Liquidity, Investment Style, and the Relation between Fund Size and Fund Performance

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Abstract

Using stock transactions data along with detailed stockholdings for a comprehensive sample of U.S. actively managed equity mutual funds from 1993 to 2002, this paper empirically examines the effect of liquidity and investment style on the relation between fund size and fund performance. Consistent with Chen, Hong, Huang, and Kubik (2004), I find a significant inverse relation between fund size and fund performance. Further, this inverse relation is stronger among funds that hold less liquid portfolios. The inverse relation between fund size and fund performance is also more pronounced among growth and high turnover funds that tend to have high demands for immediacy. Overall, this paper's findings suggest that liquidity is an important reason why fund size erodes performance.

I.   Introduction

Understanding the nature of the economies of scale in the mutual fund industry is central to the long-standing debate over the value of active fund management. Yet there is little agreement among academics or practitioners about how fund size affects fund performance. Some researchers argue that growth in fund size provides cost advantages because brokerage commissions and research costs, as well as administrative and overhead expenses, do not increase in direct proportion to fund size. Supporting this argument is the evidence that fund expense ratios decline with fund size (e.g., Tufano and Sevick (1997)).

Other researchers, however, contend that a large asset base might erode fund performance because of liquidity. Perold and Salomon (1991) argue that there are diseconomies of scale in active fund management stemming from the increased price impact associated with large transactions. Similarly, Becker and Vaughan ((2001), p. 9) argue that as a fund grows larger, "the portfolio manager loses flexibility: It becomes harder to switch in and out of positions. Executing a desired

trade will take longer or create adverse market impact price moves. The resulting reduction in the speed and nature of the portfolio adjustment will ultimately impair fund performance."

More recently, Berk and Green (2004) develop a rational model of active fund management. In their model, there are decreasing returns to scale. However, due to the competitive provision of capital by investors, the expected excess return of any fund is the same and is equal to zero. Thus, according to Berk and Green, there should be no significant relation between fund size and performance in the cross section.

The empirical literature on the relation between fund size and fund performance is limited. Grinblatt and Titman (1989) find some evidence that gross fund returns decline with fund size, but do not find a similar effect using net returns. Indro, Jiang, Hu, and Lee (1999) find a nonlinear relation between fund size and performance; performance initially increases and then decreases in fund size. More recently, Chen, Hong, Huang, and Kubik (2004) present evidence that fund size erodes performance. They find that the adverse effect of size on performance is stronger among small-cap funds. To the extent that small-cap stocks are less liquid, they argue that their evidence provides support for the hypothesis that fund size erodes performance because of liquidity.[1]

The purpose of this paper is to carefully examine the role of liquidity and investment style in determining the effect of fund size on fund performance. Chen et al. (2004) rely on an investment objective, i.e., "small-cap growth funds," to identify funds that hold relatively illiquid stocks. Their approach, while informative, can be improved by using more direct measures of liquidity. Furthermore, prior literature (e.g., Chan and Lakonishok (1995) and Keim and Madhavan (1997)) shows that investment style is a significant determinant of institutional trading costs. Therefore, examining the effect of investment style can provide additional insight into the nature of the economies of scale in active fund management.

Using stock transactions data along with detailed stockholdings for a comprehensive sample of U.S. actively managed equity mutual funds from 1993 to 2002, I construct two sets of liquidity measures for each fund's portfolio. The first set of liquidity measures are based on the quoted and effective spreads of all stocks held in a fund's portfolio. The second set of liquidity measures are functions of the stock's market capitalization as well as the relative holding size (shares held divided by average daily trading volume), which are designed to capture the level of market impact of a fund's portfolio.

Armed with these more direct (and continuous) liquidity measures, I next examine the effect of liquidity on the relation between fund size and performance by using both a portfolio approach and a cross-sectional regression approach. In the portfolio approach, I divide all sample funds into 5×5 portfolios based on the liquidity of a fund's portfolio and fund size. I evaluate the performance of each portfolio by using four standard asset pricing models, the CAPM, the Fama-French three-factor model, the Carhart (1997) four-factor model, and a conditional four-factor model (Ferson and Schadt (1996)). Regardless of which model I use, I find

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[1]Chan, Faff, Gallagher, and Looi (2005) also find a negative impact of fund size on the performance of active funds using Australian data. They show that this diseconomy of scale is related to market impact costs.

strong evidence that smaller funds earn significantly higher abnormal returns than larger funds. Consistent with the hypothesis that liquidity is an important reason why fund size erodes performance, I find that the inverse relation between fund size and fund performance is more pronounced among funds in the lower liquidity quintiles. Indeed, there is no evidence that fund size erodes performance among funds in the three most liquid quintiles.

Chan and Lakonishok (1995) and Keim and Madhavan (1997) find that investment styles significantly influence institutional trading costs: Money managers with high demands for immediacy are associated with larger market impact and greater trading costs. In particular, Chan and Lakonishok (1995) find that trading costs are higher for growth and high turnover funds. To examine how the nature of the economies of scale varies across investment styles, I divide all funds based on the average book-to-market deciles of their stockholdings and fund turnover rates. Consistent with the hypothesis that liquidity is an important reason why fund size erodes performance, I find that the adverse effect of scale on performance is more pronounced among low book-to-market (growth) funds and among high turnover funds.

I also examine the effect of liquidity on the relation between fund size and fund performance by using a cross-sectional regression approach. This approach allows me to control for other fund characteristics that may be correlated with fund performance or fund size. Consistent with Chen et al. (2004), I find evidence that fund performance is inversely related to fund size after controlling for various fund characteristics. To explore the effect of liquidity on the relation between fund size and performance, I include in the regression an interaction term between illiquidity and fund size. Consistent with the hypothesis that liquidity is an important reason why fund size erodes performance, I find the coefficient on this interaction term to be significantly negative.

An important consideration in the analysis of the effect of liquidity on the relation between fund size and fund performance is that liquidity might be endogenous. Indeed, the presence of endogenous liquidity would weaken the hypothesized effect of liquidity on the fund size/fund performance relation. Intuitively, funds that are subject to greater diseconomies of scale might optimally choose to hold more liquid portfolios, which would make it harder to find a significant positive effect of illiquidity on the inverse relation between fund size and performance. Despite the presence of this bias, I find evidence that the inverse relation between fund size and performance is more pronounced for funds that hold less liquid portfolios and for growth and high turnover funds.

Chen et al. (2004) provide evidence that, in addition to liquidity, organizational diseconomies related to hierarchy costs (Stein (2002)) also play a role in the documented diseconomy of scale within the mutual fund industry. In this paper, I focus on the role of liquidity and do not examine organizational diseconomy. I provide evidence that liquidity is an important reason why fund size erodes performance. This result by no means suggests that liquidity alone is responsible for the documented inverse relation between fund size and fund performance. Indeed, Chen et al. (2004) argue that liquidity plays a significant role only in the presence of organizational diseconomy.

This paper makes two contributions to the mutual fund literature. First, this paper contributes to recent research focusing on the relation between fund size and fund performance. Specifically, by using more direct liquidity measures of a fund's portfolio, this paper provides a rigorous analysis of the role of liquidity in determining the fund size/fund performance relation. In addition, by providing an analysis of the effect of investment style on the fund size/fund performance relation, this paper further improves one's understanding of why diseconomies of scale might exist in active fund management.

Second, this paper makes a methodological contribution. While numerous papers have examined the liquidity of individual stocks, the liquidity of managed stock portfolios, such as an equity mutual fund's portfolio, has received little direct attention in the academic literature. This paper takes a step toward filling this gap by proposing and constructing the first liquidity measures for a mutual fund's portfolio. Given that liquidity plays an important role in active fund management, these liquidity measures are likely to become useful tools in mutual fund research that examines fund performance, fund flows, and fund trading strategies.

The rest of this paper proceeds as follows. Section II describes the data and variables. Section III presents the descriptive statistics and results for several preliminary analyses. Section IV investigates the role of liquidity and investment style in determining the effect of scale on performance in active fund management. Section V concludes.

II.   Data and Variables

A.   Data and Sample

This study draws from a number of data sources. The Thomson Financial Mutual Fund Holdings database (hereafter referred to as the fund holdings database) contains quarterly stockholdings for all U.S. mutual funds. Since this dataset does not require any minimum surviving period for a fund's inclusion, it does not suffer from a survivorship bias. A detailed description of this database can be found in Wermers (2000).

The second data source is the CRSP Survivor-Bias-Free Mutual Fund Database (hereafter referred to as the CRSP mutual fund database). The CRSP mutual fund database provides information on fund returns, total net assets (TNA), fees, investment objectives, and other fund characteristics. I merge the fund holdings database with the CRSP mutual fund database by using the MFLINK file obtained from Wharton Research Data Services (WRDS).[2]

I restrict my analysis to diversified domestic equity mutual funds. Specifically, a fund is included in my sample if the fund has an ICDI investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth

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[2]The MFLINK file does not always provide a one-to-one match between the two databases. Sometimes a fund in the fund holdings database is matched with multiple funds in the CRSP mutual fund database. This is usually because the CRSP database reports each share class as a separate fund. I deal with these situations by combining multiple share classes into a single fund. There are also a number of cases where a fund in the CRSP database is matched with multiple funds in the fund holdings database. In these cases, I use other fund information such as TNA value and age to identify the best match.

and Income). I exclude index funds to focus on actively managed mutual funds.[3]
Elton, Gruber, and Blake (2001) find that the returns of the smallest funds (funds
with TNA less than $15 million) reported in the CRSP mutual fund database tend
to be biased upward. To ensure that my results are not driven by these small funds,
I remove all funds with TNA less than $15 million. In addition, to minimize the
impact of an incubator fund bias (Evans (2006)), I remove the first 18 months
of returns for each sample fund. Removal of these young funds also alleviates a
concern that these funds are more likely to be cross-subsidized by their respective
fund families (Gaspar, Massa, and Matos (2006)).

