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Is a Team Different from the Sum of its Parts? Evidence from Mutual Fund Managers

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Is a Team Different from the Sum of its Parts?

Evidence from Mutual Fund Managers

Abstract

This paper provides the first empirical test of the diversification of opinions theory and the group shift theory using real business data. Our data set covers management teams and single managers of US equity mutual funds. Our results reject the group shift theory and support the diversification of opinions theory: extreme opinions of single team managers average out and, consequently, teams make less extreme decisions than individuals do. We find that teams follow less extreme investment styles and their portfolios are less industry concentrated than those of single managers and that teams are eventually less likely to achieve extreme performance outcomes. These results hold after taking into account the impact of fund and family characteristics as well as manager characteristics. Additionally, teams exhibit a lower active share and lower risk levels, driven by a lower level of idiosyncratic risk, as compared to single-managed funds.

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1. Introduction

Many decisions in business are made by teams. This raises the question of how team decisions differ from decisions of individuals. The answer to this question has important implications for the optimal organization of companies and business units.

The literature offers two competing hypotheses. The group shift hypothesis (e.g., Moscovici and Zavalloni, 1969, Hogg et al., 1990, and Kerr, 1992) suggests that the opinion of team members shifts towards the opinion of the dominant person in a team. As that person typically holds very pronounced opinions, a team eventually gravitates towards extremes. Consequently, teams make more extreme decisions than individuals do. In contrast, the diversification of opinions hypothesis suggests that the team opinion is the average opinion of the team members. Because individual team members might have different opinions, the team decision will be a compromise (e.g., Sah and Stiglitz, 1986 and 1988). Extreme opinions of members in a team are averaged out and teams eventually make less extreme decisions than individuals do.

In this paper we analyse these two competing hypotheses by examining investment decisions of mutual fund managers. The mutual fund industry offers an ideal empirical test setting in this context for several reasons: first, the decisions of fund managers are directly reflected in the returns of the fund. Therefore, they can be easily observed. Second, fund managers have strong incentives to make optimal decisions since their salaries are directly linked to the performance outcomes of their decisions. Third, the mutual fund industry allows us to run tests based on a large number of fund managers from different firms. Thus, our results will not be driven by the priming effects of the organizational culture within a specific firm.

Our paper is the first to test the above hypotheses in a large sample of real world data from a professional business setting. Thus far, the literature on this issue consists mainly of experimental

studies (e.g., Stoner, 1961; Moskovici and Zavalloni, 1969; Davis and Hinsz, 1982; Mulvey and Klein, 1998; Cooper and Kagel, 2004). These studies typically find that teams make more extreme decisions than individuals, i.e., experimental evidence supports the group shift theory. However, it is not clear whether these experiment-based results hold for real world decisions, which are typically much more complex than the decisions made in experiments and where decisions might be less likely to go to extremes (Brown, 2000). Furthermore, financial incentives are much stronger in real world settings and the downside risk of making a wrong decision is much higher.[1]

The only other field study that compares the extremity of decisions of teams and individuals that we are aware of is Adams and Ferreira (2009). They analyze the behavior of betting pools and individual bettors in iceberg break-up betting. In contrast to the evidence presented in the experimental literature, they find that teams make less extreme decisions than individuals. However, it is not clear whether their findings on iceberg break-up betting hold in a professional business setting.

Our paper provides strong evidence for the diversification of opinions theory and rejects the group shift theory. In our sample of several thousand US equity funds, we find that teams make less extreme decisions than single managers do. Analyzing the investment styles of teams and single managers, we find that management teams are less likely to engage in extreme style bets than single managers. They deviate much less from the average styles followed by the funds in their market segment than single managers. Furthermore, we find that the industry concentration within the portfolios of team-managed funds is significantly lower than that within the portfolios of single-managed funds. While the more extreme investment decisions of single managers

[1] Chevalier and Ellision (1999a) and Kempf et al. (2009) show that the risk of job loss is an important determinant of managerial behavior in the mutual fund industry.

sometimes pay off very well, the outcomes will be very bad in other situations. Thus, it comes as no surprise that we also find that teams achieve less extreme performance outcomes than single managers. All these results are the stronger, the more members the team consists of – a finding again predicted by the diversification of opinions theory.

In addition, we show that team-managed funds are less risky than single-managed funds. This result holds independent of whether we measure risk as volatility, active share, or tracking error. This finding again supports the diversification of opinions theory. There is no clear impact of the diversity within a team on the extremeness of its decisions. This finding is consistent with the diversification of opinions theory, but contradicts the group shift theory.

We reject several alternative explanations that might explain our findings: Our results are not driven by differences in fund characteristics between team- and single-managed funds. We show that our results are also not driven by differences in personal characteristics like age or education of the individual and team managers, respectively. Our results cannot be explained by the findings in Massa et al. (2009) of differences in the marketing value of single- and team-managed funds. The role of the fund family can also not explain the differences we find between team- and single-managed funds.[2] Our results are stable with respect to various methodological approaches and we provide some evidence that our results also hold after taking into account the potential endogeneity of the management structure.

Our study contributes to three main strands of the literature. First, it contributes to the mutual fund literature. Despite the tremendously growing importance of team management in the mutual fund industry, only a little empirical research has been devoted to this issue so far. Most studies investigate performance differences between single- and team-managed funds (e.g., Prather and

[2] Fund family and fund management company are used synonymously in this paper.

Middleton, 2002 and 2006; Chen et al., 2004), while Massa et al. (2009) focuses on the decision of the fund company to disclose the names of team members and the eventual investor reactions. However, surprisingly there are barely any studies on the behavioral differences between fund management teams and single managers. Notable exceptions are Qiu (2003) and Kempf and Ruenzi (2008) who study whether teams and single managers behave differently in tournament situations. Second, our paper contributes to the management and organization literature by highlighting important behavioral differences between teams and single managers. The extant literature in this field also mainly focuses on performance differences (e.g., Cohen and Bailey, 1997; Cooper and Kagel, 2004; Rockenbach et al., 2007). Finally, our study contributes to the social psychology literature on team behavior by showing that the group shift phenomenon (that has been widely documented in experimental studies) cannot be observed in the real world business setting of mutual fund managers.

We proceed as follows. In Section 2 we briefly review the main arguments from diversification of opinions and from group shift theory and develop hypotheses that emerge from these theories. In Section 3 we introduce our data sources. In Section 4 we report the main results of our study. In Section 5 we explore several alternative explanations for our findings. In Section 6 we test further implications of the diversification of opinions and group shift theories. In Section 7 we present the results from various robustness tests and take into account the possible endogeneity of the funds' management structures. Section 8 concludes.

2. Conceptual Development and Hypotheses

2.1. Diversification of Opinions Theory

The natural hypothesis regarding the impact of team status is that there is a diversification of opinions within a team. Team decisions should eventually reflect a compromise among the decisions each member of a team would have made individually (Sah and Stiglitz, 1986). In this diversification of opinions theory it is assumed that a team is a mechanism for achieving a consensus based on a compromise that reflects the average opinion of all members. This leads to more moderate decisions made by teams than by individuals, which ultimately results in less extreme performance outcomes (Sah and Stiglitz, 1991). Except for the study by Adams and Ferreira (2009) on iceberg breakup betting mentioned above, we are aware of no other empirical study providing evidence in support of the diversification of opinions theory.

Diversification of opinions effects should be more pronounced, the more the individual member's opinions differ. Although we only analyze the relatively homogenous group of fund managers, the members of this group still differ significantly. Typically, individual fund managers who comprise a team differ with respect to their demographic characteristics, past experience and education (Bär et al., 2008) which is likely to result in differing preferences.[3] For example, some managers might prefer momentum stocks while other managers might prefer a contrarian style. If both work together in a team, diversification of opinions predicts that the team will implement a

[3] Chevalier and Ellison (1999a) provide evidence that younger managers are more risk-averse than older managers due to higher termination risk. According to Niessen and Ruenzi (2008), female managers follow less risky strategies than male managers. Bollen and Busse (2001) show that many fund managers engage in market timing, i.e., they invest more or less in risky assets depending on their expectation of the future market risk premium. Large heterogeneity in risk preferences of managers is also suggested in Koijen (2008).

strategy that is in between with respect to momentum, i.e., neither extremely momentum nor extremely contrarian.

Overall, the diversification of opinions theory predicts less extreme decisions of team-managed funds regarding the most important dimensions of the fund's investment style which include the fund's exposure to market risk and to the size, value (Fama and French, 1993), and momentum factor (Jegadeesh and Titman, 1993):

H1: Teams have less extreme investment styles than single managers do.

Another dimension of a fund's investment style is the industry concentration of its portfolio. According to the diversification of opinions theory, a team consisting of one manager who prefers automobile stocks and one manager who prefers stocks from the banking sector would end up overweighting automobile as well as bank stocks. If managing a fund individually, they would have only over weighted one industry. According to diversification of opinions theory, we thus expect the industry bets of individual managers to be diversified to some extent within a team, which eventually leads to a portfolio that is less industry concentrated than that of an individual manager:

H2: Teams hold portfolios that are less industry concentrated than those of individual fund managers.

If single managers choose more extreme investment styles and hold more industry concentrated portfolios, these investments are likely to turn out very well in some instances, but very poorly in other instances. Consequently, such strategies sometimes lead to extremely good performance outcomes and sometimes to extremely poor performance outcomes. Thus, another prediction that

directly follows from the diversification of opinions theory is that the chance of achieving an extreme (good or bad) performance outcome is lower for teams than for single managers:[4]

H3: Teams achieve less extreme performance outcomes than single managers do.

2.2. Group Shift Theory

Group shift is a consequence of social comparison theory.[5] Social comparison theory (SCT) is one of the most powerful and longstanding social psychology theories for explaining individual behavior in groups. It was first proposed by Festinger (1954). SCT is based on the idea that individuals evaluate themselves relative to others. They want to be perceived well by others and also to perceive themselves well. SCT argues for strong normative influences within a team, which leads team members to try to conform to what they perceive to be the "socially correct" opinion in this team (Baron et al., 1971). The reason underlying this process is that group members want to express an opinion that they believe is preferred by their group and particular by those group members that are dominant in the team. The latter effect is called 'upward social

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4 As the theories tested in this paper make no predictions regarding average performance, we do not include an analysis of average performance. However, in unreported tests we find that team-managed funds slightly underperform single-managed funds in our sample. This is consistent with earlier evidence (see, e.g., Chen et al., 2004).

5 Besides social comparison theory, some authors also propose alternative explanations for group shift (see Brown (2000) for an overview): According to the persuasive arguments theory (Burnstein and Vinokur, 1977) team members shift to more extreme opinions due to persuasive arguments that they might hear during group discussions and that are also in favor of their own position (Gigone and Hastie, 1993). Another explanation is based on the self-categorization theory (Turner et al., 1987). According to this theory, individuals strongly identify themselves with their group (ingroup). Thus, they try to prove their group loyalty by voicing an opinion that distances the group from other groups (outgroups) (Hogg et al., 1990). As all of these theories and the social comparison theory lead to observationally equivalent predictions, we will not try to distinguish among them in our further investigation.

comparison' which means that individuals particularly compare themselves with others that are believed to be superior in some way. Adjusting their own opinion towards the opinion of a dominant person allows for a more positive self image, because individuals then believe themselves to be more similar to the person perceived to be superior (Suls et al., 2002). This adjustment towards the opinion of the dominant person leads the opinions of teams to converge to extremes for two mutually reinforcing reasons: (1) Upward social comparison theory argues that individuals converge to the opinion of the dominant person in the group. Even if there is no formal hierarchy in a team, informal hierarchies usually develop in groups very rapidly. A large body of empirical evidence clearly shows that individuals with extreme views tend to be more confident (Sherif and Hovland, 1961) and eventually are more likely to achieve a higher status in a team (Gibb, 1947, Pruitt, 1971a). This can be explained by the fact that individuals favor those group members with the most extreme views the most (Jellison and Davis, 1973). Consequently, the (formal or informal) leader's opinion towards which other team members will converge is a pronounced opinion already. (2) Because team members strive to conform to the team opinion even more than their peers, they will start to shift their opinion even further than the initially observed preferred opinion (Brown, 1974). For example, if group members learn that the initially preferred opinion of their team is to slightly overweight value stocks, they will start to call for even more overweighting of value stocks. Consequently, the opinion of the team shifts more towards value stocks. Eventually, this can lead to a positive feedback loop leading to decisions that are even more extreme.

There is widespread experimental support for group shift theory. For example, Stoner (1961), Wallach et al. (1961), Wallach and Kogan (1965), Stoner (1968), and Pruitt and Teger (1969) show that teams make more risky decisions than individuals do, which they call 'risky shift'. Later experiments (Brown, 1965; Nordhoy, 1962; Rabow et al., 1966; Stoner, 1968; Hong, 1978)

also show evidence for a 'cautious shift', meaning that team decisions sometimes are significantly less risky than the average individual decision. Thus, group shift does not mean that teams always make more risky decisions. Rather, it predicts that some shift towards an extreme decision as compared to the average individual opinion occurs (Pruitt, 1971b).

