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Persistence and Skill in the Performance of Mutual Fund Families

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Persistence and Skill in the Performance of Mutual Fund Families

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Abstract

Prior research has shown that decisions made at fund family level can account for a substantial portion of the performance of the individual active fund managers in the family.

The question then arises whether the average fund performance of some fund families is persistently superior or inferior to that of other fund families. Using gross returns, we find that top-decile family performance persistence is comparable to that of individual funds, suggesting that families do not seem to create conditions to sustain outperformance. After ontrolling for noise in the performance measure, we find that just 3% of fund families overall are truly skilled. Families with higher t-statistics of alpha are much more likely to be truly skilled. Multi-fund families are more likely to be truly unskilled compared to single-fund families. Using net returns however, we find very little evidence of skill.

Keywords: Mutual fund family; performance; persistence; skill.

JEL classification: G23, G34

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I. Introduction

We examine persistence and skill in the performance of mutual fund families. While the performance of individual mutual fund managers is one of the most researched topics in finance, and the influence of fund family on fund manager performance has also received considerable attention (see below), few studies have analyzed the average performance of all funds belonging to a family.

Understanding fund family performance is important for a number of reasons. Firstly, from an investor perspective, the choice of fund family is significant. Many investors consider family performance when choosing funds (Elton, Gruber, and Green (2007), Brown and Wu (2016)). Fund families reduce investors' cost of switching between funds (Massa (2003)). Affiliated funds of mutual funds (AFoMFs) have been adopted by many fund families and have become popular with investors (Bhattacharya, Lee, and Pool (2013)).

Secondly, the most crucial factor affecting fund performance is the skill of the fund manager, and the decision to hire, retain or fire a fund manager (or a team) is made at the fund family level. Some families may have better talent selection and allocation skills than others. Berk, Van Binsbergen, and Liu (2017) estimate that at least 30% of the value mutual fund managers add can be attributed to the family's role in efficiently allocating capital amongst its mutual fund managers. Fang, Kempf, and Trapp (2014) show that a firm allocates its skilled managers to funds targeting inefficient markets.

Other family-level behaviour such as strategic and competitive interactions affects fund performance. Gaspar, Massa, and Matos (2006) and Bhattacharya et al. (2013) find evidence that mutual fund families transfer performance from one group of funds to another group of funds through coordinated trades. The decision to lend stock to short sellers is made for strategic family-wide considerations and are associated with with negative fund performance (Evans, Ferreira, and Porras Prado, 2017). Kempf and Ruenzi (2008) show that intra-firm competition between fund managers has important effects on managers' appetite for risk. Chen, Hong, Jiang, and Kubik (2013) find that funds outsourced to advisory firms underperform funds managed in-house.

The influence of family has also been acknowledged. Knowledge-sharing and economies of scale within fund families affect individual fund performance. Brown and Wu (2016) find evidence of cross-fund learning within families that may positively or negatively influence performance. Cici, Jaspersen, and Kempf (2016) show that the speed of information dissemination within fund families positively affects fund performance. Cici, Dahm, and Kempf (2015) and Latzko (1999) find differences in efficiency in administration and trading costs at family level that reduce costs to the funds in the family.

Given the weight of this evidence, it seems reasonable to assume that there is heterogeneity in the average fund performance of fund families, and that a substantial portion of this heterogeneity is due to decisions, policies and processes adopted at the family level. The question then arises whether some fund families are more skilled than others. Skilled fund families may be able to create an environment where the average returns of funds in the family are persistently higher (or persistently lower) than the average returns of funds in other fund families.

Specifically, in this paper, we set out to address two key questions. We first ask if the performance of some families more persistent than others, and then we examine how much family-level performance is due to skill rather than luck.

We estimate measures of performance persistence and skill for actively managed equity fund families, and for comparison we estimate the equivalent measures for individual funds. We focus on the gross benchmark-adjusted returns of US-domiciled US-equity funds drawn from the CRSP survivorship-bias free funds database for the period 1999-2017. We perform an extensive exercise to validate that the fund family associated with a fund is correct, and to take into account mergers in the fund industry over the period. Our final sample consists of 4,946 funds belonging to 1,084 families.

We first test for fund performance persistence. For periods of up to 3 years the persistence of families is up to 3% higher than that of funds. However, for 5-year periods, the probability that a top decile fund family will remain a top-decile family in the subsequent period is 0.09, which is 4 points (or 31%) smaller than the equivalent measure for individual funds (0.13). Thus there is little evidence that families create conditions to sustain fund outperformance over the long term.

Then we examine the distribution of skill in funds and families. It may be that some funds and families that have positive and significant abnormal returns may not in fact be truly skilled, rather their performance may simply be due to sampling error or luck. Using a cross-sectional bootstrap approach where we use t-statistic of benchmark-adjusted gross returns, t(alpha), as the performance measure, we estimate how many funds or families in the sample that we could expect to observe at different t(alpha) threshold values under the null hypothesis that all funds in the sample have a true alpha of zero (that is, they are neither skilled nor unskilled), but some funds or families may have significant observed t(alpha) through sampling error or luck.

For funds, these tests suggest that about 2% more funds have positive observed t(alpha) than would be expected if all managers had true t(alpha)=0, that is, if all managers were neither skilled nor unskilled. However, of the funds with positive t(alpha) in our sample, a strikingly large number perform better than expected at higher performance thresholds - for example, there are 293 more funds (6.4% of our sample) with t(alpha)>2 than would be expected under the null hypothesis that all fund managers are neither skilled nor unskilled. To put this another way, the higher the fund's observed t(alpha), the chances that the fund is truly skilled increase dramatically.

For fund families, the picture is not very different. Overall, just 3% more families have t(alpha)> 0 than would be expected under the null. However, at higher performance thresholds, the number of skilled families is much higher than expected - about 51 families (6% of our sample) with t(alpha)>2 are truly skilled. On the other hand we also find that 70 families (8% of our sample) are truly unskilled at the t(alpha)<-2 threshold. This suggests that some families seem to be able to group together highly skilled fund managers, while a slightly larger number seem to be able to group together highly unskilled ones.

We also observe that the majority of families (800) in our sample have just one actively-managed US equity fund. Therefore we divide our sample into single-fund families and multi-fund families, and when we examine persistence and skill for these subsamples, we find a divergence in results. While the 1-year top-decile performance persistence of single- and multi-fund families are about the same (0.21), the 3-year top-decile persistence measure for multi-fund families (0.28) is substantially (9 points, or 47%) higher than for single-fund families (0.19). After controlling for noise in the performance measure, we find that overall (that is, at the t(alpha)=0 threshold) there are about 4% more skilled single-fund families than unskilled ones, while there are about 4% fewer truly skilled multi-fund families than there are truly unskilled ones. However at higher t(alpha) thresholds, the proportion of truly skilled single-fund families is slightly lower than for multi-fund families; for example, 5.5% of the single fund family sample have true t(alpha)>2, while over 6% of multi-fund families are truly skilled at this threshold.

