Crowding: Evidence from Fund Managerial Structure

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Abstract

Over the past 30 years, a striking evolution in fund management structure has taken place, with the proportion of team-managed funds growing from 33% to over 70%. While many focus on the potential link to declining fund performance, our paper presents evidence that the shift to team management is likely a response to crowding: adding new managers brings fresh investment ideas which implies that any individual idea is less crowded. Our results show that funds that transition 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 the performance of managers who employ systematic investment processes is not as sensitive to inflows, suggesting 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, diversity, 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. Although average performance has declined, drawing a causal link to management structure is difficult.

We examine a number of explanations for the drift in management structure and take a different empirical strategy. 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. Hence, we focus on decreasing returns to scale (DRS)-—the tendency for performance to be eroded as funds get more inflows. Indeed, our evidence suggests team-managed funds are able to absorb significantly more inflows than solo-managed funds without diminishing performance. Importantly, we show the composition of the team is crucial. Consistent with the crowding idea, teams with diversified skills have the lowest DRS.

Evidence overwhelmingly shows average fund performance has declined over our sample period. While some researchers 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. A selection bias exists. Solo management was popular in the 1980s and 1990s—exactly when plenty of alpha was available.[2] Although a negative correlation exists 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 the following:[3]

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, keeping track of a growing number of companies is physically difficult for any one person.

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.

Mitigation of Lone Wolf risk. With more than one manager, any one manager is likely to breach a fund's risk limits. An interesting recent example was the departure of star Investco manager Neil Woodford to start his own solo-managed fund. The new fund failed spectacularly after gathering over $13 billion in investor money as a result of the manager taking oversized bets on illiquid securities.

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 the individual manager's human capital faces less risk.

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.

[3] Several advantages listed below are discussed in the existing literature. Sharpe (1981) argues team management may offer benefits from specialization of team members and diversification among managers. Barry and Starks (1984) reason that team management can reduce the agency problem between investors and managers. Sah and Stiglitz (1991) argue teams in the fund management industry achieve a diversification of style and judgment that can lead to better performance. Indeed, Patel and Sarkissian (2017) show team-managed funds take on no more risk than solo-managed funds but generate better performance. Bär et al. (2011) point out that team opinion is the average opinion of the team members and hence is more diversified than each member's opinion. However, they do not find opinion diversification leads to outperformence. Fedyk et al. (2018) claim teamwork helps offset individual overconfidence, and hence mitigates excessive performance-induced trading. Patel and Sarkissian (2021) show the team structure deters mutual fund managers from engaging in deceptive and unlawful behaviors such as portfolio pumping. Massa et al. (2010) state that a key reason for fund families to adopt team management is to retain talents and reduce the fund outflow risk during managerial turnover.

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 as the reputation is shared by team members. Hence, a team structure is a natural response of the fund family to retain their best managers.

However, disadvantages also exist.[4]

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

Expenses. Two high-quality managers are more expensive 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 share it 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. Although 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 teams with a higher level of intra-team experience diversity (termed experience diversity, which constitutes the first type of diversity we study) exhibit more resistance to the erosive performance effect of size.

To provide further evidence, we split our sample based on two alternative criteria: educational diversity and strategy automacy. Educational diversity measures diversity in team members' educational backgrounds and represents a different notion of diversity than experience diversity. We find that among team-managed funds, educa-

[4]A number of studies document the disadvantages of team management. For instance, Besedes et al. (2011) show group membership introduces a free-riding incentive and reduces effort. Chen et al. (2004) attribute the erosion of the fund performance when fund size grows to coordination costs among larger management teams. Prather and Middleton (2002) find no evidence that teams make better decisions due to various organizational costs. In the framework of Han et al. (2017), high-ability managers opt for single management, whereas low-ability managers opt for team management. Massa et al. (2010) also recognize managers may prefer a single-management structure.

tional diversity, in contrast to experience 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. Our results thus shed light on the particular form of organizational diversity that contributes to organizational performance.

On strategy automacy, we contrast discretionary and systematic funds (i.e., funds that are driven by systematic investment processes and are less reliant on individual ideas). 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 systematic investment managers have lower decreasing returns to scale—again, consistent with the notion of the crowding of ideas.

To identify the source of the difference in scale diseconomies between solo- and team-managed funds, we use the model in Pástor et al. (2020) and decompose a fund's trading costs—which is arguably the main source of decreasing returns to scale—into its turnover and portfolio liquidity, where portfolio liquidity can be further decomposed into stock liquidity and diversification. We show portfolio liquidity, in particular, diversification, is the main driver for teams' dampened response to increases in assets under management. We further show that teams that feature more experience diversity have a larger increase in portfolio diversification in response to capital inflows, consistent with our results of how intra-team experience diversity affects fund returns.

We present two important applications that build on our analysis of DRS. 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. For solo-managed funds, our analysis indicates no evidence of performance persistence at all.

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.[5] 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. Existing papers show considerable disagreement. 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.[6] 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.

Although 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 for two reasons. First, diseconomies of scale is of first-order importance in driving fund performance (as shown by the previous literature, both theoretically and empirically). Second, as opposed to the cross-sectional correlation between fund characteristics and performance, their

[5]For example, see Chen, Hong, Huang and Kubik (2004), Pástor and Stambaugh (2012), Pastor, Stambaugh, and Taylor (2015), Harvey and Liu (2016), and Zhu (2018).

[6]For additional work on the relation between fund performance and management structure, see Prather et al. (2004), 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).

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.[7] 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 empirically relevant because 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 experience 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.[8]

Our paper is organized as follows. In Section II, we describe our data. Section III presents our model. Our main results are presented in Section IV. We discuss several important implications of our results in Section V. Some concluding remarks are offered in the final section.

2 Data

2.1 Mutual Fund Data and Return Measures

Our data come from two different sources. We rely on the Morningstar Direct Mutual Fund (MDMF) database for information on fund size, fund returns, composition of fund managers, and other fund characteristics. We apply standard filters to MDMF to focus on domestic equity funds. Following the prior literature, we classify funds as solo managed when we are able to identify one manager name and as team managed

[7]For example, see 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).

[8]See, for example, Hoffman 1959, Hoffman and Maier, 1961, Bantel and Jackson, 1989, Buyl, et al., 2011, Tekleab, et al., 2016, and Bromiley and Rau, 2016.

when more than one manager is listed. To examine the driver of DRS, we obtain fund portfolio holdings data from Thomson Reuters Mutual Fund Holdings database to construct measures related to portfolio liquidity, diversification, and stock liquidity. We provide details of our data construction in Appendix A.

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)).[9]

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.

2.2 Team diversity measures

Intra-team experience diversity (DIV) We propose a novel diversity measure that is constructed based on the average pairwise correlation in returns among the various team members' previous funds.[10] We first obtain the managers' employment

[9]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.

[10]We thank Luke Taylor for suggesting the return-based diversity measure.

histories starting from year 1980.[11] We then construct the asset-weighted return series for an individual fund manager based on funds that are being managed throughout her employment history. Next, we calculate the pairwise correlations between various team members in a given fund based on their previous overlapping return series. For example, in a team of four fund managers, we would have six pairs, resulting in six correlation measures. To ensure we capture meaningful correlations of return series between fund managers, we require at least six observations of previous overlapping return series for each pair. To capture potential nonlinear return dependence, we use the Hoeffding dependence coefficient (Hoeffding (1948)), which is a rank-based nonparametric correlation measure that takes values in $(-0.5, 1)$.[12] Finally, we take the average pairwise correlation to form our main proxy for diversity.[13] A low (high) correlation indicates high (low) previous diversity of experience.

We also propose an alternative DIV measure based on the eight Morningstar-designated major investment categories (e.g., Allocation, Alternative, International Equity, etc.) and corresponds to Blau's index among team members. It is thus similar to how we construct the intra-team education diversity measure as explained below. We leave the details of its construction to the Internet Appendix. Our results on the impact of experience diversity are robust to alternative ways of constructing the DIV measure.