    Many mutual funds have multiple share classes. The CRSP mutual fund
database lists each share class as a separate fund. These share classes represent
claims on the same underlying assets, and have the same returns before expenses
and loads. They typically differ only in their fee structures (e.g., load versus no-
load) and/or in their clienteles (e.g., institutional versus retail). Because these
classes always hold the same portfolio, I combine these different classes into a
single fund in my analysis. Specifically, I sum the TNA of each share class to
obtain the TNA for the fund. For all other fund characteristics, I use the TNA-
weighted average across all share classes.

    In contrast, Chen et al. (2004) keep only one share class for the funds with
multiple share classes. Although this approach does not obviously bias their re-
sults, it leads to a downward bias on their estimate of the fund's total assets. As
a result, it might affect their analysis of the relation between fund size and fund
performance. Given the proliferation of share classes in the 1990s, this issue is
more severe after 1990.

    I obtain the market capitalization for each stock from the CRSP stock database
and calculate the book-to-market ratio using data from Compustat. I obtain in-
traday trades and quotes for all common stocks traded on NYSE, AMEX, and
Nasdaq from the Trade and Quote (TAQ) database. Since TAQ starts in 1993, the
sample period for this study is 1993–2002.[4]

B. Liquidity Measures

1. Bid-Ask Spread

    The most commonly used liquidity measures are bid-ask spreads. Thus, my
first set of liquidity measures for a fund's portfolio is based on bid-ask spreads.
More specifically, I define QS (ES) as the weighted average relative quoted spread
(effective spread) of all stocks held in a fund's portfolio:

$$(1) \qquad QS \;=\; \frac{1}{\sum\limits_{i=1}^{N} w_i} \sum\limits_{i=1}^{N} w_i \, \%QuotedSpread_i,$$

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[3]I identify index funds by searching the word "index" in fund names.
[4]In my analysis of growth and high turnover funds, I also examine extended sample periods that
go back to 1983 and 1966, respectively.

$$(2) \qquad \text{ES} \quad = \quad \frac{1}{\sum\limits_{i=1}^{N} w_i} \sum\limits_{i=1}^{N} w_i \, \%\text{EffectiveSpread}_i,$$

where w_i is the dollar value of stock i, N is the number of holdings in the portfolio, and $\%\text{QuotedSpread}_i$ and $\%\text{EffectiveSpread}_i$ are the relative quoted and effective spread of stock i. I calculate QS and ES for each fund at each quarter by using past one-quarter average spreads.

To estimate the quoted and effective spread for each stock, I start with all the trades and quotes in the TAQ database. I follow Chordia, Roll, and Subrahmanyam (2001), (2002) to purge the following trade and quote data: trades out of sequence, trades and quotes before the open or after the close, quotes not originated from the primary exchange, trades or quotes with negative prices, quotes with negative spread, quotes with spread greater than $4 or 20% of the midquote. I sign trades using the Lee and Ready (1991) algorithm: if a trade occurs above (below) the mid-point of the prevailing quote, it is classified as a buyer- (seller-) initiated trade. If a trade occurs at the mid-point of the prevailing quote, it is signed based on the tick test.

I first calculate the average quoted and effective spread for each stock on each trading day. Then for each stock I calculate the average quoted and effective spread across all trading days within a quarter. Finally, I merge these average bid-ask spreads with the fund holdings database.

2. Market Impact

Bid-ask spreads do not capture the price impact of a large trade, which can be thought of as the deviation of the trade price from the price that would have prevailed had the trade not occurred. Chan and Lakonishok (1995) and Keim and Madhavan (1997) show that the market impact and institutional trading costs increase with trade difficulty, which is positively related to relative order size and negatively related to a stock's market capitalization.

Motivated by the above studies on institutional trading costs, I construct my second set of liquidity measures as follows. I first calculate the market capitalization of each stock and then place each stock into a size decile by NYSE breakpoints. In particular, I place the largest stocks in size decile 1 and the smallest stocks in size decile 10. Following Chan and Lakonishok (1995), I define the *relative* holding size as the ratio between holding size and average daily trading volume.[5] I then use the following step function to transform the relative holding size:

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[5]It is well documented that the reported trading volumes for Nasdaq stocks are inflated. So I divide the Nasdaq volume by 2.

$$\text{(3)} \quad F\left(\frac{w_i}{\text{DVOL}_i}\right) \quad =$$

$$
\begin{cases}
1 & \text{if } 0 & < \frac{w_i}{\text{DVOL}_i} \leq 0.05 \\
2 & \text{if } 0.05 & < \frac{w_i}{\text{DVOL}_i} \leq 0.1 \\
3 & \text{if } 0.1 & < \frac{w_i}{\text{DVOL}_i} \leq 0.25 \\
4 & \text{if } 0.25 & < \frac{w_i}{\text{DVOL}_i} \leq 0.5 \\
5 & \text{if } 0.5 & < \frac{w_i}{\text{DVOL}_i} \leq 1
\end{cases}
\begin{cases}
6 & \text{if } 1 & < \frac{w_i}{\text{DVOL}_i} \leq 2 \\
7 & \text{if } 2 & < \frac{w_i}{\text{DVOL}_i} \leq 5 \\
8 & \text{if } 5 & < \frac{w_i}{\text{DVOL}_i} \leq 10 \quad, \\
9 & \text{if } 10 & < \frac{w_i}{\text{DVOL}_i} \leq 25 \\
10 & \text{if } & \frac{w_i}{\text{DVOL}_i} > 25
\end{cases}
$$

where w_i is dollar holding of stock i, and DVOL_i is the average daily dollar trading volume of stock i over the past quarter. The second set of liquidity measures, MI1 and MI2, are then defined as follows:

$$\text{(4)} \quad \text{MI1} \quad = \quad \frac{1}{\sum_{i=1}^{N} w_i} \sum_{i=1}^{N} \left[w_i \times \left(\text{SizeDecile}_i + F\left(\frac{w_i}{\text{DVOL}_i}\right) \right) \right]$$

$$\text{(5)} \quad \text{MI2} \quad = \quad \frac{1}{\sum_{i=1}^{N} w_i} \sum_{i=1}^{N} \left[w_i \times \left(\text{SizeDecile}_i \times F\left(\frac{w_i}{\text{DVOL}_i}\right) \right) \right] \quad,$$

where w_i is dollar holding of stock i, SizeDecile_i is the size decile that stock i belongs to using NYSE breakpoints, DVOL_i is the average daily dollar trading volume of stock i over the past quarter, and $F(\cdot)$ is defined in equation (3).

The use and specification of $F(\cdot)$ in equation (3) are motivated by a number of considerations. First, the market impact of a trade is unlikely to be directly proportional to the trade size. For example, a trade of 1,000 shares of Microsoft stock likely has a similar market impact to a trade of 100 shares (minimal in both cases), even though the first trade is 10 times as large as the second trade. Second, the use of $F(\cdot)$ minimizes the impact of outliers. Third, the specific cutoffs used in $F(\cdot)$ are motivated by industry practice and the empirical distribution of the relative holding size. For example, many practitioners believe that a trade size of 10% or less of daily average trading volume is usually impact free (Becker and Vaughan (2001)). Additionally, for liquidity reasons some funds require that their holdings in individual stocks be no more than 25% of average daily trading volume (Pozen (2002)). Admittedly, the number of categories and the choice of cutoffs in $F(\cdot)$ are somewhat arbitrary. Nonetheless, this specification provides a useful characterization of the market impact of institutional trades. Unreported results indicate that the paper's main findings are robust to several reasonable alternative specifications of $F(\cdot)$.

To illustrate how MI1 and MI2 are constructed, consider two funds each with a single holding. Fund X holds 10,000 shares of stock A and Fund Y holds 10,000 shares of stock B. Stock A is a large-cap stock ranked in the top size decile (decile 1). Stock B, on the other hand, is a small-cap stock ranked in the bottom size decile (decile 10). Further assume that the average daily trading volume for stock A is 100,000 shares and that the average daily trading volume for stock B

is only 1,000 shares. Thus, 10,000 shares of A are equivalent to 10% of its daily volume, while 10,000 shares of B are equivalent to 10 times of its daily trading volume. Based on equations (3), (4), and (5), Fund X has an MI1 of 3 $(1 + 2)$ and an MI2 of 2 (1×2), whereas Fund Y has an MI1 of 18 $(10 + 8)$ and an MI2 of 80 (10×8). Thus, based on either measure, Fund Y is less liquid than Fund X. This is to be expected because Fund Y holds a smaller stock with a larger relative holding size.

Both MI1 and MI2 are functions of a fund portfolio's average size decile and relative holding size, and are designed to capture the level of market impact of a portfolio. While MI1 is the average *sum* of size decile and relative holding size, MI2 is the average *product*. Despite this difference in specification, both MI1 and MI2 capture the idea that the market impact increases in relative order size and decreases in a stock's market capitalization.

I note that although the above measures of fund portfolio liquidity are based on the liquidity of underlying stocks and other portfolio characteristics such as position size, they are nonetheless imperfect measures of liquidity. Furthermore, while they are more direct measures of liquidity, unreported results suggest that these measures are highly correlated with the liquidity proxy used by Chen et al. (2004), i.e., whether a fund is a small-cap growth fund.

III. Descriptive Statistics and Preliminary Analyses

A. Descriptive Statistics

Table 1 presents the descriptive statistics for fund characteristics including liquidity. In addition to summary statistics for all sample funds as a group, I also report summary statistics for each fund size quintile separately. For each data item (e.g., expense ratio), I first calculate the TNA-weighted average across all funds for each year from 1993 to 2002, and then report a simple time-series average of the cross-sectional averages.

In each year, there are on average 1,024 funds in my sample with an average of 204 or 205 funds in each fund size quintile. The average TNA for all sample funds is $1,152.19 million. The average fund in the smallest fund size quintile has only $37.61 million in total assets, while the average fund in the largest fund size quintile has over $4 billion in total assets.