Moscovici and Zvalloni (1969), Doise (1969), and Myers and Bishop (1970) show that shifts of opinion towards more extreme opinions also occur for non-risk involving decisions. The vast experimental literature on group decision-making clearly shows that teams raise more extreme opinions and consequently make more extreme decisions than individuals.[6]

The more extreme decisions of teams predicted by group shift theory should also be observed along several dimensions of a fund's investment strategy. They should be reflected in more extreme investment styles along the style dimensions of market exposure, size, value, and momentum:

H4: Teams have more extreme investment styles than single managers do.

Furthermore, when discussing the industry allocation of funds, the team opinion will also converge to a small number of large industry bets rather than a diversified industry portfolio:

H5: Teams hold portfolios that are more heavily industry concentrated than those of single managers.

Since extremity of investment decisions and industry concentration on the one side and the extremity of performance outcomes on the other side should be positively correlated, we expect more extreme performance outcomes if group shift theory holds:

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[6] There are two terms that are often used synonymously to mean group shift: 'choice shift' and 'group polarization'. The two expressions often are not distinguished in empirical work as they regularly lead to observationally equivalent outcomes (Hinsz and Davis, 1984) and will thus also not be distinguished here.

H6: Teams achieve more extreme performance outcomes than single managers do.

Thus, the distinction between diversification of opinions theory and group shift theory leads to contradicting hypotheses with respect to investment styles (H1 vs. H4), industry concentration (H2 vs. H5) and the distribution of performance outcomes (H3 vs. H6).

3. Data

Our primary data source is the CRSP Survivor Bias Free Mutual Fund Database.[7] This database covers U.S. open-end mutual funds and provides information about fund returns, fund management structures, total net assets, investment objectives, and other fund characteristics. We focus on actively managed and broadly diversified domestic equity funds. We exclude bond funds, because there are no generally accepted style factors in bond funds. This makes it difficult to define the measures of style extremity used below. Among the equity funds, we focus on the market segments 'Long Term Growth', 'Growth & Income', and 'Aggressive Growth' (defined according to ICDI objectives). We focus on these segments because funds in these segments are all supposed to follow a broad, well-diversified investment strategy. Thus, they can be easily compared. Following the approach in Daniel et al. (1997), we aggregate multiple classes of the same fund to avoid multiple counting since the various share classes of one fund are backed by the same portfolio and run by the same portfolio manager(s).

CRSP reports management structures of funds in several ways. We classify those funds as single-managed for which CRSP provides the name of one individual fund manager. We classify funds

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[7] Source: CRSP[SM], Center for Research in Security Prices. Graduate School of Business, The University of Chicago. Used with permission. All rights reserved. For a more detailed description of the CRSP database, see Carhart (1997) and Elton et al. (2001).

as team-managed when CRSP reports "team" or "management team" as management structure or when CRSP provides the names of two or more fund managers.[8] A third category reports a manager name with the addendum "et al." or "and team". As is it not obvious how this classification differs from the team-managed and single manager funds, respectively, we exclude these funds from the final sample. For a fourth group of funds, CRSP only reports the name of a management company. These funds are also excluded from our sample since the management structure is unclear.

We follow Chen et al. (2004) and use the CRSP database for management information. This database is less used by the media and investors than, for example, Morningstar as a source of information about funds (Massa et al., 2009). This gives CRSP the useful characteristic of being a source where firms have no direct incentive to strategically manipulate their reporting. Massa et al. (2009) find that CRSP and Morningstar sometimes report different information regarding the management of the fund. However, these differences generally refer to whether several manager names rather than "team managed" are reported. In our main analysis, both cases are considered as team-managed funds. Thus, we expect no serious misclassification negatively affecting our results.

Our final sample spans the ten-year period from January 1994 to December 2003 and includes 12,339 yearly observations. The funds belong to 652 different fund management companies. Summary statistics of our sample are presented in Table I.

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[8] In 2003, in the aftermath of the fund scandals, the SEC announced a new rule according to which funds are obliged to disclose the identities of all team members. Until then, they could choose whether to disclose the names of a management team's members or not. For differences between funds that are labelled 'team managed' and funds that disclose multiple manager names, see Massa et al. (2009). In Section 5.3 we also explicitly examine differences between anonymous and identified teams.

– Insert TABLE I about here –

On average, the funds in our sample are 10.91 years old and manage over 880 million USD. The mean turnover rate is 95.62% p.a. and the mean expense ratio is 1.32% p.a. Overall, 7,576 observations (61.4%) are from single-managed funds and 4,763 observations (38.6%) are from team-managed funds. Out of the latter, roughly half of the funds disclose the team members' names ('identified teams'), while the other half are team-managed funds for which the fund company does not disclose the team members' names ('anonymous teams'). Figure 1 plots the percentage of team- and single-managed funds over time.

– Insert FIGURE 1 about here –

It covers the years of the rapid growth in team-managed funds. In 1994, only about 12% of the funds are team managed. In the following years, this percentage grows dramatically, reaching about 52% in 2003.

4. Main Results: Diversification of Opinions vs. Group Shift Theory

We start our empirical investigation with an examination of differences in investment style extremity to test Hypothesis 1 vs. Hypothesis 4 (Section 4.1), before we then analyse Hypothesis 2 vs. Hypothesis 5 by looking at industry concentration (Section 4.2) and finally investigate differences in performance extremity to test Hypothesis 3 vs. Hypothesis 6 (Section 4.3).

4.1. Extremity of Investment Styles

To capture the extremity of a fund's investment styles, we first have to quantify the extent to which a fund follows specific styles. To this end, we run the following Carhart (1997) four factor model for each fund *i* in each year *t*:

$$(1) \qquad r_{i,m,t} - r_{f,m,t} = a_{i,t} + \beta_{i,t}^{1}\left(r_{M,m,t} - r_{f,m,t}\right) + \beta_{i,t}^{2} SMB_{m,t} + \beta_{i,t}^{3} HML_{m,t} + \beta_{i,t}^{4} MOM_{m,t} + \varepsilon_{i,m,t}.$$

The dependent variable is the monthly return of fund *i* in month *m* of year *t*, $r_{i,m,t}$, less the risk free rate in this month, $r_{f,m,t}$. The independent variables are the excess return of the market portfolio over the risk-free rate, $r_{M,m,t} - r_{f,m,t}$, and the returns of the three factor-mimicking portfolios: the size factor, *SMB*, calculated as the return difference between small and large capitalization stocks, the value factor, *HML*, calculated as the return difference between high and low book-to-market stocks, and the momentum factor, *MOM*, calculated as the return difference between stocks with high and low past returns.[9] A high factor loading indicates that the fund manager follows a strategy with a high level of market risk rather than a strategy with a low level of market risk (β^1), a small-cap rather than a large-cap strategy (β^2), a value rather than a growth strategy (β^3), and a momentum rather than a contrarian strategy (β^4), respectively.

To get a first idea about the extremity of a fund's investment style we analyse the distribution of the factor loadings β^1 to β^4 from model (1) for team- and single-managed funds. If a fund follows an extreme strategy with respect to a specific style dimension, its factor loadings are more likely to be in the tail of the distribution of all fund's factor loadings in the same year. Thus,

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[9] The market, the size, and the value portfolio returns were taken from Kenneth French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, while the momentum factor was kindly provided by Mark Carhart.

if the diversification of opinions Hypothesis 1 holds, we should observe a larger fraction of single-managed funds in the most extreme percentiles of the distribution of factor loadings.[10] To examine this hypothesis, we compute the share of single-managed funds in different percentiles of the factor loading distributions. These shares are calculated as the average of the respective yearly shares over our sample period. This ensures that our results are not driven by shifting style preferences within the mutual fund industry in combination with the increased share of team-managed funds. The results are visualized in Figure 2 and summarized in Panel A of Table II.

– Insert TABLE II & FIGURE 2 about here –

In Figure 2, we plot the average share of single-managed funds in the top- and bottom 1%, 1-10%, 10-20% and middle 60%, respectively, of all factor realizations for all four dimensions of a fund's investment style (Market, SMB, HML, and MOM). For each style dimension we observe a clear U-shaped relationship. For example, the U-shaped relationship for the loadings on the market factor, β^1, shows that single-managed funds are more likely to choose investment styles with particularly high or particularly low systematic risk. We find similar relations for the loadings on the size factor, the value factor, as well as the momentum factor. Overall, these findings show that single managers are more likely to choose extreme investment styles and deliver first evidence in support of the diversification of opinions Hypothesis 1.

[10] While not the focus of this paper, in unreported tests we also compute the average factor loadings of team- and single-managed funds. We find no significant difference between team- and single-managed funds, indicating that the two groups of funds follow *on average* similar investment strategies.

This visual impression is confirmed by inspecting the underlying percentage realizations of single-managed funds in the various percentiles of the factor loading distributions presented in Panel A of Table II. In the extreme percentiles the fraction of single-managed funds is always clearly higher than in the middle percentiles. For example, the average yearly share of single-managed funds among the highest (lowest) 1% of factor loading realisations for the market factor, β^1, over our sample period is 73.87% (71.52%), while it is only about 66.39% among the three middle quintiles of the factor loadings. We obtain similar results for the factor loadings that represent the size, value, and momentum-dimension of the fund's investment style.

To examine style extremity more formally we now introduce a quantitative measure for the style extremity of a fund with respect to a specific investment style. We construct a set of four style extremity measures, *SE*, based on the four investment style dimensions. Following the same basic idea as above, we define style extremity in the sense of taking a large bet on the market, size, value, or momentum factor, i.e., having an extremely high or low loading on the *Market*, *SMB*, *HML*, and *MOM* factor (β^1 to β^4), respectively. We compute, for each fund *i* and year *t*, style extremity measures, $SE_{i,t}^F$, as the absolute difference between the fund's factor weightings, $\beta_{i,t}^F$, and the corresponding segment average, $\overline{\beta}_{i,t}^F$, as style benchmarks, where $F = 1,\ldots,4$ denotes the style dimension. The style benchmarks $\overline{\beta}_{i,t}^F$ are the average factor loadings of all funds in the same market segment as fund *i* in year *t*. We normalize this absolute difference by dividing it by the average absolute style difference in the corresponding market segment and respective year. This normalization makes our style extremity measure comparable across styles, segments, and time. The formal definition of our factor extremity measure reads:

(2) $$SE_{i,t}^{F} = \frac{\left|\beta_{i,t}^{F} - \overline{\beta}_{i,t}^{F}\right|}{\frac{1}{n} \cdot \sum_{j=1}^{n} \left|\beta_{j,t}^{F} - \overline{\beta}_{i,t}^{F}\right|}.$$

The number of funds in a specific segment and year is denoted by *n*. The average style extremity with respect to each style dimension β^1 to β^4 is 1 by construction. A higher level of $SE_{i,t}^{F}$ indicates a more extreme investment style of a fund.

According to Hypothesis 1, we expect a higher level of $SE_{i,t}^{F}$ among single-managed funds than among team-managed funds. Average extremity measures for the group of single-managed and team-managed funds for each of the four style dimensions are presented in Panel A of Table III.

– Insert TABLE III about here –

We find strong evidence indicating that teams follow less extreme investment styles than single managers. For example, the average style extremity measure with respect to the market factor is 1.04 among single-managed funds, i.e., their style extremity measure is 4% above that of an average fund in the same segment and year. The respective average style extremity measure among team-managed funds is only 0.94, i.e., their style extremity measure is 6% below average.[11] This gives rise to a difference in style extremity between team- and single-managed funds of 10%, which is significant at the 1%-level. The difference is slightly smaller for style extremity with respect to the value style dimension, but still amounts to 8.8% and is significant at the 1%-level. The strongest difference can be observed for style extremity with respect to the size

[11] The simple average of the aggregate style extremity measures for team and single-managed funds is not 1, because the number of team-managed funds in our sample is smaller than the number of single-managed funds.

dimension and the momentum dimension. Here, the differences amount to 11.2% and 14.9%, respectively. These findings are consistent with our previous evidence and provide further support for the diversification of opinions Hypothesis 1, while they allow us to reject the group shift Hypothesis 4.

4.2. Industry Concentration

If diversification of opinions theory holds, we also expect teams to hold a less industry concentrated portfolio than single managers (Hypothesis 2). To measure the industry concentration within a fund's portfolio, we use a measure that is very similar to the industry concentration measure described in Kacperczyk et al. (2005). First, each stock is assigned to one of 10 industries.[12] Then, the industry concentration measure for fund *i* in year *t*, $IC_{i,t}$, is calculated as the sum of the squared deviations of the difference between the industry weights of a fund *i* in industry *j*, $w_{i,j,t}$, and the weight of industry *j* in the total stock market, $\overline{w}_{j,t}$:[13]

$$IC_{i,t} = \sum_{j=1}^{10} (w_{i,j,t} - \overline{w}_{j,t})^2 . \quad (3)$$

As above, as a first test of our hypothesis we calculate the share of single-managed funds in different percentiles of the industry concentration distribution. The results are visualized in Figure 3 and summarized in Panel B of Table II.

