Do Families Matter in Institutional Money Management Industry
The Case of New Portfolio Openings

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Abstract

This study investigates whether family level analysis matters in the institutional money management industry by examining new portfolio openings in a large survivorship bias free sample of institutional money management families. I examine whether low-skill families that open new portfolios are successful in attracting significant new cash flows despite poor past performance in other family funds. I find that they *are* successful in attracting significant new cash flows. I also examine the future performance of these new funds. Using time varying alphas, I find that the fund families performing below average in one year create portfolios that on average underperform for up to three subsequent years. I call this combination of results the family new fund paradox. It is a paradox, because the fund flows indicate that institutional investors are not collecting and/or using information about prior family performance that would be useful in predicting the future performance of these new funds. My findings support theoretical predictions and are robust to the known persistence among the worst performing families.

JEL classification: G2, G1, L1, L2

Key words: mutual funds, pension funds, fund flows, performance persistence, window dressing.
This work is ongoing, and comments are welcome.

I. Introduction.

Several recent studies indicate that family level strategy matters in the mutual fund industry (Zhao (2002), Gaspar, Massa, and Matos (2004), Guedj and Papastaikoudi (2003), Kempf and Ruenzi (2005), Gallaher, Kaniel, and Starks (2005)). This study investigates whether family level analysis matters in the institutional money management industry by examining new portfolio openings in a large survivorship bias free sample of institutional money management families[1].

I examine whether family level data can be used to predict the future performance of newly opened portfolios. I rank families (portfolio of portfolios or portfolio universe) based on risk-adjusted return measure to examine if newly opened portfolios will perform similarly to the family performance. Surprisingly, I find that the new portfolios do fall in the same performance bracket as the family (see Table 3). Importantly, portfolios created by families from the second lowest performance bracket gain assets. This result is unexpected for three reasons. First, we do not expect to find persistence in performance among managed portfolios[2]. Second, from the flow performance literature, we do not expect portfolios with low performance to accumulate assets (Del Guercio and Tkac (2002)). Third, the persistence finding indicates that institutional investors have not used industry wide family level data while searching for portfolios, otherwise the persistence would have disappeared from the data. I call this finding the family new fund paradox.

I develop a family level rational investor response model by extending Ippolito's (1992) model. The model suggests that analyzing family past performance is beneficial to the institutional investors, who consider investing in newly opened portfolios. The institutional fund paradox is consistent with this

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[1] It is useful to think of family as portfolio of portfolios. One family employs several portfolio managers and can have as many as 30 portfolios.

[2] Numerous studies document lack of persistence in the U.S. mutual fund data. Persistence found in early papers is explained by risk and other fund characteristics as well as survivorship bias. See Carhart (1997), Wermers (2003), Carhart, Carpenter, Lynch, and Musto (2002). Mutual fund studies find unexplained persistence among poorly performing families. Similarly, persistence in institutional fund literature is expected just among the worst performing families. See Christopherson, Ferson, and Glassman (1998), Christopherson and Turner (1991), and Lakonishok, Shleifer, and Vishny (1992)

finding. The model also predicts circumstances under which rational investors will not examine family level data.

I propose an explanation to the finding of persistence. The explanation hinges on economic and information environments, which differ significantly from the environment in the mutual fund industry. I propose a strategy which pursued by sufficient number of families may cause persistence paradox. I suggest that low-skill families will open new portfolios to disguise their past underperformance and to gain assets. New portfolios do not have track record and it takes time to acquire one. Asset invested with low-skill families will likely lose value and eventually will be moved to more prosperous investment opportunities. While evaluating the low skill family strategy, I control for alternative reasons to open a new portfolio. The theoretical model suggests that this strategy is likely to succeed if investors do not consider family wide data in portfolio selection process and/or experience high switching between managers. The low-skill family strategy results in increased search costs to investors.

My sample consists of institutional money managers and does not include mutual funds. Institutional money managers are not governed by mutual fund laws and manage portfolios for pension funds, foundations, and high net worth individuals. A typical money manager services a small number of very wealthy clients.

Portfolio level activities that increase search costs have been previously studied in the context of portfolio window dressing. A typical scenario proposed by Lakonishok, Shleifer, Thaler, and Vishny (LSTV (1991)) involves purchasing the best performing stocks and selling the worst performing stocks before the semi-annual report date. Empirical evidence from these studies suggests that managers' ability to engage in search cost increasing activities is subject to information availability in the industry (Musto (1999)). For example, portfolio level data is not readily available in the mutual fund industry, where holdings are revealed just twice a year. As a result evidence consistent with window dressing is observed at the portfolio level in the mutual fund industry (Musto 1997, O'Neal 01, and Morey and O'Neal 2002).

I propose that institutional managers are most likely to engage in activities that increase search costs at a family level, not an individual portfolio level, due to the information environment in the institutional management industry. Institutional managers do not have mandatory disclosure rules and therefore information availability at the management family level is poor. This information vacuum and a lack of monitoring could enable institutional families to control how they are perceived by investors. The low-skill family strategy may succeed in this environment. However, it is common for institutional clients to regularly request holdings level data from their managers therefore making window dressing (a portfolio level cost increasing activity) more difficult for the institutional money manager.

The hiring process in the institutional management industry is conducive to the low-skill family strategy. Hiring a new manager often involves several steps such as technical screens and several rounds of interviews. The initial screens are frequently based on performance. Management families that perform below average have little chance of passing these screens for new clients. However, if they open new portfolios with no track record they stand a chance to be interviewed and hired based on non-performance criteria. Existing clients may like the composition of a new portfolio or value a service that a manager provides. In addition to security selection, managers often provide book keeping, research, and education services to their clients.

I find evidence in support of both the family new fund paradox, and its explanation, the low-skill family strategy. Low-skill families benefit from opening new portfolios, which lose value to investors, while investors do not condition their portfolio selection choice on family-wide data. Statistically we expect to find low-skill families among the poorly performing families. Univariate results show that the fund families who perform below average in one year create portfolios that will on average underperform for up to three subsequent years. Furthermore, the below average managers attract significant cash inflows into the newly created portfolios. Ex post we can observe if families manipulate portfolio outlook by changing voluntarily reported returns and by not reporting returns on all assets. Even after controlling for these activities and other family characteristics that may explain future performance, family performance determines future new portfolio performance. The portfolios created by below average managers live as long as the portfolios created by better families. This suggests that information is revealed slowly. Multivariate analysis supports the low-skill family strategy by suggesting that family membership in the second lowest bracket, but no other bracket, significantly increases the likelihood of new portfolio opening. Furthermore, the new portfolio opening decision depends on past performance controlling for alternative reasons to open new portfolios. Finally, multivariate regression shows that opening a new portfolio has an overall positive impact on a family's cash flows for the two middle brackets, especially the lowest middle bracket. The relationship between new portfolio openings and family inflows is negative for the worst families, and does not exist for the best.

Ideally, a portfolio management industry is structured in a way that helps investors to find portfolio managers with minimal search costs. This entails investors being able distinguish between skilled and low-skill managers. This study contributes to the larger question of how effective the institutional management industry structure is in matching an investor with an ideal portfolio manager. This paper suggests that within the institutional management industry family level data matters and that investors should be more aggressive in acquiring and using family level information.

The paper proceeds as follows. Section II discusses relevant literature. Section III presents investor response model and alternative portfolio opening reasons. Section IV states hypotheses. Section V describes the money management industry equity sample. Section VI presents results and section VII concludes.

II Literature Review.

A. Past Studies: Search Cost Increasing Activities in Traditional Mutual Fund Window Dressing Studies

Evidence on how mangers participate in search cost increasing activities in economic environment, where data to monitor such activities is limited, is best gathered in the mutual fund window dressing context. Anecdotal evidence from the financial press suggests that U.S. mutual fund managers engage in trading activities consistent with LSTV (1991) definition of window dressing.[3] Definitive

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[3] See Richard H. Walker speech to D.C. Bar Association, Washington, D.C. (http://www.sec.gov/news/speech/spch412.htm), 2000; The Economist, 1992, p 83; Sunday Tribune Finance, 1991, p 4; Power, Wall Street Journal, December 29, 1988, p. C1; Jasen, Wall Street Journal, July 2, 1992, p. C21.

evidence on window dressing activities is difficult to produce, because the detailed information required to uncover these activities is usually unavailable. To date, no study has caught a manager engaging in window dressing activities. Most studies, which have focused on window dressing manifested in unusual trading activities around the quarterly or annual report dates, have found evidence supporting portfolio window dressing of this form[4].

Most of the studies examine window dressing in samples of mutual fund managers. Under the Investment Act of 1940, mutual fund managers must disclose complete portfolio details at the fiscal year end and six months from that date, but at no other date. This creates an opportunity for window dressing. Equity managers encounter transaction costs in the amount of the bid ask spread. Money market managers may encounter no additional costs because the money market instruments mature quickly and proceeds need to be reinvested anyways.

Musto (1999) argues that motivation to window dress depends on manager beliefs about what investors infer from disclosures. Evidence abounds that investors value disclosures. For example, *Morningstar* analyzes and reports on disclosed portfolios to consumers. Academic researchers use disclosed portfolios to test hypotheses about undisclosed portfolios (see Sias and Starks (1997)). If money managers conclude that disclosures influence investor perception of their abilities, it is conceivable that they will dress each window that they open for investors. Similarly, if institutional management families believe that opening a new attractive portfolio may favorably influence their chances being hired even with below average past performance, they will aggressively pursue the portfolio opening strategy.

Window dressing is the primary focus in several mutual fund studies. O'Neal (2001) examines return patterns in a sample of 195 large mutual funds. He attempts to identify the return patterns consistent with managers assuming short term synthetic positions in favorable stocks around report dates. In the presence of window dressing, portfolio returns would be more highly correlated with the returns of

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[4] For Example, see Lakonishok, Shleifer, Thaler, and Vishny (1991), Lee, Porter, Weaver (1998), Morey, O'Neal (2002), O'Neal (2001), Bhana (2002), Bildersee and Kahn (1987), Musto (1997), Musto (1999), Carhart, Kaniel, Musto, and Reed (2001).

the stocks added for cosmetic purposes than with the stocks more typically held in the portfolio. He finds changes in the return-generating process around portfolio reporting periods and interprets them as evidence consistent with the presence of window dressing. O'Neal estimates that total costs from window dressing activities may amount to $1 billion annually for U.S. equity managers. Morey and O'Neal (2002) examine credit quality holdings data in a sample of U.S. bond portfolios. Consistent with the window dressing hypothesis, they find that portfolios in their sample hold significantly more government bonds during disclosure to present safer portfolios to investors[5].

B. Link between Mutual Window Dressing and Institutional Family Level Strategy.

A low-skill family's ability to gain assets by opening new portfolios is reminiscent of the window dressing scenario in which a manager hides the fact that he has been unsuccessful in identifying the best and the worst securities in advance. The *basic mechanism* of the low-skill family strategy is very similar to the mechanism of window dressing. This mechanism involves three elements: basic motivation, an information environment, and manipulating portfolio weights around report dates. First, the motivation in both cases is to retain or increase assets under management. Managers are motivated to maintain or increase the total asset level in an individual portfolio and the total portfolio of the family. Second, the ability to manipulate weights in order to increase search costs is generally the result of the economic and disclosure environment. Window dressing is plausible because there is scant mutual fund information available at a portfolio level, while low-skill family strategy is plausible because institutional manager information is poorly available at a family level.

Third, the report date for an institutional family is the announcement of a new fund. In the case of window dressing, one observes the change in weights for a single portfolio between time t and t+1. Finding an increase in weight for popular stocks just before the report is released is evidence in favor of window dressing. A family can be viewed as a portfolio of portfolios. The change in weights of all

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[5]See Musto (1997) as another example of window dressing studies. Musto documents presence of window dressing evidence among money market managers. See Appendix II for examples of window dressing studies in the context of January effect.

securities held by a family comes from either changing security weights in existing portfolios, or adding new portfolios. Observing the new openings allows us to identify families that could potentially be using the low-skill family strategy. Instead of attractive new stocks we consider an attractive new portfolio- a collection of attractive stocks. From the performance flow relationship we expect that the best performing families will see inflows and will not need to open new portfolios to gain assets as much as underperforming families. For underperforming families new portfolio openings are one of the few alternative ways to attract new assets. Low-skill families are likely to underperform and will offer new portfolios, even if they do not have any special advantage in managing these portfolios. A low-skill family's ability to gain investors by offering attractive new portfolios is similar to a manager's ability to win new investors by purchasing attractive stocks just before report dates. The biggest difference is that window dressing is examined at a portfolio level, while the low-skill family strategy is examined at a family level.

The low-skill family strategy, like the window dressing, results in value lost to investors. Window dressing activities aim to mislead investors about the portfolio composition, risk characteristics, and past performance. Investors may use incorrect benchmarks in calculating risk-adjusted returns, which may lead to an inflated performance estimate for a given mutual fund. Window dressing results in money wasted on unnecessary trade commissions and increased search costs. Similarly, a low-skill family's ability to attract money from investors results in increased search costs and lost value to these investors. The importance of the topic is underscored by the fact that over one third of the assets managed by money managers is retirement money (see Chart 1). Here the loss of value passes down to the final beneficiaries- the average employees in the economy. In this paper I will refer to both window dressing and the low-skill family strategy as search cost increasing activities.

C. Studies of Search Cost Increasing Activities: Alternative Definitions and other Industries.

Several studies expand the traditional window dressing concept to other portfolio level activities. Khorana and Servaes (1999) analyze the relationship between performance and new mutual fund starts and test for the presence of portfolio level window dressing. They expand the traditional window dressing definition to include cases where a family starts a new fund in an existing objective (e.g. domestic growth equity) if the inflows in an existing portfolio are low due to poor performance. Here a new fund is created to disguise the poor performance of an existing fund in the same objective. They do not find evidence for this form of window dressing[6].

Two studies suggest that portfolio weight adjustment window dressing is less likely in institutional investor portfolios. Lakonishok et al. ((LSV), 1991) examine quarterly portfolio reports by pension fund managers- a sub sample of my dataset. They admit that these portfolios are all disclosed because a client can call up a manager any time to find out the portfolio composition. However, Lakonishok et al. contend that investors pay more attention to year end portfolio composition and performance. This encourages a manager to window dress at the end of the year. Indeed, this study finds weak evidence that managers sell relatively more losers in quarter 4 than in quarters 1, 2, and 3. A corresponding increase in demand for winners in the fourth quarter is not found. LSV conclude that portfolio level window dressing is a response to costly monitoring by fund sponsors of individual portfolios and that it is less beneficial for large funds which are more closely monitored to use this practice. These limited findings suggest that simple weight adjustment window dressing may not work for institutional investors. The presence of academic studies on window dressing has likely further decreased such window dressing opportunities among institutional investors in recent years. Musto (1999) examines a weekly database of money market fund portfolio holdings. The data are publicly available, but cost prohibitive for individual investors. Musto finds that retail money managers window dress by shifting assets into safer government securities from more risky private-issue securities around reporting periods. This activity is not apparent among institutional money funds.

