Syracuse University

SURFACE

Economics - Faculty Scholarship

Maxwell School of Citizenship and Public Affairs

2004

Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization

Joseph Chen
University of California - Davis

Harrison G. Hong
Princeton University and National Bureau of Economic Research

Ming Huang
Cornell University

Jeffrey D. Kubik
Syracuse University

Follow this and additional works at: https://surface.syr.edu/ecn

Part of the Economics Commons

Recommended Citation

Chen, Joseph; Hong, Harrison G.; Huang, Ming; and Kubik, Jeffrey D., "Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization" (2004). *Economics - Faculty Scholarship*. 105.
https://surface.syr.edu/ecn/105

This Article is brought to you for free and open access by the Maxwell School of Citizenship and Public Affairs at SURFACE. It has been accepted for inclusion in Economics - Faculty Scholarship by an authorized administrator of SURFACE. For more information, please contact surface@syr.edu.

Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization

Joseph Chen
University of Southern California

Harrison Hong
Princeton University

Ming Huang
Stanford University

Jeffrey D. Kubik
Syracuse University

First Draft: April 2002
This Draft: May 2004

Abstract: We investigate the effect of scale on performance in the active money management industry. We first document that fund returns, both before and after fees and expenses, decline with lagged fund size, even after accounting for various performance benchmarks. We then explore a number of potential explanations for this relationship. This association is most pronounced among funds that have to invest in small and illiquid stocks, suggesting that these adverse scale effects are related to liquidity. Controlling for its size, a fund's return does not deteriorate with the size of the family that it belongs to, indicating that scale need not be bad for performance depending on how the fund is organized. Finally, using data on whether funds are solo-managed or team-managed and the composition of fund investments, we explore the idea that scale erodes fund performance because of the interaction of liquidity and organizational diseconomies.

We are indebted to Jeremy Stein and two anonymous referees for their many insightful comments. We are also grateful to David Scharfstein, Oliver Hart, Ned Elton, Jack MacDonald, Jonathan Reuter, Haicheng Li, William Rogerson, Rossen Valkanov, Lu Zheng and seminar participants at Harvard, Columbia, Berkeley, MIT, Michigan, Illinois, Stanford, Arizona, Florida, and the U. of Texas Mutual Fund Conference for their helpful comments. Hong also thanks the Finance Group at the University of Michigan for their hospitality during his visit when the paper was written. Please address inquiries to Harrison Hong at hhong@princeton.edu.

Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization

Abstract: We investigate the effect of scale on performance in the active money management industry. We first document that fund returns, both before and after fees and expenses, decline with lagged fund size, even after accounting for various performance benchmarks. We then explore a number of potential explanations for this relationship. This association is most pronounced among funds that have to invest in small and illiquid stocks, suggesting that these adverse scale effects are related to liquidity. Controlling for its size, a fund's return does not deteriorate with the size of the family that it belongs to, indicating that scale need not be bad for performance depending on how the fund is organized. Finally, using data on whether funds are solo-managed or team-managed and the composition of fund investments, we explore the idea that scale erodes fund performance because of the interaction of liquidity and organizational diseconomies.

I. Introduction

The mutual fund industry plays an increasingly important role in the US economy. Over the past two decades, mutual funds have been one of the fastest growing institutions in this country. At the end of 1980, they managed less than 150 billion dollars, but this figure had grown to over 4 trillion dollars by the end of 1997---a number that exceeds aggregate bank deposits (Pozen (1998)). Indeed, almost 50 percent of households today invest in mutual funds (Investment Company Institute (2000)). The most important and fastest growing part of this industry is funds that invest in stocks, particularly actively managed ones. The explosion of newsletters, magazines and rating services such as Morningstar attest to the fact that investors spend significant resources in identifying managers with stock-picking ability. More importantly, actively managed funds control a sizeable stake of corporate equity and play a pivotal role in the determination of stock prices (see, e.g., Grinblatt, Titman and Wermers (1995), Gompers and Metrick (2001)).

In this paper, we tackle an issue that is fundamental to understanding the role of these mutual funds in the economy---the economies of scale in the active money management industry. Namely, how does performance depend on the size or asset base of the fund? A better understanding of this issue would naturally be useful for investors, especially in light of the massive inflows that have increased the mean size of funds in the recent past. At the same time, the issue of the persistence of fund performance depends crucially on the scale-ability of fund investments (see, e.g., Gruber (1996), Berk and Green (2002)). Moreover, the nature of the economies of scale in this industry may also have implications for the agency relationship between managers and investors and the optimal compensation contract between them (see, e.g., Brown, Harlow and Starks (1996), Becker and Vaughn (2001)). Therefore, understanding the effects of fund size on fund returns is an important first step towards addressing such critical issues.

While the effect of scale on performance is an important question, it has received little research attention to date. Some practitioners point out that there are advantages to scale such as more resources for research and lower expense ratios. On the other hand, others believe that a large asset base erodes fund performance because of trading costs associated with liquidity or price impact (see, e.g., Perold and Solomon (1991), Lowenstein (1997)). Whereas a small fund can easily put all of its money in its best ideas, a lack of liquidity forces a large fund to have to invest in its not-so-good ideas and take larger positions per stock than is optimal, thereby eroding performance. Using a small sample of funds from 1974 to 1984, Grinblatt and Titman (1989) find mixed evidence that fund returns decline with fund size. Needless to say, there is no consensus on this issue.

Using mutual fund data from 1962 to 1999, we begin our investigation by using cross-sectional variation to see whether performance depends on lagged fund size. Since funds may have different styles, we adjust for such heterogeneity by utilizing various performance benchmarks that account for the possibility that they load differently on small stock, value stock and price momentum strategies. Moreover, fund size may be correlated with other fund characteristics such as fund age or turnover, and it may be these characteristics that are driving performance. Hence, we regress the various adjusted returns on not only lagged fund size (as measured by the log of total net assets under management), but also include in the regressions a host of other observable fund characteristics including turnover, age, expense ratio, total load, past year fund inflows and past year returns. A number of studies warn that the reported returns of the smallest funds (those with less than 15 million dollars in assets under management) might be upward biased. We exclude these funds from our baseline sample in estimating these regressions.

These regressions indicate that a fund's performance is inversely correlated with its lagged assets under management. For instance, using monthly gross returns (before fees and expenses are deducted), a two-standard deviation shock in the log of a fund's total assets under management this month yields anywhere from a 5.4 to a 7.7 basis points movement in next month's fund return depending on the performance benchmark (or about 65 to 96 basis points annual). The corresponding figures for net fund returns (after fees and expenses are deducted) are only slightly smaller. To put these magnitudes into some perspective, the funds in our sample on average under-perform the market portfolio by about 96 basis points after fees and expenses. From this perspective, a 65 to

96 basis points annual spread in performance is not only statistically significant but also economically important.[1]

Even after utilizing various performance benchmarks and controlling for other observable fund characteristics, there are still a number of potential explanations that might be consistent with the inverse relationship between scale and fund returns. To further narrow down the set of explanations, we proceed to test a direct implication of the hypothesis that fund size erodes performance because of trading costs associated with liquidity and price impact. If the "liquidity hypothesis" is true, then size ought to erode performance much more for funds that have to invest in small stocks, which tend to be illiquid. Consistent with this hypothesis, we find that fund size matters much more for the returns among such funds, identified as "small cap" funds in our database, than other funds.[2] Indeed, for other funds, size does not significantly affect performance. This finding strongly indicates that liquidity plays an important role in the documented diseconomies of scale.

We then delve deeper into the liquidity hypothesis by observing that liquidity means that big funds need to find more stock ideas than small ones but liquidity itself may not completely explain why they cannot go about doing this, i.e. why they cannot scale. Presumably, a large fund can afford to hire additional managers so as to cover more stocks. It can thereby generate additional good ideas so that it can take small positions in lots of stocks as opposed to large positions in a few stocks. Indeed, the vast majority of stocks with small market capitalization are untouched by mutual funds (see, e.g., Hong, Lim and Stein (2000), Chen, Hong, and Stein (2002)). So there is clearly scope for even very large funds to generate new ideas. Put another way, why cannot two small funds (directed by two different managers) merge into one large fund and still have the performance of the large one be equal to the sum of the two small ones?

[1] As we describe below, some theories suggest that the smallest funds may have inferior performance to medium sized ones because they are being run at a sub-optimally small scale. Because it is difficult to make inferences regarding the performance of the smallest funds, we do not attempt to measure such non-linearities here.
[2] Throughout the paper, we will sometimes refer to funds with little assets under management as "small funds" and funds that, by virtue of their fund style, have to invest in small stocks as "small cap funds". So small cap funds are not necessarily small funds. Indeed, most are actually quite large in terms of assets under management.

To see that assets under management need not be obviously bad for the performance of a fund organization, we consider the effect of the size of the family that the fund belongs to on its performance. Many funds belong to fund families (e.g. the famous Magellan fund is part of the Fidelity family of funds), which allows us to separately measure the effect of own size and the size of the rest of the family on fund performance. Controlling for fund size, we find that the assets under management of the other funds in the family that the fund belongs actually increases the fund's performance. A two-standard deviation shock to the size of the other funds in the family leads to about a 4 to 6 basis points movement in the fund's performance next month (or about 48 to 72 basis points movement annual) depending on the performance measure used. The effect is smaller than that of fund size on performance but is nonetheless statistically and economically significant. As we explain in detail below, the most plausible interpretation of this finding is that there are economies associated with trading commissions and lending fees at the family level. Bigger families like Fidelity are able to get better concessions on trading commissions and earn higher lending fees for the stocks held by their funds.

These two findings, fund performance declines with own size but increases with the size of the other funds in the family, are both interesting and intuitively appealing. First, in our cross-sectional regressions, it is important to control for family size in order to find a sizeable impact of fund size on performance. The reason is that these two variables are positively correlated and since family size is good for performance, it is important to control for it to identify the negative effect of fund size. Second, the finding on family size also rules out a number of alternative hypotheses for our fund size finding. For instance, it is not likely that this finding is due to large funds not caring about returns since large families apparently do make sufficient investments to maintain performance.

More importantly, these two findings make clear that liquidity and scale need not be bad for fund performance per se. In most families, major decisions are decentralized in that the fund managers make stock picks without substantial coordination among each other. So a family is an organization that credibly commits to letting each of its fund managers run their own assets. Moreover, being part of a family may economize on certain fixed costs as explained above. So, if a large fund is organized like a fund family with different managers running small pots of money, then scale need not be bad per se, just as family size does not appear to be bad for family performance.

So, given that managers care are a great deal about performance and that scale need not be bad for performance per se, why then does it appear that scale erodes fund performance because of liquidity? In the last part of our paper, we begin to explore some potential answers to this question. Whereas a small fund can be run by a single manager, a large fund naturally needs more managers and so issues of how the decision making process is organized becomes important. We conjecture that liquidity and scale affect performance because of certain organizational diseconomies. We pursue this organizational diseconomies perspective as a means to motivate additional analysis involving fund stock holdings. We want to emphasize that our analysis here is exploratory and that a number of other alternative interpretations, which we describe below, are possible.

There are many types of organizational diseconomies that lead to different predictions on why small organizations outperform large ones.[3] We conjecture that one type, known as hierarchy costs (see, e.g., Aghion and Tirole (1997), Stein (2002)), may be especially relevant for mutual funds and motivate our analysis by testing some predictions from Stein (2002). The basic premise is that in large organizations with hierarchies, the process of agents fighting for (and potentially not having) their ideas implemented will affect agents' ex-ante decisions of what ideas they want to work on. Stein (2002) argues that in the presence of such hierarchy costs, small organizations ought to outperform large ones at tasks that involve the processing of soft information, (i.e., information that cannot be directly verified by anyone other than the agent who produces it). If the information is soft, then agents have a harder time convincing others of their ideas and it becomes more difficult to pass this information up the organization.

In the context of mutual funds, soft information most naturally corresponds to research or investment ideas related to local stocks (companies located nearby to where a fund is headquartered) since anecdotal evidence indicates that investing in such companies requires that the fund process soft information like talking to CEO's as opposed to simply looking at hard information like price-earnings ratios. This means that in large funds with

[3] See Bolton and Scharfstein (1998) and Holmstrom and Roberts (1998) for surveys on the boundaries of the firm that discuss such organizational diseconomies.

hierarchies in which managers fight to have their ideas implemented, managers may end up expending too much research effort on quantitative measures of a company (i.e. hard information) so as to convince others to implement their ideas than they ideally would if they controlled their own smaller funds. All else equal, large funds may perform worse than small ones.