We find that the share of single-managed funds monotonically decreases with industry concentration. Among the top-1% industry concentrated funds it is nearly 80%, while it is only about 57% among the funds within the bottom-1% of the industry concentration distribution.

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12 For the composition of the 10 industries, see the Appendix in Kacperczyk et al. (2005).

13 We thank Clemens Sialm for sharing his industry concentration data with us.

This result is also confirmed by the average of the IC measure for all single and all team-managed funds, which is presented in Panel B of Table III. The measure is 6.8% for single-managed funds and 5.7% for team-managed funds. The difference is statistically significant at the 1% level. Overall, the results from this section provide further evidence for the diversification of opinions theory by supporting the respective Hypothesis 2 and by rejecting the group shift Hypothesis 5.

4.3. Performance Extremity

Investors are ultimately concerned about performance outcomes. Thus, we now analyze whether the behavioral differences documented above are also reflected in differences in the distribution of performance realizations between teams and single managers. Based on our previous results, we expect the more extreme styles followed by single managers to lead to a very successful or a very bad outcome depending on whether or not they bet on those styles that are most profitable. Consequently, we expect teams to achieve less extreme performance outcomes than single managers, which would support the diversification of opinions Hypothesis 3 and reject the group shift Hypothesis 6.

To test our Hypotheses 3 and 6, we use two performance measures: (i) The peer group adjusted return of a fund. It is computed as the difference between the return of a fund and the average return of all funds in the same market segment. (ii) The fund's four factor alpha according to Carhart (1997). It is calculated as the intercept from model (1).[14]

[14] There is a large debate on whether the factor mimicking portfolios represent systematic risk factors or not. We do not take a view on this question but rather interpret factor loadings as representing specific investment styles.

To get a first idea about the performance distribution, we again compute the share of single-managed funds in different percentiles of the performance distribution. The results are visualized in Figure 4.

– Insert FIGURE 4 about here –

For both performance measures, we observe a U-shaped relationship. This suggests that funds with a single manager have a higher probability of ending up in one of the extreme (top or bottom) performance percentiles while teams are more likely to be found in the middle performance percentiles. The pattern is more pronounced for peer group adjusted returns than for the four-factor alpha. This is consistent with the idea that the more extreme investment styles of single managers lead to more extreme performance outcomes. Since the Carhart (1997) four factor alphas correct for differences in investment styles, it is not surprising that the difference in performance extremity is less pronounced based on this measure. However, the still observable difference in the distributions of the four factor alphas indicates that single managers also make more extreme investment decisions along other dimensions of their investment style that we do not capture by the Carhart (1997) four factor model.

The percentage numbers in the various performance percentiles underlying Figure 4 are presented in Panel C of Table II. These numbers confirm the visual impression. If we capture performance by peer-group adjusted returns, the share of single-managed funds among the top 1% (bottom 1%) of all performance outcomes is 74.7% (73.9%), while it is only 65.8% among the middle 60%. The pattern is somewhat weaker for the Carhart (1997) four factor alpha. Here the share of single-managed funds among the top 1% (bottom 1%) of all funds is 72.0% (71.9%), while it is

66.6% in the middle three quintiles. These results are consistent with the diversification of opinions Hypothesis 3, but reject the group shift Hypothesis 6.

To further examine whether this pattern is statistically significant, we develop measures of performance extremity, $PE_{i,t}$, similar to the style extremity measures developed above. We define performance extremity as the realization of an extreme (good or bad) performance outcome. For each fund *i* in each year *t*, performance extremity measures, $PE_{i,t}$, are computed as the absolute difference between a fund's performance, $P_{i,t}$, and the average performance of all funds in the same year and segment, $\overline{P}_{i,t}$. We normalize these numbers by dividing them by the average absolute difference of all *n* funds in the corresponding market segment and respective year:

$$PE_{i,t} = \frac{\left|P_{i,t} - \overline{P}_{i,t}\right|}{\frac{1}{n} \cdot \sum_{j=1}^{n} \left|P_{j,t} - \overline{P}_{i,t}\right|} \tag{4}$$

A higher value of a performance extremity measure corresponds to a more extreme performance outcome. A fund with average performance extremity has an extremity measure of 1, by construction.

We compute performance extremity with respect to our two performance measures (peer-group adjusted returns and Carhart (1997) four factor alphas).[15] Results are presented in Panel C of Table III. The average performance extremity based on peer-group adjusted returns among single-managed funds is 1.03, while it is only 0.94 among team-managed funds. The difference in performance extremity of 8.7% is statistically significant at the 1% level. If we base performance

[15] In the case of peer-group adjusted returns we do not subtract the respective average in the same segment and year, as this measure is already defined as the difference between the return of the fund and the average return of all funds in the same segment and year.

extremity on the Carhart (1997) four factor alpha, the difference is somewhat smaller at 5.1% but still statistically significant at the 5% level.[16]

Overall, the results from this section deliver strong evidence for the diversification of opinions theory by supporting the respective Hypotheses 1 to 3, while they do not support the group shift theory but allow us to reject the respective Hypotheses 4 to 6.

5. Alternative Explanations

We now turn to an analysis of alternative explanations for our results. First, teams might be employed for funds with specific characteristics that differ from those of single-managed funds. To examine whether such differences in fund characteristics rather than management structure itself drive our results, we explicitly investigate their impact (Section 5.1). Second, we examine whether our results can be explained by the findings in Massa et al. (2009) of differences in the marketing value of single- and team-managed funds (Section 5.2). Third, we analyse whether our findings are driven by differences in the demographic characteristics of the managers that are members of a team and single managers (Section 5.3). Finally, we add family fixed effects to make sure that differences in fund family characteristics are not responsible for our findings (Section 5.4).

[16] In unreported tests, we also compute the average performance of single- and team-managed funds. We find that single managers perform marginally better. The effect is economically small and only significant for the Carhart (1997) four factor alpha. This result confirms the results from prior studies on performance differences between teams and single-managed funds (see, e.g., Chen et al., 2004).

5.1. The Impact of Differences in Fund Characteristics

It is likely that team- and single-managed funds differ with respect to their characteristics. Thus, it is possible that these differences rather than the management structure lead to the observed differences in style and performance extremity. To analyse differences in fund characteristics, we first compute the average fund characteristics from Table I separately for team- and single-managed funds. Results are presented in Table IV.

– Insert TABLE IV about here –

We find that team-managed funds indeed differ from single-managed funds along several dimensions: they tend to be younger and larger than single-managed funds. Furthermore, they have slightly lower turnover ratios and expense ratios as compared to single-managed funds. The differences in size and turnover ratio are significant at the 1% level, while the differences in age and expense ratio are significant at the 5% and 10% level, respectively. The differences are economically small. Nevertheless, they still mandate that we control for the impact of fund characteristics.

To assess the influence of the management structure and other potentially relevant fund characteristics on extremity, we use a multivariate framework. We relate the style extremity measure, $SE_{i,t}$, the industry concentration measure, $IC_{i,t}$, and the performance extremity measure, $PE_{i,t}$, to the fund's management structure and fund age, size, turnover ratio, and expense ratio:

$$SE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t} \quad (5)$$

(6) $$IC_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}$$

(7) $$PE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}$$

The team dummy, $D_{i,t}^{Team}$, equals one if fund *i* is managed by a team in year *t* and zero otherwise.[17] *Age* and *Size* are computed as the logarithm of fund age and total net assets, respectively. *Turnover* is the fund's turnover ratio and *Expenses* is the fund's expense ratio in percent. We lag these explanatory variables by one year to mitigate potential endogeneity concerns.[18] We run the regressions (5) and (7) including time- and segment-fixed effects. Results for model (5) using the style extremity measures based on each of the four investment style categories as dependent variables, for model (6), and for model (7) using performance extremity based on our two performance measures are presented in Table V.

– Insert TABLE V about here –

The results in columns 1 to 4 show that management teams choose less extreme investment style positions than single managers. This result holds for all style dimensions: the influence of the team dummy is always negative and statistically significant. The magnitude of the coefficient for the influence of the team dummy is in accordance with the results from our univariate analysis in Table III. Again, the difference is most pronounced for extremity with respect to the size and the momentum factor.

[17] We drop observations from years in which the management structure changes.

[18] We explicitly address endogeneity concerns in Section 7.2.

The results for the impact of the control variables indicate that there is generally no strong influence of fund age and the fund's expense ratio. However, mainly small funds and funds with higher turnover ratios follow more extreme investment styles. This can be explained by the higher degree of flexibility among those funds that allows them to follow such extreme styles.

Column 5 shows that the team dummy has a significant negative impact on industry concentration. The results indicate that industry concentration is lower by 1.4% among team-managed funds. This effect is even a little bit larger than the 1.1% difference documented in the univariate analysis.

The last two columns provide evidence for more extreme performance outcomes among single-managed funds than among team-managed funds. The estimated coefficient for the impact of the team dummy is -0.10 for performance extremity based on peer group adjusted returns, i.e., performance extremity is 10% lower among team-managed funds. This again agrees with the univariate evidence presented in Table III. Also consistent with our earlier findings, the effect is weaker for the Carhart (1997) four factor alpha, where the difference is only about 8%.[19]

Overall, these results show that our prior findings are not driven by differences in fund characteristics between team- and single-managed funds. They confirm our earlier evidence in support of the diversification of opinions theory and again reject the group shift theory.

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[19] In unreported regressions, we also include return volatility as an additional control variable. Its impact on style extremity, industry concentration, and performance extremity is significantly positive (for differences in return volatility between team and single-managed funds, see Section 6.2.). Alternatively, we also include the level of the variables on which our respective extremity measures are based as additional control variables. For example, in the SMB extremity regression, we include the SMB factor loading and in the peer group adjusted performance extremity regression, we include the peer group adjusted return itself as additional control variable. In all cases, our main result of a negative impact of the team dummy remains unaffected.

5.2. The Impact of the Higher Marketing Value of Single Managers

It makes sense for fund companies to advertise funds with good past performance, as the impact of advertising dollars spent is much larger for well performing funds than for other funds (Korkeamaki et al., 2007). Furthermore, in a recent paper Massa et al. (2009) argue that single managers can be of high value for mutual fund companies, because it is easier to market them as "superstars" than it would be to market a team.[20] Thus, there seems to be a complementary impact of a stellar performance and the fund's management structure on the fund's marketing value: the marketing value of a single-managed fund with a stellar performance should be higher than the marketing value of a team-managed fund with a stellar performance.

This could give rise to incentives for the fund management company to direct single-managed funds to follow more extreme strategies in order to increase the probability of having an easy to advertise fund in the fund family. This strategy makes sense only if the fund family is actually running a marketing campaign. As we have no direct data on marketing expenditures, we follow Barber et al. (2005) and Khorana and Servaes (2007) and rely on 12b-1 fees as a proxy.[21] If 12b-1 fees are particularly high, the fund management company has a lot of resources at its disposal to market the respective fund. Thus, it should be interested in the single-managed fund's achieving an extreme performance outcome. To analyze whether our results on the impact of team status hold after taking into account 12b-1 fees, we include an interaction term between a 12b-1 dummy and our team dummy. The 12b-1 dummy takes on the value one if the fund charges 12b-1 fees and zero otherwise. Estimation results are presented in Table VI. For the sake of brevity, we only

[20] The reason for this could be that customers prefer products that can be associated with personalities (Aaker, 1997).

[21] 12b-1 fees are a fee component that is explicitly used for marketing and distribution expenditures.

report the coefficients for the impact of the 12b-1 dummy, the team dummy, and the interaction term.

– Insert TABLE VI about here –

We still find a negative impact of the team dummy on our measures of investment style and performance extremity as well as industry concentration. This suggests that single managers follow a more extreme investment style, achieve more extreme performance outcomes, and hold more concentrated portfolios even if the fund does not charge 12b-1 fees. The interaction term shows that whether a fund charges 12b-1 fees or not does not have a noteworthy influence on the impact of team status on extremity and industry concentration. This suggests that our earlier results are not driven by the higher marketing value of single fund managers.

Interestingly, we find a significantly negative impact of the 12b-1 fee dummy on extremity. Funds that charge 12b-1 fees are less extreme with respect to investment style and performance, no matter whether they are single-managed or managed by a team. They also hold less concentrated portfolios. This finding might reflect the fact that funds that charge 12b-1 fees can attract new money by running a marketing campaign. Therefore, they can afford avoiding extreme investment styles that possibly lead to an extremely poor performance outcome.

5.3. The Impact of Differences in Manager Characteristics

Team managers and single managers might differ with respect to their demographic characteristics or their education. This could eventually lead to differences in investment behavior. To control for this possibility, we have to focus on single managers and identified

teams as we do not have information about the identity and personal characteristics of the members of anonymous teams.

Massa et al. (2009) argue that there is a difference in the incentives anonymous and identified teams face due to differences in the marketing value (see also Section 5.2). Thus, before we examine the impact of personal characteristics on our results, we first analyse whether anonymous and identified teams differ with respect to the extremity of their investment styles and performance outcomes. As the information on personal characteristics of managers is available to us starting in the year 1996, we focus on observations from the years 1996 to 2003 and estimate models (5), (6), and (7) for this sample period. Results are presented in Table VII.