[6] See Khorana (2001) for window dressing definition in the context of mutual fund manager activity shortly before being replaced. Carhart, Kaniel, Musto, and Reed (2001) present evidence consistent with portfolio pumping, which can be viewed as another extension of the standard window dressing definition as in Jansson (1983).

These studies suggest that window dressing may not be present at a portfolio level for institutional investors. Professional money management families may still be able to pursue similar strategies at the family level, if information to monitor families in unavailable or is not considered.

The money management family's motivation to engage in search cost increasing activities turns on how it believes information about a new portfolio is perceived by investors. Money management families voluntarily report to money management databases on a regular basis. For example, Mobius collects portfolio performance information each quarter. Investors and investment consultants use this information to evaluate portfolio performance and to screen for new investment portfolios. If low-skill families believe that advertising new portfolios in these databases will attract asset inflows from either existing or new clients, they will advertise new portfolios.

Anecdotal evidence suggests that new portfolios even from low-skill managers may help retain existing clients. Money managers report directly to officers of large investment institutions such as pension funds. Lakonishok, Shleifer, and Vishny (1992) suggest that the manager's ability to explain portfolio performance, or *story telling* ability, is frequently as important as the performance itself. New portfolios may offer *story material* for existing investors.

New investors may be attracted by a family's long term reputation rather than its recent performance. Management family reputation is believed to be an important factor in hiring decisions, especially for the largest families (see Khorana and Servaes (1999) and Lakonishok, Shleifer, and Vishny (1992)). Anecdotal evidence suggests that institutions spread their assets over several managers, where each manager is selected for a particular investment niche; for example, a manager is hired to invest only in low capitalization growth stocks (see Swensen (2000)). It is possible that investors would screen out poorly performing managers and then hire a manager based on non performance criteria such as additional services and ability to communicate his/her strategy. Under this scenario, a new portfolio with unknown performance may give a family advantage over an existing portfolio with poor past performance.

Family new fund paradox and low-skill family strategy fit Ippolito's (1992) rational consumer response model. He examines how quality is delivered in the mutual fund industry and argues that the faster consumers can detect high quality funds, the more efficient markets are. Poor managers can hide their type for a while due to the statistical noisiness of returns. Investors gather information about portfolio performance and adjust their expectations about a manager's type. Then investors adjust their investment in portfolios subject to transaction costs. In our case transaction costs include search costs for new money managers. The next section extends Ippolito's theory to institutional money management families presents known alternative reasons why a family opens new portfolio, and develops control variables.

III Rational Investor Model, Portfolio Creation Reasons, and Institutional Details.

A. Family Level Rational Investor Response Model

Ippolito (1992) develops a rational consumer response model to describe investor behavior in the mutual fund industry. This model demonstrates that under certain assumptions investors benefit from analysis of managers' past performance. I extend the model in two ways. First, I demonstrate that the logic in the model applies to performance analysis at the family level. Second, I adapt the model to the idiosyncrasies of the institutional money management industry. The original model suggests that investors benefit if they select a manager with the best past performance. I suggest that investors can also benefit if they select a manager who has passed some hurdle rate, but is not necessarily the best manger. As a result, the main research question about the persistence between family past performance and performance of newly opened portfolios is a test of this extended model.

Assumptions. Investors evaluate managers by using some risk-adjusted return measure. I propose to use Jensen's (1968) one factor and Fama and French (1993) three factor model alphas. The logic identically applies to the both models; therefore, I will use the Fama and French model as an example. Investors use net returns and assume the following return generating process.

$$R_{it}-R_{ft}= \alpha_i + \beta_{1i}(R_{mt}-R_{ft}) + \beta_{2i}(SMB_t) + \beta_{3i}(HML_t) + e_{it} \tag{1}$$

Excess rate of return in a particular year adjusted for differences in risk is

$$V_{it}= R_{it}-R_{ft}- \beta_{1i}(R_{mt}-R_{ft}) - \beta_{2i}(SMB_t) - \beta_{3i}(HML_t) = \alpha_i + e_{it} = \alpha_{it}, \tag{2}$$

where α is a manager's inherent ability. The manager's ability is expressed in returns with error e_{it}. Error is caused by uncertainty in markets which does not allow manager ability to be precisely reflected in returns.[7] The model assumes that the average error is zero and is normally and identically distributed.

If a manager's skills are reflected in returns, V_{it} is serially correlated. Investors use information about the observed serial correlation to make investment decisions.

Let us assume an economy with two manager types. High quality manager generates α_H, while low quality managers generates α_L- lower risk-adjusted performance measure than the high quality manager. The low quality manager has either zero skill or possesses skill but chooses not to use it. The manager, who chooses not to use his skills, in extreme, conducts no market research and pockets the fees. For simplicity, the low skill manager wastes fees and produces an alpha which is equal to the difference between the benchmark (passive or index fund) fees and the fees that a manager charges. This difference is denoted by "*x*". Therefore, $\alpha_L = -x$. Let α denote α_H.

1-s is the portion of assets managed by the low quality manager, while *s* is the portion of assets managed by high quality manager.

Ippolito develops a market equilibrium condition. Investors can invest either in actively managed funds or in index funds. If index funds on average offer higher alpha, investors will start switching over to index funds until index funds on average offer the same alpha as actively managed funds. The following is the equilibrium condition,

$$S\alpha - (1-S)x = 0 \tag{3}$$

[7] The error term is a theoretical error term and is not the same as the regression error term.

Note, that an alpha equal to zero means that investors get the same return as they would get from an index fund or benchmark fund. The equilibrium condition allows examining if the model is consistent with return data. Both mutual fund data and institutional money management data are consistent with the equilibrium condition.[8] This observation validates the use of the model to analyze my sample. In the real world, investors estimate *s* by observing market returns and update their understanding about *s* as new information arrives. For simplicity, let's assume that investors know *s*.

Since manager quality is unobservable, investors measure V_t for each manager.

For a high quality manager $V_t = \alpha + e_t$

For a low quality manager $V_t = -x + e_t$

With a random choice of manager an investor expects to earn

$$E = s\alpha - (1-s)x \tag{4}$$

If an investor chooses the manager with the best previous performance, he expects to earn

$$E = q\alpha - (1-q)x \tag{5}$$

Where q is the probability that V_t is drawn form the distribution with a mean α, and not the mean $-x$. By selecting the best previous performer an investor improves his chance of selecting the best manager from s to q. In other words, $q > s$.

Differences exist between the hiring processes found within institutional money management and mutual fund industries. Unlike the mutual fund industry, hiring in the institutional money management industry is a multi-step process (Del Guercio and Tkac (2002)). First, a pool of managers is selected by using some technical filter such as a return hurdle rate and fund characteristics. Second, managers are interviewed to determine the match between a client and a manager.

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[8] Ippolito (1992) demonstrates that mutual fund data is consistent with the equilibrium condition. Berzins and Trzcinka (2005) (BT) results show that institutional money management data is also consistent with the equilibrium condition. BT examine institutional manager performance between 1993 and 2004 and find that three factor gross alphas are on average in single digit basis points- positive in the first half and negative in the second half of the sample period.

Let us consider a case where investors select a manager based on a hurdle rate; e.g. positive alpha. I argue that investors are still better off pursuing this strategy rather than selecting a random manager.

Let F_H denote *1 – F(hurdle rate)* for high quality manager,

F_L denote *1 – F(hurdle rate)* for low quality manager, where F is the cumulative distribution function for α.

N_H is number of high quality managers in the sample, N_L is the number of low quality managers in the sample, then

$$q = \frac{F_H * N_H}{F_H * N_H + F_L * N_L} \qquad \text{while} \quad s = \frac{N_H}{N_H + N_L} \tag{6}$$

To prove that an investor improves his or her chances to find a high quality manager by using a hurdle rate, we need to prove that $q - s > 0$. Note that from assumptions $F_H > F_L$.

$$q - s = \frac{F_H * N_H}{F_H * N_H + F_L * N_L} - \frac{N_H}{N_H + N_L} = \frac{N_H * N_L * (F_H - F_L)}{(F_H * N_H + F_L * N_L) * (N_H + N_L)} > 0 \tag{7}$$

all members in denominator are positive, and numerator is positive because $F_H > F_L$. QED.

The gain to an investor for analyzing past returns and choosing the performer that passes the hurdle rate is

$$G = (q - s) * (\alpha + x) \tag{8}$$

The gain is positive because $q - s > 0$. Therefore, without transaction costs the strategy of choosing a manager that passes a hurdle rate dominates a strategy that invests randomly.

The same logic applies to the management families not just the individual portfolios. As noted, one reason managers have low quality is pocketing of fees and doing little research. It is conceivable that investment family level strategy and family values would lead managers to conduct themselves this way. First, investment families enjoy economies of scope by sharing research resources such as investment in databases and basic security analysis among managers. Therefore, it is very likely that decision-making about investment in market research is done at the family level. Second, it is reasonable to assume that the institutional management industry can more easily absorb the costs necessary to attract the best investment talent than the mutual fund industry because of its much larger average account size. Therefore, one can assume that effort devoted to research more than anything else sets families apart.

For simplicity let's assume that two management family types exist. High quality management family and low quality management family[9]. Then a random family has a probability *s* to be of high quality and probability of *1-s* to be of low quality. We add the assumption that the error term is independently distributed. By definition the error term reflects the difficulty in exhibiting a manager's skills in portfolio returns. This noise term is idiosyncratic to the manager and does not reflect membership in a family.

From (2) we can aggregate portfolio V_t to come up with the family V_t^f

$$V_t^f = \sum_i w_i(\alpha_i + e_{it}) = \sum_i w_i \alpha_i + \sum_i w_i e_{it} = \alpha + e_{it}^f, \tag{9}$$

where $e_{it}^f = \sum_i w_i e_{it} \sim N(\mu=0, \sigma_e, IID)$, i denotes portfolios in the family, while the w_i denotes the asset weights of these portfolios.

The equilibrium condition ensures that asset weights alpha is zero for the industry. Since alpha aggregation was asset based, the equilibrium condition is unchanged. Furthermore, investors still should gain *G* from analyzing family level data. Transaction costs slow down the reallocation of funds from one manager to another.

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[9] A simple argument suggests that family size may be important in determining aggregate family alpha. It is possible that the largest families may not successfully employ family-wide strategy. As a result a high quality family may have some non-complying managers which offer low quality portfolios. The aggregated alpha for such a family will be less than *α*. If ranked by alpha, this family will end up not among the high quality families but somewhere in the middle of the sample. This suggests that one must control for family size; this is a theoretical reason to control for family size (see LSV argument in the section *c* for the empirical reason).

The gain depends on the percentage of high quality funds (s), difference in alphas between high and low quality managers ($\alpha + x$), and variance of error (σ_e). As variance in error increases the gain in probability (q-s) from following the manager selection algorithm decreases in the short term. As a result G decreases in short term. The same argument extends to the statistical measurement error of V_t. As the error increases the gain from following the selection algorithm decreases in the short term. In the medium term, the effect is opposite (see Ippolito (1992), footnote 20). First, increase in σ_e reduces s. More low quality managers enter and survive for longer periods. Lower s corresponds to increases in q-s and G increases in medium term[10]. The above argument extends to both portfolio and family level analysis.

My research suggests the benefits of analyzing comprehensive industry wide family data before investing in new portfolios. As suggested in the section *c* family level data is difficult to obtain in the institutional money management industry. As a result most investors do not have comprehensive family level data for this analysis. The noise created by unavailability of return series or availability of limited sample sizes influences the gain investors receive from analyzing the family level data. The data problems are similar to the immediate effect of increase in the error term on the gain, G, for individual investors. Investors weigh costs against gains from of collecting and analyzing family level data. While an average investor may benefit from family level analysis, some investors may find this type of analysis unpractical. In the extreme, if investors do not collect family wide information at all, they benefit just from the portfolio level analysis. Because portfolio level analysis is not possible for newly opened portfolios, investors will only have chance s (not q) to select a high quality new portfolio.

I find support for the family level theoretical prediction in data by discovering the institutional fund paradox. This finding demonstrates that average investors would benefit from family level analysis. Family level analysis allows investors to avoid investment in portfolios that will likely under perform in future. I hypothesize that a low-skilled family marketing strategy could explain the institutional fund

[10] Note that in equilibrium $G=x (q - s) / s$. Also, the medium term result suggests that industry with poor family level data availability will have lower s (more low quality families) than industry with better family level data availability.

paradox. The low skill family strategy suggests that certain families from the *1-s* portion of the sample have an opportunity to pursue the specified marketing strategy. The strategy calls for opening new portfolios to have no track record if the performance of existing portfolios is poor. Arguably, if large number of low-skilled families pursues this strategy, data may exhibit persistence in performance.

This strategy can succeed because an average investor does not possess industry wide family information, and switching costs are high in this industry. However, there are many alternative reasons to open a new portfolio. The next section reviews new portfolio opening reasons and develops control variables for these alternative reasons.

B. New Portfolio Opening Reasons

Khorana and Servaes (1999, KS) document possible reasons for opening new portfolios in the mutual fund industry. KS suggest three main reasons. 1. Managers are interested in additional fee income. Asset inflows in industry or in a family may generate a need for new portfolios (1a). High previous family returns seem to be good launching pads for new mutual funds (1b). Families may open a new portfolio in the same style and objective as an existing portfolio if the existing portfolio suffers from poor performance and experiences asset withdrawals (1c).

I suggest that low quality families open new portfolios to have a clean track record if the average family performance has been previously poor. KS do not find the evidence for the explanation *1c*. I suggest that family opening decision is not conditioned on the existing portfolio style or type, but rather on overall performance (1d).

2. New portfolios may be more affordable to large families because of economies of scale and economies of scope (2a). However, the new portfolios may cannibalize existing portfolios by taking away assets from existing portfolios (2b).

3. Small families are simply copying larger families with new portfolio openings- follow the leader strategy (3a). This strategy seems more applicable to mutual funds. LSV suggest that small managers are highly specialized in institutional portfolio management and carefully differentiate themselves from other competitors.

Testing the low skill family strategy is equivalent to testing whether patterns in my data are consistent with the reason *1d* after controlling for the alternative opening reasons. The control variables are family and equity inflows to address *1a* and *1b*. *1c* can be viewed as a subset of *1d*; however, I use a number of closed accounts in the previous year as a control variable. Splitting sample by family size addresses *2a*, which suggests that large families may have an advantage in new portfolio opening. I separately test the portfolio opening effect on future net family flows to address the *2b*.

Although money management and mutual fund industries are related, they have significant differences, which influence the search cost increasing strategies that managers have at their disposal. The next section briefly introduces key differences between the two industries.

