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THREE ESSAYS ON MUTUAL FUNDS QIAO ZHENG 2014

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Abstract

In essay one, for an actively managed equity mutual fund, style dispersion describes how widely fund stockholdings are dispersed along size, value, and momentum dimensions. A simple benefit-cost analysis suggests that style dispersion can reflect a fund manager's investment ability and predict fund performance. Our empirical analysis confirms this. We have two major findings. First, style dispersion, especially that along size dimension, is significantly positively related with fund performance. Second, a high-size-dispersion fund manager exhibits significantly better stock selection skill than a low-size-dispersion fund manager does, especially when investing in stocks with different size characteristics from the average fund size style. We also conduct various robustness tests to show that size dispersion is distinct from all existing predictors of fund performance.

Essay two shows that family-level M&As have a negative impact on mutual fund performance. Specifically, in family-level M&As, the acquiring families keep most of the acquired funds intact, and merge the rest with a few incumbent funds. The intact acquired funds have a performance deterioration for up to 20 months. The intact incumbent funds have a performance deterioration, which is particularly pronounced in complete acquisitions, for up to 12 months. We also rule out some alternative explanations for the performance change. Finally, we show that consistent with agency theory, family-level M&As are likely to be motivated by family management's own incentives.

In essay three, using equity mutual fund data, previous studies show that team-managed funds underperform solo-managed funds, suggesting that a team is a poor incentive mechanism. In this article, we take a deeper look into the composition of mutual fund management teams. Our major finding is that not all team-managed funds underperform. Only those with poor accountability of fund managers for fund performance do. A plausible explanation for this is that poor accountability disincentivizes fund managers from acquiring information. Unlike previous studies, we conclude that a team *per se* does not represent a poor incentive mechanism. Accountability of team members is more relevant in providing incentives.

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Chapter 1

Style Dispersion and Mutual Fund Performance

Abstract

For an actively managed equity mutual fund, style dispersion describes how widely fund stockholdings are dispersed along size, value, and momentum dimensions. A simple benefit-cost analysis suggests that style dispersion can reflect a fund manager's investment ability and predict fund performance. Our empirical analysis confirms this. We have two major findings. First, style dispersion, especially that along size dimension, is significantly positively related with fund performance. Second, a high-size-dispersion fund manager exhibits significantly better stock selection skill than a low-size-dispersion fund manager does, especially when investing in stocks with different size characteristics from the average fund size style. We also conduct various robustness tests to show that size dispersion is distinct from all existing predictors of fund performance.

JEL Classification: G11; G23

Keywords: Mutual fund; Style dispersion; Fund performance

1.1 Introduction

As the mutual fund industry has grown rapidly in the past decades, there is a great demand from fund investors for knowing which funds will perform well.[1] In this article, we propose a new predictor for the performance of actively managed equity mutual funds, style dispersion. We provide the economic rationale for why style dispersion predicts fund performance, and show empirically that it indeed predicts fund performance. We also show that it is distinct from all existing predictors of fund performance.

Industry practitioners and academic researchers usually categorize an actively managed equity mutual fund using its investment style, for example, large-cap or small-cap, value or growth, and momentum or contrarian. This style measures the first moment, the mean, of the characteristics of the fund's stockholdings along size, value, and momentum dimensions. Style dispersion measures the second moment, the dispersion, of the characteristics of the fund's stockholdings along size, value, and momentum dimensions. For example, Figure 1.1 provides a snapshot taken by Morningstar of Fidelity Contrafund's (managed by William Danoff) stockholdings as of September 30, 2012. The panel on the upper right illustrates the fund's size and value dispersions. Whereas its style, the average characteristics of its stockholdings, is large-cap and growth, more than 40% of its stockholdings are dispersed surrounding large-cap and growth stocks.

[Insert Figure 1.1 here.]

Intuitively, there are three possibilities for the relation between style dispersion and the performance of an actively managed equity mutual fund. A straightforward expectation is that style dispersion is not related with fund performance. In this case, style dispersion

[1] Toward the end of 2012, the total assets under management by the U.S. mutual fund industry reached $13 trillion, with 44.4% of households investing in mutual funds (Investment Company Institute, 2013).

is a reflection of the fund manager's random choice or simply fluctuation of stock prices. However, a deeper thought suggests that style dispersion can be negatively or positively related with fund performance. Having a high level of style dispersion has benefits and costs for the fund manager. An obvious benefit is that the fund manager can take advantage of valuable investment opportunities in a larger space. An obvious cost is that the fund manager may lack sufficient expertise in some classes of stocks, and have to trade with counterparts who have expertise. If the costs are higher than the benefits, then style dispersion should be negatively related with fund performance. In this case, a high level of style dispersion is a reflection of the fund manager's opportunistic behavior. If the costs are lower than the benefits, then style dispersion should be positively related with fund performance. In this case, a high level of style dispersion is a reflection of the fund manager's superior investment ability.[2]

We start our empirical analysis by estimating style dispersion along size (market capitalization), value (book-to-market), and momentum (a stock's lagged 1-year return) dimensions for individual actively managed open-end U.S. domestic equity mutual funds. Our sample period is 1981 to 2010. We exclude index funds and sector funds because they need to hold various stocks in the stock market or in certain industries, so their high style dispersion is mechanically determined.

Next, we examine the relation between style dispersion and fund performance using both portfolio analysis and regression analysis. Consistent with the notion that style dispersion is a reflection of a fund manager's investment ability, style dispersion, especially that along size dimension, is positively related with fund performance. This result is robust (i) after controlling for risk and style differences in fund performance using various

[2]He and Xiong (2013) develop an agency-based model to show that in equilibrium, an asset management company allows only the fund managers with exceptional talent to invest outside the core fund style, implying a high level of style dispersion. An assumption of this theory is that the asset management company has good knowledge of their fund managers' investment ability.

factor models, such as CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, the Ferson-Schadt (1996) conditional four-factor model, and the Pástor-Stambaugh (2003) five-factor model; (ii) and after controlling for fund characteristics including fund total net assets (TNA), fund age, expense and turnover ratios, flow, and fund family.

Previous studies have identified various predictors of fund performance, including past fund performance and numerous holdings-based measures.[3] One may suspect that size dispersion captures similar information as these predictors. We test this question by controlling for past fund performance and Amihud and Goyenko's (2013) $1 - R^2$ of regressing fund return on factors. According to Amihud and Goyenko, $1 - R^2$ catches all the information in the existing holdings-based predictors. The relation between size dispersion and fund performance remains positive and significant.

Finally, we conduct a diagnostic analysis of the sources of fund performance associated with size dispersion using holding-based performance measures proposed by Daniel, Grinblatt, Titman, and Wermers (1997). We have two major findings. First, a high-size-dispersion fund manager exhibits better stock selection ability, but no better style-timing ability, than a low-size-dispersion fund manager does. Second, the superior stock selection ability of a high-size-dispersion fund manager, relative to a low-size-dispersion fund manager, is particularly pronounced when they invest in stocks with different size characteristics from the average size style. An interesting implication of this result that even if a low-size-dispersion fund manager had a high level of size dispersion, she still would not produce the same performance as a high-size-dispersion fund manager does.

[3]See, for example, Coval and Moskowitz (1999, 2001) on deviation from the market in terms of geographic location; Cohen, Coval, and Pástor (2005) on the similarity of fund holdings to star funds; Kacperczyk, Sialm, and Zheng (2005) on industry concentration; Kacperczyk and Seru (2007) on funds' use of public information; Alexander, Cici, and Gibson (2007) on trading against fund flows; Kacperczyk, Sialm, and Zheng (2008) on the effect of unobserved actions; and Cremers and Petajisto (2009) on the share of portfolio holdings that differ from the benchmark index holdings.

Our study is related to two strands of research in the mutual fund literature. The first strand of research, including Brown and Goetzmann (1997), Carhart (1997), Daniel, Grinblatt, Titman, and Wermers (1997), and Chan, Chen, and Lakonishok (2002), studies investment styles of actively managed equity mutual funds. An important finding of this research is that fund style, which measures the first moment, the mean, of the characteristics of a fund's stockholdings in along size, value, and momentum dimensions, gives a proper description of the risk profile of the fund. Other related studies in this research examine the migration/drift of fund style (e.g., Brown, Harlow, and H. Zhang, 2012; Wermers, 2012). We study fund style dispersion, which measures the second moment, the dispersion, of the characteristics of a fund's stockholdings along size, value, and momentum dimensions. We show that style dispersion, especially that along size dimension, is a significant indicator of the fund manager's investment ability, and predicts fund performance.

The second strand of research studies how to measure a fund manager's investment ability and, thereafter, predict fund performance. Earlier studies in this research focus on past fund performance. The general idea of these studies is that if a fund manager possesses superior investment ability, then she should produce good performance in the past.[4] Recent studies focus on the distinctiveness of fund strategy (see Footnote 3). The general idea of these studies is that to produce superior fund performance, a fund manager must deviate from natural and easy investments. If her strategy is correct, these investments should deliver above-average performance. These studies have identified numerous holdings-based predictors of fund performance. Our style dispersion can also be interpreted as a holdings-based predictor, which captures the deviation of fund holdings from the average fund style. But importantly, it is distinct from all existing predictors of fund performance.

[4]Carhart (1997) surveys the literature on the persistence of mutual fund performance. Recent developments in this literature include Kosowski, Timmermann, Wermers, and While (2006).

We organize the rest of this article as follows. Section 3.2 describes the data and construction of style dispersion. Section 3.3 tests the relation between style dispersion and fund performance. Section 1.4 tests the sources of the fund performance associated with size dispersion. Section 1.5 concludes.

1.2 Data and the Construction of Style Dispersion

1.2.1 The Sources of Data

Our sample period is 1981 to 2010. We use three databases. First, we obtain fund total net assets (TNA), fund age, expense and turnover ratios, returns, and other fund characteristics from the CRSP Survivorship Bias Free Mutual Fund database. Second, we obtain stockholdings of mutual funds from the Thomson Reuters CDA/Spectrum database. This information is collected from mutual funds' filings with the Security and Exchange Commission (SEC) and their voluntary reports. Most mutual funds disclosed their holdings quarterly, despite that they are only required to disclose their holdings semiannually. We compute the fund holdings in a quarter end using the latest report in that quarter. If a fund does not report in a quarter, we consider the fund holdings for this quarter missing. Third, we obtain stock prices and returns, market capitalization, and book-to-market from the CRSP stock price database.

We link the CRSP mutual fund database to the Thomson Reuters database using MFLINKS. To ensure the quality of matching, we also require fund TNA computed using holdings data from the Thomson Reuters database to be between 2/3 and 3/2 of fund TNA obtained from the CRSP mutual fund database.

We focus our analysis on actively managed open-end U.S. domestic equity mutual funds. We exclude index funds and sector funds because they need to hold various stocks in the stock market or in certain industries, so their high style dispersion are mechanically determined. We also apply the following filters. First, we exclude observations prior to which fund TNA never surpassed $15 million as suggested by Chen, Hong, Huang, and Kubik (2004), and observations with a report date prior to the fund organization date to control for incubation bias (Evans, 2010). Second, we exclude observations with fewer than 11 stockholdings. Third, if a fund has multiple share classes, we aggregate across the different share classes to obtain fund-level variables.

[**Insert Table 1.1 here.**]

We end up with 2,329 distinct funds and 73,861 fund-quarter observations. Panel A of Table 1.1 reports summary statistics on fund TNA, age, expense and turnover ratios, flow, and Amihud and Goyenko's (2013) $1 - R^2$. Flow is computed as the growth rate of TNA, with the appreciation of the mutual fund's assets adjusted. We assume that all the cash flows happen in the quarter end. Amihud and Goyenko's $1 - R^2$ is computed from regressing a fund monthly return on the Carhart (1997) four factors using 24 months of lagged data.

1.2.2 Constructing Style Dispersion

We construct style dispersion for individual mutual funds as follows. First, in each quarter t, we group all the common stocks listed in CRSP into quintiles along size (market capitalization), value (book-to-market), and momentum (a stock's lagged 1-year return) dimensions. We denote each stock j's quintile information as (s_{jt}, v_{jt}, m_{jt}). For example, (1, 5, 1) indicates that the stock has the smallest market capitalization, highest book-to-market, and lowest past 1-year return.

Second, we follow Daniel, Grinblatt, Titman, and Wermers (1997) to compute each fund's size, value, and momentum scores as the value-weighted average of the fund stockholdings' quintile information:

$$\begin{aligned}
\text{Size score } (\bar{s}_t) &= \sum_j w_{jt} s_{jt}, \\
\text{Value score } (\bar{v}_t) &= \sum_j w_{jt} v_{jt}, \\
\text{Mom score } (\bar{m}_t) &= \sum_j w_{jt} m_{jt},
\end{aligned}$$

where w_{jt} is stockholding j's value weight in the fund. These scores describe the average fund style. We exclude the fund's short positions (which, if any, are usually very small) from the computation.

Third, we compute fund style dispersion in size, value, and momentum based on the average distance of the fund's stockholdings from the average fund style along size, value, and momentum dimensions:

$$\begin{aligned}
\text{Size dispersion}_t &= \sum_j w_{jt} |s_{jt} - \bar{s}_t|, \\
\text{Value dispersion}_t &= \sum_j w_{jt} |v_{jt} - \bar{v}_t|, \\
\text{Mom dispersion}_t &= \sum_j w_{jt} |m_{jt} - \bar{m}_t|.
\end{aligned}$$

Three caveats are worth noting. First, index funds and sector funds need to hold various stocks in the stock market or in certain industries, so their high style dispersion is mechanically determined. We exclude these funds from our sample (see the sample selection procedure in Section 3.2). Second, it would be ideal to have a catchall dispersion measure that combines the information contained in the size, value, and momentum dispersion measures. However, we do not know how to construct such a combination reasonably. We tried some ad hoc approaches, for example, taking a simple average (not reported to save space). Our main results remain the same. Third, there are alternative ways to specify style dispersion. For example,

$$\begin{aligned}
\text{Size dispersion}_t^{Alt} &= \sqrt{\sum_j w_{jt}(s_{jt} - \bar{s}_t)^2}, \\
\text{Value dispersion}_t^{Alt} &= \sqrt{\sum_j w_{jt}(v_{jt} - \bar{v}_t)^2}, \\
\text{Mom dispersion}_t^{Alt} &= \sqrt{\sum_j w_{jt}(m_{jt} - \bar{m}_t)^2},
\end{aligned}$$

or computing dispersion using equal weights instead of using value weights. We conducted our analysis using these specifications as well as different mixes of these specifications (not reported to save space). Our main results remain the same.

1.2.3 Quantifying Style Dispersion

Panel A of Table 1.1 reports summary statistics on style dispersion. A notable observation is that the standard devision of size dispersion (0.275) is higher than those of value dispersion (0.159) and momentum dispersion (0.174). This suggests that funds demonstrate relatively high cross-sectional variation in size dispersion.

Panel B of Table 1.1 reports the correlation structure of style dispersion and other fund characteristics. There are two notable observations. First, funds with high size dispersion tend to have small TNA, high expense and turnover ratios, and high Amihud and Goyenko's (2013) $1 - R^2$. Second, small-cap funds and momentum funds tend to have high size dispersion. These observations suggest that funds with high size dispersion trade actively, so size dispersion possibly measures fund managers' investment ability.

We examine the persistence of style dispersion by running an AR(1) regression for each style dispersion at a quarterly frequency. The slope coefficients (R^2s) for size, value, and momentum dispersions are, respectively, 0.961 (0.930), 0.819 (0.660), and 0.700 (0.495). These results suggest that style dispersion, especially size dispersion, is fairly persistent.

1.3 Style Dispersion and Fund Performance

In this section, we test the relation between style dispersion and fund performance. We use both portfolio analysis and regression analysis.

1.3.1 Portfolio Evidence

We conduct the following portfolio analysis for size, value, and momentum dispersions, respectively. Take size dispersion as an example. In each month, we sort our sample funds into 10 portfolios based on size dispersion in the lagged quarter end. We compute the monthly return for each decile portfolio by weighting all the funds in the decile equally.

We use six risk- and style-adjusted performance measures. The first performance measure is the excess return of the decile over the market portfolio. The next five measures are the abnormal returns of CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, the Ferson-Schadt (1996) conditional four-factor model, and the Pástor-Stambaugh (2003) five-factor model.[5]

[5] The abnormal return is given by the intercept of the following time-series regression:

$$R_{pt} - R_{Ft} = \alpha_p + \beta_{p\mathrm{M}}(R_{Mt} - R_{Ft}) + \beta_{p\mathrm{SMB}}\mathrm{SMB}_t + \beta_{p\mathrm{HML}}\mathrm{HML}_t + \beta_{p\mathrm{MOM}}\mathrm{MOM}_t + \beta_{p\mathrm{LIQ}}\mathrm{LIQ}_t + \epsilon_{pt}.$$

The dependent variable is the portfolio return minus the risk-free rate. The explanatory variables are the returns of the five zero-investment factor portfolios. $R_{Mt} - R_{Ft}$ is the return of the market portfolio minus the risk-free rate, SMB_t is the average return of small-cap stocks minus the average return of large-cap stocks, HML_t is the average return of high book-to-market stocks minus the average return of low book-to-market stocks, MOM_t is the average return of high momentum stocks minus the average return of low momentum stocks, and LIQ_t is the average return of low liquidity stocks minus the average return of high liquidity stocks. CAPM uses the first factor. Fama and French (1993) use the first three factors. Carhart (1997) uses the first four factors. Pástor and Stambaugh (2003) use all five factors. Ferson and Schadt (1996) use the first four factors and their interaction terms with five demeaned lagged macroeconomic variables (the short-term risk-free interest rate, the term spread, the credit spread, the dividend yield of

Before-Expense Fund Performance

Table 12 reports the returns, before subtracting expenses, of the decile portfolios. Panel A reports for the deciles based on size dispersion. Column 2 shows that funds with the highest size dispersion (decile 10) outperform funds with the lowest size dispersion (decile 1) by 35 bps per month (at the 1% significance level). Column 3 uses CAPM to control for market risk. The outperformance equals 28.3 bps per month (at the 1% significance level). Column 4 uses the Fama-French (1993) three-factor model to further control for size and value. The outperformance equals 21.1 bps per month (at the 1% significance level). Column 5 uses the Carhart (1997) four-factor model to further control for momentum. The outperformance equals 17.5 bps per month (at the 1% signficance level). Column 6 uses the Ferson-Schadt (1996) conditional four-factor model to control for possible time-variation of factor loadings, and Column 7 uses the Pástor-Stambaugh (2003) five-factor model to further control for liquidity. The outperformance has little change in the magnitude and significance.

[Insert Table 1.2 here.]

Panels B (Panel C) of Table 1.2 reports for the deciles based on value (momentum) dispersion. We find no significant evidence that after using, for example, the Carhart four-factor model to control for risk and style differences, funds with high value (momentum) dispersion outperform funds with low value (momentum) dispersion.

[Insert Figure 1.2 here.]

Figure 1.2 plots the returns, before subtracting expenses, of the decile portfolios. The evidence is consistent with our above analysis. Specifically, Panel A indicates a positive

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the stock market, and the January dummy).

We obtain the market, size, value, momentum, and liquidity factor returns through WRDS.

relation between fund performance and the size dispersion. Panel B (Panel C) indicates no such a relation between fund performance and value (momentum) dispersion.

After-Expense Fund Performance

Table 1.3 reports the returns, after subtracting expenses, of the decile portfolios. The relation between size dispersion and fund performance, after expenses, remains positive and significant. For example, the Carhart abnormal return of funds with the highest size dispersion (decile 10) is higher than that of funds with the lowest size dispersion (decile 1) by 14.8 bps per month (at the 5% significance level).

[Insert Table 1.3 here.]

In what follows, we use the returns before subtracting expenses to conduct our tests. These returns describe fund managers' investment ability, which we are primarily interested in. We also conducted the following tests using the returns after subtracting expenses. The results are similar.

Subsample Analysis

We further analyze the relation between size dispersion and fund performance within subsample of funds.

[Insert Table 1.4 here.]

Table 1.4 reports the results for subsamples based on claimed investment objectives, including growth, growth and income, and income. Within the subsample of growth funds, the relation between size dispersion and fund performance is positive and significant. For example, in this subsample, the Carhart abnormal return of decile 10 funds is higher than that of decile 1 funds by 13.9 bps per month (at the 5% significance level). However, within the subsamples of growth and income funds, and income funds, this relation is not significant.

[Insert Table 1.5 here.]

Table 15 reports the results for subsamples based on fund size (TNA). Within the subsample of small funds, the positive relation between size dispersion and fund performance is very pronounced. For example, in this subsample, the Carhart abnormal return of decile 10 funds is higher than that of decile 1 funds by 25.4 bps per month (at the 1% significance level). Within the subsample of large funds, the positive relation between size dispersion and fund performance is weaker but still significant. For example, in this subsample, the Carhart abnormal return of decile 10 funds is higher than that of decile 1 funds by 15 bps per month (at the 5% significance level). Within the subsample of mid-size funds, the relation between size dispersion and fund performance is not significant.

1.3.2 Regression Evidence

We continue our analysis using the regression approach. We use the abnormal return of the Carhart (1997) four-factor model as the only performance measure here because the above portfolio analysis suggests that this model controls for risk and style differences properly.

Table 1.6 reports the regression results of the Carhart abnormal return on style dispersion. Because style dispersion is a quarterly variable, we run the regressions at a quarterly frequency.[6] In a fund quarter, we estimate the Carhart (1997) four-factor model using

[6]Foroni and Marcellino (2013) provide a survey on econometric methods for mixed frequency data. They recommend that when the dependent variable is at a higher frequency than the explanatory variables, the common solution is to lower the frequency of the dependent variable to the same frequency by taking

24 months of lagged data. We compute the three monthly abnormal returns of the fund quarter as the difference between the realized fund return and the expected return. We use as the dependent variable the average of the three monthly abnormal returns. The explanatory variables, including size, value, and momentum dispersions, are lagged by one quarter. We use the Fama-MacBeth (1973) cross-sectional regression that adjusts for heteroscedasticity and serial correlation of standard errors using Newey-West (1987) lags of order three. The Fama-MacBeth (1973) regression approach is proper for correcting for the time effect. We further control for the style fixed effect.

[Insert Table 1.6 here.]

We find here that consistent with our portfolio analysis, size dispersion is significantly positively related with fund performance. For example, Column 1 of Table 1.6 shows that a 0.275 increase in size dispersion, which corresponds to a one standard deviation increase in size dispersion, increases the monthly Carhart abnormal return in the subsequent quarter by $16.7 \times 0.275 = 4.59$ bps (at the 1% significance level).

Column 2 shows that value dispersion is not significantly related with fund performance. Columns 3 to 4 show that momentum dispersion is significantly positively related with fund performance. But after controlling size dispersion, this relation becomes weaker.

Controlling for Other Fund Characteristics

Table 1.7 reports the regression results of the Carhart abnormal return on size dispersion controlling for other fund characteristics. All these fund characteristics (explanatory variables) are lagged by one quarter, except for expense and turnover ratios, which are

aggregation or average. In our case, fund return is at the monthly frequency, whereas style dispersion is at the quarterly frequency. We therefore lower the frequency of fund return to the quarterly frequency by taking average, and run the regressions at the quarterly frequency.

lagged by one year. Fund TNA and age are skewed to the right, so we take the natural logarithms.

[Insert Table 1.7 here.]

Column 1 of Table 1.7 shows that after controlling for often-used fund characteristics, including fund TNA, age, expense and turnover ratios, and flow, size dispersion is still significantly positively related with fund performance. Specifically, a 0.275 increase in size dispersion, which corresponds to a one standard deviation increase in size dispersion, increases the monthly Carhart abnormal return in the subsequent quarter by $19.7 \times 0.275 = 5.41$ bps (at the 1% significance level).