Building on the work of Coval and Moskowitz (1999, 2001), we find that, consistent with Stein (2002), small funds, especially those investing in small stocks, are significantly more likely than their larger counterparts to invest in local stocks. Moreover, they do much better at picking local stocks than large funds.[4]

Another implication of Stein (2002) is that controlling for fund size, funds that are managed by one manager are better at tasks that involve the processing of soft information than funds managed by many managers. Consistent with Stein (2002), we find that solo-managed funds are significantly more likely than team-managed funds to invest in local stocks and to do better at picking local stocks than co-managed funds. Finally, we also find that controlling for fund size, solo-managed funds out-perform team-managed funds.

Note that such hierarchy costs are not present at the family level precisely because the family typically commits to not re-allocating resources across funds. Indeed, different funds in a family have their own boards that deal with issues such as managerial replacement. So the manager in charge of a fund generally does not have to worry about the family taking away its resources and giving it to some other fund in the family. More generally, the idea that agents' incentives are weaker when they do not have control over asset allocation or investment decisions is in the work of Grossman and Hart (1986), Hart and Moore (1990) and Hart (1995).

In sum, our paper makes a number of contributions. First, we carefully document that performance declines with fund size. Second, we establish the importance of liquidity in mediating this inverse relationship. Third, we point out that the adverse effect of scale on performance need not be inevitable because we find that family size actually

---

[4] Stein's analysis also suggests that large organizations need not under-perform small ones when it comes to processing hard information. In the context of the mutual fund industry, only passive index funds like Vanguard are likely to only rely on hard information. Most active mutual funds rely to a significant degree on soft information. Interestingly, anecdotal evidence indicates that scale is not as big of an issue for passive index funds as it is for active mutual funds.

improves fund performance. Finally, we provide some evidence that the reason fund size and liquidity does in fact erode performance may be due to organizational diseconomies related to hierarchy costs. Again, it is important to note, however, that our analysis into the nature of the organizational diseconomies is exploratory and that there are other interpretations, which we discuss below.

Our paper proceeds as follows. We describe the data in Section II and the performance benchmarks in Section III. In Section IV, we present our empirical findings. We explore alternative explanations in Section V. We conclude in Section VI.

II. Data

Our primary data on mutual funds come from the Center for Research in Security Prices (CRSP) Mutual Fund Database, which span the years of 1962 to 1999. Following many prior studies, we restrict our analysis to diversified U.S. equity mutual funds by excluding from our sample bond, international and specialized sector funds.[5] For a fund to be in our sample, it must report information on assets under management and monthly returns. Additionally, we require that it also have at least one year of reported returns. This additional restriction is imposed because we need to form benchmark portfolios based on past fund performance.[6] Finally, a mutual fund may enter the database multiple times in the same month if it has different share classes. We clean the data by eliminating such redundant observations.

Table 1 reports summary statistics for our sample. In Panel A, we report the means and standard deviations for the variables of interest for each fund size quintile, for all funds, and for funds in fund size quintiles two (next to smallest) to five (largest). Elton, Gruber and Blake (2000) warn that one has to be careful in making inferences regarding the performances of funds that have less than 15 million dollars in total net

---

[5] More specifically, we select mutual funds in the CRSP Mutual Fund database that have reported one of the following investment objectives at any point in their lives. We first select mutual funds with Investment Company Data, Inc. (ICDI) mutual fund objective of ‘aggressive growth’, ‘growth and income’, or ‘long-term growth’. We then add in mutual funds with Strategic Insight mutual fund objective of ‘aggressive growth’, ‘flexible’, ‘growth and income’, ‘growth’, ‘income-growth’, or ‘small company growth’. Finally, we select mutual funds with Wiesenberger mutual fund objective code of ‘G’, ‘G-I’, ‘G-I-S’, ‘G-S’, ‘GCI’, ‘I-G’, ‘I-S-G’, ‘MCG’, or ‘SCG’.

[6] We have also replicated our analysis without this restriction. The only difference is that the sample includes more small funds, but the results are unchanged.

assets under management. They point out that there is a systematic upward bias in the reported returns among these observations. This bias is potentially problematic for our analysis since we are interested in the relationship between scale and performance. As we will see shortly, this critique only applies to observations in fund size quintile one (smallest), since the funds in the other quintiles typically have greater than 15 million dollars under management. Therefore, we focus our analysis on the sub-sample of funds in fund size quintiles two to five. It turns out that our results are robust to whether or not we include the smallest funds in our analysis.

We utilize 3,439 distinct funds and a total 27,431 fund years in our analysis.[7] In each month, our sample includes on average about 741 funds. They have average total net assets (TNA) of 282.5 million dollars, with a standard deviation of 925.8 million dollars. The interesting thing to note from the standard deviation figure is that there is a substantial spread in TNA. Indeed, this becomes transparent when we disaggregate these statistics by fund size quintiles. Those in the smallest quintile have an average TNA of only about 4.7 million dollars, whereas the ones in the top quintile have an average TNA of over 1.1 billion dollars. The funds in fund size quintiles two to five have a slightly higher mean of 352.3 million dollars with a standard deviation of over one billion dollars. For the usual reasons related to scaling, the proxy of fund size that we will use in our analysis is the log of a fund's TNA (LOGTNA). The statistics for this variable are reported in the row right below that of TNA. Another variable of interest is LOGFAMSIZE, which is the log of one plus the cumulative TNA of the other funds in the fund's family (i.e. the TNA of a fund's family excluding its own TNA).

In addition, the database reports a host of other fund characteristics that we utilize in our analysis. The first is fund turnover (TURNOVER), defined as the minimum of purchases and sales over average TNA for the calendar year. The average fund turnover is 54.2 percent per year. The average fund age (AGE) is about 15.7 years. The funds in our sample have expense ratios as a fraction of year-end TNA (EXPRATIO) that average about 97 basis points per year. They charge a total load (TOTLOAD) of about 4.36 percent (as a percentage of new investments) on average. FLOW in month t is defined as

---

[7] At the end of 1993, we have about 1508 distinct funds in our sample, very close to the number reported by previous studies that have used this database. Moreover, the summary statistics below are similar to those reported in these other studies as well.

the fund's TNA in month t minus the product of the fund's TNA at month t-12 with the net fund return between months t-12 and t, all divided by the fund's TNA at month t-12. The funds in the sample have an average fund flow of about 24.7 percent a year. These summary statistics are similar to those obtained for the sub-sample of funds in fund size quintiles two to five.

Panel B of Table 1 reports the time-series averages of the cross-sectional correlations between the various fund characteristics. A number of patterns emerge. First, LOGTNA is strongly correlated with LOGFAMSIZE (0.40). Second, EXPRATIO varies inversely with LOGTNA (–0.31), while TOTLOAD and AGE vary positively with LOGTNA (0.19 and 0.44 respectively). Panel C reports the analogous numbers for the funds in fund size quintiles two to five. The results are similar to those in Panel B. It is apparent from Panels B and C that we need to control for these fund characteristics in estimating the cross-sectional relationship between fund size and performance.

Finally, we report in Panel D the means and standard deviations for the monthly fund returns, FUNDRET, where we measure these returns in a couple of different ways. We first report summary statistics for gross fund returns adjusted by the return of the market portfolio (simple market-adjusted returns). Monthly gross fund returns are calculated by adding back the expenses to net fund returns by taking the year-end expense ratio, dividing it by twelve and adding it to the monthly returns during the year. For the whole sample, the average monthly performance is 1 basis point with a standard deviation of 2.62 percent. The funds in fund size quintiles two to five do slightly worse, with a mean of –2 basis points and a standard deviation of 2.48 percent. We also report these summary statistics using net fund returns. The funds in our sample under-perform the market by 8 basis points per month or 96 basis points a year after fees and expenses are deducted.

These figures are almost identical to those documented in other studies. These studies find that fund managers do have the ability to beat or stay even with the market before management fees (see, e.g., Grinblatt and Titman (1989), Grinblatt, Titman and Wermers (1995), Daniel, Grinblatt, Titman and Wermers (1997)). However, mutual fund investors are apparently willing to pay a lot in fees for limited stock-picking ability, which results in their risk-adjusted fund returns being significantly negative (see, e.g., Jensen (1968), Malkiel (1995), Gruber (1996)).

Moreover, notice that smaller funds appear to outperform their larger counterparts. For instance, funds in quintile 2 have an average monthly gross return of 2 basis points, while funds in quintile 5 under-perform the market by 6 basis points. The difference of 8 basis points per month or 96 basis points a year is an economically interesting number. Net fund returns also appear to be negatively correlated with fund size, though the spread is somewhat smaller than using gross returns. We do not want to over-interpret these results since we have not controlled for heterogeneity in fund styles nor calculated any type of statistical significance in this table.

In addition to the CRSP Mutual Fund Database, we will also utilize the CDA Spectrum Database to analyze the effect of fund size on the composition of fund stock holdings and the performance of these holdings. The reason we need to augment our analysis with this database is that the CRSP Mutual Fund Database does not have any information about fund positions in individual stocks. The CDA Spectrum Database reports a fund's stock positions on a quarterly basis but it is only available starting in the early eighties and it is does not report a fund's cash positions. Wermers (2000) compared the funds in these two databases and found that the active funds represented in the two databases are comparable. So while the CDA Spectrum Database is less ideal than the CRSP Mutual Fund Database in measuring performance, it is adequate for analyzing the effects of fund size on stock positions. We will provide a more detailed discussion of this database in Section IV below.

III. Methodology

Our empirical strategy utilizes cross-sectional variation to see how fund performance varies with lagged fund size. Now, we could have adopted a fixed-effects approach by looking at whether changes in a fund's performance are related to changes in its size. However, such an approach is subject to a regression-to-the-mean bias. A fund with a year or two of lucky performance will experience an increase in fund size. But performance will regress to the mean, leading to a spurious conclusion that an increase in fund size is associated with a decrease in fund returns. Measuring the effect of fund size on performance using cross-sectional regressions is less subject to such biases. Indeed, it may even be conservative given our goal since larger funds are likely to be better funds or they would not have gotten big in the first place. We are likely to be biased toward finding any diseconomies of scale using cross-sectional variation.

However, there are two major worries that arise when using cross-sectional variation. The first is that funds of different sizes may be in different styles. For instance, small funds might be more likely than large funds to pursue small stock, value stock and price momentum strategies, which have been documented to generate abnormal returns. While it is not clear that one wants to necessarily adjust for such heterogeneity, it would be more interesting if we found that past fund size influences future performance even after accounting for variations in fund styles. The second worry is that fund size might be correlated with other fund characteristics such as fund age or turnover, and it may be these characteristics that are driving performance. For instance, fund size may be measuring whether a fund is active or passive (which may be captured by fund turnover). While we have tried our best to rule out passive funds in our sample construction, it is possible that some funds may just be indexers. And if it turns out that indexers happen to be large funds because more investors put their money in such funds, then size may be picking up differences in the degree of activity among funds.

A. Fund Performance Benchmarks

A very conservative way to deal with the first worry about heterogeneity in fund styles is to adjust for fund performance by various benchmarks. In this paper, we consider, in addition to simple market-adjusted returns, returns adjusted by the Capital Asset Pricing Model (CAPM) of Sharpe (1964). Moreover, we also consider returns adjusted using the Fama and French (1993) three-factor model and this model augmented with the momentum factor of Jegadeesh and Titman (1993), which has been shown in various contexts to provide explanatory power for the observed cross-sectional variation in fund performance (see, e.g., Carhart (1997)).

Panel A of Table 2 reports the summary statistics for the various portfolios that make up our performance benchmarks. Among these are the returns on the CRSP value weighted stock index net of the one-month Treasury rate (VWRF), the returns to the

Fama and French (1993) SMB (small stocks minus large stocks) and HML (high book-to-market stocks minus low book-to-market stocks) portfolios, and the returns to price momentum portfolio MOM12 (a portfolio that is long stocks that are past twelve month winners and short stocks that are past twelve month losers and hold for one month). The summary statistics for these portfolio returns are similar to those reported in other mutual fund studies.

Since we are interested in the relationship between fund size and performance, we sort mutual funds at the beginning of each month based on the quintile rankings of their previous-month TNA.[8] We then track these five portfolios for one month and use the entire time series of their monthly net returns to calculate the loadings to the various factors (VWRF, SMB, HML, MOM12) for each of these five portfolios. For each month, each mutual fund inherits the loadings of the one of these five portfolios that it belongs to. In other words, if a mutual fund stays in the same size quintile through out its life, its loadings remain the same. But if it moves from one size quintile to another during a certain month, it then inherits a new set of loadings with which we adjust its next month's performance.