C. Professional Money Management and Mutual Fund Industry

Mutual fund and institutional money management industries differ on characteristics that determine what portfolio information is available to investors and how easily it can be obtained. The availability of information in turn determines the type of search cost increasing strategies available to managers.

Mutual funds are highly regulated at family level. Existing laws ensure that family level information is easily obtainable. The primary law regulating mutual funds is the United States Securities and Exchange Commission (SEC) Investment Company Act of 1940. The law requires daily portfolio valuation and accounting for both share trades and outstanding shares. Maximum investment in a single asset as well as the minimum total fund size is regulated (Khorana and Servaes (1999)). The federal government regulates such investment techniques as repurchase agreements and trade in derivative contracts. Further restrictions apply to the way assets are held- they must be safeguarded by a custodian. The Act requires daily valuation of the fund's portfolios. Record keeping of the securities owned and the fund's outstanding shares is also required. Portfolio managers must register under the Investment Advisers Act of 1940 and meet accounting, reporting, and disclosure guidelines. Selling mutual fund shares to the public is regulated by state "blue sky" laws. Mutual funds must keep their prospectus up to date. They are managed externally and offer shares continually.

Despite the numerous laws governing mutual funds, portfolio level information is scarce and fund startup costs are higher than in the money management industry. Mutual funds must provide periodic reports to the SEC. Full portfolio details must be disclosed just at the fiscal year end and six months from then. Security holdings are not disclosed between semiannual report dates. However, on report dates, existing and prospective investors can obtain multiple sources of report information. Such information is available through the government, the mutual funds themselves or disseminated by private consulting and ranking agencies such as Morningstar, Inc. Del Guercio and Tkac (2002) report that startup costs of $100,000 or more in mutual funds are not unheard of, but the switching costs between mutual funds for investors are quite low.

The institutional management industry is mostly self-governed. Professional money managers do not need to register under The Investment Advisers Act of 1940. As a result, starting an additional portfolio is measurably less costly than in the mutual fund industry. However, because of search costs and additional services that these managers provide to clients, switching managers is much more expensive in the professional money management industry than in mutual funds.

In the institutional management industry, individual portfolio level information is readily available to existing institutional investors and it is relatively inexpensive to start a new money management portfolio. Holdings level data is available upon request because securities are owned by investors, not managers. However, information about every portfolio in a management family or comprehensive information about all families in the industry is not readily available to existing or new investors- making it difficult for investors to perform comparative analysis of managers. Several companies offer manager evaluation services to clients for a fee (e.g. Russell, Wilshire Associates, SEI Corporation. Mobius, a subsidiary of Check Free Corporation offers fund performance data to subscribers. They collect information for managers that are of interest to their clients. Several publications follow pension fund performance (e.g. Pensions and Investments).

While the Center for Research in Security Prices (CRSP) collects a survivorship bias free database for mutual funds, none of the commercial databases offer verifiably survivorship bias free performance data needed for family level performance ranking in the institutional management industry[11]. Survivorship bias can influence performance evaluation studies and bias conclusions (see Carhart (1997) and Carhart Carpenter, Lynch, and Musto (2002) for a discussion of survivorship bias impact on performance evaluation). As a result, individual clients or consultants would need to collect data from commercial data providers over time to construct a survivorship bias free database. It is possible that some clients do collect family level information but do not share it with others.

Anecdotal evidence suggests that the reporting structure in institutional management sponsoring organizations introduces agency problems between managers and investors which are not present in mutual funds. The large institutional accounts (e.g., corporate and government pension funds, endowment funds, Taft Hartley and union funds, insurance companies, corporate non-retirement funds) typically would have a treasurer responsible for allocating money, hiring and evaluating money managers. Treasurers typically report to the sponsoring organization's board. This extra level in the chain of responsibility introduces agency issues as discussed in Lakonishok Shleifer and Vishny (1992). Accounts with an extra agency level are typically tax exempt. Money managers also offer services to individual investors[12].

The institutional accounts, as opposed to the accounts of wealthy individual investors, tend to be very large clients for a single money management firm; they have sophisticated in-house experts and can hire consultants to evaluate a manager based upon frequent reports regarding performance, stock allocation, and strategy. For example, Del Guercio and Tkac (2002) argue that institutional management clients use such risk adjustment methods as tracking error, while their retail mutual funds counterparts use less sophisticated methods in performance evaluation. Anecdotal evidence suggests that investors specify

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[11] Piper database claims to be survivorship bias free in 1993, PSN/Effron database claims to be survivorship bias free in at least 2001.

[12] Wealthy individual investors accounted for 33% of assets in 2004 across all families and investment styles in the Mobius database.

acceptable tracking error levels in their contracts with managers. This investor sophistication suggests that management families should not be able to fool investors in the long-term.

LSV (1992) examine pension fund money managers -a sub sample of our database, and suggest that the money management industry is split into two types of managers. The split is caused by the difficulty in observing manager quality. The first type (32 families in our sample) consists of large banks and insurance companies that provide “generic” products such as index products and annuities[13]. This segment requires less skill and is based on stable long term reputation. An average family is very large, but has little interaction with clients. This part of industry is concentrated, very stable, and frequently offers passive portfolios. I call these families type-one families. LSV suggest that the type two managers (over 1900 families in our sample) exhibit high turnover in terms of assets and ranking at the top of industry. LSV compare the structure in this segment to the trendy restaurant industry segment. Portfolios are highly differentiated within styles. These managers closely interact with a pension fund’s treasurer’s office and need as much concept and story as they need past performance.

Arguably, both types of firms may potentially engage in search cost increasing activities at a management family level, but for different reasons. The introduction of new portfolios by type-one families may be less scrutinized because of their long-term reputation. The type-two families relying less on reputation may be more skilled at justifying their portfolio choice strategy (story telling) and thus have an advantage of marketing the new portfolio. I maintain that because performance information about the whole family is not readily available to investors and new portfolio performance evaluation takes a long time, low-skill family strategy is at least plausible among money management families.

The next section develops hypothesis and explains the methodology. I will start by formally introducing the family new fund paradox.

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[13] Top managers in LSV sample, which precedes my sample, are still some of the largest in my sample. The top LSV 14 manager families control one fifth of all Mobius assets and about the same proportion of equity assets (Table 9). They have low turnover ratio, low average fees, and high percentage of tax exempt assets and accounts. 32% of portfolios among these firms are passive portfolios; the same statistics for the universe of portfolios is 6%. Type-one families account for 64% of passive portfolios, but just for 10% of total portfolios.

IV. Hypothesis and Methodology

I investigate whether family level analysis matters in institutional money management industry. Family level information maters if we can use it to predict performance of newly opened portfolios. First I examine if family past performance of existing portfolios predicts family performance of newly opened portfolios. I am especially curious if persistence exists for the slightly below average families. Furthermore, do the newly opened portfolios gain or lose assets, add or destroy value? Unexpectedly, I find that the family performance persistent between existing and new portfolios; importantly, portfolios created by families from the second lowest performance bracket gain assets (see Table 3). I call the combination of these results the family new fund paradox. While this finding is consistent with the theoretical prediction, it also suggests that an average institutional client does not collect or does not use valuable family wide information.

Second, I examine if data is consistent with proposed explanation of the persistence- the low-skill family strategy. Under the low skill family strategy, the families lacking in skill exploit the finding that an average investor does not analyze family wide information and very aggressively (and successfully) open new portfolios to have a clean track record.

Let us briefly review the motivation for the low-skill family strategy. A fund family earns income by charging fees- which are proportional to the assets managed, and has an incentive to increase assets under management. From the performance flow literature we learn that assets leave families with poor performance and flow to families with good performance (see Del Guercio and Tkac (2002), Sirri and Tufano (1998), Ippolito (1992), and Patel, Zeckhauser, and Hendricks (1994)). A family with weak overall performance will lose some of its fee basis and will face more difficulty in attracting new assets than a family with strong performance. One way a family can restore its fee basis is to offer new products that attract new assets. A management family will be interested in creating such new portfolios regardless of whether it does or does not possess active management skills. Successful implementation of this strategy can cause the observed persistence between family and new portfolio performance. It is an empirical question whether evidence of the low-skill family strategy exists.

The null hypothesis for the low-skill family strategy is as follows:

A group of low-skill families aggressively open new portfolios for no other known reason but to cover poor past performance. The portfolios created by the low-skill families survive for considerable time, attract assets, but produce low risk adjusted returns.

Alternative hypothesis:

Low-skill institutional money management families invest in research and open new portfolios that create value to investors.

It is statistically more likely to find low-skill families among poor performers; therefore, examining new portfolio performance among previously poorly performing families is a way to identify evidence consistent with the low-skill family strategy. It is reasonable to assume that if a good manager had a bad year, the future performance of a new portfolio should show reversal of the bad performance and exhibit at least an average performance. However, if the new portfolios keep underperforming in future, it is very likely that the manager lacks skill. Persistent underperformance by newly created portfolios can be viewed as indicative of the presence of low-skill families. We do not expect performance persistence among the institutional money management families except for the lowest performing decile (LSV (1992) and Christopherson, Ferson, Glassman (1998)). I examine the families that perform below average but do not fall in the lowest performance bracket as potential candidates for the low-skill families.

In examination of poorly performing families, one should consider the implications of an empirical suggestion that the institutional money management industry is governed by the multi-period survival rule. Under the multi-period evaluation model, portfolios are terminated after several successive poor performance reports. Empirical evidence suggests that managers with poor performance are not immediately punished by closure of accounts (see LSV (1992) and Christopherson, Ferson, and Glassman (1998)). In fact, they are given time to correct the performance and opportunity to show that performance happened by chance and not due to a lack of skill. This observation is consistent with either the agency problem of LSV (1992) or the multi-period performance evaluation model. Carhart, Carpenter, Lynch, and Musto (2002) find mutual fund performance data to be consistent with multi-period performance evaluation. Finally, anecdotal evidence suggests that large foundations are reluctant to fire a manager unless the relationship between a manager and sponsor organization has been unsatisfactory for some time (Swensen (2000)).

Presence of the multi-period performance examination rule in an institutional money management sample would mean that a family may underperform over a couple of examination periods and still be retained. However, investors eventually expect reversal of the poor performance. Eventually a client will realize that a manager lacks active management skills and will move his assets into another portfolio. It is unclear how long it takes for an investor in the institutional money management industry to realize the quality of a manager. If the time is sufficiently long, a manager will, at least in theory, be able to raise assets by hiding his lack of skill and opening new portfolios.

I will use the following methodology to establish the family new fund paradox. I will rank institutional money management families based on asset-weighted risk-adjusted alphas. I will estimate the average future performance of the newly created portfolios by each of the families.

Test 1 of the Family New fund Paradox: Univariate New Portfolio Alpha Persistence and Assets.

The first test examines the basic idea that persistence exists between family rank in one period and new portfolio performance in the next period. I rank families based on risk-adjusted performance and calculate average performance of newly opened portfolios in subsequent periods. I group families in brackets, evaluate their performance over one year, and follow the performance of newly opened portfolios over the next three years. Simple t-tests will show if new portfolios in one bracket perform differently than new portfolios from another bracket. This analysis will uncover whether the initial performance of families persists in the newly created portfolios. Persistence is welcome among the top performing families and unwelcome for the rest. Since mutual and pension fund performance persistence literature suggests unexplained performance persistence for the bottom performers, persistence in performance of new portfolios by these families will not necessarily indicate the presence of family new fund paradox. Also, the increased level of scrutiny by investors would prevent the lowest performing families from performing search cost increasing activities. However, persistence in performance of the second lowest bracket will suggest the presence of the family new fund paradox.

Next I examine the assets that these new portfolios accumulate in the first few years of their existence. Finding that the portfolios opened by the second bracket families consistently underperform in the future yet accumulate assets would strengthen evidence in favor of the paradox.

I follow these steps in constructing the family rank. First, I calculate a value-weighted annual average of time varying alphas for all families. I rank all families based on the alphas and assign them to performance brackets. Next, I calculate the value-weighted alpha for the newly created portfolios for the next three years. Finally, I calculate the value-weighted average alpha for the brackets. I use two risk adjustment models in calculating these alphas. The first model is Fama and French's (1993) three factor model and the second model is Jensen's (1968) alpha from a market model regression.

I calculate quarterly portfolio alphas with the time varying "flexible regression" (FLS) technique developed by Kalaba and Tesfatsion (1989) and Lutkepohl and Herwartz (1996)[14]. This regression technique allows the regression coefficient vector, b_t, to evolve continuously over time in the linear model $y_t = x_t'\beta_t + \varepsilon_t$, where x_t is the $K \times 1$ vector of the independent variables at time t and ε_t is the error term with $E[\varepsilon_t] = cov(\varepsilon_t, \varepsilon_{t-j}) = 0$, and $var(\varepsilon_t) = \sigma^2$. There are two sources of error: *measurement error and dynamic error.* The measurement error is the difference between the dependent variable at time t, y_t, and its predicted value defined as:

$$sse = \sum_{t=1}^{T} [y_t - x_t'\beta_t]^2 \tag{1}$$

[14] Christopherson, Ferson, and Turner (1999) suggest the following reasons for using time varying alphas and betas: betas of underlying securities may change, managers may change beta in pursuit of alpha, or cash inflows may change cash holdings and betas. Variation in betas may or may not be related to manager's activities.

The dynamic error is the sum of squared changes in the coefficient vector from time t to time $t+1$.

$$ssd = \sum_{t=1}^{T} [\beta_{t+1} - \beta_t]' [\beta_{t+1} - \beta_t] \tag{2}$$

To estimate the model, Kalaba and Tesfatsion (1989) propose minimizing a weighted sum, γsse + $(1 - \gamma)ssd$, where the user supplies the weight $\gamma \in (0, 1)$. I have chosen to use $\gamma = .95$. Choosing this value gives a desirable balance of allowing time variation in coefficients and avoiding over fitting the data (see Berzins and Trzcinka (2005) for more on alpha calibration in the institutional money management industry)[15].

I windsorize portfolio alphas at 0.25% tails before aggregating them by using lagged asset weights to compute the family annual alphas. Portfolios created in calendar year *t-1* are excluded from the family alpha calculation for that year to avoid including new portfolios in the benchmark ranking of families. Next I rank families based on these alphas and assign them to the performance brackets. The brackets contain family rankings in the following percentage groups: bracket 1- lowest 20 percent; bracket 2- 20 to 50 percent; bracket 3- 50 to 80 percent, bracket 4- the highest 20 percent of families. Similarly, I calculate the asset weighted annual family alphas for the newly created portfolios. Family performance brackets are constructed for the year *t-1*. For each of these brackets, I estimate the average asset weighted alpha for the years *t* to *t+2*. I also calculate the total assets for each bracket for the same time period.

For robustness I perform separate analysis for the type-one and type-two families as they may exhibit different persistence patterns.

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[15] Kalaba and Tesfatsion show that the collection of all possible weighted sums attainable at time N, $\{sse, ssd \mid \beta, N\}$, is contained by a lower envelope that is bounded away from the origin. If time variation in betas exists, there is an optimal combination of the two errors that will minimize the variation below the standard OLS solution (see Berzins and Trzcinka (2005) for more discussion).