Controlling for Fund Family Effect

One may suspect that the positive relation between size dispersion and fund performance is due to a (large) fund family spillover effect. Specifically, in a large fund family, fund managers can share investment ideas or obtain advice from the research department of the family, and hence can successfully invest outside the core size style. This argument implies that the positive relation between size dispersion and fund performance should be particularly pronounced for funds affiliated with large fund families.

Column 2 of Table 1.7 tests this argument. The explanatory variable, large-family dummy, equals to 1 (0) if the fund is affiliated with top 10 fund families based on the number of fund investment objectives.[7] We use the period of 2000 to 2010 because the fund family information in the CRSP mutual fund database, the management company code, is available for this period. The coefficient on the size dispersion alone, 0.110, is significant at the 10% level, suggesting that for funds not affiliated large fund families,

[7]We also defined the large-family dummy based on family TNA. The results are almost the same.

size dispersion is significantly positively related with fund performance. The coefficient on the interaction term between size dispersion and the large-family dummy, 0.015, is not significant, suggesting that the positive relation between size dispersion and fund performance is not more pronounced for funds affiliated with large fund families than for funds not affiliated with large fund families.

Taken together, our findings are inconsistent with and, therefore, rule out the argument that the positive relation between size dispersion and fund performance is due to a (large) fund family spillover effect.

Controlling for Existing Predictors of Fund Performance

Previous studies have identified various predictors of fund performance, including past fund performance (e.g., Carhart, 1997) and numerous holdings-based measures (see Footnote 3). One may suspect that size dispersion captures similar information as these predictors. We test this question in what follows by controlling for these predictors.

Past Fund Performance

The first predictor we control for is past fund performance. The literature on the persistence of mutual fund performance argues that if a fund manager possesses superior investment ability, then she should produce good performance in the past, and should continue to produce good performance in the future.

[Insert Table 1.8 here.]

Column 1 of Table 1.8 reports the regression results of the Carhart abnormal return on size dispersion controlling for prior-year fund return. We also controlled for often-used fund characteristics (the coefficients are not reported). There are two notable findings. First, consistent with previous studies, the coefficient on the prior-year fund return, 1.039, is positive and significant. Second and importantly, the coefficient on size dispersion, 0.188, is still positive and significant.

Amihud and Goyenko's (2013) $1-R^2$

The second predictor we control for is Amihud and Goyenko's (2013) $1-R^2$ of regressing fund return on factors. According to Amihud and Goyenko, this return-based predictor is not only easy to construct, but also captures the information contained in the existing holdings-based predictors.

Column 2 of Table 1.8 reports the regression results of the Carhart abnormal return on size dispersion controlling for Amihud and Goyenko's $1-R^2$. The coefficient on size dispersion, 0.169, is still positive and significant.

Two Other Holdings-Based Predictors

We also pick out two other holdings-based predictors, and control for them. One is Kacperczyk, Sialm, and Zheng's (2005) industry concentration index (ICI), which is computed as the sum of the squared deviations of the value weights for each of ten industries held by the mutual fund from the industry weights of the market portfolio. The other is Cremers and Petajisto's (2009) Active Share, which is computed as the share of portfolio holdings that differ from the benchmark index holdings.[8]

Columns 3 to 4 of Table 1.8 report the regression results of the Carhart abnormal return on size dispersion controlling for these two holdings-based predictors. The coefficients on size dispersion, 0.176 and 0.111 respectively, are still positive and significant.

Taken together, our findings suggest that size dispersion is a distinct from all existing predictors of fund performance.

[8]Cremers and Petajisto (2009) and Petajisto (2010) describe the computation in detail. We obtain data on Active Share for the period of 1990 to 2006 from Antti Petajisto's website.

Other Controls

We considered other controls (not reported to save space). For example, we controlled for the year-end calendar effect by running the regression with the first quarter of each year excluded from our sample. Size dispersion is still significantly positively related with fund performance.

We also considered the migration/drift of fund investment style studied by Brown, Harlow, and Zhang (2012) and Wermers (2012), which is given by $|\bar{s}_t - \bar{s}_{t-1}|$, $|\bar{v}_t - \bar{v}_{t-1}|$, and $|\bar{m}_t - \bar{m}_{t-1}|$ using our notations. We have two findings. First, the correlations between style dispersion and style migration are low, suggesting that they describe different fund characteristics.[9] Second, after controlling for style migration, size dispersion is still significantly positively related with fund performance.

1.4 Sources of Fund Performance

In this section, we conduct a diagnostic analysis of the sources of fund performance associated with size dispersion. We use the two holdings-based performance measures proposed by Daniel, Grinblatt, Titman, and Wermers (1997): the "Characteristic Selectivity" measure (CS), which describes fund managers' stock selection skill; and the "Characteristic Timing" measure (CT), which describes fund managers' style timing skill.[10]

[9] Brown, Harlow, and Zhang (2012) argue that style migration reflects the fund manager experimenting with different styles before finding the right one for him.

[10] The two holdings-based performance measures are given by:

$$\begin{aligned} \mathrm{CS}_t &= \sum_j w_{j,t-1}\Big[R_{jt} - \mathrm{BR}_t(j,t-1)\Big], \\ \mathrm{CT}_t &= \sum_j \Big[w_{j,t-1}\mathrm{BR}_t(j,t-1) - w_{j,t-13}\mathrm{BR}_t(j,t-13)\Big]. \end{aligned}$$

1.4.1 Two Holdings-Based Performance Measures: CS and CT

In each month, we sort the sample funds into 10 portfolios based on size dispersion in the lagged quarter end. We then compute the CS and CT for each portfolio by weighing all funds in the portfolio equally.

[Insert Table 1.9 here.]

Table 1.9 reports the results. Column 1 shows that the CS measure of decile 10 is higher than that of decile 1 by 20.7 bps per month (at the 5% significance level). Column 2 shows that the CT measure of decile 10 is not significantly different from that of decile 1.

These findings suggest that a high-size-dispersion fund manager exhibits better stock selection ability, but no better style-timing ability, than a low-size-dispersion fund manager does.

1.4.2 Stock Selection Skill when Investing in Stocks with Similar or Different Size Characteristics from the Average Size Style

We further test fund managers' stock selection skill when investing in stocsk with similar or different size characteristics from the average size style. For a fund's stockholdings j, we compute the difference between its size characteristics and the average size style, $|s_{jt} - \bar{s}_t|$. In each month, we sort the sample funds into 10 portfolios based on size dispersion in the

R_{jt} is the return of stock-month (j, t). $\mathrm{BR}_t(j, t-k)$ is the return on a benchmark portfolio in month t. Stock j was allocated to the benchmark portfolio in month $t-k$ according to its size, book-to-market, and momentum. $w_{j,t-k}$ is stock j's value weight in the fund at the end of month $t-k$.

Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2000, 2004) describe the computation of the benchmark returns in detail. We obtain the benchmark returns from Russ Wermers' website.

lagged quarter end. In a decile, we compute the median $|s_{jt} - \bar{s}_t|$. We refer to a fund's stockholdings with $|s_{jt} - \bar{s}_t|$ higher or lower than the median as investment with similar or different size characteristics from the average size style, and compute their CS measures. We then compute the CS measures for the decile by weighing all funds in the decile equally.

[Insert Table 1.10 here.]

Table 1.10 reports the results. Column 1 shows that when investing in stocks with similar size characteristics as the average size style, the CS measure of decile 10 is not significantly different from the CS measure of decile 1. Column 2 shows that when investing in stocks with different size characteristics from the average size style, the CS measure of decile 10 is higher than the CS measure of decile 1 by 21.9 bps per month (at the 5% significance level).

Column 3 also indicates that most fund managers have similar skills when investing in stocks with similar or different size characteristics from the average size style. Therefore, their choice of investing in these two types of stocks is an equilibrium result.

To summarize, our findings suggest that the superior stock selection ability of a high-size-dispersion fund manager, relative to a low-size-dispersion fund manager, is particularly pronounced when they invest in stocks with different size characteristics from the average fund size style. An interesting implication of this result is that even if a low-size-dispersion fund manager had a high level of size dispersion, she still would not produce the same performance as a high-size-dispersion fund manager does.

1.5 Conclusions

In this article, we propose a new predictor for the performance of actively managed equity mutual funds, style dispersion. Style dispersion measures the second moment, the dispersion, of the characteristics of the fund's stockholdings along size, value, and momentum dimensions. It is a normal but little studied industry phenomenon.

A simple benefit-cost analysis suggests that style dispersion can reflect a fund manager's investment ability and predict fund performance. We conduct a thorough empirical analysis to prove this. We have two major findings. First, style dispersion, especially that along size dimension, is significantly positively related with fund performance. Second, a high-size-dispersion fund manager exhibits significantly better stock selection skill than a low-size-dispersion fund manager does, especially when investing in stocks with different size characteristics from the average fund size style. We conduct various tests to show the robustness of our results. These tests suggest that size dispersion is distinct from all existing predictors of fund performance.

References

[1] Alexander, G. J., G. Cici, and S. Gibson, 2007, Does motivation matter when assessing trade performance? An analysis of mutual funds, *Review of Financial Studies* 20, 125-150.

[2] Amihud, Y., and R. Goyenko, 2013, Mutual fund's R^2 as predictor of performance, *Review of Financial Studies* 26, 667-694.

[3] Brown, K. C., W. V. Harlow, and H. Zhang, 2012, Investment style volatility and mutual fund performance, Working Paper.

[4] Brown, S. J., and W. N. Goetzmann, 1997, Mutual fund styles, *Journal of Financial Economics* 43, 373-399.

[5] Carhart, M. M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

[6] Chan, L., H. Chen, and J. Lakonishok, 2002, On mutual fund investment styles, *Review of Financial Studies* 15, 1407-1437.

[7] Chen, J., H. Hong, M. Huang, and J. Kubik, 2004, Does fund size erode mutual fund performance? The role of liquidity and organization, *American Economic Review* 90, 1276-1302.

[8] Cohen, R., J. Coval, and L. Pástor, 2005, Judging fund managers by the company they keep, *Journal of Finance* 60, 1057-1096.

[9] Coval, J. D., and T. Moskowitz, 1999, Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 2045-2073.

[10] Coval, J. D., and T. Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811-841.

[11] Cremers, M., and A. Petajisto, 2009, How active is your fund manager? A new measure that predicts performance, *Review of Financial Studies* 22, 3329-3365.

[12] Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035-1058.

[13] Evans, R. B., 2010, Mutual fund incubation, *Journal of Finance* 65, 1581-1611.

[14] Fama, E. F., and K. R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

[15] Fama, E. F., and J. D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

[16] Ferson, W., and R. Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 51, 425-462.

[17] Foroni, C., and M. Marcellino, 2013, A survey of econometric methods for mixed frequency data, Working Paper.

[18] He, Z., and W. Xiong, 2013, Delegated asset management, investment mandates, and capital immobility, *Journal of Financial Economics* 107, 239-258.

[19] Kacperczyk, M., and A. Seru, 2007, Fund manager use of public information: New evidence on managerial skills, *Journal of Finance* 62, 485-528.

[20] Kacperczyk, M., C. Sialm, and L. Zheng, 2005, On the industry concentration of actively managed equity mutual funds, *Journal of Finance* 60, 1983-2011.

[21] Kacperczyk, M., C. Sialm, and L. Zheng, 2008, Unobserved actions of mutual funds, *Review of Financial Studies* 21, 2379-2416.

[22] Kosowski, R., A. Timmermann, R. Wermers, and H. While, 2006, Can mutual fund "stars" really pick stocks? New evidence form a bootstrap analysis, *Journal of Finance* 61, 2551-2595.

[23] Newey, W. K., and K. D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

[24] Pástor, L., and R. F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642-685.

[25] Petajisto, A., 2010, Active share and mutual fund performance, Working Paper.

[26] Wermers, R., 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transaction costs, and expenses, *Journal of Finance* 55, 1655-1703.

[27] Wermers, R., 2004, Is money really 'smart'? New evidence on the relation between mutual fund flows, manager behavior, and performance persistence, Working Paper.

[28] Wermers, R., 2012, A matter of style: The causes and consequences of style drift in institutional portfolios, Working Paper.

Figure 1.1: A Snapshot of Fidelity Contrafund's stockholdings

This figure provides a snapshot of Fidelity Contrafund's stockholdings (managed by William Danoff) as of September 30, 2012.
(Source: Morningstar website,
http://portfolios.morningstar.com/fund/summary?t=FCNTX&region=USA&culture=en-us).

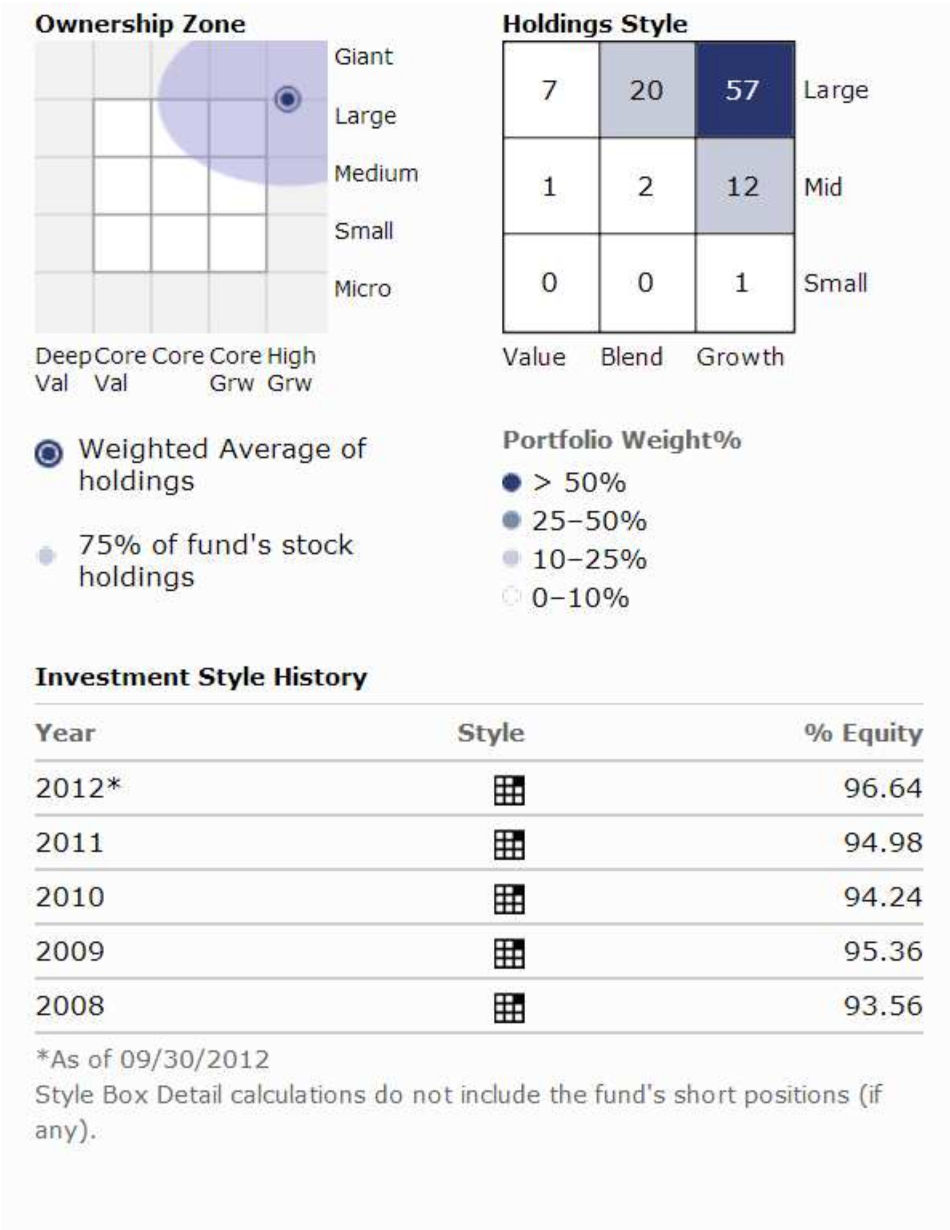


Figure 1.2: Before-Expense Returns of Portfolios Based on Style Dispersion

This figure plots the six risk- and style-adjusted returns, before expenses, of decile portfolios based on size, value, and momentum dispersions, respectively. The sample period is 1981 to 2010. In each month, we sort our sample funds into 10 portfolios based on style dispersion in the lagged quarter end (D10 has the highest style dispersion). We compute the monthly return for each portfolio by weighing all funds in the portfolio equally. We use excess return over the market (-), and abnormal returns of CAPM (- -), the Fama-French (1993) three-factor model ($\diamondsuit$), the Carhart (1997) four-factor model ($\triangle$), the Ferson-Schadt (1996) conditional four-factor model (+), and the Pástor-Stambaugh (2003) five-factor model (*).

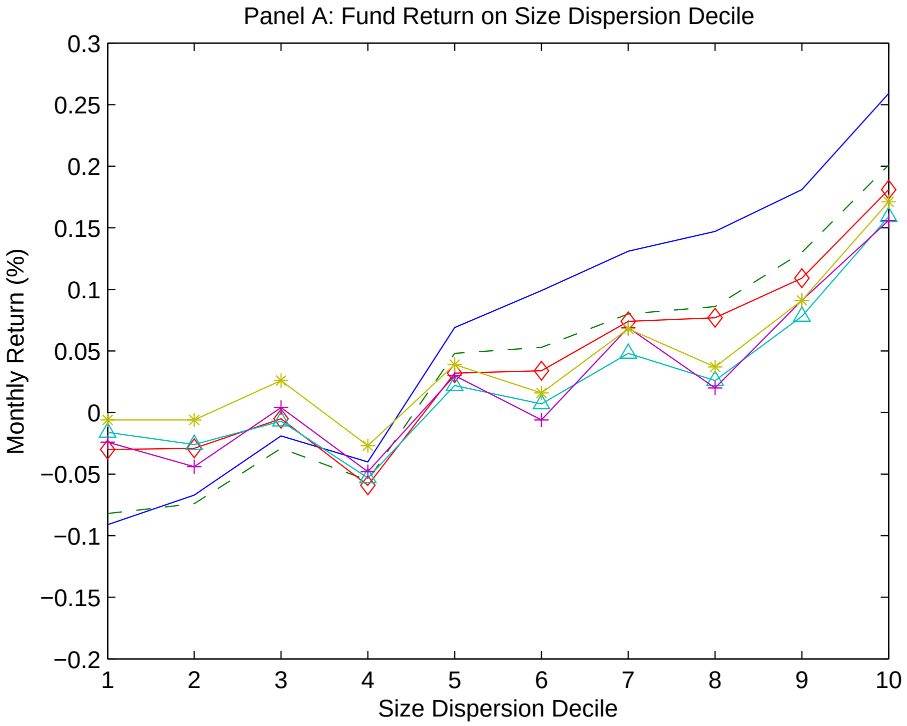
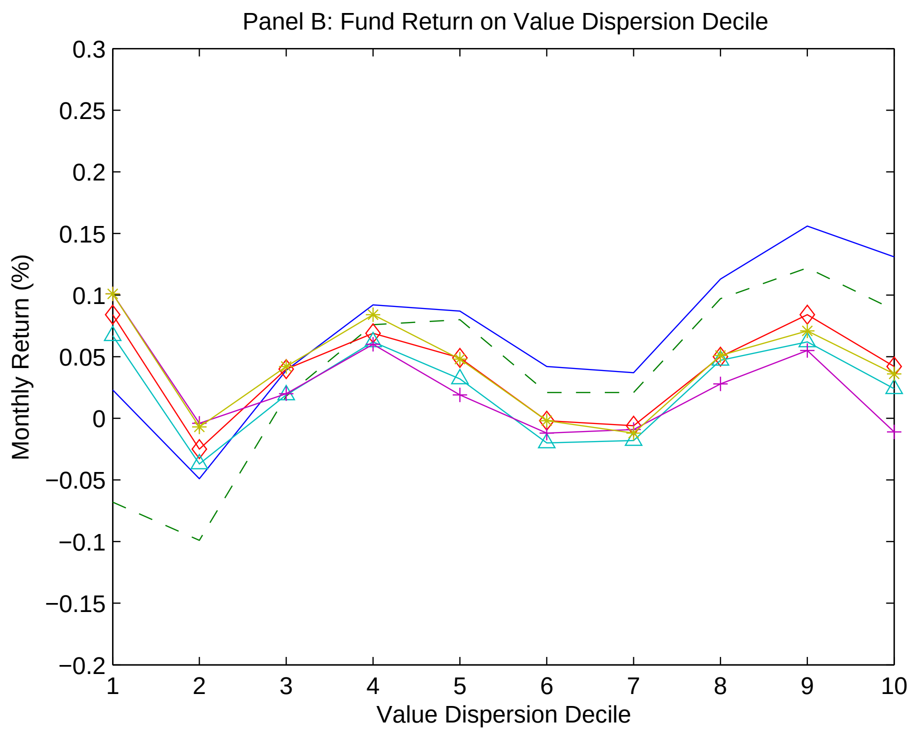


Figure 1.2 (Continued)



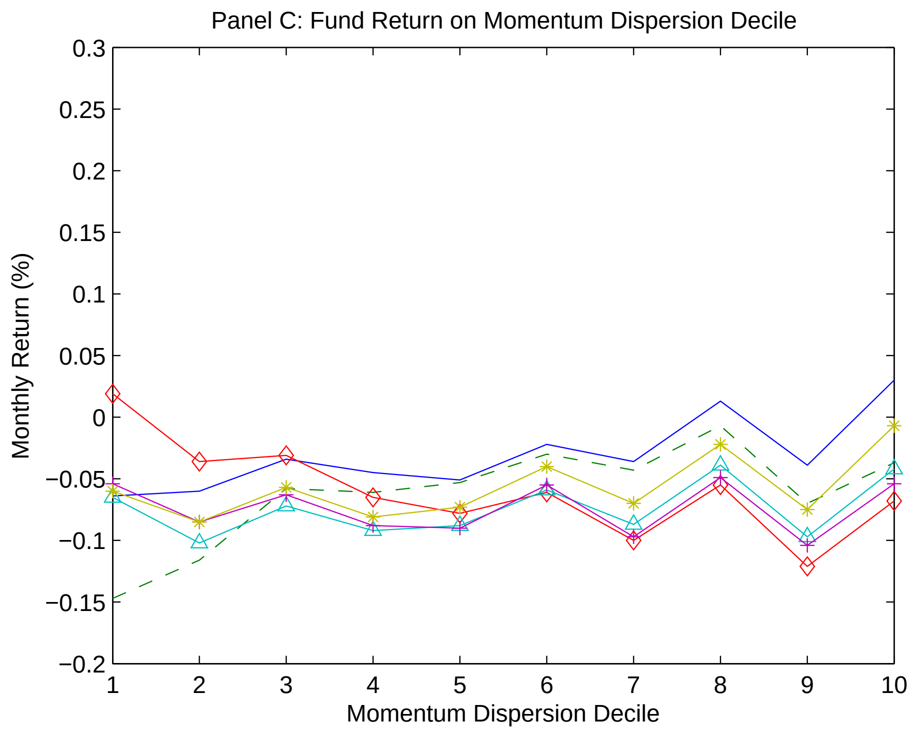


Table 1.1: Summary Statistics

This table reports the summary statistics for the sample of actively managed open-end U.S. domestic equity mutual funds. The sample period is 1981 to 2010. The sample includes 2,329 distinct funds and 73,861 fund-quarter observations. Panel A reports the time-series average of cross-sectional summary statistics. Panel B reports the time-series average of the cross-sectional pairwise correlation. All continuous variables are winsorized at the 1% and 99% levels.

