Crowding: Evidence from Fund Managerial Structure

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Abstract

Over the past 30 years, there has been a striking evolution in fund management structure with team-managed funds growing from 30% of funds to over 70% today. While much attention is focused on fund performance, our paper presents evidence that this transformation is likely a response to crowding: adding new managers brings fresh investment ideas meaning any particular idea is less likely to be crowded. Our results show that funds that transition from solo to team management have less concentrated portfolios and lower decreasing returns to scale. Consistent with the crowding of ideas, we show that diversification of team skills is important for reducing the impact of fund size on performance. We also find that the performance of managers that employ systematic investment processes are not as sensitive to inflows suggesting that discretionary managers with a limited number of ideas are more likely to run into capacity constraints.

Keywords: Mutual funds, managerial structure, diseconomies of scale, crowding, performance evaluation, decreasing returns to scale, alpha, capacity constraints, discretionary management, systematic management.

JEL: G11, G12, G14, G23, L22, L25

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1 Introduction

Many have questioned the transformation in fund management structure over the past 30-years. Today, we do not hear much discussion about "star" managers like Fidelity Magellan's Peter Lynch who retired in 1990.[1] Many have conjectured that the move to team-managed funds has led to a significant degradation of performance. While average performance has declined, it is very difficult to attribute this to management structure.

We examine a number of explanations for the drift in management structure and take a different empirical strategy. To help sort through the various explanations, we focus on decreasing returns to scale-—the tendency for performance to be eroded as funds get more inflows. Team management is a natural response to the crowding of ideas. A new manager likely brings fresh investment ideas thereby reducing the capacity burden on existing investment ideas as portfolios become less concentrated. Indeed, our evidence suggests that team-managed funds are able to absorb significantly more inflows without diminishing performance compared to solo-managed funds. Importantly, we show that the composition of the team is crucial. Consistent with the crowding idea, teams with diversified skills have the lowest decreasing returns to scale (DRS).

We also contrast discretionary and systematic (algorithmically driven) funds. Adding a new discretionary manager likely brings new ideas and decreases the capacity pressures on the existing ideas. This intuition does not necessarily cross over to investment management companies that use systematic investment processes. Indeed, we find that systematic investment managers have lower decreasing returns to scale – again, consistent with the notion of the crowding of ideas.

The evidence is overwhelming that average fund performance has declined over our sample period. While some blame team management (see, e.g., Goldman, Sun and Zhou, 2016), why would the fund industry migrate to team management if it generates a lower alpha? We argue the story is more nuanced. There is a selection bias. Solo management was popular in the 1980s and 1990s—exactly at the time when there was plenty of alpha available.[2] While there is a negative correlation between team management and performance, it is likely spurious.

[1]See, for example, "Is it better to have a team or a single manager overseeing your fund?" (Bloomberg, June 11, 2018 https://www.bloomberg.com/news/articles/2018-06-11/is-it-better-to-have-a-team-or-a-single-manager-overseeing-your-fund) and "How solo star fund managers stack up against the team players" (Financial Times, July 14, 2016 https://www.ft.com/content/fe46e73a-4831-11e6-b387-64ab0a67014c).

[2]Fidelity Magellan's solo manager Peter Lynch produced an average annual return of 29.2% from 1977 to 1990.

We start with the advantages and disadvantages of team management. The advantages include:

Additional ideas and crowding. Adding another manager likely adds new ideas (assuming the manager is not simply replicating the skills of the existing managers). Portfolios become less concentrated. These new ideas are especially helpful for performance if the current manager's ideas are getting crowded.

Complexity. As funds get larger and information becomes more plentiful, it is physically difficult for any one person to keep track of a growing number of companies.

Sounding board. In a team environment, managers can share their information/ideas and get valuable feedback on their candidate investments.

Synergy and innovation. Transitioning to a team is not necessarily additive in ideas. Diverse teams may find synergy: new ideas may arise as a result of discussions.

Spreading the blame. If you are a solo manager and your fund does poorly, it damages your reputation. In a team-managed situation, the blame is shared and there is less risk to the individual manager's human capital.

Transition. A second manager may be brought in to allow for a smooth (planned) transition or as a hedge for an unexpected departure of a manager.

Retention. In the context of a fund family, a "star" manager may be poached by another fund family or start their own fund. As the solo manager, the "star" manager gets credit for the fund performance. However, in a team structure, the individual managers get far less credit and most of the reputation goes to the fund family. Hence, a team structure is a natural response of the fund family to retain their best managers (see, e.g., Massa, Reuter and Zitzewitz 2010, Deuskar et al. 2011).

Mitigation of Lone Wolf risk. With more than one manager, it is less likely that any one manager breaches a fund's risk limits (see, e.g., Fedyk, Patel and Sarkissian, 2018, Patel and Sarkissian, 2018). An interesting recent example was the departure of star Investco manager Neil Woodford to start his own solo-managed fund. The new fund spectacularly failed after gathering over $13 billion in investor money as a result of the manager taking oversized bets on illiquid securities.

However, there are disadvantages also.

Coordination costs. Team management introduces additional complexity as multiple managers need to coordinate their activities.

Expenses. It is more expensive to have two high quality managers than a single high-quality manager.

Sharing the credit. High quality managers may prefer to go solo because they will receive full credit for good performance rather than sharing with a team. Getting full credit increases the value of their human capital and opens the possibility of moving to another fund with more attractive compensation. Indeed, some of the highest quality managers may prefer to avoid employment at team-managed funds leading to a selection effect.

Keeping these costs and benefits of team management in mind, we start by detailing strong evidence consistent with decreasing returns to scale across all funds and, importantly, the differential impact of scale diseconomies on team- versus solo-managed funds. While all funds experience some degradation of performance as they become larger, the impact on team-managed funds is much more limited. Among team-managed funds, we find that teams with a higher level of intra-team skill diversity (termed skill diversity, which constitutes the first type of diversity we study) exhibit more resistance to the erosive performance effect of size. Examining the response to fund inflows in greater detail based on holdings, we find more rapid adjustment of concentration (as proxied by the number of stocks held, e.g., Pollet and Wilson (2008)) for team-managed funds. Our results are thus consistent with our hypothesis of idea scarcity (and subsequent crowding) for fund managers and that skill diversity helps mitigate this crowding.

To provide further evidence, we split our sample based on two alternative criteria: strategy automacy and educational diversity, which measures diversity in team members' educational backgrounds and represents a different notion of diversity than skill diversity. On strategy automacy, we find that our previous results on the differential impact of scale diseconomies on solo- versus team-managed funds do not hold for systematic funds (i.e., the funds that are driven by systematic investment processes and are less reliant on individual ideas). This is consistent with the idea that crowding is less of a concern for funds that are less individual idea intensive. On educational diversity, we find that among team-managed funds, educational diversity, in contrast to skill diversity, does not lead to differences in scale diseconomies. These results may be consistent with the notion that in funds that rely on a scarce number of ideas, the addition of new ideas is better accomplished through diversity of investment experience—not diversity of formal education.

We show two important applications that build on our analysis of decreasing returns of scale. First, we calibrate the change in capacity (defined as the equilibrium size that generates a zero net alpha) when a fund switches from solo-management to team-management, documenting an economically significant increase in capacity of 25% to 53%. Second, we use managerial structure as a conditioning variable to study performance persistence, and show a higher degree of short-run alpha persistence among team-managed funds.

Our work is related to several strands of the fund evaluation literature.

First, our study is related to the literature on diseconomies of scale for active investment management, e.g., Chen, Hong, Huang and Kubik (2004), Pástor and Stambaugh (2012), Pastor, Stambaugh, and Taylor (2015), Harvey and Liu (2016), and Zhu (2018). This literature empirically studies the relation between fund size and fund performance, which, according to the theoretical work in Berk and Green (2004), is of first-order importance for the cross-section of fund performance. We add to this literature by analyzing the impact of managerial structure on diseconomies of scale. We document a large differential impact across solo- versus team-managed funds, offering new insights into the size and performance nexus.

Our work also advances the literature that attempts to better understand the relation between management structure and fund performance. There is considerable disagreement among existing papers. Prather and Middleton (2002) and Bliss, Potter and Schwarz (2008) do not find significant differences in performance between solo- and team-managed funds. Whereas Chen et al. (2004) and Bär, Kempf and Ruenzi (2011) find team-managed funds underperform solo-managed funds, more recent papers by Adams, Nishikawa and Rao (2018) and Patel and Sarkissian (2017) suggest otherwise.[3] We add another perspective based on the idea of crowding. Our empirical work controls for the potential selection bias that is driven by the evolution of management structure (i.e., shift in management structure coincides with the decrease in mutual fund performance in general)—that is, our approach is consistent with the way that Pastor, Stambaugh, and Taylor (2015) and Zhu (2018) address the endogeneity concern in previous work on the size-performance relationship. We find evidence consistent with the hypothesis that team management helps mitigate the impact of crowding. In short, we provide a new explanation for the transformation in fund managerial structure over the past 30 years.

While our paper studies mutual fund management structure, it differs from existing papers by examining the impact of fund managerial structure through the lens of diseconomies of scale. Our approach is likely useful for future studies on the relation between fund characteristics and performance because: 1. Diseconomies of scale is of first-order importance in driving fund performance (as shown by the previous literature, both theoretically and empirically); and 2. As opposed to the cross-sectional correlation between fund characteristics and performance, their relation may be better identified through time-series variation for time-varying fund characteristics, following the insight of Pastor, Stambaugh, and Taylor (2015). We choose to focus on management structure given its economically significant shift over the past 30 years.

Finally, our paper is related to the general literature in economics that studies how characteristics of team members contribute to team production, e.g., Bantel and Jackson (1989), Putnam (1994), Lazear (1999), Kor (2003), Buyl, Boone, Hendriks and Matthyssens (2011), Tekleab, Karaca, Quigley and Tsang (2016) and van Veelen and Ufkes (2019). We provide new evidence in the context of mutual fund performance, which we believe is a novel application given that team production can be accurately measured (i.e., fund performance). Our contribution is two fold. First, we show the impact of crowding—which is both theoretically motivated and empir-

[3]For additional work on the relation between fund performance and management structure, see Prather and Middleton (2002), Baks (2003), Bär, Kempf and Ruenzi (2005), Prather and Middleton (2006), Cici (2012), Goldman, Sun and Zhou (2016), Han et al. (2017), and Evans, Prado, Rizzo and Zambrana (2020).

ically relevant as it controls for the endogenous matching between performance and size—is significantly mitigated with team-managed funds. Second, we dissect team performance by analyzing a variety of team characteristics and identify intra-team skill diversity as the main driver of teams' superior performance. Our finding is thus consistent with the hypothesis of cognitive diversity (in particular, diversity in past investment experience) being a valuable resource for complex problem-solving in economics and social sciences (see, e.g., Hoffman 1959, Hoffman and Maier, 1961, Bantel and Jackson, 1989, Buyl, et al., 2011, Tekleab, et al., 2016, and Bromiley and Rau, 2016).

Our paper is organized as follows. In the second section, we describe our data. The third section presents our model. Our main results are presented in the fourth section. Some concluding remarks are offered in the final section.

2 Data

2.1 Mutual Fund Data

The primary source of data is the Morningstar Direct Mutual Fund (MDMF) database, which contains information on fund characteristics, fund monthly returns, inception dates, total net assets, investment objectives, fees, and turnover ratios. To obtain information on the composition of fund managers for each fund, we utilize the managers' employment histories that are made available in the MDMF database. Using these histories, we are able to identify managers who were working for a fund at a particular point in time. Patel and Sarkissian (2017) show that the MDMF database has a 96% match with SEC records and hence provides much more accurate information in capturing the managerial structure of a fund than other mutual fund databases (e.g., CRSP Survivorship Bias Free Mutual Fund Database). Following the prior literature, we classify funds as solo managed when we are able to identify one manager name and as team managed when there are more than one managers listed.

Given the richness of information regarding the composition of fund managers made available in the MDMF, we are able to identify funds that switch from solo-managed to team-managed funds. In doing so, we are able to estimate the potential incremental contribution of new fund managers that are hired in reducing the effect of decreasing returns to scale.[4]

We also use the Thomson Reuters Mutual Fund Holdings database to obtain information on fund stock holdings to examine whether the entry of new managers

[4] We define new managers at a fund at the end of a month as the ones who were not previously employed as fund managers by the fund (as opposed to the fund family). Therefore, our definition of new managers includes personnel movement both within and across fund families.

results in changes in the composition and concentration of stocks held by mutual funds. We first merge Thomson Reuters with CRSP using MFLINK file to obtain the WFICN identifier following Wermers (2000). We then merge back to our primary source of data (i.e., Morningstar) using CUSIP codes, ticker symbols, and fund names (if neither CUSIP codes nor ticker symbols are available).

To facilitate the comparison to the prior literature, we focus on U.S. domestic equity funds. Following the procedures used in many papers,[5] we exclude index, fixed income, international, and specialized sector funds from our sample. With the exception of total net assets, we aggregate all fund share class characteristics at the fund portfolio level using asset-weighted averages. We adjust fund total net assets (TNA) by inflation and express them in January 1, 2017 dollars. A mutual fund enters the sample after its combined TNA across all share classes exceeds $15 million in January 2017 dollars. Once a fund clears this threshold, we keep the fund in the sample even if its TNA drop below $15 million subsequently. This procedure guards against the incubation bias of Evans (2010). We exclude funds that exist prior to the reported fund starting dates and exclude observations whose fund names are missing from the MDMF database (Evans, 2010).