In the next step I verify that the family rank caries over to the newly created portfolios. If family rank is found to carry over to the new portfolios, the family new fund paradox is possible in the data.

Test 2 of the Family New fund Paradox: Transition Probability Test of Old-New Rank Persistence.

I calculate the transitional probabilities for performance brackets. I define the transitional probability for all new funds from a family to be in the i^{th} bracket at time t if a family was in the j^{th} bracket at time $t-1$. The brackets are assigned based on the family's weighted average rank at time $t-1$. Portfolios less than a year old are not included in the ranking to avoid conditioning a family's rank at $t-1$ on new portfolio performance. I calculate the weighted average rank of new portfolios for family i at time t. Just portfolios with both alphas and lagged assets are included. For example, if families by chance ended up in the second lowest bracket at t-1, the new portfolios should have a 20% probability to be in the lowest bracket, a 30% in either of middle brackets, and a 20% to fall in the top bracket. Note that brackets do not contain an equal number of firms. I expect to find significantly larger numbers than these percentages on the diagonal in a transitional probability matrix, if performance persistence exists between the family at time t and the new portfolios at time $t+1$. Finding persistence would be consistent with the presence of the family new fund paradox.

The next test formally tests if performance of new portfolios depends on previous family performance by controlling for other possible factors that may influence the new portfolio performance.

Test 3 of the Family New fund Paradox: A New Portfolio Rank- a Function of Family Rank.

I run censored Tobit regression for all families with new portfolios. This regression tests if ceteris paribus performance of new portfolios depends on the family performance and family characteristics in the previous year. This test formally established the relationship between past performance of a family and the future performance of the new portfolios in that family. In data consistent with the family new fund paradox, I expect to see a positive relationship between a family's performance and performance of the new portfolios.

The dependent variable in the Tobit regression is the performance rank in year *t* of newly created portfolios; the independent variables include the performance rank in year *t-1*.

$$\text{New Portfolio Ranked Performance}_{i,t} = a_0 + b_1 (\text{Performance Rank})_{i,t-1} + b_2 (\text{Firm Type})_{i,t-1} + b_3 (\text{Fees})_{i,t-1} + b_4 (\text{Asset Turnover})_{i,t-1} + b_5 (\text{Employee Ownership})_{i,t-1} + b_6 (\text{Revisions})_{i,t-1} + b_7 (\text{Percentage of Assets Reported})_{i,t-1} + b_8 (\text{Equity Inflows})_{i,t-1} \quad (3)$$

The next step is to test the proposed explanation for observed persistence in data- the low-skill family strategy.

Test 1 of Null Hypothesis about the Low-skill Family Strategy: New Portfolio Lifespan Test.

I calculate the average life expectancy of new portfolios for each bracket. The life expectancy shows how many quarters the new portfolio survives. The reason this has the power to test the hypothesis is that the type of a manager is revealed over time. If a manager lacks skill, the new portfolios will perform worse than the rest. If information is revealed very quickly, opening new portfolios to hide poor performance would be impractical. However, if information is revealed slowly, bad managers will be able to earn fee income before their type is revealed. Life expectancy test examines the speed of information revelation. I expect to find that in the presence of the low-skill family strategy, new portfolios from the second lowest bracket live as long as the new portfolios from top managers. If portfolios of the second lowest bracket live a shorter life than the top performers it would suggest that investors cannot be fooled and assets are withdrawn.

In the next step, I model new portfolio opening with a logistic regression. First, this test will answer if performance influences new opening decisions. It will also confirm if membership in any of the brackets alone increases the likelihood of opening a new portfolio.

Test 2 of Null Hypothesis about the Low-skill Family Strategy: A New Portfolio Opening- a Function of Family Performance.

I model a portfolio opening with a logistic regression. First, it establishes the relationship of past performance and future new portfolio openings. As discussed earlier, poor performing families have fewer ways to attract assets than better performing families; new portfolio opening is one of the ways.

Since the low-skill family strategy should manifest more within poor performing families, we should observe a negative relationship between performance and portfolio openings. This is consistent with the view that poor performing families are very aggressive in attracting assets via new portfolios. Finding a positive relationship between performance and new openings would serve as evidence against the low-skill family strategy.

Second, the logistic regression tests if a membership in a performance bracket alone significantly increases chances of new portfolio creation. It is of particular interest whether membership in the second lowest bracket increases chances of new portfolio opening. A positive finding to this question would add to the evidence in favor of the low-skill family strategy and vice versa.

I use the following logistic regression modeled after a similar regression used by Khorana and Servaes (1999) in exploring the reasons behind new portfolio openings among a sample of mutual fund companies.

Following the discussion of opening reasons in the theory section, I control for known alternative reasons to open portfolios. Control variables are discussed in a separate section.

$$\text{Opening}_{i,t} = a_0 + b_1 (\text{Performance Rank, Dummy, or Risk Prem.})_{i,t-1} + b_2 (\text{New Openings})_{i,t-1} + b_3 (\text{Portfolio Closings})_{i,t-1} + b_4 (\text{Family Equity Asset Inflows})_{i,t-1} + b_5 (\text{Firm Type})_{i,t-1} + b_6 (\text{Fees})_{i,t-1} + b_7 (\text{Asset Turnover})_{i,t-1} + b_8 (\text{Employee Ownership})_{i,t-1} + b_9 (\text{Revisions})_{i,t-1} + b_{10} (\text{Percentage of Assets Reported})_{i,t-1} + b_{11} (\text{Equity Size})_{i,t-1} + b_{12} (\text{Equity Inflows})_{i,t-1} \quad (4)$$

The next step is to test if families benefit from new opening decisions.

Test 3 of Null Hypothesis about the Low-skill Family Strategy: Family Net Inflow as a Function of Portfolios Opening Decision.

If families are successful in implementing the low-skill family strategy, then they should benefit from new portfolios in term of family level net asset inflows. To formally test this hypothesis I model family net inflows as a function of family past performance, new portfolio openings, and other control variables that are known to account for performance flow relationship. A similar test is performed by Del Guercio and Tkac (2002) for a sample of mutual funds and pension funds. Consistent with the low-skill family strategy, the middle bracket families should benefit from the new openings, while the top and bottom families should not benefit from new openings.

Control variables in logistic and Tobit regressions

Family asset turnover combined with poor performance can be viewed as a signal of distress. In addition, turnover controls for differences in transaction costs. Ownership variable is defined as percentage of a family owned by employees. The higher the ownership, the more manager and investor interests are aligned. Fees are an important control variable since the new portfolio must have a positive net return. The sign of fees is an empirical question. While Carhart (1997) finds that high fee funds do not perform as well as the low fee funds, an earlier study by Ippolito (1989) suggests that high fee funds perform well enough to offset the high fees. Hugonnier and Kaniel (2004) identify that fees influence the relationship between performance and flows in a sample of mutual funds. For example, a positive relationship is found for mutual funds with low fees.

While the sample does not include data on exact fees, I can estimate fees from fee schedules. The fees used in this paper are estimated from these schedules by using information about the average and median account size in each portfolio. Namely, an average account size (the median account size if the average is missing) for each portfolio is matched with an appropriate fee from its fee schedule.

Managers occasionally retrospectively revise portfolio returns. Revisions may happen for many reasons such as changes in portfolio composition, corrections of errors and omissions. It is possible that managers change returns to change perceptions of past performance. I have collected revision information for each portfolio in a family. The revision dummy takes a value of one if any of the portfolio returns are revised in a particular year.

I include the average percentage of the style assets that are reported in a portfolio as a control variable. Managers typically do not include all assets from a particular style in a portfolio report. The concern is that a portfolio has a representative set of assets. Managers can potentially manipulate this percentage. Most managers include practically all accounts in a portfolio. Percentage of assets included can be viewed as a quality signal.

As discussed earlier, one should control for the type of family. I use the LSV (1992) family type definition. Equity size, SP500 returns, and the time dummies should capture cyclical and time specific characteristics of new portfolio creation or performance. I use the total equity asset inflow to control for new fund creation driven by market expansion.

The next section describes construction and characteristics of the survivorship bias free database and presents the equity sample.

V. Mobius Data and Sample Description.

Mobius Database. We have compiled a unique survivorship bias free database from quarterly editions of the Mobius M-Search survey database, which allows us to perform a family level analysis. This database reports self-reported survey data on numerous characteristics of institutional money managers. A money management family (a portfolio of portfolios) usually offers several portfolios, some offer as many as 30 portfolios; each of these portfolios has its own style or objective. A typical money manager is in charge of large holdings for a small number of institutional investors. Because institutional investors do no want their account information released, money managers report data on AIMR (currently CFA Institute) composites (a value-weighted portfolio covering several investors). In this paper I refer to these composites as portfolios. I refer to money management firms either as firms or families. For each manager we know quarterly portfolio returns and annual firm and portfolio descriptive characteristics including tax treatment of accounts.

Our database is free of survivorship bias. We have collected Mobius quarterly survey reports from June, 1993 until March, 2005. Each survey provides a panel data, which itself does not include portfolios that are terminated before the date. The database that we have compiled includes terminated accounts since June 1993; it also is corrected for errors that become apparent when subsequent surveys are released. We are also able to avoid using back-filled returns in analysis because we know the quarter a portfolio enters our database by comparing subsequent survey panels.

Data is self-reported and Mobius sells the data to institutional investors and consultants. The data accuracy is a concern in a self reported database. Two studies have verified the accuracy of Mobius survey data against alternative sources (Del Guercio and Tkac (2002); Berzins and Trzcinka (2005)). Both studies concluded that the data is highly accurate. Availability of alternative private databases encourages accurate reporting.

Equity Sample. The equity sample used in this paper imposes minimal filters on the Mobius database. I include just domestic equity portfolios and exclude institutional mutual funds and experimental portfolios such as back tested data portfolios. This sample gives a complete picture of domestic equity managers in the Mobius database and represents high percentage of all equity money managers in the U.S.

There are 847 (1267) firms (portfolios) in 1993 and 992 (2718) firms (portfolios) in 2004. 79 (341) firms (portfolios) are born and 69 (208) die in an average year. The assets under management grow from $0.95 tr. to $4.3 tr. during the sample period. Seventeen percent of assets are managed in portfolios younger than two years. Table 1 reports statistics of families split by size and performance brackets. To create performance brackets families are ranked by asset weighted time varying Fama and French (1993) alphas. The lowest and highest performance brackets both contain 20 percent of families, while the middle brackets each contain 30 percent of families. Furthermore, the sample is split by family size. Type 1 families are large families offering more standardized products than the smaller type 2 families. Panel A reveals that disproportionate number of large, type 1 families belong to the middle brackets, while type 2 families are evenly distributed. This finding is consistent with the notion that large families may be more conservative. It is also consistent with the theoretical prediction that an average large high quality family alpha may be smaller than small high quality family alpha. The concentration of large families in the middle brackets explains the results from the Panel B, which suggests that more portfolios are opened by families in the middle performance brackets. Families in different brackets are not much different in tenure (Panel C). Small, type 2 families from the lowest two brackets face more litigation than the rest of the small families, while the type 1 families in the lowest and highest brackets face more litigation than the rest. The second lowest bracket of type 2 families faces the highest litigation among all small families. Table 2 presents descriptive statistics by family primary affiliation. Panels A and B indicate that small independent advisors disproportionately land in the extreme two brackets. It is consistent with LSV observation that small family performance is more volatile than big family performance. Banks and insurance companies appear conservative by disproportionately few times landing in the top bracket. When brackets are examined by client type, individual accounts appear to most often in the lowest brackets (Panel C). Panel D suggests that the best companies gain clients from referrals and direct marketing, while the worst families rely more on brokers and consultants to gain clients (Panel D).

Biases in This Study

I collect gross returns as net returns are seldom reported. I use net returns in the rare case that a gross return is missing, but net is available. This study includes all portfolios that existed during a particular year and does not exclude dead portfolios. It is free of survivorship bias in terms of Brown, Goetzmann, Ibbotson, and Ross (1992). Calculation of performance variables requires a complete set of the past eleven returns. These variables introduce some unknown methodology driven bias, which Carhart (1997) calls look-ahead-bias. I have calculated back filled return bias and determined that there is no consistent back filled return bias found in such datasets as hedge fund data. I use up to three years of back filled returns to extend the sample period in estimation of time varying coefficients. However, I do not used the time varying estimated from the back filled period dates in further analysis.

V. Discussion of Results

Table 1 (Panel B) shows that new portfolios are created by almost as many good as poor performers. The question is if we observe persistence between family and newly opened portfolio performance. Table 3 presents a portfolio opening analysis. Average family alpha for newly created portfolios over the first three years of life is between 38 and 20 basis points (Table 3 Panel A). The total assets that these new portfolios are attracting are increasing. Panel B presents results for performance brackets. In general, we observe persistence between newly opened portfolios and previous family performance. Significantly, the portfolios opened by the second lowest bracket families will have statistically significantly lower average alpha than portfolios opened by any of the two higher ranking brackets. This persistence over three years is unexpected and suggests that the data is consistent with the new fund paradox.

As expected the lowest performance bracket does not experience asset growth in new portfolios. Assets grow very slowly in the top performance bracket as well. The medium brackets experience the highest asset growth. With average annual fees estimated at 70 basis points for the sample, the second lowest bracket does not seem to add value to the investors. This further supports the null hypothesis.

Jensen's alphas exhibit the same pattern over the first two years. It is reasonable to assume that investors, in an industry consisting of sophisticated clients and consultants, use multi-factor risk adjustment models to evaluate performance. In this light Jensen's alphas may just be too noisy to perform this type of analysis over a three-year period. For brevity I will present Fama and French (1993) model results. Table 3 (Panel C) reports that these results are not dependent on the family size (measured by family type variable).

Table 4 introduces transitional probabilities. The transitional probability is the probability that a family in the respective performance bracket at time t-1 will have new portfolios in one of the four performance brackets at the time t. The transitional probability table indicates that a mass of probabilities lie on the diagonal indicating that performance of the family persists in the newly opened portfolios; all odds ratios are statistically significant at the five percent level. This further supports the family new fund paradox.

Table 5 presents results from Tobit regressions, which formally tests the link between the family's performance and the performance of newly created portfolios. The first regression reveals that there is persistence in performance between the family at time t -1 and the average performance of newly created portfolios by that family at time t. The subsequent regressions confirm that that relationship prevails in all brackets except for the very lowest bracket. I control for equity inflows, previous closures and family type. Most importantly I control for variables that we cannot observe a priori. Presence of revisions (revision dummy) and not reporting all assets may be used as tools to directly change the outlook of performance. Even after controlling for these variables, family's performance predicts new portfolio performance.