– Insert TABLE VII about here –

For easy comparison, the estimated coefficients for the impact of the team dummy for our restricted sample period 1996 to 2003 are presented in the first column. The results are very similar to those for the full sample from Table V. To check for differences between anonymous and identified teams, we construct two subsamples, one consisting of single managers and identified teams only and one consisting of single managers and anonymous teams only. The results are presented in Columns 2 and 3 of Table VII. The coefficients for the impact of the team dummy from the two subsamples are very similar to each other in terms of economic magnitude and statistical significance. This indicates that potential differences in the incentives that anonymous and identified teams might face do not lead to differences in investment style extremity and performance extremity. In both cases, we find strong evidence for more extreme

investment styles, a higher industry concentration, and more extreme performance outcomes among single managers than among teams.

We now investigate the impact of manager characteristics by focusing on a sample of single-managed funds and identified team-managed funds. The demographic information available to us includes the managers' academic degrees (Bachelor's, Master's, or PhD), their experience as measured by their industry tenure in years, and a proxy for their age based on the year in which they got a specific degree awarded (following Chevalier and Ellison, 1999b). Furthermore, we identify the gender of the managers based on their first names using the method described in Bär et al. (2008). The average characteristics of managers that belong to identified teams and those of single managers are presented in Table VIII.

– Insert TABLE VIII about here –

Managers that are part of an identified team have slightly lower average industry tenure and are somewhat younger on average. Furthermore, 67% of the identified team managers have a Master's degree while 70% of the single managers hold that degree. Among both groups, 5% have a PhD. Finally, the share of female managers is only slightly higher at 12% among identified teams as compared to 11% among single managers. However, with the exception of age, none of these differences are statistically significant.

To assess whether these individual manager characteristics have any impact on investment style and performance extremity we extend models (5), (6), and (7) by including manager characteristics as additional explanatory variables. Results are presented in Table IX.

– Insert TABLE IX about here –

Consistent with our previous evidence, we still find a significantly negative impact of the team dummy on all style extremity as well as on performance extremity measures and on industry concentration. This finding shows that our results are not driven by differences in individual manager characteristics.

Regarding our additional control variables, the only detectable effect emanates from the female gender dummy. With the exception of momentum, women follow significantly less extreme investment styles with respect to all style dimensions. They also hold less industry concentrated portfolios. These differences are also reflected in less extreme performance outcomes among female managers than among male managers. These findings are consistent with the results on differences in performance extremity between female and male single managers in Niessen and Ruenzi (2008).

Overall, the results from this section show that our earlier results cannot be explained by differences in the personal attributes of the managers that belong to teams as compared to those managing a fund alone.

5.4. The impact of family characteristics

It is possible that some families have a general investment philosophy of following specific investment styles. At the same time, some fund families are clearly dominated by teams, while others are dominated by single-managed funds. Thus, our results could be driven by families ordering their funds to follow a certain course of action. To examine the role of the fund family in

determining behavior in more detail, we add family fixed effects to all regression models.[22] This controls for the impact of general family policies on the investment behavior of all funds in the family. Results are presented in Table X.

– Insert TABLE X about here –

For the sake of brevity, we only report the estimates for the impact of the team dummy. Consistent with our earlier findings, we again find a negative impact of the team dummy on all style and performance extremity measures and a positive impact on industry concentration. The magnitude of the estimates is very similar to those documented before. These results show that team status has an important impact on fund behavior even after controlling for the impact of the family a fund belongs to.

Overall, the findings from this section show that our results are not driven by alternative explanations like differences in fund characteristics, differences in the marketing value of single managers and teams, or differences in the demographic characteristics of the managers and the fund family a fund belongs to.

6. Test of Further Theory Implications

In this section, we first examine several further implications that arise from the diversification of opinions theory and the group shift theory. They relate to the impact of team size on our main

[22] Alternatively, we explicitly add several characteristics of the family like family age, total assets under management, and number of funds managed as additional control variables. The impact of the team dummy is very similar in all cases.

results (Section 6.1) as well as to the impact of team status on additional strategy variables like risk level, tracking error, and active share (Section 6.2) and to the impact of the diversity within a team on its behavior (Section 6.3). Our following discussion shows that the analysis in Section 6.1 is discriminatory in the sense that the two theories make opposing predictions. However, only the diversification of opinions theory makes predictions regarding the impact of team status on the additional strategy variables (Section 6.2) and only the group shift theory makes predictions regarding the impact of diversity (Section 6.3). Based on our prior results, we expect to find support for the diversification of opinions hypothesis in the first two subsections, while we do not expect to find support for the hypothesis developed on the group shift theory in Section 6.3.

6.1. Impact of Team Size[23]

In the case of the identified teams, we know the number of team members. This allows for an examination of the impact of team size on fund behavior. Diversification of opinions theory predicts that the moderating effect of team status should be stronger among larger teams. This should hold true for style extremity, industry concentration, and performance extremity. Larger teams are expected to follow less extreme styles than smaller teams since the average of the team members is more likely to be close to the sample mean, the larger the team is. Regarding industry concentration, in a larger team more ideas for industry bets are combined, which leads to a stronger diversification effect. Both arguments predict that larger teams will eventually achieve less extreme performance outcomes than smaller teams. In contrast, group shift theory argues that team decisions are tilted towards the most extreme views in the team. As the probability of having a team member with an extreme view increases with team size, this theory would predict

[23] We thank an anonymous referee for suggesting this additional test.

that larger teams exhibit higher style and performance extremity as well as a higher degree of industry concentration than smaller teams.[24]

To examine the impact of team size on management behavior, we extend our basic models by replacing the team dummy with three dummies indicating small teams consisting of two managers, large teams with more than two managers and anonymous teams for which we don't know the team size:[25]

$$DepVar_{i,t} = \beta_1 D_{i,t}^{Small} + \beta_2 D_{i,t}^{Large} + \beta_3 D_{i,t}^{Unknown} + \beta_4 Age_{i,t-1} + \beta_5 Size_{i,t-1} + \beta_6 Turnover_{i,t-1} + \beta_7 Expenses_{i,t-1} + \varepsilon_{i,t} \quad (8)$$

The dummy $D_{i,t}^{Small}$ ($D_{i,t}^{Large}$) takes on the value one if the fund is managed by a team with two members (more than two members), and zero otherwise. $D_{i,t}^{Unknown}$ is a dummy taking on the value one if the fund is managed by an anonymous team, and zero otherwise. Estimation results for model (8), where $DepVar_{i,t}$ can stand for style extremity, industry concentration, and performance extremity, respectively, are presented in Table XI.

– Insert TABLE XI about here –

Columns 1 to 4 show the results for the impact of team size on style extremity. The impact of the large team dummy $D_{i,t}^{Large}$ is always larger in absolute terms than the impact of the small team dummy $D_{i,t}^{Small}$. For example, the coefficient for impact of the large team dummy on style

[24] Teger and Pruitt (1967) provide experimental evidence for a positive impact of team size on the riskiness of decisions.

[25] The number of teams with four, five, or more members is very small. Thus, we cannot split up our large team dummy further without losing too much statistical power.

extremity with respect to the market factor (0.088) is about one third larger than the coefficient for the impact of the small team dummy (0.067). We find similar relationships for the other style extremity as well as industry concentration and performance extremity measures. However, the difference is only significant at the 10% level for one of the style extremity measures. The lack of stronger statistical significance is probably due to the relatively small number of observations if we split up the team category into three subcategories. Nevertheless, the results are at least in the expected direction and offer indicative evidence that team size has a moderating effect on team behavior. This is again consistent with the predictions of the diversifications of opinion hypothesis.

6.2. Risk Levels, Tracking Error, and Active Share

We start our analysis by looking at differences in risk levels between team and single-managed funds. Diversification of opinions theory makes a clear prediction regarding the level of risk:[26] The individual industry or individual stock bets that the members of a team would have made on their own are at least partially diversified away on the team level. Consequently, we expect their diversification effect to lead to lower overall risk levels among teams. However, as the systematic component of a fund's risk cannot be diversified away, we expect that lower total risk among teams is driven by lower idiosyncratic risk among teams.

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[26] Intuition suggests that extremity and riskiness are very similar concepts and that group shift theory should thus predict more risky behavior. However, group shift theory only predicts a shift towards that opinion within a team that is expected to be the socially preferred opinion by the members. This socially preferred opinion could be to follow a risky or a safe strategy. Thus, group shift theory does not make any direct predictions regarding the level of risk and the experimental literature indeed provides evidence for both, risky- as well as cautious-shifts (see Section 2).

We measure total risk by the standard deviation of fund *i*'s return in year *t*. We follow Chevalier and Ellison (1999b) and measure systematic risk by fund *i*'s beta in year *t*, $\beta_{i,M,t}$, from a market model. Unsystematic risk is measured by the standard deviation of fund *i*'s residual fund return from this model.[27] We calculate these measures by regressing fund *i*'s excess return on the market excess return for each year in our sample:

$$(9) \qquad r_{i,m,t} - r_{f,m,t} = a_{i,t} + \beta_{i,M,t}\left(r_{M,m,t} - r_{f,m,t}\right) + e_{i,m,t}.$$

Variables are defined as in (1).

To examine the impact of team status on risk levels, we replace the dependent variable in model (5) by either total risk, systematic risk, or unsystematic risk, respectively. Results are presented in Table XII. For the sake of brevity, we only report results for the impact of the team dummy.

– Insert TABLE XII about here –

The results in Column 1 provide evidence that management teams take less total risk than single managers. The coefficient of the team dummy is negative and significant at the 1% level. This result is consistent with the findings of Adams and Ferreira (2009) who show that teams make less risky bets.[28] The results on the impact of the management structure on systematic and unsystematic risk presented in Columns 2 and 3 indicate that teams take significantly less

[27] All results remain qualitatively unchanged when using a four-factor model instead of a one-factor model.

[28] Another dimension of risk taking is the extent to which fund managers engage in risk gambles in a tournament context, where they adjust risk to achieve a top position by the end of the year (Brown et al., 1996). Qiu (2003) and Kempf and Ruenzi (2008) examine differences in tournament behavior between teams and single-managed funds. Consistent with our findings, they provide evidence that teams engage less in risk gambles.

unsystematic risk than single managers. At the same time, we cannot reject the hypothesis that the level of systematic risk does not differ between team and single-managed funds. These results are consistent with our expectations and provide further support for the diversification of opinions hypothesis.

We now turn to an analysis of differences in tracking error and active share. Diversification of opinions theory predicts that single investment ideas like bets on specific industries or even individual stocks will not become dominant within a team. Consistent with our previous results of lower industry concentration within teams (see Section 4.2), we expect that individual ideas are diversified away to a certain extent within teams. This should bring team-managed funds closer to their benchmarks than single-managed funds. We examine this prediction by comparing the active share and the tracking error that team and single-managed funds exhibit.

The active share of a fund *i* in year *t*, $AS_{i,t}$, represents the share of a fund's portfolio holdings that differ from the benchmark index holdings, as do Cremers and Petajisto (2009):

$$AS_{i,t} = \frac{1}{2} \cdot \sum_{j=1}^{N} \left| w_{i,j,t} - w_{benchmark(i),j,t} \right|,$$

where $w_{i,j,t}$ is the weight of stock *j* in fund *i*'s portfolio in year *t* and $w_{benchmark(i),j,t}$ is the weight of stock *j* in the benchmark of fund *i* in year *t*. Cremers and Petajisto (2009) select the appropriate benchmark for each fund out of a set of 19 indexes based on the overlap between the holdings of the fund with the holdings of the index. For $AS_{i,t}$, we use the same data as in Cremers and Petajisto (2009).[29]

[29] Data on active share as well as tracking error is available on http://www.petajisto.net/data.html. Cremers and Petajisto (2009) run regression (11) using daily return data from the prior six months. In our analysis,

We measure the tracking error of a fund, $TrErr_{i,t}$, like Cremers and Petajisto (2009) as

(10) $$TrErr_{i,t} = Stdev\left[\varepsilon_{i,m,t}\right]$$

where $\varepsilon_{i,m,t}$ is obtained from the following yearly regression:

(11) $$r_{i,m,t} - r_{f,m,t} = \alpha_{i,t} + \beta_{i,t} \cdot (r_{benchmark(i),m,t} - r_{f,m,t}) + \varepsilon_{i,m,t}.$$

$r_{i,m,t}$ denotes the fund's return in month *m* of year *t*, $r_{f,m,t}$ the risk free rate and $r_{benchmark(i),m,t}$ the return of the fund's benchmark.[30]

To examine the impact of team status on tracking error and active share, we replace the dependent variable in model (5) by $AS_{i,t}$ and $TrErr_{i,t}$, respectively. Results are presented in the last two columns of Table XII. In both cases, the impact of the team dummy is negative and significant at the 1% level. Again, this is consistent with our expectation of a lower active share and lower tracking error among team-managed funds and delivers confirming evidence in favor of the diversification of opinions theory.