Following the prior literature (Ding and Wermers, 2012, Wang, 2016, Patel and Sarkissian, 2017), our sample period starts in 1992 due to completeness in managerial information. To alleviate the impact of outliers, we winsorize gross returns at the 0.01 percentile, and remove records with fund size halved or doubled in a month.[6] This leads to a final sample consisting of 3,560 domestic equity funds and 688 fund families, covering 505,647 fund-month observations from 1992 to 2017.

To examine the impact of changes in management structure on fund performance, we construct various performance metrics as the dependent variables. The first performance measure is the benchmark-adjusted return, which is the difference between a fund's gross return and the fund's Morningstar designated benchmark portfolio return (e.g., Pástor, Stambaugh and Taylor (2015)).[7]

[5] See, e.g., Chen et al. (2004), Kacperczyk, Sialm and Zheng (2005), Fama and French (2010), Ferson and Lin (2014), Berk and van Binsbergen (2015), amongst others.

[6] In our sample, 0.6% (i.e., 3,050 out of 508,697) of fund/month observations are removed.

[7] Morningstar assigns each fund a category and designates a benchmark portfolio to each fund category. The Morningstar benchmark portfolios for the nine Morningstar categories are the Russell 1000 Total Return Index for LB (large blend), Russell 1000 Growth Total Return Index for LG (large growth), Russell 1000 Value Total Return Index for LV (large value), S&P Mid Cap 400 Total Return Index for MB (mid-cap blend), Russell Mid Cap Growth Total Return Index for MG (mid-cap growth), Russell Midcap Value Total Return Index for MV (mid-cap value), Russell 2000 Total Return Index for SB (small blend), Russell 2000 Growth Total Return Index for SG (small growth), and Russell 2000 Value Total Return Index for SV (small value). The Morningstar benchmark does not suffer from cherry picking bias because Morningstar categorizes funds based on their holdings rather than their reported objectives.

Following the convention of the mutual fund literature, we also consider measuring performance using abnormal returns adjusted for risk factors,

$$r_{it} = R_{it} - \sum_{k=1}^{K} \beta_{ik} f_{kt}, \tag{1}$$

where K is the number of risk factors, f_{kt} is the risk factor k at time t, and β_{ik} is the loading for the k-th factor. We consider three models, namely, the capital asset pricing model (CAPM), the Fama-French three-factor model (FF), and the Carhart four-factor model (Carhart). The risk factor returns are obtained from Ken French's website.

Morningstar designates eight major investment categories for mutual funds, namely, Allocation, Alternative, Commodities, International Equity, Municipal Bond, Taxable Bond, Sector Equity, and U.S. Equity.[8] We merge Alternative and Commodities into one category due to the limited number of commodity focused funds. The number of different investment categories ever managed by fund manager i at time t is used as a proxy for experience and skillset for manager i. We use Blau's index (Blau, 1977) to measure intra-team skill diversity (DIV) of a management team, i.e.,

$$DIV = 1 - \sum_{k=1}^{K} p_k^2,$$

where p_k corresponds to the proportion of team members in the k-th category. We set $K = 7$ which is the total number of investment categories we consider. To address the issue that one fund manager could have experience in multiple categories, we apply the following adjustment to compute p_k. For a manager with experience in m categories, her contribution to each of these m categories would be $1/m$. The proportion of team members in the k-th category p_k is computed as the total contribution of team members to this category divided by team size.[9] Given the total of $K = 7$ categories, the skill diversity measure DIV lies between 0 (minimum diversity) and 0.86 ($= 1 - 1/7$, maximum diversity).

[8]The distribution of mutual funds in these categories are: Allocation 14.5%(2,553), Alternatives 5.1% (907), Commodities 0.3% (53), International Equity 14.4% (2,548), Municipal Bonds 8.8% (1,549), Sector Equity 5.7% (1,001), Taxable Bonds 18.6% (3,277), and U.S. Equity 32.7% (5,775).

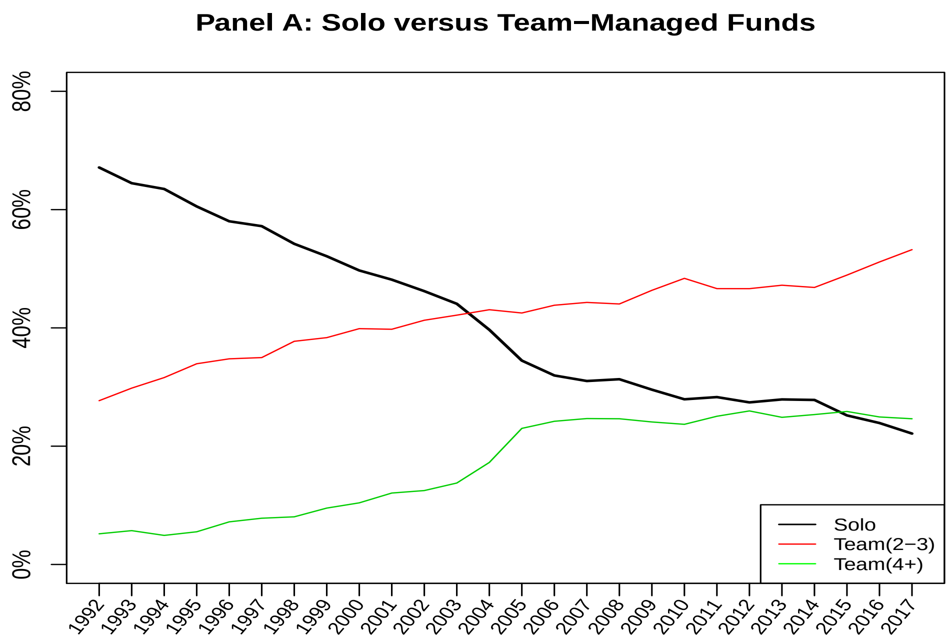
[9]For example, suppose we have two managers (A and B) in the same team, with A having experience in two categories (category 1 and 2), and B in only one category (category 2). The corresponding category proportions are $p_1 = (0.5 + 0)/2 = 0.25$ (for category 1), $p_2 = (0.5 + 1)/2 = 0.75$ (for category 2), and $p_k = 0$ for $k \geq 3$.

2.2 Summary Statistics

Figure 1 shows the distribution of U.S. domestic equity mutual funds over our sample period and across different managerial structures. As shown by the top panel of Figure 1, the proportion of solo-managed funds decreased from 67% in 1992 to 22% in 2017. The teams consisting of two to three managers are the most popular, increasing from 28% in 1992 to 53% in 2017. The proportion of large teams consisting of four or more managers increased more than four-fold from about 5% in 1992 to over 24% by 2017. The growth in team-managed funds is in line with the increase in assets under management in the equity mutual funds market. It is also consistent with the decline of the practice of naming single fund managers for the U.S. mutual fund industry as documented by Massa et al. (2010).

The bottom panel of Figure 1 shows the time series of the assets under management (as a fraction of the equity market as a whole) for equity mutual funds. We see a dramatic increase between 1992 and 2000 that almost triples the size of the mutual fund industry. This increase tapers off after 2000, leading to a stable market size that is around 16% to 18%. The non-stationarity of industry size poses a challenge to our study because, as we will show later, the average fund-level decreasing returns to scale depends on the overall industry size and is therefore also likely to be non stationary.

Given the trend in industry size in the pre-2000 sample, we report two sets of summary statistics: one corresponding to the post-2000 sample (Table 1) that we focus on in our followup analysis, the other corresponding to the full sample (Table B.1.1) that we relegate to the appendix.



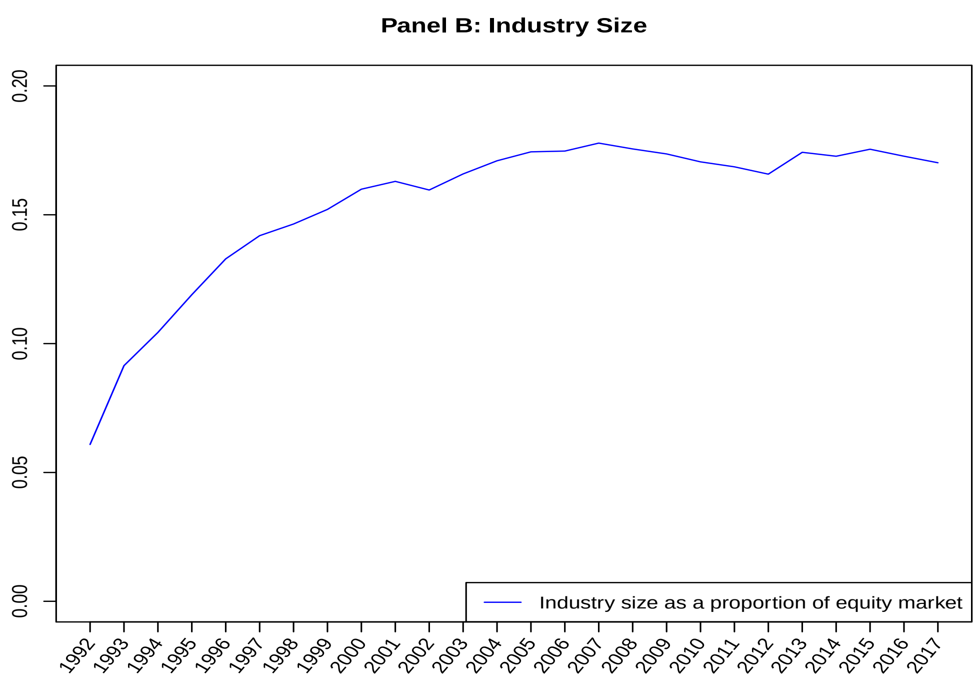


Figure 1: **Distribution of solo-managed and team-managed funds and mutual fund industry size from 1992 to 2017.** Panel A shows the distribution of solo-managed and team-managed funds. *Team (2 to 3)* refers to teams consisting of two or three managers. *Team* (4+) refers to teams consisting of four or more managers. Panel B displays the time series of active mutual fund industry size (as a fraction of the total equity market) from 1992 to 2017.

Focusing on Table 1, on average, solo-managed funds have higher turnover than team-managed funds. The distribution of fund TNA of solo-managed funds is more skewed to right than that of the team-managed funds. Further, the average fund family TNA for solo-managed funds is larger than that of team-managed funds. The bigger fund families likely have more infrastructure to implement the star system. For example, Fidelity Investments has a good track record of replacing good managers with good managers. Fidelity Magellen is one of the most famous solo-managed funds that was managed by star manager Peter Lynch. Team-managed funds on average slightly underperform solo-managed funds (e.g., the Morningstar benchmark adjusted return differs by two basis points per month), consistent with the previous literature (see, e.g., Chen et al., 2004, Bär et al., 2011). Managers for solo-managed funds are on average more experienced as indicated by a longer industry tenure. There are about 25% of the teams have no skill diversity as measured by DIV, i.e., all the managers in a team only have experience in one investment category.

Table 1: **Characteristics of Solo-Managed and Team-Managed Funds.**

The table presents summary statistics for solo-managed and team-managed funds. The sample period is from January 2000 to December 2017. The unit of observation is the fund/month. All returns (alphas) and expense ratios are annual figures. *Benchmark_adj_ret* is constructed by subtracting the Morningstar designated benchmark index return from the fund's gross return. *CAPM alpha*, *FF3 alpha* and *Carhart alpha* are risk adjusted returns using the market factor model, Fama-French 3-factor model, and Carhart 4-factor model, respectively. *Fund TNA* is the total net assets under management of a fund in millions of dollars. *Family TNA* is the total net assets under management of the fund complex to which the fund belongs in millions of dollars. Both fund and fund family TNA numbers are inflation-adjusted to January 2017 dollars. *Turnover* is defined as the minimum of aggregate purchases and sales divided by the average annual fund TNA in percentage. *Fund Age* is the time in years since the fund's inception date. *Ind Tenure* is the number of years the fund manager has been within the fund industry. *DIV* is a measure of team skill diversity.