Next we test if data is consistent with the low-skill family strategy- the proposed explanation of the paradox. For the strategy to work, information about manager quality has to be revealed slowly. Table 6 presents the univariate longevity analysis. I calculate the average percentage of the remaining family life that a new portfolio lives. The average life expectancy is statistically and economically insignificantly different between the brackets. This suggests that portfolios introduced by below average families do not live a shorter life than the portfolios of better families. This suggests that information is revealed slowly and that search cost increasing activities at the family level may be possible in this industry.

It is possible that variables used in univariate analysis proxy for other phenomenon than the proposed low-skill family strategy. After all there may be many reasons why a new portfolio is opened by underperforming family. Table 7 presents logistic regression analysis of new portfolio openings. The first regression establishes that the lower a family ranks the higher its probability of opening a new portfolio. If a family's rank decreases by one standard deviation, the chance of a new portfolio opening increases by 0.9%. Together with the positive performance flow relationship from the literature (Del Guercio and Tkac (2002)) this result underscores underperforming manager's drive to aggressively increase the fee basis with new openings[16]. Note that lower performing managers are loosing assets and thus fee income, yet they are more aggressive in opening new portfolios, which will underperform in the future. This suggests the presence of the low-skill family strategy among these managers. Results are robust to other known reasons for portfolio openings such as asset inflows, previous portfolio closures, and aggressive expansion documented by previous openings.

The next four regressions in table 7 test if membership in any of the brackets increases the chances of opening a new portfolio. All four regressions produce the membership dummy signs consistent

[16] In contrast KS did not find the link between performance and opening decision in mutual fund sample.

with the first regression result. However, the only significant dummy coefficient is in the third regression. Namely ceteris paribus- just belonging to the second lowest bracket statistically increases one's chances of opening a new portfolio. The lowest bracket consists of distressed firms which are under much scrutiny from their investors. The second lowest bracket is the most likely candidate for the low-skill family strategy. Therefore, this result is consistent with low-skill family strategy. Most of control variables are both statistically and economically significant.

Table 8 reports results on the relationship between new portfolio opening decisions and family flows. For the whole sample, new portfolio opening has a positive effect on family inflows (see panel A). The results are robust to different risk adjustment models and known variables that predict asset inflows. Panel B reports results by bracket for performance measured by Fama-French three factor alphas. Within bracket performance does not have an affect on flows; however, the opening decision does. The lowest bracket benefits from not opening new portfolios (negative relationship), while the top bracket has no relationship- the top families have inflows just from being in the top. The middle bracket families benefit from new openings. Notably, the lowest middle bracket benefits more than the highest middle bracket. This is strongly consistent with the low-skill family strategy being used in the sample. Panel C presents similar results for Jensen's alpha. The difference is that Jensen's alpha is still a significant predictor of flows within brackets. This is expected considering that Jensen's alpha is a very noisy risk-adjusted measure and may include some common factors that drive this result.

Considering this evidence I conclude that it is very plausible that a group of managers in the second lowest performance bracket engage in family level search cost increasing activities- the low skill family strategy. Surprisingly investors do not condition their investing in newly opened portfolios on family wide performance measures hence the family new fund paradox. My results permit that some investors are collecting family wide data, but the majority seem not to do so. Investors invest in new portfolios offered by the second bracket managers, but lose money over time and for some reason do not terminate these accounts or withdraw money faster than from accounts of better performing families. It is possible that these managers provide service to their clients that is valuable, and for that investors are willing to tolerate lower returns.

VI. Conclusion

This study suggests that family level analysis matters in the institutional money management industry by examining new portfolio openings in a large survivorship bias free sample of institutional money management families. I rank families based on risk-adjusted return measures to examine whether newly opened portfolios will perform similarly to family performance. Surprisingly, I find that the new portfolios do fall in the same bracket as the family. Importantly, portfolios created by families from the second lowest performance bracket gain assets. I also examine the future performance of these new funds. Using time varying alphas, I find that the fund families performing below average in one year create portfolios that on average underperform for up to three subsequent years. I call this combination of results the family new fund paradox. It is a paradox, because the fund flows indicate that institutional investors are not collecting and/or using information about prior family performance that would be useful in predicting the future performance of these new funds. My findings are robust to the known persistence among the worst performing managers.

I provide an explanation of the observed persistence that considers the poor availability of family level information in the institutional money management industry. I propose that low-skilled families open new portfolios to disguise their past underperformance and to gain assets. Assets invested with low-skilled families will likely lose value and eventually will be moved to more prosperous investment opportunities. If a sample has enough low-skilled families and information is revealed slowly we may observe the paradoxical persistence. I find evidence supporting this explanation. Portfolios created by below average families have indistinguishable lifespans from portfolios created by better families. Thus, information is revealed slowly in this industry. I find that membership in the second lowest bracket increases the probability that a manager will open a new portfolio. In other words I find that slightly below average performing managers are especially eager to expand fee basis by opening new portfolios.

Finally, family inflows are related to a family's previous decision to open a new portfolio. As expected the second lowest bracket families exhibit a positive relationship between openings and subsequent family inflows. Slightly underperforming families benefit from opening new portfolios. The best families do not benefit from openings, while the worst families benefit from not opening new portfolios. Given these findings, I conclude that it is conceivable that a group of managers with below average performance engage in search cost increasing activities by offering new portfolios that will underperform in the future.

It is conceivable that some investors collect family wide data, but do not share it. It is also possible that these managers provide service to their clients that is valuable, and for that investors are willing to tolerate lower returns.

This study suggests the value in collecting and analyzing industry-wide family level data in a managed fund industry. This supports the theoretical findings of the family level rational investor response model.

Future research

Future research should examine other ways in which managers engage in activities that increase search costs to investors. For example, managers frequently file returns one or two quarters late with data providers. This may suggest that managers are waiting for a better performance before a worse previous performance is revealed. It should also be explored if managers systematically alter backfilled returns. Simple investigation of this has not revealed that backfilled revisions are on average biased but still it is possible that a group of managers are using return revisions to change their image.

REFERENCES

Berzins, Janis, Charles A. Trzcinka, 2005, Survival and performance of pension fund money managers, *working paper,* Indiana University.

Bhana, Narendra, 2002, Window dressing by institutional investors on the Johannesburg Stock Exchange: an empirical analysis. *The Investment Analysts Journal* 39.

Bildersee, J. & Kahn, N., 1987, A preliminary test of the presence of window dressing: evidence from institutional stock trading. *Journal of Accounting, Auditing & Finance* 2, 239 - 256.

Brown, Stephen J., William N. Goetzmann, and Stephen A. Ross, 1995, Survival, *Journal of Finance*, 50.

Carhart, M., 1997, On persistence in mutual fund performance, *Journal of Finance* 50, 57-82.

Carhart, Mark M., Jennifer N. Carpenter, Anthony W. Lynch and David K. Musto, 2002, Mutual fund survivorship, *The Review of Financial Studies* 15, 5.

Carhart, Mark M., Ron Kaniel, David K. Musto, and Adam V. Reed, 2002, Leaning for the tape: evidence of gaming behavior in equity mutual funds, *The Journal of Finance* 57, 661-693.

Christopherson, Jon A. and Andrew L. Turner, 1991, Volatility and predictability of manager alpha: learning the lessons of history," *Journal of Portfolio Management* 5.

Christopherson, Jon A., Wayne E. Ferson, and Andrew L. Turner, 1999, Performance evaluation using dynamic alphas and betas, *Journal of Portfolio Management* 26, 59-72.

Christopherson, Jon A., Wayne E. Ferson, and Debra A. Glassman, 1998, Conditioning manager alphas on economic information: another look at the persistence of performance, *The Review of Financial Studies* 11, 111-142.

Del Guercio, Diane and Paula A. Tkac, 2002, The determinants of the flow of funds of managed portfolios: mutual funds versus pension funds, *Journal of Financial and Quantitative Analysis,* 523.

Fama, Eugene F. and Kenneth R. French, 1993, Common risk factors in the returns of stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene, Kenneth French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47.

Gallaher, Steve, Laura Starks, and Ron Kaniel, 2005, Madison Avenue meets Wall Street: mutual fund families, competition and advertising, *working paper*.

Gaspar, José-Miguel, Massa, Massimo and Matos, Pedro, 2004, Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization, *working paper*.

Guedj, Ilan and Papastaikoudi, Jannette, 2003, Can mutual fund families affect the performance of their funds? *working paper*.

Hart, Oliver; George L. Perry, 1992, The structure and performance of the money management industry. Comments and discussion, *Brookings Papers: Microeconomics*.

Haugen, Robert and Josef Lakonishok, 1988, The Incredible January Effect: The Stock Market's Unsolved Mystery, Dow Jones-Irwin, Homewood, III.

Hugonnier, J. and Ron Kaniel, 2004, Mutual fund portfolio choice in the presence of dynamic flows, *working paper*.

Ippolito, Richard, 1989, Efficiency with costly information: A study of mutual fund performance, *The Quarterly Journal of Economics* 104, 1-24.

Ippolito, Richard, 1992, Consumer reaction to measures of poor quality, *Journal of Law and Economics* 35, 45-70.

Jansson, Solveig, 1983, Portfolio strategy: The fine art of window dressing, *Institutional Investor* 17, 139-141.

Kalaba, R. and L. Tesfatsion, 1989, Time varying linear regression via flexible least squares*, Computers Mathematical Applications* 17, 1215-1245.

Keim, Donald, Size-related anomalies and stock return seasonality, *Journal of Financial Economics* 12, 13-32.

Kempf, Alexander and Ruenzi, Stefan, 2003 Tournaments in Mutual Fund Families, *working paper*.

Khorana, Anjay and Henri Servaes, 1999, The determinants of mutual fund starts, *Review of Financial Studies* 12, 5.

Khorana, Anjay, 2001, Performance changes following top management turnover: Evidence from open-end mutual funds, *Journal of Financial and Quantitative Analysis* 36, 371-398.

Lakonishok, J., A. Shleifer, and R. Vishny, 1992. The structure and performance of the money management industry, *Brookings Papers: Microeconomics,* 339-391.

Lakonishok, Josef; Shleifer, Andrei; Thaler, Richard; Vishny, Robert, 1991, Window dressing by pension fund managers, *The American Economic Review* 81, 227.

Lee, Cheng-Few, David C. Porter, and Daniel G. Weaver, Indirect tests of the Haugen-Lakonishok small-firm/January effect hypotheses: window dressing versus performance hedging, *The Financial Review* 33, 177-194.

Lutkepohl, Helmut and Helmut Herwartz, 1996, Specification of varying coefficient time series models via generalized flexible least squares, *Journal of Econometrics* 70, 261-290.

Morey, Matthew R.; Edward S. O'Neal, 2002, Window Dressing in Bond Mutual Funds, *working paper*.

Musto, David K., 1997, Portfolio disclosures and year-end price shifts, *Journal of Finance* 52, 1563-1588.

Musto, David K., 1999, Investment decisions depend on portfolio disclosures, *Journal of Finance* 54, 935-952.

O'Neal, Edward S., 2001, Window Dressing and Equity Mutual Funds, *working paper*.

Patel, J., R. Zeckhauser, and D. Hendricks, 1994, Investment flows and performance: evidence from mutual funds, cross-border investments and new issues, in R. Satl, R. Levitch, and R. Ramachandran, Eds., Japan, Europe and the International Financial Markets: Analytical and Empirical Perspectives, Cambridge University Press, New York.

Rao, M. J. M., 2000, Estimating time varying parameters in linear regression models using a two part decomposition of the optimal control formulation, *The Indian Journal of Statistics* 62, 433-467.

Rozeff, Michael and William Kinney, 1976, Capital market seasonality: the case of stock returns, *Journal of Financial Economics* 3, 379-402.

Sias, Richard W. and Laura T. Starks, 1997, Institutions and individuals at the turn-of-the-year, *Journal of Finance* 52, 1543-1562.

Sirri, Erik R. and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589- 1622.

Swensen, David F., 2000, Pioneering Portfolio Management, The Free Press.

Walker, Richard, October 2000, Investment management enforcement in the 21rst century, Speech by SEC Staff, Speech delivered to the D.C. Bar Association, Washington D.C.

Wermers, Russ R., 2003, Is money really smart? New evidence on the relation between mutual fund flows, manager behavior, and performance persistence, *working paper*, University of Maryland.

Zhao, Xinge, 2005, Entry decisions by mutual fund families, *working paper*.

Table 1

Family Descriptive Statistics by Performance Brackets: Count, New Openings, Tenure, and Litigation

This table presents descriptive statistics of families that offer equity portfolios, but are not classified as mutual fund companies. The family ranking is done by first calculating asset weighted time varying Fama and French (1993) alphas and then assigning families to the performance brackets. The lowest and highest performance brackets both contain 20 percent of families, while the middle brackets contain 30 percent of families. The sample is split by family size. Type 1 families are large families offering more standardized products than the smaller type 2 families. Panel A reports percentage family count in each performance bracket. Panel B counts the number of family-years new portfolios are opened and the average number of portfolios per year by family. Panel C reports average manager tenure by family as well as percentage of families that reported litigation brought against them in a particular year. The data in this panel represents all portfolios that a family offers, including fixed income and international portfolios.

Panel A: Percent of Families in Performance Brackets: Sample Split by Family Type

	All	Type 1	Type 2
Lowest	20%	14%	21%
Mid Low	30%	43%	27%
Mid High	30%	34%	29%
Highest	20%	9%	22%

Panel B: New Openings by Family

	Nr of Years a Family Opens a Portfolio	Average Portofolios per Year by a Family
Lowest 20%	220	1.5
50% to 80%	450	2.0
20% to 50%	364	2.0
Top 20%	178	1.5

Panel C: Tenure and Litigation

	Manager Avg Years in Industry	Manager Avg Years at Family	Percent of Families with Litigation
Type 2			
Lowest	16.8	7.0	2.6%
Mid Low	16.7	7.0	3.8%
Mid High	16.4	6.9	2.1%
Highest	16.2	6.4	2.3%
Type 1			
Lowest	15.1	7.5	8.8%
Mid Low	12.7	6.5	8.1%
Mid High	13.4	7.1	8.2%
Highest	12.9	6.6	10.3%

Table 2

Family Descriptive Statistics by Performance Brackets:
Families by Affiliation, Family-wide Client Types, Marketing Channels

This table presents descriptive statistics of families that offer equity portfolios, but are not classified as mutual fund companies. The family ranking is done by first calculating asset weighted time varying Fama and French (1993) alphas and then assigning families to the performance brackets. The lowest and highest performance brackets both contain 20 percent of families, while the middle brackets contain 30 percent of families. The sample is split by family size. Type 1 families are large families offering more standardized products than the smaller type 2 families. Panel A reports the breakdown of management family institutional affiliation by count, while Panel B reports the breakdown by the total equity assets. Panel C reports family-wide client types. The data in this panel represents all portfolios that a family offers, including fixed income and international portfolios. Panel D reports the marketing channels that attracted existing clients. Mobius report percentage of clients that a family attracts by different channels. While percentages add up to one for individual families, they do not add up when averaged across sample. The data in this panel represents all portfolios that a family offers, including fixed income and international portfolios.