6.3. Diversity

Many teams consist of members with different educational backgrounds, differences in experience and age, or of men and women. Such differences in personal characteristics are likely

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we use the number provided for December of the previous year (thus based on data from June to December of the previous year).

[30] Tracking error is usually defined as the standard deviation of the difference between a fund's return and the return of its benchmark, (see, e.g., Grinold and Kahn, 1999). However, this method is not appropriate to capture tracking error of actively managed funds as it implicitly assumes that the fund has a beta of one with respect to the benchmark portfolio. The approach of Cremers and Petajisto (2009) avoids this assumption.

to give rise to differences in personal opinions on what the optimal investment style might be (e.g., Bär et al., 2008). If team members differ a lot with respect to their opinions, the probability that some members have extreme positions increases. The group shift theory predicts that group opinions shift towards the opinion of the most extreme team member (see Section 2.2). Thus, this theory predicts that diverse teams tend to show more extreme behavior. In contrast, diversification of opinions makes no clear prediction with respect to the impact of diversity. According to this theory, it makes no difference whether two middle-aged managers both have preferences for a moderate industry concentration, or whether a young and an old manager with strong preferences for high and low industry concentration, respectively, work together. Diversification of opinions theory predicts moderate industry concentration in both cases.

To examine the impact of team diversity on management behavior, we evaluate the impact of the four diversity dimensions considered in Bär et al. (2008): age diversity, gender diversity, tenure diversity, and educational diversity. Age, tenure, and educational diversity are defined as the coefficient of variation of the team members' age, their industry experience, and their years of formal education in years, respectively. Gender diversity is defined like an entropy based index as $-p \cdot \ln(p) - (1-p) \cdot \ln(1-p)$, where p is the fraction of female managers in a team.[31] For men only or women only teams the measure is set equal to zero.

We test the impact of team diversity on style extremity, industry concentration, and performance extremity, respectively. To do so, we have to restrict our sample to identified teams for which we can calculate the team diversity. Information on personal characteristics of managers is available to us starting in the year 1996. Therefore, we can use only observations from the years 1996 to 2003. We modify our standard models (5) – (7) by including the four diversity measures as

[31] We use the same data as used in Bär et al. (2008).

additional explanatory variables and leaving out the team dummy. Results are presented in Table XIII.

– Insert TABLE XIII about here –

Irrespective of the diversity dimension considered, we find no noteworthy impact of diversity on style extremity, industry concentration, or performance extremity. Only 3 out of 24 coefficients are significantly positive at the 10%-level. The remaining coefficients are insignificant and show different signs. This is consistent with the diversification of opinions theory, but delivers no support for the group shift theory.

Overall, the additional tests in this section – while not always allowing us to directly discriminate between the two theories – all support the diversification of opinions theory, while we again find no evidence in favour of the group shift theory.

7. Robustness

7.1. Alternative Regression Approaches

To check for the robustness of our results, we now apply some alternative regression approaches. Particularly, instead of running our regressions with time and segment fixed effects only as above, we now add clustered standard errors on the fund level and run Fama and MacBeth (1973) regressions.[32] All results are presented in Table XIV.

[32] Results including standard errors clustered at the family level (not reported) are virtually identical and results including family fixed effects are presented in Table X in Section 5.4. Due to the small number of

– Insert TABLE XIV about here –

Our findings confirm the previous results. Irrespective of the assumptions on the structure of the error terms, our results usually show a strongly significant negative impact of the team dummy on style extremity, industry concentration, and performance extremity. The only exceptions are an insignificant impact of team status on HML style extremity and on performance extremity if performance is measured based on the Carhart (1997) alpha when we analyse results from Fama and MacBeth (1973) regressions. The latter result is consistent with our earlier result that much of the performance extremity is due to style extremity and that differences in performance extremity vanish once we control for the impact of the fund's particular investment style (Figure 4 and Panel C of Table II). Overall, the findings from Table XIV show that our results are robust.

7.2. Causality

Our analysis so far might be plagued by an endogeneity problem: it is possible that the fund management company decides (for some exogenous reason) that a fund has to follow a moderate investment style and thus hires a team to run that fund. To address this problem, we follow an instrumental variable approach using two stage least squares regressions (2SLS). We choose the fund family policy with respect to team management, $Family\,Policy$, as our instrumental variable. It is calculated as the percentage of team-managed funds in the respective fund family. In calculating this percentage we exclude the respective fund under consideration. As

changes in the management structure of funds, it is not possible to get reasonable results using a fund-fixed effects approach.

management structures are pretty uniform within fund families,[33] the dominant management strategy of a family is highly correlated with the management structure of the respective funds, i.e., the instrument is highly correlated with the probability that a fund is managed by a team or a single manager. In addition, we do not expect the management structure policy of the fund family to have a strong impact on the behavior of the managers of individual funds in terms of investment styles and performance outcomes except through its management structure.

We run several versions of the 2SLS procedure reflecting the various models we use above to examine style extremity and performance extremity, respectively. In the first stage of the 2SLS procedure we relate the team dummy variable to our instrument variable, *Family Policy*, as well as other exogenous variables. Results are reported in Panel A of Table XV.

– Insert TABLE XV about here –

In Column 1, we present first stage results using only fund characteristics and family policy as explanatory variables. We document that our instrumental variable is strongly correlated with the fund's management structure:[34] the coefficient on the *Family Policy* variable is positive and highly significant (1% level) indicating that funds have a higher probability of being team-managed when team management is the dominant management approach in that respective

[33] In our sample about 80% of all fund families are clearly dominated by one of the two management structures. In those 80% of the families more than 90% of all funds are being managed according to the same management structure.

[34] The significance at any traditional significance level indicates that our specifications do not suffer from problems associated with "weak instruments" (see Murray, 2006).

family.[35] Besides family policy, other fund characteristics have a significant influence on a fund's management structure. The younger and the larger a fund, the higher is its probability of being team-managed. The age effect reflects the fact that team management became very popular in the late nineties, a time in which a lot of new funds were established. The size effect suggests that teams are particularly employed for more extensive tasks, given that the total amount of money under management is a reasonable proxy for how extensive the task of running the fund is. The reason for this is that the potential benefits from specialization of several team members are more important in this case. Turnover and expenses are not significantly related to management structure. This indicates that employing a team does not lead to higher costs as compared to choosing a single manager approach. Although not the focus of this paper, these results provide new insights on the determinants of a fund's management structure.

In Column 2 of Panel A, we present first stage results for a regression where we additionally include manager characteristics as independent variables. Again, the impact of $Family\,Policy$ is significantly positive. We also find that team members are slightly younger than single managers. This might reflect the fact that the team approach has only become popular in recent years or that young managers are allocated to teams before they later are responsible for a fund on a standalone basis. Furthermore, females have a higher probability of working in teams rather than as single managers.

In the second stage, we redo our examinations on investment style extremity and performance extremity using the "expected management structure" from the first stage as explanatory variable instead of the team dummy used in Section 4. The main results from these second stage

[35] Strictly speaking, we cannot interpret our results in terms of probabilities, because our dependent variable is a non-transformed binary variable and we use a linear regression model. However, results are similar when estimating the relation between team management and potential determinants with a logit model.

regressions are presented in Panel B and C of Table XV, respectively. For the sake of brevity, we only present the estimate for the influence of the management structure. In Panel B we control only for fund characteristics, in Panel C we also control for manager characteristics. The results all confirm the conclusions drawn in Section 4: (i) Teams follow less extreme investment styles. This result holds for all style extremity measures. (ii) Teams achieve less extreme performance outcomes than single managers. This result is strongest for peer-group adjusted returns and less pronounced, but still significant, for Carhart (1997) four-factor alphas.[36] Overall, the results from the 2SLS analysis again provide support for the diversification of opinions theory (Hypotheses 1 to 3) and allow us to reject the group shift theory (Hypotheses 4 to 6).

8. Conclusion

This paper provides the first empirical test of the diversification of opinions theory and the group shift theory using real business data from the mutual fund industry. Our results clearly reject the group shift theory and support the diversification of opinions theory: extreme opinions of single team managers average out and teams eventually take less extreme decisions than individuals do. We find that teams follow less extreme investment styles, hold less risky portfolios and exhibit lower industry concentration within their portfolios than single-managed funds. These differences are also reflected in differences in the distribution of performance outcomes: single managers are much more likely to achieve extreme (good or bad) performance outcomes than teams. Furthermore, the differences between a team and a single manager appear to be more pronounced for larger teams than for small teams.

[36] Results (not reported) are also stable if we include unsystematic risk as an additional control variable in the first and second stage of the 2SLS.

Overall, our results of more stable and conservative behavior among team-managed funds and the growth of team management in the mutual fund industry are consistent with increased demand for stability among institutional investors in our sample period.

While our findings are based on a large sample of single and team managed funds, we think that our results have broader implications far beyond the asset management industry. Teams are now employed in many contexts, ranging from boards in publicly traded firms, top management teams and workgroups in companies, to committees in central banks and politics and many more. Our findings suggest that the extremity of decision outcomes can be influenced by organizational structures. Testing this idea in other real world contexts might be more difficult, as quantitative and objective variables for behaviour and outcomes for a sufficient number of observations are typically harder to obtain. However, given the importance of the decisions such groups regularly make, this effort seems to be worthwhile. Exploring differences between teams and individuals in other real world settings should be an interesting avenue for future research.

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Figure 1

Fund Management Structures over Time

Figure 1 shows the percentage of single-managed and team-managed funds in our sample for the period 1994 to 2003. The sample consists of all team and single-managed active equity funds from the market segments 'Long Term Growth', 'Growth & Income', and 'Aggressive Growth' from the CRSP mutual fund database.

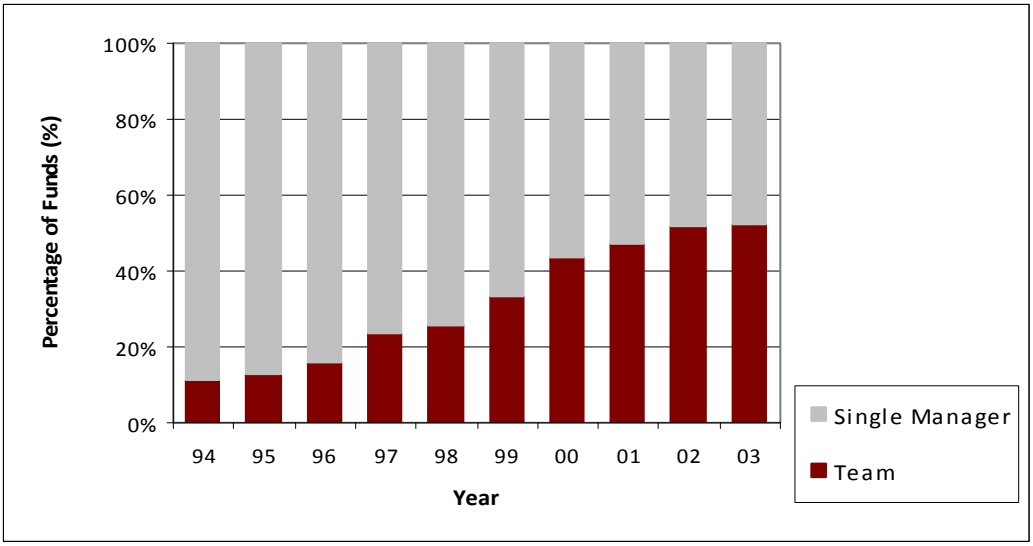

Figure 2

Extremity of Fund Style

Figure 2 shows the average yearly percentage of single-managed funds in different percentiles of the style distribution. Style is measured by the four loadings on the style factors $\beta_{i,t}^{1}$ to $\beta_{i,t}^{4}$ as determined by model (1) from the main text:

$$r_{i,m,t} - r_{f,m,t} = a_{i,t} + \beta_{i,t}^{1}\left(r_{M,m,t} - r_{f,m,t}\right) + \beta_{i,t}^{2} SMB_{m,t} + \beta_{i,t}^{3} HML_{m,t} + \beta_{i,t}^{4} MOM_{m,t} + \varepsilon_{i,m,t}.$$

The sample consists of all team and single-managed active equity funds from the market segments 'Long Term Growth', 'Growth & Income', and 'Aggressive Growth' from the CRSP mutual fund database for the period 1994 to 2003. Results are provided for each single style dimension (Market, SMB, HML, and MOM).