				Quantile				
	Fund/ Month	Mean	Std. dev.	1%	25%	50%	75%	99%
Panel A: Solo-managed funds								
Benchmark adj ret (%)	132,469	0.59	27.12	-77.48	-10.44	0.23	11.09	83.26
CAPM alpha (%)	132,469	1.61	30.22	-79.60	-11.50	0.66	13.59	89.13
FF3 alpha (%)	132,469	0.75	23.46	-65.04	-9.94	0.56	11.25	68.11
Carhart alpha (%)	132,469	0.75	22.54	-61.47	-9.83	0.53	11.05	65.40
Fund TNA ($ mil)	132,469	1,636	5,701	5	65	254	1,057	24,126
Log fund TNA	132,469	5.58	1.95	1.68	4.17	5.54	6.96	10.09
Expense ratio (%)	127,741	1.25	0.62	0.17	0.94	1.19	1.47	2.94
Turnover (%)	118,955	85	82	2	31	59	108	423
Fund Age (years)	132,469	14.15	13.49	0.54	5.50	10.58	17.51	70.68
Family TNA ($ mil)	132,306	77,000	174,011	9	814	8,956	41,654	726,276
Ind Tenure (years)	132,469	10.79	6.62	0.42	5.50	9.83	15.25	26.33
Panel B: Team-managed funds								
Benchmark adj ret (%)	278,424	0.21	21.24	-57.96	-9.25	-0.03	9.21	62.04
CAPM alpha (%)	278,424	0.87	25.58	-65.28	-10.90	0.26	11.82	74.22
FF3 alpha (%)	278,424	0.44	19.26	-51.77	-9.03	0.27	9.75	54.44
Carhart alpha (%)	278,424	0.40	18.59	-49.77	-8.92	0.25	9.56	52.68
Fund TNA ($ mil)	278,424	1,560	6,350	7	74	276	1,021	21,992
Log fund TNA	278,424	5.63	1.84	1.95	4.30	5.62	6.93	10.00
Expense ratio (%)	269,862	1.17	0.41	0.26	0.94	1.13	1.37	2.31
Turnover (%)	256,144	76	64	3	33	60	99	348
Fund Age (years)	278,424	13.75	12.66	0.51	5.47	10.59	17.76	70.47
Family TNA ($ mil)	278,103	38,327	118,797	14	1,047	10,898	32,318	686,311
Ind Tenure (years)	273,724	9.25	4.58	1.00	5.89	8.80	12.03	22.46
Skill diversity (DIV)	273,546	0.25	0.26	0.00	0.00	0.22	0.50	0.77

3 Decreasing Returns to Scale Estimation

3.1 Recursively-Demeaned Estimator

To model the relation between fund size and performance, much of the literature employs a pooled OLS panel regression (see, e.g., Chen et al., 2004, Yan, 2008, Ferreira et al., 2013):

$$r_{it} = a + bx_{it-1} + \epsilon_{it}, \tag{2}$$

where r_{it} is the risk-adjusted return for fund i at time t and x_{it-1} is the lagged natural logarithm of fund TNA. Pástor, Stambaugh and Taylor (2015) argue that this setup ignores the heterogeneity in fund skill and, hence, suffers from the omitted-variable bias. Intuitively, larger funds are more likely to be managed by the more capable hands, implying a cross-sectional relation between size and skill, which may confound the results of the pooled OLS approach. To address this issue, Pástor, Stambaugh and Taylor (2015) advocate the use of fund fixed effects model,

$$r_{it} = a_i + bx_{it-1} + \epsilon_{it}. \tag{3}$$

The fund fixed effect, a_i, soaks up variation in performance due to cross-sectional differences in fund skill. The parameter a_i represents the return on the first dollar invested in fund i, and b measures decreasing returns to scale (DRS). Because the manager's investment ideas are in finite supply and she invests in her best ideas first, returns decrease by $b \log(1 + c)$ for a c relative change in fund size.

Although the inclusion of the fund fixed effects eliminates the omitted-variable bias associated with (2), Pástor, Stambaugh and Taylor (2015) show this introduces a finite-sample estimation bias in b due to the contemporaneous correlation between fund returns and innovations in fund size (i.e., high returns are contemporaneously correlated with increases in fund size). Zhu (2018) proposes an estimator that allows for fund fixed effects while eliminating the finite-sample omitted-variable bias.[10]

[10] We adopt the approach proposed by Zhu (2018) (instead of the one in Pástor, Stambaugh and Taylor (2015)) as the original recursively-demeaned approach proposed by Pástor, Stambaugh and Taylor (2015) is lack of power from the model misspecification for the fund size process. See Zhu (2018) for more details.

Following Pástor, Stambaugh and Taylor (2015) and Zhu (2018), we define the recursively forward-demeaned variables for the i-th fund as

$$\bar{r}_{it} = r_{it} - \frac{1}{T_i - t + 1} \sum_{s=t}^{T_i} r_{is},$$
$$\bar{x}_{it-1} = x_{it-1} - \frac{1}{T_i - t + 1} \sum_{s=t}^{T_i} x_{is-1},$$
$$\bar{\epsilon}_{it} = \epsilon_{it} - \frac{1}{T_i - t + 1} \sum_{s=t}^{T_i} \epsilon_{is},$$

where T_i is the total number of observations for fund i.

Such a demeaning process eliminates the fixed effect a_i but introduces a correlation between the demeaned size, $\bar{x}_{it-1}$, and the demeaned innovation, $\bar{\epsilon}_{it}$. Using x_{it-1} as an instrumental variable, Zhu (2018) shows that an estimate of β can be obtained via two-stage least squares:

$$\bar{x}_{it-1} = \psi + \rho x_{it-1} + v_{it-1}, \tag{4}$$
$$\bar{r}_{it} = \beta \bar{x}^*_{it-1} + \bar{\epsilon}_{it}, \tag{5}$$

where $\bar{x}^*_{it-1}$ is the fitted value from the first-stage regression (4). The bias-corrected estimator for β is

$$\hat{b}_{RD} = \left(\sum_{i=1}^{N} \sum_{t=1}^{T_i - 1} \bar{x}^{*'}_{it-1} \bar{x}^*_{it-1} \right)^{-1} \left(\sum_{i=1}^{N} \sum_{t=1}^{T_i - 1} \bar{x}^{*'}_{it-1} \bar{r}_{it} \right). \tag{6}$$

The variance of the estimator is presented in the Appendix.

3.2 Managerial Structure and the DRS Parameter

Our goal is to examine whether the decreasing-returns-to-scale parameter b interacts with managerial structure. More specifically, we hypothesize that solo-managed funds may have less capacity to absorb new capital than their team-managed counterparts which leads to a crowding effect. A substantial portion of our sample funds have constant managerial structure, either solo-managed or team-managed. We call these funds non-switchers. The rest of the funds are switchers, which switch between solo and team managerial structures during the sample period.[11]

[11] In our sample, there are funds switching between different managerial structures multiple times. A fund typically changes from solo management to team management as the fund size grows. The

Constant Risk Loadings The fund risk-factor-adjusted returns are calculated as

$$r_{it} = R_{it} - \sum_{j=1}^{K} \beta_{ij} f_{jt}, \tag{7}$$

where R_{it} is the gross return (i.e., returns before deducting fees) for the i-th fund at time t, and β_{ij} is the factor loading on the j-th risk factor f_{jt}. For now, we assume that the risk factor loadings are constant and estimate them using the full sample of fund returns.[12]

After obtaining the factor-adjusted returns, we test our hypothesis separately for non-switchers and switchers.

For non-switchers, we allow managerial structures to interact with the DRS parameter by running the following DRS model:

$$r_{it} = a_i + b_S x^S_{it-1} + b_T x^T_{it-1} + \epsilon_{it}, \tag{8}$$

where x^S_{it-1} is the logarithm of fund TNA if the i-th fund is solo managed, and 0 otherwise, and x^T_{it-1} is the logarithm of fund TNA if the i-th fund is team managed, and 0 otherwise. By construction, the parameter b_S captures the impact of fund size for solo-managed funds, and b_T captures that for team-managed funds. The difference of the DRS parameters is $b_S - b_T$. The standard error for the difference $b_S - b_T$ is calculated based on the covariance matrix of the model estimates.

For switchers, we allow managerial structures to interact with both the DRS parameter and a fund's average skill level (a_i), that is

$$r^S_{it} = a^S_i + b_S x_{it-1} + \epsilon_{it}, \tag{9}$$

$$r^T_{it} = a^T_i + b_T x_{it-1} + \epsilon_{it}, \tag{10}$$

where r^S and r^T are the subsample of returns when funds are under solo management or team management, respectively. To estimate the parameters in Eq (9) and (10), we

opposite is true when fund size shrinks. To avoid transient switches that make our DRS estimates noisy since an accurate estimation of the DRS parameter usually requires a long time series (also, some of these transient switches are also likely due to data errors), we require six or more consecutive observations for a fund under a fixed management structure.

[12]We are aware of the potential look-ahead bias that is introduced by estimating the factor loadings using the full sample. We later show our results are robust to the way that we estimate factor loadings. In particular, using holdings-based estimates for factor loadings, which are immune to look-ahead biases, we obtain similar results.

cannot simply break the intercept of (8) into two pieces, i.e., including the interaction of managerial structures and intercept,

$$r_{it} = a_i^S + a_i^T + b_S x_{it-1}^S + b_T x_{it-1}^T + \epsilon_{it}.$$

This is because a demeaned process cannot remove two fixed effects for a fund, causing issues in the estimation. Instead, we split a switcher fund into two funds, one containing observations under solo management and the other containing observations under team management. To be included in the solo-management subsample, we require a minimum of 12 monthly observations for a fund in order to reliably use the recursively-demeaned estimator. The same requirement applies to a fund included in the team-management subsample. Therefore, we end up with $2N$ new funds for N switchers. We then estimate (8) on these $2N$ new funds.

To test the difference in the DRS parameter for the two groups (i.e., $d = \hat{b}_S - \hat{b}_T$), we use the standard error assuming the independence between $\hat{b}_S$ and $\hat{b}_T$. Note that our choice is likely conservative because $\hat{b}_S$ and $\hat{b}_T$ are plausibly positively correlated as they are estimated with the same set of funds under different managerial structure. Taking this positive correlation into account implies a smaller standard error (hence a larger t-statistic) than the one we use. We therefore also pay attention to the economic magnitude of d in comparison to $\hat{b}_S$ and $\hat{b}_T$.

Time-Varying Risk Loadings To better capture the potential time variability in risk loadings, we follow the existing literature (see, e.g., Jiang, Yao and Yu, 2007) to construct betas that are based on portfolio holdings. These beta estimates take into account the time variation in risk loadings within a given management regime and, more importantly, the potential change in risk loadings across different management regimes that may confound our analysis on the difference in DRS. After estimating holding-based risk loadings, we obtain the factor-adjusted returns. The rest of our tests are the same as in the above case with constant risk loadings.

3.3 Time-Varying DRS

Before we study the impact of managerial structure on DRS, we document a new set of results that highlight the time variation in the average DRS among funds, which extends the analysis in Pastor, Stambaugh, and Taylor (2015) and Zhu (2018).[13] In particular, given the evolution of the industry size as documented previously, we split our sample into the pre-2000 (i.e., 1992-1999) and the post-2000 period, and study DRS separately for these two periods.

[13]While Pastor, Stambaugh, and Taylor (2015) study the impact of industry size on individual fund performance, Zhu (2018) examines the impact of individual fund size. Our results highlight the interaction between industry size and individual fund size.

Table 2 presents our estimation results. For the pre-2000 period, the estimates of DRS are close to zero, and are not significant statistically. In contrast, the post-2000 period, over which the industry size reaches its peak and remains relatively stable, leads to DRS estimates that are highly significant, both economically and statistically.[14]

Industry size is an important conditioning variable that affects fund-level DRS. When industry size is low so capacity constraints are not binding, ideas are less crowded, leading to a low or close to zero fund-level DRS. Given our goal of studying cross-sectional difference in DRS (in particular, the impact of managerial structure on DRS), we focus on the post-2000 period in our followup analysis. In particular, we ask the question: when the industry as a whole is crowded so fund-level decreasing returns to scale becomes prevalent, which variables help mitigate the impact of DRS?

4 Empirical Results

We report two sets of empirical results. One is based on constant risk loadings, and the other is based on risk loadings estimated with the holdings data. Given that the two sets of results are similar, we focus on the first set in describing our main results.

4.1 Main Results

4.1.1 Constant Risk Loadings

Non-switchers We identify 1,618 non-switchers out of the 3,261 unique funds we have. Amongst these 1,618 funds, 308 funds are solo-managed, and 1,310 funds are team-managed during our sample period. Panel A of Table 3 shows the large estimates of DRS across both groups of funds, consistent with the previous literature. Solo-managed funds exhibit a much larger negative impact of size than the team-managed fund group. For example, a typical fund under solo management has a coefficient of -0.0050 (under benchmark-adjusted fund returns), which implies a decrease of 35 bps ($= -0.0050 \times log(2)$) per annum if it doubles its size over a year. However, for a team-managed fund, the DRS coefficient is -0.0024 (benchmark-adjusted fund returns), which implies a decrease of 17 bps per annum if it doubles its size. The differences are statistically significant under all risk adjustment methods.

The analysis above is consistent with the crowding hypothesis that team management helps mitigate the size impact on returns. Note that there can be substantial

[14]Our results add to the previous literature that documents the shift in mutual fund performance around 2000 (e.g., Bhojraj, Cho, and Yehuda, 2012 and Phillips, Pukthuanthong, and Rau, 2014).

Table 2: **Time-Varying DRS**

We estimate the DRS parameter b using (6) for fund/month observations under solo management (*Solo*), fund/month observations under team management (*Team*), and all fund/month observations (*All funds*). Panel A reports the estimates for the 1992-1999 subperiod over which the mutual fund industry has experienced rapid growth. Panel B reports the results for the 2000-2017 subperiod over which the relative industry size is stable. "Benchmark" corresponds to the case where the Morningstar designated benchmark index return is subtracted from the fund's total return. "CAPM", "FF3", and "Carhart" adjusted fund returns using the market model, Fama-French 3-factor model, and Carhart 4-factor model, respectively. The t-statistics clustered by fund are reported in parentheses.

Panel A: Subperiod: 1992 – 1999			
	Solo	Team	All funds
Benchmark	0.0005	0.0004	0.0007
	(0.98)	(0.80)	(1.82)
CAPM	-0.0009	-0.0003	-0.0007
	(-1.44)	(-0.41)	(-1.48)
FF3	-0.0004	-0.0001	-0.0002
	(-0.89)	(-0.33)	(-0.69)
Carhart	-0.0003	-0.0002	-0.0002
	(-0.74)	(-0.64)	(-0.77)
Panel B: Subperiod: 2000 – 2017			
	Solo	Team	All funds
Benchmark	-0.0043	-0.0020	-0.0024
	(-5.96)	(-10.88)	(-11.05)
CAPM	-0.0075	-0.0039	-0.0045
	(-7.98)	(-15.26)	(-15.45)
FF3	-0.0047	-0.0021	-0.0025
	(-6.27)	(-12.09)	(-11.72)
Carhart	-0.0044	-0.0020	-0.0024
	(-6.21)	(-12.19)	(-11.69)

heterogeneity amongst teams. For instance, team size can vary considerably across teams. Further, team members can have different experiences and skills. We next explore whether these forms of heterogeneity impact the DRS estimates.