The average age of all sample funds is 13.92 years. The average turnover rate is approximately 92% per year and the average expense ratio is 1.26%. As one might expect, fund age increases with fund size, while the turnover rate and expense ratio decrease with fund size.

The average sample fund holds 5.94% cash and 91.82% stock. Smaller funds tend to hold more cash and less stock, although this relation is not monotonic. The average fund holds 110 stocks. As expected, larger funds hold substantially more stocks. For example, the average fund in the largest fund size quintile holds 162 stocks, whereas the average fund in the smallest fund size quintile holds only 72 stocks. As a group, fund managers prefer large stocks and growth stocks as evi-

TABLE 1

Descriptive Statistics

Table 1 presents the summary statistics for fund characteristics. The sample period is 1993–2002. I obtain mutual fund stockholdings from Thomson Financial. Fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth and Income). I combine different share classes into a single fund. I exclude index funds and funds with total net assets less than $15 million. I exclude the first 18 months of data for each sample fund. Stock characteristics are from Compustat and the CRSP stock database. Size and BM deciles are by NYSE breakpoints. Size decile 1 contains the largest stocks. BM decile 1 contains the value stocks. Transaction-level data are from the Trade and Quote (TAQ) database. QS, ES, MI1, and MI2 are liquidity measures as defined in equations (1), (2), (4), and (5), respectively.

		Fund Size Quintile				
Data Item	All Funds	1 (small)	2	3	4	5 (large)
Number of Funds	1,024	204	205	205	205	205
Total Net Assets (TNA) $mil	1,152.19	37.61	109.46	255.29	642.07	4,718.24
Fund Age (AGE)–Year	13.92	8.17	10.43	11.84	15.72	23.42
Turnover (TURN) %	92.22	97.30	94.45	95.48	95.18	78.58
Expense Ratio (EXP) %	1.26	1.42	1.33	1.28	1.23	1.05
12b-1 Fee (12B1) %	0.20	0.17	0.18	0.21	0.23	0.21
Total Load (LOAD) %	2.07	1.64	1.89	2.14	2.24	2.42
Cash %	5.94	5.91	6.09	5.77	5.81	6.13
Stock %	91.82	92.40	90.91	92.28	91.91	91.60
Number of Holdings	109.64	71.83	84.37	102.08	128.14	161.72
Size Decile (SIZE)	2.20	2.60	2.38	2.39	2.16	1.48
BM Decile (BM)	6.36	6.14	6.37	6.38	6.44	6.45
Quoted Spread (QS) %	0.38	0.42	0.41	0.39	0.37	0.32
Effective Spread (ES) %	0.28	0.31	0.30	0.28	0.27	0.23
Market Impact (MI1)	6.79	5.91	6.18	6.84	7.25	7.75
Market Impact (MI2)	14.87	12.22	13.69	16.15	16.85	15.44

denced by the average size decile of 2.20 (decile 1 containing the largest stocks) and the average book-to-market decile of 6.36 (decile 1 containing value stocks).[6]

Turning attention to liquidity measures, I find that the QS is 0.38% and the ES is 0.28% for the average sample fund. Both QS and ES decrease in fund size. For example, the average QS is 0.42% for the smallest fund size quintile, but is only 0.32% for the largest fund size quintile. This result suggests that larger funds tend to hold more liquid stocks. However, this does not necessarily mean that their portfolios are more liquid. Indeed, based on the second set of liquidity measures that capture market impact, I find that larger funds' portfolios tend to be *less* liquid. The average MI1 (MI2) for the smallest fund size quintile is 5.91 (12.22), but increases to 7.75 (15.44) for the largest fund size quintile. This is to be expected. Larger funds on average have larger holding sizes (despite more holdings), which make their portfolios less liquid.

Table 2 presents the correlations among liquidity measures and various fund characteristics. I compute cross-sectional correlations each year, and then report the simple time-series average of cross-sectional correlations. Several correlations are noteworthy. All four liquidity measures are positively correlated with each other. Larger funds, older funds, and funds in larger fund families tend to hold more liquid stocks with lower quoted and effective spreads. Funds that charge lower fees tend to invest in less liquid stocks. MI1 and MI2 are both inversely related to fund size, consistent with the result reported in Table 1.

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[6]I place the largest stocks in size decile 1 (as opposed to decile 10) and stocks with the highest book-to-market ratio in the book-to-market decile 1 (as opposed to decile 10) to facilitate subsequent analyses of the interaction effect between fund size and liquidity.

TABLE 2

Time-Series Averages of Cross-Sectional Correlations

Table 2 presents the correlations between various fund characteristics including liquidity. The sample period is 1993–2002. I obtain mutual fund stockholdings from Thomson Financial. Fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth and Income). I combine different share classes into a single fund. I exclude index funds and funds with total net assets less than $15 million. I exclude the first 18 months of data for each sample fund. Stock characteristics are from Compustat and the CRSP stock database. LOGTNA is the logarithm of fund total net assets. LOGFAM is the logarithm of the fund family's total net assets. LOGAGE is the logarithm of fund age. EXP is expense ratio. TURN is the turnover. LOAD is the total load. Transaction-level data are from the Trade and Quote (TAQ) database. QS, ES, MI1, and MI2 are liquidity measures as defined in equations (1), (2), (4), and (5), respectively. I first calculate the correlation for each quarter and then report the time-series average correlations. ** indicates significance at the 5% level.

	LOGTNA	LOGFAM	LOGAGE	EXP	TURN	LOAD	QS	ES	MI1	MI2
LOGTNA	1.00									
LOGFAM	0.55**	1.00								
LOGAGE	0.45**	0.11**	1.00							
EXP	−0.30**	−0.23**	−0.22**	1.00						
TURN	−0.06	0.02	−0.09**	0.17**	1.00					
LOAD	0.12**	0.19**	0.16**	0.35**	−0.01	1.00				
QS	−0.13**	−0.10**	−0.13**	0.18**	0.01	−0.06**	1.00			
ES	−0.13**	−0.10**	−0.13**	0.19**	0.01	−0.06**	0.99**	1.00		
MI1	0.21**	0.03	0.03	0.10**	−0.04	−0.06**	0.72**	0.72**	1.00	
MI2	0.08**	−0.03	−0.03	0.12**	−0.06**	−0.08**	0.76**	0.76**	0.96**	1.00

To assess how portfolio liquidity has changed over time, I plot in Figure 1 the average liquidity of equity mutual funds' portfolios from 1993 to 2002. Based on quoted or effective spreads, the liquidity of equity mutual funds' portfolios has improved dramatically from 1993 to 2002. For example, the average quoted spread declined from approximately 0.6% in 1993 to approximately 0.2% in 2002, while the average effective spread declined from around 0.4% to approximately 0.15% over the same period. These results are to be expected given the evidence that the bid-ask spreads of U.S. stocks declined substantially over the past decade or so (see, e.g., Chordia et al. (2001) and Jones (2002)). Figure 1 shows two episodes of significant decline in bid-ask spreads. The first occurred in the first half of 1997 when the Nasdaq implemented an order handling reform and the NYSE changed the minimum tick size from 1/8 of a dollar to 1/16 of a dollar. The second significant decline in bid-ask spreads occurred in early 2001, when decimalization was implemented in all U.S. stock exchanges.

The average liquidity of mutual fund portfolios has also improved over my sample period based on MI1 or MI2, but the improvement is both less dramatic and less consistent than that of bid-ask spreads. Over 1993–2002, the average MI1 decreases by only 20% from about 7.5 to 6, while MI2 decreases from about 17 to 11. Moreover, both MI1 and MI2 have steadily *increased* from mid-1999 to the end of 2002.

B. Preliminary Analyses

Before examining the impact of liquidity on the relation between fund size and performance, I first conduct two preliminary analyses to better understand the behavior of the liquidity of equity mutual funds' portfolios. Specifically, in Section III.B.1, I examine the relation between fund liquidity and various fund characteristics. In Section III.B.2, I examine the impact of fund liquidity on fund cash holdings.

FIGURE 1

Average Liquidity of U.S. Equity Mutual Funds' Portfolios, 1993–2002

Figure 1 plots the average liquidity of U.S. equity mutual funds' portfolios for the period 1993–2002. I obtain mutual fund stockholdings from Thomson Financial. Fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth and Income). I exclude index funds and funds with total net assets less than $15 million. I exclude the first 18 months of data for each sample fund. I combine different share classes into a single fund. Transaction-level data are from the Trade and Quote (TAQ) database. QS, ES, MI1, and MI2 are liquidity measures as defined in equations (1), (2), (4), and (5), respectively.
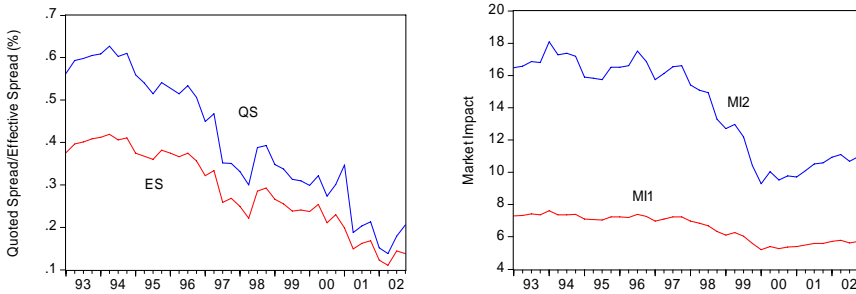
1.   Liquidity and Fund Characteristics

In this subsection, I examine the relation between the liquidity of a fund's portfolio and various fund characteristics including fund size, fund family size, fund age, number of holdings, turnover, expense ratio, and total load. I use the Fama and MacBeth (1973) methodology. Specifically, I run a cross-sectional regression of liquidity each year, and then calculate the mean yearly coefficient estimates over the entire sample period. The *t*-statistics are adjusted for serial correlation using the Newey-West method.