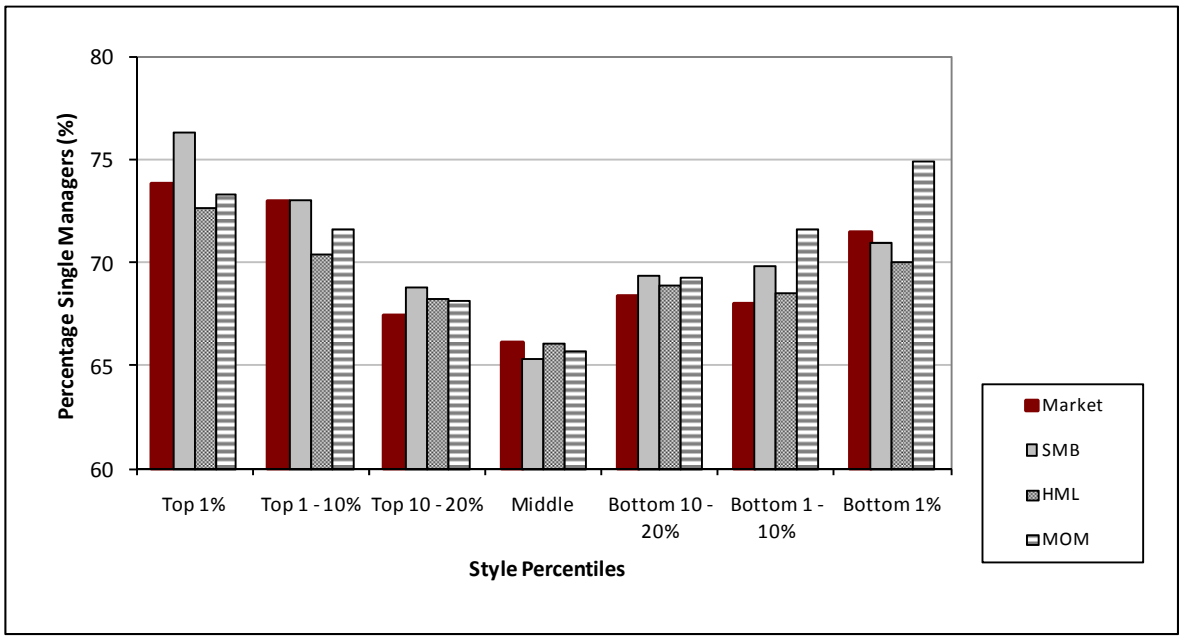

Figure 3

Industry Concentration

Figure 3 shows the average yearly percentage of single-managed funds in different percentiles of the industry concentration distribution. The sample consists of all team and single-managed active equity funds from the market segments 'Long Term Growth', 'Growth & Income' and 'Aggressive Growth' from the CRSP mutual fund database for the period 1994 to 2003. Industry concentration is measured as in Kacperczyk et al. (2005).

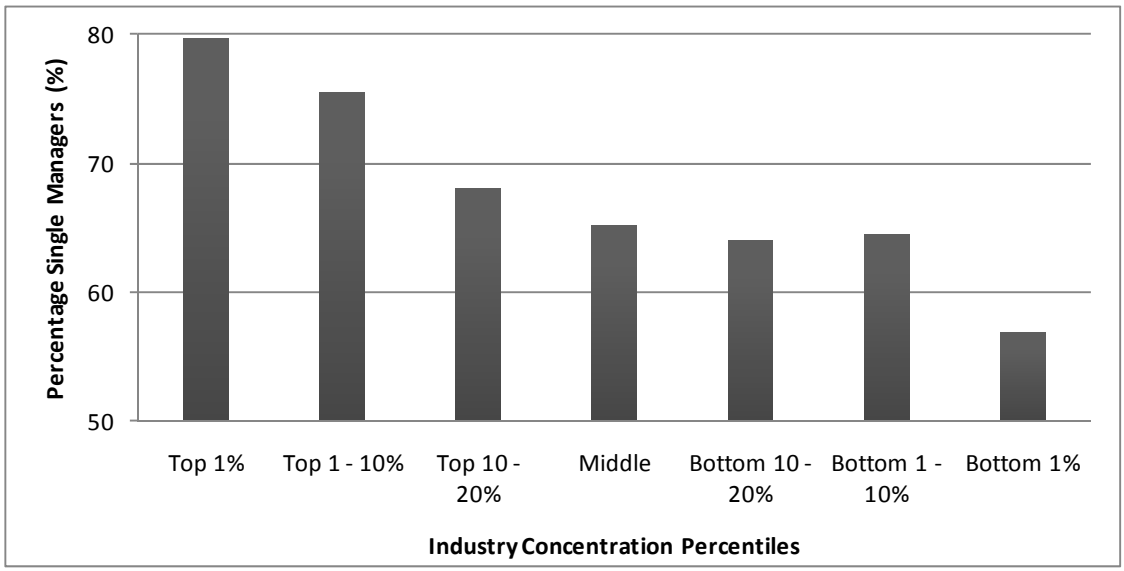

Figure 4

Extremity of Fund Performance

Figure 4 shows the average yearly percentage of single-managed funds in different percentiles of the performance distribution. The sample consists of all team and single-managed active equity funds from the market segments 'Long Term Growth', 'Growth & Income', and 'Aggressive Growth' from the CRSP mutual fund database for the period 1994 to 2003. The performance is measured by peer group (PG) adjusted returns and the Carhart (1997) four factor alpha. Peer group adjusted returns are computed by subtracting the average return of all funds in the same segment and year from the fund's return. The four factor alpha is determined as the $\alpha_{i,t}$ from model (1) from the main text:

$$r_{i,m,t} - r_{f,m,t} = \alpha_{i,t} + \beta_{i,t}^{1}\left(r_{M,m,t} - r_{f,m,t}\right) + \beta_{i,t}^{2} SMB_{m,t} + \beta_{i,t}^{3} HML_{m,t} + \beta_{i,t}^{4} MOM_{m,t} + \varepsilon_{i,m,t}$$

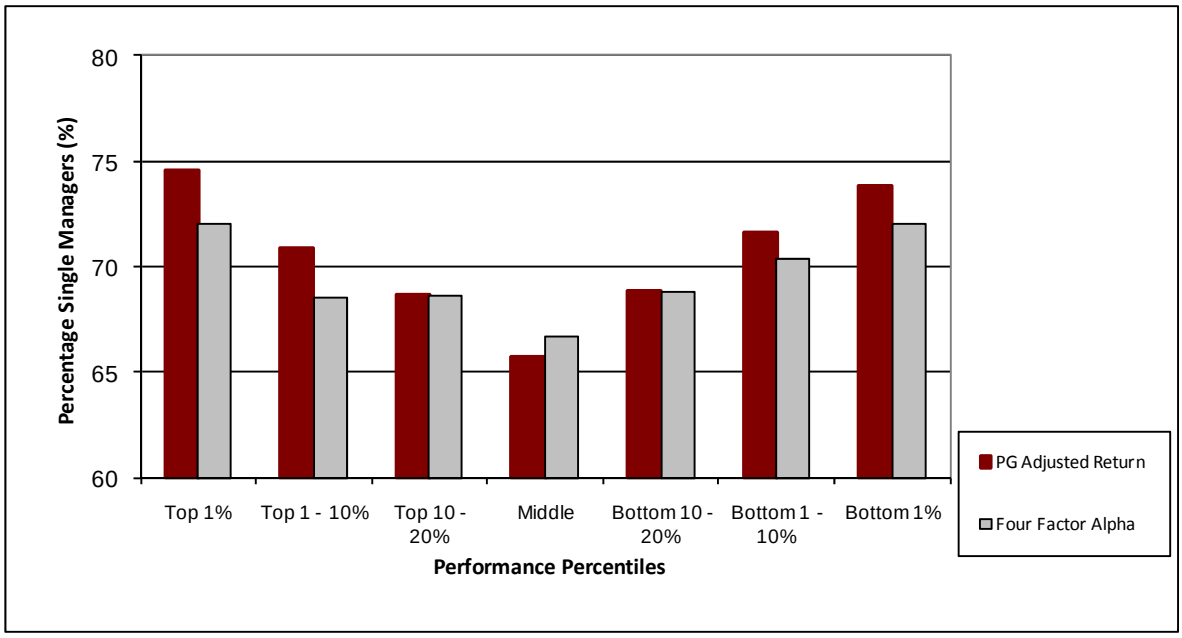

Table I

Summary Statistics

Table I presents summary statistics of the funds in our sample. The sample consists of all team and single-managed active equity funds from the market segments 'Long Term Growth', 'Growth & Income', and 'Aggressive Growth' from the CRSP mutual fund database for the period 1994 to 2003. The number of yearly observations is 12,339.

	Mean	**Median**	**Std Dev**
Age (in Years)	10.91	6.00	13.06
Size (in Mio USD)	882.05	166.00	2,830.73
Turnover (in Percent)	95.62	71.22	84.75
Expense Ratio (in Percent)	1.32	1.25	0.50

Table II

Percentages of Single Managers in the Factor Loading, Industry Concentration, and Performance Distributions

Table II shows the average yearly percentage of single-managed funds in various percentiles of the style, industry concentration, and performance distributions. The sample consists of all team and single-managed active equity funds from the market segments 'Long Term Growth', 'Growth & Income', and 'Aggressive Growth' from the CRSP mutual fund database for the period 1994 to 2003. Panel A presents results for fund styles, as determined by the four loadings on the style factors $\beta_{i,t}^{1}$ to $\beta_{i,t}^{4}$ from model (1) from the main text:

$$r_{i,m,t} - r_{f,m,t} = \alpha_{i,t} + \beta_{i,t}^{1}\left(r_{M,m,t} - r_{f,m,t}\right) + \beta_{i,t}^{2} SMB_{m,t} + \beta_{i,t}^{3} HML_{m,t} + \beta_{i,t}^{4} MOM_{m,t} + \varepsilon_{i,m,t}$$

Results are provided for each single style dimension (Market, SMB, HML, and MOM). Panel B presents results for the fund's industry concentration (IC) calculated as in Kacperzyk et al. (2005). Panel C presents results for fund performance as determined by peer group adjusted returns and the Carhart (1997) four factor alpha. Peer group adjusted returns (Adj. Return) are computed by subtracting the average return of all funds in the same segment and year from a fund's raw return. The four factor alpha (4F-Alpha) is determined as the $\alpha_{i,t}$ from model (1).

	Percentage Single Manager						
	Top 1%	**Top 1 – 10%**	**Top 10 – 20%**	**Middle 60%**	**Bottom 10 – 20%**	**Bottom 1 – 10%**	**Bottom 1%**
Panel A							
Market	73.87	73.07	67.63	66.39	68.52	68.09	71.52
SMB	76.43	73.19	69.05	65.65	69.51	70.00	71.13
HML	72.82	70.78	68.39	66.43	69.12	68.90	70.32
MOM	73.38	71.70	68.09	65.80	69.30	71.71	74.86
Panel B							
IC	79.69	75.37	68.11	65.19	64.00	64.42	56.92
Panel C							
Adj. Return	74.70	70.99	68.79	65.84	68.99	71.69	73.93
4F-Alpha	71.97	68.32	68.63	66.58	68.79	70.34	71.85

Table III

Extremity and Industry Concentration Measures

Table III shows the average yearly extremity and industry concentration of single managers and management teams as well as the respective difference. The sample consists of all team and single-managed active equity funds from the market segments 'Long Term Growth', 'Growth & Income', and 'Aggressive Growth' from the CRSP mutual fund database for the period 1994 to 2003. In Panel A, results for style extremity are presented. Style extremity is computed as the absolute difference between a fund's style, as determined by the four loadings on the style factors $\beta_{i,t}^{1}$ to $\beta_{i,t}^{4}$ from model (1) from the main text

$$r_{i,m,t} - r_{f,m,t} = \alpha_{i,t} + \beta_{i,t}^{1}\left(r_{M,m,t} - r_{f,m,t}\right) + \beta_{i,t}^{2}SMB_{m,t} + \beta_{i,t}^{3}HML_{m,t} + \beta_{i,t}^{4}MOM_{m,t} + \varepsilon_{i,m,t},$$

and the average style of all the funds in the same segment and year. This difference is normalized by dividing it by the average absolute difference of all funds in the same segment and year. Results for each single style dimension (Market, SMB, HML and MOM) are presented. In Panel B, industry concentration (IC) is calculated as in Kacperczyk et al. (2005). In Panel C, results for performance extremity based on peer-group adjusted returns and Carhart (1997) four factor alphas are presented. Peer group adjusted returns (Adj. Return) are computed by subtracting the average return of all funds in the same segment and year from a fund's raw return. The four factor alpha (4F-Alpha) is determined as the $\alpha_{i,t}$ from model (1). Performance extremity is computed as the absolute difference between a fund's performance and the average performance of all the funds in the same segment and year. This absolute difference is normalized by dividing it by the average absolute difference of all funds in the same segment and year. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Single Manager	Team	Difference
Panel A			
Market	1.036	0.940	0.096***
SMB	1.042	0.930	0.112***
HML	1.032	0.944	0.088***
MOM	1.056	0.907	0.149***
Panel B			
IC	0.068	0.057	0.011***
Panel C			
Adj. Return	1.027	0.940	0.087***
4F-Alpha	1.012	0.961	0.051**

Table IV

Characteristics of Team- and Single-managed Funds

Table IV presents summary statistics of the sample funds grouped by their management structure (team and single manager). The last column shows the differences in fund characteristics between team- and single-managed funds. The sample consists of all team and single-managed active equity funds from the market segments 'Long Term Growth', 'Growth & Income', and 'Aggressive Growth' from the CRSP mutual fund database for the period 1994 to 2003. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Team (Mean)	**Single Manager (Mean)**	**Difference (Mean)**
Age (in Years)	10.43	11.21	-0.78**
Size (in Mio USD)	921.12	857.49	63.63***
Turnover (in Percent)	94.02	96.63	-2.61***
Expense Ratio (in Percent)	1.28	1.36	-0.08*