We first calculate the average team size for each of the 1,310 team-managed non-switchers during our sample period. We then classify team-managed funds into small teams (less than four fund managers) versus large teams (four or more managers).[15] This process leads to 798 small teams and 512 large teams. Panel B of Table 3 shows the DRS estimates for the small- and large-sized teams, respectively.

[15]The team size distribution is highly skewed to the right. Teams of 2-3 managers are the most common, accounting for two thirds of team-managed funds. The rest have four or more managers. We therefore categorize team-managed funds into two groups: one with 2-3 managers and the other with 4+ managers. In the Appendix, we report results for alternative ways of categorizing team sizes. They are largely consistent with our results in Table 3.

Table 3: **Decreasing Returns to Scale on Non-Switchers.**

This table presents estimates of the decreasing returns to scale (DRS) on funds which do not switch between solo management and team management between January 2000 and December 2017. The DRS parameters are estimated using model (8). Amongst the non-switchers, there are 308 funds always solo-managed (*Solo*), and 1,310 funds always team-managed (*Team*). Panel A examines the DRS estimate for solo- and team-managed funds. The column *Diff* shows the difference in DRS between solo-managed and team-managed funds. Panel B examines the DRS estimate for small and big teams. Out of the 1,310 team-managed non-switching funds, 798 funds are managed by small teams (less than 4 fund managers) (*ST*), and 512 funds are managed by large teams (4 or more managers) (*LT*). The DRS for solo and these two types of team-managed funds, together with their difference are reported. Panel C examines the DRS estimate for teams with different levels of skill diversity. Out of the 1,310 team-managed funds, there are 1,272 funds that have information on skill diversity (DIV). We split these funds into two groups: high DIV (636 funds, with DIV above the mean) and low DIV (636 funds). The DRS for solo and these two types of team-managed funds, together with their difference are reported. "Benchmark" corresponds to the case where the Morningstar designated benchmark index return is subtracted from the fund's gross return. "CAPM", "FF3", and "Carhart" adjusted fund returns using the market model, Fama-French 3-factor model, and Carhart 4-factor model, respectively. The t-statistics clustered by fund are reported in the parentheses.

Panel A: Solo vs Team

	Solo	Team	Diff
Benchmark	-0.0050	-0.0024	-0.0026
	(-4.04)	(-9.28)	(-2.06)
CAPM	-0.0080	-0.0047	-0.0032
	(-5.99)	(-14.35)	(-2.35)
FF3	-0.0059	-0.0026	-0.0032
	(-4.78)	(-11.15)	(-2.58)
Carhart	-0.0052	-0.0026	-0.0026
	(-4.62)	(-11.42)	(-2.27)

Panel B: Small Team (ST) and Large Team (LT)

	ST	LT	ST-LT
Benchmark	-0.0023	-0.0025	0.0002
	(-7.04)	(-6.06)	(0.34)
CAPM	-0.0047	-0.0048	0.0000
	(-10.99)	(-8.53)	(0.04)
FF3	-0.0026	-0.0027	0.0001
	(-8.77)	(-6.87)	(0.15)
Carhart	-0.0026	-0.0026	0.0000
	(-8.96)	(-7.07)	(0.04)

Panel C: Low DIV Team and High DIV Team

	Low DIV	High DIV	Low - High
Benchmark	-0.0030	-0.0018	-0.0013
	(-8.33)	(-4.72)	(-2.47)
CAPM	-0.0056	-0.0038	-0.0018
	(-11.57)	(-7.92)	(-2.63)
FF3	-0.0031	-0.0022	-0.0008
	(-9.56)	(-6.22)	(-1.71)
Carhart	-0.0031	-0.0022	-0.0009
	(-10.02)	(-6.28)	(-1.87)

The difference in DRS between small teams and large teams are insignificant, both statistically and economically. Therefore, the difference in DRS is mainly driven by solo versus team management and not by team size. The results point to the diminishing benefit of expanding the size of the team which is consistent with increased coordination costs.

We next consider the impact of diversity of team skill (DIV) on DRS. There are 38 out of our 1,310 team-managed funds with DIV information missing for more than half of the fund month records, which we exclude from this part of the analysis. We divide the remaining 1,272 funds by their average team DIV. The group consisting of funds with DIV above (below) the mean is labeled as high (low) DIV group (636 funds). Panel C of Table 3 shows the DRS estimates for these two groups of funds.

High DIV funds exhibit a lower (i.e., less negative) DRS than low DIV funds. In particular, across different benchmark models, teams with a high DIV have a 27%–42% lower DRS estimate than teams with a low DIV and the difference is statistically significant. These results point to the potential importance of intra-team diversity in reducing the effects of crowding.

One limitation of our tests for non-switchers is that funds are likely not randomly assigned to solo or team management, complicating any causal inference of fund size on performance. For example, one concern is that solo- and team-managed funds may differ systematically in regard to their investment strategy/style. Different investment styles have different size capacities with some investment styles being more scale-friendly than others. For example, a large-blend portfolio can accommodate a larger fund size (i.e., a smaller magnitude of DRS) than an investment strategy that focuses on small illiquid stocks.

To address this concern, we examine the investment style composition of solo- and team-managed non-switchers. Table B.3.1 in the Appendix displays the composition of nine Morningstar investment styles. We see no large difference in the investment style composition between solo- and team-managed non-switchers. The percentages of solo-managed funds focus on large, mid and small capitalization stocks are 54.5%, 19%, and 26.6%, compared to 54.8%, 21.9% and 23.3% for team-managed funds. We further investigate the DRS estimates across different style groups in the Appendix.

Switchers A better way to address the endogeneity concern about the assignment of managerial structure is to examine the change in DRS among switcher funds. We test the hypothesis that, holding everything else constant, a fund that switches from solo management to team management experiences a smaller impact of size on performance. Following the analysis for non-switchers, we also consider heterogeneity across teams.

We identify 1,643 funds out of the 3,261 unique sample funds as switchers which swap between solo management and team management during the period between 2000 to 2017. We exclude observations of funds that have fewer than six consecutive monthly return observations under a certain managerial structure. This process excludes 286 funds. For the remaining 1,357 switchers, we further subdivide the sample by the DIV of teams when funds are under team management. We exclude funds with DIV information missing for more than half of the fund-month records. This leads to the exclusion of 25 funds. The remaining 1,332 funds are ranked by the average DIV and then divided into two groups: the high DIV group (666 funds, with DIV above the mean), and the low DIV group (666 funds).[16]

Table 4 reports the results for three sets of sample: all switchers, switchers with a high DIV, and switchers with a low DIV.[17] The differences between b_S (DRS estimate under solo management) and b_T (DRS estimate under team management) are reported and the t-statistics for the differences are calculated assuming the independence of the two DRS estimates and, hence, are likely conservative.

Focusing on all switchers, the results in Table 4 suggest a modest reduction in decreasing returns to scale when funds switch from solo to team management. Both the magnitude and statistical significance depend on the benchmark model. However, under each model, the difference is negative. The economic effect is largest from the CAPM adjustment (DRS reduced by 22% — significant at the 10% level) and smallest for the benchmark adjustment (DRS reduced by 17% — not significant).

We further investigate the change in DRS by partitioning our sample into the high and low DIV groups. We see a large change in DRS only among funds with a high DIV and insignificant results (both economically and statistically) among funds with a low DIV. This is consistent with diversity providing new ideas and mitigating the impact of crowding.

Our results also shed light on existing papers such as Massa, Reuter and Zitzewitz (2010), who show that one of the underlying reasons for fund families to adopt team management is to avoid fund flow risk when there is a managerial turnover for solo-managed funds. Funds that change managerial structures mainly due to this fund flow risk likely will add managers with a similar skill set to the incumbent manager and are therefore likely classified as low DIV funds in our sample. Our results suggest that adding a low DIV manager has no effect on DRS.

While our hypothesis of crowding naturally leads us to consider skill diversity, other definitions of intra-team diversity are also available. In the Appendix, we consider educational diversity. We find that, in contrast to work experience diversity, there is no significant difference in DRS between funds with different levels of educational diversity. We provide details of our analysis in the Appendix.

[16] As a robustness check, we grouped by terciles and found similar results.

[17] Different from Table 3, we do not split our sample by team size as few funds transition from a solo-managed fund to a large team. For example, the probability of a solo-managed fund to a team of more than three managers is 8%.

Table 4: **Decreasing Returns to Scale for Switchers.**

This table presents DRS estimates on funds which switch between single and team management structure between January 2000 and December 2017. There are in total 1,357 switcher funds which have at least twelve monthly observations under each managerial structure. Panel A is for DRS estimates between solo-managed and team-managed funds. In Panel B, we further partition the switcher sample by the DIV of teams when funds are under team management. 25 funds are excluded from this analysis due to missing DIV scores. The remaining 1,332 funds are divided into two groups: the high DIV group (666 funds) and the low DIV group (666 funds). For each of the three sample sets – all switchers, switchers with high DIV and switchers with low DIV, we estimate their DRS under solo management and under team management, and calculate the difference in DRS between solo-managed and team-managed structures. The t-statistics clustered by fund are reported in the parentheses. "Benchmark" corresponds to the case where the Morningstar designated benchmark index return is subtracted from the fund's gross return. "CAPM", "FF3", and "Carhart" adjusted fund returns using the market model, Fama-French 3-factor model, and Carhart 4-factor model, respectively.

Panel A: Solo vs Team			
	Solo	Team	Diff
Benchmark	-0.0024	-0.0020	-0.0004
	(-6.17)	(-6.85)	(-0.75)
CAPM	-0.0051	-0.0040	-0.0011
	(-10.23)	(-10.55)	(-1.75)
FF3	-0.0025	-0.0020	-0.0005
	(-6.94)	(-7.07)	(-1.09)
Carhart	-0.0025	-0.0020	-0.0005
	(-7.12)	(-7.25)	(-1.19)

Panel B: Low DIV Team and High DIV Team			
	Low DIV	High DIV	Low - High
Benchmark	-0.0026	-0.0014	-0.0012
	(-6.26)	(-3.35)	(-2.10)
CAPM	-0.0048	-0.0033	-0.0015
	(-8.50)	(-6.36)	(-1.91)
FF3	-0.0026	-0.0014	-0.0012
	(-6.73)	(-3.44)	(-2.07)
Carhart	-0.0024	-0.0015	-0.0009
	(-6.48)	(-3.82)	(-1.73)

Combined Sample Our previous analysis studies the switcher and non-switcher samples separately. In the Appendix, we report results based on the pooled sample. Our results are robust when we use the combined sample.

4.1.2 Holding-Based Risk Loadings

We merge Morningstar mutual fund data with Thomson Reuters quarterly fund holdings data. This procedure results in 2,031 matched funds for the period from 2000 to 2017. Our matched sample consists of 940 non-switchers and 1,091 switchers. The 940 non-switchers are made up of 166 solo-managed funds and 774 team-managed funds. Using the threshold on DIV from the overall data, we define high DIV and low DIV funds on the team-managed funds. Out of the 774 non-switcher teams, 348 teams have high DIV and 401 teams have low DIV. The 1,091 switchers comprise 525 funds from the high DIV group, and 547 funds from the low DIV group.

Table 5 reports our results with holding-based beta estimates under the CAPM (Table B.4.1 in the Appendix is the full table that considers all benchmark models). Overall, these results are fairly consistent with and oftentimes stronger than our previous results with regression-based beta estimates. For instance, focusing on high DIV switchers, the reduction in DRS for team-managed funds relative to solo-managed funds is 26%.[18] Our results suggest that time variability in risk estimates does not have a large impact on our results with regression-based beta estimates.

Table 5: **Decreasing Returns to Scale with Holding-Based Fund Risk Loadings and under the CAPM**

We construct fund betas based on portfolio holdings. At each quarter end, we obtain funds' portfolio holdings from Thomson Reuters. We obtain each component stock's risk loadings using daily stock returns over the past six months, and then value weight them to obtain risk loadings at the fund level. We use these loadings to obtain CAPM, Fama-French 3-factor model (FF3), and Carhart 4-factor model (Carhart) adjusted returns. We focus on CAPM for the current table — the full table that consider all four benchmark models is given in Table B.4.1 in the Appendix. We report the DRS estimates for non-switcher funds in Panel A (counterpart is Panel A and C of Table 3, for switcher funds in Panel B (counterpart is Table 4), and for combined sample in Panel C. Skill diversity (i.e., DIV) groups are formed using the full-sample cutoffs. We also report the DRS estimates for different DIV groups.

	Solo	Team	Diff	Low DIV	High DIV	Low-High
Non-switchers	-0.0086	-0.0063	-0.0023	-0.0085	-0.0060	-0.0025
	(-7.93)	(-12.32)	(-1.93)	(-12.40)	(-7.45)	(-2.34)
Switchers	-0.0066	-0.0060	-0.0007	-0.0072	-0.0049	-0.0023
	(-10.01)	(-12.41)	(-0.80)	(-10.70)	(-7.21)	(-2.38)
Combined	-0.0078	0.0065	-0.0013	-0.0081	-0.0059	-0.0022
	(-13.59)	(-17.58)	(-1.90)	(-15.97)	(-10.72)	(-2.99)

[18]The reduction ranges from 25% to 43% across the benchmark models reported in Table B.4.1 in the Appendix.

4.2 Additional Evidence

4.2.1 Evidence Based on Holdings

The empirical results above are consistent with our conjecture that funds managed by teams, especially the ones with diverse skills, can better deal with the adverse impact of larger fund size than their solo-managed peers. We attribute this reduced performance sensitivity to size to more high-quality investment ideas generated by a team of fund managers which naturally leads to less crowding. We now test this directly using portfolio holdings data. Is it the case that there are more ideas with team vs. solo-managed funds?