Panel B reports the loadings of the five fund-size (TNA) sorted mutual fund portfolios using the CAPM:

$$R_{i,t} = \alpha_i + \beta_i \, VWRF_t + \varepsilon_{i,t} \qquad t=1,\dots,T \qquad (1)$$

where $R_{i,t}$ is the (net fund) return on one of our five fund-size sorted mutual fund portfolios in month t in excess of the one-month T-bill return, α_i is the excess return of that portfolio, β_i is the loading on the market portfolio, and $\varepsilon_{i,t}$ stands for a generic error term that is uncorrelated with all other independent variables. As other papers have found, the average mutual fund has a beta of around 0.91, reflecting the fact that mutual funds hold some cash or bonds in their portfolios. Notice that there is only a slight variation in the market beta (β_i's) from the smallest to the largest fund size portfolio: the smallest portfolio has a somewhat smaller beta, but not by much.

[8] We also sort mutual funds by their past twelve-month returns to form benchmark portfolios. Our results are unchanged when using these benchmark portfolios. We omit these results for brevity.

Panel C reports the loadings for two additional performance models, the Fama-French three-factor model and this three-factor model augmented by a momentum factor:

$$R_{i,t} = \alpha_i + \beta_{i,1}\, VWRF_t + \beta_{i,2}\, SMB_t + \beta_{i,3}\; HML_t + \varepsilon_{i,t} \qquad t=1,\ldots,T \qquad (2)$$

$$R_{i,t} = \alpha_i + \beta_{i,1}\, VWRF_t + \beta_{i,2}\, SMB_t + \beta_{i,3}\; HML_t + \beta_{i,4}\, MOM12_t + \varepsilon_{i,t} \quad t=1,\ldots,T \quad (3)$$

where $R_{i,t}$ is the (net fund) return on one of our five size-sorted mutual fund portfolios in month t in excess of the one-month T-bill return, α_i is the excess return, β_i's are loadings on the various portfolios, and $\varepsilon_{i,t}$ stands for a generic error term that is uncorrelated with all other independent variables. We see that small funds tend to have higher loadings on SMB and HML, but large funds tend to load a bit more on momentum. For instance, the loading on SMB for the three-factor model for funds in quintile 1 is 0.29 while the corresponding loading for funds in quintile 5 is 0.08. And whereas large funds load negatively on HML (–0.06 for the largest funds), the smallest funds load positively on HML (0.03). (Falkenstein (1996) also finds some evidence that larger funds tend to play large and glamour stocks by looking at fund holdings.)

We have also re-done all of our analysis by calculating these loadings using gross fund returns instead of net fund returns. The results are very similar to using net fund returns. So for brevity, we will just use the loadings summarized in Table 2 to adjust fund performance below (whether it be gross or net returns). Using the entire time series of a particular fund (we require at least 36 months of data), we also calculate the loadings separately for each mutual fund using Equations (1)-(3). This technique is not as good in the sense that we have a much more selective requirement on selection and the estimated loadings tend to be very noisy. In any case, our results are unchanged, so we omit these results for brevity.

B. Regression Specifications

To deal with the second concern related to the correlation of fund size with other fund characteristics, we analyze the effect of past fund size on performance in the regression framework proposed by Fama and MacBeth (1973), where we can control for the effects of other fund characteristics on performance. Specifically, the regression specification that we utilize is

$$FUNDRET_{i,t} = \mu + \phi\, LOGTNA_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t} \qquad i=1,\ldots,N \tag{4}$$

where $FUNDRET_{i,t}$ is the return (either gross or net) of fund i in month t adjusted by various performance benchmarks, μ is a constant, $LOGTNA_{i,t-1}$ is the measure of fund size, and $\mathbf{X}_{i,t-1}$ is a set of control variables (in month t-1) that includes $LOGFAMSIZE_{i,t-1}$, $TURNOVER_{i,t-1}$, $AGE_{i,t-1}$, $EXPRATIO_{i,t-1}$, $TOTLOAD_{i,t-1}$, and $FLOW_{i,t-1}$. In addition, we include in the right hand size $LAGFUNDRET_{i,t-1}$, which is the past year return of the fund. Here, $\varepsilon_{i,t}$ again stands for a generic error term that is uncorrelated with all other independent variables. The coefficient of interest is ϕ, which captures the relationship between fund size and fund performance, controlling for other fund characteristics. γ is the vector of loadings on the control variables. We then take the estimates from these monthly regressions and follow Fama and MacBeth (1973) in taking their time series means and standard deviations to form our overall estimates of the effects of fund characteristics on performance.

We will also utilize an additional regression specification given by the following:

$$\begin{aligned} FUNDRET_{i,t} = {} & \mu + \phi_1\, LOGTNA_{i,t-1} + \phi_2\, Ind_{\{Style\}} + \phi_3\, LOGTNA_{i,t-1}\, Ind_{\{Style\}} \\ & + \gamma \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t} \qquad i=1,\ldots,N \end{aligned} \tag{5}$$

where the dummy indicator $Ind_{\{Style\}}$ (that equals one if a fund belongs to a certain style category and zero otherwise) and the remaining variables are the same as in Equation (3). The coefficient of interest is ϕ_3, which measures the differential effect of fund size on returns across different fund styles. It is important to note that we do not attempt to measure whether the relationship between fund performance and fund size may be non-linear. While some theories might suggest that very small funds may have inferior performance to medium sized ones because they are being operated at a sub-optimally small scale, we are unable to get at this issue because inference regarding the performance of the smallest funds is problematic for the reasons articulated in Section III.

IV. Results

A. Relationship between Fund Size and Performance

In Table 3, we report the estimation results for the baseline regression specification given in Equation (4). We begin by reporting the results for gross fund returns. The sample consists of funds from fund size quintiles two to five. Notice that the coefficient in front of LOGTNA is negative and statistically significant across the four performance measures. The coefficients obtained using either market-adjusted or CAPM-adjusted returns are around –0.028 with t-statistics of around three. Since one standard deviation of LOGTNA is 1.38, a two standard deviation shock to fund size means that performance changes by –0.028 times 2.8, or 8 basis points per month (96 basis points per year). For the other two performance benchmarks, the 3-factor and 4-factor adjusted returns, the coefficients are slightly smaller at –0.02, but both are still statistically significant with t-statistics of between 2.1 and 2.5. For these coefficients, a two standard deviation shock to fund size means that performance changes by around 70 basis points annual.

To put these magnitudes into some perspective, observe that a standard deviation of mutual fund returns is around 10% annual, with slight variations around this figure depending on the performance measure. Hence, a two standard deviation shock in fund size yields a movement in next year's fund return that is approximately 10% of the annual volatility of mutual funds (96 basis points divided by 10%). Another way to think about these magnitudes is that the typical fund has a gross fund performance net of the market return that is basically near zero. As a result, a spread in fund performance of anywhere from 70 to 96 basis points a year is quite economically significant.

Table 3 also reveals a number of other interesting findings. The only other variables that are statistically significant besides fund size are LOGFAMSIZE and LAGFUNDRET. Interestingly, LOGFAMSIZE predicts better fund performance. We will have much more to say about the coefficient in front of LOGFAMSIZE later. But it is important to emphasize at this point that it is important to control for family size in order to find a sizeable impact of fund size on performance. The reason is that fund and family size are positively correlated and since family size is good for performance, it is important to control for it to identify the negative effect of fund size. This is a major reason why other studies that have had fund size as a control variable in explaining fund returns do not find any significant effect. As a result, these studies really only mention fund size in passing and do not provide any analysis whatsoever.

The fact that the coefficient in front of LAGFUNDRET is significant suggests that there is some persistence in fund returns. As for the rest of the variables, some come in with expected signs, though none are statistically significant. The coefficient in front of EXPRATIO is negative, consistent with industry observations that larger funds have lower expense ratios. The coefficients in front of TOTLOAD and TURNOVER are positive as these two variables are thought to be proxies for whether a fund is active or passive. Fund flow has a negligible ability to predict fund returns and the age of the fund comes in with a negative sign but is statistically insignificant.

We next report the results of the baseline regression using net fund returns. The coefficient in front of LOGTNA is still negative and statistically significant across all performance benchmarks. Indeed, the coefficient in front of LOGTNA is only slightly smaller using net fund returns than using gross fund returns. The observations regarding the economic significance of fund size made earlier continue to hold. If anything, they are even more relevant in this context since the typical fund tends to under-perform the market by about 96 basis points annually. The coefficients in front of the other variables have similar signs as those obtained using gross fund returns. Importantly, keep in mind that the coefficient in front of LOGFAMSIZE is just as statistically and economically significant using net fund returns as gross fund returns.

In Table 4, we present various permutations involving the regression specification in Equation (4) to see if the results in Table 3 are robust. In Panel A, we present the results using all the funds in our sample, including those in the smallest fund size quintile. As we mentioned earlier, the performance of the funds in the bottom fund size quintile are biased upwards, so we should not draw too much from this analysis other than that our results are unchanged by including them in the sample. For brevity, we only report the coefficients in front of LOGTNA and LOGFAMSIZE. Using gross fund returns, the coefficient in front of LOGTNA ranges from –0.019 to –0.026 depending on the performance measure. For net fund returns, it ranges from –0.015 to –0.022. All the coefficients are statistically significant at the 5% level, with the exception of the coefficient obtained using 3-factor adjusted net fund returns. The coefficient in this instance is only significant at the 10% level of significance. The magnitudes are somewhat smaller using the full sample than the sample that excludes the smallest quintile but this difference is not large, however. Moreover, the coefficients in front of LOGFAMSIZE are similar in magnitude to those obtained in Table 3. As such, we conclude that our key findings in Table 3 are robust to including all funds in the sample.

In Panel B, we attempt to predict a fund's cumulative return next year rather than its return next month. Not surprisingly, we find similar results to those in Table 3. The coefficient in front of LOGTNA is negative and statistically significant across all performance benchmarks. Indeed, the economic magnitudes implied by these estimates are similar to those obtained in Table 3. These statements apply equally to LOGFAMSIZE.

In Panels C and D, we split our benchmark sample in half to see whether our estimates on LOGTNA and LOGFAMSIZE depend on particular sub-periods, 1963 to 1980 and 1981 to 1999. It appears that LOGTNA has a strong negative effect on performance regardless of the sub-periods since the economic magnitudes are very similar to those obtained in Table 3. We would not be surprised if the coefficients were not statistically significant since we have smaller sample sizes in Panels C and D. But even with only half the sample size, LOGTNA comes in significantly for a number of the performance measures. In contrast, it appears that the effect of LOGFAMSIZE on performance is much more pronounced in the latter half of the sample.

The analyses in Tables 3 and 4 strongly indicate that fund size is negatively related to future fund performance. Moreover, we are able to rule out that this relationship is driven by differences in fund styles or mechanical correlations of fund size with other observable fund characteristics. However, there still remain a number of potential explanations for this relationship.

Three potential explanations come to mind. First, the lagged fund size and performance relationship is due to transactions costs associated with liquidity or price impact. We call this the "liquidity hypothesis". Second, perhaps investors in large funds are less discriminating about returns than investors in small funds. One reason why this might be the case is that large funds such as Magellan are better at marketing and are able to attract investors through advertising. In contrast, small funds without such marketing operations may need to rely more on better performance to attract and maintain investors. We call this the "clientele hypothesis". Third, fund size is inversely related to performance because of fund incentives to lock in assets under management after a long string of good past performances.[9] When a fund is small and has little reputation, the manager goes about the business of stock picking. But as the fund gets large because of good past performance, the manager may for various reasons lock in his fund size by being passive (or a "closet indexer" as practitioners put it). We call this the "agency-risk-taking hypothesis". The general theme behind the second and third hypotheses is that after funds reach a certain size, they do not care about maximizing returns any longer.

B. The Role of Liquidity: Fund Size, Fund Styles and the Number of Stocks in a Fund's Portfolio

In order to narrow down the list of potential explanations, we design a test of the liquidity hypothesis. To the extent that liquidity is driving our findings above, we would expect to see that fund size matters much more for performance among funds that have to invest in small stocks (i.e. stocks with small market capitalization) than funds that get to invest in large stocks. The reason is that small stocks are notoriously illiquid. As a result, funds that have to invest in small stocks are more likely to need new stock ideas with asset base growth, whereas large funds can simply increase their existing positions without being hurt too much by price impact.

Importantly, this test of the liquidity hypothesis also allows us to discriminate between the other two hypotheses. First, existing research finds that there is little variation in incentives between "small cap" funds (i.e. funds that have to invest in small stocks) and other funds (see, e.g., Almazan, et al. (2001)). Hence, this prediction ought

[9] More generally, it may be that after many years of good performance, bad performance follows for whatever reason. We are offering here a plausible economic mechanism for why this might come about. The ex ante plausibility of this alternative story is, however, somewhat mixed. On the one hand, the burgeoning empirical literature on career concerns suggests that fund managers ought to be bolder with past success (see, e.g., Chevalier and Ellison (1999) and Hong, Kubik and Solomon (2000)). On the other hand, the fee structure means that funds may want to lock in assets under management because investors are typically slow to pull their money out of funds (Brown, Harlow and Starks (1996), Chevalier and Ellison (1997)).

to help us discriminate between our hypothesis and the alternative “agency-risk-taking” story involving fund incentives. Moreover, since funds that have to invest in small stocks tend to do better than other funds, it is not likely that our results are due to the clienteles of these funds being more irrational than those investing in other funds. This allows us to distinguish the liquidity story from the clientele story.