Intra-team education diversity (EDU) The information on the educational backgrounds of mutual fund managers is obtained from the 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 11 broad field categories as specified in the International Standard Classification of Education (ISCED).[14] Out of the 5,915 fund managers with education data, we find 71.7% had a

[11] We focus on fund managers' employment histories starting from 1980 because there is only 1.06% (244 out of 23,037) of all fund managers having a starting employment date prior to 1980.

[12] To check for robustness, we also tried other correlation measures such as Pearson, Spearman, and Kendall correlations. Our empirical results are qualitatively similar.

[13] Our results would be qualitatively similar if we were to calculate our diversity measure based on time-weighted average. This measure takes into account the number of previous overlapping months between fund managers, and therefore assigns a higher weight to fund managers with a longer tenure.

[14] See http://uis.unesco.org/en/topic/international-standard-classification-education-isced. The board field categories include the following: (1) generic program and qualifications; (2) education; (3)

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 (Blau, 1977) to measure intra-team education diversity (EDU) of a management team, that is,

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

where p_k corresponds to the proportion of team members in the k-th category. We set $K = 11$, which is the total broad field categories as specified by ISCED. Given the total of $K = 11$ categories, EDU lies between 0 (minimum diversity) and 0.91 ($= 1 - 1/11$, maximum diversity).

2.3 Summary Statistics

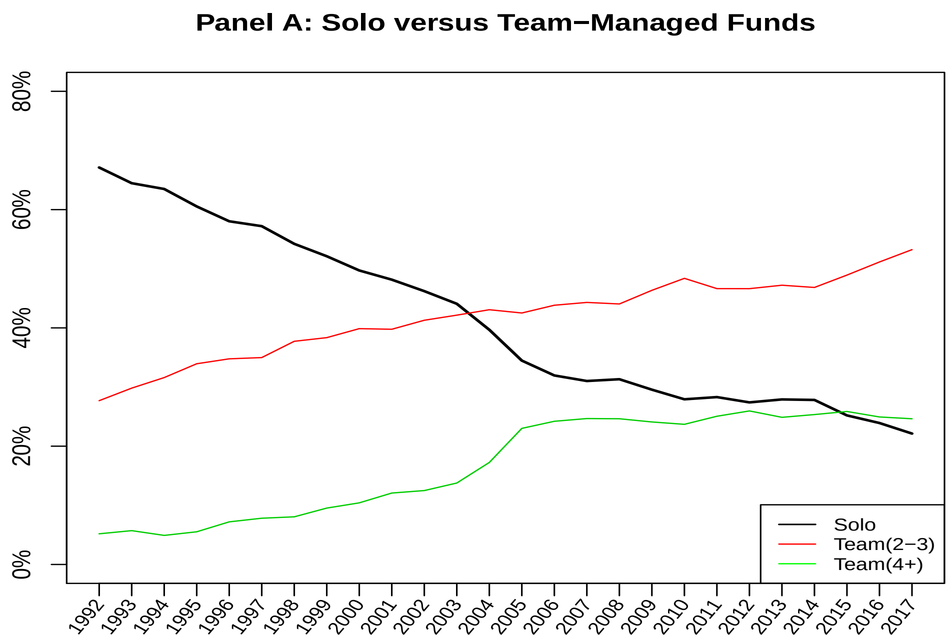
Figure 1 shows the distribution of U.S. domestic equity mutual funds over our sample period and across different managerial structures. As shown by the top panel of Figure 1, the proportion of solo-managed funds decreased from 67% in 1992 to 22% in 2017. The teams consisting of two to three managers 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 show later, the average fund-level DRS depends on the overall industry size and is therefore also likely to be non-stationary.

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.

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 IA.1.1) that we relegate to the Internet Appendix.

Focusing on Table 1, on average, solo-managed funds have a higher turnover rate than team-managed funds. The distribution of fund TNA of solo-managed funds is more skewed to the 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 anecdotally 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.



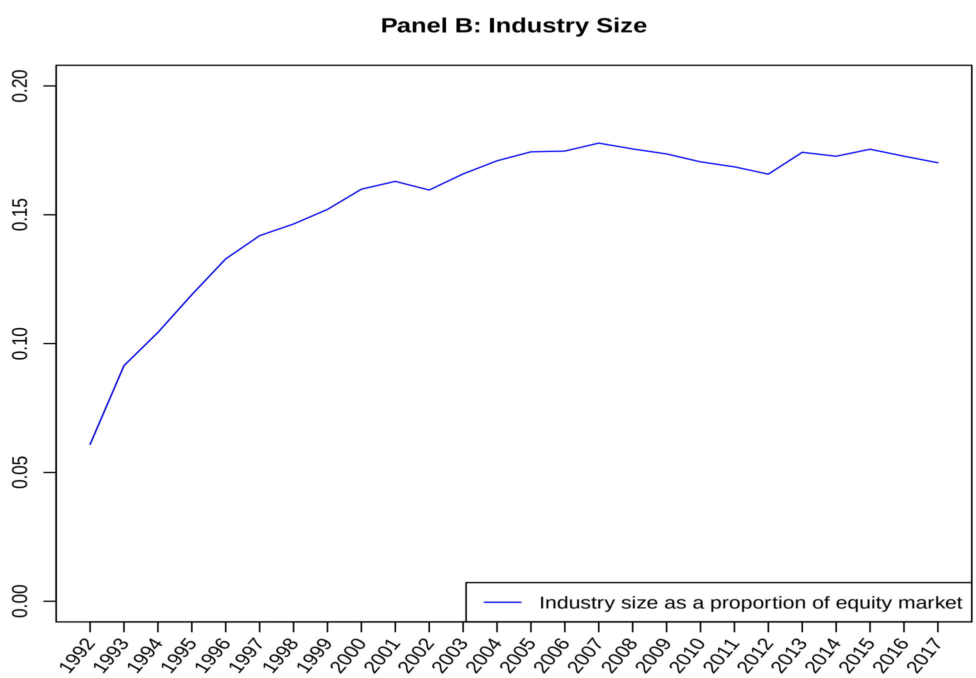


Figure 1: **Distribution of solo-managed and team-managed funds and mutual fund industry size from 1992 to 2017.** Panel A shows the distribution of solo-managed and team-managed funds. *Team (2 to 3)* refers to teams consisting of two or three managers. *Team* (4+) refers to teams consisting of four 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.

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 second column lists the total number and frequency of observations. The unit of observation is the fund/month for *M*, fund/quarter for *Q*, and fund/year for *A*. 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. *Ind Tenure* is the number of years the fund manager has been within the fund industry. *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. *Portfolio Liquidity*, *Stock Liquidity* and *Diversification* are constructed following the definition by Pástor et al. (2020). *DIV* is a measure of within-team experience diversity. *EDU* is a measure of within-team education diversity.