Finally we examine skill using net-of-fee benchmark-adjusted returns. Not surprisingly, the evidence for skill is much weaker than when using gross benchmark-adjusted returns. Using net returns we find that over 19% of our sample have true t(alpha)<0. At the t(alpha)>2 threshold however there is a tiny glimmer of hope - 3 families with t(alpha)>2 (0.3% of our sample) are truly skilled when net alpha is the skill measure.

Given the volume of research focused on fund performance, there is surprisingly little literature that focuses directly on fund family performance. In their working paper, Guedj and Papastaikoudi (2003) report that performance persistence is more prevalent within big fund families, suggesting that families purposefully allocate resources across funds in an unequal way. The closest study to ours is that by Berk et al. (2017) who examine capital reallocation decisions of mutual fund firms. They find evidence that the aggregate dollar value-added of mutual fund firms is persistent, that is, firms that added value in the past keep adding value in the future. While Berk et al focus on the narrow (but important) topic of capital allocation within fund families, we take a broader approach, applying a range of tests for skill, comparing the distribution of fund family skill with the distribution of fund skill, and analyzing a broader set of potential determinants of fund family skill.

II. Performance Persistence and Skill

A. Background

The analysis of skill in the mutual fund industry has been focused at the fund level. The evidence for skill at the fund level (Fama and French (2010), Barras, Scaillet, and Wermers (2010)) suggests that most mutual fund managers exhibit little true skill, and if skill does exist, it is concentrated in the right tail of the cross-sectional distribution of fund alphas.

At the family level, there is no such analysis. However, the pieces of evidence suggest that asset management firms seem to know what enhances performance. Empirical evidence shows that firms coordinate actions across funds in the complex in order to enhance the performance of funds that are the most valuable to the family, even if this comes at the expense of the performance of other member funds (Gaspar et al., 2006) or that firms allocate skilled managers to funds targeting inefficient markets (Fang et al., 2014). Berk et al. (2017) hypothesise that the family has informational advantages and show evidence that the decision of adding a manager or removing a fund from a manager add value to investors.

Typically mutual fund families focus on increasing their assets under management (AUM) because family revenues are proportional to AUM and are not directly impacted by fund performance. Nevertheless, performance is indirectly of interest to fund families as investors show sensitiveness to past performance. Nanda, Wang, and Zheng (2004) show that star funds have positive spillover effects on flows into other funds in the family. But overall family skill might be diluted by incentives to create AUM revenue. For instance, families might be tempted to launch new trendy styles funds that increase overall AUM but hardly create value for investors (Cheng, Massa, and Zhang (2018) find evidence that globalization has allowed low skilled families to adopt a strategy of launching cross-border funds that deliver lower performance and offer lower diversification benefits to investors).

This leads to two opposing hypotheses for the distribution of skill in fund families. First, it may be that small number of truly skilled funds are dispersed among a number of different firms. In this case, we could see little skill in the cross-sectional distribution of skill in fund families, even in the right tail. This is because the one or two skilled funds in a family could be dominated by unskilled ones, and thus have little effect on fund family performance. The alternative hypothesis is that most skilled funds are concentrated in just a small number of fund families. In this case we could see evidence of skill just in the individual families located at the extreme right tail.

B. Data

Our mutual fund data are drawn from the CRSP survivorship-bias-free US Mutual Fund database[1]. We restrict the sample to actively managed US-focused equity funds, and exclude funds-of-funds, closed-end, index tracking, international and offshore funds[2]. We eliminate multiple share classes to avoid double-counting funds. Although multiple share classes are listed as separate funds in CRSP, they have the same holdings, the same manager, and the same returns before expenses and loads. We sum the total net assets (TNA) of the share classes to estimate the total TNA for the fund. We follow Pástor, Stambaugh, and Taylor (2015) and adjust fund TNA to 2017 US dollars by dividing the TNA at the end of each year by the total market value of all stocks in CRSP at the end of the same year, and multiplying by the total market value of all stocks in CRSP at the end of 2017. Pástor et al. (2015) argue that this inflator makes size capture the size of the industry relative to the universe of stocks that funds can buy. We exclude fund-months where the expense ratio is missing, and fund-months before the fund reaches $15 million (in 2017 US dollars) in TNA (Evans,

[1]We are grateful to Doshi, Elkamhi, and Simutin (2015) for sharing their SAS scripts for accessing the CRSP Mutual Fund database.

[2]Although we exclude the returns of index funds and international funds as dependent variables, we keep a monthly count and sum of monthly TNA for use as explanatory variables.

2010).

To identify fund families, we use the management company code field that is available for each fund in CRSP since 1999, and we use the management company name to complement the management company code where necessary. The relationship between management company codes and management company names is 1 to n, where n can be greater than or equal to 1. We take steps to clean this data. We standardize management company names; for example some names are identical except for the use of abbreviations, so we expand abbreviations such as "mgmt" to "management". Then for funds with the same management company name but where the management company code is present for some funds while it is missing for the others, we fill in the management company codes for the funds where it is missing. There are a number of cases where two or more unrelated management companies are allocated the same management company code. Using data manually collected from management company websites, we identify these cases and we create new management company codes for each distinct family. For a small number of management company names, the management company code is missing, but in most of these cases it is clear from the management company name which management company code is applicable; for example, the management company code is missing for eight funds where "PIMCO" is the first word in the management company name, so we use the PIMCO management company code for these funds. Finally, for some management company names the management company code is missing and the management company does not appear to belong to any existing family; in these cases we create a new management company code. Where a fund changed family during the sample period, we use the management company code and name for the family that the fund belonged to the longest, and drop the fund-months when the fund did not belong to that family. Our final sample consists of 4,946 equity funds, belonging to 1,084 fund families, for the period January 1, 1999 to December 31, 2017.

Table I gives annualized statistics for funds and families for each year in the sample period (Figure 1 gives a graphical overview). In our sample, the number of active fund families each year has stayed in the 430-540 range since 2000, likewise the number of active funds each year has been fairly stable (1990-2017). The total unadjusted TNA of all funds in the sample (dashed line in Panel B of Figure 1) has risen significantly from about $1.5 trillion in 2000 to about $3 trillion in 2017. The unadjusted TNA value has also fluctuated over the period, especially around the financial crisis period of 2007-2008 which saw total TNA drop by about 40% from $2.5 trillion in 2007 to just over $1.5 trillion in 2009. When TNA values are adjusted to 2017 dollars however, the total TNA (solid line in Figure 1 Panel B) rose from $3.3 trillion in 1999 to $4.2 trillion in 2007, but by 2017 total TNA fell back to 1999 levels. The graph of adjusted TNA is relatively flat compared to unadjusted TNA, and while 2007 marked a turning point in adjusted TNA, the 2007-2009 drop was not as marked as for unadjusted TNA. Note that if we did not drop fund-months where a fund changed family, the total TNA values would be substantially higher. For comparison, Panel C of Figure 1 gives the total TNA of all actively-managed US equity funds in the CRSP mutual fund database.