In the CRSP Mutual Fund Database, we are fortunate that each fund self-reports its style, and so we look for style descriptions containing the words “small cap”. It turns out that one style, “Small Cap Growth”, fits this criterion. Funds in this category are likely to have to invest in small stocks by virtue of their style designation. So, we identify funds in our sample as either Small Cap Growth if it has ever reported itself as such or “Not Small Cap Growth”. (Funds rarely change their self-reported style.) Unfortunately, funds with this designation are not prevalent until the early eighties. So, throughout the analysis in this section, we limit our sample to 1981 to 1999. During this period, there are on average 165 such funds each year. The corresponding number for the overall sample during this period is about 1000. So, Small Cap Growth represents a small but healthy slice of the overall population. Also, the average TNA of these funds is 212.9 million dollars with a standard deviation of 566.7 million dollars. The average TNA of a fund in the overall sample during this latter period is 431.5 million dollars with a standard deviation of 1.58 billion dollars. So, Small Cap Growth funds are smaller than the typical fund. But they are still quite big and there is a healthy fund size distribution among them, so that we can measure the effect of fund size on performance.

Table 5 (Panel A) reports what happens to the results in Table 3 when we augment the regression specifications by including a dummy indicator $\text{Ind}_{\{\text{not SCG}\}}$ (that equals one if a fund is not Small Cap Growth and zero otherwise) and an additional interaction term involving LOGTNA and $\text{Ind}_{\{\text{not SCG}\}}$ as in Equation (5). We first report the results for gross fund returns. The coefficient in front of LOGTNA is about –0.06 (across the four performance benchmarks). Importantly, the coefficient in front of the interaction term is positive and statistically significant (about 0.04 across the four performance benchmarks). This is the sign predicted by the liquidity hypothesis since it says that for Not Small Cap Growth funds, there is a smaller effect of fund size on performance. The effect is economically interesting as well. Since the two coefficients,

–0.06 and 0.04, are similar in magnitude, this means that a sizeable fraction of the effect of fund size on performance comes from small cap funds. The results using net fund returns reported are similar.

In Panel A of Table 5, we compared Small Cap Growth funds to all other funds. In Panel B of Table 5, we delve a bit deeper into the "liquidity hypothesis" by looking at how fund performance varies with fund size depending on whether or not a fund is a Large Cap fund---one that is supposed to invest in large-cap stocks.[10] We augment the regression specification of Table 3 by introducing a dummy variable $Ind_{\{LC\}}$ (which equals one if a fund is a Large Cap fund and zero otherwise) and an additional interaction term involving LOGTNA and $Ind_{\{LC\}}$ as in Equation (5). We first report the results for gross fund returns. The coefficient in front of LOGTNA is about –0.03 (across the four performance benchmarks). Importantly, the coefficient in front of the interaction term is positive and statistically significant (about 0.03 across the four performance benchmarks). This is the sign predicted by the liquidity hypothesis since it says that for Large Cap funds, there is no effect of fund size on performance. The results using net fund returns reported are similar.

These findings suggest that liquidity plays an important role in eroding performance. Moreover, as many practitioners have pointed out, since managers of funds get compensated on assets under management, they are not likely to voluntarily keep their funds small just because it hurts the returns of their investors, who may not be aware of the downside of scale (see Becker and Vaughn (2001) and Section V below for further discussion).[11]

However, as we pointed out in the beginning of the paper, liquidity means that large funds need to find more stock ideas than small funds, but it does not therefore

[10] We merged the CRSP Mutual Fund database and the CDA Spectrum Database so that we have information on the stocks held by the funds in our sample. We have verified that mutual funds with the self-reported fund style of "Small Cap Growth" do indeed invest in stocks with a much lower market capitalization than held by funds of other styles. In contrast, mutual funds whose self-reported fund style is "Growth and Income" invest in much larger stocks when compared to funds with other styles. As a result, we characterize these funds as Large Cap Funds in our analysis above. Moreover, we have also verified that Small Cap funds hold stocks that are more illiquid in the sense that the stocks in their portfolios tend to have much larger Kyle lambdas and bid-ask spreads than the stocks held by funds of other styles. Moreover, Large Cap funds hold stocks that are much more liquid than those held by funds of other styles.

[11] A related literature finds that mutual fund investors are susceptible to marketing (see, e.g., Gruber (1996), Sirri and Tufano (1998) and Zheng (1999)).

follow that they cannot. Indeed, large funds can go out and hire more managers to follow more stocks. To see that this is possible, we calculate some basic summary statistics on fund holdings by fund size quintiles. Since the CRSP Mutual Fund Database does not have this information, we turn to the CDA Spectrum Database. We take data from the end of September 1997 and calculate the number of stocks held by each fund. The median fund in the smallest fund size quintile has about 16 stocks in its portfolio, while the median fund in the largest fund size quintile has only about 66 stocks in its portfolio, even though the large funds are many times bigger than their smaller counterparts. These numbers make clear that large funds do not significantly scale up the number of stocks that they hold or cover relative to their smaller counterparts. Yet, there is plenty of scope for them to do so given the thousands of stocks available.

C. The Role of Organization: The Effect of Family Size on Performance

To see that assets under management need not be obviously bad for the performance of a fund organization, recall from Table 3 that controlling for fund size, assets under management of the other funds in the family that the fund belongs to actually increases the fund's performance. The coefficient in front of LOGFAMSIZE is roughly 0.007 regardless of the performance benchmark used. One standard deviation of this variable is 2.75, so a two standard deviation shock in the size of the family that the fund belongs to leads to about a 3.85 basis points movement in the fund's performance next month (or about 46 basis points movement annual) depending on the performance measure used. The effect is smaller than that of fund size on returns but is nonetheless statistically and economically significant. In other words, assets under management are not bad for a fund organization's performance per se.

In Table 6, we extend our analysis of the effect of family size on fund returns by seeing whether this effect varies across fund styles. Our hope is that family size is just as important for Small Cap Growth funds as for other funds. After all, it is these funds that are most affected by scale. For us to claim that scale is not bad per se, even accounting for liquidity, we would like to find that the benefits of family size are derived by even funds that are most affected by liquidity. To see whether this is the case, we augment the regression specification in Table 5 by adding an interaction term involving

LOGFAMSIZE and the dummy indicator $Ind_{\{not\ SCG\}}$ (that equals one if a fund is not Small Cap Growth and zero otherwise). The variable of interest is the coefficient in front of this interaction term.

Panel A presents the regression results for funds in fund size quintiles two to five. The coefficient in front of this interaction term is positive but is not statistically significant. In other words, it does not appear that there are major differences between the effect of family size on performance among Small Cap Growth funds and other funds. This finding is consistent with our story. To make sure that this finding holds more generally, we re-estimate this regression specification using all funds. Now, the coefficient in front of the interaction term is negative, but is again not statistically significant. Using either sample, it does not appear that the effect of family size is limited to Not Small Cap Growth funds. So we can be assured that funds do benefit from being part of a large family.

These findings, fund performance declines with own fund size but increases with the size of the other funds in the family, fit nicely with anecdotal evidence from industry practitioners (see, e.g., Pozen (1998), Fredman and Wiles (1998)). One plausible interpretation of the family size finding is that it is capturing economies of scale associated with marketing. However, this begs the question of why a fund's expense ratio is not capturing this scale effect since a fund's expense ratio is on the right hand size of the cross-sectional fund return regressions.

It turns out that the expense ratio reported by mutual funds only accounts for management, administrative and marketing fees.[12] Trading commissions charged by brokers and lending fees for (shorting) stocks are not treated as part of expenses but are simply deducted or added onto income and hence net returns. It is well known that there are tremendous economies associated with trading commissions and lending fees at the family level. Bigger families like Fidelity are able to get better concessions on trading commissions and earn higher lending fees for the stocks held by their funds.

It is difficult to figure out these trading commissions because families bury them in their fund prospectuses. Nonetheless, practitioners believe these costs are substantial and can be as much as a couple of percent a year. Hence, the spread in performance

[12] See Hechinger (2004) for a detailed discussion of mutual fund expense accounting.

between funds belonging to large versus those in small families can be easily accounted for by the economies of scale in trading commissions and lending fees at the family level.[13]

Importantly, according to industry anecdotes, in most families, major decisions are decentralized in that the fund managers make stock picks without substantial coordination with other managers. Managers in charge of different funds choose stocks as they see fit without worrying about resources being taken away from them by the family. So a family is an organization that credibly commits to letting each of its fund managers run their own assets.

As such, the family size finding makes clear that liquidity and scale need not be bad for fund performance depending on how the fund is organized. After all, if a large fund is organized like a fund family with a bunch of little funds run by different managers, then scale need not be bad per se, just as family size does not appear to be bad for family performance.

More importantly, the finding regarding family size also helps us to further rule out alternative hypotheses related to managers of large funds not caring about maximizing net returns. This line of argument is not likely behind our findings since managers in large families apparently do care enough about net fund returns to make sufficient investments to maintain performance at the family level. Moreover, most of the extant evidence on fund flows indicate that managers care about net fund returns since better past returns lead to larger assets under management (see, e.g., Sirri and Tufano (1998) and Lynch and Musto (2003)).

D. Organizational Diseconomies and Fund Performance

If managers care about net fund returns and scale need not be bad for performance per se, why then does it appear that scale erodes fund performance because of liquidity? We hypothesize that in addition to liquidity, fund size erodes performance because of organizational diseconomies. To make things concrete, imagine that there is a small fund

---

[13]IvKovic (2002) argues that being part of a large family may improve performance because of other spillovers. In his analysis of family size, he happened to control for fund size and found that fund size indeed erodes performance. Though the goal of his paper was not to examine fund size, it is comforting to know that some of our baseline results have been independently verified.

company X with one fund operated by one manager who picks the stocks. Since the fund is small, the manager can easily invest the assets under management by generating a few stock ideas. Now imagine that there is a large fund Y in which the manager no longer has the capacity to invest all the money. So the manager needs other co-managers to help him run the fund. For fund Y, the stock picks need to be coordinated among many more agents and therefore organizational form (e.g. flat versus hierarchical forms) becomes important. So organizational diseconomies may arise.

There are many types of organizational diseconomies that lead to different predictions on why small organizations outperform large ones. One set of diseconomies, from the work of Williamson (1975, 1988), includes bureaucracy and related coordination costs. Another set of diseconomies comes from the influence-cost literature (see, e.g., Milgrom and Roberts (1988)). Yet another set of diseconomies centers on the adverse effects of hierarchies (or authority) for the incentives of agents who do not have any control over asset-allocation decisions (see, e.g., Aghion and Tirole (1997), Stein (2002)).

Interestingly, the findings in Tables 3 and 6 already allow us to discriminate among different types of organizational diseconomies. For instance, if Williamsonian diseconomies are behind the relationship between size and performance, then one expects that funds that belong to large families do worse, since bureaucracy ought to be more important in huge fund complexes. The fact that we do not find this indicates that bureaucracy is not likely an important reason behind why performance declines with fund size.

We conjecture that hierarchy costs may be especially relevant for mutual funds. We take a closer look at the effect of organizational diseconomies due to hierarchy costs on fund performance by testing some predictions from Stein (2002). Stein (2002) argues that in the presence of such hierarchy costs, small organizations ought to outperform large ones at tasks that involve the processing of soft information, (i.e., information that cannot be directly verified by anyone other than the agent who produces it). The basic premise is that in larger organizations with hierachies, the process of agents fighting to have their ideas implemented will affect outcomes. If the information is soft, then agents have a hard time convincing others of their ideas and it is more difficult to pass this information up the organization.[14]

In the context of mutual funds, this means that in funds in which managers fight to have their ideas implemented, efforts to uncover certain investment ideas in this setting are diminished relative to a situation in which the managers control their own smaller funds. For instance, managers may end up expending too much research effort on quantitative measures of a company (i.e. hard information) so as to convince others to implement their ideas even though more time and effort might ideally be invested in talking to CEOs of companies and getting an impression of them (i.e. soft information). All else equal, large funds may perform worse than small ones.

Note that one of our previous results---that fund performance does not decline with family size---is consistent with Stein (2002) since hierarchy costs are not present at the family level precisely because the family typically commits to not re-allocating resources across funds. Different funds in a family have their own boards that deal with issues such as managerial replacement. So the manager in charge of a fund generally does not have to worry about the family taking away its resources and giving it to some other fund in the family.

Below, we test several predictions of Stein (2002) to see if the inverse relationship between fund size and performance is indeed influenced by organizational diseconomies.