Panel A: Solo-managed funds				Quantile				
	Obs.(Freq.)	Mean	Std. dev.	1%	25%	50%	75%	99%
Benchmark adj ret (%)	132,469 (M)	0.59	27.12	-77.48	-10.44	0.23	11.09	83.26
CAPM alpha (%)	132,469 (M)	1.61	30.22	-79.60	-11.50	0.66	13.59	89.13
FF3 alpha (%)	132,469 (M)	0.75	23.46	-65.04	-9.94	0.56	11.25	68.11
Carhart alpha (%)	132,469 (M)	0.75	22.54	-61.47	-9.83	0.53	11.05	65.40
Fund TNA ($ mil)	132,469 (M)	1,636	5,701	5	65	254	1,057	24,126
Log fund TNA	132,469 (M)	5.58	1.95	1.68	4.17	5.54	6.96	10.09
Expense ratio (%)	127,741 (M)	1.25	0.62	0.17	0.94	1.19	1.47	2.94
Fund Age (years)	132,469 (M)	14.15	13.49	0.54	5.50	10.58	17.51	70.68
Family TNA ($ mil)	132,306 (M)	77,000	174,011	9	814	8,956	41,654	726,276
Ind Tenure (years)	132,469 (M)	10.79	6.62	0.42	5.50	9.83	15.25	26.33
Turnover (%)	9,774 (A)	84	81	2	31	59	108	423
Portfolio liquidity (%)	25,750 (Q)	4.90	7.36	0.03	0.65	2.26	6.59	34.98
Stock liquidity	25,750 (Q)	10.64	10.38	0.13	1.19	8.96	16.79	43.06
Diversification (%)	25,750 (Q)	0.80	1.65	0.01	0.21	0.46	0.89	6.54
Panel B: Team-managed funds								
Benchmark adj ret (%)	278,424 (M)	0.21	21.24	-57.96	-9.25	-0.03	9.21	62.04
CAPM alpha (%)	278,424 (M)	0.87	25.58	-65.28	-10.90	0.26	11.82	74.22
FF3 alpha (%)	278,424 (M)	0.44	19.26	-51.77	-9.03	0.27	9.75	54.44
Carhart alpha (%)	278,424 (M)	0.40	18.59	-49.77	-8.92	0.25	9.56	52.68
Fund TNA ($ mil)	278,424 (M)	1,560	6,350	7	74	276	1,021	21,992
Log fund TNA	278,424 (M)	5.63	1.84	1.95	4.30	5.62	6.93	10.00
Expense ratio (%)	269,862 (M)	1.17	0.41	0.26	0.94	1.13	1.37	2.31
Fund Age (years)	278,424 (M)	13.75	12.66	0.51	5.47	10.59	17.76	70.47
Family TNA ($ mil)	278,103 (M)	38,327	118,797	14	1,047	10,898	32,318	686,311
Ind Tenure (years)	273,724 (M)	9.25	4.58	1.00	5.89	8.80	12.03	22.46
Turnover (%)	21,595 (A)	76	65	2	32	60	99	362
Portfolio liquidity (%)	54,790 (Q)	5.04	6.75	0.07	0.77	2.45	6.87	31.61
Stock liquidity	54,790 (Q)	9.52	9.52	0.13	0.87	7.82	15.57	39.62
Diversification (%)	54,790 (Q)	1.00	1.77	0.04	0.28	0.57	1.06	7.62
Experience diversity (DIV)	261,886 (M)	0.75	0.23	0.13	0.59	0.77	0.97	1.00
Education diversity (EDU)	132,334 (M)	0.10	0.20	0.00	0.00	0.00	0.00	0.64

In terms of the suite of fund activeness measures used by Pástor et al. (2020), team-managed funds, on average, have a lower portfolio turnover, higher portfolio liquidity, lower stock liquidity, and higher portfolio diversification than their solo-managed peers.

For the diversity measures we study, the team experience diversification measure ranges from 0.13 to 1 and has a mean of 0.75, which indicates low intra-team experience diversity overall (note an experience diversity equalling 1 means a perfect correlation among team members, implying the lowest degree of diversification). Around 75% of the teams have no education diversity as measured by EDU; that is, all the managers in a team share the same ISCED education background.

3 DRS 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 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 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 a 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 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.[15]

Following Pástor, Stambaugh and Taylor (2015) and Zhu (2018), we present the recursively demeaned DRS estimator in Appendix B. We also discuss its estimation uncertainty, which will be useful when we test the difference in DRS between different groups of funds.

3.2 Managerial Structure and the DRS Parameter

Our goal is to examine whether the DRS 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 a constant managerial structure, either solo managed or team managed. We call these funds non-switchers. The rest of the funds are switchers that switch between solo and team managerial structures during the sample period.[16]

Suppose we obtain the factor-model adjusted returns in (1). For now, we assume the risk-factor loadings are constant, estimated using the full sample of fund returns.[17] With the adjusted returns, we test our hypothesis separately for non-switchers and switchers.

[15] We adopt the approach proposed by Zhu (2018) (instead of the one in Pástor, Stambaugh and Taylor (2015)), because the original recursively demeaned approach proposed by Pástor, Stambaugh and Taylor (2015) lacks power in detecting diseconomies of scale at the fund level. See Zhu (2018) for more details.

[16] In our sample, funds are switching between different managerial structures multiple times. A fund typically changes from solo management to team management as the fund size grows. The opposite is true when fund size shrinks. To avoid transient switches that make our DRS estimates noisy because 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.

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

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

$$r_{it} = a_i + b_S x^S_{it-1} + b_T x^T_{it-1} + \epsilon_{it}, \tag{4}$$

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.[18] 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 between 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 (see Appendix B).

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

$$r_{it} = a^S_i + a^T_i + b_S x^S_{it-1} + b_T x^T_{it-1} + \epsilon_{it}. \tag{5}$$

We cannot apply our demeaned estimator directly to (5), because a demeaned process cannot remove two fixed effects for a fund. 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 (4) on these $2N$ new funds and carry out statistical inference.

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

[18]Note that for non-switchers, they are either always solo managed or always team managed. As a result, for a particular fund i, one set of the explanatory variable (i.e., either x^S_{it-1} or x^T_{it-1}) will be always zero. Hence, a single intercept a_i is sufficient to absorb the fixed effects: we do not need to have two separate intercepts of a^S_i and a^T_i.

extends the analysis in Pastor, Stambaugh, and Taylor (2015) and Zhu (2018).[19] 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.

Table 2 presents our estimates. 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.[20]

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 which variables help mitigate the impact of DRS when the industry as a whole is crowded so fund-level DRS becomes prevalent?

4 Empirical Results

4.1 Main Results

4.1.1 Non-switchers

We identify 1,618 non-switchers out of the 3,261 unique funds we have. Of 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

[19]Whereas 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.

[20]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 (14) 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 in which the Morningstar-designated benchmark index return is subtracted from the fund's total 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 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)

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 across all risk-adjustment methods.

The analysis above is consistent with the crowding hypothesis that team management helps mitigate the size impact on returns. Note substantial heterogeneity can exist among teams. For instance, team members can have different experiences and skills. We next explore whether the skill heterogeneity affects the DRS estimates.

We next consider the impact of diversity of team experience (DIV) on DRS. Of our 1,310 team-managed funds, 68 have DIV information missing for more than half of the fund-month records, which we exclude from this part of the analysis. We

Table 3: **DRS for Non-switchers.**

This table presents estimates of the decreasing returns to scale (DRS) on funds that do not switch between solo management and team management between January 2000 and December 2017. The DRS parameters are estimated using model (4). Of the non-switchers, 308 funds are always solo managed (*Solo*) and 1,310 funds are 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 teams with different levels of experience diversity. Of the 1,310 team-managed funds, 1,242 have information on experience diversity (DIV). We split these funds into two groups: high DIV (621 funds, with DIV below the median) and low DIV (621 funds). The DRS for solo and these two types of team-managed funds, together with their difference, are reported. "Benchmark" corresponds to the case in which 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: 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: Solo(S), Low DIV and High DIV Team

	Solo (S)	Low DIV	High DIV	S - Low	S - High	Low - High
Benchmark	-0.0050	-0.0030	-0.0018	-0.0020	-0.0032	-0.0012
	(-4.04)	(-7.86)	(-5.31)	(-1.56)	(-2.47)	(-2.26)
CAPM	-0.0080	-0.0053	-0.0039	-0.0027	-0.0041	-0.0014
	(-5.99)	(-10.98)	(-7.75)	(-1.91)	(-2.86)	(-1.95)
FF3	-0.0059	-0.0031	-0.0021	-0.0028	-0.0038	-0.0010
	(-4.78)	(-8.96)	(-6.25)	(-2.19)	(-3.00)	(-2.15)
Carhart	-0.0052	-0.0031	-0.0020	-0.0022	-0.0032	-0.0010
	(-4.62)	(-9.15)	(-6.46)	(-1.84)	(-2.73)	(-2.24)

divide the remaining 1,242 funds into two groups by their average team DIV. The group consisting of funds with average return correlation below (above) the median is labeled as high- (low-) DIV groups (621 funds). Panel B 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% to 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 IA.2.1 in Internet Appendix IA.2 lists 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 focusing on large-, mid- and small-capitalization stocks are 54.5%, 19%, and 26.6%, respectively, compared to 54.8%, 21.9% and 23.3%, respectively, for team-managed funds. We further investigate the DRS estimates across different style groups in Internet Appendix IA.4.