Panel A: Fund Characteristics

Variables	Mean	Median	Minimum	Maximum	Standard Deviation
TNA (in millions)	549.611	158.300	9.131	9050.550	1193.893
Fund Age	14.125	11.375	1.658	67.383	10.998
Expense Ratio	0.012	0.012	0.004	0.025	0.004
Turnover Ratio	0.990	0.784	0.050	4.564	0.812
Flow	0.026	-0.002	-0.366	0.831	0.154
Quarterly Raw return	0.028	0.027	-0.114	0.169	0.042
Amihud and Goyenko's (2013) $1 - R^2$	0.096	0.078	0.012	0.426	0.071
Size Score	3.835	4.145	1.094	4.968	0.959
Value Score	2.581	2.572	1.296	4.087	0.502
Mom Score	3.317	3.312	1.791	4.729	0.518
Size Dispersion	0.655	0.676	0.050	1.287	0.275
Value Dispersion	1.100	1.116	0.670	1.445	0.159
Mom Dispersion	1.117	1.136	0.551	1.487	0.174

Panel B: Correlation Structure

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	Size Dispersion	1.000												
(2)	Value Dispersion	0.107	1.000											
(3)	Mom Dispersion	0.090	0.195	1.000										
(4)	TNA	-0.098	0.029	0.050	1.000									
(5)	Fund Age	-0.044	-0.005	0.014	0.289	1.000								
(6)	Expense Ratio	0.199	-0.011	-0.041	-0.233	-0.237	1.000							
(7)	Turnover Ratio	0.160	0.106	0.004	-0.090	-0.112	0.214	1.000						
(8)	Flow	0.027	0.015	-0.018	0.001	-0.149	0.045	0.046	1.000					
(9)	Quarterly Raw Return	0.057	0.020	-0.004	0.011	-0.001	-0.012	0.030	-0.016	1.000				
(10)	$1 - R^2$	0.206	-0.015	-0.107	-0.113	-0.049	0.197	0.161	0.019	0.020	1.000			
(11)	Size Score	-0.428	0.042	-0.012	0.136	0.186	-0.216	-0.065	-0.059	-0.033	-0.124	1.000		
(12)	Value Score	-0.027	0.446	0.128	-0.022	-0.062	-0.047	-0.022	0.012	0.025	0.069	0.186	1.000	
(13)	Mom Score	0.135	-0.086	-0.295	-0.005	0.005	0.099	0.244	0.052	0.049	-0.023	-0.252	-0.430	1.000

Table 1.2: Before-Expense Returns of Portfolios Based on Style Dispersion

This table reports the six risk- and style-adjusted returns (%), before expenses, of decile portfolios based on the size, value, and momentum dispersions, respectively. The sample period is 1981 to 2010. In each month, we sort our sample funds into 10 portfolios based on style dispersion in the lagged quarter end (D10 has the highest style dispersion). We compute the monthly return for each portfolio by weighing all funds in the portfolio equally. We use excess return over the market, and abnormal returns of CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, the Ferson-Schadt (1996) conditional four-factor model, and the Pástor-Stambaugh (2003) five-factor model. The *t*-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

Panel A: Deciles Based on Size Dispersion

	Size Dispersion (1)	Excess Return (2)	CAPM (3)	Fama French (4)	Carhart (5)	Ferson Schadt (6)	Pástor Stambaugh (7)
D1	0.090	-0.091**	-0.082**	-0.030	-0.016	-0.024	-0.006
		(-2.23)	(-2.00)	(-0.77)	(-0.41)	(-0.67)	(-0.14)
D2	0.210	-0.067	-0.074*	-0.029	-0.026	-0.044	-0.006
		(-1.59)	(-1.77)	(-0.70)	(-0.63)	(-1.22)	(-0.15)
D3	0.308	-0.019	-0.029	-0.005	-0.007	0.004	0.026
		(-0.39)	(-0.60)	(-0.11)	(-0.14)	(0.09)	(0.54)
D4	0.414	-0.040	-0.055	-0.059	-0.053	-0.048	-0.027
		(-0.76)	(-1.04)	(-1.13)	(-1.00)	(-1.09)	(-0.50)
D5	0.529	0.069	0.048	0.032	0.022	0.030	0.039
		(1.06)	(0.73)	(0.57)	(0.39)	(0.59)	(0.67)
D6	0.614	0.099	0.053	0.034	0.007	-0.006	0.016
		(1.22)	(0.66)	(0.56)	(0.12)	(-0.11)	(0.25)
D7	0.678	0.131	0.080	0.074	0.048	0.069	0.068
		(1.47)	(0.92)	(1.31)	(0.84)	(1.28)	(1.18)
D8	0.747	0.147	0.086	0.077	0.026	0.020	0.037
		(1.46)	(0.88)	(1.28)	(0.44)	(0.37)	(0.61)
D9	0.840	0.181*	0.130	0.109*	0.078	0.091	0.091
		(1.83)	(1.34)	(1.89)	(1.34)	(1.61)	(1.56)
D10	1.053	0.259***	0.201**	0.181***	0.159***	0.156***	0.171***
		(2.71)	(2.16)	(3.40)	(2.94)	(2.88)	(3.12)
D10-D1		0.350***	0.283***	0.211***	0.175***	0.180***	0.176***
		(3.17)	(2.64)	(3.40)	(2.80)	(2.94)	(2.78)

Table 1.2 (Continued)

Panel B: Deciles Based on Value Dispersion

	Value Dispersion (1)	Excess Return (2)	CAPM (3)	Fama French (4)	Carhart (5)	Ferson Schadt (6)	Pástor Stambaugh (7)
D1	0.811	0.023	-0.068	0.084	0.067	0.101	0.101
		(0.20)	(-0.62)	(1.18)	(0.92)	(1.37)	(1.39)
D2	0.952	-0.049	-0.099	-0.025	-0.037	-0.004	-0.007
		(-0.65)	(-1.36)	(-0.47)	(-0.69)	(-0.09)	(-0.13)
D3	1.017	0.039	0.018	0.040	0.019	0.020	0.042
		(0.64)	(0.30)	(0.85)	(0.39)	(0.46)	(0.88)
D4	1.063	0.092	0.076	0.069	0.062	0.060	0.084*
		(1.62)	(1.34)	(1.42)	(1.26)	(1.38)	(1.70)
D5	1.102	0.087	0.080	0.049	0.032	0.019	0.048
		(1.62)	(1.48)	(1.16)	(0.76)	(0.49)	(1.10)
D6	1.136	0.042	0.021	-0.002	-0.020	-0.012	-0.002
		(0.77)	(0.40)	(-0.04)	(-0.42)	(-0.31)	(-0.03)
D7	1.169	0.037	0.021	-0.006	-0.018	-0.009	-0.012
		(0.66)	(0.37)	(-0.13)	(-0.37)	(-0.20)	(-0.25)
D8	1.205	0.113*	0.097	0.050	0.047	0.028	0.051
		(1.88)	(1.61)	(1.02)	(0.94)	(0.61)	(0.99)
D9	1.253	0.156**	0.122*	0.084	0.062	0.055	0.071
		(2.36)	(1.88)	(1.57)	(1.15)	(1.12)	(1.30)
D10	1.353	0.131*	0.088	0.042	0.024	-0.011	0.036
		(1.76)	(1.21)	(0.72)	(0.40)	(-0.20)	(0.60)
D10-D1		0.108	0.156	-0.042	-0.043	-0.112	-0.065
		(1.07)	(1.57)	(-0.52)	(-0.53)	(-1.37)	(-0.79)

Table 1.2 (Continued)

Panel C: Deciles Based on Momentum Dispersion

	Mom Dispersion (1)	Excess Return (2)	CAPM (3)	Fama French (4)	Carhart (5)	Ferson Schadt (6)	Pástor Stambaugh (7)
D1	0.787	-0.064	-0.147	0.019	-0.065	-0.054	-0.060
		(-0.46)	(-1.09)	(0.20)	(-0.72)	(-0.59)	(-0.65)
D2	0.958	-0.060	-0.116	-0.036	-0.102*	-0.085	-0.085
		(-0.67)	(-1.33)	(-0.59)	(-1.71)	(-1.47)	(-1.41)
D3	1.028	-0.034	-0.058	-0.031	-0.072	-0.063	-0.057
		(-0.52)	(-0.89)	(-0.62)	(-1.43)	(-1.26)	(-1.12)
D4	1.078	-0.045	-0.061	-0.065	-0.092**	-0.088**	-0.081*
		(-0.85)	(-1.15)	(-1.51)	(-2.13)	(-2.29)	(-1.84)
D5	1.118	-0.051	-0.053	-0.078*	-0.088*	-0.090**	-0.073
		(-0.99)	(-1.03)	(-1.69)	(-1.87)	(-2.30)	(-1.54)
D6	1.155	-0.022	-0.030	-0.061	-0.059	-0.055	-0.040
		(-0.41)	(-0.54)	(-1.22)	(-1.16)	(-1.34)	(-0.78)
D7	1.191	-0.036	-0.043	-0.100*	-0.087	-0.097**	-0.070
		(-0.61)	(-0.72)	(-1.80)	(-1.53)	(-2.02)	(-1.23)
D8	1.231	0.013	-0.007	-0.055	-0.039	-0.049	-0.022
		(0.21)	(-0.10)	(-0.93)	(-0.66)	(-1.01)	(-0.36)
D9	1.279	-0.039	-0.070	-0.121**	-0.097	-0.104*	-0.075
		(-0.57)	(-1.03)	(-2.03)	(-1.61)	(-1.93)	(-1.23)
D10	1.385	0.030	-0.037	-0.068	-0.042	-0.054	-0.007
		(0.33)	(-0.43)	(-0.94)	(-0.58)	(-0.80)	(-0.10)
D10-D1		0.094	0.110	-0.086	0.023	-0.000	0.053
		(0.68)	(0.78)	(-0.69)	(0.19)	(-0.00)	(0.42)

Table 1.3: After-Expense Returns of Portfolios Based on Style Dispersion

This table reports the six risk- and style-adjusted returns (%), after expenses, of the bottom and top decile portfolios based on size, value, and momentum dispersions, respectively. The sample period is 1981 to 2010. In each month, we sort our sample funds into 10 portfolios based on style dispersion in the lagged quarter end (D10 has the highest style dispersion). We compute the monthly return for each portfolio by weighing all funds in the portfolio equally. We use excess return over the market, and abnormal returns of CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, the Ferson-Schadt (1996) conditional four-factor model, and the Pástor-Stambaugh (2003) five-factor model. The *t*-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

	Excess Return (1)	CAPM (2)	Fama French (3)	Carhart (4)	Ferson Schadt (5)	Pástor Stambaugh (6)
Panel A: Deciles Based on Size Dispersion						
D1	-0.180***	-0.171***	-0.119***	-0.105***	-0.114***	-0.095**
	(-4.40)	(-4.16)	(-3.11)	(-2.71)	(-3.14)	(-2.41)
D10	0.143	0.085	0.066	0.043	0.039	0.055
	(1.50)	(0.92)	(1.23)	(0.80)	(0.73)	(1.00)
D10-D1	0.324***	0.257**	0.184***	0.148**	0.153**	0.149**
	(2.93)	(2.39)	(2.97)	(2.37)	(2.50)	(2.36)
Panel B: Deciles Based on Value Dispersion						
D1	0.023	-0.068	0.084	0.067	0.101	0.101
	(0.20)	(-0.62)	(1.18)	(0.92)	(1.37)	(1.39)
D10	0.131*	0.088	0.042	0.024	-0.011	0.036
	(1.76)	(1.21)	(0.72)	(0.40)	(-0.20)	(0.60)
D10-D1	0.108	0.156	-0.042	-0.043	-0.112	-0.065
	(1.07)	(1.57)	(-0.52)	(-0.53)	(-1.37)	(-0.79)
Panel C: Deciles Based on Momentum Dispersion						
D1	0.042	-0.040	0.125	0.042	0.053	0.047
	(0.30)	(-0.30)	(1.36)	(0.45)	(0.59)	(0.50)
D10	0.136	0.068	0.038	0.063	0.052	0.099
	(1.50)	(0.79)	(0.52)	(0.86)	(0.77)	(1.34)
D10-D1	0.093	0.109	-0.087	0.022	-0.001	0.052
	(0.67)	(0.78)	(-0.70)	(0.18)	(-0.01)	(0.41)

Table 1.4: Subsamples Based on Claimed Investment Objective

This table reports the six risk- and style-adjusted returns (%), before expenses, of the bottom and top decile portfolios based on size dispersion within subsamples based on fund claimed investment objectives, including growth, growth and income, and income. The sample period is 1981 to 2010. In each month, we sort the funds in each subsample into 10 portfolios based on size dispersion in the lagged quarter end (D10 has the highest style dispersion). We compute the monthly return for each portfolio by weighing all funds in the portfolio equally. We use excess return over the market, and abnormal returns of CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, the Ferson-Schadt (1996) conditional four-factor model, and the Pástor-Stambaugh (2003) five-factor model. The *t*-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

	Size Dispersion (1)	Excess Return (2)	CAPM (3)	Fama French (4)	Carhart (5)	Ferson Schadt (6)	Pástor Stambaugh (7)
Panel A: Growth							
D1	0.100	-0.092**	-0.089*	-0.010	0.000	-0.023	0.007
		(-2.02)	(-1.94)	(-0.24)	(0.00)	(-0.59)	(0.16)
D10	1.108	0.230**	0.172*	0.155***	0.139**	0.135**	0.152***
		(2.53)	(1.95)	(2.78)	(2.45)	(2.36)	(2.64)
D10-D1		0.322***	0.261**	0.165**	0.139**	0.158**	0.145**
		(3.04)	(2.52)	(2.53)	(2.11)	(2.43)	(2.16)
Panel B: Growth and Income							
D1	0.029	-0.048	-0.003	0.026	0.042	0.052	0.041
		(-0.74)	(-0.06)	(0.60)	(0.99)	(1.12)	(0.94)
D10	0.896	0.244*	0.291**	0.051	0.104	0.029	0.070
		(1.87)	(2.26)	(0.53)	(1.10)	(0.30)	(0.73)
D10-D1		0.275*	0.279*	0.036	0.074	-0.024	0.044
		(1.82)	(1.84)	(0.35)	(0.72)	(-0.23)	(0.42)
Panel C: Income							
D1	0.042	-0.075	0.007	-0.001	0.023	0.048	0.033
		(-0.72)	(0.07)	(-0.01)	(0.36)	(0.75)	(0.50)
D10	0.903	0.130	0.262**	0.066	0.122	0.038	0.067
		(0.89)	(2.13)	(0.81)	(1.56)	(0.49)	(0.86)
D10-D1		0.213	0.272**	0.078	0.112	-0.002	0.047
		(1.61)	(2.10)	(0.76)	(1.09)	(-0.02)	(0.46)

Table 1.5: Subsamples Based on Fund Size (TNA)

This table reports the six risk- and style-adjusted returns (%), before expenses, of the bottom and top decile portfolios based on size dispersion within subsamples based on fund size (TNA). The sample period is 1981 to 2010. In each month, we sort the funds in each subsample into 10 portfolios based on size dispersion in the lagged quarter end (D10 has the highest style dispersion). We compute the monthly return for each portfolio by weighing all funds in the portfolio equally. We use excess return over the market, and abnormal returns of CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, the Ferson-Schadt (1996) conditional four-factor model, and the Pástor-Stambaugh (2003) five-factor model. The *t*-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

	Size Dispersion (1)	Excess Return (2)	CAPM (3)	Fama French (4)	Carhart (5)	Ferson Schadt (6)	Pástor Stambaugh (7)
Panel A: Small Fund TNA							
D1	0.077	-0.109*	-0.111*	-0.054	-0.038	-0.018	-0.017
		(-1.74)	(-1.75)	(-0.88)	(-0.60)	(-0.29)	(-0.27)
D10	1.117	0.268***	0.226**	0.206***	0.216***	0.230***	0.237***
		(2.70)	(2.29)	(2.79)	(2.87)	(2.99)	(3.11)
D10-D1		0.377***	0.337***	0.261***	0.254***	0.248***	0.254***
		(3.24)	(2.90)	(2.99)	(2.86)	(2.65)	(2.81)
Panel B: Mid Fund TNA							
D1	0.099	-0.007	0.016	0.040	0.064	0.027	0.066
		(-0.13)	(0.32)	(0.80)	(1.26)	(0.55)	(1.27)
D10	1.046	0.275**	0.201*	0.191***	0.162**	0.143**	0.163**
		(2.51)	(1.91)	(2.88)	(2.43)	(2.08)	(2.39)
D10-D1		0.281**	0.185	0.150*	0.098	0.116	0.097
		(2.12)	(1.46)	(1.80)	(1.17)	(1.39)	(1.14)
Panel C: Large Fund TNA							
D1	0.095	-0.139***	-0.142***	-0.056	-0.057	-0.047	-0.036
		(-2.70)	(-2.73)	(-1.19)	(-1.18)	(-1.01)	(-0.74)
D10	0.979	0.213**	0.160	0.146**	0.093*	0.084	0.092
		(2.08)	(1.60)	(2.55)	(1.65)	(1.51)	(1.60)
D10-D1		0.352***	0.302**	0.202***	0.150**	0.131*	0.127*
		(2.92)	(2.53)	(2.66)	(1.97)	(1.76)	(1.65)

Table 1.6: Regressing the Carhart Abnormal Return on Style Dispersion

This table reports the regression results of the Carhart abnormal return (%), before expenses, on style dispersion. The sample period is 1981 to 2010. The regressions are run at a quarterly frequency. The dependent variable, the Carhart abnormal return, measures the average monthly abnormal performance in a quarter, which is estimated using the Carhart (1997) four-factor model based on 24 months of lagged data. All explanatory variables are lagged by one quarter. We also control for the style fixed effect. We use the Fama-MacBeth (1973) cross-sectional regression that adjusts for heteroscedasticity and serial correlation of standard errors using Newey-West (1987) lags of order three. The *t*-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)
Size Dispersion	0.167***			0.163***
	(3.41)			(3.19)
Value Dispersion		0.053		-0.034
		(0.53)		(-0.37)
Mom Dispersion			0.173**	0.150*
			(2.00)	(1.83)
Intercept	-0.045	-0.000	-0.134	-0.155
	(-1.33)	(-0.00)	(-1.29)	(-1.09)
Style FE	YES	YES	YES	YES
No. of Observations	65,631	65,631	65,631	65,631

Table 1.7: Regressing the Carhart Abnormal Return on Size Dispersion Controlling for Various Fund Characteristics

This table reports the regression results of the Carhart abnormal return (%), before expenses, on size dispersion controlling for other fund characteristics. The sample period is 1981 to 2010. The regressions are run at a quarterly frequency. The dependent variable, the Carhart abnormal return, measures the average monthly abnormal performance in a quarter, which is estimated using the Carhart (1997) four-factor model based on 24 months of lagged data. All explanatory variables are lagged by one quarter, except for expense and turnover ratios, which are lagged by one year. The large-family dummy equals 1 (0) for funds affiliated with the top ten fund families with the largest number of investment objectives. Fund family information for the period of 2000 to 2010 is obtained from the CRSP database. We also control for the style fixed effect. We use the Fama-MacBeth (1973) cross-sectional regression that adjusts for heteroscedasticity and serial correlation of standard errors using Newey-West (1987) lags of order three. The t-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

	(1)	(2)
Size Dispersion	0.197***	0.110*
	(4.15)	(2.02)
Size Dispersion×Large-Family Dummy		0.015
		(0.23)
Large-Family Dummy		0.017
		(0.62)
ln(TNA)	-0.140***	-0.005
	(-2.64)	(-0.24)
$(\ln(TNA))^2$	0.012**	-0.000
	(2.55)	(-0.06)
ln(Fund Age)	0.011	0.039**
	(0.58)	(2.17)
Expense Ratio	-7.419*	0.667
	(-1.70)	(0.42)
Turnover Ratio	0.008	-0.014
	(0.35)	(-0.45)
Flow	0.329***	0.148
	(2.70)	(1.02)
Intercept	0.321*	-0.080
	(1.77)	(-0.66)
Style FE	YES	YES
No. of Observations	63,463	44,465

Table 1.8: Regressing the Carhart Abnormal Return on Size Dispersion Controlling for Existing Predictors of Fund Performance

This table reports the regression results of the Carhart abnormal return (%), before expenses, on size dispersion controlling for existing predictors of fund performance. The sample period is 1981 to 2010. The regressions are run at a quarterly frequency. The dependent variable, the Carhart abnormal return, measures the average monthly abnormal performance in a quarter, which is estimated using the Carhart (1997) four-factor model based on 24 months of lagged data. The explanatory variables, including size dispersion, Amihud and Goyenko's (2013) $1 - R^2$, Kacperczyk, Sialm, and Zheng's (2005) industry concentration index (ICI), and Cremers and Petajisto's (2009) Active Share, are lagged by one quarter. We obtain data on Active Share for the period of 1990 to 2006 from Antti Petajisto's website. We also control for often-used fund characteristics, and the style fixed effect. We use the Fama-MacBeth (1973) cross-sectional regression that adjusts for heteroscedasticity and serial correlation of standard errors using Newey-West (1987) lags of order three. The t-statistics are given in parentheses. *, **, and *** indicate significance levels of the 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)
Size Dispersion	0.188***	0.169***	0.176***	0.111**
	(3.51)	(3.64)	(3.82)	(2.28)
Prior-Yr Fund Ret	1.039***			
	(3.59)			
$1 - R^2$		0.028		
		(0.14)		
ICI			-0.020	
			(-0.10)	
Active Share				0.207
				(1.44)
Intercept	0.153	0.371**	0.268	0.219
	(0.80)	(2.17)	(1.54)	(1.08)
Control for Other Fund Characteristics	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
No. of Observations	63,463	63,209	58,773	28,755

Table 1.9: Holdings-Based Performance Measures of Portfolios Based on Size Dispersion

This table reports the two holdings-based performance measures proposed by Daniel, Grinblatt, Titman, and Wermers (1997), the "Characteristic Selectivity" measure CS (%) and the "Characteristic Timing" measure CT (%), of decile portfolios based on size dispersion for the period of 1981 to 2010. In a month, we sort our sample funds into 10 portfolios based on size dispersion in the lagged quarter end (D10 has the highest size dispersion). We compute the monthly CS and CT measures for each portfolio by weighing all funds in the portfolio equally. The t-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

	CS (1)	CT (2)
D1	-0.065	-0.050*
	(-0.26)	(-1.70)
D2	-0.040	-0.021
	(-0.15)	(-0.74)
D3	0.014	-0.044
	(0.06)	(-1.52)
D4	-0.082	-0.000
	(-0.31)	(-0.00)
D5	-0.007	-0.004
	(-0.02)	(-0.18)
D6	-0.007	-0.020
	(-0.03)	(-0.72)
D7	0.003	-0.015
	(0.01)	(-0.55)
D8	-0.010	-0.023
	(-0.03)	(-0.89)
D9	0.018	0.002
	(0.06)	(0.07)
D10	0.142	-0.019
	(0.49)	(-0.67)
D10-D1	0.207**	0.030
	(2.09)	(0.90)

Table 1.10: CS of Investment with Similar (Different) Size Characteristics to (from) the Average Size Style

This table reports the "Characteristic Selectivity" measure CS (%) of investment with similar (different) size characteristics to (from) the average size style. The sample period is 1981 to 2010. For a fund's stockholdings j, we compute the difference between its size characteristics and the average size style, $|s_{jt} - \bar{s}_t|$. In each month, we sort the sample funds into 10 portfolios based on size dispersion in the lagged quarter end (D10 has the highest size dispersion). In a decile, we compute the median $|s_{jt} - \bar{s}_t|$. We refer to a fund's stockholdings with $|s_{jt} - \bar{s}_t|$ higher or lower than the median as investment with similar or different size characteristics from the average size style, and compute their CS measures. We then compute the CS measures for the decile by weighing all funds in the decile equally. The t-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

	Investment with Similar Size Characteristics to Average Size Style (1)	Investment with Different Size Size Characteristics from Average Size Style (2)	Difference (3)=(2)-(1)
D1	-0.025	-0.061	-0.036
	(-0.10)	(-0.23)	(-0.51)
D2	-0.046	-0.017	0.029
	(-0.18)	(-0.06)	(0.40)
D3	0.013	0.048	0.035
	(0.05)	(0.17)	(0.40)
D4	-0.074	-0.067	0.006
	(-0.28)	(-0.24)	(0.10)
D5	-0.035	0.021	0.056
	(-0.13)	(0.07)	(0.84)
D6	-0.048	0.041	0.089*
	(-0.16)	(0.14)	(1.82)
D7	-0.066	0.109	0.174***
	(-0.22)	(0.35)	(2.78)
D8	-0.042	0.020	0.061
	(-0.14)	(0.06)	(1.04)
D9	-0.049	0.086	0.135**
	(-0.16)	(0.28)	(2.31)
D10	0.145	0.158	0.013
	(0.49)	(0.53)	(0.19)
D10-D1	0.170	0.219**	
	(1.51)	(2.11)	

Chapter 2

The Impact of Family-Level M&As on Mutual Fund Performance

Abstract

We show that family-level M&As have a negative impact on mutual fund performance. Specifically, in family-level M&As, the acquiring families keep most of the acquired funds intact, and merge the rest with a few incumbent funds. The intact acquired funds have a performance deterioration for up to 20 months. The intact incumbent funds have a performance deterioration, which is particularly pronounced in complete acquisitions, for up to 12 months. We also rule out some alternative explanations for the performance change. Finally, we show that consistent with agency theory, family-level M&As are likely to be motivated by family management's own incentives.

