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Do mutual fund managers time market liquidity? ☆

Charles Cao[a], Timothy T. Simin[a], Ying Wang[b,*]

[a] Pennsylvania State University, University Park, PA, USA
[b] University at Albany, State University of New York, Albany, NY, USA

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Abstract

This paper examines mutual fund managers' ability to time market-wide liquidity. Using the CRSP mutual fund database, we find strong evidence that over the 1974–2009 period, mutual fund managers demonstrate the ability to time market liquidity at both the portfolio level and the individual fund level. Liquidity timing predicts future fund performance and the difference in the risk-adjusted returns between top and bottom liquidity-timing funds is approximately 2% per year. Funds exhibiting liquidity-timing ability tend to have longer histories, higher expense ratios, and higher turnover rates.
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*Corresponding author. Tel.: +1 518 442 4978.
E-mail address: ywang@albany.edu (Y. Wang).

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1. Introduction

The literature on the timing ability of mutual fund managers has traditionally focused on managers' ability to time market returns or volatility. There is little evidence that fund managers successfully time the market by increasing (decreasing) portfolio exposure prior to market advances (declines) (e.g., Treynor and Mazuy, 1966; Chang and Lewellen, 1984; Henriksson, 1984; Ferson and Schadt, 1996; Graham and Harvey, 1996; Becker, Ferson, Myers, and Schill, 1999).[1] On the other hand, Busse (1999) documents that fund managers demonstrate the ability to time market volatility by increasing (reducing) portfolio exposure to the market when the market is less (more) volatile. In this paper, we investigate the traditional timing issue from a new perspective by examining mutual fund managers' ability to time market liquidity. Specifically, we test whether fund managers adjust market exposure when market liquidity changes.

We focus on liquidity timing for several reasons. First, there is a clear connection between market-wide liquidity and mutual fund performance. For example, during the 2008 financial crisis, massive market-wide liquidity squeezes were coupled with dramatic stock market declines. If fund managers can correctly predict future market liquidity conditions, they can adapt their portfolio exposure accordingly to alleviate losses and improve performance. As fund performance affects investor money flows and hence manager compensation, mutual fund managers are incentivized to adjust asset allocation according to market liquidity conditions. Secondly, while market returns lack sufficient persistence to be reliably predictable, market liquidity, like market volatility, is more persistent. Therefore, it might be easier for fund managers to time market liquidity than market returns. Finally, the asset pricing literature has identified market liquidity as a state variable that is important for asset pricing. For example, Acharya and Pedersen (2005) show that persistent positive shocks to liquidity predict high future liquidity, which lowers required future returns and raises contemporaneous prices; therefore, a high liquidity state is associated with high contemporaneous returns and vice versa. Given the co-movement of market liquidity and market returns, it is natural to ask whether market liquidity is an important factor for asset allocation decisions.

To understand how fund managers might time market liquidity when making asset allocation decisions, consider a simple scenario in which funds either hold cash or invest in stocks. Since market liquidity co-moves with market returns, fund managers with liquidity-timing ability shift out of cash and into stocks to increase market exposure prior to higher market liquidity (and hence higher market returns). Similarly, fund managers shift out of stocks and into cash to reduce exposure to the equity market prior to more illiquid markets (and hence market declines). Based on the above intuition, if managers demonstrate the ability to time market liquidity, we expect a positive relation between funds' systematic risk (market beta) and market liquidity.

Using the CRSP Survivorship-Bias-Free Mutual Fund Database, we examine mutual fund managers' liquidity-timing ability during the period of 1974–2009. In the empirical analysis, we use two measures of market liquidity to evaluate the liquidity-timing ability of

[1]Notable exceptions that document significant market timing ability include Bollen and Busse (2001), who use daily fund returns, and Jiang, Yao, and Yu (2007) and Huang and Wang (2010), who employ a holdings-based approach. A recent study by Cao, Chen, Liang, and Lo (2011) finds that hedge fund managers possess liquidity timing ability.

fund managers: the Pastor and Stambaugh (2003) liquidity measure and the Amihud (2002) illiquidity measure. We first document significant and positive liquidity-timing ability at the portfolio level by showing that fund managers increase (reduce) portfolio exposure when the market is more liquid (illiquid). In particular, we find that when market liquidity is one standard deviation above its mean, ceteris paribus, the average mutual fund portfolio's market beta is 5.5% higher.