4.1.2 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.[21] 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 that switch 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

[21] Fedyk et al. (2018) also address some endogeneity concerns by using switchers. Unfortunately, similar to papers in the mutual fund literature, we are not able to completely rule out alternative explanations. Unobservable information (i.e., information that is unrelated to fund size, performance, etc.) may exist that correlates with both a fund's switching decision and its DRS.

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, thus leading to the exclusion of 26 funds. The remaining 1,331 funds are ranked by the average return correlation and then divided into two groups: the high-DIV group (666 funds, with correlation below the median), and the low-DIV group (665 funds).[22]

Table 4 reports the results for three sets of samples: all switchers, switchers with a high DIV, and switchers with a low DIV. The differences between b_S (DRS estimate under solo management) and b_T (DRS estimate under team management) are reported.

Focusing on all switchers, the results in Table 4 suggest a modest reduction in DRS when funds switch from solo to team management. The magnitude and statistical significance depend on the benchmark model. Nonetheless, under each model, the difference is negative. The economic effect is largest for 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 observation 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 one of the underlying reasons for fund families to adopt team management is to avoid fund flow risk when managerial turnover occurs 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 adding a low-DIV manager has no significant effect on DRS.

4.1.3 Robustness checks

We perform three major robustness checks.

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

Table 4: **DRS for Switchers.**

This table presents DRS estimates on funds that switch between single and team management structure between January 2000 and December 2017. In total, 1,357 switcher funds have at least 12 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. Twenty-six funds are excluded from this analysis due to missing DIV scores. The remaining 1,331 funds are divided into two groups: the high-DIV group (666 funds) and the low-DIV group (665 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 parentheses. "Benchmark" corresponds to the case in which 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.

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: Solo(S), Low DIV Team and High DIV Team

	Solo (S)	Low DIV	High DIV	S - Low	S - High	Low - High
Benchmark	-0.0024	-0.0023	-0.0015	-0.0001	-0.0009	-0.0008
	(-6.17)	(-5.88)	(-4.74)	(-0.12)	(-1.76)	(-1.62)
CAPM	-0.0051	-0.0049	-0.0030	-0.0002	-0.0021	-0.0019
	(-10.23)	(-8.92)	(-8.10)	(-0.25)	(-3.34)	(-2.84)
FF3	-0.0025	-0.0026	-0.0014	0.0001	-0.0011	-0.0012
	(-6.94)	(-6.51)	(-4.79)	(0.19)	(-2.44)	(-2.50)
Carhart	-0.0025	-0.0024	-0.0015	-0.0001	-0.0010	-0.0010
	(-7.12)	(-6.41)	(-5.27)	(-0.12)	(-2.28)	(-2.03)

Holding-Based Risk Loadings Our previous analysis is based on constant risk loadings, which may be prone to look-ahead bias and may also ignore potential interactions between managerial structure and fund risks. To address these concerns, we calculate holding-based risk loadings by merging Morningstar mutual fund data with Thomson Reuters quarterly fund-holdings data. In Internet Appendix IA.3, we report results based on the holding-based risk loadings. Our results suggest time variability in risk estimates does not have a material impact on our results with regression-based beta estimates.

Combined Sample Our previous analysis studies the switcher and non-switcher samples separately. In Internet Appendix IA.4, we report results based on the pooled sample. Our results are robust when we use the combined sample.

Alternative DIV Measure In Internet Appendix IA.5, we report results based on the alternative DIV measure that corresponds to the Blau's index for designated Morningstar investment categories. We show our results are robust when we use this alternative measure.

4.2 Additional Results

Whereas our hypothesis of crowding naturally leads us to consider experience diversity, other measures of team heterogeneity are also available. In this section, we consider educational diversity, team size, and systemic funds. We find that, in contrast to experience diversity, no significant difference in DRS exists between funds with different levels of educational diversity and team size. Furthermore, managerial structure does not seem to influence the DRS among systemic funds.

4.2.1 Education diversity and team size

We first investigate whether team education diversity (EDU)—another diversity measure that is distinct from experience diversity—affects DRS. We are somewhat constrained by the education information available. For non-switchers, we have education information for 1,218 out of the 2,667 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, 407 funds) and the group without education diversity (EDU $= 0$, 811 funds).

We investigate whether DRS interacts with EDU. Panel A of Table IA.6.1 (Internet Appendix IA.6) presents the DRS estimation results for teams with high and low EDU. Unlike DIV, EDU does not seem to influence fund DRS. In particular, funds with a high EDU do not seem to exhibit a different DRS than funds with a low EDU. We therefore conclude that investment-specific experience diversity, rather than diversity in general, improves funds by reducing the DRS.

We then consider the effect of team size on the DRS parameter. We calculate the average team size for each of the 2,667 team-managed funds during our sample period. We then classify team-managed funds into small teams (less than four fund managers) and large teams (four or more managers).[23] This process leads to 2,088 small teams and 579 large teams. Panel B of Table IA.6.1 shows the DRS estimates for the small and large teams, respectively.

The difference in DRS between small teams and large teams is 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 also report results for alternative ways of categorizing team sizes. Instead of grouping teams into large and small teams, we have a finer-scale size, for example, 2, 3, 4, and 5+. In Internet Appendix IA.2 (in particular, Figure IA.2.1), we report results for alternative ways of categorizing team sizes. They are largely consistent with our results in Table IA.6.1.

4.2.2 Man vs. machine

In this section, we study the differential impact of managerial structure on discretionary versus systematic funds. Our focus is on systematic funds given that their algorithmically driven investment processes would seemingly rely less on managers to generate trade ideas. As such, one can reasonably expect 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, a Morningstar Direct classification snapshot should provide a reasonable approximation. Indeed, using the Securities Exchange Commission's (SEC) structured data extracted from exhibits of mutual fund prospectuses tagged in eXtensible Business Reporting Language (XBRL) from December 2010 to March 2019, we confirm

[23]The team size distribution is highly skewed to the right. Teams of two to three 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 two to three managers and the other with four or more managers.

that a very low percentage of funds change their investment approach (i.e., discretionary vs. systematic) throughout the period.[24]

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 apply constant risk loadings to calculate fund risk-adjusted returns.

Table IA.6.2 (Internet Appendix IA.6) reports the DRS estimates for systematic funds. Our results indicate 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.[25] Our results are thus consistent with Evans et al. (2018) and Abis (2020), who also document the contrast in performance and strategy space between discretionary and quantitative funds.

5 Further Implications

5.1 Source of Reduced DRS under Team Management

In the theoretical framework by Pástor et al. (2020), the DRS comes from trading costs. Consider a fund with assets under management (AUM, A), turnover (T), and

[24]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 we analyze 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 89.5% 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 vs. discretionary) throughout the period.

[25]Because 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.

portfolio liquidity (L). The expected total trading cost over a single period is modeled as

$$C(A, T, L) = \theta A^{\gamma} T^{\lambda} L^{-\phi}, \tag{6}$$

where $\gamma > 1$, $\lambda > 0$, and $\phi > 0$. The fund's proportional trading cost as a function of A is

$$q(A, T, L) = C(A, T, L)/A = \theta A^{(\gamma-1)} T^{\lambda} L^{-\phi}. \tag{7}$$

This proportional trading cost increases with fund size (assuming $\gamma > 1$) and leads to DRS. Therefore, the decreased return amount bx (in our previous DRS regressions) is roughly equal to $q(A, T, L)$. Denoting $x = A^{(\gamma-1)}$, a measure for fund size, we have

$$b = \theta T^{\lambda} L^{-\phi}. \tag{8}$$

(8) implies the DRS parameter is a function of fund turnover and portfolio liquidity. The fund size measure x is not necessarily the dollar amount of AUM. When $\gamma = 2$, using the dollar amount of AUM in the DRS regression is best. When $1 < \gamma < 2$, $A^{(\gamma-1)}$ is a value lower than the dollar amount of AUM. In this paper, we use $x = ln(A)$, which roughly sets $\gamma = 1.18$.