More ideas can be manifested via a large number of stock holdings and/or a less concentrated holdings. We consider both channels in our analysis. We define the number of unique stocks held by fund i by the end of quarter t as NS_{it}. For concentration, we use the industry concentration measure in Kacperczyk, Sialm and Zheng (2005) and denote it as IC_{it}.[19] Our hypothesis is that compared with solo-managed funds, team-managed funds increase the number of stocks NS_{it} faster while reduce industry concentration IC_{it} more in response to growth in assets.

We run the following regression with quarterly data:

$$\begin{aligned} Y_{it} = &\beta_0 + (\beta_1 + \beta_2 * Team_{it}) \log FundTNA_{it-1} \\ &+ StyleFE + YearFE + \epsilon_{it}, \end{aligned} \tag{11}$$

where the response variable Y_{it} is either the logarithm of the number of unique stocks held by fund i by the end of quarter t ($\log NS_{it}$) or industry concentration (IC_{it}), and $\log FundTNA_{it-1}$ is the logarithm of the lagged fund TNA. The dummy variable $Team_{it}$ equals 1 if the fund is under team management in the majority of months of quarter t. The style fixed effects (i.e., $StyleFE$) control for style-related investment opportunities.[20] The year fixed effects (i.e., $YearFE$) are used to control for changes in the investment opportunity over time. A fund's response to asset growth is captured by β_1 when it is under solo-management, and $(\beta_1 + \beta_2)$ when it is under team-management. Our hypothesis indicates β_2 being positive when portfolio diversification is measured by the number of unique stocks, and negative when portfolio diversification is measured by industry concentration.

[19] Industry concentration at time t for mutual fund i is defined as follows. Based on stock holdings, we calculate the value weights the fund allocates to the 10 industries (as defined in Kacperczyk, Sialm and Zheng (2005)) as $\{w_{i,j,t}\}_{j=1}^{10}$. Let the total market weights for the 10 industries be $\{\widehat{w}_{j,t}\}_{j=1}^{10}$. Then industry concentration is defined as the sum of the squared deviations of the value weights from the market weights, i.e., $IC_{it} = \sum_{j=1}^{10}(w_{i,j,t} - \widehat{w}_{j,t})^2$.

[20] We consider the same nine Morningstar investment styles as analyzed in Table B.3.1.

Table 6: **Fund diversification with managerial structure**

We analyze how quarterly portfolio diversification changes with growth in fund size under different management structure for all funds, the high DIV and low DIV subsamples, respectively. For fund i at the end of quarter t, $Team_{it}$ is a dummy variable which equals 1 if the fund is under team management in the majority of months of quarter t (and 0 otherwise), and $\log FundTNA_{it}$ is the logarithms of the TNA of the fund. The style fixed effects (i.e., $StyleFE$) control for style-related investment opportunities. The year fixed effects (i.e., $YearFE$) are used to control for changes in the investment opportunity over time. The portfolio diversification measure in Panel A is the logarithm of the number of unique stocks held by fund i by the end of quarter t. The diversification measure in Panel B is the fund's industry concentration (IC) calculated as in Kacperzyk et al. (2005). The t-statistics clustered by fund are reported in parentheses.

Panel A: Number of stocks in a fund			
	All funds	Low DIV	High DIV
$\log FundTNA_{it-1}$	0.0826***	0.1033***	0.0721***
	(9.74)	(9.93)	(5.65)
$Team_{it} * \log FundTNA_{it-1}$	0.0092**	-0.0053	0.0206***
	(2.03)	(-0.94)	(2.89)
Constant	3.8344***	3.5591***	3.9492***
	(69.71)	(48.50)	(52.39)
Style FE	yes	yes	yes
Year FE	yes	yes	yes
Observations	71,089	37,969	36,774
Adj-R^2	0.122	0.171	0.113

Panel B: Fund industry concentration			
	All funds	Low DIV	High DIV
$\log FundTNA_{it-1}$	-0.0003	-0.0005	-0.0002
	(-0.823)	(-1.120)	(-0.497)
$Team_{it} * \log FundTNA_{it-1}$	-0.000545**	-4.75E-05	-0.00137***
	(-2.475)	(-0.162)	(-4.171)
Constant	0.0263***	0.0272***	0.0293***
	(11.04)	(7.93)	(9.40)
Style FE	yes	yes	yes
Year FE	yes	yes	yes
Observations	71,089	37,969	36,774
Adj-R^2	0.064	0.05	0.082

***, **, * represent 1%, 5% and 10% level of significance under the assumption of a single test.

Table 6 reports our results. As a response to growth in assets, a fund significantly increases the number of unique stocks held. The speed of increase is higher if a fund is under team management. When splitting the funds into high DIV and low DIV subsamples, we find that the team-effect mainly comes from the high DIV group of funds, consistent with the idea that experience diversity helps reduce crowding. In terms of industry concentration, the typical response to growth in assets is a decline, albeit not significant. Further, team management is associated with a significant decline which again mainly comes from the high DIV group of funds as revealed by the subsample analysis. The economic magnitude is large as well. To ease our interpretation, we focus on the specification where the response variable is the log number of stocks. We fix the logarithm of TNA at the average level (which is 5.6 or $270 million according to Table 1). Compared with solo-management, the percentage increase in the number of stocks held when a fund is under team management is estimated to be 5.1% ($= 0.0092 * 5.6$) across all funds, and 11.5% ($= 0.0206 * 5.6$) across the high DIV group of funds.

4.2.2 Man vs. Machine

In this section, we study the differential impact of managerial structure on discretionary and systematic funds. Our focus is on systematic funds given that their algorithmically driven investment processes would seemingly have less reliance on managers to generate trade ideas. As such, it is reasonable to expect that the differences in DRS between solo-managed and team-managed systematic funds to be minimal.

Given that few mutual funds change their investment classification during their lifetime, Morningstar Direct classification snapshot should provide a reasonable approximation. Indeed, using Securities Exchange Commission (SEC)'s structured data extracted from exhibits of mutual fund prospectuses tagged in eXtensible Business Reporting Language (XBRL) from December 2010 to March 2019, we confirm that a very low percentage of funds change their investment approach (i.e., discretionary vs. systematic) throughout the period.[21]

Using the natural language processing algorithm detailed in Harvey et al. (2017), we identify 234 funds in our sample (7%) as systematic funds. Due to the limited sample, we carry out the DRS analysis by pooling non-switchers and switchers. To investigate the impact of managerial structure on the DRS estimate, we split the sample into solo-managed and team-managed fund-month observations. In terms of the fund-month observations, 32% are solo managed and 68% are team managed. We estimate constant risk loadings to calculate fund risk-adjusted returns.

[21] The SEC's structured data can be obtained from the following link: https://www.sec.gov/dera/data/mutual-fund-prospectus-risk-return-summary-data-sets. From this dataset, we obtain the principal investment strategy (PIS) section of the prospectus for all mutual funds. To ensure that we analyse the PIS section of U.S. domestic equity funds, we exclude any PIS section that mentions any of the following keywords: outside the U.S., non U.S., emerging, world, global, international, foreign, asia-pacific, bond, debt, fixed-income, municipal, treasury, exchange traded, index, passive, money market, fund of funds, target-date, commodity, commodities, derivative, short position, options, futures, swap, and forward. Out of 1,419 unique domestic equity funds, we find that 89.5% of funds are classified as discretionary and around 8.7% are classified as systematic funds. The remaining 1.8% are funds that change their investment strategies (in our context, systematic versus discretionary) throughout the period.

Table 7 reports the DRS estimates for systematic funds. Our results indicate that managerial structure does not seem to influence the DRS of systematic funds. Across the full sample, the difference in DRS between solo-managed funds and team-managed funds is insignificant, both statistically and economically.[22]

Table 7: **DRS Analysis on Systematic Funds**

This table presents the DRS estimation results for 234 funds that follow systematic investment strategies. To examine the impact of managerial structure on the DRS estimate, we split the sample into solo-managed and team-managed fund-month observations. There are 8,421 fund-month observations under solo management and 17,921 fund-month observations under team management. "Benchmark" corresponds to the case where the Morningstar designated benchmark index return is subtracted from the fund's gross return. "CAPM", "FF3", and "Carhart" adjust fund returns using the market model, Fama-French 3-factor model, and Carhart 4-factor model, respectively. The t-statistics clustered by fund are reported in the parentheses.

	Solo	Team	Diff
Benchmark	-0.0013	-0.0008	-0.0005
	(-1.41)	(-1.26)	(-0.42)
CAPM	-0.0030	-0.0017	-0.0013
	(-2.48)	(-2.75)	(-0.92)
FF3	-0.0017	-0.0009	-0.0008
	(-1.78)	(-2.07)	(-0.74)
Carhart	-0.0019	-0.0010	-0.0009
	(-2.14)	(-2.43)	(-0.89)

4.3 Further Implications

4.3.1 Capacity Change

The existence of economies or diseconomies of scale in fund management is important in both theory and practice. In theory, scale diseconomies give rise to equilibrium conditions in the market for fund management services related to the generation of active returns, as exemplified by the models of Berk and Green (2004) and Berk and van Binsbergen (2015). For industry practitioners, the idea of scale diseconomies as a fund grows in size is manifested as the concept of capacity, which is defined as the cutoff TNA below which investors expect to benefit from active management.

To quantify the degree of scale diseconomies and contrast the results under different managerial structures, we follow Berk and van Binsbergen (2015) and Zhu (2018) to calibrate the capacity change when a fund undergoes a certain change in man-

[22]Since systematic funds only represents a small fraction of our full sample of funds, results for discretionary funds are very similar to our main results. We therefore do not report them.

agerial structure. Whereas Zhu (2018) focuses on capacity for funds that belong to different size groups, we are more interested in capacity for funds that adapt different managerial structures.

We define capacity as the size which equates gross alpha with fees charged. When gross alpha is modelled as $a - b \log size$, the implied capacity (i.e., capacity that leads to a zero net alpha) is $\exp((a - f)/b)$, where f represents fund fees. A decrease in the magnitude of the DRS parameter b would lead to an increase in capacity. Our previous empirical results show b is different under different managerial structures. To capture the impact on capacity when funds change managerial structures, we need the estimates of b under both solo and team management. Unfortunately, for non-switchers we do not have the estimates of the DRS parameter under alternative managerial structures. For switchers, we focus on those with high DIV since our previous results indicate a significant change in b when a fund changes from solo management to team management.[23]

First, we aggregate the TNA of these 666 switchers and calculate the TNA-weighted fund returns for any given month. We assume the following relation holds between the aggregated fund TNA and TNA-weighted returns:

$$r_t = a - bx_{t-1} + \epsilon_t,$$

where r_t is the TNA-weighted return at time t, and x_{t-1} is the logarithm of the aggregated fund TNA at time $t-1$. We obtain the estimate for the DRS parameter b for the switchers with high DIV from Panel B in Table 4. Parameter a is obtained as

$$a = \frac{1}{T} \sum_{t=1}^{T} (r_t + bx_{t-1}).$$

The average fund fee is taken to be the TNA-weighted fund expense ratios of these 666 funds, which is about 9.6 bps per month. Notice that we use monthly fund expenses to calculate capacity in order to match the monthly return data. Table 8 reports our results that measure the change in capacity when funds switch from solo management to team management.

Regardless of the assumed risk models, the degree of diseconomies of scale is smaller under team management, as we show previously. However, a negative correlation exists between the estimates of parameter a and b, making a also smaller under team management. The overall change in capacity is estimated to be around 25% to 53% when a fund switches from solo management to team management. For the particular group of funds we focus on, the total TNA in December of 2017 stands at \$655

[23] We report in Table B.5.1 in the Appendix the results for funds with low DIV. Capacities for team-managed low DIV funds do not differ much from those of solo-managed funds, which is expected given the little difference in DRS between solo and team management with low DIV as documented in previous tables.

Table 8: **Capacity Increase for the Switcher Group with High DIV**

For the group of switchers with high DIV, this table reports the change of capacity when they switch from solo management to team management. We define capacity as the size which equates gross alpha with fees charged. When gross alpha is modeled as $a - b \log size$, the implied capacity is $\exp((a-f)/b)$, where f is fund fees. The estimate for the DRS parameter b is from Panel B in Table 4. We then estimate a given the DRS parameter b. The average fund fee is taken to be the TNA-weighted fund expense ratios of these high DIV funds, which is about 9.6 bps per month. Notice that we use monthly fund expenses to calculate capacity in order to match the monthly return data. Capacity (in billion) is calculated as $\exp((a-f)/b)$. The last column *Cap. Inc.* reports the increase in capacity when funds switch from solo management to team management. The last row shows the aggregated TNA for these switching funds with high DIV at the end of our sample period, which is December 2017. "Benchmark" corresponds to the case where the Morningstar designated benchmark index return is subtracted from the fund's gross return. "CAPM", "FF3", and "Carhart" adjust fund returns using the market model, Fama-French 3-factor model, and Carhart 4-factor model, respectively.

	Solo			Team			Cap. Inc.
	a	b	Capacity	a	b	Capacity	
Benchmark	0.0316	0.0024	348.337	0.0191	0.0014	434.273	25%
CAPM	0.0674	0.0051	455.360	0.0454	0.0033	697.514	53%
FF3	0.0333	0.0025	408.851	0.0195	0.0014	569.470	39%
Carhart	0.0333	0.0025	408.866	0.0209	0.0015	581.215	42%
Group TNA in Dec 2017 (billions)				$655.0			

billion, which indicates that the industry exceeds its capacity by $84 billion based on our average capacity estimate (i.e., the average across four benchmark models). In contrast, it would have exceeded its capacity by $250 billion if funds did not change management structure and remained solo managed.