Panel A: Affiliation by Count

	Bank	Broker	Independent	Insurance & Others
Type 2				
Lowest	3%	5%	88%	3%
Mid Low	9%	5%	81%	5%
Mid High	7%	6%	85%	3%
Highest	3%	6%	88%	3%
Type 1				
Lowest	24%	6%	52%	17%
Mid Low	30%	6%	49%	16%
Mid High	25%	9%	51%	15%
Highest	23%	3%	69%	5%

Panel B: Affiliation by Total Equity Assets

Type 2				
Lowest	5%	6%	85%	4%
Mid Low	14%	3%	74%	9%
Mid High	10%	5%	76%	9%
Highest	4%	5%	85%	5%
Type 1				
Lowest	23%	4%	34%	39%
Mid Low	49%	3%	38%	10%
Mid High	20%	10%	56%	14%
Highest	19%	2%	76%	4%

Table 2 (Continued)

Panel C: Family-wide Client Types

	Corporate Retire..	Government Retire..	Insurance Companies	Individual Accounts	Endowm., Foundat.	Taft Hartley	Corporate Non Retire..	Other
Type 2								
Lowest	20%	14%	9%	14%	8%	6%	4%	25%
Mid Low	20%	12%	8%	15%	8%	8%	5%	24%
Mid High	24%	12%	9%	11%	7%	7%	3%	27%
Highest	22%	14%	13%	13%	9%	6%	4%	19%
Type 1								
Lowest	19%	8%	5%	17%	4%	4%	3%	41%
Mid Low	25%	16%	5%	5%	4%	3%	3%	39%
Mid High	21%	12%	5%	5%	5%	3%	4%	45%
Highest	16%	8%	5%	5%	3%	2%	1%	59%

Panel D: Clients of Families Introduced by ...

	Broker	Consultants	Marketing	Clients
Type 2				
Lowest	32	26	44	29
Mid Low	32	26	42	28
Mid High	29	24	45	30
Highest	28	22	49	33
Type 1				
Lowest	28	28	47	20
Mid Low	17	30	49	21
Mid High	19	32	51	21
Highest	21	30	50	24

Table 3

Portfolio Opening Analysis: New Portfolio Performance Conditional on Family's Past Performance

This table presents new portfolio risk adjusted performance measure, alpha. Time varying alphas are calculated by using either Fama and French (1993) three factor model or Jensen's (1968) one factor model. Panel B splits sample in performance brackets. To create brackets I evaluate family performance in the year *t-1*. First, I compute the asset weighted time varying family alpha for the year *t-1*. The families are ranked based on these alphas and assigned to the performance brackets. The lowest bracket consists of the families in the lowest 20 percent of rank; the second bracket contains families from the 21 to 50 percent lowest rank; the third bracket contains families from 51 to 80 percent in rank and the last bracket contains the remaining 20 percent of families. Then I compute the asset valued average performance for portfolios opened in year *t* for years *t* to *t* plus two. This table presents both assets and average alphas for these new portfolios. The alphas of adjacent brackets are statistically significantly different at 5% level except for year *t+2* for Jensen's alphas.

Panel A: All Families

α_t	α_{t+1}	α_{t+2}	TA_t	TA_{t+1}	TA_{t+2}
Fama-French Alphas					
0.38	0.27	0.20	1,578,621	1,784,189	1,981,050
Jensen's Alphas					
0.44	0.39	0.48	1,578,621	1,784,189	1,981,050

Panel B: Performance by Bracket

Bracket	α_t	α_{t+1}	α_{t+2}	TA_t	TA_{t+1}	TA_{t+2}
Fama-French Alphas						
1	-0.04	-0.09	-0.12	106,482	104,412	109,950
2	0.15	0.09	0.06	713,909	826,272	931,699
3	0.56	0.46	0.36	481,388	576,842	665,566
4	1.14	0.88	0.70	90,144	89,295	93,472
Rest	0.39	0.23	0.18	186,699	187,369	180,363
Jensen's Alphas						
1	-0.25	-0.07	0.31	149,172	156,379	151,621
2	0.36	0.41	0.56	546,058	599,570	587,267
3	0.56	0.48	0.51	594,265	720,777	914,107
4	1.63	1.13	0.86	102,427	120,094	147,692
Rest	0.10	0.00	0.09	186,699	187,369	180,363

Table 3 (Continued)

This table presents new portfolio risk adjusted performance measure, alpha. Time varying alphas are calculated by using either Fama and French (1993) three factor model or Jensen's (1968) one factor model. Panel B splits sample in performance brackets. To create brackets I evaluate family performance in the year *t-1*. First, I compute the asset weighted time varying family alpha for the year *t-1*. The families are ranked based on these alphas and assigned to the performance brackets. The lowest bracket consists of the families in the lowest 20 percent of rank; the second bracket contains families from the 21 to 50 percent lowest rank; the third bracket contains families from 51 to 80 percent in rank and the last bracket contains the remaining 20 percent of families. Then I compute the asset valued average performance for portfolios opened in year *t* for years *t* to *t* plus two. This table presents both assets and average alphas for these new portfolios. The alphas of adjacent brackets are statistically significantly different at 5% level except for year *t+2* for Jensen's alphas. The sample is split on family type. Type one families are large standardized families and offer standardized products; type two families are small families and offer more specialized portfolios.

Panel C: Performance by Bracket and Type (Size)

Bracket	α_t	α_{t+1}	α_{t+2}	TA_t	TA_{t+1}	TA_{t+2}
Type 2 Families, Fama French Alphas						
1	0.01	-0.03	-0.06	33,174	27,950	35,038
2	0.24	0.20	0.19	90,054	101,327	122,689
3	0.61	0.50	0.36	116,271	124,253	135,760
4	1.10	0.81	0.63	22,762	30,209	36,589
Rest	0.53	0.38	0.31	93,217	95,197	78,311
Type 1 Families, Fama French Alphas						
1	-0.19	-0.25	-0.28	73,308	76,462	74,912
2	0.07	-0.01	-0.07	623,855	724,945	809,010
3	0.49	0.41	0.36	365,117	452,588	529,806
4	1.26	1.07	0.92	67,382	59,086	56,883
Rest	-0.12	-0.30	-0.29	93,481	92,172	102,052
Type 2 Families, Jensen's Alphas						
1	-0.51	-0.27	0.25	26,893	27,976	32,343
2	0.49	0.58	0.77	108,511	102,494	92,460
3	0.82	0.63	0.53	92,647	111,174	141,941
4	1.72	1.31	1.07	34,210	42,094	63,330
Rest	0.14	0.04	0.08	93,217	95,197	78,311
Type 1 Families, Jensen's Alphas						
1	0.46	0.49	0.45	122,279	128,403	119,278
2	0.21	0.21	0.32	437,547	497,076	494,807
3	0.24	0.30	0.49	501,618	609,602	772,165
4	1.34	0.58	0.22	68,217	78,000	84,361
Rest	-0.02	-0.14	0.13	93,481	92,172	102,052

Table 4

New Portfolio Performance: Transitional Probability Analysis

This table depicts transitional probabilities. Rows represent families in the respective performance bracket at time t-1; while columns represent probability for new portfolios to be in one of the four performance brackets at the time t. I use the same performance brackets as in table 3 (panel C). First asset weighted time varying Fama and French (1993) alpha is computed for the year *t-1*. The families are ranked based on these alphas and assigned to the performance brackets. The lowest bracket consists of the families in the lowest 20 percent of rank; the second bracket contains families from the 21 to 50 percent lowest rank; the third bracket contains families from 51 to 80 percent in rank and the last bracket contains the remaining 20 percent of families. The diagonal elements are all significantly different from the values that we expect by chance. All odds ratios for the diagonal elements are significant at 5% level.

		Family's Performance Bracket By New Portfolios in Year t			
	Brackets	1	2	3	4
Family's Performance Bracket in year t-1	1	43%	31%	14%	11%
	2	19%	38%	29%	14%
	3	14%	28%	38%	20%
	4	14%	22%	31%	33%

Table 5

Future Performance Analysis- Tobit Regressions

The dependent variable is asset weighted Fama and French (1993) alpha rank of newly created portfolios in year t+1. The variable is between 0 and 1; the family quality increases as the rank variable gets smaller. The independent variable is measured in the year t. *Equity Portfolios Ended* is the number of equity portfolios ended in year *t-1*. *Rank FF3* is the asset weighted time varying Fama and French (1993) alpha rank. The family quality increases as the number decreases. The variable is between 0 and 1, normalized by dividing ordinal rank by the number of families in that year. *Type one* firm dummy is 1 if a family is a type one family- a large family offering standardized products. *Family fees* and turnover are asset weighted variables. *Employee ownership* is the percentage of family ownership. *Revision dummy* is one if the family has revised any of the portfolio returns during the year. *Percent Assets Reported* is the asset weighted average for the family of percentage of assets included in portfolios. *YF1* to *YF4* are time dummies. The sign "***" indicates the statistical significance at 1%, "**" at 5%, while "*" at 10%.

	Full Sample		Full Sample		Low Rank t-1		Mid Low Rank t-1		Mid High Rank t-1		High Rank t-1	
Intercept	-0.5902		0.3291	***	5.3487		-0.1230		-0.2174		-4.6510	
Equity Portfolios Ended	0.0055		0.0008		0.1228		-0.0239		0.0080		1.8537	
RankFF3	2.1691	**	0.3383	***	4.4526		1.4404	***	1.5116	**	9.6857	
Typ1Firm	0.1059		0.0165									
FeesVW	-0.0036		-0.0005				-0.0038	**	-0.0018		0.0213	
TurnVW	0.0021		0.0003				0.0002		0.0013		0.0099	
Employees Ownership	-0.0010		-0.0002		-0.0032		-0.0002		-0.0005		-0.0070	
RevisionDum	-0.0117		-0.0018		5.4023		-0.0578		-0.1435		0.4786	
Percent Assets Reported	-0.0020		-0.0003		-0.0974	**	0.0000		0.0000		-0.0231	
Equity Inflow	-0.0049	*	-0.0008	**	0.0130		-0.0016		-0.0037	*	-0.0371	
YF1	0.3260		0.0503	*	1.7306		0.2113	*	0.3099		-1.0609	
YF2	0.1635		0.0255		1.3872		0.1076		0.1573		-2.8567	*
YF4	-0.0072		-0.0007		1.3808		-0.1371		0.2745		-2.6610	
_Sigma	0.6873				2.1889		0.4063		0.4732		1.3549	
n	1034		1034		1034		1034		1034		1034	
AIC	-97				-4.5262		-24.9008		-6.7493		-46.4029	
Schwarz Criterion	-28				31.1911		26.9231		41.4863		-7.7053	
R-Square			0.1142									
Adj R-Sq			0.1038									

Table 6

Univariate Longevity Comparison

This table described the longevity of newly created portfolios. Families are ranked by asset weighted time varying Fama and French (1993) alphas. The new portfolio relative life span is the percentage of quarters that the portfolio lives of the family's total remaining quarters. Portfolios terminating early are percentage of portfolios that terminate before the end of the family's life. Percent of remaining sample years is calculated as the ratio of portfolio life over the remaining sample life.

	New Portfolio Relative Life Span	Portfolios Terminating Early	Years To Death	Perc Years of Remain Sample Life	Count
Type2, FF3 Model					
Low	0.893	0.200	6.696	0.889	171
MiLo	0.878	0.253	6.826	0.935	235
MiHi	0.888	0.224	6.955	0.952	221
High	0.895	0.198	6.807	0.930	135
Type1, FF3 Model					
Low	0.817	0.371	8.245	0.957	49
MiLo	0.846	0.308	7.265	0.952	215
MiHi	0.844	0.304	6.979	0.934	143
High	0.781	0.360	7.419	0.966	43

Table 7

Modeling Probability of New Portfolio Creation by Family: Logistic Regression Results

The dependent variable is 1 if a new portfolio is created at time *t*; the independent variables are for time *t-1*. Pseudo R-squared is defined as 1 minus the log likelihood ratio at maximum over log likelihood ratio at zero. It is referred to as McFadden's likelihood ratio. The economic significance (the numbers with "%" sign) is the percentage increase in the probability of opening a new fund when a variable is increased by one standard deviation from its mean. For binary variables, this number is the percentage increase in the probability of a new start when the variable increases from zero to one. *Family Rank FF3* is asset weighted time varying Fama and French (1993) alpha rank. The family quality increases as the number decreases. The variable is between 0 and 1, normalized by dividing ordinal rank by the number of families in that year. The variable *New Equity Portfolio Count* and *Closed Equity Portfolio Count* is the number of portfolios either closed or started by a family in the year *t-1*. *Risk premium* is family return minus SP500 return. Type one firm dummy is 1 if a family is a type one family- a large family offering standardized products. *Family fees* and *turnover* are asset weighted variables. Fees are estimated from a fee schedule. *Employee ownership* is the percentage family ownership. *Revision dummy* is one if the family has revised any of the portfolio returns during the year. *Percent Assets Reported* is the asset weighted average for the family of percentage of assets included in portfolios. *Equity Inflow* is the total annual equity inflow in our sample. *YF1* to *YF4* are time dummies. The regression is run for the full sample under different specifications (specifications A to F). The sign "***" indicates the statistical significance at 1%, "**" at 5%, while "*" at 10%.