D.1 Fund Size and Fund Investments

One prediction of Stein (2002) is that we expect that small funds are better than large ones, which are more likely to have hierarchies, at the processing of soft information. To test this prediction, we compare the investments of large and small funds in local stocks (companies located near where a fund is headquartered). Investing in such

[14] Stein's analysis also indicates that large organizations may actually be very efficient at processing hard information. In the context of the mutual fund industry, one can think of passive funds that mimic indices as primarily processing hard information. As such, one would expect these types of funds to not be very much affected by scale. Two pieces of evidence are consistent with this prediction. First, Vanguard seems to dominate the business for index funds. Indeed, for indexers, being large is an asset since one can then acquire better tracking technologies and better computer programmers. Second, our evidence in Table 5, that fund size only affects small cap funds, is consistent with this observation since most index funds, which tend to mimic the S&P 500 index, trade predominantly large stocks.

companies requires that the organization process soft information as opposed to a strictly quantitative investing approach, which would typically process hard information like price-to-earnings ratios.

Our work in testing this prediction builds on the very interesting work of Coval and Moskowitz (1999, 2001) whose central thesis is that mutual fund managers do have ability when it comes to local stocks. Anecdotal evidence indicates that this ability comes in the form of processing soft information like talking and evaluating CEOs of local companies. They find that funds can earn superior returns on their local investments. We focus on the effect of size on investment among small cap funds. We are also interested in the effect of family size on the composition of fund investments.

The CDA Spectrum Database does not have the same information on fund characteristics as the CRSP Mutual Fund Database. Luckily, we are able to construct from the fund stock holdings data a proxy for fund size, which is simply the value of the fund's stock portfolio at the end of a quarter. While this is not exactly the same as asset base since funds hold cash and bonds, we believe that the proxy is a reasonable one since we can look at the tails of the size distribution to draw inferences, i.e. compare very small funds to other funds. Moreover, the noise in our fund size measure does not obviously bias our estimates.

In addition, we can construct better style controls for each fund by looking at their stock holdings. We use a style measure constructed by Daniel, Grinblatt, Titman and Wermers (1997), which we call the DGTW style adjustments. For each month, each stock in our sample is characterized by where they fall in the (across stocks) size quintiles, book-to-market quintiles and price momentum quintiles. So a stock in the bottom of the size, book-to-market and momentum quintiles in a particular month would be characterized by a triplet (1,1,1). For each fund, we can characterize its style along the size, book-to-market and momentum dimension by taking the average of the DGTW characteristics of the stocks in their portfolio weighted by the percentage of the value of their portfolio that they devote to each stock. We can then define a small cap fund as one whose DGTW size measure falls in the bottom 10 percent when compared to other funds.

Table 7 reports the effect of fund size on the percentage of the value of a fund's portfolio devoted to local stocks, where locality is defined relative to the headquarters of the funds as in Coval and Moskowitz (1999, 2001). More specifically, a stock is considered a local fund investment if the headquarter of the company is in the same Census region as the mutual fund's headquarter.[15] The dependent variable is the value of the local stocks in the fund portfolio divided by the total value of the stocks in the fund portfolio. The first independent variable is SMALLFUND, which is a dummy variable that equals one if the fund is in the bottom 10% of the fund size distribution. SMALLCAPFUND equals one if a fund has an average DGTW size score for its stocks that is in the bottom 10% across funds. The regressions always have Fund City Effects (i.e. the city where the fund is headquartered) as controls.

From column (1), small funds are more likely to invest a larger percentage of their portfolio in local stocks, as do small cap funds. The average percentage of stocks that are local in a funds' portfolio is 16.57%. The coefficient on SMALLFUND is 0.0759. That means that being a small fund increases the amount of local stocks a fund owns by 0.0759 divided by 0.1657 or 46%. In column (2), the coefficient of interest is the interaction term involving small and small cap funds. It is positive and statistically significant which is consistent with our conjecture. The coefficient of 0.1244 means that being a small fund and a small cap fund raises the percentage of local stock investments on average by 0.1244 divided by 0.1657 or 75%.

One interesting question is the degree to which family size affects a fund's investment policy. In column (3), we add a family size proxy as measured by the number of funds in the family. The coefficient in front of this variable is positive but the economic magnitude is small and it only attracts a t-stat of 1. In other words, family size does not have an effect on whether a fund invests in local stocks. If we defined family size as the log of the assets of the other funds in the fund's family, then we get similarly small economic magnitudes and t-stats near zero. For brevity, we omit these additional results. Again, one can interpret this result as consistent with Stein's model to the extent that fund size has an effect on fund action but not family size.

---

[15] There are nine Census regions: New England (CT, ME, NH, RI, VT); Middle Atlantic (NJ, NY, PA); East North Central (IL, IN, MI, OH, WI); West North Central (IA, KS, MN, MO, NE, ND, SD); South Atlantic (DE, FL, GA, MD, NC, SC, VA, WV); East South Central (AL, KY, MS, TN); West South Central (AR, LA, OK, TX); Mountain (AZ, CO, ID, MT, NE, NM, UT, WY); and Pacific (AK, CA, HI, OR, WA).

However, these findings may also be consistent with larger funds having more resources to travel to visit companies that are not located nearby. To distinguish between this explanation and our preferred explanation that small funds and funds belonging to larger families are better at the processing of soft information, we see in Table 8 whether the local stocks picked by small funds do better than those picked by large funds. The dependent variable is the return to the fund's investments in local stocks. In column (1), we find that small funds and small cap funds not only invest more of their assets in local stocks but also do better at investing in them. The standard deviation of local stock investment returns in our sample is 0.2077. So being a small fund raises local return by 0.0258 divided by 0.2077 or 12% of a standard deviation. In column (2), we add an interaction term involving these two variables and find that the performance difference between small funds and other funds is especially big in small cap funds. In column (3), we add in a family size proxy as measured by the number of funds in the family. The coefficient is positive but is statistically insignificant. So a fund that belongs to a large family does not do better in their local stock investments. Similar results obtain using total net assets for the family.

The findings in Table 8 suggest that the performance differences between small and large funds have something to do with their different ability to invest in local stocks. Note that Tables 7 and 8 only report the results using the cross-section in September 1997. We have replicated our analysis using the other quarters in the period of 1997 to 1998. The results are very robust across quarters.

D.2 Management Structure and the Composition of Fund Investments

Perhaps a more direct implication of Stein's model is to look at the relationship between the management structure of a fund and the fund's investments. To the extent that a fund is co-managed (managed by a team) means that there is more fighting to implement ideas, then we should find that controlling for fund size, funds run by committee should invest less in local stocks (i.e. managers should pitch hard-information stock ideas) and do worst in these soft-information stocks.

To test this prediction, we obtain data on the number of managers running a fund for the cross-section of funds described in Tables 7 and 8. In the CRSP database, there is a field which lists the names of managers that are in charge of picking stocks. We create a new variable MT, which captures how many managers are running the fund. If there is only one name, then MT equals 1. If there are two names, then MT equals 2 and so forth. The maximum number of names in the database is four. Moreover, a small fraction of the funds are listed as "Team Managed". For these funds, we set MT equal to 4 as well. So, MT can takes on values of 1, 2, 3 or 4. From reading the prospectuses of various funds, it appears that funds that have co-managers do make decisions within a committee. We lose a fraction of the cross-section of funds in Tables 7 and 8 because some funds did not have entries in the manager field.

In Table 9, we consider the effect of managerial structure on the composition of fund investments in local stocks and the performance of these local investments. The first column of Table 9 is similar to those in Table 7 except that we have added a dummy variable MULTI-MANAGER, which equals 1 when MT is greater than 1 and is zero otherwise, as an additional explanatory variable. Moreover, since we are concerned with isolating the effect of managerial structure, we have introduced into this regression very conservative fund size, family size and style controls. Even with these conservative controls, the coefficient in front of MULTI-MANAGER is -0.012 with a t-stat of 1.75. In other words, a solo-managed fund is significantly more likely to invest in local stocks than team-managed funds. The economic magnitude is smaller than that of being a small fund but is still economically interesting. In this sample, the average percentage of stocks that are local in a funds' portfolio is 15.2%. Since the coefficient on MULTI-MANAGER is -0.012, this means that being a committee-managed fund decreases the amount of local stocks a fund owns by 0.012 divided by 0.152 or about 8%.

The second column of Table 9 is similar to those in Table 8 except that we have added the variable MULTI-MANAGER as an additional explanatory variable for the performance of fund local investments. Again, we have introduced into this regression very conservative fund size, family size and style controls. The coefficient in front of MULTI-MANAGER is -0.0190 with a t-stat of 1.73, suggesting that co-managed funds also do worst at picking local companies. The standard deviation of local stock investment returns in this sample is 0.186. So being a committee-managed fund decreases local return by 0.0190 divided by 0.186 or 10% of a standard deviation. Both findings are consistent with Stein's model.

D.3 Management Structure and Fund Performance

Finally, we look to see whether solo-managed funds out-perform team-managed ones after controlling for fund size. Our prior is that organization form might be a less powerful predictor of performance than size. The reason is that few managers would turn away more money even if it hurts net fund returns for investors. But conditional on a certain fund size, one might think that the fund would choose the better organizational form to maximize net fund returns. In other words, conditional on size, form may be a less powerful predictor of performance. Moreover, we are much more limited in terms of data when looking at the effect of managerial structure on fund performance. Whereas we are able to obtain data on fund size back to the sixties, we are only able to obtain data on managerial structure back to 1992 because the data on how many managers are running a fund is unavailable from CRSP before 1992. As before, we create the MT variable for as many funds as we can back to 1992. Despite these caveats, it is nonetheless interesting to look at the effect of managerial structure on fund performance.

The result for the effect of management structure on fund returns is given in Table 10. The upshot is that all the previous results regarding fund size continue to hold. For instance, the coefficient in front of fund size is the same as in Table 3. Now, we find that funds run by committee under-perform by about 4 basis points a month or 48 basis points a year. This effect is economically smaller than the effect of fund size but is statistically significant. Again, this finding on performance is consistent with Stein's model.

V. Alternative Explanations and Further Discussions

In Section IV, we have already ruled out a number of alternative explanations for our findings in establishing the role of liquidity and organization in influencing the relationship between fund size and performance. In this section, we discuss additional alternative explanations. One institutional reason for our finding may be that it is easier for fund families to manipulate the performance of small funds in small cap stocks. While this alternative explanation is possible, we do not think that it is driving our results for several reasons. First, we exclude the very smallest funds for which this is likely and our results are unchanged. Moreover, in analysis that is not reported for reasons of brevity, we have also dropped out very young funds, for which such manipulation is most likely and our results are again unchanged. Finally, such manipulation cannot account for the relationship between fund size and the composition of fund investments as well as the relationship between managerial structure and fund investments and performance documented in Section IV.D.

Besides such institutional reasons, it may be the case that our findings are due to other organizational-related issues as well the hierarchy cost hypothesis presented in Section IV.D. For instance, many managers often talk about how difficult it is train new hires when their fund gets big and they need to find help. We view such comments as broadly supportive of our contention that organization matters for fund performance.

Ideally, we would like to have information about the incentives inside fund organizations. For instance, our hierarchy cost hypothesis also suggests that a crucial unobservable determinant of fund performance is the nature of the incentives inside the fund. More concretely, suppose that the organizational diseconomies are due to the adverse effects of a hierarchy on managerial effort. Then an optimal organizational structure is to limit managers to a small pot of money and let them manage it as they choose. With such an organizational structure, scale may not affect performance. This is exactly what happens at the family level and probably why performance does not decline with family size.

Our analysis here is similar to the work of Berger, Miller, Petersen, Rajan and Stein (2002). They test the idea in Stein (2002) that small organizations are better than large ones in activities that require the processing of soft information in the context of bank lending to small firms. They find that large banks are less willing than small ones to lend to informationally difficult credits such as firms that do not keep formal financial records. They also find that large banks lend at a greater distance, interact more impersonally with their borrowers, have shorter and less exclusive relationships and do not alleviate credit constraints as effectively. Interestingly, they find that the size of the bank-holding company that a bank belongs to does not affect the lending policies of the bank. In other words, size itself is not necessarily bad for banks. This finding is related to our finding regarding the neutral to beneficial effects of family size on fund performance. They argue that their findings are most consistent with the property-rights approach of Grossman-Hart-Moore regarding the disadvantages of integration.

Our paper is also related to other papers that attempt to test the basic Grossman-Hart-Moore insight in particular settings. Notable examples include Baker and Hubbard (2000) whose work centers on the trucking industry and the question of whether drivers should own the trucks they operate and Simester and Wernerfelt (2000) who look at the ownership of tools in the carpentry industry.