4.3.2 Alpha Persistence

Equilibrium models such as Berk and Green (2004) offer an explanation for the lack of alpha persistence via the channel of decreasing returns to scale. In equilibrium, rational investors allocate more capital to funds that perform well in the past, and these extra funds make it more difficult for fund managers to generate positive alphas in the future due to crowding. Empirically, capital may not respond to performance fast enough to completely eliminate alphas, leaving room for short-run alpha persistence. As such, the degree of decreasing returns to scale may influence the degree of alpha persistence. We explore this idea by highlighting the difference in the degree of alpha persistence under alternative managerial structures.

In principle, one can interact our main variable of interest (i.e., managerial structure) with any alpha predictor (e.g., R-square as in Amihud and Goyenko (2013), active share as in Cremers and Petajisto (2009), etc.) that has been documented by the previous literature to show that the predictive power is enhanced by conditioning on team management (i.e., less crowding). We focus on alpha persistence (i.e., how past alphas predict future alphas) given that it has been extensively studied by the previous literature.[24]

We split fund-month observations by managerial structure and study performance persistence for solo-managed and team-managed funds separately. Previous empirical evidence demonstrates that the teams with high DIV have higher resistance to scale diseconomies. Hence, our analysis focus on performance comparison of funds managed by solo and teams with high DIV.[25]

Two approaches are available to evaluate performance persistence: the sorting approach and the regression approach. The sorting approach is not suitable for our purpose of comparing performance persistence across fund groups. While allocating funds to coarse performance groups based on in-sample performance rankings, we are unable to control for the magnitude of sorting-period alphas. This issue is important because the literature has documented that solo-managed funds tend to generate alphas with larger magnitudes in both tails of the cross-sectional alpha distribution than team-managed funds (Chen et al., 2004, Bär et al., 2011). Consistent with this literature, the summary statistics in Table 1 show that the alphas of solo-managed funds are larger than those of team-managed funds. We therefore use the regression approach to control for the sorting-period alphas.

The details of our test procedure is as follows. Following Busse, Goyal and Wahal (2010), we use benchmark-adjusted returns to estimate ranking-period alphas. Beginning at the end of 2000, we calculate the prior annual benchmark-adjusted returns at end of each month. We then calculate fund performance over the subsequent evaluation period. We consider four evaluation periods: first month, quarter, six months, and year. For each managerial structure and evaluation period combination, we only include funds with returns available throughout both the ranking period and the evaluation period under that managerial structure. For example, to estimate persistence at the six-month horizon for team-managed funds, a fund needs to be team-managed for at least 18 months (12 months for the ranking period and 6 months for the evaluation period). For each evaluation period, we run the following panel regression

$$\alpha_{i,t+k} = a_i + (\lambda_{Solo} I_{i,t}^{Solo} + \lambda_{Team} I_{i,t}^{Team})\alpha_{i,t} + \epsilon_{i,t+k}, \tag{12}$$

where $\alpha_{i,t}$ is the ranking period alpha for fund i at time t, $\alpha_{i,t+k}$ is the holding period alpha for fund i over the holding period from $t+1$ to $t+k$, a_i is the fund fixed effect, $I_{i,t}^{Solo}$ ($I_{i,t}^{Team}$) is an indicator variable that equals 1 if the fund is under solo (team)

[24]To be consistent with the majority of the literature, we use simple OLS alpha estimates to study performance persistence. See Jones and Shanken (2005) and Harvey and Liu (2018) and shrinkage-based alpha estimates.

[25]Results for teams with low DIV are reported in Table B.7.1 in the Appendix.

management and zero otherwise, and λ_{Solo} (λ_{Team}) is the corresponding persistence parameter. We report the estimates of (12) in Table 9.

Table 9: **Persistence Regressions**

We run the panel regression $\alpha_{i,t+k} = a_i + (\lambda_{Solo} I_{i,t}^{Solo} + \lambda_{Team} I_{i,t}^{Team})\alpha_{i,t} + \epsilon_{i,t+k}$ and report the estimation results for λ_{Solo} (λ_{Team}), which captures performance persistence under solo (team) management. We report results for four holding periods: the first month, the first quarter, the first six months, and the first year. Panel A, B, and C adjust fund returns by the market model ("CAPM"), Fama-French 3-factor model ("FF3"), and Carhart 4-factor model ("Carhart"). The t-statistics clustered by fund are reported in the parentheses.

Panel A: CAPM alpha				
	One month	Three months	Six months	One year
λ_{Solo}	0.0027	0.0083	0.0074	-0.0061
	(1.32)	(1.41)	(0.65)	(-0.29)
λ_{Team}	0.0051	0.0109	0.0203	0.0310
	(3.02)	(2.24)	(2.21)	(1.91)
Panel B: FF3 alpha				
	One month	Three months	Six months	One year
λ_{Solo}	-0.0010	-0.0009	-0.0159	-0.0533
	(-0.59)	(-0.19)	(-1.77)	(-3.50)
λ_{Team}	0.0031	0.0061	0.0015	-0.0150
	(2.57)	(1.75)	(0.21)	(-1.17)
Panel C: Carhart alpha				
	One month	Three months	Six months	One year
λ_{Solo}	0.0012	0.0030	-0.0061	-0.0291
	(0.74)	(0.66)	(-0.69)	(-1.98)
λ_{Team}	0.0043	0.0093	0.0097	0.0083
	(3.83)	(2.75)	(1.42)	(0.67)

We focus on the Carhart 4-factor model to interpret our results in Table 9. Previous literature documents significant short-run alpha persistence when all funds are included in the cross section. Our results show that short-run persistence is only present in team-managed funds, thereby providing a separation of performance persistence in the cross section. In particular, the parameter estimate of λ_{Team} is significant over the 1-month to 3-month horizon and has a much larger magnitude than λ_{Solo}, which is not statistically significant over any horizon.[26]

To complete our analysis, in Table B.8.1 of the Appendix, we estimate flow-performance sensitivity for solo- and team-managed funds. We find that, conditional on the same positive alpha in the past, team-managed funds attract more flows than

[26]Our results for low DIV funds in Table B.7.1 in the Appendix further shows that while there is some evidence for performance persistence for team-managed funds with a low DIV, the evidence is weaker (both in terms of statistical significance and the economic magnitude of the persistence parameter estimate) than that presented in Table 9.

their solo-managed counterparts. Therefore, holding alphas constant, if DRS were the same for both solo- and team-managed funds, the larger inflows team-managed funds attract imply that teams' performance should deteriorate more, leading to less performance persistence, which contradicts our results in Table 9.

Now combining the evidence in Table 9 and Table B.8.1 in the Appendix, we offer an explanation for our results in Table 9. Although investment skill persists to some extent, fund flows erode (if inflow) or enhance (if outflow) performance due to DRS. Importantly, DRS affects solo- and team-managed funds differently by having a larger impact on solo-managed funds. Conditional on a high alpha in the past, even though team-managed funds attract modestly higher inflows compared to solo-managed funds (based on our results in Table B.8.1), their performance still decreases less compared to solo-managed funds due to their much lower DRS. As a result, they display more performance persistence compared to their solo-managed counterparts. The higher flow-performance sensitivity for team-managed funds as documented in Table B.8.1 is consistent with the notion that rational investors partially recognize the higher capacity in absorbing capital for team-managed funds and therefore allocate more capital. However, the additional capital allocated is not enough to offset the difference in DRS between the two groups of funds, allowing team-managed funds to have more persistence in generating alphas. Therefore, different from the equilibrium outcome in Berk and Green (2004) where fund flows completely eradicate the difference in performance across funds, a partial balancing of performance due to fund flows is more consistent with our empirical findings.

Our results thus highlight the value of using predictors of DRS (fund managerial structure in our context) as a conditioning variable to enhance alpha persistence within a certain group of funds. While we focus on managerial structure in our paper, alternative predictors of DRS may exist.

5 Conclusions

Over the past 30 years, the managerial structure of the fund management industry has been dramatically transformed. Solo management once represented vast majority of funds and now it is less than 30%. At the same time, performance has eroded. Some have tried to link the shift in management structure to the decline in performance. However, establishing causality is fraught with challenges.

We take a different approach. We argue that the transformation in managerial structure (solo to team) is a natural result of crowding. Specifically, it is well established that increasing flows into existing funds will degrade performance (decreasing returns to scale). When funds flow into a solo managed fund, more money is allocated to a small set of ideas leading to deteriorated performance. However, funds that switch from solo to team managed will likely have additional ideas, putting less pressure on any existing idea.

Our empirical results are consistent with our crowding hypothesis. We find that the decreasing returns to scale are significantly less for team managed funds compared to solo-managed funds. We further test our idea with two additional experiments.

If a fund moves from solo to team but brings in a new manager that has very similar experience to the existing manager, this will unlikely provide an abundance of new ideas. We separate the teams into those with diversity of work experience and those that do not. Our results show that teams with diversity are significantly more capable of absorbing larger flows. Indeed, a shift from solo to a diversified team increases capacity by approximately 25%.

Our second experiment examines funds that follow systematic (algorithmically) driven investment strategies and those that follow discretionary stock selection methods. Algorithmically driven funds have no constraint on the number of ideas. Indeed, their models may quantitatively analyze every stock in the universe. Hence, it is reasonable to expect that there would be little or no difference between solo and team-managerial structure with respect to decreasing returns to scale in systematically oriented funds. Consistent with our hypothesis, our empirical results show no difference in decreasing returns across management structure.

Finally, we address the issue of alpha persistence. Theory such as Berk and Green (2004) suggests that investments flow into positive alpha funds driving the alpha to zero. It is an empirical question as to how fast this happens. Our results show that team managed funds exhibit some persistence. As capital flows into these team-managed funds, they are much more resilient than solo-management funds for an identical initial level of alpha.

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Appendix A: Recursive Demeaned Estimator and its Inferences

The recursively-demeaned estimator (6) can be expressed using x_{it}, $\bar{x}_{it}$, and $\bar{r}_{it}$. For fund i, denote the vectors of its forward-demeaned response, the forward-demeaned regressor, and the instrumental variable as

$$\bar{\boldsymbol{r}}_i = \begin{pmatrix} \bar{r}_{i1} \\ \bar{r}_{i2} \\ \vdots \\ \bar{r}_{iT_i-1} \end{pmatrix}, \quad \bar{\boldsymbol{x}}_i = \begin{pmatrix} \bar{x}_{i0} \\ \bar{x}_{i1} \\ \vdots \\ \bar{x}_{iT_i-2} \end{pmatrix}, \text{ and } \boldsymbol{z}_i = \begin{pmatrix} 1 & x_{i0} \\ 1 & x_{i1} \\ \vdots & \\ 1 & x_{iT_i-2} \end{pmatrix}.$$

The bias-corrected estimator is

$$\hat{b}_{RD} = \left(\sum_{i=1}^{N} \bar{\boldsymbol{x}}_i' \boldsymbol{z}_i (\boldsymbol{z}_i' \boldsymbol{z}_i)^{-1} \boldsymbol{z}_i' \bar{\boldsymbol{x}}_i \right)^{-1} \left(\sum_{i=1}^{N} \bar{\boldsymbol{x}}_i' \boldsymbol{z}_i (\boldsymbol{z}_i' \boldsymbol{z}_i)^{-1} \boldsymbol{z}_i' \bar{\boldsymbol{r}}_i \right). \tag{13}$$

To perform inference for the recursively-demeaned estimator, we calculate its variance clustered by fund as

$$\text{var}(\hat{b}_{RD}) = (\Omega_{xx})^{-1} \Phi_{ux} (\Omega_{xx})^{-1}, \tag{14}$$

where $\Omega_{xx} = \sum_{i=1}^{N} \sum_{t=1}^{T_i-1} \bar{x}^{*\prime}_{it-1} \bar{x}^{*}_{it-1}$ and $\Phi_{ux} = \sum_{i=1}^{N} \sum_{t=1}^{T_i-1} \sum_{s=1}^{T_i-1} (\bar{x}^{*\prime}_{it-1} \hat{\bar{\epsilon}}_{it})(\bar{x}^{*\prime}_{is-1} \hat{\bar{\epsilon}}_{is})'$. Note that $\hat{\bar{\epsilon}}_{it} = \bar{y}_{it} - \hat{b}_{RD} \bar{x}_{it-1}$. The t test and Wald test based on $\text{var}(\hat{b}_{RD})$ satisfy the usual properties.

Appendix B: Additional Results

Appendix B.1: Cross-sectional Characteristics of the Equity Mutual Fund Sample from 1992 to 2017

Table B.1.1: **Characteristics of Solo-Managed and Team-Managed Funds.**

The table presents summary statistics for solo-managed and team-managed funds. The sample period is from January 1992 to December 2017. The unit of observation is the fund/month. All returns (alphas) and expense ratios are annual figures. *Benchmark_adj_ret* is constructed by subtracting the Morningstar designated benchmark index return from the fund's gross return. *CAPM alpha*, *FF3 alpha* and *Carhart alpha* are risk adjusted returns using the market factor model, Fama-French 3-factor model, and Carhart 4-factor model, respectively. *Fund TNA* is the total net assets under management of a fund in millions of dollars. *Family TNA* is the total net assets under management of the fund complex to which the fund belongs in millions of dollars. Both fund and fund family TNA numbers are inflation-adjusted to January 2017 dollars. *Turnover* is defined as the minimum of aggregate purchases and sales divided by the average annual fund TNA in percentage. *Fund Age* is the time in years since the fund's inception date. *Ind Tenure* is the number of years the fund manager has been within the fund industry. *DIV* is a measure of team skill diversity.