Pástor et al. (2020) further decompose portfolio liquidity (L) as

$$L = \text{Stock liquidity} \times \text{Diversification}. \tag{9}$$

Based on (8) and (9), the DRS is positively related to fund turnover and negatively related to portfolio liquidity, stock liquidity, and portfolio diversification.

We have shown team management significantly reduces the magnitude of b. We now investigate the channel via which team management affects b, that is, whether team management affects fund turnover, portfolio liquidity, stock liquidity, and/or portfolio diversification.

We run the following regression:

$$\begin{aligned} Y_{it} = &\beta_0 + (\beta_1 + \beta_2 \times Team_{it}) \log FundTNA_{it-1} \\ &+ StyleFE + YearFE + \epsilon_{it}, \end{aligned} \tag{10}$$

where the response variable Y_{it} is either the logarithm of the turnover, portfolio liquidity, portfolio diversification, or stock liquidity, and $\log FundTNA_{it-1}$ is the logarithm of the lagged fund TNA. We use annual data in the turnover regression and quarterly data for all other regressions. The dummy variable $Team_{it}$ equals 1 if the fund is under team management in the majority of months of quarter/year t. The style fixed effects (i.e., $StyleFE$) control for style-related investment opportunities.[26] 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.

Panel A of Table 5 demonstrates that the main way for teams to reduce the DRS is through diversification. In particular, team management significantly increases portfolio liquidity compared with solo management. By further decomposing portfolio liquidity into diversification and stock liquidity, stock liquidity does appear to become significantly lower under team management. But this decrease in stock liquidity is overwhelmed by the increase in diversification, resulting in the overall increase in portfolio liquidity under team management.

We further investigate how different types of teams we consider affect portfolio diversification. Panel B of Table 5 reports the results. Regression (1) shows teams with high DIV (i.e., experience diversity) significantly increase portfolio diversification compared with teams with low DIV. Regression (2) shows high-EDU teams do not show significantly higher diversification than their low-EDU peers. Regression (3) indicates portfolio diversification does seem to increase with team size. However, this increase is only marginally significant and is substantially smaller in magnitude than that with DIV. Regression (4) compares solo versus team management among systemic funds. The fund managerial structure change from solo to team has no significant impact on portfolio diversification.

[26] We consider the same nine Morningstar investment styles as analyzed in Table IA.2.1.

Table 5: **Exploring the Source of Reduced DRS under Team Management**

This table presents results from eight regressions corresponding to (10). In Panel A, results from four regressions are reported with dependent variables noted in the column headers. All dependent variables are measured in logs. $Turnover$ is annual, and the other variables $PortLiquidity$, $Diversification$, and $StockLiquidity$ are quarterly. $Team$ is a dummy variable that equals 1 if the fund is under team management, and 0 otherwise, and $logTNA$ is the logarithm of the fund TNA. Both the style fixed effects (i.e., $StyleFE$) and the year fixed effects (i.e., $YearFE$) are included. In Panel B, the dependent variable is portfolio diversification. Regressions (1) to (3) focus on funds under team management and study the incremental contribution of experience diversity (High-DIV teams), education diversity (High-EDU teams), and team size (Large Team). Regression (4) investigates the impact of fund size under different managerial structures (solo vs. team) for systemic funds. The t-statistics clustered by funds are reported in parentheses.

Panel A: Portfolio characteristics				
	Turnover	Port Liquidity	Diversification	Stock Liquidity
logTNA	-0.0560***	0.1299***	0.1395***	-0.0096**
	(-7.32)	(15.26)	(13.98)	(-1.98)
Team× logTNA	0.0024	0.0165***	0.0218***	-0.0054**
	(0.52)	(3.79)	(4.45)	(-2.14)
Style FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Observations	34,303	136,952	136,952	136,952
Adj R-squared	0.087	0.640	0.234	0.880

Panel B: Diversification				
	(1)	(2)	(3)	(4)
logTNA	0.1035***	0.1058***	0.1103***	0.0984**
	(9.44)	(6.41)	(10.65)	(2.86)
High DIV×logTNA	0.0461***			
	(7.06)			
High EDU×logTNA		0.0157		
		(1.54)		
Large Team×logTNA			0.0207**	
			(2.01)	
Team×logTNA				0.0171
				(0.46)
Style FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Observations	91,104	44,291	92,935	8,810
Adj R-squared	0.249	0.218	0.243	0.149

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

5.2 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 managerial 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 that 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, because our previous results indicate a significant change in b when a fund changes from solo management to team management.[27]

First, we aggregate the TNA of the 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:

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

[27] We report in Table IA.7.1 in Internet Appendix IA.7 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.

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 8.5 bps per month. Notice that we use monthly fund expenses to calculate capacity in order to match the monthly return data. Table 6 reports our results that measure the change in capacity when funds switch from solo management to team management.

Table 6: **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 that 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 8.5 bps per month. Note we use monthly fund expenses to calculate capacity in order to match the monthly return data. Capacity (in billions) 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 in which 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	0.0320	0.0024	430.084	0.0210	0.0015	577.679	34%
CAPM	0.0681	0.0051	537.334	0.0417	0.0030	820.792	53%
FF3	0.0336	0.0025	496.749	0.0197	0.0014	713.406	44%
Carhart	0.0337	0.0025	501.069	0.0211	0.0015	736.733	47%
Group TNA in Dec 2017 (billions)				$724.2			

Regardless of the assumed risk models, the degree of diseconomies of scale is smaller under team management, as we showed 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 34% 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 \$724 billion, which is in line with our average capacity estimate (i.e., the average across four benchmark models). In contrast, it would have exceeded its capacity by \$230 billion if funds had not changed their management structures and remained solo managed.

5.3 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 generating positive alphas more difficult for fund managers 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 DRS 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 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.[28]

We split fund-month observations by managerial structure and study performance persistence for solo-managed and team-managed funds separately. Our previous empirical evidence demonstrates the teams with high DIV have a higher resistance to scale diseconomies. Hence, our analysis focuses on comparison of the performance of solo-managed funds and teams with high DIV.[29]

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. When allocating

[28]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.

[29]Results for teams with low DIV are reported in Table IA.8.1 in Internet Appendix IA.8.

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 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 are described as follows. Following Busse, Goyal and Wahal (2010), we use benchmark-adjusted returns to estimate ranking-period alphas.[30] Beginning at the end of 2000, we calculate the prior annual benchmark-adjusted returns at the 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:

$$\alpha_{i,t+k} = a_i + (\lambda_{Solo} I_{i,t}^{Solo} + \lambda_{Team} I_{i,t}^{Team})\alpha_{i,t} + \epsilon_{i,t+k}, \tag{11}$$

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) management, and 0 otherwise, and λ_{Solo} (λ_{Team}) is the corresponding persistence parameter. We report the estimates of (11) in Table 7.

We focus on the Carhart 4-factor model to interpret our results in Table 7. Previous literature documents significant short-run alpha persistence when all funds are included in the cross section. Our results show 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

[30]Given that momentum contributes significantly to short-run alpha persistence, adjusting alphas based on benchmark factors is important. We therefore only report results based on factor models. We focus on the Carhart 4-factor model to interpret our findings.

Table 7: **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. Panels 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 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)

the one-month to three-month horizon and has a much larger magnitude than λ_{Solo}, which is not statistically significant over any horizon.[31]

To complete our analysis, in Table IA.9.1 of Internet Appendix IA.9, 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 their solo-managed counterparts. Therefore, holding alphas constant, if DRS were the same for both solo- and team-managed funds, the larger inflows that team-managed funds attract imply teams' performance should deteriorate more, leading to less performance persistence, which contradicts our results in Table 7.

[31]Our results for low-DIV funds in Table IA.8.1 in Internet Appendix IA.8 further show that although some evidence exists 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 7.