Table 3 shows the time-series averages of coefficient estimates from yearly regressions. The dependent variables of these regressions are the four liquidity measures, QS, ES, MI1, and MI2, respectively. Column 1 reports the results on the quoted spread. Larger funds and older funds tend to hold portfolios with lower average quoted spreads. These results are statistically significant. In addition, higher turnover funds tend to hold more liquid stocks. This result is consistent with the idea that fund managers who trade actively try to minimize transactions costs by holding more liquid stocks. Funds that charge higher fees hold less liquid stocks, suggesting perhaps that the investment expertise in illiquid stocks might be more difficult to obtain and hence is more valuable. The results regarding effective spreads are qualitatively similar to those regarding quoted spreads.

Turning to measures of market impact, I find that MI1 is positively related to expense ratios and negatively related to turnover and total load. These results are consistent with those on quoted and effective spreads. In contrast to the results based on quoted and effective spreads, I find that larger funds hold less liquid portfolios in that they have significantly higher MI1. This is not surprising because larger funds tend to hold larger positions. Funds with more holdings tend to have higher market impact. This result initially appears counterintuitive. Since more holdings should be related to a smaller position size, one might have expected a larger number of holdings to be associated with lower market impact. Unreported results indicate that the above finding is primarily due to the fact that

TABLE 3

Fund Characteristics and Liquidity of Equity Mutual Funds' Stock Portfolios

Table 3 examines the relation between portfolio liquidity and various fund characteristics. The sample period is 1993–2002. I obtain mutual fund stockholdings from Thomson Financial. Fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth and Income). I combine different share classes into a single fund. I exclude index funds and funds with total net assets less than $15 million. I exclude the first 18 months of data for each sample fund. Stock characteristics are from Compustat and the CRSP stock database. Transaction-level data are from the Trade and Quote (TAQ) database. QS, ES, MI1, and MI2 are liquidity measures as defined in equations (1), (2), (4), and (5), respectively. I use the Fama-MacBeth (1973) method. Numbers in parentheses are t-statistics that are based on Newey-West standard errors. ** indicates significance at the 5% level.

| Independent Variables | Dependent Variable | | | |
	QS	ES	MI1	MI2
Intercept	0.154**	0.098	−0.087	−7.454**
	(2.18)	(1.80)	(−0.13)	(−3.68)
Log TNA	−0.012**	−0.009**	0.692**	1.699**
	(−2.96)	(−2.92)	(9.05)	(5.41)
Log Family TNA	−0.001	−0.001	−0.126**	−0.537**
	(−0.54)	(−0.62)	(−6.38)	(−6.54)
Log Fund Age	−0.014**	−0.010**	−0.113**	−0.705**
	(−3.27)	(−3.44)	(−2.18)	(−3.26)
Log Number of Holdings	0.043**	0.033**	0.594**	2.880**
	(2.32)	(2.33)	(6.00)	(11.45)
Turnover	−0.017**	−0.010**	−0.261**	−1.558**
	(−2.58)	(−2.12)	(−4.83)	(−5.65)
Expense Ratio	0.158**	0.119**	2.057**	8.239**
	(4.69)	(5.05)	(13.08)	(12.68)
Total Load	−0.016**	−0.012**	−0.264**	−1.051**
	(−9.42)	(−10.43)	(−13.38)	(−15.53)
Average R^2	0.08	0.08	0.13	0.10

funds with a larger number of holdings also tend to hold smaller stocks.[7] The results concerning MI2 are qualitatively similar to those concerning MI1.

2. Liquidity and Fund Cash Holdings

Funds can meet large redemptions by either altering cash balances or by selling stocks. Thus, there might be a trade-off between a fund's cash holding and the liquidity of a fund's stockholdings. Intuitively, if a fund's stockholdings are not liquid, the fund might need to hold a large amount of cash to compensate for the lack of liquidity in its stockholdings. To test this hypothesis, I regress fund cash holdings on various fund characteristics including the liquidity of a fund's portfolio. I use Fama and MacBeth's (1973) methodology. Specifically, I estimate a cross-sectional regression of cash holdings each year, and then report the average regression coefficients. The t-statistics are again adjusted for serial correlation using the Newey-West method.

Table 4 shows the regression results. I find that fund cash holdings are positively related to fund size, turnover, and expense ratios. More importantly, I find that fund cash holdings are significantly positively related to the illiquidity of a fund's portfolio regardless of which liquidity measure I use. All of the coefficients on liquidity are positive and statistically significant at the 1% level. The results are also economically significant. All else equal, a two-standard deviation

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[7]I am unable to control for the size decile of the stockholdings in this regression because size decile enters directly into the dependent variables, MI1 and MI2. See equations (4) and (5).

increase in QS is associated with an increase in fund cash holdings by 1.3%. Table 1 reports that the average cash holdings of all funds is 5.94%. Therefore, the above amount is economically meaningful. The economic significance is similar when I use market impact measures, MI1 and MI2. For example, a two-standard deviation increase in MI1 is associated with an increase of fund cash holdings by 1.4%. Overall, these results suggest that a trade-off exists between cash balances and the liquidity of stockholdings.

TABLE 4

Fund Cash Holdings and Liquidity of Equity Mutual Funds' Stock Portfolios

Table 4 presents the regression of fund cash holdings on various fund characteristics including liquidity. The sample period is 1993–2002. I obtain mutual fund stockholdings from Thomson Financial. Fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth and Income). I combine different share classes into a single fund. Fund cash holdings are in percent. I exclude index funds and funds with total net assets less than $15 million. I exclude the first 18 months of data for each sample fund. Stock characteristics are from Compustat and the CRSP stock database. Transaction-level data are from the Trade and Quote (TAQ) database. QS, ES, MI1, and MI2 are liquidity measures as defined in equations (1), (2), (4), and (5), respectively. I use the Fama-MacBeth (1973) method. Numbers in parentheses are t-statistics that are based on Newey-West standard errors. ** indicates significance at the 5% level.

| | Dependent Variable: Fund Cash Holdings | | | |
Independent Variables	QS	ES	MI1	MI2
Intercept	0.692 (0.84)	0.737 (0.91)	0.841 (1.11)	1.164 (1.50)
Log TNA	0.382** (3.91)	0.379** (3.85)	0.211** (2.35)	0.281** (2.90)
Log Family TNA	−0.147** (−2.36)	−0.146** (−2.34)	−0.129** (−2.11)	−0.131** (−2.14)
Log Fund Age	0.241 (1.74)	0.243 (1.75)	0.247 (1.82)	0.255 (1.87)
Turnover	0.513 (1.28)	0.505 (1.26)	0.532 (1.34)	0.545 (1.38)
Total Load	−0.075 (−1.16)	−0.075 (−1.15)	−0.054 (−0.85)	−0.062 (−0.99)
Expense Ratio	2.147** (6.08)	2.137** (6.07)	2.074** (6.15)	2.139** (6.31)
QS	2.242** (4.40)			
ES		2.970** (5.09)		
MI1			0.216** (14.21)	
MI2				0.046** (13.49)
Average R^2	0.05	0.05	0.05	0.05

IV.   The Effect of Liquidity and Investment Style on the Relation between Fund Size and Fund Performance

A.   Overview

Chen et al. (2004) provide a comprehensive analysis of the relation between fund size and fund performance. Using a cross-sectional regression approach, they find that fund size erodes performance. Further, Chen et al. (2004) divide funds into small-cap funds and non-small-cap funds, and find that the adverse

effect of size on performance is stronger among small-cap funds. To the extent that small-cap stocks are less liquid, they argue that the evidence provides support for the liquidity hypothesis.

In this section, I first confirm Chen et al.'s (2004) finding of diseconomies of scale in active fund management. I then extend Chen et al. (2004) to provide a more rigorous analysis of the effect of liquidity on the relation between fund size and fund performance. Specifically, instead of using the investment objective "small-cap growth funds" to proxy for liquidity, I use two sets of more direct liquidity measures. I also examine the effect of investment style on the relation between fund size and fund performance.

In my empirical analysis, I use two approaches—a time-series portfolio approach and a cross-sectional regression approach. In the portfolio approach, I form portfolios based on fund size and liquidity. Portfolio performance is evaluated by using several standard asset pricing models. In the cross-sectional regression approach, I follow Chen et al. (2004) to run cross-sectional regressions of risk-adjusted fund returns on various fund characteristics including fund size and liquidity. The advantage of the cross-sectional regression approach is that it allows controlling for other fund characteristics. Sections IV.B and IV.C contain more details about these methods.

B.   Empirical Results—Time-Series Portfolio Approach

1.   Method

At the end of each quarter, I divide all sample funds into quintiles based on their TNA of the previous quarter. I rebalance these portfolios each quarter. I then compute equal-weighted monthly returns for each quintile. I evaluate the performance of these portfolios by using several one- and multi-factor models. Specifically, I use the CAPM model, the Fama-French (1996) three-factor model, the Carhart (1997) four-factor model, and a conditional four-factor model. Following prior literature, I use alpha, the intercept term in the regression of fund portfolio returns on risk factors, as the performance measure. As argued by Carhart (1997), one of the advantages of the portfolio regression approach is that it does not suffer from survivor bias and look-ahead bias. Below is the Carhart (1997) four-factor model:

$$(6) \quad r_{p,t} - r_{f,t} \quad = \quad \alpha + b \cdot \text{MKT}_t + s \cdot \text{SMB}_t + h \cdot \text{HML}_t + u \cdot \text{UMD}_t + e_t,$$

where $r_{p,t}$ is the return on the portfolio, $r_{f,t}$ is the risk-free rate, and MKT, SMB, HML, and UMD are market factor, size factor, book-to-market factor, and the momentum factor, respectively. Note that the CAPM model and the Fama-French three-factor model are both nested in the Carhart four-factor model.

