institutional ($\%$ Classes) (t-1)	0.175	0.38	-0.004	0.98	0.067	0.73	-0.127	0.48
Dist = Insurance (% Classes) (t-1)	2.188		2.253	0.00	2.121	0.00	2.173	0.00
Dist = Proprietary (% Classes) (t-1)	0.968		0.899	0.00	1.031	0.00	0.944	0.00
Intercept	6.197		5.595	0.00	5.692	0.00	5.179	0.00
Year Dummies	incl	=	incl	nded	incl	nded	incl	uded
Likelihood Ratio p-value Pseudo R-Souared	$0.00 \\ 0.53$		$0.00 \\ 0.52$		0.00		$0.00 \\ 0.52$	
N	3,466		3,882		3,466		3,884	

Table III.8: Logit Models of Subadvised Flag, 2004 Family Level: This table presents the results of a series of logit models of subadvising by mutual fund families. The dependent variable is a dummy variable set to one if the class is subadvised (Panel A), or if the family has at least one subadvised portfolio (Panel B). Panel A presents results based on annual 2004 class data only, Panel B presents results based on annual 2004 family level data. Gross Alpha and Gross Return refer to pre-expense measures. Net Alpha^{**} and Net Return^{**} refer to 4-factor α and return net of expenses (including non-12b-1 and 12b-1 fees) and total load annualized over seven years. All performance and expense measures are net of broad SI-derived category averages.

Panel A: Class, 2004 Data with Perf and E_X	Exp vars:							
	Gross A	Gross Alpha (t)	Gross R	Gross Return (t)	Net Alp	Net Alpha ^{**} (t)	Net Return ^{**} (t)	${\rm trn}^{**}$ (t)
	β	p-value	β	p-value	β	p-value	β	p-value
Parent = Other $(t-1)$	1.209	0.00	1.266	0.00	1.213	0.00	1.237	0.00
Parent = Financial Svs (t-1)	-0.423	0.01	-0.252	0.05	-0.415	0.01	-0.289	0.02
Parent = Insurance $(t-1)$	1.041	0.00	1.461	0.00	1.047	0.00	1.454	0.00
Parent = Bank $(t-1)$	0.206	0.19	0.253	0.05	0.220	0.16	0.230	0.07
Privately Owned $(t-1)$	-0.015	0.91	-0.083	0.45	-0.011	0.94	-0.067	0.54
Mutualized $(t-1)$	0.518	0.00	0.722	0.00	0.515	0.00	0.721	0.00
Buried Flag $(t-1)$	-0.579	0.00	-0.831	0.00	-0.575	0.00	-0.849	0.00
ForeignOwned Flag (t-1)	0.269	0.02	0.404	0.00	0.257	0.02	0.418	0.00
Performance (Cat. Adj. %) (t-1)	0.553	0.00	0.007	0.01	0.347	0.00	0.007	0.01
Non-12B1 Expenses (Cat. Adj. %) (t-1)	-0.027	0.60	0.052	0.13				
12b-1 Fees (Cat. Adj. %) (t-1)	-0.061	0.63	0.087	0.37				
Total Load/7 (Cat. Adj. %) (t-1)	-0.028	0.18	-0.007	0.67				
Redemption Fee Fund (t-1)	-0.393	0.00	-0.472	0.00	-0.383	0.00	-0.468	0.00
Focus $(t-1)$	-0.255	0.32	0.030	0.88	-0.255	0.32	0.062	0.75
Relatedness (t-1)	-1.521	0.00	-1.614	0.00	-1.512	0.00	-1.624	0.00
Log of Age (Years) (t-1)	-0.521	0.00	-0.382	0.00	-0.516	0.00	-0.358	0.00
Turnover (t-1)	-0.041	0.16	-0.039	0.03	-0.043	0.13	-0.036	0.04
Log of Total Net Assets (t-1)	0.066	0.01	0.098	0.00	0.075	0.00	0.087	0.00
Log of Family Total Net Assets (t-1)	-0.333	0.00	-0.311	0.00	-0.331	0.00	-0.314	0.00
Flows $(\%)$ (t-1)	0.004	0.25	0.000	0.70	0.005	0.24	0.000	0.70
Log of $\#$ Shareholder Accts (t-1)	0.058	0.02	-0.005	0.76	0.055	0.02	-0.002	0.90
Money Market (t-1)	-0.666	0.00	-0.622	0.00	-0.649	0.00	-0.630	0.00
Sector (t-1)	0.634	0.44	0.358	0.66	0.624	0.45	0.390	0.64
International (t-1)	0.558	0.00	0.301	0.00	0.550	0.00	0.317	0.00
Bond-Income $(t-1)$	-0.917	0.00	-1.188	0.00	-0.928	0.00	-1.182	0.00
Growth-Income $(t-1)$	0.202	0.06	-0.153	0.06	0.197	0.06	-0.138	0.09
Dist = Bank Proprietary (% Classes) (t-1)	-0.202	0.22	-0.125	0.34	-0.215	0.18	-0.152	0.23
Dist = Direct (% Classes) (t-1)	-0.247	0.10	-0.217	0.08	-0.280	0.04	-0.268	0.01
Dist = Institutional (% Classes) (t-1)	-0.132	0.37	-0.110	0.31	-0.161	0.21	-0.163	0.05
Dist = Insurance (% Classes) $(t-1)$	-1.269	0.00	-1.254	0.00	-1.261	0.00	-1.270	0.00
Dist = Proprietary (% Classes) (t-1)	0.337	0.03	0.592	0.00	0.339	0.03	0.592	0.00
Intercept Year Dummies		0.00 luded		0.00 uded	2.329 Incl	0.00 uded		0.00 uded
Likelihood Ratio Pseudo-RSq	$745.89\\0.09$	0.00	$1590.74 \\ 0.13$	0.00	$742.99\\0.09$	0.00	$1610.85 \\ 0.13$	0.00
N	8,124		12,461		8,124		12,615	