VI. Conclusion

To the best of our knowledge, we are the first to find strong evidence that fund size erodes performance. We then move on to consider various explanations for why this might be the case. We find that this relationship is not driven by heterogeneity in fund styles, fund size being correlated with other observable fund characteristics, or any type of survivorship bias. Instead, we find that the effect of fund size on fund returns is most pronounced for funds that play small cap stocks. This suggests that liquidity is an important reason behind why size erodes performance. Moreover, we argue that organizational diseconomies related to hierarchy costs may also play a role in addition to liquidity in the documented diseconomies of scale. Consistent with this view, we find that the size of a fund's family does not significantly erode fund performance. Finally, using data on whether funds are solo-managed or team-managed and the composition of fund investments, we find that organizational diseconomies affects the relationship between fund size and performance along the lines predicted by Stein (2002).

Importantly, our findings have relevance for the ongoing research into the question of Coase (1937) regarding the determinants of the boundaries of the firm. While an enormous amount of theoretical research has been done on this question, there has been far less empirical work. Our findings suggest that mutual funds may be an invaluable laboratory with which to study related issues in organization. Unlike most corporations, data on mutual funds are plentiful because of disclosure regulations and the tasks and performance of mutual funds are measurable. We plan to better refine our understanding of the nature of organizations in the future using this laboratory.

References

Aghion, Philippe and Jean Tirole, 1997, Formal and real authority in organizations, *Journal of Political Economy* 105, 1-29.

Almazan, Andres, Keith C. Brown, Murray Carlson and David A. Chapman, 2001, Why constrain your mutual fund manager?, University of Texas Working Paper.

Baker, George P. and Thomas Hubbard, 2000, Contractibility and asset ownership: Onboard computers and governance in US trucking, NBER Working Paper #7634.

Becker, Stan and Greg Vaughan, 2001, Small is beautiful, *Journal of Portfolio Management* (Summer), 9-17.

Berger, Allen N., Nathan H. Miller, Mitchell A. Petersen, Raghuram G. Rajan, and Jeremy C. Stein, 2002, Does function follow organizational form? Evidence from the lending practices of large and small banks, Harvard University Working Paper.

Berk, Jonathan and Richard C. Green, 2002, Mutual fund flows and performance in rational markets, U.C. Berkeley Working Paper.

Bolton, Patrick, and David S. Scharfstein, 1998, Corporate finance, the theory of the firm, and organizations, *Journal of Economic Perspectives* 12, 95-114.

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

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance*, Vol. LII, 57-82.

Chen, Joseph, Harrison Hong and Jeremy C. Stein, 2002, Breadth of ownership and stock returns, *Journal of Financial Economics* 66, 171-205.

Chevalier, Judith A., and Glenn D. Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167-1200.

Chevalier, Judith A., and Glenn D. Ellison, 1999, Career concerns of mutual fund managers, *Quarterly Journal of Economics* 114, 389-432.

Coase, Ronald H., 1937, The nature of the firm, *Economica* 4, 386-405.

Coval, Joshua D. and Tobias J. Moskowitz, 1999, Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 2045-2074.

Coval, Joshua D. and Tobias J. Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 4, 811-841.

Daniel, Kent, Mark Grinblatt, Sheridan Titman and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance*, 52, 1035-1058.

Elton, Edwin J., Martin J. Gruber and Christopher R. Blake, 2001, A first look at the accuracy of the CRSP Mutual Fund Database and a comparison of the CRSP and Morningstar Mutual Fund Databases, *Journal of Finance*, Vol. LVI, 2415-2430.

Falkenstein, Eric G., 1996, Preferences for stock characteristics as revealed by mutual fund portfolio holdings, *Journal of Finance*, 51, 111-135.

Fama, Eugene F. and French, Kenneth R., 1993, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F. and MacBeth, James D., 1973, "Risk, Return and Equilibrium: Empirical Tests," *Journal of Political Economy* 81, 607-636.

Fredman, Albert J. and Russ Wiles, 1998, *How Mutual Funds Work*, (Prentice Hall, New Jersey).

Gompers, Paul and Andrew Metrick, 2001, "Institutional investors and equity prices," *Quarterly Journal of Economics* 116, 229-259.

Grinblatt, Mark and Sheridan Titman, 1989, Mutual fund performance: An analysis of quarterly portfolio holdings, *Journal of Business* 62, 393-416.

Grinblatt, Mark, Sheridan Titman and Russ Wermers, 1995, Momentum investment strategies, portfolio performance and herding: A study of mutual fund behavior, *American Economic Review*, 85, 1088-1105.

Grossman, Sanford J. and Oliver D. Hart, 1986, The costs and benefits of ownership: A theory of vertical and lateral integration, *Journal of Political Economy* 94, 691-719.

Gruber, Martin J., 1996, Another puzzle: The growth in actively managed mutual funds, *Journal of Finance*, Vol. LI, 783-810.

Hart, Oliver D., 1995, *Firms, Contracts and Financial Structure* (Oxford University Press, Oxford).

Hart, Oliver D. and John Moore, 1990, Property rights and the nature of the firm, *Journal of Political Economy* 98, 1119-1158.

Hechinger, John, 2004, Deciphering funds' hidden costs, *Wall Street Journal*, March 17, D1-D2.

Holmstrom, Bengt and John Roberts, 1998, The boundaries of the firm revisited, *Journal of Economic Perspectives* 12, 73-94.

Hong, Harrison, Jeffrey D. Kubik, and Amit Solomon, 2000, Security analysts' career concerns and the herding of earnings forecasts, *RAND Journal of Economics* 31, 121-144.

Hong, Harrison, Terence Lim and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance*, Vol. LV, 265-295.

Investment Company Institute, 2000, *Mutual Fund Fact Book*, (Investment Company Institute: Washington DC).

IvKovic, Zoran, 2002, Spillovers in mutual fund families: Is blood thicker than water? University of Illinois Working Paper.

Jegadeesh, Narasimhan and Titman, Sheridan, 1993, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance* 48, 93-130.

Jensen, Michael C., 1968, The performance of mutual funds in the period 1945-1964, *Journal of Finance*, 50, 549-572.

Lowenstein, Roger, 1997, Frightened funds: Is there a master in the house?, *Wall Street Journal*.

Lynch, Anthony W. and David Musto, 2003, How investors interpret past fund returns, *Journal of Finance*, forthcoming.

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

Milgrom, Paul R. and John Roberts, 1988, An economic approach to influence activities in organizations, *American Journal of Sociology* 94 *Supplement*, 154-179.

Newey, Whitney K. and Kenneth D. West, 1987, A simple positive-definite heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Perold, Andre and Robert S. Salomon, 1991, The right amount of assets under management, *Financial Analysts Journa*l, 47, 31-39.

Pozen, Robert C., 1998, *The Mutual Fund Business*, (Cambridge, Mass: MIT Press).

Prather, Larry J. and Karen 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.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425-42.

Simester, Duncan and Birger Wernefelt, 2000, Determinants of asset ownership: A study of carpentry trade, Working Paper, MIT.

Sirri, Eric R and Peter Tufano, 1998, Costly search and mutual fund inflows, *Journal of Finance* 53, 1589-1622.

Stein, Jeremy C., 2002, Information production and capital allocation: Decentralized vs. hierarchical firms, *Journal of Finance*, forthcoming.

Wermers, Russ, 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs and expenses, *Journal of Finance*, Vol. LV, 1655-1695.

Williamson, Oliver E., 1975, *Markets and Hierarchies: Analysis and Antitrust Implications*, (Collier MacMillan, New York).

Williamson, Oliver E., 1988, Corporate finance and corporate governance, *Journal of Finance*, 43, 567-591.

Zheng, Lu, 1999, Is money smart? A study of mutual fund investors' fund selection ability, *Journal of Finance*, Vol. LIV, 901-933.

Table 1: Summary Statistics

This table reports summary statistics for the funds in our sample. The Number of Funds is the number of mutual funds that meet our selection criteria for being an active mutual fund in each month. TNA is the total net assets under management in millions of dollars. LOGTNA is the logarithm of TNA. LOGFAMSIZE is the logarithm of one plus the assets under management of the other funds in the family that the fund belongs to (excluding the asset base of the fund itself). TURNOVER is fund turnover, defined as the minimum of aggregate purchases and sales of securities divided by the average TNA over the calendar year. AGE is the number of years since the organization of the fund. EXPRATIO is the total annual management fees and expenses divided by year-end TNA. TOTLOAD is the total front-end, deferred and rear-end charges as a percentage of new investments. FLOW is the percentage new fund flow into the mutual fund over the past year. TNA, LOGFAMSIZE and FLOW are reported monthly. All other fund characteristics are reported once a year. FUNDRET is the monthly market-adjusted fund return. These returns are calculated before (gross) and after (net) deducting fees and expenses. Panel A reports the time-series averages of monthly cross-sectional averages and monthly cross-sectional standard deviations (shown in brackets) of fund characteristics. Panels B and C report the time-series averages of the cross-sectional correlations between fund characteristics. Panel D reports the time-series averages of monthly cross-sectional averages of market-adjusted fund returns. In Panels A and B, fund size quintile 1 (5) has the smallest (largest) funds. The sample is from January 1963 to December 1999.

Panel A: Time-series averages of cross-sectional averages and standard deviations.

	Mutual Fund Size Quintile					All	Quintiles
	1	2	3	4	5	Funds	2-5
Number of Funds	148.2	147.8	147.8	147.8	147.3	741.4	590.6
TNA	4.7	22.2	60.6	165.4	1164.7	282.5	352.3
($ million)	[3.2]	[7.2]	[16.6]	[54.8]	[1797.1]	[925.8]	[1022.7]
LOGTNA	1.09	2.94	3.96	4.94	6.45	3.87	4.57
($ million)	[1.01]	[0.34]	[0.27]	[0.33]	[0.75]	[1.92]	[1.38]
LOGFAMSIZE	3.70	4.52	5.29	5.91	7.00	5.28	5.68
($ million)	[2.98]	[2.89]	[2.72]	[2.56]	[2.16]	[2.92]	[2.75]
TURNOVER	42.07	55.68	59.09	61.20	52.17	54.17	57.07
(% per year)	[83.03]	[74.00]	[68.60]	[64.28]	[54.56]	[71.84]	[67.21]
AGE	8.17	11.90	14.82	18.43	25.16	15.67	17.57
(years)	[8.54]	[10.73]	[12.85]	[14.38]	[15.06]	[13.96]	[14.33]
EXPRATIO	1.29	1.08	0.94	0.85	0.68	0.97	0.89
(% per year)	[1.11]	[0.59]	[0.46]	[0.37]	[0.31]	[0.68]	[0.48]
TOTLOAD	3.41	4.19	4.32	4.57	5.28	4.36	4.59
(%)	[3.32]	[3.32]	[3.34]	[3.39]	[2.88]	[3.36]	[3.32]
FLOW	30.79	30.66	26.97	21.27	13.54	24.67	23.13
(% per year)	[113.55]	[113.36]	[101.66]	[84.08]	[59.04]	[102.64]	[96.60]

Panel B: Time-series averages of (monthly) correlations between fund characteristics.
[Using all funds]

	TNA	LOG-TNA	LOG-FAMSIZE	TURN-OVER	AGE	EXP-RATIO	TOT-LOAD	FLOW
TNA	1.00	0.56	0.24	-0.05	0.27	-0.19	0.10	-0.03
LOGTNA		1.00	0.40	0.06	0.44	-0.31	0.19	-0.07
LOGFAMSIZE			1.00	0.08	0.08	-0.19	0.25	-0.01
TURNOVER				1.00	0.01	0.17	0.05	-0.01
AGE					1.00	-0.13	0.19	-0.18
EXPRATIO						1.00	-0.05	0.08
TOTLOAD							1.00	-0.04
FLOW								1.00

Panel C: Time-series averages of (monthly) correlations between fund characteristics.
[Excluding smallest 20% of funds]

	TNA	LOG-TNA	LOG-FAMSIZE	TURN-OVER	AGE	EXP-RATIO	TOT-LOAD	FLOW
TNA	1.00	0.66	0.23	-0.08	0.24	-0.24	0.09	-0.03
LOGTNA		1.00	0.35	-0.05	0.37	-0.36	0.13	-0.07
LOGFAMSIZE			1.00	0.07	0.03	-0.17	0.22	-0.01
TURNOVER				1.00	-0.04	0.26	0.03	0.01
AGE					1.00	-0.18	0.17	-0.19
EXPRATIO						1.00	0.01	0.10
TOTLOAD							1.00	-0.05
FLOW								1.00

Panel D: Time-series averages of (monthly) cross –sectional averages of market-adjusted fund returns.