Ferson and Schadt (1996) propose a conditional performance evaluation model based on predetermined conditioning variables to account for time-varying risk premiums and time-varying betas. They show that conditional alphas can differ

significantly from unconditional alphas. As a robustness check, I also estimate the following conditional performance evaluation model:

$$
(7) \quad r_{p,t} - r_{f,t} = \alpha + b_1 \cdot \text{MKT}_t + b_2 \cdot \text{DP}_{t-1} \cdot \text{MKT}_t + b_3 \cdot \text{DEF}_{t-1} \cdot \text{MKT}_t
$$
$$
+ b_4 \cdot \text{TERM}_{t-1} \cdot \text{MKT}_t + b_5 \cdot \text{TB3M}_{t-1} \cdot \text{MKT}_t
$$
$$
+ s \cdot \text{SMB}_t + h \cdot \text{HML}_t + u \cdot \text{UMD}_t + e_t,
$$

where DP is the S&P 500 index dividend yield, DEF is the default spread, TERM is the term premium, and TB3M is the three-month T-bill rate.[8] In this model, I allow the market beta to be a linear function of predetermined variables. Alternative specifications of the conditional model do not affect the qualitative results.

2.   The Relation between Fund Size and Fund Performance

I begin my analysis by first examining whether there are diseconomies of scale for actively managed equity mutual funds over my sample period 1993–2002. Table 5 shows the alphas for fund size portfolios. Specifically, Panel A of Table 5 reports the alphas estimated from gross returns and Panel B reports the alphas estimated from net returns.[9]

In each panel of Table 5, I present four alphas, the CAPM alpha, the Fama-French three-factor alpha, the Carhart four-factor alpha, and the conditional four-factor alpha. Regardless of which alpha measure I use, the smallest size quintile performs significantly better than the largest fund size quintile. For example, when using the CAPM model, I find that funds in the smallest quintile outperform funds in the largest quintile by 23 basis points per month. When I use the Carhart (1997) model, this difference decreases slightly to 17 basis points per month, but is still statistically significant at the 1% level.

Panel B of Table 5 shows the results for net returns. As expected, the alphas calculated from net returns are lower than those calculated from gross returns (by approximately 1/12 of the expense ratio). The smallest funds continue to outperform the largest funds in each alpha measure, but by slightly smaller amounts than those obtained using gross returns. For example, using the Carhart (1997) model, the smallest funds outperform the largest funds by 14 basis points per month (compared to 17 basis points reported in Panel A). This is to be expected because smaller funds tend to charge higher fees. Therefore, the difference in after-expense returns between small and large funds is smaller than the difference in before-expense returns.

Overall, results in Table 5 confirm the Chen et al. (2004) finding that small funds significantly outperform large funds for my sample period. Comparing the results of Chen et al. (2004) to mine, I find that the inverse relation between fund size and fund performance is more pronounced for my sample period (1993–2002) than for the earlier period. Specifically, Chen et al. ((2004), Table 2) report differences between small funds and large funds of 0.11%, 0.06%, and 0.08% per month using the one-, three-, and four-factor models, respectively. The corresponding numbers are 0.20%, 0.13%, and 0.14% in my paper.

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[8]These conditioning variables are differences from their respective unconditional means.

[9]I calculate the fund's monthly gross return by adding 1/12 of the fund's annual expense ratio to the monthly net return.

TABLE 5

The Relation between Fund Size and Fund Performance, Portfolio Approach

Table 5 examines the relation between fund size and fund performance. The sample period is 1993–2002. I obtain mutual fund stockholdings from Thomson Financial. Fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth and Income). I combine different share classes into a single fund. I exclude index funds and funds with total net assets less than $15 million. I exclude the first 18 months of data for each sample fund. Gross returns are calculated by adding back 1/12 of the annual expense ratio to the net return. Stock characteristics are from Compustat and the CRSP stock database. Transaction-level data are from the Trade and Quote (TAQ) database. QS, ES, MI1, and MI2 are liquidity measures as defined in equations (1), (2), (4), and (5), respectively. I use four models to evaluate fund performance: CAPM, Fama-French three-factor model, Carhart four-factor model, and the conditional four-factor model as described in equations (7) and (8). Numbers in parentheses are t-statistics. ** indicates significance at the 5% level.

			Fund Size Quintile			Difference
α	1 (small)	2	3	4	5 (large)	1 − 5
Panel A. Alphas Estimated Using Gross Returns (% per month)						
CAPM	0.18	0.06	0.03	−0.06	−0.05	0.23**
	(1.54)	(0.51)	(0.25)	(−0.51)	(−0.68)	(3.39)
Fama-French 3-Factor	0.11	−0.00	0.01	−0.08	−0.06	0.16**
	(1.37)	(−0.02)	(0.09)	(−1.09)	(−0.97)	(3.14)
Carhart 4-Factor	0.10	−0.01	−0.03	−0.10	−0.07	0.17**
	(1.23)	(−0.16)	(−0.45)	(−1.20)	(−1.19)	(3.18)
Conditional 4-Factor	0.14	0.01	0.00	−0.08	−0.06	0.20**
	(1.71)	(0.18)	(0.04)	(−0.97)	(−0.93)	(3.87)
Panel B. Alphas Estimated Using Net Returns (% per month)						
CAPM	0.06	−0.05	−0.07	−0.16	−0.14	0.20**
	(0.52)	(−0.45)	(−0.60)	(−1.41)	(−1.85)	(2.94)
Fama-French 3-Factor	−0.01	−0.11	−0.10	−0.19	−0.14	0.13**
	(−0.17)	(−1.50)	(−1.33)	(−2.43)**	(−2.48)**	(2.55)
Carhart 4-Factor	−0.02	−0.12	−0.14	−0.20	−0.16	0.14**
	(−0.25)	(−1.60)	(−1.86)	(−2.50)**	(−2.65)**	(2.63)
Conditional 4-Factor	0.02	−0.09	−0.10	−0.18	−0.15	0.17**
	(0.27)	(−1.20)	(−1.27)	(−2.18)**	(−2.29)**	(3.27)

There are two possible explanations for this difference. First, the size differential between large and small funds has widened substantially over 1962–2002. On average, funds in the largest quintile are 36 times as large as funds in the smallest quintile during 1962–1992. However, this ratio increases to 130 on average during 1993–2002. If there are indeed diseconomies of scale in the mutual fund industry, then with everything else equal, one might expect a greater return differential between small funds and large funds during 1993–2002.

The second possible explanation is that stock returns have become more dispersed over time. This suggests that the potential reward for superior stock-picking skills might have increased. A fund manager who picks the 95th percentile stock would outperform the fund manager who picks the 5th percentile stock by an average of 38% per month during 1962–1992. However, this overperformance increases to 55% during 1993–2002. While this upward trend does not directly explain the difference between my results and those in Chen et al. (2004), it provides a possible explanation.[10]

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[10] Unreported results indicate that the greater negative impact of fund size on performance documented in this paper is not due to differences in empirical methods between this paper and Chen et al. (2004).

3. The Effect of Liquidity

Results in the previous section confirm Chen et al.'s (2004) finding that fund size erodes performance. To test if the above result is related to liquidity, I divide all funds into 5 × 5 portfolios based on the liquidity of a fund's portfolio and fund size. To the extent that larger funds underperform smaller funds because of liquidity, one would expect that the inverse relation between fund size and fund performance is more pronounced among funds with less liquid stockholdings.

Table 6 consists of four panels corresponding to the four liquidity measures. The results are remarkably consistent across all four liquidity measures: The adverse effect of scale on performance is more pronounced for funds with less liquid portfolios. Indeed, there is no evidence that small funds outperform large funds for the three most liquid quintiles. For example, the smallest funds outperform the largest funds by 35 basis points per month among funds with the highest QS. The difference is 17 basis points and is statistically significant among the second highest QS quintile. However, among funds in the remaining three QS quintiles, the smallest funds do not significantly outperform the largest funds. In fact, among funds in the second lowest QS quintile, the smallest funds actually underperform the largest funds by 4 basis points per month. The results regarding ES, MI1, and MI2 are generally similar. Specifically, the smallest funds outperform the largest funds only for the least liquid portfolios. Overall, these results provide strong support for the hypothesis that liquidity is an important reason why fund size erodes performance.

4. The Effect of Investment Style

Chan and Lakonishok (1995) find that the total trading costs are higher for growth and high turnover funds. Intuitively, since growth and high turnover funds tend to employ short-term trading strategies (e.g., momentum strategy), they have relatively high demands for immediacy in their trades. Thus, one might expect that the adverse effect of fund size on performance is greater among these funds.

To examine the effect of investment style on the relation between fund size and fund performance, I divide all funds into 5 × 5 portfolios based on the average book-to-market deciles (or the fund's turnover rate) and fund size. Table 7 reports the results on the performance of these portfolios. In Panel A, I sort funds by average book-to-market decile and fund size. Results in Panel A indicate that the diseconomies of scale are most pronounced among growth funds. In particular, the smallest funds outperform the largest funds by 16 basis points per month among growth funds. This evidence is consistent with the idea that growth funds tend to have high demands for immediacy and, therefore, their trades are associated with larger market impact and greater trading costs.

There is also some evidence that fund size erodes performance among value funds; for funds with the highest book-to-market ratios, the smallest funds outperform the largest funds. Although value funds generally act as liquidity providers and therefore should have low price impact, their holdings may be quite illiquid because value funds tend to hold out of favor stocks, which have lower trading volume and smaller market capitalizations. Therefore, these funds might still suffer from significant diseconomies of scale.

TABLE 6

The Effect of Liquidity on the Relation between Fund Size and Fund Performance,
Portfolio Approach

Table 6 reports Carhart four-factor alphas (% per month) for portfolios sorted on liquidity and fund size. The sample period is 1993–2002. I obtain mutual fund stockholdings from Thomson Financial. Fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth and Income). I combine different share classes into a single fund. I exclude index funds and funds with total net assets less than $15 million. I exclude the first 18 months of data for each sample fund. Transaction-level data are from the Trade and Quote (TAQ) database. QS, ES, MI1, and MI2 are liquidity measures as defined in equations (1), (2), (4), and (5), respectively. Numbers in parentheses are t-statistics. ** indicates significance at the 5% level.