Panel A: Class, 2004 Data with Perf and Exp vars:

Panel B: Family-Level, 1994-2004 Data with Pert and Exp vars:	l Pert and	d Exp vars						
	Gross A	Gross Alpha (t)	Gross F	Gross Return (t)	Net Alp	Net Alpha ^{**} (t)	Net Ret	Net Return ^{**} (t)
	β	p-value	β	p-value	β	p-value	β	p-value
Parent = Other $(t-1)$	1.806	0.00	1.781	0.00	1.798	0.00	1.785	0.00
Parent = Financial Svs (t-1)	0.284	0.12	0.182	0.29	0.331	0.07	0.227	0.18
= Insurance	0.694	0.00	0.647	0.00	0.700	0.00	0.667	0.00
Parent = Bank (t-1)	0.032	0.86	-0.127	0.48	0.003	0.99	-0.145	0.42
Privately Owned (t-1)	0.013	0.93	0.011	0.94	-0.008	0.96	-0.002	0.99
Mutualized $(t-1)$	0.118	0.55	0.275	0.14	0.052	0.79	0.214	0.25
Buried Flag (t-1)	-0.579	0.00	-0.549	0.00	-0.560	0.00	-0.539	0.00
Foreign Owned Flag (t-1)	0.074	0.66	0.047	0.77	0.023	0.89	0.013	0.94
Performance (Cat. Adj. %) (t-1)	0.059	0.74	-0.011	0.00	-0.022	0.87	-0.011	0.00
Non-12B1 Expenses (Cat. Adj. %) (t-1)	-0.025	0.68	-0.041	0.52				
12b-1 Fees (Cat. Adj. $\%$) (t-1)	1.183	0.00	1.057	0.00				
N	-0.026	0.44	-0.033	0.30				
% Classes w/ Redemption Fee (t-1)	0.279	0.03	0.286	0.02	0.227	0.08	0.241	0.05
	-2.576	0.00	-2.641	0.00	-2.540	0.00	-2.621	0.00
Log of Age (Years) (t-1)	-0.336	0.00	-0.299	0.00	-0.358	0.00	-0.325	0.00
Turnover $(t-1)$	0.009	0.78	-0.006	0.83	0.015	0.63	-0.002	0.93
Log of Total Net Assets (t-1)	-0.070	0.05	-0.055	0.08	-0.086	0.01	-0.062	0.03
Flows (%) (t-1)	0.000	0.77	0.000	0.57	0.000	0.81	0.000	0.53
# Accounts (t-1)	0.241	0.00	0.216	0.00	0.270	0.00	0.239	0.00
$\operatorname{Cash}\left(\operatorname{Avg}\%\right)(\operatorname{t-1})$	-0.001	0.70	-0.003	0.37	-0.002	0.57	-0.003	0.31
Stocks $(Avg \%)$ (t-1)	-0.004	0.10	-0.005	0.04	-0.005	0.03	-0.006	0.01
2	-1.223	0.00	-0.902	0.00	-1.220	0.00	-0.909	0.00
$\mathbf{s})$	-0.180	0.69	0.000	1.00	0.023	0.96	0.156	0.72
J	-0.995	0.00	-0.938	0.00	-0.921	0.01	-0.891	0.00
Classes) (t-	-1.257	0.00	-1.298	0.00	-1.290	0.00	-1.328	0.00 0.00
Classes) (t-1)	0.756	0.00	0.526	0.01	0.748	0.00	0.532	0.01
Dist = Bank Proprietary (% Classes) (t-1)	1.029	0.00	1.105	0.00	0.972	0.00	1.052	0.00
= Direct (% CL	-0.658	0.00	-0.684	0.00	-0.779	0.00	-0.769	0.00
-	0.740	0.00	0.742	0.00	0.663	0.00	0.685	0.00
57	1.139	0.00	1.220	0.00	1.128	0.00	1.223	0.00
Dist = Proprietary (% Classes) (t-1)	0.381		0.486	0.02	0.320	0.15	0.420	0.05
Intercept Year Dummies	0.627 Incl	0.18 uded	0.803 Inc	0.05 luded	0.418 Incl	0.36 uded	0.622 Inc	0.13 luded
Likelihood Ratio p-value	0.00		0.00	_	0.00		0.00	
Pseudo R-Squared N	0.28 3.466		0.27		0.27 3.466		0.27 3 884	
	0,010		100,0		0010		100°0	