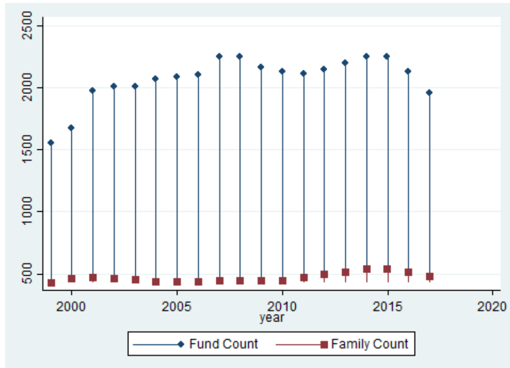
Table II gives monthly summary statistics for fund and family variables used in this study.

C. Performance persistence - Markov transition probabilities

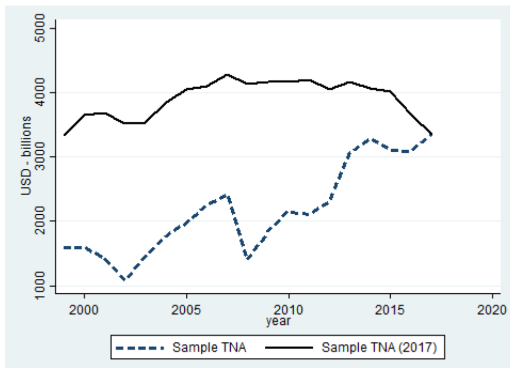
We begin our examination of skill by analyzing performance persistence using a Markov transition probability model. We estimate the persistence of fund and family benchmark-adjusted gross returns. Each year, benchmark-adjusted gross returns of each fund (or of each family) are calculated (by monthly compounding). The returns for each year are grouped into ten performance deciles, numbered from 1 to 10, 1 being the bottom decile, and 10 being the top decile. The decile of each fund (or family) in one period is checked against its decile in the next period to compute the Markov probability of a fund (or family) changing decile between periods. We repeat the test using 1, 3 and 5-year periods.

Family benchmark-adjusted returns are estimated as the value-weighted average benchmark-

Panel A - Sample Fund and Family Count



Panel B - Sample TNA



Panel C - Industry TNA

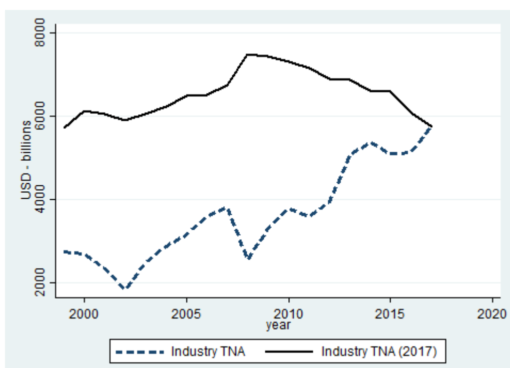


Figure 1. Fund and Family Count and TNA

These graphs give annualized counts and Total Net Assets (TNA) for funds and families in our sample, and the total mutual fund industry TNA. The sample consists of actively managed US equity funds in the CRSP Survivorship-bias-free US mutual fund database. Where a fund changed family during the sample period, we keep the fund-months for the family that the fund belonged to the longest, and drop the fund-months when the fund did not belong to that family. Panel A gives the number of funds and fund families in our sample that are active in December of each year of the sample period (1999-2017). Panel B gives the sum of TNA of all active funds at the end of each year. The dashed line gives the total unadjusted TNA, the solid line gives total TNA adjusted to 2017 US dollars by dividing the TNA at the end of each year by the total market value of all stocks in CRSP at the end of the same year, multiplied by the total market value of all stocks in CRSP at the end of 2017. Panel C gives the total TNA of all actively-managed US equity funds in the CRSP Survivorship-bias-free US mutual fund database.

Table I Annualized Fund and Family Total Net Assets

This table presents annualized summary statistics for the Total Net Assets (TNA) of the funds and fund families in our sample. TNA values are in thousands of 2017 US dollars.

		Funds				Fund Families			
Year	Total TNA	Count	Mean TNA	Median TNA	TNA Std Dev	Count	Mean TNA	Median TNA	TNA Std Dev
1999	3,340,343	1549	2,156	334	7,209	430	7,768	388	38,136
2000	3,658,754	1676	2,183	375	6,821	461	7,937	403	38,898
2001	3,685,729	1971	1,870	346	5,781	473	7,792	470	36,622
2002	3,511,759	2011	1,746	341	5,388	459	7,651	604	35,742
2003	3,535,887	2005	1,764	358	5,580	453	7,805	598	37,100
2004	3,858,192	2065	1,868	385	5,950	433	8,910	728	39,310
2005	4,057,624	2089	1,942	408	6,260	440	9,222	755	39,679
2006	4,102,536	2100	1,954	408	6,549	435	9,431	708	39,419
2007	4,276,382	2250	1,901	385	6,762	442	9,675	519	40,003
2008	4,129,587	2250	1,835	371	6,829	443	9,322	492	37,951
2009	4,161,925	2162	1,925	395	6,540	443	9,395	531	38,004
2010	4,167,006	2127	1,959	416	6,151	443	9,406	504	38,302
2011	4,197,374	2115	1,985	420	6,001	471	8,912	447	37,544
2012	4,054,159	2146	1,889	406	5,725	496	8,174	409	35,769
2013	4,169,968	2197	1,898	414	5,635	517	8,066	352	35,672
2014	4,062,406	2245	1,810	371	5,461	542	7,495	267	34,522
2015	4,009,062	2246	1,785	341	5,573	542	7,397	276	35,713
2016	3,658,477	2129	1,718	337	5,314	516	7,090	264	33,416
2017	3,355,818	1960	1,712	309	5,310	483	6,948	251	33,151

adjusted returns of the funds in the family. We estimate benchmark-adjusted fund returns (alpha) using a Fama-French-Carhart model:

$$R_{it}^e = \alpha_i + \beta_i^{mkt} MKT_t + \beta_i^{sml} SML_t + \beta_i^{hml} HML_t + \beta_i^{wml} WML_t + \epsilon_{it} \tag{1}$$

where R_{it}^e is the gross fund return in excess of the risk-free rate for fund i in month t, MKT_t, SML_t, HML_t, and WML_t are the realizations of the four benchmark portfolios (excess return on the market, small minus big, high minus low, and winners minus losers) and β_i are benchmark sensitivities of the ith fund, which can be estimated by regressing the fund return on to the benchmarks, and α_i is the return in excess of the benchmarks, that is, the benchmark-adjusted return. We interpret the regressors MKT_t, SML_t, HML_t, and