Now combining the evidence in Table 7 and Table IA.9.1, we offer an explanation for our results in Table 7. 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 than solo-managed funds (based on our results in Table IA.9.1), their performance still decreases less than that of solo-managed funds, due to their much lower DRS. As a result, they display more performance persistence than their solo-managed counterparts. The higher flow-performance sensitivity for team-managed funds as documented in Table IA.9.1 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) in which fund flows 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. Although we focus on managerial structure in our paper, alternative predictors of DRS may exist.

6 Conclusions

Over the past 30 years, the managerial structure of the fund management industry has been dramatically transformed. Solo management once represented the vast majority of funds and now it represents less than 25%. 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 the transformation in managerial structure (solo to team) is a natural result of crowding. Specifically, the fact that increasing flows into existing funds will degrade performance (decreasing returns to scale) is well established. When funds flow into a solo-managed fund, more money is allocated to a limited 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 existing ideas.

Our empirical results are consistent with our crowding hypothesis. We find the decreasing returns to scale are significantly less for team-managed funds than for 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 whose experience is very similar to that of the existing manager, an abundance of new ideas will likely emerge. We separate the teams into those with a diversity of work experience and those without. Our results show that teams with diversity are significantly more capable of absorbing larger flows. Indeed, a shift from a 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, the expectation that little or no difference would be found between solo and team-managerial structure with respect to decreasing returns to scale in systematically oriented funds is reasonable. Consistent with our hypothesis, our empirical results show no difference in decreasing returns across management structure.

Finally, we address the issue of alpha persistence. Theories such as Berk and Green's (2004) suggests investments flow into positive alpha funds, driving the alpha to zero. How fast this happens is an empirical question. Our results show 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: Data Construction

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, and fees. 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 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).

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 who are hired, in reducing the effect of decreasing returns to scale.[32]

To facilitate the comparison to the prior literature, we focus on U.S. domestic equity funds. Following the procedures used in many papers,[33] 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.[34] This approach 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 source of the relation between managerial structure and DRS, we rely on the theoretical framework in Pástor et al. (2020) and consider turnover, port-

[32] 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.

[33] See, for example, Chen et al. (2004), Kacperczyk, Sialm and Zheng (2005), Fama and French (2010), Ferson and Lin (2014), Berk and van Binsbergen (2015), and others.

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

folio liquidity, diversification, and stock liquidity as potential candidates. Turnover is defined as the minimum of aggregate purchases and sales divided by the average annual fund TNA in percentage from Morningstar Direct database, which is at the annual frequency. The other three variables require fund-holdings information, which we collect from Thomson Reuters Mutual Fund Holdings database.[35] Portfolio liquidity is as defined in (3) of Pástor et al. (2020), which takes into account the number of stocks in the portfolio, the portfolio's weight on stock i, and the weight on stock i in a market-cap-weighted benchmark portfolio.[36] The portfolio liquidity measure takes values between 0 and 1. Diversification is defined in (24) of Pástor et al. (2020), which takes into account the number of stocks in the portfolio (i.e., coverage) and the extent to which the portfolio's weights resemble market-cap weights (i.e., balance). Lastly, stock liquidity is defined in (23) of Pástor et al. (2020), which captures the liquidity of stock i relative to all stocks in the benchmark. As such, the stock liquidity measure would be higher (lower) than 1 if the portfolio's holdings have a higher (smaller) average market capitalization than the average stock in the benchmark. Portfolio liquidity, diversification, and stock liquidity are at the quarterly frequency.

[35] We first merge Thomson Reuters with CRSP using the 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).

[36] The market portfolio includes ordinary common shares (CRSP share code with first digit equal to 1) and REIT shares of beneficial interest (CRSP share code of 48). See Appendix B of Pastor, Stambaugh, and Taylor (2020) for more information.

Appendix B: Recursive Demeaned Estimator and Its Inferences

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 an estimate of β can be obtained via two-stage least squares:

$$\bar{x}_{it-1} = \psi + \rho x_{it-1} + v_{it-1}, \tag{12}$$
$$\bar{r}_{it} = \beta \bar{x}^*_{it-1} + \bar{\epsilon}_{it}, \tag{13}$$

where $\bar{x}^*_{it-1}$ is the fitted value from the first-stage regression (12). The bias-corrected estimator for β is

$$\hat{b}_{RD} = \left(\sum_{i=1}^{N} \sum_{t=1}^{T_i - 1} \bar{x}^{*\prime}_{it-1} \bar{x}^*_{it-1} \right)^{-1} \left(\sum_{i=1}^{N} \sum_{t=1}^{T_i - 1} \bar{x}^{*\prime}_{it-1} \bar{r}_{it} \right). \tag{14}$$

The recursively-demeaned estimator (14) 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

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

The bias-corrected estimator is

$$\hat{b}_{RD} = \left(\sum_{i=1}^{N} \bar{\boldsymbol{x}}_i' \boldsymbol{z}_i (\boldsymbol{z}_i' \boldsymbol{z}_i)^{-1} \boldsymbol{z}_i' \bar{\boldsymbol{x}}_i \right)^{-1} \left(\sum_{i=1}^{N} \bar{\boldsymbol{x}}_i' \boldsymbol{z}_i (\boldsymbol{z}_i' \boldsymbol{z}_i)^{-1} \boldsymbol{z}_i' \bar{\boldsymbol{r}}_i \right). \tag{15}$$

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

$$\mathrm{var}(\hat{b}_{RD}) = (\Omega_{xx})^{-1}\Phi_{ux}(\Omega_{xx})^{-1}, \tag{16}$$

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 $\hat{\bar{\epsilon}}_{it} = \bar{y}_{it} - \hat{b}_{RD}\bar{x}_{it-1}$. The t-test and Wald test based on $\mathrm{var}(\hat{b}_{RD})$ satisfy the usual properties.

Internet Appendix: Additional Results

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

Table IA.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 second column lists the total number and frequency of observation. 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. *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. *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. *Portfolio Liquidity*, *Stock Liquidity*, and *Diversification* are constructed following the definition by Pástor et al. (2020). *DIV* is a measure of within-team experience diversity. *EDU* is a measure of within-team education diversity.

Panel A: Solo-managed funds				Quantile				
	Obs.(Freq.)	Mean	Std. dev.	1%	25%	50%	75%	99%
Benchmark adj ret (%)	185,830 (M)	0.53	27.51	-75.93	-11.21	0.12	11.64	83.24
CAPM alpha (%)	185,830 (M)	0.86	30.94	-83.96	-12.51	0.31	13.54	90.40
FF3 alpha (%)	185,830 (M)	0.42	24.32	-66.31	-10.80	0.21	11.33	70.74
Carhart alpha (%)	185,830 (M)	0.43	23.40	-63.29	-10.56	0.24	11.10	67.58
Fund TNA ($ mil)	185,830 (M)	1,541	5,545	5	63	237	963	23,203
Log fund TNA	185,830 (M)	5.52	1.93	1.60	4.15	5.47	6.87	10.05
Expense ratio (%)	177,564 (M)	1.25	0.60	0.17	0.94	1.19	1.49	2.87
Fund Age (years)	185,830 (M)	13.32	13.67	0.41	4.36	9.25	16.79	68.18
Family TNA ($ mil)	179,907 (M)	66,466	158,724	9	666	7,241	35,981	714,358
Ind Tenure (years)	185,830 (M)	9.57	6.57	0.42	4.33	8.25	13.67	26.33
Turnover (%)	13,707 (A)	84	79	2	32	60	109	423
Portfolio liquidity (%)	35,460 (Q)	4.58	7.06	0.04	0.60	2.06	6.05	33.66
Stock liquidity	35,460 (Q)	11.35	10.91	0.14	1.54	9.50	17.74	45.39
diversification (%)	35,460 (Q)	0.69	1.45	0.01	0.17	0.37	0.77	5.41
Panel B: Team-managed funds								
Benchmark adj ret (%)	319,817 (M)	0.23	22.11	-60.61	-9.66	-0.03	9.61	65.07
CAPM alpha (%)	319,817 (M)	0.60	26.68	-70.88	-11.49	0.16	12.04	77.65
FF3 alpha (%)	319,817 (M)	0.30	20.13	-54.26	-9.51	0.14	9.91	57.58
Carhart alpha (%)	319,817 (M)	0.26	19.41	-52.48	-9.40	0.15	9.76	55.12
Fund TNA ($ mil)	319,817 (M)	1,540	6,169	7	71	270	1,000	22,092
Log fund TNA	319,817 (M)	5.61	1.85	1.89	4.27	5.60	6.91	10.00
Expense ratio (%)	308,228 (M)	1.18	0.42	0.25	0.94	1.14	1.39	2.37
Fund Age (years)	319,817 (M)	13.34	12.81	0.44	4.89	9.96	17.31	69.30
Family TNA ($ mil)	315,352 (M)	36,462	112,861	14	991	10,082	31,143	645,858
Ind Tenure (years)	312,595 (M)	8.82	4.66	0.81	5.33	8.36	11.69	22.21
Turnover (%)	97,733 (A)	77	64	2	33	61	100	342
Portfolio liquidity (%)	62,347 (Q)	4.88	6.59	0.06	0.73	2.37	6.65	30.81
Stock liquidity	62,347 (Q)	9.90	9.91	0.12	0.95	8.13	15.97	41.48
diversification (%)	62,347 (Q)	0.93	1.68	0.03	0.26	0.52	0.99	7.21
Experience diversity (DIV)	292,907 (M)	0.75	0.23	0.12	0.59	0.78	0.98	1.00
Education diversity (EDU)	158,069 (M)	0.10	0.20	0.00	0.00	0.00	0.00	0.64