	Mutual Fund Size Quintile					All	Quintiles
	1	2	3	4	5	Funds	2-5
FUNDRET	0.09%	0.02%	0.03%	-0.06%	-0.06%	0.01%	-0.02%
(Gross)	[3.04%]	[2.64%]	[2.61%]	[2.46%]	[2.00%]	[2.62%]	[2.48%]
FUNDRET	-0.02%	-0.07%	-0.05%	-0.13%	-0.12%	-0.08%	-0.09%
(Net)	[3.04%]	[2.64%]	[2.61%]	[2.46%]	[2.00%]	[2.62%]	[2.48%]

Table 2: Summary Statistics for Performance Benchmarks

This table reports the loadings of the five (equal-weighted) TNA-sorted fund portfolios on various factors. Panel A reports the summary statistics for the factors. VWRF is the return on the CRSP value-weighted stock index in excess of the one-month Treasury rate. SMB is the return on a portfolio of small stocks minus large stocks. HML is the return on a portfolio long high book-to-market stocks and short low book-to-market stocks. MOM12 is the return on a portfolio long stocks that are past twelve-month winners and short those that are past twelve-month losers. Panel B reports the loadings calculated using the CAPM. Panel C reports the loadings calculated using the Fama-French (1993) 3-Factor model and this model augmented with the momentum factor (4-Factor model). The sample period is from January 1963 to December 1999.

Panel A: Summary statistics of the factors.

Factor	Mean return	SD of return	Cross-correlations			
			VWRF	SMB	HML	MOM12
VWRF	0.58%	4.37%	1.00	0.32	-0.39	-0.02
SMB	0.17%	2.90%		1.00	-0.16	-0.30
HML	0.34%	2.63%			1.00	-0.15
MOM12	0.96%	3.88%				1.00

Panel B: Loadings calculated using the CAPM

	CAPM	
Portfolio	Alpha	VWRF
1 (small)	0.04%	0.87
2	-0.02%	0.91
3	-0.01%	0.93
4	-0.09%	0.92
5 (large)	-0.07%	0.91

Panel C: Loadings calculated using the 3-Factor model and the 4-Factor model

	3-Factor model				4-Factor model				
Portfolio	Alpha	VWRF	SMB	HML	Alpha	VWRF	SMB	HML	MOM12
1 (small)	0.01%	0.82	0.29	0.03	-0.02%	0.82	0.30	0.04	0.03
2	-0.03%	0.84	0.27	-0.01	-0.09%	0.85	0.30	0.00	0.05
3	0.01%	0.87	0.22	-0.05	-0.06%	0.87	0.25	-0.03	0.06
4	-0.06%	0.87	0.18	-0.05	-0.13%	0.87	0.20	-0.04	0.06
5 (large)	-0.05%	0.88	0.08	-0.06	-0.10%	0.88	0.10	-0.05	0.05

Table 3: Regression of Fund Performance on Lagged Fund Size

This table shows the Fama-Macbeth (1973) estimates of monthly fund returns regressed on fund characteristics lagged one month. The sample includes only funds that fall within fund size quintiles two to five. Fund returns are calculated before (gross) and after (net) deducting fees and expenses. These returns are adjusted using the market model, the CAPM, the Fama-French (1993) 3-Factor model, and the 4-Factor model. The dependent variable is FUNDRET. LOGTNA is the natural logarithm of TNA. LOGFAMSIZE is the natural logarithm of one plus the size of the family that the fund belongs to. TURNOVER is fund turnover and AGE is the number of years since the organization of the mutual fund. EXPRATIO is the total annual management fees and expenses divided by TNA. TOTLOAD is the total front-end, deferred and rear-end charges as a percentage of new investments. FLOW is the percentage new fund flow into the mutual fund over the past one year. LAGFUNDRET is the cumulative (buy-hold) fund return over the past twelve months. The sample is from January 1963 to December 1999. The t-statistics are adjusted for serial correlation using Newey-West (1987) lags of order three and are shown in parentheses.

	Gross fund returns				Net fund returns			
	Market-Adj	Beta-Adj	3-Factor	4-Factor	Market-Adj	Beta-Adj	3-Factor	4-Factor
INTERCEPT	0.056	0.087	0.080	0.019	0.026	0.056	0.049	-0.011
	(0.96)	(1.63)	(1.28)	(0.30)	(0.44)	(1.05)	(0.79)	(0.18)
$LOGTNA_{i,t-1}$	-0.028	-0.028	-0.023	-0.020	-0.025	-0.025	-0.020	-0.018
	(3.02)	(3.04)	(2.42)	(2.15)	(2.75)	(2.76)	(2.16)	(1.89)
$LOGFAMSIZE_{i,t-1}$	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007
	(2.26)	(2.27)	(2.22)	(2.21)	(2.33)	(2.34)	(2.29)	(2.28)
$TURNOVER_{i,t-1}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.85)	(0.86)	(0.85)	(0.83)	(0.77)	(0.78)	(0.77)	(0.75)
$AGE_{i,t-1}$	-0.001	-0.001	-0.001	-0.001	0.000	0.000	-0.001	-0.001
	(0.62)	(0.62)	(0.64)	(0.63)	(0.52)	(0.53)	(0.55)	(0.54)
$EXPRATIO_{i,t-1}$	-0.004	-0.004	-0.007	-0.007	-0.039	-0.038	-0.041	-0.041
	(0.11)	(0.09)	(0.18)	(0.18)	(0.97)	(0.95)	(1.04)	(1.05)
$TOTALLOAD_{i,t-1}$	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(1.26)	(1.25)	(1.26)	(1.29)	(1.21)	(1.20)	(1.21)	(1.25)
$FLOW_{i,t-1}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.50)	(0.50)	(0.51)	(0.49)	(0.47)	(0.47)	(0.48)	(0.46)
$LAGFUNDRET_{i,t-1}$	0.029	0.028	0.028	0.029	0.029	0.029	0.029	0.029
	(6.00)	(5.98)	(6.00)	(5.99)	(6.03)	(6.01)	(6.03)	(6.02)
No. of months	444	444	444	444	444	444	444	444

Table 4: Regression of Fund Returns on Lagged Fund Size, Robustness Checks

This table presents robustness checks of the regression specification in Table 3. In Panel A, the sample includes all funds. In Panel B, the dependent variable is twelve-month fund returns and the regressions are non-overlapping. In Panel C, the sample consists of only observations from 1963 to 1980. In Panel D, the sample consists of only observations from 1981 to 1999. LOGTNA is the natural logarithm of TNA. LOGFAMSIZE is the natural logarithm of one plus the size of the family that the fund belongs to. Estimates of the intercept and other independent variables are omitted for brevity. The other independent variables include TURNOVER, AGE, EXPRATIO, TOTLOAD, FLOW, and LAGFUNDRET. The t-statistics are adjusted for serial correlation using Newey-West (1987) lags of order three and are shown in parentheses.

Panel A: Sample includes all funds

	Gross fund returns				Net fund returns			
	Market-Adj	Beta-Adj	3-Factor	4-Factor	Market-Adj	Beta-Adj	3-Factor	4-Factor
$LOGTNA_{i,t-1}$	-0.023	-0.026	-0.019	-0.021	-0.020	-0.022	-0.015	-0.017
	(2.59)	(2.94)	(2.22)	(2.48)	(2.16)	(2.49)	(1.76)	(2.02)
$LOGFAMSIZE_{i,t-1}$	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
	(1.99)	(2.03)	(1.99)	(2.05)	(2.10)	(2.15)	(2.11)	(2.17)
No. of months	444	444	444	444	444	444	444	444

Panel B: Dependent variable is twelve-month (non-overlapping) fund returns

	Gross fund returns				Net fund returns			
	Market-Adj	Beta-Adj	3-Factor	4-Factor	Market-Adj	Beta-Adj	3-Factor	4-Factor
$LOGTNA_{i,t-1}$	-0.436	-0.440	-0.345	-0.312	-0.402	-0.406	-0.312	-0.280
	(3.26)	(3.27)	(2.40)	(2.19)	(3.07)	(3.07)	(2.20)	(1.99)
$LOGFAMSIZE_{i,t-1}$	0.088	0.089	0.088	0.088	0.090	0.091	0.090	0.090
	(2.05)	(2.06)	(2.05)	(2.07)	(2.10)	(2.12)	(2.11)	(2.12)
No. of years	37	37	37	37	37	37	37	37

Panel C: Sample period is from 1963 to 1980

	Gross fund returns				Net fund returns			
	Market-Adj	Beta-Adj	3-Factor	4-Factor	Market-Adj	Beta-Adj	3-Factor	4-Factor
$LOGTNA_{i,t-1}$	-0.035	-0.034	-0.021	-0.019	-0.032	-0.032	-0.019	-0.016
	(2.41)	(2.42)	(1.51)	(1.33)	(2.22)	(2.23)	(1.32)	(1.15)
$LOGFAMSIZE_{i,t-1}$	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.49)	(0.50)	(0.45)	(0.44)	(0.56)	(0.58)	(0.53)	(0.52)
No. of months	216	216	216	216	216	216	216	216

Panel D: Sample period is from 1981 to 1999

	Gross fund returns				Net fund returns			
	Market-Adj	Beta-Adj	3-Factor	4-Factor	Market-Adj	Beta-Adj	3-Factor	4-Factor
$LOGTNA_{i,t-1}$	-0.021	-0.022	-0.024	-0.022	-0.019	-0.019	-0.022	-0.019
	(1.84)	(1.86)	(1.93)	(1.71)	(1.64)	(1.65)	(1.74)	(1.53)
$LOGFAMSIZE_{i,t-1}$	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012
	(2.53)	(2.53)	(2.50)	(2.50)	(2.55)	(2.55)	(2.52)	(2.52)
No. of months	228	228	228	228	228	228	228	228

Table 5: Effect of Fund Size on Performance by Fund Style

This table reports the Fama-Macbeth (1973) estimates of monthly fund returns regressed on fund characteristics lagged one month. The sample includes only funds that fall within fund size quintiles two to five. Fund returns are calculated before (gross) and after (net) deducting fees and expenses. These fund returns are adjusted using the market model, the CAPM, the Fama-French (1993) 3-Factor model, and the 4-Factor model. In Panel A, the regression specification is the one in Table 3 but augmented with $IND_{\{not\ SCG\}}$, which is a dummy variable that equals one if the self-reported fund style is not Small Cap Growth and zero otherwise and this indicator variable interacted with LOGTNA. In Panel B, instead of $IND_{\{not\ SCG\}}$, we augment the regression with $IND_{\{LC\}}$ which is a dummy variable that equals one if the fund style is identified as a Large Cap fund. The sample is from January 1981 to December 1999. The t-statistics are adjusted for serial correlation using Newey-West (1987) lags of order three and are shown in parentheses.

Panel A: Small Cap Growth Funds

	Gross fund returns				Net fund returns			
	Market-Adj	Beta-Adj	3-Factor	4-Factor	Market-Adj	Beta-Adj	3-Factor	4-Factor
INTERCEPT	0.205	0.257	0.320	0.263	0.175	0.226	0.289	0.231
	(1.27)	(1.53)	(2.44)	(1.98)	(1.08)	(1.34)	(2.20)	(1.75)
$IND_{\{not\ SCG\}}$	-0.250	-0.252	-0.260	-0.262	-0.249	-0.251	-0.259	-0.261
	(1.54)	(1.55)	(1.62)	(1.63)	(1.53)	(1.54)	(1.61)	(1.62)
$LOGTNA_{i,t-1}$	-0.058	-0.058	-0.063	-0.061	-0.055	-0.056	-0.060	-0.058
	(3.15)	(3.17)	(3.40)	(3.29)	(3.03)	(3.05)	(3.28)	(3.17)
$LOGTNA_{i,t-1}$ *	0.040	0.041	0.043	0.044	0.040	0.041	0.043	0.044
$IND_{\{not\ SCG\}}$	(2.36)	(2.39)	(2.53)	(2.56)	(2.35)	(2.37)	(2.52)	(2.55)
$LOGFAMSIZE_{i,t-1}$	0.012	0.012	0.011	0.011	0.012	0.012	0.012	0.012
	(2.57)	(2.57)	(2.54)	(2.54)	(2.59)	(2.59)	(2.57)	(2.56)
$TURNOVER_{i,t-1}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.62)	(1.61)	(1.62)	(1.61)	(1.57)	(1.56)	(1.57)	(1.57)
$AGE_{i,t-1}$	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.98)	(0.97)	(0.98)	(0.97)	(0.87)	(0.87)	(0.88)	(0.87)
$EXPRATIO_{i,t-1}$	-0.018	-0.018	-0.019	-0.019	-0.062	-0.062	-0.064	-0.063
	(0.44)	(0.43)	(0.46)	(0.44)	(1.49)	(1.48)	(1.52)	(1.51)
$TOTALLOAD_{i,t-1}$	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.54)	(0.54)	(0.52)	(0.52)	(0.48)	(0.47)	(0.46)	(0.46)
$FLOW_{i,t-1}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.96)	(0.95)	(0.90)	(0.92)	(1.02)	(1.02)	(0.96)	(0.99)
$FUNDRET_{i,t-1}$	0.022	0.022	0.021	0.021	0.022	0.022	0.022	0.022
	(3.45)	(3.45)	(3.43)	(3.42)	(3.48)	(3.48)	(3.45)	(3.45)
No. of months	228	228	228	228	228	228	228	228