Table V

Influence of Fund Characteristics on Extremity and Industry Concentration

Table V shows the results of regression models (5) to (7) from the main text:

$$SE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}.$$

$$IC_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}$$

$$PE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}$$

The dependent variable is a measure for the fund's style extremity, industry concentration, and performance extremity, respectively. Style extremity is computed as the normalized absolute difference between a fund's style, as determined by the four loadings on the style factors $\beta_{i,t}^{1}$ to $\beta_{i,t}^{4}$ from model (1) from the main text, and the average style of all the funds in the same segment and year. Results for each single style dimension (Market, SMB, HML, and MOM) are presented. Industry concentration (IC) is the industry concentration within a fund's portfolio as defined in Kacperczyk et al. (2005). Performance extremity is computed as the normalized absolute difference between a fund's performance and the average absolute performance of all the funds in the same segment and year. Results for peer group adjusted returns (Adj. Return) and Carhart (1997) four factor alphas (4F-Alpha) are presented. The independent variables are a team dummy, $D_{i,t}^{Team}$, which equals one if fund *i* is managed by a team in year *t*, and zero otherwise, the fund's age, size, turnover ratio, and expense ratio. All regressions are estimated with time and segment fixed effects. The R^2 is provided in the last row. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Style Extremity				**Concentration**	**Performance Extremity**	
	Market	**SMB**	**HML**	**MOM**	**IC**	**Adj. Return**	**4F-Alpha**
Team Dummy	-0.083***	-0.144***	-0.051**	-0.181***	-0.014***	-0.100***	-0.079**
Age	0.039*	0.018	0.031	0.050***	0.002	0.030	0.029
Size	-0.076***	-0.056***	-0.051***	-0.086***	-0.002***	-0.035*	-0.032*
Turnover	0.106***	0.047***	0.044***	0.132***	0.006***	0.129***	0.113**
Expenses	0.019	0.020	0.024	0.029	0.026**	0.027*	0.032*
R^2	0.081	0.041	0.042	0.061	0.131	0.083	0.078

Table VI

Influence of 12b-1 Fees on Extremity and Industry Concentration

Table VI shows the results of extended versions of the regression models (5) to (7) from the main text:

$$SE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 D_{i,t}^{12b-1} + \beta_3 D_{i,t}^{Team} \cdot D_{i,t}^{12b-1} + \beta_4 Age_{i,t-1} + \beta_5 Size_{i,t-1} + \beta_6 Turnover_{i,t-1} + \beta_7 Expenses_{i,t-1} + \varepsilon_{i,t} .$$

$$IC_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 D_{i,t}^{12b-1} + \beta_3 D_{i,t}^{Team} \cdot D_{i,t}^{12b-1} + \beta_4 Age_{i,t-1} + \beta_5 Size_{i,t-1} + \beta_6 Turnover_{i,t-1} + \beta_7 Expenses_{i,t-1} + \varepsilon_{i,t}$$

$$PE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 D_{i,t}^{12b-1} + \beta_3 D_{i,t}^{Team} \cdot D_{i,t}^{12b-1} + \beta_4 Age_{i,t-1} + \beta_5 Size_{i,t-1} + \beta_6 Turnover_{i,t-1} + \beta_7 Expenses_{i,t-1} + \varepsilon_{i,t}$$

The dependent variable is a measure for the fund's style extremity, industry concentration, and performance extremity, respectively. Style extremity is computed as the normalized absolute difference between a fund's style, as determined by the four loadings on the style factors $\beta_{i,t}^{1}$ to $\beta_{i,t}^{4}$ from model (1) from the main text, and the average style of all the funds in the same segment and year. Results for each single style dimension (Market, SMB, HML, and MOM) are presented. Industry concentration (IC) is the industry concentration within a fund's portfolio as defined in Kacperczyk et al. (2005). Performance extremity is computed as the normalized absolute difference between a fund's performance and the average absolute performance of all the funds in the same segment and year. Results for peer group adjusted returns (Adj. Return) and Carhart (1997) four factor alphas (4F-Alpha) are presented. The independent variables are a team dummy, $D_{i,t}^{Team}$, which equals one if fund *i* is managed by a team in year *t*, and zero otherwise, a 12b-1 dummy, $D_{i,t}^{12b-1}$, which equals one if fund i charges 12b-1 fees in year *t*, and zero otherwise, an interaction term between those two dummies, the fund's age, size, turnover ratio, and expense ratio. All regressions are estimated with time and segment fixed effects. The R^2 is provided in the last row. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Style Extremity				**Concentration**	**Performance Extremity**	
	Market	**SMB**	**HML**	**MOM**	**IC**	**Adj. Return**	**4F-Alpha**
Team Dummy	-0.117***	-0.143***	-0.021	-0.148***	-0.015***	-0.060	-0.121**
Team * 12b1 Dummy	0.083*	0.029	-0.011*	-0.049	0.001	-0.017*	0.024
12b1 Dummy	-0.163***	-0.113***	-0.168***	-0.099***	-0.015***	-0.200***	-0.173***
Fund Characteristics	YES	YES	YES	YES	YES	YES	YES
R^2	0.081	0.041	0.042	0.061	0.131	0.083	0.078

Table VII

Influence of Identification Status on Extremity and Industry Concentration

Panel A of Table VII shows the results of regression (5) from the main text for a restricted sample period (1996 – 2003):

$$SE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}.$$

The dependent variable is a measure for the fund's style extremity. Style extremity is computed as the normalized absolute difference between a fund's style, as determined by the four loadings on the style factors $\beta_{i,t}^{1}$ to $\beta_{i,t}^{4}$ from model (1) from the main text and the average style of all the funds in the same segment and year. The first column presents the results for the basic regression with a team dummy, $D_{i,t}^{Team}$, which equals one if fund *i* is managed by a team in year *t*, and zero otherwise, the fund's age, size, turnover ratio, and expense ratio as independent variables. Results in Column 2 (3) are based on a sample consisting only of single managers and identified teams (single managers and anonymous teams). Only results for the coefficient on the Team Dummy are presented for each of the single style dimension (Market, SMB, HML, and MOM).

Panel B shows the results from regression (6) from the main text for the period 1996 – 2003:

$$IC_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}$$

The dependent variable is the industry concentration (IC) within a fund's portfolio as defined in Kacperczyk et al. (2005).

Panel C shows the results from regression (7) from the main text for the period 1996 – 2003:

$$PE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}$$

The dependent variable is a measure for the fund's performance extremity. Performance extremity is computed as the normalized absolute difference between a fund's performance and the average absolute performance of all the funds in the same segment and year. Results for peer group adjusted returns (Adj. Return) and Carhart (1997) four factor alphas (4F-Alpha) are presented. All regressions are estimated with time and segment fixed effects. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	All Teams	Identified Teams	Anonymous Teams
Panel A			
Market	-0.089***	-0.082***	-0.096***
SMB	-0.150***	-0.144**	-0.153***
HML	-0.057**	-0.054**	-0.058***
MOM	-0.181***	-0.179***	-0.181***
Panel B			
IC	-0.013***	-0.011**	-0.018***
Panel C			
Adj. Return	-0.100***	-0.087**	-0.108***
4F-Alpha	-0.081*	-0.074*	-0.087**

Table VIII

Demographic Characteristics of Single Managers and Identified Team Members

Table VIII presents summary statistics on the demographic characteristics of managers of identified teams and single managers. The last column shows the differences in demographic characteristics between team managers and single managers. The sample consists of all identified team and single-managed active equity funds from the market segments 'Long Term Growth', 'Growth & Income', and 'Aggressive Growth' from the CRSP mutual fund database for the period 1996 to 2003. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Team Manager (Mean)	Single Manager (Mean)	Difference (Mean)
Experience (in Years)	7.24	7.56	-0.31
Age (in Years)	44.09	45.64	-1.54*
Master (%)	0.67	0.70	-0.03
PhD (%)	0.05	0.05	-0.00
Female (%)	0.12	0.11	0.01

Table IX

Influence of Manager Characteristics on Extremity and Industry Concentration

Results in Table IX are based on a sample consisting of all identified team- and single-managed active equity funds from the market segments 'Long Term Growth', 'Growth & Income', and 'Aggressive Growth' from the CRSP mutual fund database for the period 1996 to 2003. Panel A of Table IX shows the results from a modified version of regressions (5) to (7) from the main text:

$$SE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Experience_{i,t-1} + \beta_3 Age_{i,t-1} + \beta_4 Gender_{i,t-1} + \beta_5 Master_{i,t-1} + \beta_6 PhD_{i,t-1} + \sum_j \beta_j Fund\ Char_{i,t-1}^{j} + \varepsilon_{i,t}$$

$$IC_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Experience_{i,t-1} + \beta_3 Age_{i,t-1} + \beta_4 Gender_{i,t-1} + \beta_5 Master_{i,t-1} + \beta_6 PhD_{i,t-1} + \sum_j \beta_j Fund\ Char_{i,t-1}^{j} + \varepsilon_{i,t}$$

$$PE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Experience_{i,t-1} + \beta_3 Age_{i,t-1} + \beta_4 Gender_{i,t-1} + \beta_5 Master_{i,t-1} + \beta_6 PhD_{i,t-1} + \sum_j \beta_j Fund\ Char_{i,t-1}^{j} + \varepsilon_{i,t}$$

The dependent variable is a measure for the fund's style extremity, industry concentration, and performance extremity, respectively. Style extremity is computed as the normalized absolute difference between a fund's style, as determined by the four loadings on the style factors $\beta_{i,t}^{1}$ to $\beta_{i,t}^{4}$ from model (1) from the main text, and the average style of all the funds in the same segment and year. Results for each single style dimension (Market, SMB, HML, and MOM) are presented. Industry concentration (IC) is the industry concentration within a fund's portfolio as defined in Kacperczyk et al. (2005). Performance extremity is computed as the normalized absolute difference between a fund's performance and the average absolute performance of all the funds in the same segment and year. Results for peer group adjusted returns (Adj. Return) and Carhart (1997) four factor alphas (4F-Alpha) are presented. The independent variables are a team dummy, $D_{i,t}^{Team}$, which equals one if fund *i* is managed by a team in year *t*, and zero otherwise, manager experience, manager age, manager gender, and the highest academic degree of the manager (master and PhD), as well as fund characteristics (the fund's age, size, turnover ratio, and expense ratio). All regressions are estimated with time and segment fixed effects. The R^2 is provided in the last row. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Style Extremity				**Concentration**	**Performance Extremity**	
	Market	**SMB**	**HML**	**MOM**	**IC**	**Adj. Return**	**4F-Alpha**
Team Dummy	-0.070**	-0.144**	-0.052**	-0.191***	-0.015***	-0.090***	-0.070*
Experience	0.012	0.004*	0.000	0.004	0.002*	0.011	0.006
Age	-0.007	0.002	0.003	0.005	0.001*	-0.009*	-0.003
Master's	0.086*	0.051	0.056*	0.139**	-0.004	0.013*	0.011
PhD	0.079	0.066	-0.018	0.010*	-0.021	-0.047	-0.012
Female	-0.039**	-0.012*	-0.031**	0.006	-0.018**	-0.027**	-0.002
Fund Characteristics	YES	YES	YES	YES	YES	YES	YES
R^2	0.085	0.049	0.051	0.088	0.149	0.085	0.078

Table X

Family Fixed Effects

Table X shows the results of regression models (5) to (7) from the main text:

$$SE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}.$$

$$IC_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}$$

$$PE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}$$

The dependent variable is a measure for the fund's style extremity, industry concentration, and performance extremity, respectively. Style extremity is computed as the normalized absolute difference between a fund's style, as determined by the four loadings on the style factors $\beta_{i,t}^{1}$ to $\beta_{i,t}^{4}$ from model (1) from the main text, and the average style of all the funds in the same segment and year. Results for each single style dimension (Market, SMB, HML, and MOM) are presented. Industry concentration (IC) is the industry concentration within a fund's portfolio as defined in Kacperczyk et al. (2005). Performance extremity is computed as the normalized absolute difference between a fund's performance and the average absolute performance of all the funds in the same segment and year. Results for peer group adjusted returns (Adj. Return) and Carhart (1997) four factor alphas (4F-Alpha) are presented. The independent variables are a team dummy, $D_{i,t}^{Team}$, which equals one if fund *i* is managed by a team in year *t*, and zero otherwise, the fund's age, size, turnover ratio, and expense ratio. All regressions are estimated with family fixed effects in addition to time and segment fixed effects. The R^2 is provided in the last row. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Style Extremity				Concentration	Performance Extremity	
	Market	**SMB**	**HML**	**MOM**	**IC**	**Adj. Return**	**4F-Alpha**
Team Dummy	-0.069**	-0.124***	-0.061**	-0.164***	0.015***	–0.113***	–0.081**
Fund Characteristics	YES	YES	YES	YES	YES	YES	YES
Families (Fixed Effects)	YES	YES	YES	YES	YES	YES	YES
R²	0.077	0.049	0.049	0.078	0.165	0.080	0.082