Table II Summary Statistics

This table presents summary statistics for variables used in this study. The variables are described in detail in the Appendix. Panel A presents fund-level variables, Panel B presents family level variables. Fund data (Panel A) are by fund-month, family data (Panel B) are by family-month. summary statistic are the following number of observations (n), mean, standard deviation (sd) and percentile values (px)

	Panel A - Fund-level Variables							
	n	mean	sd	p1	p25	p50	p75	p99
gret	378,433	0.0075	0.0505	-0.1404	-0.0167	0.0106	0.0355	0.1306
galpha	378,433	0.0001	0.0231	-0.0658	-0.0091	0.0001	0.0093	0.0654
exp_ratio_m	378,433	0.001	0.001	0.0002	0.0008	0.001	0.0012	0.0022
fund_size	378,433	1,938	4,237	7	127	483	1,681	28,162
	Panel B - Family-level Variables							
	n	mean	sd	p1	p25	p50	p75	p99
vwfgret	89,800	0.0065	0.0469	-0.1297	-0.0153	0.0086	0.0318	0.122
vwfgalpha	89,800	0	0.0215	-0.0611	-0.0076	0	0.0076	0.0597
fly_exp_ratio_vwa	89,800	0	0.0016	0	0.0008	0.001	0.0012	0.0029
fly_ptna_av	89,778	1,424	5,598	4	86	320	1,175	14,105
fly_size	89,778	9,813	40,637	16	131	670	5,269	150,774

WML_t as diversified passive benchmark returns that capture patterns in average returns during our sample period. The benchmark data we use are the four North American Fama-French-Carhart factors downloaded from Kenneth French's website.

Table III presents the transition probabilities within the top two deciles and the bottom two deciles (the other decile transition probabilities are omitted to save space) for periods of 1, 3 and 5 years. For 1- and 3- year periods, top decile return persistence is stronger for families than for funds. For example, for the 3 year period, the probability of a top decile family in one period being a top decile fund in the following period is 0.23, while the same measure for families is 0.20. However for the 5-year period, the pattern is reversed - top-decile persistence for families is 0.09, while for funds it is 0.13, a difference of 0.04. As a side note, it is interesting to observe that off diagonal values are substantially high also, showing that a family can go easily from the top to the bottom decile

Table III Markov Transition Probabilities

This table presents the probability of the decile performance ranking of a fund or family changing from one period to the next. Each period, benchmark-adjusted gross returns of each fund (or family) are calculated (by monthly compounding). The returns for each period are grouped into 10 performance deciles, numbered from 1 to 10, 1 being the bottom decile, 10 being the top decile. The decile of each fund (or family) in one period is checked against its decile in the next period to compute the Markov probability of a fund (or family) changing decile between periods. The probabilities are estimated for periods of 1, 3, and 5 years. The results for the two bottom deciles (1, 2) and the two top deciles (9, 10) are given.

	Families				Funds			
	1-year				1-year			
	1	2	9	10	1	2	9	10
1	0.23	0.11	0.08	0.19	0.22	0.11	0.08	0.17
2	0.12	0.10	0.11	0.05	0.11	0.11	0.11	0.09
9	0.09	0.11	0.12	0.10	0.09	0.10	0.13	0.11
10	0.19	0.09	0.12	0.23	0.18	0.09	0.11	0.21
Obs	6806				28785			
	3-year				3-year			
1	0.20	0.11	0.13	0.12	0.24	0.15	0.07	0.11
2	0.10	0.17	0.09	0.12	0.11	0.15	0.06	0.12
9	0.07	0.10	0.13	0.12	0.09	0.07	0.14	0.13
10	0.15	0.07	0.12	0.23	0.15	0.07	0.14	0.20
Obs	1691				6885			
	5-year				5-year			
1	0.13	0.13	0.03	0.39	0.18	0.10	0.09	0.16
2	0.06	0.09	0.03	0.12	0.10	0.07	0.13	0.10
9	0.14	0.14	0.14	0.09	0.09	0.12	0.13	0.12
10	0.21	0.09	0.06	0.09	0.24	0.08	0.06	0.13
Obs	583				3054			

D. *Separating skill from luck - Cross-sectional bootstrap*

The cross-sectional bootstrap controls for the fact that some fund families may have positive and significant observed alpha due to luck, or sampling error, even if their true alpha is zero. Furthermore the test allows the data-driven estimation of p-values for the null that alpha is zero based on the actual distribution of skill in the sample rather than assuming that skill follows a parametric normal distribution. These bootstrap p-values allow us to determine the location of skill in the distribution rather than assuming it is located just in the tails. The cross-sectional bootstrap was first applied to mutual funds by Kosowski, Timmermann, Wermers, and White (2006), and was refined further by Fama and French (2010).

We start by estimating family benchmark-adjusted gross returns using Equation 1 where the dependent variable is value-weighted average gross returns of the funds in the family, less the risk-free rate. We then create a zero-alpha pseudo time series of monthly excess returns where, for each family, the alpha is subtracted from the excess return. Then we generate 1,000 bootstrap samples where 228 months of data (there are 228 months in our sample period) are randomly selected (with replacement) from the zero-alpha pseudo timeseries[3]. For each bootstrap sample, we regress each family's zero-alpha returns on the benchmarks (we require each family to have at least 8 monthly observations). Thus we have 1,000 distributions where each family's true alpha is set to zero by construction, but due to sampling error or luck, some families may have observed alphas that are significantly different from zero. If the number of families in the real sample with significantly positive observed alpha is greater than the average number of lucky families in the 1000 bootstrap samples, then it can be inferred that some families in the real sample must be truly skilled rather than just lucky.

We use t-statistic of alpha, t(alpha), as the main measure of performance, as the t-statistic has superior statistical properties relative to alpha because alpha estimates have

[3]This cross-sectional bootstrap approach is close to that used by Fama and French (2010), and allows for cross-correlation between excess returns and the benchmarks.

differing precision across fund families with varying lives and portfolio volatilities (Kosowski et al. (2006)). In the tables we follow Fama and French (2010) and report the cumulative proportion of bootstrap samples where the percentile t(alpha) is less than the percentile t(alpha) in the actual sample ("%<Actual").

The results are presented in Table IV. For the funds in our sample, the percentage of the bootstrap samples that produce lower values of t(alpha) than the actual t(alpha) at the same percentile (bootstrap %<Actual) are close to zero up until about the 40th percentile, where the bootstrap percentage is 25% (this is equivalent to a bootstrap p-value of 0.75). From the 50th percentile, the t(alpha)'s bootstrap p-values exceed the parametric p-values. We find evidence of statistically significant fund-level skill above the 70th percentile (bootstrap p-value < 0.05), suggesting that more funds are truly skilled than would be expected if we assumed the distribution of fund skill followed a parametric normal distribution.