JEL Classification: G23; G34

Keywords: Merger and acquisition; Fund family; Mutual fund; Fund performance

2.1 Introduction

Mutual funds represent an important part of the financial services industry. Toward the end of 2012, the total assets under management by the U.S. mutual fund industry reached \$13 trillion, with 44.4% of households investing in mutual funds (Investment Company Institute, 2013). Because most mutual funds are sponsored by fund families, the organizational behavior of fund families and its impact on fund performance has attracted extensive attention.[1] In two important articles, Chen et al. (2004) and Pollet and Wilson (2008) show that on average, mutual funds in large fund families outperform mutual funds in small fund families. Chen et al. (2004) attribute this to economies of scale.

Can one infer from this finding that any method that increases fund family size improves mutual fund performance? The answer to this question has important implications. Fund family size can grow roughly by three methods. First, the sponsored funds produce good performance and, therefore, have an increase in fund size. Second, good fund performance and/or a successful marketing campaign based on it attracts inflows of new money. Third, two separate fund families are combined through family-level M&As (or simply, family M&As).[2] Whereas the first two methods are "organic" but tend to be slow and gradual in increasing fund family size, the third method is dramatic and more effective. If the answer to the above question is yes, then industry practitioners should actively seek family M&As, and regulators should pass rules to encourage family M&As.

[1] In a fund sponsorship, the fund family nominates fund managers, handles sales and advertising, etc., for the mutual fund, and in return collects various fees from fund investors. Gaspar et al. (2006) provide the statistics on the prevalence of mutual fund families.

[2] In a family M&A, the acquiring family pays the target family, and acquires all or some of the fund sponsorships held by the target family. Examples of complete acquisitions include Wells Fargo Advantage Funds' merger with Evergreen Fund families in early 2010. Examples of partial acquisitions include John Hancock Funds' adoption of the Robeco Boston Partners Mid Cap Value Fund, which was then re-launched as John Hancock Disciplined Value Mid Cap Fund, in July 2010.

In this article, we examine this question by testing the impact of family M&As on mutual fund performance. Intuitively, this impact can be positive or negative. The benefit of family M&As is that there can be a gain of economies of scale. Bhojraj et al. (2012) show that mutual funds in large fund families have information advantage over those in small fund families. Combining two fund families can also save overhead, advertising, and other expenses. The cost of family M&As is that the following reorganization can be detrimental to operation of funds because it causes rebalancing of portfolios, interruption of existing investment philosophy and practices, etc.[3] The reorganization can have other expenses, such as legal, accounting, combining offices, relocating fund managers, etc.

If the effect of economies of scale (benefit of family M&As) dominates the effect of reorganization (cost of family M&As), then family M&As should increase fund performance. In this case, we should also see that small fund families are likely to engage in family M&As because they can gain the most. If the effect of reorganization (cost of family M&As) dominates the effect of economics of scale (benefit of family M&As), then family M&As should decrease fund performance. In this case, family M&As are likely a reflection of agency problems. According to Jensen's (1986) free cash flow hypothesis, management of fund families have personal incentives to acquire. Often-mentioned incentives include building an "empire," diversifying human capital, etc. Because large and complex (measured by the number of distinct fund investment objectives) fund families usually have more resources to spend, we should see that large and complex fund families are likely to acquire.

Our findings are consistent with the case in which the effect of reorganization (cost of

[3]After BlackRock acquired State Street Research & Management Co. in 2005, it replaced State Street's large-cap stock-picking capabilities with its computer-based program for managing large-cap assets, a decision that affected approximately 17% of BlackRock's mutual fund assets. An anonymous source close to State Street said, "They called this an integration of the business. It is not an integration" (Wall Street Journal, January 17, 2005).

family M&As) dominates the effect of economics of scale (benefit of family M&As). Specifically, in family M&As, the acquiring families keep most of the acquired funds intact, and merge the rest with a few incumbent funds. After family M&As, the intact acquired funds have a performance deterioration for up to 20 months. The intact incumbent funds have a performance deterioration, which is particularly pronounced in complete acquisitions, for up to 12 months. We also rule out some alternative explanations for the performance change. Finally, we show that consistent with Jensen's (1986) free cash flow hypothesis, large and complex fund families are more likely to acquire. Taken together, we conclude that not every method that increases fund family size, especially not family M&As, improves mutual fund performance. Therefore, fund families should seek "organic" growth, not family M&As.

Our analysis is as follows. First, we build a unique sample of 251 family M&A for the period of 2001 to 2010. In 162 (89) of these family M&As, the acquiring families acquired all (some) of the fund sponsorships held by the target families. In the case of complete (partial) acquisitions, 626 (183) funds were transferred from the target families to the acquiring families. In both types of acquisitions, the acquiring families keep most of the acquired funds intact, and merge the rest into a few incumbent funds.

Second, we examine the impact of family M&As on fund performance. We use a "matching" fund approach to account for the possible selection bias in family M&As and the following fund mergers. We find that the intact acquired funds have a performance (before expenses) deterioration of for up to 20 months. The intact incumbent funds have a performance deterioration, which is pronounced in complete acquisitions, for up to 12 months. A plausible explanation for this is that as we discussed above, the post-M&A reorganization is detrimental to the operation of the acquired funds. This reorganization is also detrimental to the operation of the incumbent funds because the focus of the family management is diverted, which goes to a greater extent in complete acquisitions.

The long-run but still temporary (up to 20 months or 12 months) performance deterioration of these funds helps us rule out two alternative explanations. Take the intact acquired funds as an example. The first alternative explanation is the "favoritism" explanation, according to which fund families often engage in a building-a-"star" strategy by transferring fund performance through, for example, allocation of profitable IPOs (Nanda et al., 2004; and Gaspar et al., 2006). If the intact acquired funds that used to be favored by the old families are no longer favored by the new families, then there will be a decrease in the performance of these funds. The second alternative explanation is the "pure luck" explanation, according to which a good pre-M&A performance of the intact acquired funds is due to pure luck. After family M&As, they run out of luck and, therefore, have a decrease in performance. Both explanations imply a permanent performance deterioration for the intact acquired funds. We find, however, that the performance deterioration is temporary (up to 20 months).

We find no evidence that family M&As cause a change in the performance, before expenses, of the incumbent funds used to merge the acquired funds, or in the performance of the funds remaining in the target families in the case of partial acquisitions. We don't study the acquired funds merged into the incumbent funds because after family M&As, these funds no longer exist.

Third, we examine other impacts of family M&As on fund expenses, turnover, and flow. There is no evidence that family M&As decrease fund expenses. We even find evidence that the acquiring families increase fund expenses, suggesting that they pass some reorganization expenses to fund investors. There is no evidence that family M&As enhance fund liquidity by reducing fund turnover. Here we measure fund liquidity using fund turnover, a lower level of which indicates that the fund does not need to sell often to meet the liquidity demand such as a large amount of redemption. There is no evidence that family M&As attract new money inflow, suggesting no positive reaction from fund investors. This finding also suggests that family M&As do not strengthen the acquiring families' competitive advantage.[4]

Finally, we use the multinomial logistic regression approach to examine why fund families engage in family M&As. We find that large and complex fund families are likely to acquire, and that complex fund families are likely to be a target. These findings are consistent with Jensen's (1986) free cash flow hypothesis as we discussed above. We also find that fund families experiencing losses of market shares to rivals are likely to be a target, suggesting that the competition condition is also an important determinant of family M&As.[5]

The main contribution of our study is to the literature on the organizational behavior of mutual fund families. In two closely related articles, Chen et al. (2004) and Pollet and Wilson (2008) show that on average, funds in large fund families outperform funds in small fund families.[6] A naïve interpretation of this finding is that any method that increases fund family size improves fund performance. We show that this is not true. Although family-level M&As increases fund family size dramatically and effectively, they actually decrease fund performance.

Other related studies in this literature show that fund families can adopt family strate-

[4]Another impact of family M&As is due to the fact that fund families usually allow fund investors to switch among member funds in the same family without paying an additional load. As family M&As bring more funds under one roof, fund investors' switch option in the same family becomes more valuable. However, we are not able to examine this impact quantitatively.

[5]Although family M&As are likely to be motivated by fund family management's own incentives, we are not able to examine their impact on family shareholder wealth by looking at stock return or the acquisition price due to limitation of data. Most fund families are privately held companies or subsidiaries of banks. They neither have stock price nor have obligations to disclose the family M&A information to the public.

[6]IvKovic (2002) has a similar finding.

gies that do not necessarily benefit fund investors by increasing fund performance (e.g., Massa, 2003; Nanda et al., 2004; Gaspar et al., 2006; and Bhattacharya et al., 2013). We show that fund families often engage in family-level M&As, which are likely to be motivated by fund family management's own incentives and decrease fund performance.

Our study is also related to two other literatures. First, our study is related to the literature on M&As at the mutual fund level. Jayaraman et al. (2002), Zhao (2005), and Khorana et al. (2007) show that in fund-level mergers, poor-performing funds are often merged into good-performing funds, the purpose of which is to cover up their poor performance. We show that in family M&As, the acquiring families keep most of the acquired funds intact, and merge the rest with a few incumbent funds (this causes a small overlapping with fund-level M&As). Importantly, our main finding on the negative impact of family M&As on fund performance concentrates on the intact acquired and intact incumbent funds, which do not overlap with fund-level M&As.

Second, our study is related to a small line of research on corporate M&As. Maksimovic and Phillips (2001), Schoar (2002), and Maksimovic et al. (2011) examine data on plants (corresponding our funds) of manufacturing firms (corresponding our fund families). They show that the acquired plants have an increase in productivity. Schoar (2002) refers to this as a "new toy" effect, according to which management of the acquiring firms shifts focus towards the new segments. We show that in family M&As, both the acquired funds and the incumbent funds have a performance deterioration. This finding evidences that the post-M&A reorganization is detrimental to the operation of both groups of funds.

We organize the rest of the article as follows. Section 3.2 describes data and the procedure we use to identify family M&As. Section 3.3 tests the impact of family M&As on fund performance. Section 2.4 tests other impacts of family M&As on fund expenses, turnover, and flow. Section 2.5 tests the determinants of family M&As. Section 3.5

concludes.

2.2 Data and Identification of Family M&As

2.2.1 The Source of Data

We obtain fund information, including TNA, fund age, expense and turnover ratios, return, investment objective, management company code, etc., from the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund database. We also compute fund flow as the monthly appreciation of fund TNA. We follow Gruber (1996) and Zheng (1999) to adjust for fund return, and assume that all flows happen at the month end. For funds with multiple share classes, we aggregate across the different share classes to obtain fund-level variables.

2.2.2 Identifying Family M&As

We use the management company code (mgmt_cd) to identify fund families for the period of 2001 to 2010. Our sample begins in 2001 because most of the management company code data are available as of 2000.

We use two steps to identify family M&As. In Step 1, we use the CRSP database to obtain an initial sample of family M&As. Specifically, we identify a family M&A event if in a given month, one or several mutual funds sign off their old management company (the target family with an old mgmt_cd) and sign in a new management company (the acquiring family with a new mgmt_cd). We count all the following fund switches from the target family to the acquiring family. If the last fund switch is within 12 months after the first fund switch, then we include all these fund switches in this family M&A event. If the last fund switch is more than 12 months after the first fund switch, then we include all the fund switches within the 12 months in this family M&A event, and the fund switches outside the 12 months in other M&A(s) between these two families.[7]

We extend the family M&A window 5 months prior to the first fund switch because there can be a delay of reporting in the CRSP database. Therefore, the duration of a family M&A window ranges from 6 months to 18 month. To ensure the quality of the identification of family M&As, we also require that in a family M&A, the total TNA of the acquired funds is at most twice of the total TNA of the acquiring family's incumbent funds.

In Step 2, we conduct a comprehensive and detailed search of news media (using FACTIVA), company website, and SEC filings based on the initial sample of family M&As. This search is necessary because Step 1 may not give a precise sample of family M&As due to several problems of using the management company code (mgmt_cd) in the CRSP database. First, in the CRSP database, the change of a fund's management company code can be due to a simple name change of the management company. Second, although they have different management company codes, the acquiring family and the target family can be in fact different investment arms of the same company. Third, after a family M&A, the acquiring family can assume the name and the management company code of the target family. In Step 2, we eliminate the first two cases and correct the third case in our sample of family M&As. We also ensure that the transaction date from news media, company website, or SEC filings is in our family M&A window.

We observe several cases in which the acquiring family keeps using the target family as

[7] There are rare cases in which the last fund switch is more than 12 months after the first fund switch. We checked news media, company website, and SEC filings, and found that they are indeed separate (partial) M&A transactions between the same two families.

sub-advisor for the acquired fund(s).[8] We also count these cases as family M&As because fund sponsorships have switched.

2.2.3 Distribution of Family M&As

Table 2.1 reports the distribution of family M&As by year for the period of 2001 to 2010. Panel A (Panel B) reports for complete (partial) acquisitions. Over the entire sample period, we identify 251 family M&As. In 162 (89) of these family M&As, the acquiring families acquired all (some) of the fund sponsorships held by the target families. In the case of complete acquisitions, 626 funds were transferred from the target families to the acquiring families. 74.6% (467/626) of the acquired funds emerged intact after the family M&A window. 25.4% (159/626) of the acquired funds were merged into the acquiring families' incumbent funds during the family M&A window. In the case of partial acquisitions, 183 funds were transferred from the target families to the acquiring families. 54.1% (99/183) of the acquired funds emerged intact after the family M&A window. 45.9% (84/183) of the acquired funds were merged into the acquiring families' incumbent funds during the family M&A window. There are still 1268 funds remaining in the target families.

[Insert Table 2.1 here.]

We adopt two simplifications here. First, a small number of the funds that emerged intact from the family M&A window are merged in the months following family M&As. We tried to treat these funds as intact funds (suppose that the fund-level mergers are not part of the family M&A transaction) or as merged funds (suppose that the fund-level mergers are part of the family M&A transaction). The results are almost the same. We report only the result for treating these small number of funds as intact funds. Second, there are rare

[8] See Chen et al. (2013) for a detailed analysis of outsourcing mutual fund management.

cases in which an acquired fund from the target family is used to merge another acquired fund (21 cases), or an incumbent fund from the acquiring family (2 cases). We do not study these funds because the number of these funds is too small to conduct a meaningful statistical test.

[Insert Table 2.2 here.]

Table 2.2 reports the distribution of funds involved in family M&As by category. The largest category is domestic equity funds, representing about 64.9% (525/809) of the acquired funds. The second largest category is balanced funds, representing about 15.9% (129/809) of the acquired funds. The third largest category is foreign equity funds, representing about 12.6% (102/809) of the acquired funds. Fixed income bonds represent only 6.3% (51/809) of the acquired funds.

2.3 The Impact of Family M&As on Fund Performance

We adjust fund performance for risk and style differences using the objective-adjusted return (OAR, which equals the fund return minus the value-weighted average return on a portfolio comprising all other funds with the same investment objective). We compute OAR based on the fund return before subtracting expenses. We examine fund expenses separately in Section 2.4.

We use OAR for two reasons. First, OAR has been used often as a convenient and reasonably good measure to adjust for risk and style differences for not only domestic equity funds but also other types of mutual funds. Examples of studies using OAR include Gaspar et al. (2006) on a study of fund families, and Jayaraman et al. (2002) on a study of fund-lever mergers.

Second, one may suggest using factor models (e.g., Carhart, 1997) or characteristics-based models (e.g., Daniel et al., 1997) to adjust for risk and style differences. These models are applicable to domestic equity mutual funds. We used them for our sample of domestic equity funds, and found similar results (not reported to save space, but available from the authors upon request). However, they are not applicable to other types of funds, such as balanced funds and foreign equity funds, which constitute a large fraction of our sample funds. We searched the literature but found no commonly agreed factor models for these funds.

We obtain fund investment objective information from the CRSP database (level-4 style code).[9] For examples, investment objectives for domestic equity funds include large cap, mid cap, small cap, growth, growth and income, income, etc.; investment objectives for fixed income funds include short duration, intermediate duration, high yield, etc. A concern for using CRSP investment objective in our study is that it may change after family M&As. We use two approaches to mitigate this concern.

First, we follow Daniel et al. (1997) to compute domestic equity funds' investment styles along the dimensions of size and book-to-market using fund stockholdings information obtained from Thomson Reuters CDA/Spectrum database. We find that the holdings-based styles of the domestic equity mutual funds rarely change after family M&As. This is consistent with SEC's regulation that fund investment style cannot deviate significantly from that specified in fund prospectus in order to protect fund investor interests.

Second, we replace CRSP investment objective using the holdings-based style, and redo all the tests using domestic equity funds (not reported to save space). Our main results are almost the same. A disadvantage of using the holdings-based style in our study is that

[9]In 2012, the CRSP releases the style code, which combines information from three different sources, including Wiesenberger, Strategic Insight, and Lipper, over the life of the database.

this style applies only to domestic equity funds, which constitutes only part of our sample funds.

2.3.1 Pre-M&A Fund Performance and TNA

Before we proceed to examine the impact of family M&As on fund performance, we take a look at the pre-M&A fund performance and TNA of involved funds.

Table 2.3 reports the performance (OAR) per month of involved funds by category in the 12 months prior to the family M&A window. A notable observation is that the intact acquired funds have better pre-M&A performance than the merged acquired funds do. For example, in the domestic equity fund category, the pre-M&A OAR of the intact acquired funds is 8.6 bps per month, which is significantly positive at the 10% level; the pre-M&A OAR of the merged acquired funds is -37.8 bps per month, which is significantly negative at the 1% level.

[Insert Table 2.3 here.]

Table 2.4 reports the TNA of involved funds by category right before the family M&A window. We have two observations. First, funds from the acquiring families have larger size than funds from the target families do. For example, in the domestic equity fund category, the mean size of the intact incumbent funds is about twice (930.841/433.646) of the mean size of the intact acquired funds. Second, among the acquired funds, the intact funds have larger size than the merged funds do. For example, in the domestic equity fund category, the mean size of the intact acquired funds is about three times (433.64/150.570) of the mean size of the merged acquired funds.

[Insert Table 2.4 here.]

The analysis of pre-M&A fund performance and TNA suggests that family M&As and the following fund mergers may cause a potential selection bias in fund performance. To see this, suppose that one examines the impact of family M&As on the performance of, for example, an intact acquired fund by testing whether the fund's post-M&A performance is similar as, higher than, or lower than the pre-M&A level. This test won't be precise because if there is a reversion of fund performance, then a documented (if any) lower post-M&A performance can just reflect the good pre-M&A performance and cannot be ascribed to family M&As.[10]

Therefore, we examine the impact of family M&As on fund performance using a "matching" fund approach, which accounts for the potential selection bias and quantifies the extra effect due to family M&As. Specifically, for a fund involved in a family M&A, we identify a matching fund from those not caught in any family M&A. We require that the matching fund have the same investment objective, the same decile information on pre-M&A fund performance (OAR), and the closest pre-M&A fund TNA as the treatment fund does. If the treatment fund performs similarly as, outperforms, or underperforms the matching fund in the post-M&A period, then we state that family M&As cause no change, an improvement, or a deterioration in the performance of the treatment fund.

2.3.2 Intact Acquired Funds

Table 2.5 uses a regression analysis to compare the performance of the intact acquired funds and the performance of their matching funds in the first 12 months after family M&As. We use the OAR per month as the dependent variable, and include in the regression all the monthly observations for the intact acquired funds (indicated by a dummy variable

[10]Berk and Green (2004) present a model showing that superior fund performance tends to revert to normal level.

TRE=1, where TRE stands for "treatment") and their matching funds (indicated by TRE=0) in the post-M&A 12 months. We use the panel regression that includes style fixed effects and time fixed effects. The standard errors are clustered at the fund level.

[Insert Table 5 here.]

Column 1 of Table 2.5 shows that the coefficient on the TRE dummy, -0.105, is significantly negative at the 1% level, suggesting that an intact acquired fund underperforms its matching fund by 10.5 bps per month in the post-M&A 12 months. Column 2 controls for other fund characteristics that can be related with fund performance. These fund characteristics are lagged by one month, except for expense and turnover ratios, which are contemporaneous. Fund TNA and age are skewed to the right, so we take the natural logarithms. The coefficient on the TRE dummy, -0.140, remains significantly negative at the 1% level. The larger magnitude (-0.140 vs. -0.105) suggests further underperformance.

In what follows, we analyze the performance deterioration of the intact acquired funds in detail.

Manager Turnover

Do Family M&As cause abnormal turnover of fund managers? To answer this question, we retrieve from the CRSP database for the 566 intact acquired funds (467 from complete acquisitions and 99 from partial acquisitions; see Table 2.1) in our sample the fund manager information right before and after the family M&A window (the average duration of our window is 12 months). We manually eliminate the funds that do not have precise fund manager information, for example, team or missing data. This leaves us 348 funds, which are run by 543 managers before the window. After the window, 92 funds, or 27.1% of the 348 funds, observe a change in the composition of fund managers. 135 fund managers, or 24.9% of the 543 pre-M&A managers, have left. This percentage seems to be at the reasonable level because Khorana (1996) finds that the average tenure of mutual fund managers is around 4 to 5 years, which is equivalent to an annual turnover rate of 20% to 25%.

Columns 3 of Table 2.5 tests whether turnover of fund managers contributes to the performance deterioration of the intact acquired funds. We set the manager turnover dummy for an intact acquired fund and its matching fund to be 1 (0) if the intact acquired fund has (doesn't have) a change in the composition of fund managers during the family M&A window. The coefficient on the TRE dummy alone, -0.152, is significantly negative at the 5% level, suggesting that an intact acquired fund with no manager turnover underperforms its matching fund by 15.2 bps per month in the post-M&A 12 months. The coefficient on the interaction term between the TRE dummy and the manager turnover dummy, 0.068, suggests that the underperformance of an intact acquired fund with manager turnover (relative to its matching fund) is lower than the underperformance of an intact acquired fund with no manager turnover (relative to its matching fund) by 6.8 bps per month. However, this result is not significant.