Table XI

Influence of Team Size on Extremity and Industry Concentration

Table XI shows the results of regression model (8) from the main text:

$$DepVar_{i,t} = \beta_1 D_{i,t}^{Small} + \beta_2 D_{i,t}^{Large} + \beta_3 D_{i,t}^{Unknown} + \beta_4 Age_{i,t-1} + \beta_5 Size_{i,t-1} + \beta_6 Turnover_{i,t-1} + \beta_7 Expenses_{i,t-1} + \varepsilon_{i,t}.$$

The dependent variable is a measure for the fund's style extremity, industry concentration, and performance extremity, respectively. Style extremity is computed as the normalized absolute difference between a fund's style, as determined by the four loadings on the style factors $\beta_{i,t}^{1}$ to $\beta_{i,t}^{4}$ from model (1) from the main text, and the average style of all the funds in the same segment and year. Results for each single style dimension (Market, SMB, HML, and MOM) are presented. Industry concentration (IC) is the industry concentration within a fund's portfolio as defined in Kacperczyk et al. (2005). Performance extremity is computed as the normalized absolute difference between a fund's performance and the average absolute performance of all the funds in the same segment and year. Results for peer group adjusted returns (Adj. Return) and Carhart (1997) four factor alphas (4F-Alpha) are presented. The independent variables are $D_{i,t}^{Small}$ ($D_{i,t}^{Large}$), a dummy taking on the value one, if the fund is managed by a team with two members (more than two members), and zero otherwise, and $D_{i,t}^{Unknown}$, a dummy taking on the value one, if the fund is managed by an anonymous team whose size we don't know, and zero otherwise. The other independent variables are the fund's age, size, turnover ratio, and expense ratio. All regressions are estimated with time and segment fixed effects. The R^2 is provided in the next to last row. The last row presents the difference between the coefficient estimates for $D_{i,t}^{Small}$ and $D_{i,t}^{Large}$. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Style Extremity				Concentration	Performance Extremity	
	Market	**SMB**	**HML**	**MOM**	**IC**	**Adj. Return**	**4F-Alpha**
Small Team Size Dummy	–0.067**	–0.130***	–0.0338*	–0.161***	-0.008***	–0.080***	–0.060*
Large Team Size Dummy	–0.088***	–0.146***	–0.0583**	–0.172***	-0.012**	–0.105***	–0.077**
Unknown Team Size Dummy	–0.090***	–0.150***	–0.0537**	–0.213***	-0.015***	–0.106*	–0.078**
Fund Characteristics	YES	YES	YES	YES	YES	YES	YES
R^2	0.072	0.048	0.048	0.072	0.101	0.078	0.080
Difference = Small - Large	-0.021*	-0.017	-0.025	-0.012	-0.004	-0.025	-0.017

Table XII

Influence of Team Status on Risk Levels, Active Share, and Tracking Error

Table XII shows the results of the regression models of the following kind:

$$DepVar_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}\,.$$

The dependent variable is a measure for the fund's total risk, systematic risk, unsystematic risk, active share, or tracking error, respectively. We measure total risk by the standard deviation of fund *i*'s return in year *t*. Systematic risk is defined as fund *i*'s beta in year *t*, $\beta_{i,M,t}$, from a market model. Unsystematic risk is measured by the standard deviation of fund *i*'s residual fund return from this model. The active share of a fund represents the share of a fund's portfolio holdings that differ from the benchmark index holdings. The tracking error of a fund is measured as shown in equations (10) to (11) of the main text.. The independent variables are a team dummy, $D_{i,t}^{Team}$, which equals one if fund *i* is managed by a team in year *t*, and zero otherwise, the fund's age, size, turnover ratio, and expense ratio. All regressions are estimated with time and segment fixed effects. The R^2 is provided in the last row. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Total Risk	**Systematic Risk**	**Unsystematic Risk**	**Active Share**	**Tracking Error**
Team Dummy	-0.002***	-0.009	-0.002***	-0.017***	-0.008***
Fund Characteristics	YES	YES	YES	YES	YES
R^2	0.434	0.227	0.429	0.337	0.288

Table XIII

Influence of Team Diversity on Extremity and Industry Concentration

Results in Table XIII are based on a sample consisting of all identified team-managed active equity funds from the market segments 'Long Term Growth', 'Growth & Income', and 'Aggressive Growth' from the CRSP mutual fund database for the period 1996 to 2003. Table XIII shows the results of the regression models of the following kind:

$$DepVar_{i,t} = \beta_1 Div(Ten)_{i,t} + \beta_2 Div(Edu)_{i,t} + \beta_3 Div(Gen)_{i,t} + \beta_4 Div(Age)_{i,t} + \beta_5 Age_{i,t-1} + \beta_6 Size_{i,t-1} + \beta_7 Turnover_{i,t-1} + \beta_8 Expenses_{i,t-1} + \varepsilon_{i,t}$$

The dependent variable is a measure for the fund's style extremity, industry concentration, and performance extremity, respectively. Style extremity is computed as the normalized absolute difference between a fund's style, as determined by the four loadings on the style factors $\beta^1_{i,t}$ to $\beta^4_{i,t}$ from model (1) from the main text, and the average style of all the funds in the same segment and year. Results for each single style dimension (Market, SMB, HML, and MOM) are presented. Industry concentration (IC) is the industry concentration within a fund's portfolio as defined in Kacperczyk et al. (2005). Performance extremity is computed as the normalized absolute difference between a fund's performance and the average absolute performance of all the funds in the same segment and year. Results for peer group adjusted returns (Adj. Return) and Carhart (1997) four factor alphas (4F-Alpha) are presented. The independent variables are measures for the diversity of the industry tenure, $Div(Ten)_{i,t}$, educational background, $Div(Edu)_{i,t}$, gender, $Div(Gen)_{i,t}$, and age, $Div(Age)_{i,t}$, of the team members, the fund's age, size, turnover ratio, and expense ratio. All regressions are estimated with time and segment fixed effects. The R^2 is provided in the last row. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Style Extremity				Concentration	Performance Extremity	
	Market	**SMB**	**HML**	**MOM**	**IC**	**Adj. Return**	**4F-Alpha**
Tenure Diversity	-0.018	-0.014	-0.118	0.181	0.016	0.067	0.073
Educational Diversity	-0.163	-0.024	0.335	-0.127	-0.016	0.421*	0.008
Gender Diversity	0.798	0.044	-0.133	-0.052	-0.004	0.045	0.008
Age Diversity	0.834*	0.741*	0.691	0.746	0.036	0.509	0.536
Fund Characteristics	YES	YES	YES	YES	YES	YES	YES
R^2	0.078	0.056	0.015	0.079	0.027	0.008	0.056

Table XIV

Robustness: Clustered Standard Errors & Fama-MacBeth (1973) Regressions

Table XIV shows the results of regression models (5) to (7) from the main text:

$$SE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}.$$

$$IC_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}$$

$$PE_{i,t} = \beta_1 D_{i,t}^{Team} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Turnover_{i,t-1} + \beta_5 Expenses_{i,t-1} + \varepsilon_{i,t}$$

The dependent variable is a measure for the fund's style extremity, industry concentration, and performance extremity, respectively. Style extremity is computed as the normalized absolute difference between a fund's style, as determined by the four loadings on the style factors $\beta_{i,t}^{1}$ to $\beta_{i,t}^{4}$ from model (1) from the main text, and the average style of all the funds in the same segment and year. Results for each single style dimension (Market, SMB, HML, and MOM) are presented. Industry concentration (IC) is the industry concentration within a fund's portfolio as defined in Kacperczyk et al. (2005). Performance extremity is computed as the normalized absolute difference between a fund's performance and the average absolute performance of all the funds in the same segment and year. Results for peer group adjusted returns (Adj. Return) and Carhart (1997) four factor alphas (4F-Alpha) are presented. The independent variables are a team dummy, $D_{i,t}^{Team}$, which equals one if fund *i* is managed by a team in year *t*, and zero otherwise, the fund's age, size, turnover ratio, and expense ratio.

In Panel A, results for regressions including segment and time fixed effects as well as standard errors clustered at the fund level are presented. In Panel B, regressions for Fama and MacBeth (1973) regressions with segment fixed effects are presented. The R^2 is provided in the last row. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Standard Errors Clustered at the Fund Level

	Extremity Investment Style				Concentration	Extremity Performance	
	Market	**SMB**	**HML**	**MOM**	**IC**	**Adj. Return**	**4F-Alpha**
Team Dummy	-0.083***	-0.144**	-0.051**	-0.181***	-0.014***	-0.100**	-0.079**
Fund Characteristics	YES	YES	YES	YES	YES	YES	YES
R²	0.076	0.045	0.049	0.067	0.123	0.074	0.072

Panel B: Fama and MacBeth (1973) Regressions

	Extremity Investment Style				Concentration	Extremity Performance	
	Market	**SMB**	**HML**	**MOM**	**IC**	**Adj. Return**	**4F-Alpha**
Team Dummy	-0.0229**	-0.1286**	-0.009	-0.1286**	-0.0029*	-0.0573**	0.0001
Fund Characteristics	YES	YES	YES	YES	YES	YES	YES
R²	0.089	0.062	0.089	0.082	0.147	0.099	0.086

Table XV

Two Stage Least Squares Results

Table XV shows the results of 2 SLS regressions with time and segment fixed effects. The sample consists of all team and single-managed active equity funds from the market segments 'Long Term Growth', 'Growth & Income', and 'Aggressive Growth' from the CRSP mutual fund database for the period 1994 to 2003. The models including manager characteristics are estimated using a restricted sample that contains only funds managed by a single manager or an identified team for the period 1996 to 2003. Panel A presents results for the first stage regressions. The dependent variable is a team dummy, which takes on the value one if the fund is managed by a team, and zero otherwise. In Column 1, the independent variables are the fund family policy with respect to team management (instrument) computed as the share of team-managed funds in the family, fund age, fund size, the fund's turnover ratio, and its expense ratio. In Column 2, the fund manager's age, education, and gender are added as additional independent variables.
Panel B and C present the results for the second stage regressions. For sake of brevity, we only report the coefficients for the impact of team status. In both panels, the dependent variable is a measure for the funds style extremity, industry concentration, and performance extremity, respectively. Style extremity is computed as the normalized absolute difference between a fund's style, as determined by the four loadings on the style factors $\beta_{i,t}^{1}$ to $\beta_{i,t}^{4}$ from model (1) from the main text, and the average style of all the funds in the same segment and year. Results for each single style dimension (Market, SMB, HML, and MOM) are presented. Industry concentration (IC) is the industry concentration within a fund's portfolio as defined in Kacperczyk et al. (2005). Performance extremity is computed as the normalized absolute difference between a fund's performance and the average absolute performance of all the funds in the same segment and year. Results for peer group adjusted returns (Adj. Return) and Carhart (1997) four factor alphas (4F-Alpha) are presented. The independent variables in Panel B are the team-status of the fund based on the first stage regression results as well as the same independent variables as in Column 1 of Panel A (except for the instrumental variable). The independent variables in Panel C are the team-status of the fund based on the first stage regression results as well as the same independent variables as in Column 2 of Panel A (except for the instrumental variable).
The R^2 is provided in the last row. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: First Stage

	Team Management Dummy	
Family Policy	0.957***	0.958***
Age	-0.004**	-0.003**
Size	0.003***	0.003***
Turnover	-0.002	-0.003*
Expenses	-0.058	-0.041
Experience	-	-0.042
Mgr Age	-	-0.035*
Master's	-	-0.013
PhD	-	-0.105
Female	-	0.009*
R^2	0.660	0.668

Table XV

(Continued)

Panel B: Second Stage – Without Controlling for Manager Characteristics

	Extremity Investment Style				Concentration	Extremity Performance	
	Market	**SMB**	**HML**	**MOM**	**IC**	**Adj. Return**	**4F-Alpha**
Team Dummy	-0.077***	-0.168***	-0.049**	-0.177***	-0.015***	-0.124***	-0.073**
Manager Characteristics	NO	NO	NO	NO	NO	NO	NO
Fund Characteristics	YES	YES	YES	YES	YES	YES	YES
R^2	0.079	0.046	0.035	0.072	0.080	0.080	0.073

Panel C: Second Stage – Controlling for Manager Characteristics

	Extremity Investment Style				Concentration	Extremity Performance	
	Market	**SMB**	**HML**	**MOM**	**IC**	**Adj. Return**	**4F-Alpha**
Team Dummy	-0.075***	-0.161***	-0.061**	-0.190***	-0.019***	-0.119***	-0.699**
Manager Characteristics	YES	YES	YES	YES	YES	YES	YES
Fund Characteristics	YES	YES	YES	YES	YES	YES	YES
R^2	0.079	0.048	0.038	0.079	0.073	0.085	0.077

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