Among funds with different investment objectives, aggressive growth funds demonstrate the most significant liquidity-timing ability, followed by growth and growth-and-income funds, while income funds do not exhibit liquidity timing ability. As aggressive growth funds tend to tilt more heavily towards small-cap stocks and thus hold more illiquid assets (Chen, Hong, Huang, and Kubik, 2004), the results suggest that funds with more illiquid holdings are more likely to successfully time market liquidity. The results are robust to the exclusion of the 1987 market crash and the 2008 financial crisis, a sub-period analysis, the use of an alternative liquidity measure, and the inclusion of a liquidity risk factor. In addition, we show that liquidity timing, as well as volatility timing documented by Busse (1999), is an important component of the strategies of active mutual fund managers.

We also evaluate the liquidity timing ability of mutual fund managers at the individual fund level using a bootstrap approach similar to that of Jiang, Yao, and Yu (2007). The bootstrap analysis indicates that the liquidity-timing ability of top fund managers cannot simply be attributed to luck. In addition, we demonstrate that liquidity timing predicts future fund performance. Sorting funds based on the liquidity timing coefficients every year, we find that funds in the highest decile outperform those in the lowest decile by approximately 2% per year during the 1974–2009 period. Finally, we examine the cross-sectional relationship between liquidity-timing ability and fund characteristics and document that liquidity timers tend to have longer histories, higher expense ratios, and higher turnover rates.

This paper is part of the growing mutual fund timing literature pioneered by Treynor and Mazuy (1966). In particular, it is related to the literature on conditional mutual fund performance (e.g., Ferson and Schadt, 1996; Christopherson, Ferson, and Glassman, 1998; Becker, Ferson, Myers, and Schill, 1999; Ferson and Qian, 2004) and volatility timing (e.g., Busse, 1999). These studies examine fund managers' ability to time market returns conditional on a set of publicly available information variables or their ability to time market volatility. In contrast, we investigate fund managers' ability to time market liquidity, thus offering a new perspective on the traditional timing issue.

The remainder of the paper is organized as follows: Section 2 describes our mutual fund data and the liquidity measures. Section 3 presents the portfolio-level analysis of liquidity timing. In Section 4, we use a bootstrap approach to examine liquidity-timing ability at the individual fund level, evaluate the out-of-sample performance of liquidity-timing funds, and investigate the cross-sectional relationship between liquidity-timing ability and fund characteristics. Section 5 concludes.

2. Data

2.1. Mutual funds

Our mutual fund data come from the CRSP Survivor-Bias-Free US Mutual Fund Database. Following other mutual fund performance studies (e.g., Ferson and Schadt, 1996; Busse, 1999), we only include domestic equity funds in our sample. Specifically, we include funds with investment objectives of aggressive growth, growth, growth-and-income, and income.[2] Index funds are removed from our sample, as their objective is to replicate the performance of a benchmark index and they are unlikely to exhibit any form of timing. We identify index funds by the identifier (index_fund_flag) provided in the CRSP database. If the identifier is not available, we identify index funds by their names. For funds with multiple share classes, we aggregate the total net assets (TNAs) of individual share classes and calculate the fund-level variables (such as return, expense ratio, turnover rate, and flows) as the TNA-weighted averages across different share classes of the same fund. As is commonly done with these data, we winsorize the fund data at both the upper and lower 0.25% levels to mitigate the impacts of outliers. Finally, we exclude observations where the fund-year is earlier than the reported year in which the fund was organized to reduce the impact of the backfill bias.

Due to a lack of an aggressive growth fund category and data omissions in the early years of the database, our sample starts from January 1974 and ends in December 2009. The final sample includes 5,423 unique equity funds, among which there are 1,313 aggressive growth funds, 2,050 growth funds, 1,579 growth-and-income funds, and 481 income funds. We also isolate survivors from non-survivors. As of December 2009, 2,968 funds are still alive with the remaining 2,455 being defunct.