Table III.8 continued Panel B: Family-Level, 1994-2004 Data with Perf and Exp vars: Table III.9: Linear Models of Subadvising by Families, 2004 Family Level: This table presents the results of a series of linear models of subadvising by mutual fund families. The dependent variable is the fraction of portfolios within the given family which are subadvised. Results are based on annual 2004 data only. *Gross Alpha* and *Gross Return* refer to pre-expense measures. *Net Alpha*** and *Net Return*** refer to 4-factor α and return net of expenses (including non-12b-1 and 12b-1 fees) and total load annualized over seven years. Heteroscedasticity consistent standard errors are used to calculate all p-values. All performance and expense measures are net of broad SI-derived category averages.

Family-Level, 2004 Data	-							
	Gross /	Gross Alpha (t)	Gross I	Gross Return (t)	Net $Al_{\rm I}$	Net Alpha ^{$**$} (t)	Net Ret	Net Return ^{**} (t)
	β	p-value	β	p-value	β	p-value	β	p-value
= Other (t-	0.200	0.00	0.221	0.00	0.195	0.00	0.220	0.00
	-0.055	0.00	-0.073	0.00	-0.053	0.00	-0.073	0.00
Parent = Insurance (t-1)	0.106	0.00	0.094	0.00	0.107	0.00	0.096	0.00
Parent = Bank (t-1)	-0.054	0.00	-0.072	0.00	-0.059	0.00	-0.075	0.00
Privately Owned $(t-1)$	-0.016	0.37	-0.016	0.34	-0.065	0.01	-0.015	0.36
Mutualized $(t-1)$	0.040	0.11	0.060	0.02	-0.053	0.02	0.058	0.02
Buried Flag $(t-1)$	-0.019	0.18	-0.022	0.12	-0.017	0.22	-0.019	0.16
ForeignOwned Flag (t-1)	-0.030	0.08	-0.026	0.11	-0.031	0.07	-0.029	0.07
Adj. %) (t-1)	0.003	0.01	-0.001	0.00	0.003	0.01	-0.001	0.00
Non-12B1 Expenses (Cat. Adj. %) (t-1)	-0.009	0.00	-0.009	0.00				
	0.046	0.16	0.036	0.23				
\sim	0.005	0.21	0.002	0.50				
$\frac{1}{20}$ Classes w/ Redemption Fee (t-1)	0.024	0.17	0.021	$0.18 \\ 0.18$	0.025	$0.14 \\ 0.22$	0.022	0.16
$\begin{array}{c} \text{FOCUS} \\ \text{Low of } \Delta \text{ma } (\text{Veare}) \ (+_1) \end{array}$	-0.196	0.00	-0.199	0.00	-0.195	0.00	-0.198	0.00
Thrnover (t-1)	-0.001	0.87	0.000	0.00	-0.001	0.0	0000	0.02
Log of Total Net Assets (t-1)	-0.034	0.00	-0.033	0.00	-0.034	0.00	-0.031	0.00
Flows (%) (t-1)	0.000	0.71	0.000	0.08	0.000	0.63	0.000	0.06
Log of $\#$ Accounts (t-1)	0.020	0.00	0.018	0.00	0.022	0.00	0.019	0.00
Stocks $(Avg \%)$ (t-1)	0.000	0.28	0.000	0.25	0.000	0.23	0.000	0.24
$\operatorname{Cash}\left(\operatorname{Avg}\%\right)(\operatorname{t-1})$	0.000	0.64	0.000	0.28	0.000	0.58	0.000	0.27
Money Market (% Classes) (t-1)	-0.091	0.00	-0.052	0.07	-0.088	0.00	-0.049	0.09
t-1)	0.016	0.76	0.068	0.20	0.027	0.60	0.077	0.15
\sim	-0.102	0.00	-0.071	0.01	-0.098	0.00	-0.069	0.01
asses) (t	-0.091	0.00	-0.089	0.00	-0.086	10.0	-0.082	10.0
\sim	001.0	0.00	000.0	0.00	11110	0.00	0.009	0.00
Dist = Bank Pronrietary (% Classes) (b-1) Dist = Bank Pronrietary (% Classes) (t-1)	0.125	0.00	0.034	0.00	0.411	0.00	0.134	0.00
= Direct (% Classes)	0.003	0.86	-0.005	0.77	-0.013	0.36	-0.013	0.36
= Institutional (% Cla	0.213	0.00	0.207	0.00	0.206	0.00	0.204	0.00
= Insurance (% Cl_8	0.069	0.08	0.067	0.09	0.067	0.09	0.072	0.07
$\tilde{\mathbb{C}}$	0.061	0.01	$0.074 \\ 0.433$	0.00	0.063 0.482	0.00	0.075	0.00
Adjusted R-Squared	0.17		0.17		0.17		0.17	
_	3,466	1/100	3,882		3,466		3,884	
\sim 1 Net of NoII-12D-1 expenses, 12D-1 lees, and total load/	na total l	0au/ /						

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