To summarize, we find no evidence that turnover of fund managers contributes to the performance deterioration of the intact acquired funds.

Equity Funds vs. Non-Equity Funds

Column 4 of Table 2.5 tests whether equity funds have a more pronounced performance deterioration than non-equity funds do. We set the equity fund dummy for an intact acquired fund and its matching fund to be 1 (0) if the intact acquired fund is (isn't) an equity fund. The coefficient on the TRE dummy alone, -0.160, is significantly negative at the 10% level, suggesting that a non-equity fund underperforms its matching fund by 16 bps per month in the post-M&A 12 months. The coefficient on the interaction term between the TRE dummy and the equity fund dummy, 0.025, suggests that the underperformance of an equity fund (relative to its matching fund) is lower than the underperformance of a non-equity fund (relative to its matching fund) by 2.5 bps per month. However, this result is not significant.

To summarize, we find no evidence that equity funds have a more pronounced performance deterioration than non-equity funds do.

Complete Acquisitions vs. Partial Acquisitions

Column 5 of Table 2.5 tests whether complete acquisitions cause a more pronounced performance deterioration for the intact acquired funds than partial acquisitions do. We set the complete acquisition dummy for an intact acquired fund and its matching fund to be 1 (0) if there is a complete (partial) acquisition. The coefficient on the TRE dummy alone, -0.197, is significantly negative at the 5% level, suggesting that in partial acquisitions, an intact acquired fund underperforms its matching fund by 19.7 bps per month in the post-M&A 12 months. The coefficient on the interaction term between the TRE dummy and the complete acquisition dummy, 0.067, suggests that the underperformance of an intact acquired fund in complete acquisitions (relative to its matching fund) is lower than the underperformance of an intact acquired fund in partial acquisitions (relative to its matching fund) by 6.7 bps per month. However, this result is not significant.

To summarize, we find no evidence that complete acquisitions cause a more pronounced performance deterioration for the intact acquired funds than partial acquisitions do.

Long-Run Performance

We further examine the long-run performance of the intact acquired funds. Figure 2.1 depicts the cumulative average OAR of the intact acquired funds over their matching funds in the post-M&A 36 months. A notable observation is that the performance deterioration of the intact acquired funds lasts for up to 20 months after family M&As. After that, the performance of these funds begins to stabilize.

[Insert Figure 2.1 here.]

Discussions

Our findings on the performance deterioration of the intact acquired funds are consistent with the case in which the effect of reorganization (cost of family M&As) dominates (see our discussion in Section 3.1). Particularly, the post-M&A reorganization is detrimental to the operation of these funds because it causes rebalancing of portfolios, interruption of existing investment philosophy and practices, etc.

Our finding on the long run performance of these funds also helps us rule out two alternative explanations. The first is the "favoritism" explanation. According to this explanation, fund families often engage in a building-a-"star" strategy by transferring fund performance through, for example, allocation of profitable IPOs (Nanda et al., 2004; and Gaspar et al., 2006). If the intact acquired funds that used to be favored by the old families are no longer favored by the new families, then there will be a decrease in the performance of these funds. The second is the "pure luck" explanation. According to this explanation, the good pre-M&A performance of the intact acquired funds is due to pure luck. After family M&As, they run out of luck and, therefore, have a decrease in performance. Both explanations imply a permanent performance deterioration for the intact acquired funds. We find, however, that the performance deterioration is temporary (for up to 20 months).

2.3.3 Intact Incumbent Funds

Table 2.6 uses a regression analysis to compare the performance of the intact incumbent funds and the performance of their matching funds in the first 12 months after family M&As. We use the OAR per month as the dependent variable, and include in the regression all the monthly observations for the intact incumbent funds (indicated by TRE=1) and their matching funds (indicated by TRE=0) in the post-M&A 12 months.

[Insert Table 2.6 here.]

Column 1 of Table 2.6 shows that the coefficient on the TRE dummy, -0.028, is significantly negative at the 5% level, suggesting that an intact incumbent fund underperforms its matching fund by 2.8 bps per month in the post-M&A 12 months. Column 2 controls for other fund characteristics that can be related with fund performance. The coefficient on the TRE dummy, -0.036, remains significantly negative at the 5% level. The larger magnitude (-0.036 vs. -0.028) suggests further underperformance.

In what follows, we analyze the performance deterioration of the intact incumbent funds in detail.

Equity Funds vs. Non-Equity Funds

Column 3 of Table 2.6 tests whether equity funds have a more pronounced performance deterioration than non-equity funds do. The coefficient on the TRE dummy, -0.032, suggests that a non-equity fund underperforms its matching fund by 3.2 bps per month in the post-M&A 12 months. This result is economically significant, though not statistically significant. The coefficient on the interaction term between the TRE dummy and the equity fund dummy, -0.005, suggests that the underperformance of an equity fund (relative to its matching fund) is higher than the underperformance of a non-equity fund (relative to its matching fund) by 0.5 bps per month. However, this result is not significant.

To summarize, we find no evidence that equity funds have a more pronounced performance deterioration than non-equity funds do.

Complete Acquisitions vs. Partial Acquisitions

Column 4 of Table 2.6 tests whether complete acquisitions cause a more pronounced performance deterioration for the intact incumbent funds than partial acquisitions do. The coefficient on the TRE dummy alone, 0.001, is not significant, suggesting that in partial acquisitions, an intact incumbent fund does not significantly underperform its matching fund in the post-M&A 12 months. The coefficient on the interaction term between the TRE dummy and the complete acquisition dummy, -0.056, suggests that the underperformance of an intact incumbent fund in complete acquisitions (relative to its matching fund) is higher than the underperformance, if any, of an intact incumbent fund in partial acquisitions (relative to its matching fund) by 5.6 bps per month. This result is significant at the 10% level.

To summarize, we find evidence that complete acquisitions cause a more pronounced performance deterioration for the intact incumbent funds than partial acquisitions do.

Long-Run Performance

We further examine the long-run performance of the intact incumbent funds. Figure 2.1 depicts the cumulative average OAR of the intact incumbent funds over their matching funds in the post-M&A 36 months.

We have two observations. First, the performance deterioration of the intact incumbent funds lasts for up to 12 months after family M&As. After that, the performance of these funds begins to stabilize. Second, the performance deterioration of these funds has a smaller scale and lasts for a shorter period than that of the intact acquired funds does. This is not surprising because these funds have a larger number and size than the intact acquired funds do.

Discussions

Our findings on the performance deterioration of the intact incumbent funds are also consistent with the case in which the effect of reorganization (cost of family M&As) dominates (see our discussion in Section 3.1). Particularly, the post-M&A reorganization diverts the focus of the family management from the incumbent funds, leading to the underperformance of these funds. This diversion of focus goes to a greater extent in complete acquisitions. Schoar (2002) points out a similar "new (old) toy" effect using plant-level data of manufacturing firms in the context of corporate M&As.

2.3.4 Merging Incumbent Funds

Table 2.7 uses a regression analysis to compare the performance of the merging incumbent funds and the performance of their matching funds in the first 12 months after family M&As. We use the OAR per month as the dependent variable, and include in the regression all the monthly observations for the merging incumbent funds (indicated by TRE=1) and their matching funds (indicated by TRE=0) in the post-M&A 12 months.

[Insert Table 2.7 here.]

Column 1 (2) shows that the coefficient on the TRE dummy before (after) controlling for other fund characteristics, 0.026 (0.036), is not significant. These results suggest that family M&As cause no change in the performance of the merging incumbent funds in the post-M&A 12 months.

We further examine long-run performance of the merging incumbent funds (not reported to save space), and find similar results.

Our result that the merging incumbent funds have no significant performance change is in contrast with existing research on mergers at the fund level (e.g., Jayaraman et al., 2002; Zhao, 2005; and Khorana et al., 2007), which shows that on average the merging funds have a performance deterioration. This difference is due to the matching fund approach we use to analyze fund performance. The matching fund approach accounts for the potential selection bias due to family M&As and the following fund mergers. Previous studies don't take into consideration this potential selection bias. They use an approach which effectively compares the pre- and post-merger performance of the merging funds. We also used their approach to analyze fund performance, and found a similar result as theirs.

2.3.5 Funds Remaining in the Target Families

Table 2.8 uses a regression analysis to compare the performance of the funds remaining in the target families and the performance of their matching funds in the first 12 months after family M&As. We use the OAR per month as the dependent variable, and include in the regression all the monthly observations for the funds remaining in the target families (indicated by TRE=1) and their matching funds (indicated by TRE=0) in the post-M&A 12 months.

[Insert Table 2.8 here.]

Column 1 (2) shows that the coefficient on the TRE dummy before (after) controlling for other fund characteristics, -0.004 (-0.000), is not significant. These results suggest that family M&As cause no change in the performance of the funds remaining in the target families in the post-M&A 12 months.

We further examine long-run performance of the funds remaining in the target families (not reported to save space), and find similar results.

2.4 Other Impacts of Family M&As

In this section, we examine other impacts of family M&As by looking at fund expenses, turnover, and flow.

2.4.1 Expenses

We examine the impact of family M&As on fund expenses using a similar "matching" fund approach as in Section 3.3. Specifically, for a fund involved in a family M&A, we identify a matching fund from those not caught in any family M&A. We require that the matching fund have the same investment objective, the same decile information on pre-M&A fund TNA, and the closest pre-M&A expense ratio as the treatment fund does. We use a regression analysis to compare the expense ratio of the treatment fund and the expense ratio of the matching fund during the post-M&A period.

[Insert Table 2.9 here.]

Table 2.9 reports the regression results for different types of involved funds (indicated by TRE=1) and their matching funds (indicated by TRE=0) using the monthly expense ratio in the 12-month post-M&A period as the dependent variable. We use the panel regression that includes style fixed effects and time fixed effects. The standard errors are clustered at the fund level. We find no evidence that family M&As decrease fund expenses. We even find evidence that the expense ratio of the intact incumbent funds increases after family M&As (Columns 3 to 4).

The increase in fund expenses can be due to the post-M&A reorganization, which incurs extra expenses such as legal, accounting, combining offices, relocating fund managers, etc. The acquiring families seemingly choose to pass the expenses to fund investors.

2.4.2 Turnover

Existing research shows that mutual funds in large fund families are less likely to suffer from extreme liquidity events. For example, Bhattacharya et al. (2013) show that a large fund family can inject new money into a member fund facing a large amount of redemption through affiliated funds of mutual funds. This effectively bails out the fund from the potential asset "fire sales" (Coval and Stafford, 2007).

As family M&As increase the fund family size, do they actually enhance fund liquidity? We test this question using a similar "matching" fund approach as above. We focus on fund turnover ratio, a lower level of which indicates that the fund does not need to sell often to meet the liquidity demand. Specifically, for a fund involved in a family M&A, we identify a matching fund from those not caught in any family M&A. We require that the matching fund have the same investment objective, the same decile information on pre-M&A fund TNA, and the closest pre-M&A turnover ratio as the treatment fund does. We use a regression analysis to compare the turnover ratio of the treatment fund and the turnover ratio of the matching funds during the post-M&A period.

[Insert Table 2.10 here.]

Table 2.10 reports the regression results for different types of involved funds (indicated by TRE=1) and their matching funds (indicated by TRE=0) using the monthly turnover ratio in the post-M&A 12 months as the dependent variable. We use the panel regression that includes style fixed effects and time fixed effects. The standard errors are clustered at the fund level. We find no evidence that family M&As decrease fund turnover ratio. We even find evidence that the turnover ratio of the intact incumbent funds increases after family M&As (Columns 3 to 4).

We interpret our findings on fund turnover as evidence that family M&As do not enhance fund liquidity. It is also possible that our test cannot pick out the enhancement of fund liquidity because extreme liquidity shocks, such as a large amount of redemption, do not happen often during the post-M&A 12 months for both a treatment fund and its matching fund.

2.4.3 Fund Flow

We test fund investors' response to family M&As using the objective-adjusted flow (OAF), which equals the fund flow minus the value-weighted average flow on a portfolio comprising all other funds with the same investment objective.

Figure 2.2 depicts the cumulative average objective-adjusted flow (OAF) for each type of funds in the acquiring families in the post-M&A 36 months. It also depicts the cumulative average OAF for the acquiring families. The family OAF is computed as the value-weighted average of fund OAF.

[Insert Figure 2.2 here.]

The intact acquired funds observe a positive cumulative average OAF, suggesting that these funds have extra inflows of new money relative to peer funds. This is not surprising because fund families usually allow fund investors to switch among member funds in the same family without paying an additional load. As an acquiring family brings in newly acquired funds, existing fund investors of the family can switch their investment from the incumbent funds to the newly acquired funds.

Both the intact incumbent funds and the merging incumbent funds observe a negative cumulative average OAF, suggesting that these funds have extra outflows of money relative to peer funds. A plausible explanation for this is that as above-mentioned, existing fund investors of the acquiring families can switch their investment from the incumbent funds to the newly acquired funds. The intact incumbent funds may also have outflows of money because of the deterioration of their post-M&A performance.

The net cumulative average OAF of the acquiring families tends to be negative, suggesting that on average, the acquiring families even lose clients to rivals.

2.5 The Determinants of Family M&As

We test the determinants of family M&As using a multinomial logistic regression. Table 2.11 reports the regression results. The dependent variable takes one of three possible outcomes for a fund family in a calendar year: (1) be an acquiring family, (2) be a target family, or (3) no family M&A activity (the reference category). For example, if the fund family starts to acquire in 2005, that is, the family M&A window starts in 2005, then the fund family has the first outcome in 2005. Here we don't distinguish between complete and partial acquisitions because it is not clear what new insights this can add. All the explanatory variables are lagged by one year, except for those indicated by "lagged," which are lagged by an additional year. We compute the family-level variables using the value-weighted average of fund-level variables. We also control for time fixed effects.

[Insert Table 2.11 here.]

Column 1 reports the coefficients for the first outcome (be an acquiring family). The coefficients on ln(family TNA) and the number of fund investment objectives, 0.358 and 0.088, are significantly positive at the 1% level, suggesting that large and complex fund families are likely to acquire. Column 2 reports the coefficients for the second outcome (be a target family). The coefficient on the number of fund investment objectives, 0.087, is significantly positive at the 1% level, suggesting that complex fund families are likely to be a target. The coefficient on the past 1-year OAF, -1.013, is significantly negative at the 1% level, suggesting that fund families experiencing losses of market shares to rivals are likely to be a target.

To summarize, our findings on the determinants of family M&As are consistent with Jensen's (1986) free cash flow hypothesis, according to which management of fund families have personal incentives, such as building an "empire," diversifying human capital, etc., to acquire. Large and complex fund families are likely to acquire because they usually have more resources to spend. Our findings also suggest that the competition condition is an important determinant of family M&As.

2.6 Conclusions

In this article, we study the organizational behavior of mutual fund families. The motivation of our study is based on Chen et al. (2004) and Pollet and Wilson (2008), who show that on average, mutual funds in large fund families outperform those in small fund families. Fund family size can grow not only "organically" through sponsored funds producing good fund performance and attracting inflows of new money, but also dramatically and more effectively through family M&As. We ask the question whether any method that increases fund family size improves mutual fund performance. We focus on family M&As.

We find that despite increasing fund family size, family M&As have a negative impact on fund performance. Specifically, in family M&As, the acquiring families keep most of the acquired funds intact, and merge the rest with a few incumbent funds. After family M&As, the intact acquired funds have a performance deterioration for up to 20 months. The intact incumbent funds have a performance deterioration, which is particularly pronounced in complete acquisitions, for up to 12 months. We also rule out several alternative explanations for the performance change. Finally, we show that consistent with agency theory, family M&As are likely to be motivated by fund family management's own incentives.

We conclude that the method that increases fund family size matters. Fund families should seek "organic" growth, not family M&As.

References

[1] Berk, J., and R. Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269-1295.

[2] Bhattacharya, U., J. H. Lee, and V. K. Pool, 2012, Conflicting family values in mutual fund families, *Journal of Finance*, forthcoming.

[3] Bhojraj, S., Y. J. Cho, and N. Yehuda, 2012, Mutual fund family size and mutual fund performance: The role of regulatory changes, *Journal of Accounting Research* 50, 647-684.

[4] Brown, K., and V.W. Harlow, and L. Starks, 1996, Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry, *Journal of Finance* 51, 85-110.

[5] Carhart, M. M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

[6] Chen, J., H. Hong, M. Huang, and J. D. Kubik, 2004, Does fund size erode mutual fund performance? The role of liquidity and organization, *American Economic Review* 90, 1276-1302.

[7] Chen, J., H. Hong, W. Jiang, and J. D. Kubik, 2013, Outsourcing mutual fund

management: Firm boundaries, incentives, and performance, *Journal of Finance* 68, 523-558.

[8] Chevalier, J., and G. Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167-1200.

[9] Chevalier, J., and G. Ellison, 1999, Career concerns of mutual fund managers, *Quarterly Journal of Economics* 114, 389-432.

[10] Coval, J., and E. Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479-512.

[11] Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035-1058.

[12] Gaspar, J., M. Massa, and P. Matos, 2006, Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization, *Journal of Finance* 61, 73-104.

[13] Gruber, M. J., 1996, Another puzzle: The growth in actively managed mutual funds, *Journal of Finance* 51, 783-810.

[14] IvKovic, Z., 2002, Spillovers in mutual fund families: Is blood thicker than water? Working Paper.

[15] Jayaraman, N., A. Khorana, and E. Nelling, 2002, An analysis of the determinants and shareholder wealth effects of mutual fund mergers, *Journal of Finance* 57, 1521-1551.

[16] Jensen, M. C., 1986, Agency costs of free cash flow, corporate finance and takeovers, *American Economic Review* 76, 323-329.

[17] Khorana, A., 1996, Top management turnover: An empirical investigation of mutual fund managers, *Journal of Financial Economics* 40, 403-427.

[18] Khorana, A., P. Tufano, and L. Wedge, 2007, Board structure, mergers, and shareholder wealth: A study of the mutual fund industry, *Journal of Financial Economics* 85, 571-598.

[19] Malkiel, B. G., 1995, Returns from investing in equity mutual funds 1971-1991, *Journal of Finance* 50, 549-572.

[20] Maksimovic, V., and G. Phillips, 2001, The market for corporate assets: Who engages in mergers and asset sales and are there gains? *Journal of Finance* 56, 2019-2065.

[21] Maksimovic, V., G. Phillips, and N. R. Prabhala, 2011, Post-merger restructuring and the boundaries of the firm, *Journal of Financial Economics* 102, 317-343.

[22] Massa, M., 2003, How do family strategies affect fund performance? when performance-maximization is not the only game in town, *Journal of Financial Economics* 67, 249-304.

[23] Nanda, V., Z. J. Wang, and L. Zheng, 2004, Family values and the star phenomenon: Strategies of mutual fund families, *Review of Financial Studies* 17, 667-698.

[24] Pollet, J. M., and M. Wilson, 2008, How does size affect mutual fund behavior? *Journal of Finance* 63, 2941-2969.

[25] Schoar, A., 2002, Effects of corporate diversification on productivity, *Journal of Finance* 57, 2379-2403.

[26] Zhao, X., 2005, Exit decisions in the U.S. mutual fund industry, *Journal of Business* 78, 1365-1401.

[27] Zheng, L., 1999, Is money smart? A study of mutual fund investors' fund selection ability, *Journal of Finance* 54, 901-933.

Table 2.1: Distribution of Family M&As by Year

This table reports the distribution of family M&As by year for the period of 2001 to 2010. Panel A (Panel B) reports for complete (partial) acquisitions. We also report the numbers of the acquired funds that remain intact or are merged into the acquiring families' incumbent funds (the merged funds), and the acquiring families' incumbent funds that remain intact or are used to merge the acquired funds (the merging funds), and the funds remaining in the target families in the case of partial acquisitions.

Panel A: Complete Acquisitions

	#Family	Acquired Funds			Incumbent Funds		
	M&As	Intact	Merged	Total	Intact	Merging	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2001	24	69	11	80	342	10	352
2002	31	65	28	93	524	26	550
2003	7	5	6	11	142	5	147
2004	17	37	26	63	333	25	358
2005	20	65	29	94	337	17	354
2006	25	90	19	109	588	19	607
2007	7	1	19	20	167	15	182
2008	11	37	5	42	252	5	257
2009	10	24	6	30	189	6	195
2010	10	74	10	84	169	7	176
Sum	162	467	159	626	3043	135	3178
Distinct funds		458	159	617	1545	119	1664

Panel B: Partial Acquisitions

	#Family	Acquired Funds			Incumbent Funds			Funds Remaining
	M&As	Intact	Merged	Total	Intact	Merging	Total	in Target Families
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2001	12	9	15	24	175	14	189	155
2002	15	22	5	27	216	4	220	243
2003	9	10	10	20	145	9	154	32
2004	10	10	4	14	219	3	222	166
2005	14	9	13	22	342	11	353	263
2006	5	2	3	5	68	1	69	64
2007	4	1	19	20	64	15	79	85
2008	5	3	2	5	109	2	111	68
2009	9	7	13	20	109	10	119	116
2010	6	26	0	26	80	0	80	76
Sum	89	99	84	183	1527	69	1596	1268
Distinct funds		96	84	180	1162	68	1230	967

Table 2.2: Distribution of Involved Funds by Category

This table reports the distribution of funds involved in family M&As by category for the period of 2001 to 2010. We report for the acquired funds that remain intact or are merged into the acquiring families' incumbent funds (the merged funds), and the acquiring families' incumbent funds that remain intact or are used to merge the acquired funds (the merging funds), and the funds remaining in the target families in the case of partial acquisitions.

	Acquired Funds			Incumbent Funds			Funds Remaining in Target Families
	Intact	Merged	Total	Intact	Merging	Total	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Domestic Equity	354	171	525	2608	137	2745	738
Foreign Equity	81	21	102	699	18	717	212
Fixed Income	39	12	51	352	9	361	104
Balanced	90	39[a]	129	892	40[b]	932	209
Mortgage Backed	2	0	2	19	0	19	5
Sum	566	243	809	4570	204	4774	1268
Distinct	545	243	788	1999	182	2181	967

[a,b]There are several cases in which the acquiring families use an incumbent balanced fund to merge an acquired fund of other category. Therefore, in the balanced fund category, there are more merging incumbent funds than merged acquired funds.

Table 2.3: Pre-M&A Performance (OAR) of Involved Funds

This table reports the mean objective-adjusted return (OAR) per month of involved funds in the pre-M&A 12 months for the period of 2001 to 2010. We report for the acquired funds that remain intact or are merged into the acquiring families' incumbent funds (the merged funds), and the acquiring families' incumbent funds that remain intact or are used to merge the acquired funds (the merging funds), and the funds remaining in the target families in the case of partial acquisitions. The t-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1% .

OAR per month (%) in the pre-M&A 12 months

	Acquired Funds		Incumbent Funds		Funds Remaining
	Intact	Merged	Intact	Merging	in Target Families
	(1)	(2)	(3)	(4)	(5)
Domestic Equity	0.086*	-0.378***	-0.010	0.015	0.074*
	(1.91)	(-6.93)	(-0.55)	(0.28)	(1.87)
Foreign Equity	-0.103	-0.518***	-0.045	-0.149	-0.168**
	(-1.11)	(-3.49)	(-1.08)	(-0.68)	(-2.27)
Fixed Income	-0.001	0.105	0.042	-0.010	-0.003
	(-0.01)	(0.51)	(1.43)	(-0.03)	(-0.05)
Balanced	0.122	-0.254**	-0.058**	0.013	0.114
	(1.39)	(-2.17)	(-2.28)	(0.18)	(1.64)
Mortgage Backed	-0.010	.	-0.327	.	-0.131
	(-0.01)	.	(-1.32)	.	(-0.57)

Table 2.4: Pre-M&A TNA of Involved Funds

This table reports the mean TNA of involved funds immediately prior to the family M&A window for the period of 2001 to 2010. We report for the acquired funds that remain intact or are merged into the acquiring families' incumbent funds (the merged funds), and the acquiring families' incumbent funds that remain intact or are used to merge the acquired funds (the merging funds), and the funds remaining in the target families in the case of partial acquisitions.