	A			B			C			D			E			F		
N	7,945			9,342			9,342			9,342			9,342			9,342		
Pseudo R-squared	0.074			0.094			0.095			0.094			0.094			0.094		
Intercept	-0.243			-0.744	*		-0.816	*		-0.699			-0.743	*		-0.798	*	
Family Equity Inflow	-0.013		-0.3%															
New Equity Portfolio Count	0.218	***	2.4%	0.183	***	1.9%	0.182	***	1.9%	0.182	***	1.9%	0.182		1.9%	0.183	***	1.9%
Closed Equity Portfolio Count	0.243	***	1.5%	0.140	***	0.9%	0.139	***	0.9%	0.140	***	0.9%	0.139	***	0.9%	0.144	***	0.9%
Family Rank FF3	0.272	**	0.9%															
Low Quartile Dummy FF3				0.040		0.5%												
MiLow Quartile Dummy FF3							0.145	**	1.7%									
MiHigh Quartile Dummy FF3										-0.101		-1.2%						
High Quartile Dummy FF3													-0.124		-1.4%			
Annual Family Risk Premium																0.004		0.7%
Type1 Family Dummy				0.933	***	13.7%	0.915	***	13.4%	0.932	***	13.6%	0.923		13.5%	0.932	***	13.6%
Fees VW	-0.010	***	-3.2%	-0.005	***	-1.6%	-0.005	***	-1.6%	-0.005	***	-1.6%	-0.005	***	-1.6%	-0.005	***	-1.6%
Turnover VW	0.005	***	2.7%	0.004	***	2.3%	0.004	***	2.4%	0.004	***	2.3%	0.004		2.4%	0.004	***	2.3%
Perc. Owned by Employees	-0.004	***	-2.1%	-0.002	***	-1.1%	-0.002	***	-1.1%	-0.002	***	-1.2%	-0.002	***	-1.1%	-0.002	***	-1.1%
Revision Dumy	0.652	***	7.7%	0.769	***	9.2%	0.764	***	9.1%	0.769	***	9.2%	0.765		9.1%	0.766	***	9.1%
Percent Assets in Style VW	-0.005	***	-1.5%	-0.006	***	-1.9%	-0.006	***	-1.9%	-0.006	***	-1.9%	-0.006		-1.8%	-0.006	***	-1.9%
Equity Size	-0.240	**	-2.5%	-0.279	***	-2.8%	-0.278	***	-2.8%	-0.280	***	-2.8%	-0.279	***	-2.8%	-0.270	***	-2.7%
Inflow Equity	0.002	**	1.4%	0.002	**	1.6%	0.002	**	1.6%	0.002	**	1.6%	0.002	**	1.6%	0.002	**	1.5%
SP 500 Return	0.008	***	2.1%	0.009	***	2.1%	0.009	***	2.1%	0.009	***	2.1%	0.009	***	2.1%	0.009	***	2.2%
YF1	-1.094	***		-1.177	***		-1.172	***		-1.176	***		-1.175	***		-1.117	***	
YF2	-0.623	***		-0.663	***		-0.662	***		-0.664	***		-0.662	***		-0.607	***	
YF4	-0.480	***		-0.469	***		-0.467	***		-0.469	***		-0.468	***		-0.437	***	

Table 8

New Portfolios Opening-Flow Analysis

This table describes flow performance relationship in the institutional money management industry. The dependent variable is *Family Equity Inflow* at year *t.* Inflows from portfolios that are created in year t are excluded. All independent variables are as of year *t - 1*. *Rank FF3* is asset weighted time varying Fama and French (1993) alpha rank. The variable is between 0 and 1, normalized by dividing ordinal rank by the number of families in that year. The family quality increases as the rank variable gets smaller. The variable *Equity Portfolios Ended* and *Equity Portfolios Started* is the number of portfolios either closed or started by a family in the year *t-1*. Risk premium is family return minus SP500 return. Type one firm dummy is 1 if a family is a type one family- a large family offering standardized products. *Family fees* and *turnover* are asset weighted variables. Fees are estimated from a fee schedule. *Employee ownership* is the percentage family ownership. *Revision dummy* is one if the family has revised any of the portfolio returns during the year. *Percent Assets Reported* is the asset weighted average for the family of percentage of assets included in portfolios. *Equity Inflow* is the total annual equity inflow in our sample. *YF1* to *YF4* are time dummies. The sign "***" indicates the statistical significance at 1%, "**" at 5%, while "*" at 10%. The number following "*" indicate the economic significance. For portfolios started and ended the economic significance equals the net impact in billions of dollars of adding or liquidating one portfolio. For the type variable this indicates the effect of changes in variable from zero to one. For the other variables the significance is the net flows in billions of dollars if the variable grows by one standard deviation from its mean.

Panel A. All Families

	Fama-French Alphas			Jensen's Alphas			Risk Premium		
Intercept	-0.0787			0.0382			-0.2839	**	
Family Equity Inflow	0.3114	***	0.6367	0.3089	***	0.6316	0.3100	***	0.6338
Number of Equity Portfolios Started	0.1491	***	0.1491	0.1488	***	0.1488	0.1501	***	0.1501
Numfber of Equity Portfolios Ended	0.0774			0.0866	*	0.0866	0.0957	*	0.0957
Rank FF3	-0.2522	***	-0.0700						
Rank Jensen				-0.4669	***	-0.1284			
Annual Risk Premium							0.0118	***	0.1549
Control Variables									
Type 1 Firm Dummy	-0.1019			-0.0967			-0.0990		
Value Weighted Fees	-0.0003			-0.0003			-0.0001		
Value Weighted Turnover	-0.0003			-0.0004			-0.0002		
Employees Ownership	0.0004			0.0003			0.0004		
Revision Dummy	0.0141			0.0135			0.0204		
Percent Assets Reported	0.0017	*	0.0475	0.0015	*	0.0422	0.0016	*	0.0439
Equity Inflow	-0.0004			-0.0004			-0.0001		
YF1	0.0636			0.0806			0.1396	*	
YF2	0.0290			0.0383			0.1543	**	
YF4	0.2423	**		0.2455	**		0.2509	**	
n	7203			7203			7203		
R-Square	0.0958			0.0982			0.0992		
Adj R-Sq	0.0940			0.0964			0.0974		

Table 8 (Continued)

This table splits the sample up by brackets to demonstrate that new portfolio flow relationship depends on membership in a particular performance bracket. Here families are ranked based on value weighted Fama-French three factor alpha.

Panel B. New Portfolios Opening-Flow Analysis by Bracket with Fama-French 3 Factor Alpha Rank

	Low Quartile			Mid Low Quartile			Mid High Quartile			High Quartile		
Intercept	-0.4987			-0.2079			0.1469			0.3002		
Family Equity Inflow	0.3663	***	0.3803	0.2876	***	0.8444	0.2551	***	0.3656	0.4303	***	0.7841
Number of Equity Portfolios Started	-0.0851	**	-0.0851	0.2762	***	0.2762	0.0877	***	0.0877	-0.0594		
Numfber of Equity Portfolios Ended	0.0424			0.2299	*	0.2299	0.0001			-0.1359		
Rank FF3	0.0304			-0.5243			-0.0363			-0.8631		
Control Variables												
Type 1 Firm Dummy	-0.2877	***	-0.2877	-0.3745	**	-0.3745	0.1310			0.3223	*	0.3223
Value Weighted Fees	0.0015			-0.0010			-0.0002			-0.0006		
Value Weighted Turnover	0.0002			-0.0012			-0.0007			0.0007		
Employees Ownership	0.0007			0.0002			0.0010			-0.0014		
Revision Dummy	0.0341			-0.0841			0.0332			0.1684	*	0.0842
Percent Assets Reported	0.0020	**	0.0536	0.0057	**	0.1625	-0.0005			-0.0019		
Equity Inflow	-0.0024	***	-0.1220	-0.0023			0.0005			0.0032	**	0.1667
YF1	0.1484	*		0.3583	*		-0.2070	**		-0.0565		
YF2	0.0154			0.2580			-0.2636	***		0.2286	*	
YF4	0.3297	***		0.6386	**		-0.0518			-0.0558		
n	1336			2271			2263			1333		
R-Square	0.1950			0.0909			0.0821			0.1860		
Adj R-Sq	0.1865			0.0853			0.0764			0.1774		

Table 8 (Continued)

This table splits the sample up by brackets to demonstrate that new portfolio flow relationship depends on membership in a particular performance bracket. Here families are ranked based on value weighted Jensen's alpha.

Panel C. New Portfolios Opening-Flow Analysis with Jensen's Alpha Rank

	Low Quartile			Mid Low Quartile			Mid High Quartile			High Quartile		
Intercept	-0.3337	**		-0.0629			0.2890	*		0.3112		
Family Equity Inflow	0.3624	***	0.3762	0.2849	***	0.8365	0.2530	***	0.3626	0.4282	***	0.7803
Number of Equity Portfolios Started	-0.0857	**	-0.0857	0.2769	***	0.2769	0.0872	***	0.0872	-0.0642		
Numfber of Equity Portfolios Ended	0.0464			0.2438	**	0.2438	0.0046			-0.1311		
Rank Jensen	-0.1996	**	-0.0528	-0.7786	***	-0.1799	-0.3317	***	-0.0794	-0.5134	***	-0.1294
Control Variables												
Type 1 Firm Dummy	-0.2743	***	-0.2743	-0.3733	**	-0.3733	0.1352	*	0.1352	0.3195	*	0.3195
Value Weighted Fees	0.0014			-0.0010			-0.0002			-0.0007		
Value Weighted Turnover	0.0002			-0.0016			-0.0008			0.0008		
Employees Ownership	0.0007			0.0002			0.0009			-0.0013		
Revision Dummy	0.0339			-0.0793			0.0301			0.1689	*	0.0844
Percent Assets Reported	0.0019	**	0.0514	0.0052	**	0.1480	-0.0005			-0.0018		
Equity Inflow	-0.0024	***	0.0003	-0.0025			0.0005			0.0033	**	0.0005
YF1	0.1763	**		0.3809	*		-0.2119	**		-0.0379		
YF2	0.0290			0.2272			-0.2647	***		0.2923	**	
YF4	0.3037	**		0.6278	**		-0.0297			-0.0010		
n	1336			2271			2263			1333		
R-Square	0.1974			0.0938			0.0851			0.1897		
Adj R-Sq	0.1889			0.0882			0.0794			0.1811		

Appendix I. Database and Data Description.

This section describes the Mobius database, which, in addition to the equity portfolios, covers fixed income, balanced, and real estate portfolios (Chart 1). Real estate data is limited and is not included in the total. Domestic equity managers are by far the dominating segment of all managers. The complete survey database that we have constructed covers 1125 (3249) families (portfolios) in 1993 and 1279 (5639) families (portfolios) in 2004. 108 (759) firms (portfolios) are born and 91 (550) die in an average year (Table 10). The total assets under management grow from \$2.60 tr. to \$11.81 tr. during the sample period. Ten percent of assets are institutional mutual fund assets. In December 2004 58% of assets are managed by independent advisors, 23% by banks, and the rest by mutual fund firms, brokers and insurance companies.

Managers in Mobius database are often slow reporting returns. Returns are frequently reported with one or more quarter lags. Having quarterly survey panels allows me to find a missing return for a certain date in a later survey. An important question is whether this process introduces any bias.[17] I do not find either consistently positive or negative bias in back reported data in the Mobius database. This leads to 1.2% missing returns at the beginning and 6.6% missing returns at the end of the equity sample period. 95% of equity portfolios include terminated accounts in return calculation at the beginning of sample and 99% include at the end. While about half of portfolios are audited in the sample, three quarters comply with AIMR standards at the end of sample. One third of equity portfolios follow socially responsible strategy. Rather than reporting fees, Mobius reports fee schedule for portfolios. Considering individual investor account size in equity portfolios I have estimated that an average equity portfolio fee in my sample is 76 basis points. Commissions are subtracted from returns and returns are gross of fees. Managers set the minimum time that they have an investor as a client before the investor is added to a portfolio report. This number starts at 2.7 months and ends at 1.6 months at the end of the sample.

In our equity sample between 60 and 84 percent of investors are tax-exempt either by assets or by count. Among tax-exempt institutions are university endowments, non-profit foundations, and pension

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[17] For example, Malkiel and Saha in a 2004 working paper find significant bias in back reported hedge fund returns.

sponsors. However, most portfolios contain both taxable and tax exempt investor money. Just between 30 and 40 percent of portfolios are pure tax exempt equity portfolios.

Table 11 reports a distribution of new equity funds over the last eleven years. We observe that the internet bubble years experienced the largest growth in funds; fund growth decreased in 2000 with a slow market and is starting to pick up again in 2001. In the middle of the sample period there have been more growth fund births than value fund births but the trend seems to have reversed after the burst of the internet bubble. Except for a surge in small cap fund assets in 2000, small cap funds have been the slowest growing category.

Independent advisors are the largest group of managers (Chart 1). They are followed by banks, brokers and insurance companies. About one third of new clients are introduced by direct marketing, the rest is split between broker, consultant, and other client introductions. 28 percent of all assets, including fixed income and balanced, are from individual accounts, 32% from government retirement, corporate retirement and Taft Hartley accounts.

Employees own two thirds of all families that reported ownership (Table 12). Individual managers have spent on average 6.8 years at a family. On average there are over twenty managers per family; almost three join and two leave every year. Families with equity portfolios controlled a total of $18.2tr. in 2004. This is a self reported asset number for the whole family. If we add assets from individual portfolios for these families, we get $11tr. Thus, not completely all assets are reported at a portfolio level.

Table 13 present an average return for domestic equity portfolios. The best years were before the internet bubble burst and the worst right after. The standard deviations of account level returns that enter each portfolio were at the highest during the bubble years.

Table 14 reports flow analysis for the Mobius database. Domestic equity portfolios have enjoyed inflows between $70tr. and $427tr. per year. For two years, 1999 and 2000, value domestic equity funds experienced outflows. Growth funds did not see net outflows. At the end of the Asian crisis (1998) and internet bubble (2001) disproportional money was moved to domestic fixed accounts. Balanced funds have seen net outflows most of the time.

Table 9

Sample of Top Money Managers Reported by LSV (1992) for 1990

This table reports 15 managers from our sample, who are the largest managers reported by LSV (1992) in table 15, excluding Fidelity, as our sample does not include mutual funds. LSV and our sample periods do not overlap. The following is the list of firms: Bankers Trust, Wells Fargo, Metropolitan Life, Prudential Asset, Aetna Life, State Street Bank, J. P. Morgan, Mellon Capital, CIGNA Investments, Pacific Investment, Northern Trust, Alliance Capital, GE Investments, and Equitable Capital. In LSV these firms totaled $539B. None of the families are mutual funds. *Just equity portfolios. **Equity, excluding commingled funds. ***Portfolios often do not include all assets from all accounts in the report. All variables are cross section averages unless otherwise indicated.

Panel A. LSV Descriptive Statistics

Year	Accounts	New Accounts	Lost Accounts	Professionals	Prof. Joined	Prof. Left	Median Acct $,000	Avg. Acct $,000
1993	526.50	61	23	103	7	4	358,713	245,687
1994	847.68	113	205	90	9	6	75,838	243,051
1995	780.35	88	93	91	6	6	121,983	274,778
1996	879.47	130	70	105	9	5	296,574	349,429
1997	930.95	175	80	112	8	6	269,685	497,406
1998	1,305.65	384	89	125	11	6	335,516	548,937
1999	2,165.18	1108	166	131	13	11	289,454	486,771
2000	4,748.88	1677	296	155	18	17	398,406	456,087
2001	5,060.71	945	1376	172	20	15	215,322	397,065
2002	5,078.18	284	754	181	15	21	205,947	325,057
2003	5,823.81	281	218	216	16	18	355,989	589,309

Panel B. LSV Descriptive Statistics (Continued)

Year	Total Assets $M	Total Assets*	Total Assets**	Assets % of Mobius	Tax Ex. Asset %	% Assets Included***	Turnover	Fees
1993	887,783	234,870	160,584	19%	83%	82	52	0.47%
1994	1,049,497	256,152	184,375	19%	77%	81	57	0.53%
1995	1,472,287	407,488	243,691	19%	77%	86	59	0.54%
1996	1,901,036	505,625	281,228	19%	73%	83	64	0.56%
1997	2,625,613	811,940	369,228	22%	74%	81	60	0.58%
1998	3,133,500	1,057,428	499,757	22%	78%	81	54	0.55%
1999	3,867,589	1,384,587	672,136	23%	78%	80	55	0.57%
2000	3,937,090	1,248,151	600,471	22%	72%	81	57	0.60%
2001	4,201,679	1,238,333	653,803	22%	74%	82	56	0.54%
2002	3,968,710	1,112,047	600,255	23%	72%	78	58	0.56%
2003	5,074,341	1,388,201	683,874	24%	71%	74	55	0.95%

Table 10

Descriptive Statistics for Mobius Database

This table is a complete view of a Mobius database. The sample starts in quarter two, 1993 and ends in quarter 4, 2004. The sample includes domestic and international managers. These managers cover equity, fixed income, and balanced investment styles. Assets are in millions of dollars.