Appendix IA.2: Style Decomposition for Non-switchers and Team Size Categories

Table IA.2.1 presents the style decomposition for non-switchers by managerial structure.

Table IA.2.1: **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's 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

We also report results for alternative ways of categorizing team sizes. Instead of grouping teams into large and small teams, we have finer-scale size, for example, 2, 3,4, and 5+. Figure IA.2.1 plots the DRS estimates based on the FF4-adjusted returns for solo and different size teams. They are largely consistent with our results in Table IA.6.1.

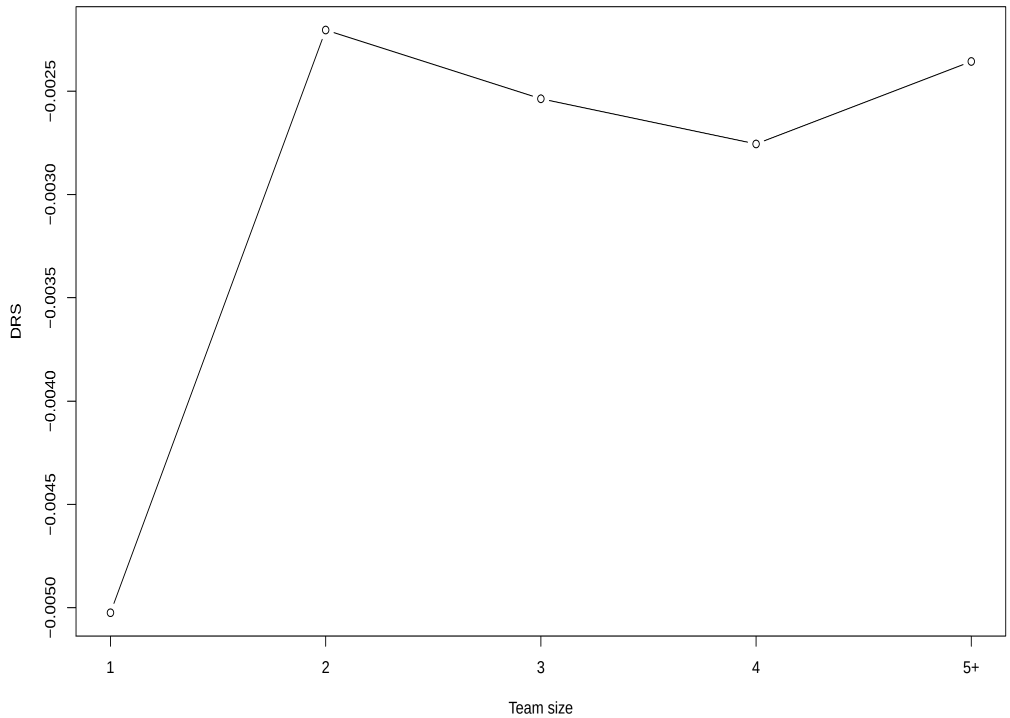

Figure IA.2.1: **Non-switcher DRS Estimates Conditional on Team Size.** This figure plots the DRS estimates based on the FF4-adjusted returns. We calculate the average team size for non-switchers in our sample (308 solo funds and 1,310 team funds). Among team funds, the distribution of team size is as follows: 453 teams have 2 managers, 345 have 3 managers, 199 have 4 managers, and 313 have 5 or more managers.

Appendix IA.3: Analysis Using 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. Of the 774 non-switcher teams, 348 have high DIV and 401 have low DIV. The 1,091 switchers comprise 525 funds from the high-DIV group and 547 funds from the low-DIV group.

Table IA.3.1 reports our results with holdings-based beta estimates. Overall, these results are fairly consistent with and often 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 ranges from 25% to 43% across the benchmark models. Our results suggest time variability in risk estimates does not have a large impact on our results with regression-based beta estimates.

Table IA.3.1: **DRS with Holdings-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 Panels A and C of Table 3, for switcher funds in Panel B (counterpart is Table 4), and for the combined sample in Panel C. Experience 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 IA.4: Pooled Sample and by Fund Style

Table IA.4.1 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 IA.4.1: **DRS on Pooled Sample and by Fund Style**

This table presents DRS estimation results for the 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. Panels B, C, and D are results conditional on fund style. Because 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 in which 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 (3261 funds)						
Benchmark	-0.0040	-0.0025	-0.0015	-0.0030	-0.0017	-0.0014
	(-7.13)	(-11.36)	(-2.54)	(-10.17)	(-5.73)	(-3.35)
CAPM	-0.0075	-0.0050	-0.0025	-0.0055	-0.0030	-0.0025
	(-12.07)	(-17.91)	(-3.67)	(-13.87)	(-7.28)	(-4.35)
FF3	-0.0046	-0.0027	-0.0019	-0.0030	-0.0020	-0.0010
	(-8.30)	(-13.22)	(-3.20)	(-10.92)	(-7.65)	(-2.50)
Carhart	-0.0043	-0.0027	-0.0016	-0.0030	-0.0020	-0.0010
	(-8.32)	(-13.80)	(-2.86)	(-11.30)	(-8.14)	(-2.43)
Panel B: Fund style – large cap (1926 funds)	Solo	Team	Diff	Low DIV	High DIV	Low - High
Benchmark	-0.0025	-0.0024	-0.0002	-0.0030	-0.0016	-0.0015
	(-5.01)	(-6.84)	(-0.35)	(-6.11)	(-3.70)	(-2.26)
CAPM	-0.0030	-0.0019	-0.0011	-0.0025	-0.0012	-0.0013
	(-6.17)	(-5.61)	(-1.81)	(-5.06)	(-2.76)	(-2.03)
FF3	-0.0021	-0.0019	-0.0004	-0.0025	-0.0012	-0.0013
	(-5.23)	(-6.26)	(-0.70)	(-5.75)	(-3.18)	(-2.29)
Carhart	-0.0020	-0.0019	-0.0002	-0.0024	-0.0012	-0.0012
	(-5.14)	(-6.77)	(-0.36)	(-6.27)	(-3.49)	(-2.25)
Panel C: Fund style – mid cap (902 funds)	Solo	Team	Diff	Low DIV	High DIV	Low - High
Benchmark	-0.0047	-0.0018	-0.0029	-0.0024	-0.0008	-0.0016
	(-4.64)	(-4.24)	(-2.63)	(-3.95)	(-1.78)	(-2.00)
CAPM	-0.0098	-0.0063	-0.0035	-0.0066	-0.0049	-0.0017
	(-9.36)	(-11.95)	(-2.96)	(-8.85)	(-7.90)	(-1.71)
FF3	-0.0068	-0.0037	-0.0030	-0.0042	-0.0025	-0.0016
	(-6.65)	(-8.63)	(-2.76)	(-6.62)	(-5.52)	(-2.01)
Carhart	-0.0065	-0.0037	-0.0028	-0.0041	-0.0026	-0.0015
	(-6.82)	(-8.85)	(-2.68)	(-6.64)	(-5.87)	(-1.91)
Panel D: Fund style – small cap (822 funds)	Solo	Team	Diff	Low DIV	High DIV	Low - High
Benchmark	-0.0061	-0.0035	-0.0026	-0.0045	-0.0021	-0.0024
	(-5.23)	(-7.63)	(-2.16)	(-6.84)	(-3.73)	(-2.70)
CAPM	-0.0122	-0.0091	-0.0031	-0.0096	-0.0076	-0.0019
	(-9.58)	(-14.43)	(-2.30)	(-11.38)	(-9.05)	(-1.58)
FF3	-0.0062	-0.0033	-0.0029	-0.0040	-0.0023	-0.0017
	(-5.48)	(-7.71)	(-2.50)	(-6.51)	(-4.34)	(-2.06)
Carhart	-0.0057	-0.0033	-0.0024	-0.0040	-0.0021	-0.0019
	(-5.32)	(-8.03)	(-2.21)	(-6.80)	(-4.45)	(-2.38)