Pre-M&A TNA ($million)

	Acquired Funds		Incumbent Funds		Funds Remaining in Target Families
	Intact	Merged	Intact	Merging	
	(1)	(2)	(3)	(4)	(5)
Domestic Equity	433.646	150.570	930.841	1334.311	609.997
Foreign Equity	292.595	62.386	712.717	900.889	370.063
Fixed Income	390.008	171.092	1230.139	601.456	2993.479
Balanced	1268.124	194.467	1449.925	2155.318	987.007
Mortgage Backed	19.250	.	539.953	.	781.620

Table 2.5: The Impact of Family M&As on the Performance of the Intact Acquired Funds

This table reports the regression results of the post-M&A objective-adjusted return (OAR) on a TRE dummy and other fund characteristics for the period of 2001 to 2010. We include in the regression all the monthly observations for the intact acquired funds (indicated by TRE=1) and their matching funds based on investment objective, pre-M&A OAR and TNA (indicated by TRE=0) in the first 12 months after family M&As. An intact acquired fund and its matching fund have the manager turnover dummy, 1 (0), if the intact acquired fund has (does't have) a change in the composition of fund managers during the family M&A window; the equity fund dummy, 1 (0), if the intact acquired fund is (isn't) an equity fund; and the complete acquisition dummy, 1 (0), if there is a complete (partial) acquisition. All the other explanatory variables are lagged by one month, except for expense and turnover ratios, which are contemporaneous. We use the panel regression that includes time fixed effects and style fixed effects. We cluster standard errors at the fund level. The t-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

Table 2.5 (Continued)

Dependent Variable: OAR per month (%) in the first 12 months after family M&As

	(1)	(2)	(3)	(4)	(5)
TRE	-0.105***	-0.140***	-0.152**	-0.160*	-0.197**
	(-3.05)	(-3.49)	(-2.56)	(-1.83)	(-2.32)
TRE× Manager Turnover			0.068		
			(0.57)		
TRE× Equity Fund				0.025	
				(0.26)	
TRE× Complete Acquisition					0.067
					(0.74)
Manager Turnover			-0.097		
			(-1.07)		
Equity Fund				1.079***	
				(7.60)	
Complete Acquisition					-0.027
					(-0.41)
ln(TNA)		-0.012	-0.023	-0.012	-0.013
		(-0.71)	(-0.95)	(-0.71)	(-0.74)
ln(Fund Age)		0.090**	0.099*	0.090**	0.091**
		(2.02)	(1.85)	(2.02)	(2.03)
Expense Ratio (%)		0.035	0.077	0.034	0.035
		(0.70)	(1.17)	(0.68)	(0.69)
Turnover Ratio		0.015	0.025	0.015	0.014
		(0.47)	(0.60)	(0.49)	(0.44)
Fund Flow		0.519**	0.640*	0.518**	0.522**
		(2.29)	(1.91)	(2.29)	(2.29)
Fund Raw Return		0.024**	0.023	0.024**	0.024**
		(2.05)	(1.43)	(2.05)	(2.05)
ln(Family TNA)		0.008	0.008	0.008	0.009
		(0.69)	(0.48)	(0.68)	(0.72)
Time Fixed Effects	YES	YES	YES	YES	YES
Style Fixed Effects	YES	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES	YES
No. of Fund-Month Obs.	11,520	9,160	5,862	9,160	9,160

Table 2.6: The Impact of Family M&As on the Performance of the Intact Incumbent Funds

This table reports the regression results of the post-M&A objective-adjusted return (OAR) on a TRE dummy and other fund characteristics for the period of 2001 to 2010. We include in the regression all the monthly observations for the intact incumbent funds (indicated by TRE=1) and their matching funds based on investment objective, pre-M&A OAR and TNA (indicated by TRE=0) in the first 12 months after family M&As. An intact incumbent fund and its matching fund have the equity fund dummy, 1 (0), if the intact incumbent fund is (isn't) an equity fund; and the complete acquisition dummy, 1 (0), if there is a complete (partial) acquisition. All the other explanatory variables are lagged by one month, except for expense and turnover ratios, which are contemporaneous. We use the panel regression that includes time fixed effects and style fixed effects. We cluster standard errors at the fund level. The *t*-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

Dependent Variable: OAR per month (%) in the first 12 months after family M&As

	(1)	(2)	(3)	(4)
TRE	-0.028**	-0.036**	-0.032	0.001
	(-2.17)	(-2.42)	(-0.72)	(0.03)
TRE× Equity Fund			-0.005	
			(-0.11)	
TRE× Complete Acquisition				-0.056*
				(-1.89)
Equity Fund			-0.505	
			(-0.86)	
Complete Acquisition				0.039*
				(1.88)
ln(TNA)		-0.026***	-0.026***	-0.026***
		(-4.26)	(-4.26)	(-4.21)
ln(Fund Age)		0.053***	0.053***	0.053***
		(3.64)	(3.64)	(3.63)
Expense Ratio (%)		0.005	0.005	0.006
		(0.31)	(0.30)	(0.36)
Turnover Ratio		-0.029***	-0.028***	-0.029***
		(-2.68)	(-2.68)	(-2.71)
Fund Flow		0.450***	0.450***	0.449***
		(3.49)	(3.49)	(3.48)
Fund Raw Return		0.041***	0.041***	0.040***
		(8.64)	(8.64)	(8.62)
ln(Family TNA)		0.012**	0.012**	0.012**
		(2.56)	(2.56)	(2.52)
Time Fixed Effects	YES	YES	YES	YES
Style Fixed Effects	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES
No. of Fund-Month Obs.	86,135	65,500	65,500	65,500

Table 2.7: The Impact of Family M&As on the Performance of the Merging Incumbent Funds

This table reports the regression results of the post-M&A objective-adjusted return (OAR) on a TRE dummy and other fund characteristics for the period of 2001 to 2010. We include in the regression all the monthly observations for the merging incumbent funds (indicated by TRE=1) and their matching funds based on investment objective, pre-M&A OAR and TNA (indicated by TRE=0) in the first 12 months after family-M&As. All the other explanatory variables are lagged by one month, except for expense and turnover ratios, which are contemporaneous. We use the panel regression that includes time fixed effects and style fixed effects. We cluster standard errors at the fund level. The t-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

Dependent Variable: OAR per month (%) in the first 12 months after family M&As		
	(1)	(2)
TRE	0.026	0.036
	(0.56)	(0.70)
ln(TNA)		-0.014
		(-0.55)
ln(Fund Age)		0.085
		(1.61)
Expense Ratio (%)		-0.001
		(-0.02)
Turnover Ratio		-0.065
		(-1.57)
Fund Flow		-0.054
		(-0.14)
Fund Raw Return		0.006
		(0.41)
ln(Family TNA)		0.009
		(0.46)
Time Fixed Effects	YES	YES
Style Fixed Effects	YES	YES
Cluster SE	YES	YES
No. of Fund-Month Obs.	4,572	3,781

Table 2.8: The Impact of Family M&As on the Performance of the Funds Remaining in the Target Families

This table reports the regression results of the post-M&A objective-adjusted return (OAR) on a TRE dummy and other fund characteristics for the period of 2001 to 2010. We include in the regression all the monthly observations for the funds remaining in the target families (indicated by TRE=1) and their matching funds based on investment objective, pre-M&A OAR and TNA (indicated by TRE=0) in the first 12 months after family-M&As. All the other explanatory variables are lagged by one month, except for expense and turnover ratios, which are contemporaneous. We use the panel regression that includes time fixed effects and style fixed effects. We cluster standard errors at the fund level. The t-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

Dependent Variable: OAR per month (%) in the first 12 months after family M&As		
	(1)	(2)
TRE	-0.004	-0.000
	(-0.15)	(-0.02)
ln(TNA)		-0.012
		(-1.09)
ln(Fund Age)		0.022
		(0.76)
Expense Ratio (%)		-0.002
		(-0.06)
Turnover Ratio		0.016
		(0.65)
Fund Flow		0.518**
		(2.44)
Fund Raw Return		0.040***
		(4.88)
ln(Family TNA)		-0.000
		(-0.03)
Time Fixed Effects	YES	YES
Style Fixed Effects	YES	YES
Cluster SE	YES	YES
No. of Fund-Month Obs.	23,312	18,332

Table 2.9: The Impact of Family M&As on Fund Expenses

This table reports the regression results of the post-M&A expense ratio on a TRE dummy and other fund characteristics for the period of 2001 to 2010. We include in the regression all the monthly observations for each type of involved funds (indicated by TRE=1) and their matching funds based on investment objective, pre-M&A TNA and expense ratio (indicated by TRE=0) in the first 12 months after family-M&As. All the other explanatory variables are lagged by one month. We use the panel regression that includes time fixed effects and style fixed effects. We cluster standard errors at the fund level. The *t*-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

Dependent Variable: expense ratio (%) in the first 12 months after family M&As

	Intact Acquired Funds		Intact Incumbent Funds		Merging Incumbent Funds		Funds Remaining in Target Families	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TRE	0.041	0.026	0.059***	0.060***	0.033	0.019	0.014	0.022
	(1.54)	(0.83)	(5.75)	(5.31)	(0.80)	(0.44)	(0.78)	(1.06)
ln(TNA)		-0.035***		-0.052***		-0.059***		-0.037***
		(-2.83)		(-11.39)		(-2.93)		(-4.44)
ln(Fund Age)		0.044		0.036***		0.074*		0.034
		(1.51)		(3.21)		(1.96)		(1.62)
Fund Flow		-0.253**		-0.230***		-0.163		-0.098
		(-2.42)		(-4.98)		(-1.57)		(-1.31)
Fund Raw Return		0.004		0.002**		-0.001		0.002
		(1.57)		(2.54)		(-0.38)		(1.43)
ln(Family TNA)		-0.013		-0.026***		-0.028*		-0.011*
		(-1.46)		(-7.74)		(-1.94)		(-1.87)
Time Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Style Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES	YES	YES
No. of Fund-Month Obs.	10,532	8,579	78,297	60,198	4,174	3,425	21,036	16,534

Table 2.10: The Impact of Family M&As on Fund Turnover

This table reports the regression results of the post-M&A turnover ratio on a TRE dummy and other fund characteristics for the period of 2001 to 2010. We include in the regression all the monthly observations for each type of involved funds (indicated by TRE=1) and their matching funds based on investment objective, pre-M&A TNA and turnover ratio (indicated by TRE=0) in the first 12 months after family-M&As. All the other explanatory variables are lagged by one month. We use the panel regression that includes time fixed effects and style fixed effects. We cluster standard errors at the fund level. The t-statistics are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

Dependent Variable: turnover ratio in the first 12 months after family M&As

	Intact Acquired Funds		Intact Incumbent Funds		Merging Incumbent Funds		Funds Remaining in Target Families	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TRE	0.020	-0.003	0.106***	0.065***	0.094	0.035	0.077**	0.028
	(0.40)	(-0.06)	(5.52)	(3.03)	(1.15)	(0.45)	(2.34)	(0.81)
ln(TNA)		-0.017		-0.103***		-0.112***		-0.060***
		(-0.97)		(-12.67)		(-2.95)		(-5.40)
ln(Fund Age)		-0.028		-0.026		-0.079		-0.086**
		(-0.45)		(-1.25)		(-0.96)		(-2.41)
Fund Flow		0.087		-0.219**		-0.893***		-0.184
		(0.45)		(-2.21)		(-2.70)		(-1.33)
Fund Raw Return		0.001		-0.006***		-0.012*		-0.000
		(0.31)		(-3.23)		(-1.67)		(-0.02)
ln(Family TNA)		0.008		0.021***		0.026		0.020*
		(0.56)		(3.16)		(0.93)		(1.95)
Time Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Style Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES	YES	YES
No. of Fund-Month Obs.	10,212	8,233	77,947	60,669	4,331	3,524	20,750	16,310

Table 2.11: Multinomial Logistic Regression Evidence: Determinants of Family M&As

This table reports the results of a multinomial logistic regression for the period of 2001 to 2010. The dependent variable takes one of three possible outcomes for a fund family in a calendar year: (1) be an acquiring family, (2) be a target family, or (3) no M&A activity (the reference case). All the explanatory variables are lagged by one year, except for those indicated by "lagged", which are lagged by an additional year. We compute the family-level variables using the value-weighted average of fund-level variables. We also control for time fixed effects. The p-values are given in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%.

	Be an Acquirer (1)	Be a Target (2)
ln(Family TNA)	0.358***	0.012
	(0.00)	(0.80)
No. of Investment Objectives	0.088***	0.087***
	(0.00)	(0.00)
1-Year OAR	-0.003	-0.008
	(0.76)	(0.31)
1-Year OAR, Lagged	0.007	-0.002
	(0.27)	(0.68)
1-Year OAF	-0.030	-1.013***
	(0.92)	(0.00)
1-Year OAF, Lagged	-0.101	0.019
	(0.24)	(0.72)
Expense Ratio (%)	0.347*	-0.018
	(0.09)	(0.91)
Turnover Ratio	0.002	-0.004
	(0.98)	(0.95)
Time Fixed Effects	YES	
No. of Family-Year Obs.	5,188	

Figure 2.1: Long-Run Post-M&A Performance of the Intact Acquired (Incumbent) Funds

This figure depicts the cumulative average objective-adjusted return (OAR) of the intact acquired (incumbent) funds over their matching funds in the post-M&A 36 months.

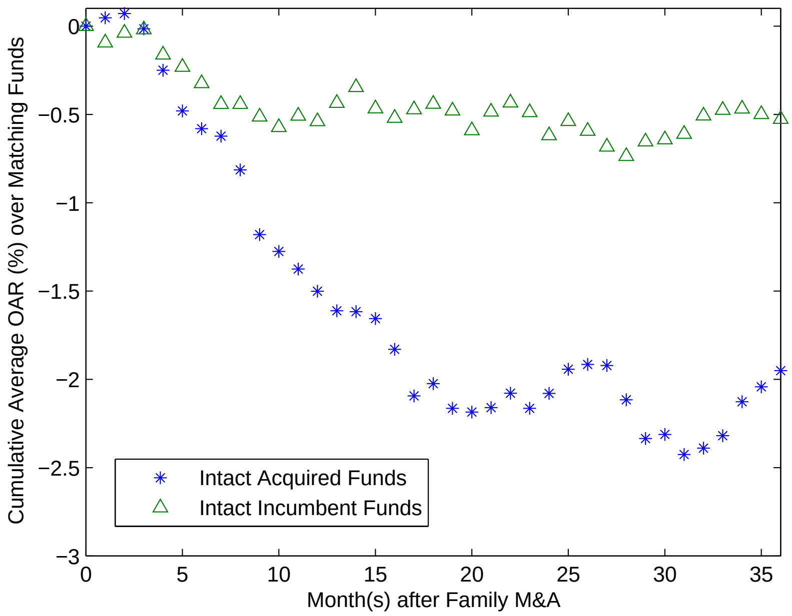
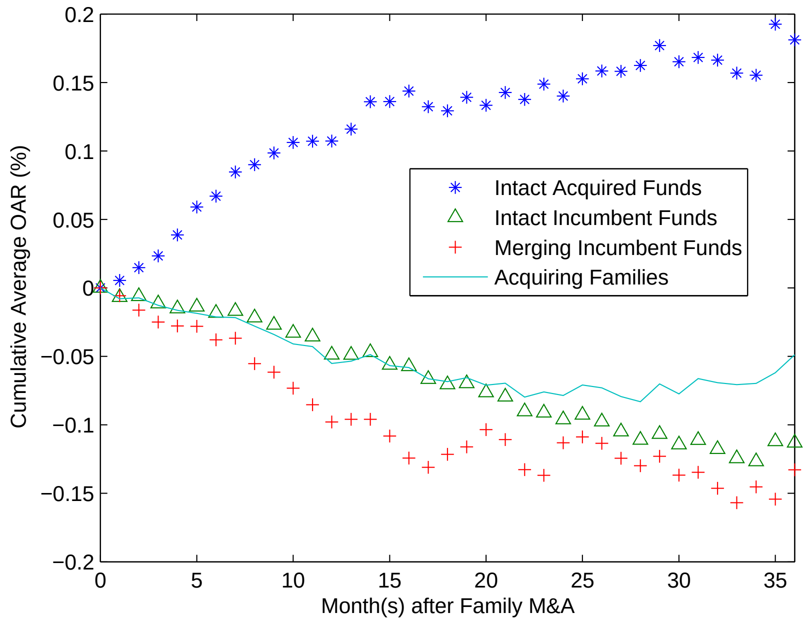


Figure 2.2: Post-M&A Flows of the Funds in the Acquiring Families

This figure depicts the cumulative average objective-adjusted flow (OAF) for each type of funds in the acquiring families in the post-M&A 36 months. It also depicts the acquiring families' cumulative average OAF. Family OAF is computed as the value-weighted average of fund OAF.



Chapter 3

Team, Incentives, and Performance

Abstract

Using equity mutual fund data, previous studies show that team-managed funds underperform solo-managed funds, suggesting that a team is a poor incentive mechanism. In this article, we take a deeper look into the composition of mutual fund management teams. Our major finding is that not all team-managed funds underperform. Only those with poor accountability of fund managers for fund performance do. A plausible explanation for this is that poor accountability disincentivizes fund managers from acquiring information. Unlike previous studies, we conclude that a team *per se* does not represent a poor incentive mechanism. Accountability of team members is more relevant in providing incentives.

JEL Classification: G11; G23; L22

Keywords: Team; Incentive; Mutual fund; Fund performance; Accountability

3.1 Introduction

A team is an important organizational form used often in modern corporations. Examples of a team include the senior management of a firm, a board of directors, and various committees. There have been extensive theoretical studies on the incentive effect of teams (e.g., Alchian and Demsetz, 1972; Kandel and Lazear, 1992; Stein, 2002). However, empirical studies on this topic have been much fewer.[1]

Recently, researchers have used equity mutual fund data to test the incentive effect of a team. In an important article, Chen, Hong, Huang, and Kubik (henceforth CHHK, 2004) show that team-managed funds significantly underperform solo-managed funds, suggesting that a team represents a poor incentive mechanism. In this article, we take a deeper look into the composition of mutual fund management teams. We show that the underperformance of team-managed funds is concentrated in those with poor accountability of fund managers. A plausible explanation is that poor accountability disincentivizes fund managers from acquiring information. We conclude that a team *per se* does not represent a poor incentive mechanism. Accountability of team members is more relevant in providing incentives.

Suppose that an asset management company needs to organize the management of one of its sponsored funds. It can use either a team of fund managers or a solo manager to run the fund. We distinguish between two team approaches. In the first team approach, every fund manager works "part-time" for the fund in that every fund manager is also managing another fund at the same time. In the second team approach, at least one fund manager works "full-time" for the fund in that she is not managing another fund at the same time.

[1]See, for example, Leibowitz and Tollison (1980) and Gaynor and Gertler (1995) on law firms or medical group partnerships; Hansen (1997), Boning, Ichniowski, and Shaw (2001), and Hamilton, Nickerson, and Owan (2003) on manufacturing or service firms. Nalbantian and Schotter (1997) use experimental data.

We are particularly interested in the first team approach. An obvious advantage of this team approach is that it is cost efficient because the asset management company can easily assemble a task force from existing fund managers. The second team approach and the solo-manager approach typically require a new hire of a "full-time" or solo fund manager, which is relatively expensive and time consuming. The disadvantage of the first team approach is that it can cause an incentive problem. Intuitively, it is difficult for the asset management company to hold any fund manager accountable for fund performance and thereafter reward/punish her properly. Knowing this, she has few incentives to work hard. In contrast, the second team approach and the solo-manager approach cause less of an incentive problem. The asset management company can hold the "full-time" or solo fund manager accountable. Knowing this, she has incentives to work hard.

Throughout this article, we refer to the first team approach as the poor-accountability team approach. We refer to the second team approach as the good-accountability team approach.

Our intuition here is based on Holmström (1979). He points out that in an economic organization, poor observability of an agent's effort, which implies poor accountability, deteriorates the incentive provision and thereafter decreases performance. Grossman and Hart (1986) and Hart and Moore (1990) discuss property rights theory of the firm in a similar vein. In their framework, when an agent faces ambiguity about what her share of output should be, she has few incentives to make firm-specific investment.

Our empirical analysis is as follows. First, we use a Morningstar database, which provides precise fund manager information, to identify the fund management approach for individual open-end U.S. domestic equity mutual funds. Our sample period of January 1998 to December 2012 reveals that the poor-accountability team approach has been used increasingly often. In January 1998, for instance, 139 (or 15%) of our sample equity funds were managed using this team approach. In December 2012, this number (percentage) had increased to 885 (44%).[2] In fact, the increase in funds managed using this team approach accounts for most of the increase in team-managed funds.

A simple analysis suggests that funds managed using the poor-accountability team approach have a low expense ratio relative to funds managed using the good-accountability team approach and solo-managed funds. This finding suggests that asset management companies increasingly use the poor-accountability team approach because of its cost efficiency. Moreover, possibly due to the lower expense ratio, funds managed using this team approach are attractive to retirement savers. (As we will show, however, the lower expense ratio does not offset the underperformance.) This finding is consistent with the notion that retirement savers are unlikely to be business savvy.[3]

Second, we examine the performance of funds managed using the poor-accountability team approach, funds managed using the good-accountability team approach, and solo-managed funds. We use both portfolio analysis and regression analysis. Our major finding is that whereas funds managed using the poor-accountability team approach significantly underperform solo-managed funds, funds managed using the good-accountability team approach perform similarly to solo-managed funds. This result is robust (i) after we control for risk and style differences using various factor models, such as CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and the Pástor-Stambaugh (2003) five-factor model; and (ii) after we control for other fund characteristics, including fund total net assets (TNA), age, expense and turnover ratios, flow, and various

[2]For the whole universe of U.S. mutual funds, 436 (or 19%) of mutual funds were managed using the poor-accountability team approach in January 1998. This number (percentage) had increased to 2,343 (43%) in December 2012.

[3]For example, Benartzi and Thaler (2001), Madrian and Shea (2001), Agnew, Balduzzi, and Sunden (2003), Duflo and Saez (2003), Huberman and Jiang (2006), and Carroll, Choi, Laibson, Madrian, and Metrick (2009) show that retirement savers have a tendency to rebalance and trade infrequently and to follow default options. This inertia indicates that they are unlikely to be business savvy.

fixed effects.

Finally, we examine the causes of the underperformance of funds managed using the poor-accountability team approach. As we have discussed, a plausible explanation for the underperformance of these funds is that poor accountability disincentivizes fund managers from acquiring information. We design tests to rule out three alternative explanations. The first alternative explanation is that managers of these funds have severe a free rider problem, so that no one works hard, which leads to underperformance. We match a fund managed using the poor-accountability team approach and a fund managed using the good-accountability team approach by requiring that they have the same number of fund managers. The treatment fund still underperforms the matching fund, even though they have a free rider problem of the same scale. The second alternative explanation is that managers of these funds simply have poor quality. We match a fund managed using the poor-accountability team approach and a solo-managed fund by requiring that they have a fund manager in common. The treatment fund still underperforms the matching fund, even though they have the same manager quality. The third alternative explanation is that asset management companies deliberately use the poor-accountability team approach for funds that perform poorly for reasons unrelated to the management structure. However, we find a significant performance improvement (deterioration) after a fund switches from the poor-accountability team approach to the good-accountability team approach or the solo-manager approach (from the good-accountability team approach or the solo-manager approach to the poor-accountability team approach).