	Fund Size Quintile					Difference 1 − 5	
Quintile	1 (small)	2	3	4	5 (large)		
Panel A. QS							
1 (low)	−0.05	−0.03	−0.04	−0.09	−0.15	0.10	(1.16)
2	−0.10	−0.11	−0.17	−0.14	−0.05	−0.04	(−0.82)
3	−0.06	−0.12	−0.20	−0.26	−0.16	0.10	(1.48)
4	−0.15	−0.18	−0.15	−0.32	−0.32	0.17**	(2.22)
5 (high)	0.19	−0.09	−0.10	−0.15	−0.17	0.35**	(4.04)
Panel B. ES							
1 (low)	−0.05	−0.02	−0.05	−0.07	−0.11	0.06	(1.47)
2	−0.09	−0.10	−0.17	−0.17	−0.11	0.02	(0.31)
3	−0.05	−0.13	−0.18	−0.26	−0.07	0.02	(0.30)
4	−0.12	−0.17	−0.12	−0.29	−0.39	0.27**	(2.99)
5 (high)	0.17	−0.12	−0.13	−0.17	−0.22	0.38**	(3.81)
Panel C. MI1							
1 (low)	−0.15	−0.03	−0.06	−0.06	−0.08	−0.06	(−1.04)
2	−0.04	−0.08	−0.16	−0.19	−0.10	0.06	(0.64)
3	−0.05	−0.19	−0.23	−0.13	−0.13	0.08	(0.62)
4	−0.09	−0.20	−0.13	−0.25	−0.16	0.08	(0.61)
5 (high)	0.03	−0.09	−0.14	−0.31	−0.22	0.26**	(3.06)
Panel D. MI2							
1 (low)	−0.11	−0.02	−0.06	−0.07	−0.06	−0.06	(−0.82)
2	−0.08	−0.10	−0.16	−0.19	−0.13	0.04	(0.45)
3	−0.02	−0.23	−0.28	−0.14	−0.16	0.14	(1.02)
4	−0.04	−0.26	−0.07	−0.23	−0.16	0.12	(1.21)
5 (high)	0.02	−0.10	−0.13	−0.24	−0.21	0.23**	(2.63)

In Panel B of Table 7, I sort funds by turnover and fund size. I find evidence that, among the three highest turnover quintiles, the smallest funds significantly outperform the largest funds. In contrast, small funds do not outperform large funds among the two lowest turnover quintiles.

As a comparison with Chen et al. (2004), I also sort funds into small-cap funds and non-small-cap funds. I classify small-cap funds similarly as Chen et al. (2004): Any fund that has ever had a Wiesenberger fund type code or Strategic Insight's fund objective code of "SCG" is classified as a small-cap fund. Panel C of Table 7 presents the results. Consistent with Chen et al. (2004), funds in the smallest size quintile significantly outperform funds in the largest size quintile among small-cap funds but not among non-small-cap funds.

To check the robustness of my results, I also extend the analysis of value/growth funds back to 1983 and the analysis of turnover to 1966.[11] The results for these extended periods are presented in Appendix A. Overall, these extended sample periods display similar patterns to those in 1993–2002. That is, I find the inverse relation between fund size and fund performance is stronger among

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[11]The turnover data are missing for all funds in 1991. I replace these missing data with the turnover in 1990.

TABLE 7

The Effect of Investment Style on the Relation between Fund Size and Fund Performance,
Portfolio Approach

Table 7 reports Carhart four-factor alphas (% per month) for portfolios sorted on liquidity and fund size. The sample period is 1993–2002. I obtain mutual fund stockholdings from Thomson Financial. Fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth and Income). I combine different share classes into a single fund. I exclude index funds and funds with total net assets less than $15 million. I exclude the first 18 months of data for each sample fund. Transaction-level data are from the Trade and Quote (TAQ) database. BM deciles are by NYSE breakpoints (decile 1 contains the highest book-to-market stocks). Numbers in parentheses are t-statistics. ** indicates significance at the 5% level.

Panel A. Portfolios Based on Book-to-Market Decile

	Fund Size Quintile					Difference 1 − 5	
BM Portfolio	1 (small)	2	3	4	5 (large)		
1 (value)	0.08	−0.07	−0.11	−0.11	−0.09	0.17**	(2.46)
2	−0.12	−0.02	−0.12	−0.15	−0.06	−0.06	(−0.86)
3	−0.16	−0.26	−0.13	−0.27	−0.16	−0.00	(−0.03)
4	−0.02	−0.15	−0.24	−0.27	−0.14	0.12**	(1.77)
5 (growth)	−0.05	−0.11	−0.06	−0.22	−0.21	0.16**	(2.17)

Panel B. Portfolios Based on Fund Turnover

	Fund Size Quintile					Difference 1 − 5	
Turnover Portfolio	1 (small)	2	3	4	5 (large)		
1 (low)	−0.08	−0.03	−0.13	−0.09	−0.04	−0.04	(−0.70)
2	−0.12	−0.04	−0.15	−0.22	−0.11	−0.01	(−0.13)
3	−0.02	−0.11	−0.14	−0.16	−0.07	0.14**	(1.81)
4	−0.07	−0.20	−0.23	−0.25	−0.24	0.17**	(2.30)
5 (high)	0.04	−0.11	−0.16	−0.32	−0.19	0.23**	(1.87)

Panel C. Portfolios Based on Whether Fund is a Small-Cap Fund

	Fund Size Quintile					Difference 1 − 5	
	1 (small)	2	3	4	5 (large)		
Small-Cap Funds	0.09	−0.12	−0.08	−0.27	−0.30	0.38**	(3.87)
Non-Small-Cap Funds	−0.08	−0.10	−0.12	−0.19	−0.12	0.04	(0.81)

growth funds and high turnover funds. However, these results are substantially weaker both economically and statistically. In addition, the results are sensitive to whether I use gross returns or net returns.

C.   Empirical Results—Cross-Sectional Regression Approach

1.   Method

In this section, I use a cross-sectional regression approach to examine the effect of liquidity and investment style on the relation between fund size and fund performance. Specifically, I regress one-month-ahead risk-adjusted fund returns (i.e., alphas) on various fund characteristics including fund size and measures of liquidity. Using this approach mitigates a concern that the relation between fund size and performance may be driven by their mutual relations with other fund characteristics.

For ease of comparison, I follow the approach of Chen et al. (2004) to estimate factor loadings for each fund. Specifically, I divide all funds into five quintiles by fund size. I track these five portfolios for one quarter and then use the entire time series of their monthly returns to estimate the loadings to various risk factors (MKT, SMB, HML, and UMD). For each month, each fund inherits the loadings of one of the five fund size quintiles that it belongs to. The one-month-

ahead expected fund return is then calculated by using the above factor loadings along with the realized factor returns (including return on the risk-free asset) for the next month. Finally, the risk-adjusted return is calculated as the difference between the realized fund return and the expected fund return.

To gauge the robustness of my results to various asset pricing models, I again consider four different models—the CAPM, the Fama-French three-factor model, the Carhart four-factor model, and a conditional four-factor model. For brevity, I only report results on the Fama-French three-factor alpha or Carhart four-factor alpha in this section. The results for the CAPM alpha and the conditional four-factor alpha are qualitatively similar and are available upon request.

The control variables used in my cross-sectional regressions are similar to those used by Chen et al. (2004) and include fund family size, expense ratio, fund age, turnover, total load, lagged fund flow, and lagged fund return. I calculate both lagged fund flow and lagged fund return using the past one year's data. In particular, the lagged one-year fund flow is defined as:

$$(8) \qquad \text{FLOW}_t \quad = \quad \frac{\text{TNA}_{t+1} - \text{TNA}_t \left(1 + R_t\right) - \text{MGTNA}_t}{\text{TNA}_t},$$

where R_t is the fund return and MGTNA_t is the assets acquired from merger.

The specification of the cross-sectional regression is as follows:

$$(9) \qquad \alpha_{i,t} \quad = \quad a + b_1 \text{LOGTNA}_{i,t-1} + b_2 \text{LOGFAM}_{i,t-1} + b_3 \text{EXP}_{i,t-1}$$
$$+ b_4 \text{LOGAGE}_{i,t-1} + b_5 \text{TURNOVER}_{i,t-1} + b_6 \text{LOAD}_{i,t-1}$$
$$+ b_7 \text{LAGFLOW}_{i,t-1} + b_8 \text{LAGFUNDRET}_{i,t-1} + e_{i,t},$$

where α_t is the one-month-ahead risk-adjusted fund return, LOGTNA is the logarithm of fund TNA, LOGFAM is the logarithm of the fund family's TNA, EXP is the fund's expense ratio, LOGAGE is the logarithm of the fund's age, LOAD is the fund's total load, LAGFLOW is the lagged one-year fund flow, and LAGFUNDRET is the lagged one-year fund return.

Following Chen et al. (2004), I use the Fama-MacBeth (1973) method. I estimate the above cross-sectional regression each month and report the time-series average coefficients. The statistical significance of the average coefficients is evaluated based on Newey-West standard errors.