For families, there is also evidence of skill, although it is slightly weaker than for funds. Bootstrap p-values fall below 0.05 from about the 70th percentile, and are below 0.01 from the 90th percentile. Thus we find more evidence that fund families are truly skilled than if we assumed a parametric normal distribution.

Figure 2 provides a graphical view of the results. For different t(alpha) threshold values, the cross-sectional bootstrap allows us to estimate the number of funds/families with t(alpha)'s above this threshold that we would expect to observe due to sampling error. We compare this with the number of actual funds/families in our sample whose actual observed t(alpha) is greater than the threshold.

At the t(alpha)>0 threshold, we see that about 50 more funds (or about 2% of our sample) have actual observed t(alpha)>0 than would be expected if all funds were neither skilled nor unskilled (true t(alpha)=0). This outperformance gets even stronger as the threshold is raised. At t(alpha)=2, 437 funds have actual t(alpha) that is greater than 2, while the number we would expect to see is 144. In other words, 293 funds with actual t(alpha)>2 are truly skilled.

Table IV Cross-sectional Bootstrap - Percentiles of t(alpha) for Funds and Families

This table presents the cross-sectional bootstrap results for funds and fund families at specific percentiles of the t-statistic of alpha t(alpha). Panel A gives the results for funds, and Panel B gives results for families. t(alphas) are estimated using gross returns in a Fama-French-Carhart model. Column (1) gives the t(alpha) percentile (%-ile), the remaining columns give statistics for the fund or family located at that percentile: column (2) is the alpha, column (3) is the t-statistic of alpha t(alpha), column (4) gives the expected proportion (percentage divided by 100) of funds or families whose t(alpha) is less than the actual if normality is assumed (parametric %<Actual), column (5) is the proportion of the bootstrap samples that produce lower values of t(alpha) than the actual t(alpha) at the same percentile (bootstrap %<Actual), and column (6) is the ranking by t(alpha) of the fund or family in the sample (1 is lowest rank).

Panel A - Funds

%-ile (1)	alpha (2)	Actual t(alpha) (3)	parametric %<Actual (4)	bootstrap %<Actual (5)	rank (6)
min	-0.124	-23.223	0	0	1
1	-0.433	-4.501	0	0	46
5	-0.2	-2.872	0.002	0	229
10	-0.449	-2.104	0.019	0	457
20	-0.087	-1.301	0.098	0.001	914
30	-0.161	-0.801	0.213	0.024	1370
40	-0.033	-0.353	0.362	0.249	1827
50	0.016	0.025	0.51	0.592	2283
60	0.029	0.402	0.656	0.9	2740
70	0.148	0.818	0.792	0.985	3196
80	0.151	1.281	0.898	0.997	3653
90	0.193	1.954	0.973	1	4109
95	0.083	2.665	0.996	1	4337
99	0.709	4.171	1	1	4520
max	0.604	10.07	1	0.984	4565

Panel B - Families

%-ile (1)	alpha (2)	Actual t(alpha) (3)	parametric %<Actual (4)	bootstrap %<Actual (5)	rank (6)
min	-0.182	-8.433	0	0.001	1
1	-0.35	-4.074	0	0.001	9
5	-0.168	-2.756	0.003	0	45
10	-0.384	-2.08	0.02	0	89
20	-0.197	-1.361	0.088	0.004	177
30	-0.284	-0.841	0.201	0.034	265
40	-0.051	-0.412	0.341	0.151	353
50	0.007	0.068	0.527	0.663	441
60	0.1	0.425	0.664	0.857	529
70	0.165	0.804	0.788	0.948	617
80	0.101	1.221	0.888	0.971	705
90	0.314	1.915	0.971	0.997	793
95	0.484	2.541	0.994	1	837
99	0.314	3.876	1	0.998	872
max	0.262	9.509	1	0.612	880

For families, the number of families with actual t(alpha)>0 is marginally (3%) higher than would be expected due to sampling error alone. However for higher t(alpha) thresholds, the number of families with actual t(alpha) greater than the threshold is much higher than the number predicted by the cross-sectional bootstrap. At the t(alpha)>2 threshold, 79 families have actual t(alpha)>2 which is 51 more than expected, implying that about 28 families in our sample are truly skilled. Another way of interpreting this result is that there is a 51/79 = 0.65 probability that a family with t(alpha)>2 is truly skilled.

Comparing right tail results with left tail results however, it is clear that more funds and families are truly unskilled at higher absolute t(alpha) thresholds than are truly skilled. 293 more funds than expected have t(alpha)>2 (about 6.5% of our fund sample), while 362 more funds than expected have t(alpha)<-2 (about 8% of our fund sample). For families, the situation is similar; 51 more families than expected have t(alpha)>2 (6% of our sample) while 70 more families than expected have t(alpha)<-2 (almost 8% of our family sample).

Thus the cross-sectional bootstrap shows that substantial numbers of truly skilled funds and families do exist, notwithstanding these are outnumbered by the truly unskilled funds and families.

E. Separating skill from luck - False discovery rate

The second technique we use to separate luck from skill is the false discovery rate, which allows us to estimate the proportions of truly skilled fund families and truly unskilled fund families while controlling for noise (false positives) in the distribution of skill. The general statistical technique was developed by Storey (2002), and applied to mutual funds by Barras et al. (2010). The technique works by first estimating the proportion of true zero-alpha fund families in the sample, and then extrapolating to estimate the proportions of truly positive alpha (skilled) and truly negative alpha (unskilled) fund families.

The false discovery rate allows the estimation of the proportions of funds and families that are truly skilled (t(alpha) >0), truly unskilled (t(alpha) <0), or neither skilled nor