We also examine the investment behavior of funds managed using the poor-accountability team approach. Relative to funds managed using the good accountability team approach and solo-managed funds, these funds exhibit low levels of industry concentration (Kacperczyk, Sialm, and Zheng, 2005), local holdings (Coval and Moskowitz, 1999, 2001), and unsystematic risk; they also invest inactively (i.e., most fund performance is explained by factor returns; Amihud and Goyenko, 2013). All these findings are consistent with the notion that poor accountability disincentivizes fund managers from acquiring private information on industry and on local companies.

Our study belongs to the economic literature on industry organization. There have been extensive theoretical studies on the incentive effect of teams. For example, Alchian and Demsetz (1972) point out the free rider problem. Kandel and Lazear (1992) argue that the free rider problem may be mitigated by peer pressure. Stein (2002) suggests that a team may form a hierarchy, which prevents communication and the acquisition of soft information. Other related theories study the design of incentive schemes in teams. Holmström (1982) is a classical example.

Recently, empirical researchers have used equity mutual fund data to test the incentive effect of a team. In a closely related study, CHHK (2004) show that team-managed funds significantly underperform solo-managed funds, suggesting that a team is a poor incentive mechanism. Our study shows that not all team-managed funds underperform. Only those with poor accountability of fund managers underperform. We emphasize the importance of the composition of a team in providing incentives.

Other related studies using similar equity mutual fund data find weak or no evidence that team-managed funds underperform solo-managed funds. For example, Bär, Kempf, and Ruenzi (2005) find weak evidence of underperformance. Prather and Middleton (2002) and Bliss, Potter, and Schwarz (2008) find no evidence of underperformance. Patel and Sarkissian (2013) are an exception. They find that team-managed funds significantly outperform solo-managed funds. Dass, Nanda, and Wang (2013) study balanced funds. They show that team-managed funds exhibit better security selection performance, but worse market timing performance, than solo-managed funds. The overall returns across the two management structures are similar.

We organize the rest of this article as follows. Section 3.2 describes the data. Section 3.3 examines fund performance. Section 3.4 examines the causes of fund performance. Section 3.5 concludes.

3.2 Data

Our sample period is January 1998 to December 2012. We obtain mutual fund and fund manager data from the Morningstar Direct database. The Morningstar database includes all historical records of mutual funds and is free of survivorship bias. It also provides precise fund manager information. For example, it reports that the Vanguard Equity-Income fund was managed by George U. Sauter [2003-08-08 2005-09-23], Joel M. Dickson [2003-08-08 2005-09-23], James P. Stetler [2003-12-31 present], etc. We infer from this information whether a fund is managed by a team of fund managers or a solo fund manager. To avoid possible reporting errors in the Morningstar database, we eliminate the fund-months in which a team has more than 10 members and in which a team or a solo manager manages more than 10 funds.

In the case of team-managed funds, we identify the fund-months in which every member of the team works "part-time" for the fund in that every member of the team is also managing another fund at the same time. According to our earlier discussion, these observations have poor accountability of fund managers. The other fund-months have at least one fund manager who works "full-time" for the fund in that she is not managing another fund at the same time. These observations have good accountability of fund managers. Here we consider only the universe of mutual funds in the Morningstar database. We are not able to identify whether a mutual fund manager also manages a hedge fund or holds a senior position in the asset management company. In this case, the fund manager will be classified as a "full-time" manager, and the mutual fund will be classified as having good accountability. We consider this a limitation of our study, although it is unlikely to change our results.[4]

We focus our empirical analysis on open-end U.S. domestic equity mutual funds. Morningstar categorizes the investment styles of these funds as large-cap growth, large-cap blend, large-cap value, mid-cap growth, mid-cap blend, mid-cap value, small-cap growth, small-cap blend, or small-cap value. We exclude sector funds because these funds may invest in foreign countries. Some funds have multiple share classes. We aggregate the share classes to obtain fund-level information.

[Insert Figure 3.1 here.]

We end up with 2,245 distinct equity mutual funds and 269,284 fund-month observations. Figure 3.1 plots the numbers and percentages for funds managed using the poor-accountability team approach, funds managed using the good-accountability team approach, and solo-managed funds. A notable observation is that the poor-accountability team approach has been used increasingly often. In January 1998, for instance, 139 (or 15%) of our sample funds were managed using this team approach. In December 2012, this number (percentage) had increased to 885 (44%). Importantly, the increase in funds managed using this team approach accounts for most of increase in team-managed funds. If we exclude these funds, the number and percentage of the remaining team-managed funds, which have good accountability of fund managers, increase at the same speed as those of solo-managed funds do.

[Insert Table 3.1 here.]

[4]Nohel, Wang, and Zheng (2010) study side-by-side management of mutual funds and hedge funds.

Table 3.1 reports for each type of fund the summary statistics on fund TNA, fund age, expense and turnover ratios, flow, the number of fund managers, and monthly return, before expenses. We compute the flow as the growth rate of TNA. We adjust for the appreciation of TNA and assume that all cash flows happen at the month end. The mean (median) number of fund managers in a team may not be an integer because we report time-series average of cross-section mean (median). On average, a team consists of two or three fund managers.

3.2.1 Why the Poor-Accountability Team Approach?

We use a simple analysis to study why asset management companies increasingly use the poor-accountability team approach. Data limitations prevent us from using a more complicated analysis, such as a logistic regression, to study this question. Morningstar gives only a snapshot of a fund's most recent information on the affiliated asset management company. We tried to retrieve asset management company information from other databases, such as CRSP, but linking Morningstar and CRSP causes a big loss of data.

Expenses

Intuitively, an asset management company may find the poor-accountability team approach cost efficient because it can easily assemble a team from existing fund managers. Using the good-accountability team approach and the solo-manager approach typically requires a new hire of a "full-time" or solo fund manager, which is relatively expensive and time consuming. To test this intuition, it would be ideal to look at the total compensation of a team. However, we are not aware of any database that provides detailed fund manager compensation information. Instead, we look at fund expenses, which tend to be low if the asset management company does not have to pay the team very much.

Table 3.1 provides evidence consistent with our intuition. The mean expense ratio of funds managed using the poor-accountability team approach is 115 bps per annum, which is higher than that of funds managed using the good-accountability team approach, 123.6 bps per annum, and that of solo-managed funds, 118.3 bps per annum.

However, the lower expenses of funds managed using the poor-accountability team approach can not offset their underperformance. Table 3.1 shows that the mean return, before expenses, of these funds is 67.3 bps per month, whereas the mean returns of funds managed using the good-accountability team approach and of solo-managed funds are 73 bps per month. We further show in Section 3.3 that this underperformance is robust after we control for risk and style differences in fund performance, as well as fund characteristics. The underperformance of these funds, 5.7 bps per month, is much higher than the lower expenses.

Clientele

Who invests in funds managed using the poor-accountability team approach? The Morningstar database provides snapshot information on whether a fund receives investment from retirement plans. We find that retirement savers invest in an unusually large proportion of funds managed using the poor-accountability team approach. For example, in 2012, 13% of these funds receive investment from retirement plans, whereas this percentage is only 7% for other funds, including funds managed using the good-accountability team approach and solo-managed funds.

An important literature in economics and finance shows that retirement savers exhibit significant inertia and are unlikely to be business savvy (see the citations in Footnote 3). Our finding suggests that retirement savers are attracted by the lower expenses of funds managed using the poor-accountability team approach, even though the lower expenses can not offset the underperformance.

3.3 Fund Performance

In this section, we examine the performance of funds managed using the poor-accountability team approach, funds managed using the good-accountability team approach, and solo-managed funds. We use both portfolio analysis and regression analysis.

3.3.1 Portfolio Analysis

We construct three portfolios of funds managed using the poor-accountability team approach, funds managed using the good-accountability team approach, and solo-managed funds. We compute the monthly return of each portfolio by weighing all funds in the portfolio equally. We use the before-expense fund returns because these returns describe fund managers' investment performance, which we are primarily interested in.

We use five risk- and style-adjusted performance measures. The first performance measure is the excess return of the portfolio over the market portfolio. The next four measures are the abnormal returns of CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and the Pástor-Stambaugh (2003) five-factor model.[5]

[5]The abnormal return is given by the intercept of the following time-series regression:

$$R_{pt} - R_{Ft} = \alpha_p + \beta_{p\mathrm{M}}(R_{Mt} - R_{Ft}) + \beta_{p\mathrm{SMB}}\mathrm{SMB}_t + \beta_{p\mathrm{HML}}\mathrm{HML}_t + \beta_{p\mathrm{MOM}}\mathrm{MOM}_t + \beta_{p\mathrm{LIQ}}\mathrm{LIQ}_t + \epsilon_{pt}.$$

The dependent variable is the portfolio return minus the risk-free rate. The explanatory variables are the returns of the five zero-investment factor portfolios. $R_{Mt} - R_{Ft}$ is the market portfolio return minus the risk-free rate, SMB_t is the average return of small-cap stocks minus the average return of large-cap stocks, HML_t is the average return of high book-to-market stocks minus the average return of low book-to-market stocks, MOM_t is the average return of high momentum stocks minus the average return of low momentum stocks, and LIQ_t is average return of low liquidity stocks minus the average return of high liquidity stocks. CAPM uses the first factor. Fama and French (1993) use the first three factors. Carhart (1997) uses the first four factors. Pástor and Stambaugh (2003) use all five factors. We obtain the market, size, value, momentum, and liquidity factor returns through WRDS.

[Insert Table 3.2 here.]

Table 3.2 reports the portfolio results. Column 5 shows that the portfolio of funds managed using the poor-accountability team approach underperforms the portfolio of solo-managed funds by 5.7 bps per month (at the 1% significance level). The underperformance equals 5.6 bps per month (at the 1% significance level) after we use CAPM to control for market risk, 5.2 bps per month (at the 5% significance level) after we use the Fama-French (1993) three-factor model to further control for size and value, 5.1 bps per month (at the 5% significance level) after we use the Carhart (1997) four-factor model to further control for momentum, and 5.1 bps per month (at the 5% significance level) after we use the Pástor-Stambaugh (2003) five-factor model to further control for liquidity.

Column 6 shows that the portfolio of funds managed using the good-accountability team approach performs similarly to the portfolio of solo-managed funds.

In sum, our findings suggest that not all team-managed funds underperform solo-managed funds. Only those managed using the poor-accountability team approach do.

Subsample

Table 3.3 reports the portfolio results within subsamples. To save space, we report only the Carhart abnormal return. Panel A considers subsamples of small-cap, mid-cap, and large-cap funds according to Morningstar classification. Panel B considers subsamples of value, blend, and value funds according to Morningstar classification. Panel C considers subsamples of small-TNA, mid-TNA, and large-TNA funds.

[Insert Table 3.3 here.]

Consistent with our preceding analysis, the underperformance of team-managed funds relative to solo-managed funds is mainly concentrated in those managed using the poor-accountability team approach. Specifically, Column 5 shows that within subsamples of small-cap funds, mid-cap funds, blend funds, mid-TNA funds, and large-TNA funds, funds managed using the poor-accountability team approach significantly underperform solo-managed funds. In sharp contrast, only within the subsample of mid-cap funds, funds managed using the good-accountability team approach significantly underperform solo-managed funds.

3.3.2 Regression Analysis

We continue our analysis using multivariate regressions. The previous portfolio analysis indicates that the Carhart (1997) four-factor model controls for risk and style differences properly, so we use the Carhart abnormal return as our only performance measure here.

The regression analysis has two main differences from the portfolio analysis. First, it can simultaneously control for other fund variables that may affect fund performance. Second, it takes into consideration the possibility that the factor loadings of individual funds may vary over time because the Carhart (1997) four-factor model is estimated based on the recent data.[6]

[Insert Table 3.4 here.]

Table 3.4 reports the regression results. We use the panel regression approach and run the regression at a monthly frequency. The dependent variable, the Carhart abnormal return, is the difference between a fund-month's realized return and expected return from the Carhart (1997) four-factor model estimated based on 24 months of lagged data. We include TNA, fund age, expense and turnover ratios, and flow as explanatory variables. All

[6]Ferson and Schadt (1996) point out that risk levels and risk premia may move together, which causes factor loadings of funds in an unconditional factor model to vary over time.

these variables are lagged by one month, except for turnover ratio, which is contemporary.[7] TNA and fund age are skewed to the right, so we take the natural logarithms. We include style and time fixed effects. Standard errors are clustered at the fund level.

Columns 1 and 2 replicate the CHHK (2004) test. The team dummy equals 1 if a fund-month is managed by a team and 0 otherwise. Column 1 shows that before we control for other fund characteristics, the coefficient on the team dummy, -0.023, is negative and significant at the 5% level. Column 2 shows that after we control for other fund characteristics, the coefficient on the team dummy, -0.019, is negative and significant at the 10% level. Therefore, consistent with CHHK (2004), on average team-managed funds underperform solo-managed funds.

Columns 3 and 4 include two dummies, which represent the two team approaches. The PAT dummy equals 1 if a fund-month is managed using the poor-accountability team approach and 0 otherwise. The GAT dummy equals 1 if a fund-month is managed using the good-accountability team approach and 0 otherwise. Column 3 shows that before we control for other fund characteristics, the coefficient on the PAT dummy, -0.04, is negative and significant at the 1% level. The coefficient on the GAT dummy is not significant. Column 4 shows that after we control for other fund characteristics, the coefficient on the PAT dummy, -0.031, remains negative and significant at the 1% level. The coefficient on the GAT dummy is still not significant. Therefore, funds managed using the poor-(good-)accountability team approach underperform (perform similarly to) solo-managed funds.

In sum, our findings here are broadly consistent with those from our portfolio analysis. Not all team-managed funds underperform solo-managed funds. Only those managed using the poor-accountability team approach do.

[7] Morningstar assigns the same level of turnover ratio to a fund for a whole calendar year. We also tried to lag turnover ratio by one year (not reported to save space). The results are similar.

3.4 The Causes of Fund Performance

As Holmström (1979) suggests, a plausible explanation for the underperformance of funds managed using the poor-accountability team approach is that poor accountability disincentivizes fund managers from acquiring information. One might give three alternative explanations. In what follows, we design tests to rule out these explanations. We also examine the investment behavior of these funds, shedding light on the impact of poor accountability on fund managers' incentives.

3.4.1 Ruling Out Several Alternative Explanations

The "Free Rider" Explanation

According to the "free rider" explanation, funds managed using the poor-accountability team approach have a severe free rider problem, so that no fund manager works hard, which leads to underperformance. Stein (2002) also points out that a team may form a hierarchy, which prevents communication and the acquisition of soft information. Here we don't distinguish between this mechanism and the "free rider" explanation because they give similar predictions for the effects of team structure on incentives and performance.

[Insert Table 3.5 here.]

In Table 3.5, we test the "free rider" explanation using a matching fund approach. We match a fund managed using the poor-accountability team approach and a fund managed using the good-accountability team approach. We require that they have the same number of fund managers, the same investment style, and the closest TNA. The "free rider" explanation suggests that they should perform similarly because they have the same team size and are subject to the same scale of free rider problem. However, our portfolio analysis shows that the treatment fund still underperforms the matching fund. For example, Row 4 shows that the underperformance in the Carhart abnormal return equals 5.1 bps per month (at the 5% significance level). We therefore rule out the "free rider" explanation.

The "Poor-Quality Manager" Explanation

According to the "poor-quality manager" explanation, managers of funds using the poor-accountability team approach simply have poor quality, so it is not surprising that they perform poorly.

[Insert Table 3.6 here.]

In Table 3.6, we test the "poor-quality manager" explanation using a matching fund approach. We match a fund managed using the poor-accountability team approach and a solo-managed fund. We require that they have a fund manager in common, the same investment style, and the closest TNA. The "poor-quality manager" explanation suggests that they should perform similarly because they have the same manager quality. However, our portfolio analysis shows that the treatment fund still underperforms the matching fund. For example, although Row 4 shows that the underperformance in the Carhart abnormal return, 7.6 bps per month, isn't statistically significant, Row 5 shows that after we use the Pástor-Stambaugh (2003) five-factor model to further control for liquidity, the underperformance, -8.9 bps per month, is significant at the 10% level. We therefore rule out the "poor-quality manager" explanation.

The Causality Problem: A Dynamic Analysis

One might suspect that asset management companies deliberately use the poor-accountability team approach for funds that perform poorly for reasons unrelated to the management structure. If this is true, then our analysis of fund management and fund performance will have a causality problem.

[Insert Figure 3.2 here.]

In Figure 3.2, we test this causality problem using a dynamic analysis. In Panel A, we identify 1,491 funds switching from the poor-accountability team approach to the good-accountability team approach or the solo-manager approach. We plot the equally weighted average of their cumulative objective-adjusted return (OAR, which equals the fund return minus the value-weighted average return of a portfolio comprising all other funds with the same investment objective) in the 36 months around the switch.[8] In the 18 months before the switch, the cumulative OAR decreases sharply, indicating a poor performance. In the 18 months after the switch, the cumulative OAR stabilizes, indicating a performance improvement.

We find consistent evidence in Panel B of Figure 3.2. Here we identify 1,279 funds switching from the good-accountability team approach or the solo-manager approach to the poor-accountability team approach. In the 18 months before the switch, the cumulative OAR increases, indicating a fairly good performance. In the 18 months after the switch, the cumulative OAR decreases, indicating a performance deterioration.

In sum, our findings here suggest that there is a significant performance improvement (deterioration) after a fund switches from the poor-accountability team approach to the good-accountability team approach or the solo-manager approach (from the good-accountability team approach or the solo-manager approach to the poor-accountability team approach). We, therefore, rule out the causality problem.

[8] We don't use abnormal returns of factor models here because it is not clear which data should be used to estimate the factor models during a structural change.

3.4.2 Investment Behavior

In what follows, we examine the investment behavior of funds managed using the poor-accountability team approach. We continue to use the matching fund approach because it effectively controls for team size and manager quality.

[Insert Table 3.7 here.]

Industry Concentration

We follow Kacperczyk, Sialm, and Zheng (2005) to compute a fund-month's industry concentration index (ICI) as the sum of the squared deviations of the value weights for each of ten industries held by the mutual fund from the industry weights of the market portfolio. The portfolio weights are computed using the latest holdings information obtained from the Thomson Reuters CDA/Spectrum database.[9]

Row 1 of Table 3.7 shows that funds managed using the poor-accountability team approach have a relatively low level of industry concentration. Specifically, the ICI of these funds is lower than that of the matching funds based on team size, investment style, and TNA, or that of the matching solo-managed funds based on fund manager, investment style, and TNA by 0.007 (at the 1% significance level).

Local Holdings

We follow CHHK (2004) to compute a fund-month's local holdings. We divide the stock-holdings of the fund-month into local stocks and non-local stocks. A stock is considered a local stock if the company's headquarters and the fund's headquarters are located in the

[9] The CDA/Spectrum database collects information on the stockholdings of mutual funds from their filings with the Security and Exchange Commission (SEC) and their voluntary reports. Most mutual funds disclose their holdings quarterly, even though they are only required to disclose their holdings semiannually.

same census region.[10] We compute the local holdings as the total value weight of local stocks held by the fund, adjusted by deducting the total value weight of all stocks in the census region in the market portfolio.

Row 2 of Table 3.7 suggests that funds managed using the poor-accountability team approach have a relatively low level of local holdings. Specifically, the local holdings of these funds are lower than those of the matching funds based on team size, investment style, and TNA by 0.6% (at the 1% significance level). The local holdings of these funds are higher than those of the matching solo-managed funds based on fund manager, investment style, and TNA by 0.8%, but this result is only marginally significant.

Risk-Taking

For a fund-month, we estimate the Carhart (1997) four-factor model using daily returns. We compute the unsystematic risk as the standard deviation of the residuals.

Row 3 of Table 3.7 shows that funds managed using the poor-accountability team approach have a relatively low level of unsystematic risk-taking. Specifically, the unsystematic risk of these funds is lower than that of the matching funds based on team size, investment style, and TNA by 1.2 bps per day (at the 1% significance level), and is lower than that of the matching solo-managed funds based on fund manager, investment style, and TNA by 2.7 bps per day (at the 1% significance level).

Active Investing

We follow Amihud and Goyenko (2013) to measure active investing for a fund-month using $1-R^2$ of the Carhart (1997) four-factor model estimated from daily returns (i.e., the extent

[10]There are nine census regions in the U.S., including New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific.

to which the fund performance is explained by factor returns).

Row 4 of Table 3.7 shows that funds managed using the poor-accountability team approach invest relatively inactively. Specifically, the active investing measure of these funds is lower than that of the matching funds based on team size, investment style, and TNA by 0.9% (at the 1% significance level), and is lower than that of the matching solo-managed funds based on fund manager, investment style, and TNA by 0.8% (at the 1% significance level).

Discussion

To summarize, funds managed using the poor-accountability team approach exhibit relatively low levels of industry concentration (Kacperczyk, Sialm, and Zheng, 2005), local holdings (Coval and Moskowitz, 1999, 2001), and unsystematic risk; they also invest inactively (Amihud and Goyenko, 2013).

All these findings are consistent with the notion that poor accountability disincentivizes fund managers from acquiring private information on industry and on local companies. Specifically, fund managers tend to concentrate their portfolios in industries (Kacperczyk, Sialm, and Zheng, 2005) and local companies (Coval and Moskowitz, 1999, 2001) about which they have an information advantage. Low levels of industry concentration and local holdings indicate that they have few incentives to acquire private information. As they rely mostly on public information to invest, it is not surprising that they take a low level of unsystematic risk and invest inactively.

3.5 Conclusions

Previous studies have used equity mutual fund data to test the incentive effect of a team. An important finding of these studies is that team-managed funds underperform solo-managed funds (e.g., CHHK, 2004), suggesting that a team is a poor incentive mechanism.

In this article, we take a deeper look into the composition of mutual fund management teams. Our major finding is that not all team-managed funds underperform. Only those with poor accountability of fund managers for fund performance do. We further show that a plausible explanation for the underperformance is that poor accountability disincentivizes fund managers from acquiring information. Unlike previous studies, we conclude that a team *per se* does not represent a poor incentive mechanism. Accountability of team members is more relevant in providing incentives.

References

[1] Alchian, A. A., and H. Demsetz, 1972, Production, information costs, and economic organization, *American Economic Review* 62, 777-795.

[2] Agnew, J., P. Balduzzi, and A. Sunden, 2003, Portfolio choice and trading in a large 401(k) Plan, *American Economic Review* 93, 193-215.

[3] Amihud, Y., and R. Goyenko, 2013, Mutual fund's R^2 as predictor of performance, *Review of Financial Studies* 26, 667-694.

[4] Bär, M., A. Kempf, and S. Ruenzi, 2005, Team management and mutual funds, Working Paper.

[5] Benartzi, S., and R. Thaler, 2001, Naive diversification strategies in Defined Contribution Savings Plans, *American Economic Review* 91, 79-98.

[6] Bliss, R., M. Potter, and C. Schwarz, 2008, Performance characteristics of individual vs. team managed mutual funds, *Journal of Portfolio Management* 34, 110-119.

[7] Boning, B., C. Ichniowski, and K. Shaw, 2001, Opportunity counts: Teams and the effectiveness of production incentives, Working Paper, NBER, 2001.

[8] Carhart, M. M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

[9] Carroll, G. D., J. J. Choi, D. Laibson, B. C. Madrian, and A. Metrick, 2009, Optimal defaults and active decisions, *Quarterly Journal of Economics* 124, 1639-1674.