2. The Relation between Fund Size and Fund Performance

In this subsection, I first establish the relation between fund size and fund performance. Table 8 reports the results. The first column presents the results for the Fama-French three-factor alpha calculated using gross returns. Consistent with Chen et al. (2004), I find that fund performance is significantly positively related to the size of the fund family and lagged fund return. The positive association between fund family size and performance is consistent with the idea that large families may economize on certain fixed costs such as those on brokerage service, research, marketing, and distribution. The positive relation between lagged fund return and fund performance suggests that there is some persistence in fund performance. In addition, I find a negative relation between fund returns

TABLE 8

The Effect of Fund Size on Fund Performance, Cross-Sectional Regression Approach

Table 8 examines the relation between fund size and fund performance. The sample period is 1993–2002. I obtain mutual fund stockholdings from Thomson Financial. Fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth and Income). I combine different share classes into a single fund. I exclude index funds and funds with total net assets less than $15 million. I exclude the first 18 months of data for each sample fund. Gross returns are calculated by adding back 1/12 of annual expense ratio to the net return. Stock characteristics are from Compustat and the CRSP stock database. I calculate both lagged fund flow and lagged fund return using past one year's data. Transaction-level data are from the Trade and Quote (TAQ) database. QS, ES, MI1, and MI2 are liquidity measures as defined in equations (1), (2), (4), and (5), respectively. I use the Fama-MacBeth (1973) method. Numbers in parentheses are t-statistics that are based on Newey-West standard errors. ** indicates significance at the 5% level.

| | Dependent Variable | | | |
| | Gross Return | | Net Return | |
Independent Variables	3-Factor α	4-Factor α	3-Factor α	4-Factor α
Intercept	−0.288	−0.258	−0.311	−0.280
	(−0.83)	(−0.74)	(−0.89)	(−0.81)
Log TNA	−0.045**	−0.054**	−0.044**	−0.053**
	(−2.81)	(−3.30)	(−2.75)	(−3.25)
Log Family TNA	0.020**	0.019**	0.020**	0.019**
	(2.66)	(2.61)	(2.63)	(2.59)
Expense Ratio	0.028	0.028	−0.045	−0.046
	(0.33)	(0.32)	(−0.53)	(−0.53)
Log Fund Age	0.025	0.026	0.025	0.026
	(1.53)	(1.63)	(1.55)	(1.64)
Turnover	0.039	0.039	0.038	0.038
	(0.98)	(0.98)	(0.97)	(0.97)
Total Load	−0.005	−0.005	−0.006	−0.006
	(−0.68)	(−0.71)	(−0.81)	(−0.83)
Lagged Fund Flow	−0.111**	−0.114**	−0.111**	−0.115**
	(−2.39)	(−2.42)	(−2.40)	(−2.42)
Lagged Fund Return	0.028**	0.028**	0.028**	0.028**
	(2.91)	(2.90)	(2.94)	(2.94)
Average R^2	0.21	0.21	0.21	0.21

and lagged fund flow, suggesting that large fund inflows may disrupt fund management and adversely affect fund performance.

More importantly, the fund performance is significantly negatively related to lagged fund size. This result is statistically significant at the 1% level regardless of which alpha measure I use. The effect of size on performance is also economically significant. On average, a two-standard deviation increase in the logarithm of fund TNA is associated with a decrease in fund performance by almost 18 basis points per month, which translates to over 2% per year. In comparison, Chen et al. (2004) document that in their sample period a two-standard deviation increase in the logarithm of fund TNA is associated with a decrease of performance by less than 1% per year. This is consistent with my portfolio results where I show that the return differential between small funds and large funds is greater in my sample than in those documented in Chen et al. (2004).

The results for the Carhart four-factor alpha and alphas calculated using net returns are similar to those reported above. Overall, consistent with Chen et al. (2004), I find strong and robust evidence of an inverse relation between fund size and fund performance.

3.   The Effect of Liquidity

To test if the diseconomies of scale are attenuated by liquidity, I include in the cross-sectional regressions an interaction term between fund liquidity and lagged fund size. If fund size erodes fund performance because of liquidity, then one would expect the coefficient on this interaction term to be significantly negative, indicating that fund size erodes performance more among funds that are less liquid.

Panel A of Table 9 reports the results for the spread-based liquidity measures. The dependent variable is the Carhart four-factor alpha.[12] Similar to Table 8, I find that fund performance is significantly positively related to fund family size and lagged fund return, while significantly negatively related to lagged fund flow. More importantly, I find that the coefficient in front of the interaction term between QS (or ES) and lagged fund size is negative in all four regressions. This result suggests that the inverse relation between fund size and performance is more negative for less liquid funds. In regressions (1) and (2), the coefficients on the interaction term are statistically significant at the 1% level (t-stat = −3.05 and −3.05). When I add lagged fund size in regressions (3) and (4), the coefficients on the interaction term are still negative but not statistically significant (t-stat = −1.21 and −1.40). The above insignificant result might be partly explained by endogenous liquidity. As stated in the Introduction, the presence of endogenous liquidity would bias against finding a significant positive effect of illiquidity on the inverse relation between fund size and fund performance.

Panel B of Table 9 presents the results regarding market impact measures. The qualitative results are similar to those reported in Panel A; the coefficient on the interaction term between market impact and lagged fund size is negative in all regressions and is statistically significant in two out of four regressions. Overall, results in Table 9 indicate that the inverse relation between fund size and fund performance is stronger among funds that hold less liquid portfolios.

4.   The Effect of Investment Style

To examine the effect of investment style, I follow an approach similar to that in the previous subsection. Specifically, I include the interaction term between book-to-market deciles (or turnover rate) and lagged fund size in the cross-sectional regression. Table 10 reports the results. I find that fund performance is positively related to fund family size and negatively related to lagged fund size. Similar to Table 9, I find that the coefficients in front of the interaction terms are all negative, indicating that the inverse relation between fund size and performance is more pronounced for growth and high turnover funds. Overall, the cross-sectional regression results reported in Tables 9 and 10 are consistent with the hypothesis that liquidity is an important reason why fund size erodes performance.

I again extend the analysis of growth/value funds back to 1983 and the analysis of turnover to 1966. The results are reported in Appendix B. Overall, the results for these extended sample periods are similar to those reported for 1993–

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[12]Results on the CAPM-alpha, Fama-French three-factor alpha, or the conditional four-factor alpha are qualitatively similar. For brevity, these results are not reported.

TABLE 9

The Effect of Liquidity on the Relation between Fund Size and Fund Performance,
Cross-Sectional Regression Approach

Table 9 examines the effect of liquidity on the relation between fund size and fund performance. The sample period is 1993–2002. I obtain mutual fund stockholdings from Thomson Financial. Fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth and Income). I combine different share classes into a single fund. I exclude index funds and funds with total net assets less than $15 million. I exclude the first 18 months of data for each sample fund. Stock characteristics are from Compustat and the CRSP stock database. I calculate both lagged fund flow and lagged fund return using past one year's data. Transaction-level data are from the Trade and Quote (TAQ) database. QS, ES, MI1, and MI2 are liquidity measures as defined in equations (1), (2), (4), and (5), respectively. I use the Fama-MacBeth (1973) method. Numbers in parentheses are t-statistics that are based on Newey-West standard errors. ** indicates significance at the 5% level.

Independent Variables	Dependent Variable: Carhart 4-Factor Alpha							
	(1)		(2)		(3)		(4)	
Panel A. Spreads								
Intercept	−0.514	(−1.42)	−0.507	(−1.40)	−0.401	(−1.04)	−0.400	(−1.04)
Log TNA × QS	−0.087**	(−3.05)			−0.033	(−1.21)		
QS	0.585**	(2.18)			0.303	(1.03)		
Log TNA × ES			−0.117**	(−3.05)			−0.051	(−1.40)
ES			0.743**	(2.10)			0.394	(1.00)
Log TNA					−0.038**	(−2.07)	−0.037**	(−2.04)
Log Family TNA	0.011	(1.52)	0.011	(1.53)	0.019**	(2.55)	0.019**	(2.53)
Expense Ratio	−0.029	(−0.47)	−0.029	(−0.48)	−0.035	(−0.57)	−0.036	(−0.59)
Log Fund Age	0.003	(0.24)	0.003	(0.21)	0.023	(1.53)	0.022	(1.50)
Turnover	0.038	(0.94)	0.038	(0.95)	0.038	(0.98)	0.038	(0.95)
Total Load	−0.006	(−1.06)	−0.006	(−1.08)	−0.006	(−1.05)	−0.006	(−1.06)
Lagged Fund Flow	−0.109**	(−2.47)	−0.110**	(−2.50)	−0.110**	(−2.48)	−0.111**	(−2.51)
Lagged Fund Return	0.027**	(2.93)	0.027**	(2.97)	0.027**	(2.93)	0.027**	(2.97)
Average R^2		0.27		0.27		0.27		0.28
Panel B. Market Impact								
Intercept	−0.547	(−1.38)	−0.452	(−1.29)	−0.412	(−1.09)	−0.347	(−0.99)
Log TNA × MI1	−0.654**	(−2.37)			−0.270	(−1.24)		
MI1	0.051	(1.14)			0.031	(0.85)		
Log TNA × MI2			−0.186**	(−2.64)			−0.065	(−1.05)
MI2			0.014	(1.46)			0.008	(0.89)
Log TNA					−0.034	(−1.32)	−0.042**	(−2.47)
Log Family TNA	0.014	(1.95)	0.009	(1.34)	0.018**	(2.15)	0.018**	(2.25)
Expense Ratio	−0.051	(−0.85)	−0.039	(−0.62)	−0.055	(−0.93)	−0.051	(−0.83)
Log Fund Age	0.015	(0.96)	−0.002	(−0.12)	0.024	(1.63)	0.023	(1.58)
Turnover	0.038	(0.94)	0.037	(0.90)	0.038	(0.93)	0.036	(0.90)
Total Load	−0.005	(−1.04)	−0.006	(−1.47)	−0.005	(−0.92)	−0.005	(−1.12)
Lagged Fund Flow	−0.095**	(−2.25)	−0.096**	(−2.24)	−0.095**	(−2.24)	−0.097**	(−2.25)
Lagged Fund Return	0.026**	(2.75)	0.026**	(2.75)	0.026**	(2.74)	0.026**	(2.74)
Average R^2		0.32		0.30		0.32		0.30

2002. More specifically, I find the coefficient on the interaction term between fund size and book-to-market or turnover to be negative in all regressions and significantly negative in two cases.