				Quantile				
	Fund/ Month	Mean	Std. dev.	1%	25%	50%	75%	99%
Panel A: Solo-managed funds								
Benchmark adj ret (%)	185,830	0.53	27.51	-75.93	-11.21	0.12	11.64	83.24
CAPM alpha (%)	185,830	0.86	30.94	-83.96	-12.51	0.31	13.54	90.40
FF3 alpha (%)	185,830	0.42	24.32	-66.31	-10.80	0.21	11.33	70.74
Carhart alpha (%)	185,830	0.43	23.40	-63.29	-10.56	0.24	11.10	67.58
Fund TNA ($ mil)	185,830	1,541	5,545	5	63	237	963	23,203
Log fund TNA	185,830	5.52	1.93	1.60	4.15	5.47	6.87	10.05
Expense ratio (%)	177,564	1.25	0.60	0.17	0.94	1.19	1.49	2.87
Turnover (%)	165,892	85	80	2	32	60	109	423
Fund Age (years)	185,830	13.32	13.67	0.41	4.36	9.25	16.79	68.18
Family TNA ($ mil)	179,907	66,466	158,724	9	666	7,241	35,981	714,358
Ind Tenure (years)	185,830	9.57	6.57	0.42	4.33	8.25	13.67	26.33
Panel B: Team-managed funds								
Benchmark adj ret (%)	319,817	0.23	22.11	-60.61	-9.66	-0.03	9.61	65.07
CAPM alpha (%)	319,817	0.60	26.68	-70.88	-11.49	0.16	12.04	77.65
FF3 alpha (%)	319,817	0.30	20.13	-54.26	-9.51	0.14	9.91	57.58
Carhart alpha (%)	319,817	0.26	19.41	-52.48	-9.40	0.15	9.76	55.12
Fund TNA ($ mil)	319,817	1,540	6,169	7	71	270	1,000	22,092
Log fund TNA	319,817	5.61	1.85	1.89	4.27	5.60	6.91	10.00
Expense ratio (%)	308,228	1.18	0.42	0.25	0.94	1.14	1.39	2.37
Turnover (%)	292,278	77	64	2	33	61	100	341
Fund Age (years)	319,817	13.34	12.81	0.44	4.89	9.96	17.31	69.30
Family TNA ($ mil)	315,352	36,462	112,861	14	991	10,082	31,143	645,858
Ind Tenure (years)	312,595	8.82	4.66	0.81	5.33	8.36	11.69	22.21
Skill diversity (DIV)	311,213	0.24	0.26	0.00	0.00	0.22	0.50	0.77

Appendix B.2: Alternative Team Size Categorization

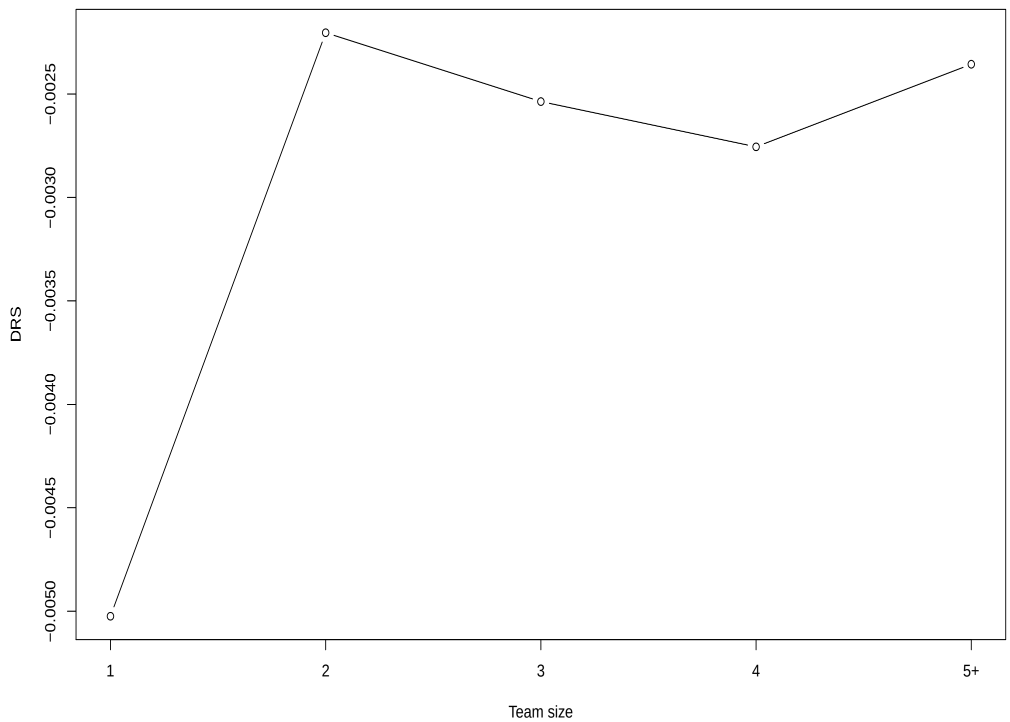

Figure B.2.1: **Non-switcher DRS Estimates Conditional on Team Size.** This figure plots the DRS estimates based on the Morningstar benchmark-adjusted returns. We calculate the average team size for non-switchers in our sample (308 solo funds and 1310 team funds). Among team funds, the distribution of team size is: 453 teams have 2 managers, 345 have 3 managers, 199 have 4 managers, and 313 have 5 or more managers.

Appendix B.3: Pooled Sample and by Fund Style

Table B.3.1 presents the style decomposition for solo- and team-managed funds. Table B.3.2 reports the DRS estimates for the pooled sample (i.e., switcher and non-switcher funds combined) and three style subsamples classified by fund size.

Table B.3.1: **Composition of Investment Styles for Non-Switchers.**

This table reports the proportion of non-switching funds that belong to different investment styles. The investment style follows Morningstar nine investment categories.

	Large Blend	Large Growth	Large Value	Mid Blend	Mid Growth	Mid Value	Small Blend	Small Growth	Small Value
Solo (%)	17.5	21.6	15.3	5.9	9.0	4.2	9.5	12.1	5.0
Team (%)	17.9	19.6	17.3	5.1	10.6	6.2	7.6	9.8	5.9

Table B.3.2: **DRS Conditional on Fund Style**

This table presents DRS estimation results for switchers and nonswitchers combined sample. Columns 2-4 present DRS estimation results under solo-management, team-management, and the difference (Diff = Solo - Team). Columns 5-7 present DRS estimation results for teams with low and high diversity, and the corresponding difference (Low-High). Panel A is for the full combined sample. Panel B, C and D are results conditional on fund style. Due to a fund can switch its investment style over time, the summation of the funds by style are larger than the total number of funds in the sample. "Benchmark" corresponds to the case where the Morningstar designated benchmark index return is subtracted from the fund's gross return. "CAPM", "FF3", and "Carhart" adjust fund returns using the market model, Fama-French 3-factor model, and Carhart 4-factor model, respectively. The t-statistics clustered by fund are reported in the parentheses.

	Solo	Team	Diff	Low DIV	High DIV	Low-High
Panel A: Combined funds (2975 funds)						
	(-6.37)	(-11.25)	(-2.16)	(-10.36)	(-5.49)	(-3.55)
CAPM	-0.0064	-0.0044	-0.0020	-0.0053	-0.0034	-0.0019
	(-10.50)	(-16.79)	(-3.07)	(-14.07)	(-9.57)	(-3.65)
FF3	-0.0039	-0.0023	-0.0016	-0.0029	-0.0018	-0.0011
	(-7.24)	(-12.64)	(-2.77)	(-11.50)	(-6.52)	(-3.06)
Carhart	-0.0037	-0.0023	-0.0014	-0.0029	-0.0018	-0.0011
	(-7.32)	(-12.91)	(-2.59)	(-11.66)	(-6.80)	(-2.99)
Panel B: Fund style – large cap (1775 funds)						
	Solo	Team	Diff	Low DIV	High DIV	Low-High
Benchmark	-0.0021	-0.0021	0.0000	-0.0031	-0.0016	-0.0015
	(-3.78)	(-7.08)	(0.06)	(-6.88)	(-3.86)	(-2.52)
CAPM	-0.0027	-0.0018	-0.0008	-0.0029	-0.0011	-0.0017
	(-4.49)	(-6.13)	(-1.27)	(-5.96)	(-2.82)	(-2.77)
FF3	-0.0019	-0.0017	-0.0002	-0.0025	-0.0012	-0.0013
	(-3.94)	(-6.80)	(-0.31)	(-6.53)	(-3.45)	(-2.41)
Carhart	-0.0018	-0.0017	-0.0001	-0.0025	-0.0012	-0.0013
	(-3.88)	(-7.10)	(-0.11)	(-7.00)	(-3.58)	(-2.63)
Panel C: Fund style – mid cap (895 funds)						
	Solo	Team	Diff	Low DIV	High DIV	Low-High
Benchmark	-0.0059	-0.0014	-0.0045	-0.0017	-0.0009	-0.0008
	(-3.42)	(-3.91)	(-2.55)	(-3.90)	(-1.55)	(-1.07)
CAPM	-0.0131	-0.0050	-0.0082	-0.0057	-0.0037	-0.0020
	(-4.65)	(-8.42)	(-2.84)	(-7.07)	(-4.60)	(-1.72)
FF3	-0.0068	-0.0025	-0.0044	-0.0031	-0.0021	-0.0010
	(-4.01)	(-6.65)	(-2.51)	(-6.02)	(-3.36)	(-1.24)
Carhart	-0.0065	-0.0023	-0.0041	-0.0031	-0.0021	-0.0010
	(-4.02)	(-6.68)	(-2.51)	(-6.11)	(-3.35)	(-1.25)
Panel D: Fund style – small cap (778 funds)						
	Solo	Team	Diff	Low DIV	High DIV	Low-High
Benchmark	-0.0071	-0.0026	-0.0045	-0.0036	-0.0014	-0.0023
	(-4.35)	(-6.63)	(-2.67)	(-5.95)	(-2.88)	(-2.96)
CAPM	-0.0137	-0.0061	-0.0076	-0.0067	-0.0054	-0.0013
	(-5.66)	(-9.79)	(-3.05)	(-7.40)	(-6.57)	(-1.09)
FF3	-0.0089	-0.0027	-0.0062	-0.0031	-0.0016	-0.0015
	(-4.28)	(-6.76)	(-2.92)	(-5.80)	(-3.32)	(-2.04)
Carhart	-0.0085	-0.0027	-0.0057	-0.0028	-0.0018	-0.0011
	(-4.40)	(-6.80)	(-2.91)	(-5.58)	(-3.72)	(-1.56)

Appendix B.4: Analysis Using Holding-Based Risk Loadings

Table B.4.1: **Decreasing Returns to Scale with Holding-Based Fund Risk Loadings.**

We construct fund betas based on portfolio holdings. At each quarter end, we obtain funds' portfolio holdings from Thomson Reuters. We obtain each component stock's risk loadings using daily stock returns over the past six months, and then value weight them to obtain risk loadings at the fund level. We use these loadings to obtain CAPM, Fama-French 3-factor model (FF3), and Carhart 4-factor model (Carhart) adjusted returns. We report the DRS estimates for non-switcher funds in Panel A (counterpart is Panel A and C of Table 3, for switcher funds in Panel B (counterpart is Table 4), and for combined sample in Panel C. Skill diversity (i.e., DIV) groups are formed using the full-sample cutoffs. We also report the DRS estimates for different DIV groups.

	Panel A: Non-switchers (940 funds)					
	Solo	Team	Diff	Low DIV	High DIV	Low-High
Benchmark	-0.0049	-0.0034	-0.0015	-0.0036	-0.0023	-0.0013
	(-6.11)	(-10.25)	(-1.76)	(-8.35)	(-4.27)	(-1.84)
CAPM	-0.0086	-0.0063	-0.0023	-0.0085	-0.0060	-0.0025
	(-7.93)	(-12.32)	(-1.93)	(-12.40)	(-7.45)	(-2.34)
FF3	-0.0060	-0.0035	-0.0025	-0.0040	-0.0027	-0.0013
	(-6.35)	(-10.35)	(-2.47)	(-9.19)	(-4.74)	(-1.90)
Carhart	-0.0075	-0.0046	-0.0030	-0.0049	-0.0033	-0.0016
	(-7.20)	(-11.98)	(-2.67)	(-10.13)	(-5.26)	(-2.00)
	Panel B: Switchers (1091 funds)					
	Solo	Team	Diff	Low DIV	High DIV	Low-High
Benchmark	-0.0032	-0.0027	-0.0006	-0.0036	-0.0019	-0.0017
	(-6.78)	(-7.57)	(-0.98)	(-7.11)	(-3.68)	(-2.42)
CAPM	-0.0066	-0.0060	-0.0007	-0.0072	-0.0049	-0.0023
	(-10.01)	(-12.41)	(-0.80)	(-10.70)	(-7.21)	(-2.38)
FF3	-0.0033	-0.0025	-0.0008	-0.0033	-0.0019	-0.0013
	(-6.42)	(-6.65)	(-1.21)	(-6.12)	(-3.67)	(-1.77)
Carhart	-0.0038	-0.0029	-0.0009	-0.0037	-0.0023	-0.0014
	(-7.01)	(-7.30)	(-1.37)	(-6.21)	(-4.25)	(-1.69)
	Panel C: Combined sample (2031 funds)					
	Solo	Team	Diff	Low DIV	High DIV	Low-High
Benchmark	-0.0038	-0.0031	-0.0007	-0.0036	-0.0023	-0.0014
	(-8.97)	(-12.32)	(-1.44)	(-10.77)	(-5.96)	(-2.71)
CAPM	-0.0078	0.0065	-0.0013	-0.0081	-0.0059	-0.0022
	(-13.59)	(-17.58)	(-1.90)	(-15.97)	(-10.72)	(-2.99)
FF3	-0.0041	-0.0030	-0.0011	-0.0035	-0.0024	-0.0011
	(-8.61)	(-11.62)	(-2.01)	(-10.16)	(-6.29)	(-2.10)
Carhart	-0.0055	-0.0037	-0.0018	-0.0044	-0.0029	-0.0015
	(-10.63)	(-13.07)	(-3.01)	(-11.41)	(-6.96)	(-2.60)

Appendix B.5: Capacity Change for Low DIV Switchers

This appendix presents results on capacity change for the group of switchers with low DIV.