[10] Chen, J., H. Hong, M. Huang, and J. Kubik, 2004, Does fund size erode mutual fund performance? The role of liquidity and organization, *American Economic Review* 90, 1276-1302.

[11] Coval, J. D., and T. Moskowitz, 1999, Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 2045-2073.

[12] Coval, J. D., and T. Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811-841.

[13] Dass, N., V. Nanda, and Q. Wang, 2013, Allocation of decision rights and the investment strategy of mutual funds, *Journal of Financial Economics* 110, 254-277.

[14] Duflo, E., and E. Saez, 2003, The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment, *Quarterly Journal of Economics* 118, 815-842.

[15] Fama, E. F., and K. R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

[16] Ferson, W., and R. Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 51, 425-462.

[17] Gaynor, M., and P. J. Gertler, 1995, Moral hazard and risk spreading in medical partnerships, *Rand Journal of Economics* 26, 591-613.

[18] Grossman, S. J., and O. Hart, 1986, The costs and benefits of ownership: A theory of vertical and lateral integration, *Journal of Political Economy* 94, 691-719.

[19] Hamilton, B. H., J. A. Nickerson, and H. Owan, 2003, Team incentives and worker heterogeneity: An empirical analysis of the impact of teams on productivity and participation, *Journal of Political Economy* 111, 465-497.

[20] Hansen, D. G., 1997, Worker performance and group incentives: A case study, *Industrial and Labor Relations Review* 51, 37-49.

[21] Hart, O., and J. Moore, 1990, Property rights and the nature of the firm, *Journal of Political Economy* 98, 1119-1158.

[22] Holmström, B., 1979, Moral hazard and observability, *Bell Journal of Economics* 10, 74-91.

[23] Holmström, B., 1982, Moral hazard in teams, *Bell Journal of Economics* 13, 324-340.

[24] Huberman, G., and W. Jiang, 2006, Offering versus choice in 401(k) Plans: Equity exposure and number of funds, *Journal of Finance* 61, 763-801.

[25] Kacperczyk, M., C. Sialm, and L. Zheng, 2005, On the industry concentration of actively managed equity mutual funds, *Journal of Finance* 60, 1983-2011.

[26] Kandel, E., and E. P. Lazear, 1992, Peer pressure and partnerships, *Journal of Political Economy* 100, 801-817.

[27] Leibowitz, A., and R. D. Tollison, 1980, Free riding, shirking, and team production in legal partnerships, *Economic Inquiry* 18, 380-394.

[28] Madrian, B., and D. F. Shea, 2001, The power of suggestion: Inertia in 401(k) participation and savings behavior, *Quarterly Journal of Economics* 116, 1149-1187.

[29] Nalbantian, H. R., and A. Schotter, 1997, Productivity under group incentives: An experimental study, *American Economic Review* 87, 314-341.

[30] Nohel, T., Z. J. Wang, and L. Zheng, 2010, Side-by-side management of hedge funds and mutual funds, *Review of Financial Studies* 23, 2342-2373.

[31] Pástor, L., and R. F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642-685.

[32] Patel, S., and S. Sarkissian, 2013, To group or not to group? Evidence from mutual funds, Working Paper.

[33] Prather, L. J., and K. L. Middleton, 2002, Are $N + 1$ heads better than one? The case of mutual fund managers, *Journal of Economic Behavior and Organization* 47, 103-120.

[34] Stein, J. C., 2002, Information production and capital allocation: Decentralized versus hierarchical firms, *Journal of Finance* 57, 1891-1921.

Figure 3.1: Numbers and Percentages of Funds Using Different Approaches by Month

Panel A plots numbers and Panel B plots percentages of open-end U.S. domestic equity mutual funds managed using the poor-accountability team (PAT) approach, the good-accountability team (GAT) approach, and the solo-manager approach by month. The sample period is January 1998 to December 2012.

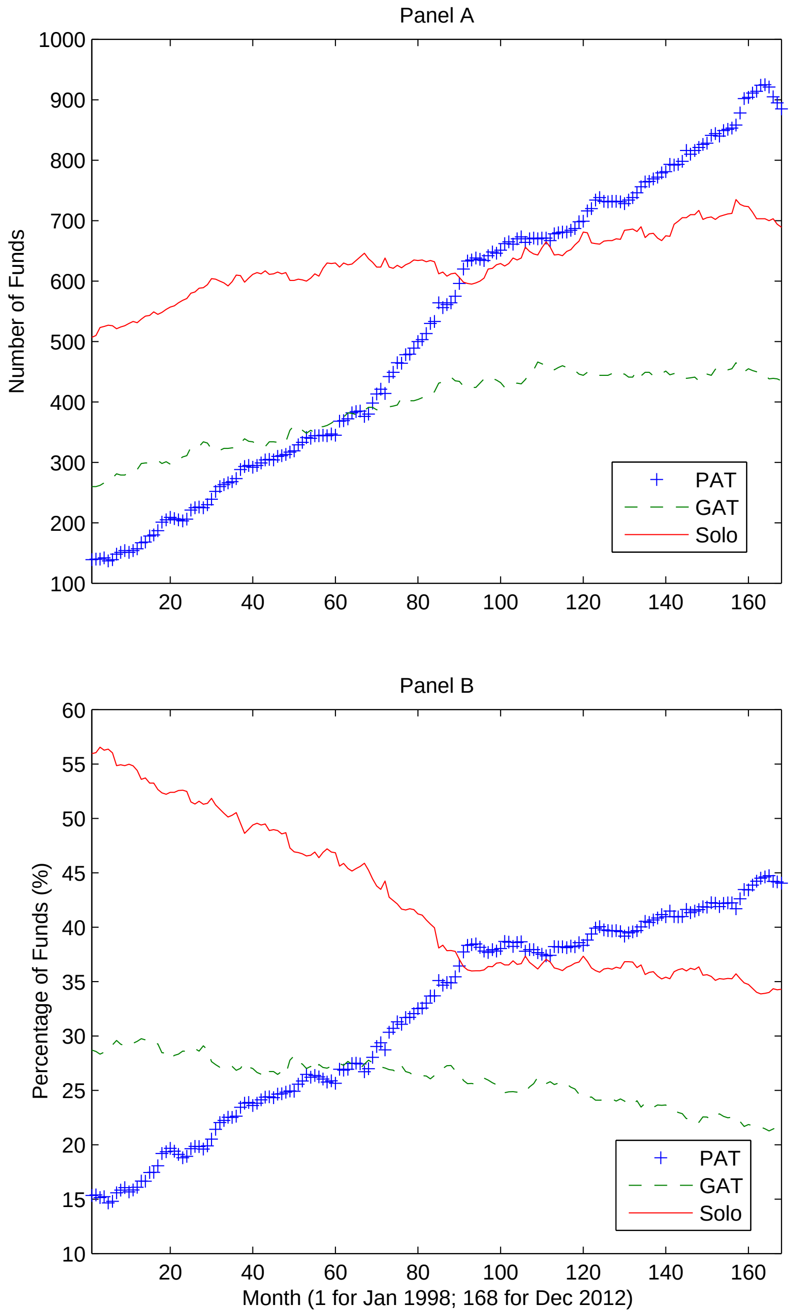


Figure 3.2: The Cumulative OAR around the Switch between Approaches

This figure plots the equally weighted cumulative OAR (%), before expenses, in the 36 months around the switch between approaches. Panel A considers 1,491 funds switching from the poor-accountability team (PAT) approach to the good-accountability team (GAT) approach or the solo-manager approach. Panel B considers 1,279 funds switching from the GAT approach or the solo-manager approach to the PAT approach. The sample period is January 1998 to December 2012.

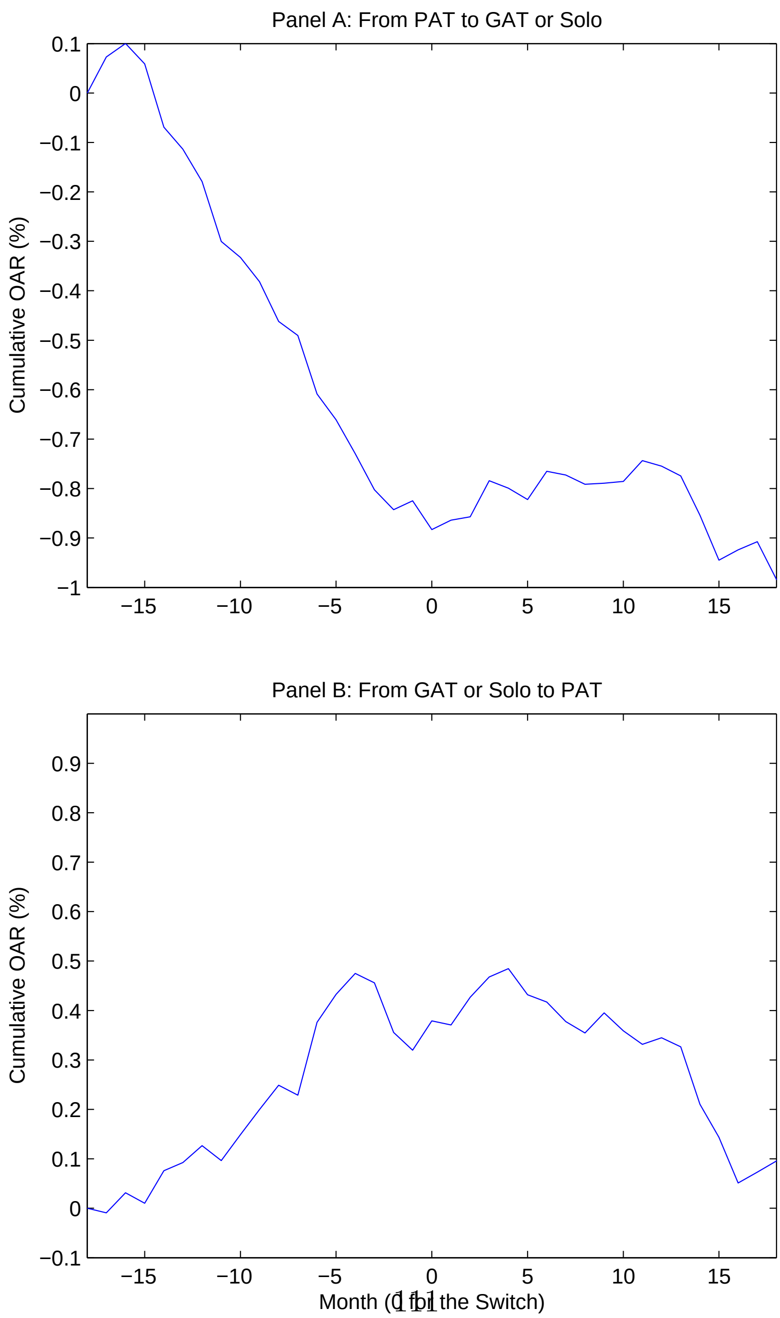


Table 3.1: Summary Statistics

This table reports the time-series average of cross-sectional summary statistics of open-end U.S. domestic equity mutual funds. The sample period is January 1998 to December 2012. The sample includes 2,245 distinct funds and 269,284 fund-month observations. We consider funds managed using the poor-accountability team (PAT) approach, funds managed using the good-accountability team (GAT) approach, and solo-managed funds. All continuous variables are winsorized at the 1% and 99% levels.

		PAT			GAT			Solo		
		Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
(1)	TNA ($million)	1062.948	256.470	2377.335	1115.961	193.509	2936.356	1407.310	234.732	3375.343
(2)	Fund Age	11.995	9.069	11.067	13.291	9.764	12.928	13.241	10.075	12.161
(3)	Expense Ratio (%)	1.150	1.128	0.425	1.236	1.208	0.385	1.183	1.187	0.480
(4)	Turnover Ratio	0.795	0.623	0.669	0.779	0.615	0.654	0.798	0.557	0.757
(5)	Flow (%)	1.056	0.015	5.609	0.980	-0.003	5.504	0.870	-0.013	5.298
(6)	No. of Managers	2.965	2.447	1.321	3.005	2.439	1.441	1.000	1.000	0.000
(7)	Monthly Return (%), Before Expenses	0.673	0.641	2.112	0.730	0.701	2.201	0.730	0.699	2.235

Table 3.2: Fund Performance: Before-Expense Portfolio Returns

This table reports the five risk- and style-adjusted returns (% per month), before expenses, for the portfolios of funds managed using the poor-accountability team (PAT) approach, funds managed using the good-accountability team (GAT) approach, and solo-managed funds. The sample period is January 1998 to December 2012. We compute the monthly portfolio return by weighing all funds in the portfolio equally. We use the excess return over the market portfolio and the abnormal returns of CAPM, the Fama-French (FF, 1993) three-factor model, the Carhart (1997) four-factor model, and the Pástor-Stambaugh (PS, 2003) five-factor model. The t-statistics are given in parentheses. The differences in these returns, along with their t-statistics, between the portfolio of funds managed using the PAT or GAT approach and the portfolio of solo-managed funds are also reported. *, **, and *** indicate significance levels of 10%, 5%, and 1%.

		PAT	GAT	Solo	Diff		
		(1)	(2)	(3)	(4)=(1)-(2)	(5)=(1)-(3)	(6)=(2)-(3)
(1)	Excess Ret	0.160**	0.222***	0.217***	-0.062**	-0.057***	0.005
		(2.38)	(3.04)	(3.14)	(-2.49)	(-2.82)	(0.23)
(2)	CAPM	0.157**	0.230***	0.213***	-0.073***	-0.056***	0.017
		(2.32)	(3.16)	(3.08)	(-3.44)	(-2.78)	(0.91)
(3)	FF	0.084	0.139***	0.136***	-0.054***	-0.052**	0.003
		(1.64)	(2.80)	(2.67)	(-2.90)	(-2.55)	(0.16)
(4)	Carhart	0.085	0.136***	0.136***	-0.051***	-0.051**	-0.000
		(1.64)	(2.72)	(2.65)	(-2.72)	(-2.51)	(-0.03)
(5)	PS	0.051	0.100**	0.102**	-0.050**	-0.051**	-0.002
		(0.99)	(2.05)	(2.02)	(-2.60)	(-2.47)	(-0.11)

Table 3.3: Fund Performance: Before-Expense Portfolio Returns within Subsamples

This table reports the Carhart abnormal return (% per month), before expenses, for the portfolios of funds managed using the poor-accountability team (PAT) approach, funds managed using the good-accountability team (GAT) approach, and solo-managed funds within subsamples. Panel A considers subsamples of small-cap, mid-cap, and large-cap funds. Panel B considers subsamples of value, blend, and growth funds. Panel C considers subsamples of large-TNA, mid-TNA, and small-TNA funds. The sample period is January 1998 to December 2012. We compute the monthly portfolio return by weighing all funds in the portfolio equally. The t-statistics are given in parentheses. The differences in these returns, along with their t-statistics, between the portfolio of funds managed using the PAT or GAT approach and the portfolio of solo-managed funds are also reported. *, **, and *** indicate significance levels of 10%, 5%, and 1%.

		PAT	GAT	Solo	Diff		
		(1)	(2)	(3)	(4)=(1)-(2)	(5)=(1)-(3)	(6)=(2)-(3)
Panel A: Cap-Based Subsamples							
(1)	Small-Cap	0.053	0.147**	0.141*	-0.095***	-0.088***	0.006
		(0.65)	(2.03)	(1.87)	(-2.61)	(-3.09)	(0.23)
(2)	Mid-Cap	0.142	0.189**	0.256***	-0.046	-0.113***	-0.067**
		(1.56)	(2.24)	(3.06)	(-1.20)	(-2.64)	(-2.10)
(3)	Large-Cap	0.081**	0.109***	0.085**	-0.028	-0.004	0.024
		(2.17)	(2.99)	(2.20)	(-1.38)	(-0.18)	(1.37)
Panel B: Value, Blend, and Growth Subsamples							
(4)	Value Funds	0.120*	0.116	0.131**	0.005	-0.010	-0.015
		(1.78)	(1.63)	(2.02)	(0.17)	(-0.37)	(-0.66)
(5)	Blend Funds	0.045	0.117**	0.113**	-0.072***	-0.068***	0.004
		(0.84)	(2.48)	(2.24)	(-3.33)	(-2.79)	(0.18)
(6)	Growth Funds	0.122	0.157**	0.160**	-0.036	-0.038	-0.002
		(1.64)	(2.27)	(2.39)	(-1.29)	(-1.25)	(-0.10)
Panel C: TNA-Based Subsamples							
(7)	Small-TNA Funds	0.166**	0.222***	0.211***	-0.056	-0.045	0.011
		(2.47)	(3.45)	(3.45)	(-1.28)	(-1.19)	(0.38)
(8)	Mid-TNA Funds	0.083	0.146**	0.139**	-0.063**	-0.056*	0.007
		(1.46)	(2.49)	(2.28)	(-2.04)	(-1.86)	(0.25)
(9)	Large-TNA Funds	0.063	0.083*	0.106**	-0.020	-0.043*	-0.023
		(1.33)	(1.87)	(2.29)	(-0.97)	(-1.88)	(-1.14)

Table 3.4: Fund Performance: Panel Regression Evidence

This table reports the panel regression results. The sample period is January 1998 to December 2012. We run the regression at a monthly frequency. The dependent variable, the Carhart abnormal return (% per month), before expenses, is the difference between a fund-month's realized return and expected return from the four-factor model of Carhart (1997) estimated based on 24 months of lagged data. The "team" dummy equals 1 if a fund-month is managed by a team and 0 otherwise. The "PAT" dummy equals 1 if a fund-month is managed using the poor-accountability team approach and 0 otherwise. The "GAT" dummy equals 1 if a fund-month is managed using the good-accountability team approach and 0 otherwise. All other explanatory variables are lagged by one month, except for turnover ratio, which is contemporary. We take the natural logarithms of fund TNA and age because both variables are skewed to the right. We include style and time fixed effects. Standard errors are clustered at the fund level. The t-statistics are given in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)
Team Dummy	-0.023**	-0.019*		
	(-2.26)	(-1.78)		
PAT Dummy			-0.040***	-0.031***
			(-3.75)	(-2.87)
GAT Dummy			-0.002	-0.004
			(-0.18)	(-0.28)
ln(TNA)		-0.029***		-0.029***
		(-8.36)		(-8.28)
ln(Age)		0.009		0.008
		(1.08)		(0.94)
Expense		0.335		0.172
		(0.23)		(0.12)
Turnover		-0.025**		-0.025**
		(-2.39)		(-2.37)
Flow		0.862***		0.862***
		(6.64)		(6.64)
Time FE	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES
No. of Fund-Month Obs	244,913	231,416	244,913	231,416

Table 3.5: Fund Performance: Before-Expense Portfolio Returns; Matching by Team Size, Style, and TNA

This table reports the five risk- and style-adjusted returns (% per month), before expenses, for the portfolios of treatment funds managed using the poor-accountability team (PAT) approach and matching funds managed using the good-accountability team (GAT) approach. The sample period is January 1998 to December 2012. A treatment PAT fund and its matching GAT fund have the same team size, the same investment style, and the closest TNA. We compute the monthly portfolio return by weighing all funds in the portfolio equally. We use the excess return over the market and the abnormal returns of CAPM, the Fama-French (FF, 1993) three-factor model, the Carhart (1997) four-factor model, and the Pástor-Stambaugh (PS, 2003) five-factor model. The *t*-statistics are given in parentheses. The differences in these returns, along with their *t*-statistics, between the portfolios of treatment funds and matching funds are also reported. *, **, and *** indicate significance levels of 10%, 5%, and 1%.

		Matching by Team Size, Style, and TNA		
		PAT	GAT	Diff
		(1)	(2)	(3)
(1)	Excess Ret	0.171**	0.230***	-0.060**
		(2.60)	(3.38)	(-2.26)
(2)	CAPM	0.165**	0.234***	-0.069***
		(2.51)	(3.43)	(-2.89)
(3)	FF	0.097*	0.152***	-0.055**
		(1.92)	(3.15)	(-2.41)
(4)	Carhart	0.098*	0.149***	-0.051**
		(1.93)	(3.06)	(-2.22)
(5)	PS	0.064	0.119**	-0.054**
		(1.28)	(2.47)	(-2.35)

Table 3.6: Fund Performance: Before-Expense Portfolio Returns; Matching by Fund Manager, Style, and TNA

This table reports the five risk- and style-adjusted returns (% per month), before expenses, for the portfolios of treatment funds managed using the poor-accountability team (PAT) approach and matching solo-managed funds. The sample period is January 1998 to December 2012. A treatment PAT fund and its matching solo-managed fund have a fund manager in common, the same investment style, and the closest TNA. We compute the monthly portfolio return by weighing all funds in the portfolio equally. We use the excess return over the market and the abnormal returns of CAPM, the Fama-French (FF, 1993) three-factor model, the Carhart (1997) four-factor model, and the Pástor-Stambaugh (PS, 2003) five-factor model. The t-statistics are given in parentheses. The differences in these returns, along with their t-statistics, between the portfolios of treatment funds and matching funds are also reported. *, **, and *** indicate significance levels of 10%, 5%, and 1%.

		Matching by Manager, Style, and TNA		
		PAT	Solo	Diff
		(1)	(2)	(3)
(1)	Excess Ret	-0.012	0.126**	-0.138**
		(-0.16)	(2.10)	(-2.38)
(2)	CAPM	-0.019	0.120**	-0.139**
		(-0.26)	(2.00)	(-2.40)
(3)	FF	-0.034	0.074	-0.108**
		(-0.46)	(1.36)	(-1.97)
(4)	Carhart	-0.003	0.073	-0.076
		(-0.04)	(1.34)	(-1.54)
(5)	PS	-0.031	0.058	-0.089*
		(-0.44)	(1.04)	(-1.77)

Table 3.7: Investment Behavior

This table reports the equally weighted average levels of the industry concentration index (ICI), local holdings, unsystematic risk-taking, and active investing for treatment funds managed using the poor-accountability team (PAT) approach, matching funds managed using the good-accountability team (GAT) approach, and matching solo-managed funds. The sample period is January 1998 to December 2012. A treatment PAT fund and its matching GAT fund have the same team size, the same investment style, and the closest TNA. A treatment PAT fund and its matching solo-managed fund have a fund manager in common, the same investment style, and the closest TNA. For a fund-month, ICI is computed following Kacperczyk, Sialm, and Zheng (2005) as the sum of the squared deviations of the value weights for each of ten industries held by the mutual fund from the industry weights of the market portfolio. We follow CHHK (2004) to define a stock as a local stock if the company's headquarters and the fund's headquarters are located in the same census region. Local holdings is computed as the total value weight of local stocks held by the fund, adjusted by deducting the total value weight of all stocks in the census region in the market portfolio. We estimate the Carhart (1997) four-factor model using daily returns. The unsystematic risk is computed as the standard deviation of the residuals. Active investing is computed following Amihud and Goyenko (2013) as the $1 - R^2$. The differences in these levels, along with their t-statistics, between treatment funds and matching funds are also reported. *, **, and *** indicate significance levels of 10%, 5%, and 1%.

		Matching by Team Size, Style, and TNA			Matching by Manager, Style, and TNA		
		PAT	GAT	Diff	PAT	Solo	Diff
		(1)	(2)	(3)	(4)	(5)	(6)
(1)	ICI	0.055	0.062	-0.007***	0.047	0.053	-0.007***
				(-11.10)			(-8.27)
(2)	Local Holdings	-0.004	0.003	-0.006***	-0.010	-0.017	0.008*
				(-5.74)			(1.83)
(3)	Unsystematic Risk (% per day)	0.280	0.292	-0.012***	0.232	0.259	-0.027***
				(-12.17)			(-7.95)
(4)	Active Investing	0.064	0.073	-0.009***	0.049	0.057	-0.008***
				(-19.67)			(-7.91)