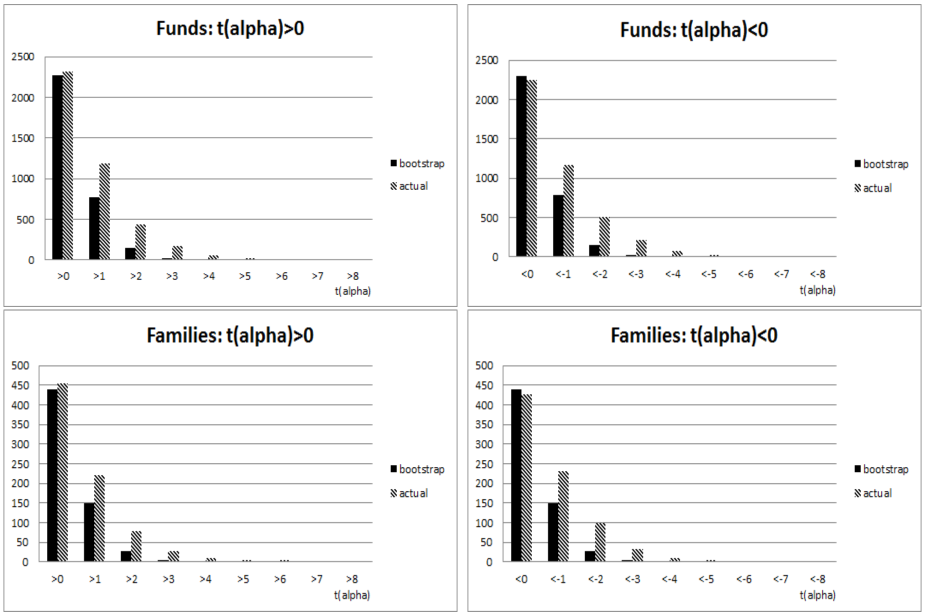


Figure 2. Actual and Bootstrap t(alpha) Counts for Funds and Families

These graphs compare the number of funds (on the top) or fund families (on the bottom) that have actual t(alpha)'s above (on the left) or below (on the right) certain threshold values compared with the number predicted by the cross-sectional bootstrap where the true fund and family alpha's are set to zero by construction.

unskilled (t(alpha)=0). As in the previous section, we apply the test to funds and families. The t(alpha) p-values used in the test are the bootstrap p-values estimated in the previous section.

Table V presents the results. The proportion of neither skilled nor unskilled funds and families is slightly higher for funds (68%) than for families (67%). However the proportion of truly skilled funds (16%) is higher than the proportion of truly skilled families (14%). Also, the proportion of truly unskilled funds (16%) is lower than the proportion of truly unskilled families (19%).

Table V False Discovery Rate for Funds and Families

This table presents the False Discovery Rate (FDR) results for funds and families. FDR allows estimation of the proportion of funds and families that are truly skilled (that is, the true alpha of these funds and families is positive and significant), truly unskilled (the true alpha of these funds and families is negative and significant), or that are neither skilled nor unskilled (the true alpha is not significantly different from zero). The parameters used for the estimation are threshold p-value $\lambda = 0.6$ and significance level $\gamma = 0.4$.

	Funds	Families
skilled	0.16	0.14
unskilled	0.16	0.19
neither skilled or unskilled	0.68	0.67

III. Other Tests

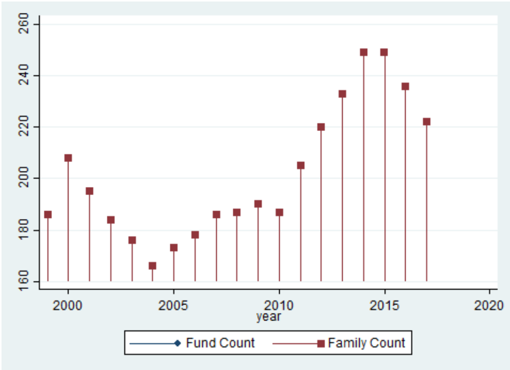
A. Single-fund versus Multi-fund Families

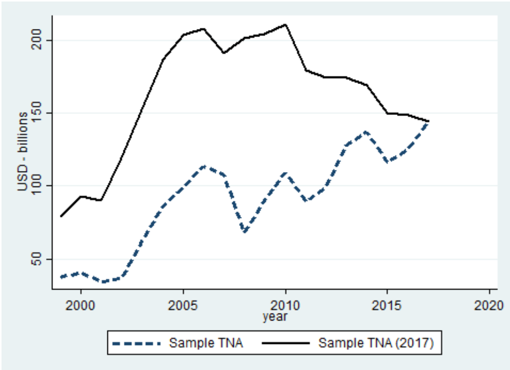
A growing number of fund families of our sample consist of just one actively managed fund focused on US equities. Panel A of Figure 3 shows that the number of single-fund families in our sample has risen from 165 in 2004, to a peak of 249 in 2014, before dropping back to 222 in 2017. The amount of capital managed by these single-fund families has also increased, growing from $93 billion (adjusted to 2017 USD) in 2000 to $211 billion in 2010, before falling back in 2017 to $144 billion. The number and TNA of multi-fund families in our sample, on the other hand, has been relatively stable since about 2000 (Panel B of Figure 3); around 270 multi-fund families manage around $3.9 trillion.

We divide our sample into single-fund families and multi-fund families and estimate the Markov transition probabilities. Table VI presents the results. The probability of top-decile persistence between one 1-year period and the next is quite similar for funds, single-fund families and multi-fund families, between 0.19 and 0.21. Looking at the 3-year period, however, marked differences emerge. For funds and single-fund families, top-decile persistence is about 0.20, while for multi-fund families, top-decile persistence is highest at 0.28.

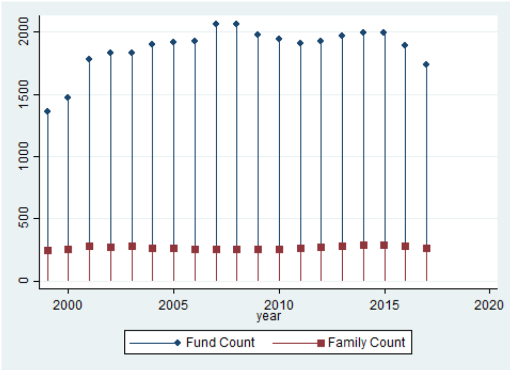
We then apply the cross-sectional bootstrap test to estimate how many of each type of family are truly skilled or truly unskilled. Figure 4 gives the results. The number of single-

Panel A - Single-Fund Families





Panel B - Multi-Fund Families



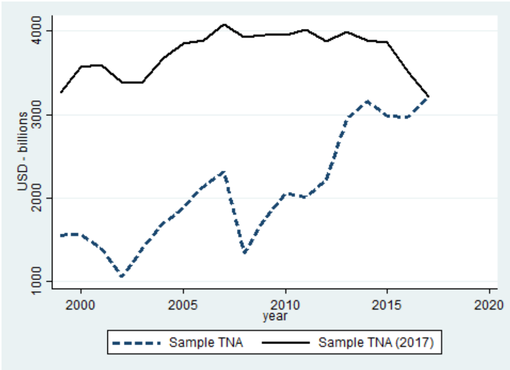


Figure 3. Single-Fund and Multi-Fund Count and TNA

These graphs give the number and TNA of single-fund (Panel A) and multi-fund (Panel B) families that are active in December of each year of the sample period. The solid line gives TNA values are adjusted to 2017 US dollars, the dashed line gives unadjusted TNA values.