Table 1 reports the characteristics of our mutual fund sample broken down according to the investment objective and survivorship status. Fund age is defined as the number of years between the last return date in the database and the first date when the fund was offered averaged across funds within each fund category. Fund size (TNAs), expense ratios, turnover rates, and monthly flows are first averaged over time for each fund, and then averaged across funds within each investment-objective category. We use normalized flow, which is defined as

$$flow_t = \frac{TNA_t - TNA_{t-1}(1 + R_t)}{TNA_{t-1}} \tag{1}$$

where TNA_t is the TNAs at the end of month t and R_t is the month-t return. On average, equity mutual funds have an age of 11 years, total net assets of \$390 million, an annual expense ratio of 1.34%, an annual turnover rate of 105%, and monthly flows of 1.20%. Among funds with different investment objectives, aggressive growth funds have the highest expense ratios and turnover rates, followed by growth, growth-and-income, and income funds. Income funds have the largest total net assets while the growth-and-income funds have the highest flows. Compared with non-survivors, survivors are on average

[2] We classify mutual funds based on the objective codes reported by Wiesenberger, Strategic Insight, and Lipper. Aggressive growth funds are those with Wiesenberger codes of SCG, AGG, and MCG; Strategic Insight codes of AGG and SCG; or Lipper codes of CA, LSE, MR, and SG. Growth funds include those with Wiesenberger codes of G, G-S, S-G, GRO, and LTG; Strategic Insight codes of G, GRO, and GMC; or Lipper code of G. Growth-and-income funds are those with Wiesenberger codes of GCI, G-I, G-I-S, G-S-I, I-G, I-G-S, I-S-G, S-G-I, S-I-G, and GRI; Strategic Insight code of GRI; or Lipper codes of GI and MC. Income funds are those with Wiesenberger codes of I, I-S, IEQ, and ING; Strategic Insight code of ING; or Lipper codes of I and EI. Funds are assigned to each category in the order of Wiesenberger, Lipper, and Strategic Insight. For example, if a mutual fund has the Wiesenberger code of LTG, the Lipper code of GI, and the Strategic Insight code of AGG, it is classified as a long-term growth fund.

Table 1
Summary statistics of fund characteristics.

Summary statistics of fund characteristics from January 1974 to December 2009. Columns 2–8 report the characteristics for aggregative growth, growth, growth-and-income, income, surviving, non-surviving, and all equity funds, respectively. Age is defined as the number of years between the last return date in the database and the first date when the fund was offered, and averaged across funds within each fund category. Size ($millions), expense ratios (percentages), turnover rates (percentages), and monthly flows [percentages of total net assets (TNAs)] are first averaged over time for each fund, and then averaged across funds within each fund category. The last two rows report the time series mean (in percentages) and standard deviation (in percentages) of monthly returns, respectively, on the equal-weighted portfolios of mutual funds within each fund category.

	Aggressive growth	Growth	Growth & income	Income	Survivors	Non-survivors	All Equity Funds
Number of funds	1,313	2,050	1,579	481	2,968	2,455	5,423
Age (years)	11.04	10.31	11.59	10.73	12.35	9.13	10.90
Size ($mil)	348.09	352.26	413.86	589.45	623.24	108.63	390.23
Expense ratio (%/year)	1.54	1.40	1.18	1.04	1.18	1.52	1.34
Turnover rate (%/ year)	150.73	96.53	87.98	67.21	97.54	114.34	104.92
Monthly flow (% of TNA)	0.69	0.47	2.62	1.03	2.89	-0.86	1.20
Average return (%)	1.04	0.88	0.89	0.80	1.00	0.80	0.92
Return Std. Dev. (%)	5.18	4.49	4.02	2.73	4.34	4.42	4.36

larger funds with longer histories, lower expense ratios and turnover rates, and higher flows.

We construct equal-weighted portfolios of aggressive growth, growth, growth-and-income, income, surviving, non-surviving, and all equity funds, and then compute the monthly return series for each portfolio. The last two rows of Table 1 report the time series mean and standard deviation of monthly returns of each investment category. Among the four investment categories, aggressive growth funds have the highest returns and volatility. Compared with defunct funds, the surviving funds on average have higher returns, but slightly lower volatility.