Appendix IA.5: Alternative DIV Measure

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.[37] 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 manager i's experience and skillset. We use Blau's index (Blau, 1977) to measure intra-team experience diversity (DIV) of a management team, that is,

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

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.[38] Given the total of $K = 7$ categories, DIV lies between 0 (minimum diversity) and 0.86 ($= 1 - 1/7$, maximum diversity).

[37] 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).

[38] 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 $k \geq 3$.

Table IA.5.1: **Alternative Intra-team Experience Diversity Blau DIV**

This table presents DRS estimation results using an alternative DIV measure. Panel A is for pooled team-managed funds divided into low-DIV teams (1,302 funds) and high-DIV teams (1,302 funds). The corresponding DRS and the difference ($Low - High$) are presented. Panel B is for non-switching team-managed funds. Again, the group is divided into low-DIV teams (636 funds) and high-DIV teams (636 funds). Panel B is for switching funds. The funds are divided into low-DIV teams (666 funds) and high-DIV teams (666 funds). "Benchmark" corresponds to the case in which 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.

Panel A: All teams	Low DIV		High DIV		Low-High	
Benchmark	-0.0029	(-10.36)	-0.0015	(-5.49)	-0.0014	(-3.55)
CAPM	-0.0053	(-14.07)	-0.0034	(-9.57)	-0.0019	(-3.65)
FF3	-0.0029	(-11.50)	-0.0018	(-6.52)	-0.0011	(-3.06)
FF4	-0.0029	(-11.66)	-0.0018	(-6.80)	-0.0011	(-2.99)
Panel B: Non-switchers	Low DIV		High DIV		Low-High	
Benchmark	-0.0030	(-8.33)	-0.0018	(-4.72)	-0.0013	(-2.47)
CAPM	-0.0056	(-11.57)	-0.0038	(-7.92)	-0.0018	(-2.63)
FF3	-0.0031	(-9.56)	-0.0022	(-6.22)	-0.0008	(-1.71)
FF4	-0.0031	(-10.02)	-0.0022	(-6.28)	-0.0009	(-1.87)
Panel C: Switchers	Low DIV		High DIV		Low-High	
Benchmark	-0.0026	(-6.26)	-0.0014	(-3.35)	-0.0012	(-2.10)
CAPM	-0.0048	(-8.50)	-0.0033	(-6.36)	-0.0015	(-1.91)
FF3	-0.0026	(-6.73)	-0.0014	(-3.44)	-0.0012	(-2.07)
FF4	-0.0024	(-6.48)	-0.0015	(-3.82)	-0.0009	(-1.73)

Appendix IA.6: Education Diversity and Man vs. Machine

Table IA.6.1: **Education Diversity (EDU) and Team Size**

This table presents DRS estimation results for team-managed funds conditional on education diversity (EDU) and average team size. Panel A is for education diversity. These funds are divided by education diversity (EDU) of teams into low-EDU teams (811 funds) and high-EDU teams (407 funds). The corresponding DRS and the difference (Diff = Low - High) are presented. Panel B is for team size. These funds are divided by the average size of teams into small teams (2,088 funds) and large teams (579 funds). The corresponding DRS parameters and their difference are presented. "Benchmark" corresponds to the case in which 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 parentheses.

Panel A: Education (EDU) diversity						
	Low EDU		High EDU		Diff	
Benchmark	-0.0029	(-7.16)	-0.0023	(-4.39)	-0.0006	(-0.91)
CAPM	-0.0051	(-10.09)	-0.0056	(-6.90)	0.0004	(0.47)
FF3	-0.0031	(-8.46)	-0.0026	(-5.10)	-0.0005	(-0.73)
FF4	-0.0030	(-8.45)	-0.0028	(-5.69)	-0.0002	(-0.27)
Panel B: Small team vs. large team						
	Small Team		Large Team		Diff	
Benchmark	-0.0025	(-9.97)	-0.0025	(-5.44)	0.0000	(0.01)
CAPM	-0.0050	(-16.08)	-0.0051	(-7.85)	0.0002	(0.22)
FF3	-0.0026	(-11.54)	-0.0028	(-6.36)	0.0002	(0.36)
FF4	-0.0027	(-12.09)	-0.0028	(-6.58)	0.0001	(0.23)

Table IA.6.2: **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. We identify 8,421 fund-month observations under solo management and 17,921 under team management. "Benchmark" corresponds to the case in which 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)

Appendix IA.7: 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 665 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 665 funds, which is about 9 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 5.2.

Table IA.7.1 reports the change in capacity when low-DIV funds switch from solo management to team management. Because 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 IA.7.1: **Capacity Increase for the Switcher Group with Low DIV**

For the group of switchers with low DIV, this table reports the change in capacity when they switch from solo management to team management. We define capacity as the size that 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 9 bps per month. Notice 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 in which 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	0.0317	0.0024	378.277	0.0305	0.0023	388.322	3%
CAPM	0.0677	0.0051	483.237	0.0651	0.0049	486.517	1%
FF3	0.0335	0.0025	452.096	0.0348	0.0026	456.200	0%
Carhart	0.0334	0.0025	449.308	0.0321	0.0024	451.016	0%
Group TNA in Dec 2017 (billions)				$643.4			

Appendix IA.8: Alpha Persistence

Table IA.8.1: **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. Panels 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 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 IA.9: 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:

$$\begin{aligned} Flow_{it+k} =& \beta_1 Team_{it} + \beta_2 \alpha_{it} + \beta_3 Team_{it} * \alpha_{it} + \beta_4 \log FundAge_{it} + \beta_5 risk_{it} \\ &+ \beta_6 expense_{it} + \beta_7 \log FundTNA_{it-1} + \beta_8 \log FamTNA_{it-1} \\ &YearFE + FundFE + \epsilon_{it}, \end{aligned} \tag{17}$$

where $Flow_{it+k}$ represents the net percentage TNA growth for fund i in the period from t to $t+k$.[39] 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 the riskiness of fund alpha, which is calculated as the standard deviation of the 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, respectively. 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 IA.9.1 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 $Team_{it} * \alpha_{it}$.

[39] 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 IA.9.1: **Flow-Performance Sensitivity**

We analyze the link between flows and various fund characteristics using the regression model (17). 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. 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 the riskiness of fund alpha, which is calculated as the standard deviation of the 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, respectively. 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

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

Appendix IA.10: FAQ

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

  Yes. For example, if an analyst is promoted to a fund manager, our definition will treat her as a new manager. The reason is that we only have fund manager information, and 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.