Panel B: Large Cap Funds

	Gross fund returns				Net fund returns			
	Market-Adj	Beta-Adj	3-Factor	4-Factor	Market-Adj	Beta-Adj	3-Factor	4-Factor
INTERCEPT	0.016	0.068	0.128	0.068	-0.017	0.035	0.095	0.034
	(0.19)	(0.84)	(1.72)	(0.92)	(0.20)	(0.43)	(1.27)	(0.47)
$IND_{\{LC\}}$	-0.119	-0.121	-0.119	-0.120	-0.112	-0.114	-0.112	-0.113
	(1.31)	(1.33)	(1.33)	(1.34)	(1.23)	(1.25)	(1.24)	(1.26)
$LOGTNA_{i,t-1}$	-0.029	-0.029	-0.032	-0.029	-0.027	-0.027	-0.029	-0.027
	(2.22)	(2.24)	(2.45)	(2.25)	(2.02)	(2.05)	(2.26)	(2.05)
$LOGTNA_{i,t-1}$ *	0.031	0.031	0.031	0.031	0.030	0.030	0.030	0.030
$IND_{\{LC\}}$	(2.29)	(2.32)	(2.34)	(2.36)	(2.23)	(2.26)	(2.28)	(2.30)
$LOGFAMSIZE_{i,t-1}$	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011
	(2.54)	(2.54)	(2.51)	(2.51)	(2.58)	(2.58)	(2.55)	(2.55)
$TURNOVER_{i,t-1}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.80)	(1.79)	(1.80)	(1.79)	(1.75)	(1.75)	(1.76)	(1.75)
$AGE_{i,t-1}$	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(1.26)	(1.25)	(1.26)	(1.25)	(1.17)	(1.17)	(1.17)	(1.16)
$EXPRATIO_{i,t-1}$	-0.020	-0.019	-0.021	-0.020	-0.065	-0.065	-0.066	-0.065
	(0.49)	(0.48)	(0.52)	(0.50)	(1.63)	(1.62)	(1.66)	(1.64)
$TOTALLOAD_{i,t-1}$	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.35)	(0.35)	(0.34)	(0.35)	(0.30)	(0.30)	(0.29)	(0.29)
$FLOW_{i,t-1}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.84)	(0.82)	(0.77)	(0.79)	(0.89)	(0.88)	(0.83)	(0.85)
$FUNDRET_{i,t-1}$	0.020	0.020	0.020	0.020	0.021	0.020	0.020	0.020
	(3.10)	(3.09)	(3.07)	(3.07)	(3.13)	(3.12)	(3.10)	(3.09)
No. of months	228	228	228	228	228	228	228	228

Table 6: Effect of Family Size on Performance by Fund Style

This table reports the Fama-Macbeth (1973) estimates of monthly fund returns regressed on fund characteristics lagged one month. Fund returns are calculated before (gross) and after (net) deducting fees and expenses. These returns are adjusted using the market model, the CAPM, the Fama-French (1993) 3-Factor model, and the 4-Factor model. The regression specification is the one in Table 5 but augmented with $Ind_{\{not\ SCG\}}$, which is a dummy variable which equals one if the self-reported fund style is Not Small Cap Growth and zero otherwise, interacted with LOGFAMSIZE. Estimates of the intercept and the other independent variables are omitted for brevity. The other independent variables include TURNOVER, AGE, EXPRATIO, TOTLOAD, FLOW, and LAGFUNDRET. The sample is from January 1981 to December 1999. The t-statistics are adjusted for serial correlations using Newey-West (1987) and are shown in parentheses.

Panel A: Fund size quintiles 2-5

	Gross fund returns				Net fund returns			
	Market-Adj	Beta-Adj	3-Factor	4-Factor	Market-Adj	Beta-Adj	3-Factor	4-Factor
$LOGTNA_{i,t-1}$	-0.051	-0.052	-0.056	-0.054	-0.048	-0.049	-0.053	-0.051
	(2.83)	(2.86)	(3.13)	(3.02)	(2.70)	(2.72)	(3.01)	(2.89)
$LOGTNA_{i,t-1}$ *	0.033	0.034	0.036	0.037	0.033	0.033	0.036	0.036
$IND_{\{not\ SCG\}}$	(1.94)	(1.98)	(2.12)	(2.15)	(1.93)	(1.96)	(2.10)	(2.14)
$LOGFAMSIZE_{i,t-1}$	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007
	(0.70)	(0.70)	(0.69)	(0.70)	(0.70)	(0.70)	(0.69)	(0.70)
$LOGFAMSIZE_{i,t-1}$ *	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
$IND_{\{not\ SCG\}}$	(0.41)	(0.41)	(0.41)	(0.40)	(0.42)	(0.42)	(0.42)	(0.41)
No. of months	228	228	228	228	228	228	228	228

Panel B: All fund size quintiles 1-5

	Gross fund returns				Net fund returns			
	Market-Adj	Beta-Adj	3-Factor	4-Factor	Market-Adj	Beta-Adj	3-Factor	4-Factor
$LOGTNA_{i,t-1}$	-0.067	-0.070	-0.071	-0.072	-0.064	-0.067	-0.068	-0.069
	(3.67)	(3.83)	(3.87)	(3.91)	(3.51)	(3.67)	(3.71)	(3.76)
$LOGTNA_{i,t-1}$ *	0.065	0.065	0.067	0.066	0.065	0.065	0.067	0.066
$IND_{\{not\ SCG\}}$	(3.52)	(3.52)	(3.61)	(3.56)	(3.53)	(3.53)	(3.62)	(3.57)
$LOGFAMSIZE_{i,t-1}$	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012
	(1.13)	(1.13)	(1.11)	(1.11)	(1.15)	(1.15)	(1.13)	(1.13)
$LOGFAMSIZE_{i,t-1}$ *	-0.003	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
$IND_{\{not\ SCG\}}$	(0.23)	(0.21)	(0.23)	(0.21)	(0.23)	(0.21)	(0.22)	(0.21)
No. of months	228	228	228	228	228	228	228	228

Table 7: Effect of Fund and Family Size on Investments in Local Stocks

This table shows the effect of fund and family size on mutual fund investments in local stocks. The dependent variable is the percentage of the value of a fund's portfolio invested in local stocks. SMALLFUND equals one if a fund's size is in the bottom 10% of the fund size distribution and zero otherwise. SMALLCAPFUND equals one if a fund's Daniel, Grinblatt, Titman and Wermers (1997) small cap style score is in the bottom 10% across funds. FAMILYSIZE is the number of funds in the family that the fund belongs to. Momentum Effects and Book to Market Effects control for other differences in fund styles. Data is from the end of September 1997. Robust t-statistics are reported in parentheses.

	(1)	(2)	(3)
SMALLFUND	0.0759 (9.49)	0.0580 (6.74)	0.0584 (6.79)
SMALLCAPFUND	0.0515 (6.28)	0.0340 (3.86)	0.0341 (3.88)
SMALLFUND * SMALLCAPFUND		0.1244 (5.58)	0.1229 (5.80)
FAMILYSIZE			0.0001 (1.01)
Momentum Effects	Yes	Yes	Yes
Book to Market Effects	Yes	Yes	Yes
Fund City Effects	Yes	Yes	Yes

Table 8: Effect of Fund and Family Size on the Performance of Investments in Local Stocks

This table shows the effect of fund and family size on the performance of mutual fund investments in local stocks. The dependent variable is the 4-quarter return to fund investments in local stocks. SMALLFUND equals one if a fund's size is in the bottom 10% of the fund size distribution and zero otherwise. SMALLCAPFUND equals one if a fund's Daniel, Grinblatt, Titman and Wermers (1997) small cap style score is in the bottom 10% across funds. FAMILYSIZE is the number of funds in the family that the fund belongs to. Momentum Effects and Book to Market Effects control for other differences in fund styles. Data is from the end of September 1997. Robust t-statistics are reported in parentheses.

	(1)	(2)	(3)
SMALLFUND	0.0258 (1.83)	0.0143 (0.94)	0.0150 (9.87)
SMALLCAPFUND	0.1190 (8.21)	0.1078 (6.95)	0.1079 (6.96)
SMALLFUND * SMALLCAPFUND		0.0795 (2.02)	0.0776 (1.96)
FAMILYSIZE			0.0002 (1.02)
Momentum Effects	Yes	Yes	Yes
Book to Market Effects	Yes	Yes	Yes
Fund City Effects	Yes	Yes	Yes

Table 9: Effect of Management Structure on the Amount and Performance of Investments in Local Stocks

This table shows the effect of fund management structure on the holdings and performance of mutual fund investments in local stocks. The dependent variable in column (1) is the percentage of the value of a fund's portfolio invested in local stocks. The dependent variable in column (2) is the 4-quarter return to fund investments in local stocks. MULTI-MANAGER is an indicator that the fund is managed by more than one person. Fundsize Effects, Family Size Effects, Momentum Effects, Book to Market Effects and Style effects control for other differences in fund styles. Fund City Effects are indicators for the city the fund is located. Data is from the end of September 1997. Robust t-statistics are reported in parentheses.

	Holdings	Returns
	(1)	(2)
MULTI-MANAGER	-0.0102 (-1.75)	-0.0190 (-1.73)
Fundsize Effects	Yes	Yes
Family Size Effects	Yes	Yes
Momentum Effects	Yes	Yes
Book to Market Effects	Yes	Yes
Style Effects	Yes	Yes
Fund City Effects	Yes	Yes

Table 10: Effect of Fund Management Structure on Performance

This table reports the Fama-Macbeth (1973) estimates of monthly fund returns regressed on fund characteristics lagged one month. The sample includes only funds that fall within fund size quintiles two to five. Fund returns are calculated before (gross) and after (net) deducting fees and expenses. These returns are adjusted using the market model, the CAPM, the Fama-French (1993) 3-Factor model, and the 4-Factor model. The regression specification is the one in Table 3 but augmented with $MULTI\text{-}MANAGER_i$, which is a dummy variable that equals one if the fund is managed by two or more individuals or by a team. The sample is from January 1992 to December 1999. The t-statistics are adjusted for serial correlation using Newey-West (1987) lags of order three and are shown in parentheses.

	Gross fund returns				Net fund returns			
	Market-Adj	Beta-Adj	3-Factor	4-Factor	Market-Adj	Beta-Adj	3-Factor	4-Factor
INTERCEPT	-0.069	-0.018	0.039	-0.008	-0.092	-0.042	0.014	-0.032
	(0.66)	(0.19)	(0.25)	(0.05)	(0.88)	(0.44)	(0.09)	(0.21)
$MULTI\text{-}MANAGER_i$	-0.040	-0.040	-0.041	-0.041	-0.040	-0.041	-0.042	-0.042
	(2.22)	(2.23)	(2.30)	(2.30)	(2.26)	(2.27)	(2.34)	(2.34)
$LOGTNA_{i,t-1}$	-0.024	-0.023	-0.026	-0.025	-0.022	-0.022	-0.025	-0.023
	(2.34)	(2.30)	(1.98)	(1.83)	(2.19)	(2.15)	(1.86)	(1.70)
$LOGFAMSIZE_{i,t-1}$	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016
	(2.38)	(2.38)	(2.38)	(2.38)	(2.40)	(2.39)	(2.40)	(2.39)
$TURNOVER_{i,t-1}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.28)	(1.29)	(1.28)	(1.29)	(1.26)	(1.26)	(1.26)	(1.26)
$AGE_{i,t-1}$	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.64)	(0.65)	(0.64)	(0.64)	(0.60)	(0.61)	(0.59)	(0.59)
$EXPRATIO_{i,t-1}$	-0.002	-0.002	-0.003	-0.003	-0.043	-0.043	-0.045	-0.045
	(0.03)	(0.03)	(0.04)	(0.04)	(0.54)	(0.54)	(0.55)	(0.55)
$TOTALLOAD_{i,t-1}$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.28)	(0.29)	(0.30)	(0.29)	(0.36)	(0.36)	(0.37)	(0.37)
$FLOW_{i,t-1}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.64)	(1.68)	(1.68)	(1.69)	(1.64)	(1.68)	(1.68)	(1.69)
$FUNDRET_{i,t-1}$	0.030	0.030	0.029	0.029	0.031	0.030	0.030	0.030
	(3.38)	(3.38)	(3.34)	(3.34)	(3.41)	(3.41)	(3.37)	(3.37)
No. of months	96	96	96	96	96	96	96	96