2.2. Liquidity measures

We use the Pastor and Stambaugh (2003) liquidity measure for the primary analysis and follow their methodology to re-construct the measure. Specifically, we start with the following regression for stock i in month t:

$$r^e_{i,d+1,t} = \theta_{i,t} + \varphi_{i,t} r_{i,d,t} + \gamma_{i,t} sign\left(r^e_{i,d,t}\right) \cdot v_{i,d,t} + \epsilon_{i,d+1,t}, \qquad d = 1,\ldots,D_{i,t}, \tag{2}$$

where $\gamma_{i,t}$ is the liquidity measure for stock i in month t; $r_{i,d,t}$ is the return on stock i on day d in month t; $r^e_{i,d,t}$ is defined as $r_{i,d,t} - r_{m,d,t}$, where $r_{m,d,t}$ is the return on the CRSP value-weighted market portfolio on day d in month t; $v_{i,d,t}$ is the dollar volume for stock i on day d in month t; and $D_{i,t}$ is the number of days for stock i in month t. The intuition is that the more illiquid the stock, the greater the return reversal for a given order flow, which is roughly measured as the signed volume. We then estimate market liquidity as the scaled equal-weighted average of the liquidity measures of individual stocks on the NYSE and AMEX:

$$\gamma_t = P^M_{t-1} \frac{1}{N_t} \sum_{i=1}^{N_t} \gamma_{i,t} \tag{3}$$

where γ_t is the measure of market liquidity for month t, N_t is the number of stocks in month t, and P^M_{t-1} is the ratio of the total market value at the end of month $t-1$ to the total market value at the end of July 1962. In general, the Pastor and Stambaugh (2003) liquidity measure is expected to be negative and larger in magnitude when the market is more illiquid.

As market liquidity is not readily observable, we are concerned that our results might be sensitive to the choice of liquidity measure. Therefore, we use the Amihud (2002) illiquidity measure to cross-validate our results. Amihud measures the illiquidity of stock i in month t, $ILLIQ^i_t$, as follows:

$$ILLIQ^i_t = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|R^i_{td}|}{V^i_{td}} \tag{4}$$

where $D_{i,t}$ is the number of valid days in month t for stock i, and R^i_{td} and V^i_{td} are stock i's return and dollar volume (in millions) on day d in month t, respectively. The intuition is to measure the effect a given trading volume has on returns. Following Acharya and Pedersen (2005), we construct a normalized Amihud measure of illiquidity, c^i_t, as follows:

$$c^i_t = \min\left(0.25 + 0.30 ILLIQ^i_t P^M_{t-1}, 30.00\right) \tag{5}$$

where P^M_{t-1} is the scaling factor defined in a similar way as in Eq. (3); the parameters 0.25 and 0.30 are chosen such that the normalized illiquidity for size-decile portfolios has a similar distribution to the effective half spread; and the normalized illiquidity is capped at 30% to eliminate outliers. Finally, we construct a measure of market illiquidity, c_t, as the equal-weighted average of the illiquidity measures of individual stocks on the NYSE and

Table 2
Summary statistics of liquidity measures.

Summary statistics of Pastor and Stambaugh's (2003) liquidity measure (PS Liquidity) and Amihud's (2002) illiquidity measure (Amihud Illiquidity) from January 1974 to December 2009. Panel A presents summary statistics of both liquidity measures. Panel B reports Pearson correlations of the two liquidity estimators and the CRSP value-weighted market portfolio returns. **Significant at the 5% level.

Panel A: Summary statistics	Obs.	Mean	Median	Std. Dev.
PS liquidity	432	−0.03	−0.02	0.06
Amihud illiquidity	432	1.02	0.97	0.23

Panel B: Pearson correlations	PS liquidity	Amihud illiquidity	CRSP market return
PS liquidity	1.00		
Amihud illiquidity	−0.28**	1.00	
CRSP market return	0.29**	−0.24**	1.00

AMEX:

$$c_t = \frac{1}{N_t}\sum_{i=1}^{N_t} c_t^i \tag{6}$$

where N_t is the number of stocks in month t. The Amihud illiquidity measure is a proxy for market impact and is expected to be positive and larger when the market is more illiquid.

Table 2 presents summary statistics of the two liquidity measures. As expected, the Pastor and Stambaugh (2003) measure is negative with a mean (median) value of –0.03 (–0.02), indicating a roughly 2–3% cross-sectional average liquidity cost of trading \$1 million in 1962 ‘‘stock market’’ dollars. The Amihud (2002) measure is positive with a mean (median) of 1.02 (0.97), indicating that the average price impact is around 1%. Panel B reports the correlations among the two liquidity measures and the CRSP value-weighted market portfolio returns. We find that the two measures are significantly and negatively related to each other, with a correlation of −0.28. The Pastor and Stambaugh liquidity measure is significantly and *positively* correlated with market returns, while the Amihud illiquidity measure is significantly and *negatively* correlated with market returns. This suggests that a high (low) level of market liquidity is associated with high (low) market returns.