V. Conclusions

This paper examines the effect of liquidity and investment style on the relation between fund size and fund performance. Using stock transactions data along with detailed stockholdings for a comprehensive sample of U.S. actively managed equity mutual funds from 1993 to 2002, I propose and construct two sets of liquidity measures for each fund's stock portfolio. The first set of liquidity measures are the weighted average quoted and effective spread of a fund's portfolio. The second set of liquidity measures are constructed as functions of the stock's market

TABLE 10

The Effect of Investment Style on the Relation between Fund Size and Fund Performance, Cross-Sectional Regression Approach

Table 10 examines the effect of investment style on the relation between fund size and fund performance. The sample period is 1993–2002. I obtain mutual fund stockholdings from Thomson Financial. Fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth and Income). I combine different share classes into a single fund. I exclude index funds and funds with total net assets less than $15 million. I exclude the first 18 months of data for each sample fund. Stock characteristics are from Compustat and the CRSP stock database. I calculate both lagged fund flow and lagged fund return using past one year's data. Transaction-level data are from the Trade and Quote (TAQ) database. QS, ES, MI1, and MI2 are liquidity measures as defined in equations (1), (2), (4), and (5), respectively. BM deciles are by NYSE breakpoints (decile 1 contains the highest book-to-market stocks). I use the Fama-MacBeth (1973) method. Numbers in parentheses are t-statistics that are based on Newey-West standard errors. ** indicates significance at the 5% level.

Independent Variables	Dependent Variable: 4-Factor Alpha							
	(1)		(2)		(3)		(4)	
Intercept	−0.173	(−0.44)	−0.466	(−1.46)	−0.201	(−0.46)	−0.352	(−1.11)
Log TNA × BM	−0.006**	(−2.76)			−0.004	(−0.51)		
BM	0.005	(0.06)			0.013	(0.16)		
Log TNA × Turnover			−0.030**	(−2.73)			−0.014	(−1.20)
Log TNA					−0.010	(−0.18)	−0.040**	(−2.36)
Log Family TNA	0.014**	(2.17)	0.011	(1.74)	0.014**	(2.02)	0.020**	(2.72)
Expense Ratio	−0.066	(−0.81)	−0.022	(−0.26)	−0.066	(−0.84)	−0.037	(−0.43)
Log Fund Age	0.020	(1.19)	0.003	(0.18)	0.020	(1.27)	0.026	(1.65)
Turnover	0.030	(0.92)	0.185**	(4.24)	0.030	(0.93)	0.101**	(2.15)
Total Load	−0.003	(−0.44)	−0.007	(−0.97)	−0.003	(−0.44)	−0.007	(−0.90)
Lagged Fund Flow	−0.085	(−1.85)	−0.115**	(−2.44)	−0.085	(−1.87)	−0.114**	(−2.43)
Lagged Fund Return	0.022**	(2.49)	0.028**	(2.93)	0.023**	(2.50)	0.028**	(2.93)
Average R^2		0.28		0.21		0.29		0.21

capitalization as well as the relative holding size, and are designed to capture the level of market impact of a fund's portfolio.

I examine the effect of liquidity on the relation between fund size and performance by using both a portfolio approach and a cross-sectional regression approach. In the portfolio approach, I divide all sample funds into portfolios based on liquidity and fund size. I evaluate the performance of each portfolio by using four standard models. Consistent with the hypothesis that liquidity is an important reason why fund size erodes performance, I find that the inverse relation between fund size and fund performance is more pronounced among funds in the lower liquidity quintiles.

In the cross-sectional regression approach, I regress risk-adjusted fund returns on various fund characteristics including fund size and liquidity. After controlling for other fund characteristics, I still find evidence that the inverse relation between fund size and fund performance is stronger among funds that hold less liquid portfolios.

I also examine the extent to which the nature of the economies of scale varies across investment styles. Consistent with the liquidity hypothesis, I find evidence that the adverse effect of scale on performance is more pronounced among growth and high turnover funds, which tend to have high demands for immediacy in their trades.

The liquidity measures constructed in this study can be used to analyze a number of important issues in the mutual fund literature. For example, mutual funds are required by law to redeem and issue fund shares on a daily basis. Prior literature (e.g., Edelen (1999)) finds that this liquidity provision imposes signifi-

cant direct and indirect costs on the funds. Naturally, the magnitude of this cost depends critically on the liquidity of a fund's portfolio. Therefore, it would be interesting to examine how liquidity interacts with fund flows in affecting fund performance. In addition, liquidity affects the extent to which daily fund returns are predictable. Chalmers, Edelen, and Kadlec (2001) show that this predictability arises primarily as a result of nonsynchronous trading and might lead to exploitable trading opportunities. Given the positive relation between liquidity and trading frequency, one might expect that the fund return predictability is stronger among funds with less liquid holdings. An analysis of the relation between liquidity and the predictability of daily fund returns would be useful for identifying funds that are susceptible to market timing abuses. These topics will be pursued in future research.

APPENDIX A

Differences in Alpha between the Smallest Fund Quintile and the Largest Fund Quintile by Investment Styles
for Extended Sample Periods

This table reports the difference in alpha (% per month) between the smallest quintile funds and the largest quintile funds. The sample period is 1983–2002 for Panel A and 1966–2002 for Panel B. I obtain mutual fund stockholdings from Thomson Financial. Fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth and Income). I combine different share classes into a single fund. I exclude index funds and funds with total net assets less than $15 million. I exclude the first 18 months of data for each sample fund. BM deciles are by NYSE breakpoints (decile 1 contains the highest book-to-market stocks). Fund turnover data in 1991 are missing and replaced with 1990 turnover data. I use four models to evaluate fund performance: CAPM, Fama-French three-factor model, Carhart four-factor model, and the conditional four-factor model as described in equations (7) and (8). ** indicates significance at the 5% level.

Panel A. Book-to-Market

α	Fund Portfolios Based on Book-to-Market Decile				
	1 (value)	2	3	4	5 (growth)
Gross Returns					
CAPM	0.11**	−0.03	−0.01	−0.01	0.11
Fama-French 3-Factor	0.06	−0.03	0.02	0.01	0.16**
Carhart 4-Factor	0.06	−0.03	0.01	−0.01	0.13**
Conditional 4-Factor	0.07	0.01	0.04	0.02	0.11**
Net Returns					
CAPM	0.07	−0.08	−0.05	−0.06	0.06
Fama-French 3-Factor	0.02	−0.07	−0.02	−0.04	0.10
Carhart 4-Factor	0.02	−0.07	−0.03	−0.06	0.07
Conditional 4-Factor	0.05	−0.03	0.01	−0.04	0.05

Panel B. Turnover

α	Fund Portfolios Based on Turnover				
	1 (low)	2	3	4	5 (high)
Gross Returns					
CAPM	0.04	0.08	0.18**	0.26**	0.08
Fama-French 3-Factor	0.09	0.02	0.11	0.18**	0.00
Carhart 4-Factor	0.07	0.01	0.09	0.18**	0.03
Conditional 4-Factor	0.04	0.03	0.06	0.18**	0.05
Net Returns					
CAPM	0.00	0.03	0.13	0.23**	0.04
Fama-French 3-Factor	0.05	−0.02	0.06	0.14**	−0.03
Carhart 4-Factor	0.02	−0.04	0.04	0.14**	−0.01
Conditional 4-Factor	−0.00	−0.01	0.02	0.15**	0.01

APPENDIX B

The Effect of Investment Style on the Relation between Fund Size and Fund Performance for Extended Sample Periods,
Cross-Sectional Regression Approach

This table examines the effect of investment style on the relation between fund size and fund performance. The sample period is 1983–2002 for the first two regressions and is 1966–2002 for the last two regressions. I obtain mutual fund stockholdings from Thomson Financial. Fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of "AG" (Aggressive Growth), "LG" (Long-Term Growth), or "GI" (Growth and Income). I combine different share classes into a single fund. I exclude index funds and funds with total net assets less than $15 million. I exclude the first 18 months of data for each sample fund. Stock characteristics are from Compustat and the CRSP stock database. I calculate both lagged fund flow and lagged fund return using past one year's data. BM deciles are by NYSE breakpoints (decile 1 contains the highest book-to-market stocks). Fund turnover data in 1991 are missing and replaced with 1990 turnover data. I use the Fama-MacBeth (1973) method. Numbers in parentheses are t-statistics that are based on Newey-West standard errors. ** indicates significance at the 5% level.

	Dependent Variable: Carhart (1997) 4-Factor Net Alpha							
Independent Variables	1983–2002		1983–2002		1966–2002		1966–2002	
Intercept	−0.227	(−0.89)	−0.247	(−0.89)	−0.350	(−2.36)	−0.248	(−1.51)
Log TNA × BM	−0.003**	(−1.73)	−0.002	(−0.49)				
BM	−0.003	(−0.06)	0.001	(0.01)				
Log TNA × Turnover					−0.048**	(−2.39)	−0.024	(−1.04)
Log TNA			−0.003	(−0.11)			−0.031**	(−2.04)
Log Family TNA	0.009	(1.03)	0.009	(1.05)	0.014	(1.83)	0.022	(2.51)
Expense Ratio	−0.074	(−1.44)	−0.075	(−1.46)	−0.069	(−1.27)	−0.089	(−1.52)
Log Fund Age	0.036**	(2.04)	0.037**	(2.06)	0.008	(0.42)	0.017	(0.90)
Turnover	0.037	(1.50)	0.037	(1.49)	0.257**	(3.03)	0.129	(1.23)
Total Load	−0.005	(−1.40)	−0.005	(−1.39)	−0.001	(−0.28)	−0.001	(−0.19)
Lagged Fund Flow	−0.060	(−1.29)	−0.058	(−1.24)	−0.160**	(−2.26)	−0.156**	(−2.19)
Lagged Fund Return	0.015**	(2.69)	0.015**	(2.69)	0.023**	(5.26)	0.023**	(5.24)
Average R^2		0.28		0.28		0.24		0.25

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