Table VI Markov transition probabilities for single- and multi-fund families

This table presents the probability of the decile performance ranking of a fund, a single-fund family, or a multi-fund family changing from one period to the next. Each period, benchmark-adjusted gross returns of each fund (or family) are calculated (by monthly compounding). The returns for each period are grouped into 10 performance deciles, numbered from 1 to 10, 1 being the bottom decile, 10 being the top decile. The decile of each fund (or family) in one period is checked against its decile in the next period to compute the Markov probability of a fund (or family) changing decile between periods. The probabilities are estimated for periods of 1, 3, and 5 years. The results for the two bottom deciles (1, 2) and the two top deciles (9, 10) are given.

	Single-fund Families							
	1-year				3-year			
1	0.19	0.13	0.05	0.18	0.19	0.03	0.06	0.19
2	0.09	0.10	0.09	0.07	0.04	0.19	0.11	0.11
9	0.08	0.10	0.08	0.14	0.04	0.18	0.11	0.14
10	0.18	0.08	0.17	0.21	0.16	0.09	0.09	0.19
Obs	2230				440			
	Multi-fund Families							
	1-year				3-year			
1	0.21	0.12	0.08	0.18	0.21	0.15	0.12	0.09
2	0.11	0.13	0.13	0.09	0.13	0.14	0.11	0.10
9	0.10	0.12	0.13	0.08	0.08	0.11	0.08	0.13
10	0.19	0.09	0.09	0.22	0.15	0.07	0.11	0.28
Obs	4341				1112			

fund families with t(alpha)>0 is slightly higher than what would be expected if all families in the sample had the same level of skill. 323 single-fund families have actual t(alpha)>0, which is 25 more than would be expected under the null; thus about 4% of our sample are truly skilled at this threshold.

At higher t(alpha) thresholds we see that single-fund families are more likely to be truly skilled. For example, under the null hypothesis, we would expect to see 19 single-fund families with t(alpha)>2, but we actually observe 53, suggesting that 34 families (about 5.5% of the single-fund family sample) are truly skilled.

For multi-fund families, however, there is evidence of skill, but it is more skewed towards the right-tail than for single-fund families. Under the null hypothesis, we would expect to see 142 families with t(alpha)>0, instead we observe just 130. However we observe 26 fund families with actual t(alpha)>2, 17 more than the number predicted by the cross-sectional bootstrap, implying that 6% of the multi-fund family sample are truly skilled at this threshold.

Looking at the left tail, there is evidence that some families are truly unskilled. Families with smaller t(alpha)'s are increasingly likely to be truly unskilled. At the t(alpha)<-2 threshold, 42 families, or almost 7% of the single-fund family sample, are truly unskilled, while for multi-fund families the picture is even more negative: 36 families of the multi-fund family sample have observed t(alpha)<-2 compared to 8 expected under the null. In other words, 28 families, about 10% of the multi-fund family sample, are truly unskilled. If a multi-fund family has observed t(alpha)<-2, there is $28/36 = 0.78$ probability that it is truly unskilled. Thus the cross-sectional test results suggest that single-fund families are generally more skilled than multi-fund families.

B. Gross vs net returns

In general in this paper we use benchmark-adjusted gross-of-fee returns to estimate family performance. In this section we will examine skill, and the determinants of skill, using

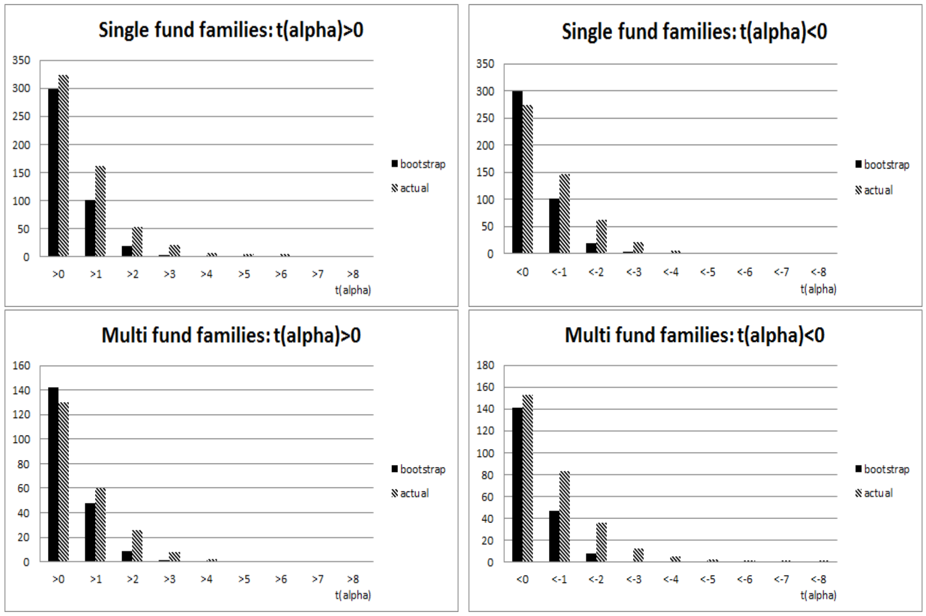


Figure 4. Actual and Bootstrap t(alpha) Counts for Single-fund and Multi-fund Families
These graphs compare the number of single-fund families (top graphs) or multi-fund families (bottom graphs) that have actual t(alpha)'s above (left graphs) or below (right graphs) certain threshold values compared with the number predicted by the cross-sectional bootstrap where the true family alpha's are set to zero by construction.

benchmark-adjusted net-of-fee returns to estimate family performance.

Figure 5 gives the cross-sectional bootstrap results. The evidence is that extremely few families are truly skilled when net-of-fee benchmark-adjusted returns is the performance measure. Only at thresholds of t(alpha)>2 is the number of families with actual t(alpha) greater than the number expected if all families were neither skilled nor unskilled, and even then they are very few. At the t(alpha)>2 threshold, only 3 families are truly skilled. On the other hand, there is substantial evidence that many families are truly unskilled. At the t(alpha)<0 threshold, 611 families have actual t(alpha)<0 versus an expected value of 440. In other words 171 families, or 19% of the sample, are truly unskilled.