We aggregate the TNA of these 666 switchers with low DIV and calculate the TNA-weighted fund returns for any given month. The average fund fee for this group is taken to be the TNA-weighted fund expense ratios of these 666 funds, which is about 10.0 bps per month. We use the estimates for the DRS parameter b for the switchers with low DIV from Panel B in Table 4. The parameter a given the DRS parameter b is estimated following the procedures in Section 4.3.1.

Table B.5.1 reports the change in capacity when low DIV funds switch from solo management to team management. Since the values of DRS stay essentially the same for low DIV funds under different managerial structures, the capacity change associated with switching is minimal.

Table B.5.1: **Capacity Increase for the Switcher Group with Low DIV**

For the group of switchers with low DIV, this table reports the change of capacity when they switch from solo management to team management. We define capacity as the size which equates gross alpha with fees charged. When gross alpha is modeled as $a - b \log size$, the implied capacity is $\exp((a - f)/b)$, where f is fund fees. The estimate for the DRS parameter b is from Panel B in Table 4. We then estimate a given the DRS parameter b. The average fund fee is taken to be the TNA-weighted fund expense ratios of these low DIV funds, which is about 10.0 bps per month. Notice that we use monthly fund expenses to calculate capacity in order to match the monthly return data. Capacity (in billion) is calculated as $\exp((a - f)/b)$. The last column *Cap. Inc.* reports the increase in capacity when funds switch from solo management to team management. The last row shows the aggregated TNA for these switching funds with low DIV at the end of our sample period, which is December 2017. "Benchmark" corresponds to the case where the Morningstar designated benchmark index return is subtracted from the fund's gross return. "CAPM", "FF3", and "Carhart" adjust fund returns using the market model, Fama-French 3-factor model, and Carhart 4-factor model, respectively.

	Solo			Team			Cap. Inc.
	a	b	Capacity	a	b	Capacity	
Benchmark	0.0313	0.0024	533.641	0.0347	0.0026	530.140	-1%
CAPM	0.0672	0.0051	561.302	0.0630	0.0048	565.874	1%
FF3	0.0334	0.0025	622.042	0.0349	0.0026	616.245	1%
Carhart	0.0332	0.0025	626.315	0.0327	0.0024	628.655	0%
Group TNA in Dec 2017 (billions)				$730.0			

Appendix B.6: Education

This section investigates whether team education diversity — another diversity measure that is distinct from skill diversity — affects DRS. The information on the educational backgrounds of mutual fund managers are obtained from Morningstar Direct database. It includes: (1) the highest degree qualification obtained by the fund manager, (2) the corresponding year when the degree was obtained, (3) the most recent university attended by the fund manager, and (4) the education major pursued by the fund manager. In this study, we categorize educational background based on the eleven broad field categories as specified in the International Standard Classification of Education (ISCED).[27] Out of the 5,915 fund managers with education data, we find 71.7% had business, administration or law background followed by social sciences, journalism, and information (15.4%), arts and humanities (4.9%), natural sciences, mathematics and statistics (4.7%), and the remaining categories. We use Blau's index to measure intra-team education diversity (EDU).

We are somewhat constrained by the education information available. For non-switchers, we have education information for 669 out of the 1,310 team-managed funds. Most teams have no diversity in terms of education, with EDU being strictly 0. We therefore divide funds into the group with education diversity (EDU > 0, 264 funds) and the group without education diversity (EDU $= 0$, 405 funds). For switchers, we have education information for 549 out of 1,347 funds. We further divide these 549 funds into the group with education diversity (EDU > 0, 143 funds) and the group without diversity (EDU $= 0$, 406 funds).

We investigate whether DRS interacts with EDU. Table B.6.1 presents the DRS estimation results for non-switchers (Panel A) and switchers (Panel B). Unlike DIV, EDU does not seem to influence fund DRS. In particular, funds with a high EDU do not seem to exhibit a difference DRS than funds with a low EDU. We therefore conclude that investment-specific skill diversity, rather than diversity in general, makes funds better by reducing the DRS.

[27] See http://uis.unesco.org/en/topic/international-standard-classification-education-isced. The board field categories include: (1) generic programmes and qualifications; (2) education; (3) arts and humanities; (4) social sciences, journalism and information; (5) business, administration and law; (6) natural sciences, mathematics and statistics; (7) information and communication technologies; (8) engineering, manufacturing and construction; (9) agriculture, forestry, fisheries and veterinary; (10) health and welfare; and (11) services.

Table B.6.1: **Intra-Team Education Diversity (EDU) and DRS**

This table presents DRS estimation results for team-managed funds conditional on education diversity (EDU). Panel A is for team-managed non-switchers. These funds are divided by education diversity (EDU) of teams into low EDU teams (405 funds) and high EDU teams (264 funds). The corresponding DRS and the difference (Diff = Low - High) are presented. Panel B is for switchers when they are under team management. Again, these funds are divided by education diversity (EDU) of teams into low EDU teams (406 funds) and high EDU teams (143 funds). The corresponding DRS parameters and their difference are presented. "Benchmark" corresponds to the case where the Morningstar designated benchmark index return is subtracted from the fund's gross return. "CAPM", "FF3", and "Carhart" adjust fund returns using the market model, Fama-French 3-factor model, and Carhart 4-factor model, respectively. The t-statistics clustered by fund are reported in the parentheses.

	Panel A: Non-switching teams		
	Low EDU (405 funds)	High EDU (264 funds)	Diff
Benchmark	-0.0026	-0.0020	-0.0006
	(-5.92)	(-3.54)	(-0.90)
CAPM	-0.0046	-0.0051	0.0005
	(-7.63)	(-5.79)	(0.48)
FF3	-0.0028	-0.0025	-0.0003
	(-6.78)	(-4.57)	(-0.48)
Carhart	-0.0027	-0.0026	-0.0001
	(-6.72)	(-5.00)	(-0.18)
	Panel B: Switching teams		
	Low EDU (406 funds)	High EDU (143 funds)	Diff
Benchmark	-0.0025	-0.0021	-0.0004
	(-4.08)	(-2.77)	(-0.42)
CAPM	-0.0046	-0.0055	0.0009
	(-6.49)	(-3.92)	(0.57)
FF3	-0.0028	-0.0020	-0.0008
	(-5.05)	(-2.28)	(-0.72)
Carhart	-0.0026	-0.0022	-0.0003
	(-4.89)	(-2.55)	(-0.33)

Appendix B.7: Alpha Persistence

Table B.7.1: **Persistence Regressions: Solo vs. Low DIV funds**

We run the panel regression $\alpha_{i,t+k} = a_i + (\lambda_{Solo} I_{i,t}^{Solo} + \lambda_{Team} I_{i,t}^{Team})\alpha_{i,t} + \epsilon_{i,t+k}$ and report the estimation results for λ_{Solo} (λ_{Team}), which captures performance persistence under solo (team) management. We report results for four holding periods: the first month, the first quarter, the first six months, and the first year. Panel A, B, and C adjust fund returns by the market model ("CAPM"), Fama-French 3-factor model ("FF3"), and Carhart 4-factor model ("Carhart"). The t-statistics clustered by fund are reported in the parentheses.

Panel A: CAPM alpha				
	One month	Three months	Six months	One year
Solo	0.0022	0.0073	0.0062	-0.0110
	(1.06)	(1.23)	(0.55)	(-0.52)
Team	0.0034	0.0100	0.0189	0.0209
	(2.40)	(2.39)	(2.32)	(1.37)
Panel B: FF3 alpha				
	One month	Three months	Six months	One year
Solo	-0.0017	-0.0024	-0.0183	-0.0603
	(-0.98)	(-0.50)	(-2.00)	(-3.98)
Team	0.0008	0.0029	-0.0038	-0.0305
	(0.66)	(0.87)	(-0.60)	(-2.49)
Panel C: Carhart alpha				
	One month	Three months	Six months	One year
Solo	0.0006	0.0017	-0.0081	-0.0361
	(0.34)	(0.36)	(-0.92)	(-2.46)
Team	0.0024	0.0067	0.0064	-0.0006
	(2.16)	(2.18)	(1.06)	(-0.05)

Appendix B.8: Fund Flow-Performance Sensitivity

We study the relation between fund flows and fund characteristics (including managerial structure and past returns) by running the following linear regression model

$$\begin{aligned} Flow_{it+k} =& \beta_1 Team_{it} + \beta_2 \alpha_{it} + \beta_3 Team_{it} * \alpha_{it} + \beta_4 \log FundAge_{it} + \beta_5 risk_{it} \\ & + \beta_6 expense_{it} + \beta_7 \log FundTNA_{it-1} + \beta_8 \log FamTNA_{it-1} \\ & YearFE + FundFE + \epsilon_{it}, \end{aligned} \tag{15}$$

where $Flow_{it+k}$ represents the net percentage TNA growth for fund i in the period from t to $t+k$.[28] We consider $k = 1, 3, 6$, and 12, corresponding to one month, one quarter, six months, and one year. The dummy variable $Team_{it}$ equals 1 if the fund is under team management during the period $t-12$ to $t+k$. The fund return α_{it} is the morningstar benchmark adjusted returns in the previous 12 months leading up to t for fund i. The variable $risk_{it}$ captures riskiness of fund alpha, which is calculated as the standard deviation of previous 12 monthly benchmark-adjusted fund returns. The variables $\log FundAge_{it}$, $expense_{it}$, $\log FundTNA_{it}$ and $logFamTNA_{it-1}$ are the logarithm of fund age, fund expense, the logarithm of the fund TNA and the fund family TNA. The fund fixed effects control for fund-related flow differences. The year fixed effects are used to control for changes in fund flows over time.

Table B.8.1 reports the estimation results. Across all four fund flow periods considered, we can see that holding historical fund alpha constant, team managed funds attract significantly more inflows as indicated by the estimated coefficients for the interaction term $Team_{it} * \alpha_{it}$.

[28] Fund flow is defined as the net growth in fund assets beyond reinvested dividends. Formally, it is calculated as $Flow_{it} = \frac{TNA_{it}}{TNA_{it-1}} - (1 + R^n_{it})$.

Table B.8.1: **Flow-Performance Sensitivity**

We analyze the link between flows and various fund characteristics using the regression model (15). The variable $Flow_{it+k}$ represents the net percentage growth for fund i in the period from t to $t+k$. We consider $k = 1, 3, 6$, and 12, corresponding to one month, one quarter, six months and one year period. The dummy variable $Team_{it}$ equals 1 if the fund is under team management during the period $t-12$ to $t+k$. The fund return α_{it} is the morningstar benchmark adjusted returns in the previous 12 months leading upto t for fund i. The variable $risk_{it}$ captures riskiness of fund alpha, which is calculated as the standard deviation of previous 12 monthly benchmark-adjusted fund returns. The variables $\log FundAge_{it}$, $expense_{it}$, $\log FundTNA_{it}$ and $logFamTNA_{it-1}$ are the logarithm of fund age, fund expense, the logarithm of the fund TNA and the fund family TNA. The fund fixed effects control for fund-related flow differences. The year fixed effects are used to control for changes in the fund flows over time. The t-statistics clustered by fund are reported in parentheses.

	$Flow_{it+1}$	$Flow_{it+3}$	$Flow_{it+6}$	$Flow_{it+12}$
$Team_{it}$	-0.0017	-0.0055	-0.0127	-0.0435*
	(-1.59)	(-1.58)	(-1.51)	(-1.70)
α_{it}	0.0955***	0.2860***	0.5396***	0.8207***
	(14.54)	(13.97)	(12.63)	(9.17)
$Team_{it} * \alpha_{it}$	0.0310***	0.1010***	0.2187***	0.5841***
	(3.23)	(3.24)	(3.01)	(3.27)
$\log FundAge_{it}$	-0.0203***	-0.0568***	-0.1054***	-0.1890***
	(-15.46)	(-13.51)	(-10.87)	(-7.03)
$risk_{it}$	0.0685*	0.2742**	0.6296**	1.9926**
	(1.677)	(2.068)	(2.055)	(2.542)
$Expense_{it}$	-0.0538***	-0.1841***	-0.3725**	-0.6428
	(-2.78)	(-2.68)	(-2.16)	(-1.17)
$\log FundTNA_{it}$	-0.0056***	-0.0226***	-0.0637***	-0.2021***
	(-9.10)	(-10.37)	(-11.49)	(-11.74)
$\log FamTNA_{it}$	0.0010	0.0025	0.0024	-0.0100
	(1.13)	(0.86)	(0.32)	(-0.44)
Year FE	yes	yes	yes	yes
Fund FE	yes	yes	yes	yes
Observations	185,612	179,119	169,543	151,004
R2-Adj	0.102	0.207	0.274	0.336

***, **, * represent 1%, 5% and 10% level of significance.

Appendix C: FAQ

- *Do internally promoted managers count as new managers?*

  Yes. For example, if an analyst is promoted to a fund manager, she will be treated as a new manager by our definition. This is because we only have fund manager information, but not other personnel. Before the analyst becomes a manager, she was not in our database. Only when she got promoted did we identify her name and classify her as a "new" manager even though she was not really new to the fund.