Date	Families			Portfolios					
	Births	Deaths	Total	Birth	New Firms	Exist. Firms	Death	Accum Port	Total Assets
12-93	1155	48	1125	3340	3125	215	159	3249	2,596,786
12-94	173	82	1220	823	394	429	319	3773	3,034,481
12-95	170	92	1307	860	369	491	419	4265	4,102,724
12-96	134	108	1317	828	285	543	437	4599	5,038,805
12-97	92	117	1309	759	208	551	539	4900	6,309,089
12-98	123	107	1317	910	246	664	616	5154	7,645,340
12-99	87	99	1314	709	191	518	731	5245	9,028,314
12-00	88	94	1296	670	187	483	561	5261	8,761,297
12-01	86	75	1303	717	172	545	499	5478	8,870,755
12-02	87	89	1295	777	178	599	649	5579	8,492,375
12-03	62	95	1285	586	90	496	634	5619	10,438,094
12-04	91	87	1279	712	178	534	654	5639	11,807,539

Table 11

Descriptive Statistics Equity Sample

This table describes the equity sample used in this study. The sample starts in quarter two, 1993 and ends in quarter four, 2004. The sample includes domestic and international equity managers and excludes mutual funds and experimental portfolios such as back tested data portfolios. Assets are in millions of dollars. Young assets are assets of portfolios that are no more than two years old. For portfolios that existed at the beginning of the sample, I do not know the birth date. I included them in this column if they had no more than 13 returns available including back filled returns before the beginning of the sample. Note, some portfolios report returns back for several decades. Median investor assets size is in thousands. I substituted the median value with average value if median was not available. Best minus worst is the best annual investor minus worst annual investor return reported in one portfolio. It is averaged across portfolios.

Date	Families				Portfolios										
	Births	Deaths	Total	Total Type 1	Birth	Birth New Firms	Death	Total	Total Type 1	Assets	Assets Type 1	Young Assets	Median Investor Type 2	Median Investor Type 1	Best - Worst
12-93	920	25	847	385	1302	95	26	1267	336	950,785	572,983	111,134	17,984	204,856	6.37
12-94	119	56	913	543	288	149	27	1443	382	987,756	590,665	176,297	16,341	203,383	4.83
12-95	125	66	972	151	313	150	147	1630	476	1,399,764	859,226	235,651	20,373	276,744	6.90
12-96	87	73	982	154	309	110	174	1756	537	1,800,138	1,132,121	357,975	23,698	350,242	5.46
12-97	65	81	979	152	321	77	197	1906	588	2,443,354	1,606,736	503,755	28,679	416,078	6.03
12-98	87	82	973	152	418	105	232	2076	699	3,033,089	2,073,523	566,729	27,952	412,854	7.37
12-99	69	69	987	152	345	104	267	2176	740	3,732,253	2,538,704	585,094	30,360	450,501	10.29
12-00	67	65	981	152	326	90	212	2267	775	3,436,464	2,282,421	517,753	28,241	406,898	7.68
12-01	69	55	1001	153	370	95	187	2452	869	3,184,282	2,148,656	405,788	25,827	317,593	5.41
12-02	67	61	1003	150	404	99	248	2593	930	2,691,688	1,807,352	432,745	21,832	266,448	4.29
12-03	51	75	1005	147	276	56	285	2644	960	3,609,568	2,433,365	587,531	28,924	363,000	5.15
12-04	66	75	992	141	385	100	307	2718	957	4,310,956	2,830,858	714,587	35,007	476,620	2.96

Chart 1

Descriptive Statistics on Institutions, and Sources of Assets and Clients

Panels one and two are at a portfolio level for domestic equity portfolios; panels three and four are at family levels and include all, not just equity portfolios.

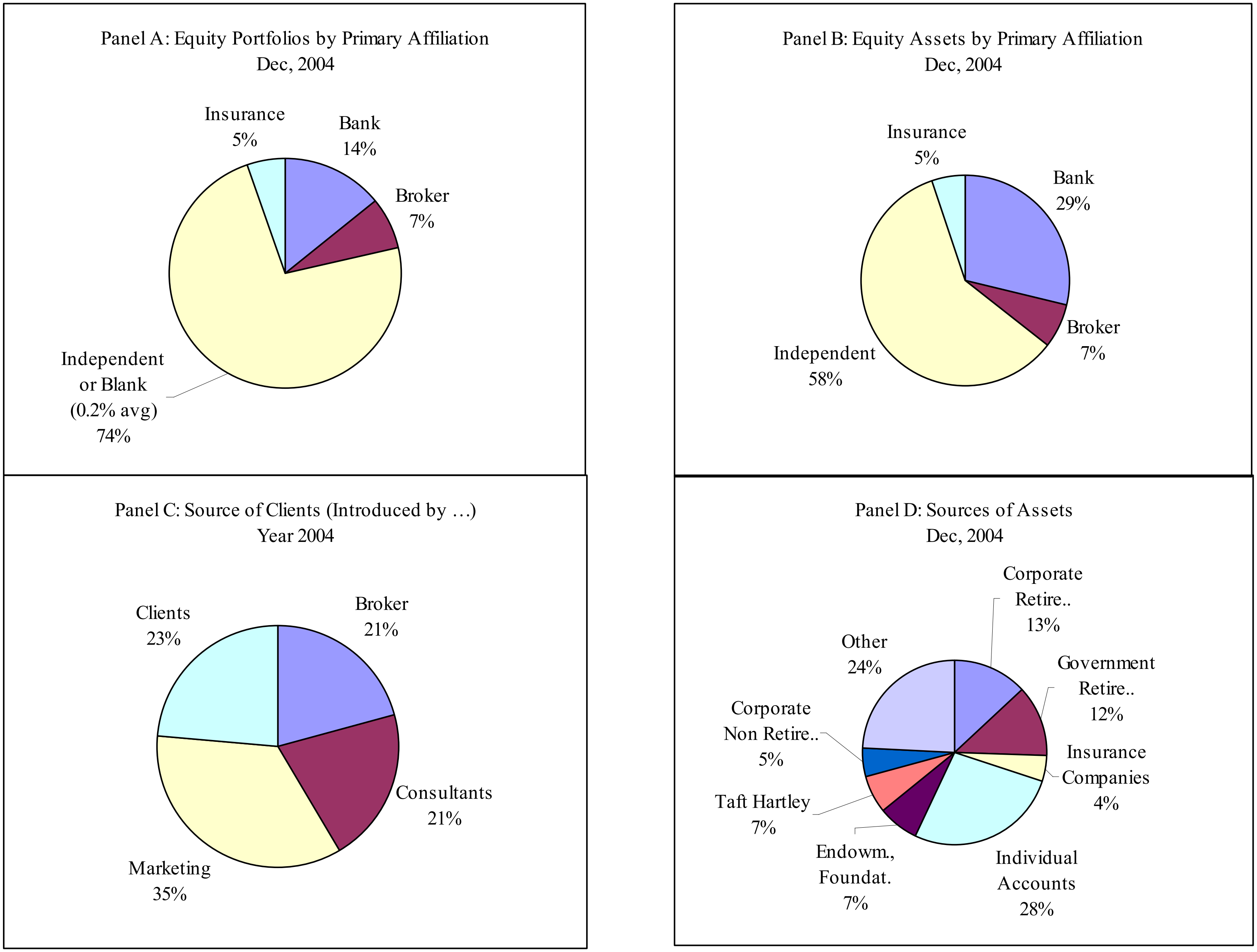

Table 12

Annual Statistics: All Firms in Sample between Firm Birth and Death, Equity Sample

This table describes the equity sample used in this study. Assets are in millions of dollars. The numbers are for the equity sample. All variables are averages unless indicated otherwise.

YearID	Own By Empl.	Own Females	Yrs At Firm	Litigation	Judgem. Against	New Accounts	Lost Accounts	Total Prof	Prof Joined	Prof Left	Sum Total Assets	Sum Total Accounts	Sum Total Profession.
1993	68.4	19.8	6.2	25	8	64.5	44.7	16.1	1.9	1.0	4,036,783	273,745	12,134
1994	67.4	20.1	6.3	29	16	51.0	40.8	17.2	2.2	1.2	4,495,909	312,751	14,191
1995	67.7	20.1	6.5	40	20	51.5	34.4	17.8	2.0	1.3	6,166,983	366,772	15,150
1996	67.5	19.9	6.6	33	18	63.1	33.4	19.7	2.2	1.3	7,815,204	356,118	17,572
1997	67.6	19.0	6.9	31	13	70.3	28.6	20.9	2.5	1.5	9,682,028	381,155	18,666
1998	67.4	18.4	6.8	34	15	76.4	35.7	21.9	2.6	1.5	11,660,159	455,412	19,776
1999	68.2	18.4	6.9	33	22	125.7	57.0	23.7	2.5	1.8	13,458,298	501,693	20,410
2000	68.4	18.2	6.9	37	26	162.2	65.8	26.0	3.5	2.4	13,698,443	604,117	21,933
2001	69.8	18.3	6.9	35	21	126.1	98.1	26.7	2.7	2.2	14,362,267	672,130	22,735
2002	69.0	17.9	7.0	34	28	123.4	121.9	27.5	2.7	2.4	13,220,142	681,830	23,215
2003	69.3	16.9	7.0	39	24	119.5	84.3	29.9	2.6	2.7	16,190,607	674,336	24,980
2004	68.4	14.6	6.9	62	27	128.9	106.2	36.8	3.1	2.4	18,208,971	670,752	27,556

Table 13

Annual Statistics: Portfolio Cross Section

This table describes the equity sample used in this study. All numbers are returns. For example 1.00 means one percent annual return. The numbers are for the equity sample.

YearID	Best Minus Worst Account Return	Annual Equal Weighted Return	Annual Value Weighted Return	Avg Return St. Deviation
1993	0.28	10.1	9.0	3.3
1994	0.22	0.1	0.1	4.7
1995	0.17	30.3	34.3	3.6
1996	0.15	21.4	22.0	3.2
1997	0.14	25.9	28.6	9.3
1998	0.07	18.5	24.3	15.7
1999	0.12	24.9	25.5	12.3
2000	0.20	1.3	-2.9	8.1
2001	0.07	-2.0	-6.6	15.5
2002	0.06	-17.4	-18.9	11.4
2003	0.06	34.0	32.0	9.2
2004	0.06	14.6	13.6	6.0

Table 14

Inflow Analysis: Inflows in Millions of Dollars by Category

This table describes flows of assets between different sub samples of all institutional money management industry. All assets are in millions of dollars.

Panel A. Flows between Assets Classes

	Domestic Equity (DEQ)		Intl. and Mixed Equity		DEQ Value	DEQ Growth	DEQ Rest
YearID	Infl	Nr Port	Infl	Nr Port	Infl	Infl	Infl
1993	963,195	1268	246,385	322	306,887	297,981	358,326
1994	70,482	1511	140,071	441	25,988	24,164	20,329
1995	119,715	1700	120,069	560	39,463	24,074	56,177
1996	161,561	1844	125,980	659	88,708	54,726	18,127
1997	232,307	1999	116,610	747	70,179	11,678	150,450
1998	249,914	2224	72,628	799	89,966	94,645	65,303
1999	261,247	2315	114,104	823	-53,246	137,482	177,010
2000	88,377	2389	187,795	817	-70,166	108,529	50,014
2001	289,064	2512	221,261	840	118,215	69,317	101,532
2002	325,256	2704	166,796	870	99,471	90,333	135,453
2003	376,484	2715	145,095	845	111,813	85,828	178,844
2004	427,978	2796	90,727	802	238,170	67,246	122,563

Panel B. Flows between Assets Classes (Continued)

	Domestic Fixed		Balanced		Int. Balanced	Int. Fixed	Mutual Funds
YearID	Infl	Nr Port	Infl	Nr Port	Infl	Infl	Infl
1993	735,140	825	391,055	606.00	8,494	71,666	149,398
1994	130,047	973	1,550	668.00	10,330	41,198	129,173
1995	160,276	1,102	-12,377	701.00	44,892	20,293	75,026
1996	233,217	1,177	8,549	685.00	-7,145	31,280	52,469
1997	192,406	1,248	-13,739	653.00	11,622	38,987	66,067
1998	469,592	1,323	-53,399	621.00	4,943	24,568	78,370
1999	217,008	1,334	-6,731	552.00	28,262	59,383	8,316
2000	163,086	1,289	-42,069	516.00	-17,249	35,071	5,845
2001	546,717	1,294	-21,467	470.00	14,222	-38,158	109,755
2002	201,677	1,297	11,178	442.00	-8,505	73,857	108,377
2003	238,014	1,293	-16,203	392.00	-4,440	49,836	37,528
2004	277,020	1,296	-7,340	345.00	45,089	55,586	-54,178

Appendix II. Window dressing studies related to the January Effect.

Window dressing has been cited as a possible cause of Rozeff and Kinney's (1976) and Keim's (1983) January effect. These studies examine window dressing as an alternative explanation for the January effect. The January effect is a large upward shift of small capitalization stock prices relative to large stock prices in January. Haugen and Lakonishok (1988) suggest that the January effect could be a result of portfolio rebalancing. Fund managers buy popular stocks at the end of year, sell them shortly thereafter, and invest in small stocks. These small stocks appreciate in value and outperform benchmarks. Performance hedging and tax-loss selling are alternative hypotheses to window dressing. For example, Sias and Starks (1997) conclude that tax-loss selling among individual investors rather than institutional window dressing influences the January effect. They come to this conclusion after relating ownership to stock returns in a domestic common stock sample. In this sample the January effect is driven primarily by stocks with greater individual ownership; however, institutions are found biased towards buying winners. Lee, Porter and Weaver (1998) reject window dressing as a cause of the January effect. They examine January performance for funds with different fiscal year endings. Funds with other than December fiscal year endings are in a better position to benefit from predictable return patterns around the year end. However, these funds exhibit no different performance than the December fiscal year end funds[18].

[18] See Dyl and Maberly (1992), Ritter (1988) as other example rejecting window dressing as an explanation of January effect. Note, that these studies do not reject presence of window dressing as such.