IV. Conclusions

The debate on skill in the mutual fund industry has focused on individual fund managers. This paper, on the other hand, presents an analysis of the existence of skill at the fund-family

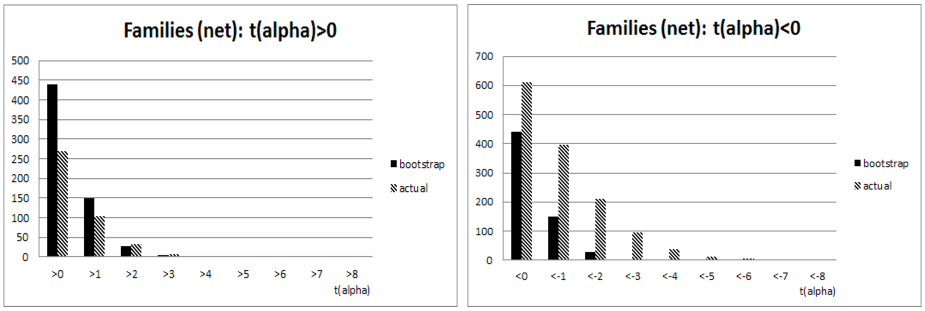


Figure 5. Actual and Bootstrap t(alpha) Counts for Using Net Returns
These graphs give the number of families that have actual t(alpha)'s estimated using net-of-fee above or below certain threshold values compared with the number predicted by the cross-sectional bootstrap where the true family net-of-fee alpha's are set to zero by construction.

level. Using a sample of actively managed US equity funds and families domiciled in the US, the results presented in this paper show that some fund families exist whose funds have persistent short-term performance, on average. A larger proportion of fund families perform persistently well than individual funds, which suggests that some families have a higher concentration of skilled funds. These skilled families may be better at creating conditions where fund managers outperform.

However the performance measure used to estimate short-term persistence - benchmark-adjusted returns measured over 1, 3, or 5 years - is potentially noisy, due to luck or sampling error. In tests that separate skill from luck using the full history of returns for each family, we find there are many families with positive benchmark-adjusted returns who are not in fact truly skilled. The truly skilled families that do exist tend to cluster to the right of the performance distribution and have a t-statistic of alpha that is greater than 1. On the other hand, many truly unskilled fund families also exist - families with a t-statistic of alpha less than -2 have at least a 70% chance of being truly unskilled rather than just unlucky.

Families that manage just one fund have slightly higher skill levels, and are less likely to be truly unskilled. There may be a self-selection explanation for this. As they are dependent on a unique source of revenues, these firms might engage in more effort to perform well. Many single-fund families are likely to be start-ups as they are smaller and younger than multi-fund families. Fund managers that select to start or join a single-fund family are likely to be confident that they have the skills to make it a success, otherwise they would be unlikely take this highly risky career step.

From an investor perspective however, the picture is bleak. Extremely few fund families are truly skilled when benchmark-adjusted net returns is the skill measure, and a high proportion of fund families are truly unskilled.

While we go to some lengths to ensure that our results paint as precise a picture as possible of family skill, some caveats are required. To associate fund performance as closely as possible to family performance, we link each fund to the one family that it belonged to the longest during the sample period, and drop fund-months where the fund belonged to other families. This means that the sample size, in terms to total TNA of all funds in the sample, is smaller than the total TNA of the mutual fund industry. Also, an extensive exercise was required to ensure funds were linked to the correct family, and while we believe most fund-family relationships in our sample are correct, there is still a small risk that some are misidentified either due to errors in the CRSP mutual fund database or in our own cleaning exercise.

We also ignore, for now, the effects of family flows. It would be reasonable to expect that more skilled fund families attract higher inflows into the funds that belong to the family. It would be interesting to explore how family flows and family skill interact. We leave this question to future research.

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Appendix

Appendix A. Variable Definitions

This table presents definitions of fund and family level variables used in this study. All variables are estimated monthly, except where specified otherwise.

gret	Fund gross return, that is, the fund's net return plus one twelfth of the fund's annual expense ratio
exp_ratio_m	Fund expense ratio, that is, one twelfth of the fund's annual expense ratio
vwfgret	Family gross return, estimated as the average gross return (gret) of all funds in the family weighted by their TNA
fly_ptna	Family TNA (in 2017 USD), estimated as the sum of the TNA (in 2017 USD) of each fund in the family. The adjustment to 2017 USD is done as follows: the fund's (unadjusted) TNA is first divided by the total value of all stocks in CRSP for that month, and then multiplied by the total value of all stocks in CRSP at the end of December 2017.
ind_size	Industry size, estimated as the sum of the unadjusted TNA of all active funds, divided by the total value of all stocks in CRSP
fly_ptna_av	Average monthly TNA (in 2017 USD) of all funds in the family
fly_exp_ratio_vwa	Average expense ratio for the family, estimated as the average monthly fund expense ratio weighted by fund TNA
fly_age	Family age in months, estimated as the age of the oldest fund in the family
fly_fund_age_av	Average age in months of all funds in the family
fly_total_fund_n	The number of actively managed US-focused equity funds, excluding funds-of-funds, closed-end, index tracking, international and offshore funds, and funds with less than than $15 million in TNA (in 2017 USD)
fly_idx_fund_n	The number of index funds in the family
fly_ppn_n_idx	The number of index funds in the family, expressed as a proportion of the the number of actively managed funds in the family (fly_total_fund_n)
fly_ppn_tna_idx	The TNA of index funds in the family, expressed as a proportion of the the TNA of actively managed funds in the family (fly_ptna)
fly_n_osource	The number of outsourced funds in the family. Outsourced funds are funds whose fund name is different from their advisor name.
fly_ppn_n_osource	The number of outsourced funds in the family, expressed as a proportion of the the number of actively managed funds in the family (fly_total_fund_n)
fly_ppn_tna_osource	The TNA of outsourced funds in the family, expressed as a proportion of the the TNA of actively managed funds in the family (fly_ptna)
fly_retail_fund_n	The number of retail funds in the family.
fly_ppn_n_retail	The number of retail funds in the family, expressed as a proportion of the the number of actively managed funds in the family (fly_total_fund_n)
fly_ppn_tna_retail	The TNA of retail funds in the family, expressed as a proportion of the the TNA of actively managed funds in the family (fly_ptna)
fly_inst_fund_n	The number of institutional funds in the family.
fly_ppn_n_inst	The number of institutional funds in the family, expressed as a proportion of the the number of actively managed funds in the family (fly_total_fund_n)
fly_ppn_tna_inst	The TNA of institutional funds in the family, expressed as a proportion of the the TNA of actively managed funds in the family (fly_ptna)
fly_team_fund_n	The number of team-managed funds in the family.
fly_ppn_n_team	The number of team-managed funds in the family, expressed as a proportion of the the number of actively managed funds in the family (fly_total_fund_n)
fly_ppn_tna_team	The TNA of team-managed funds in the family, expressed as a proportion of the the TNA of actively managed funds in the family (fly_ptna)
fly_intl_fund_n	The number of funds in the family that focus on international (non-US) stocks.
fly_ppn_n_intl	The number of international funds in the family, expressed as a proportion of the the number of actively managed funds in the family (fly_total_fund_n)
fly_ppn_tna_intl	The TNA of international funds in the family, expressed as a proportion of the the TNA of actively managed funds in the family (fly_ptna)
fly_public	Dummy variable equal to 1 if the family is publicly listed
n_launched	Number of new funds launched by the family in a year
n_closed	Number of funds terminated by the family in a year

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