3. Empirical analysis

In this section, we examine whether mutual fund managers time market liquidity at the aggregate portfolio level. We first present evidence of liquidity timing and then check whether the results are robust to the exclusion of the 1987 market crash and the 2008 financial crisis, a sub-period analysis, and the use of an alternative liquidity measure. We also examine liquidity timing in the presence of market timing and volatility timing. Finally, we control for a potentially omitted liquidity risk factor in additional robustness tests.

3.1. Tests of market liquidity timing

In the empirical analysis, we first consider the standard Carhart (1997) four-factor model to explain the time series of mutual fund returns:

$$R_{pt} = \alpha_p + \beta_{mp}R_{mt} + \beta_{SMB,p}SMB_t + \beta_{HML,p}HML_t + \beta_{UMD,p}UMD_t + \epsilon_{pt} \tag{7}$$

where R_{pt} is the month-t return on portfolio p in excess of the 1-month T-bill return; R_{mt} is the month-t excess return on the CRSP value-weighted market portfolio; SMB_t, HML_t, and UMD_t are the month-t returns on factor-mimicking portfolios for size, book-to-market equity, and 1-year momentum in stock returns, respectively.

To account for liquidity timing, we follow the traditional timing literature on market return timing and volatility timing, and allow the market beta to be time-varying. Specifically, we use a first-order Taylor series expansion to express market beta as a linear function of market liquidity in excess of its time series average:

$$\beta_{mp} = \beta_{0mp} + \gamma_{mp}\left(L_{mt} - \overline{L}_m\right) \tag{8}$$

where L_{mt} is the market liquidity measure for month t, and $\overline{L}_m$ is the time series mean of market liquidity measures. This specification is motivated by Treynor and Mazuy (1966), Ferson and Schadt (1996), and Busse (1999), who specify time-varying market betas as a linear function of market returns or market volatility. Eq. (8) shows how the market risk of a mutual fund portfolio varies with market liquidity. Substituting Eq. (8) into Eq. (7) gives our four-factor liquidity-timing model:

$$R_{pt} = \alpha_p + \beta_{0mp} R_{mt} + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \beta_{UMD,p} UMD_t + \gamma_{mp} (L_{mt} - \overline{L}_m) R_{mt} + \epsilon_{pt} \quad (9)$$

In estimating Eq. (9), we use the Pastor and Stambaugh (2003) liquidity measure for our primary analysis. In addition, in each month t, we use the average liquidity estimate over the previous 60 months ([$t-60$, $t-1$]) as a proxy for the mean of liquidity ($\overline{L}_m$).[3] The coefficient γ_{mp} measures the liquidity-timing ability of fund managers. A significant and positive γ_{mp} coefficient indicates that mutual fund managers correctly anticipate high (low) market liquidity and increase (reduce) market exposure accordingly. When γ_{mp} is significant and negative, mutual fund managers incorrectly anticipate market liquidity or perversely increase market exposure when market liquidity is anticipated to be low.

Table 3 reports the regression results for the equal-weighted portfolios of aggressive growth, growth, growth-and-income, income, surviving, non-surviving, and all equity funds, respectively. The t-statistics (in parentheses) are calculated using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with one lag. As can be seen from the table, the liquidity-timing coefficient for the portfolio of all equity funds is significantly positive at the 1% level. The timing coefficient of 0.84 indicates that in a month when market liquidity is one standard deviation (i.e., 0.06 from Panel A of Table 2) above its mean, ceteris paribus, the average mutual fund portfolio's market beta is higher by 0.05 (0.84×0.06), which is roughly 5.5% of the market beta of 0.91 when aggregate liquidity is at its average level.

For the subgroups with different investment objectives, all the liquidity-timing coefficients are significantly positive except for the portfolio of income funds. In particular, aggressive growth funds demonstrate the most significant and positive liquidity-timing ability, followed by growth and growth-and-income funds. The estimated timing coefficients are 1.10, 0.78, and 0.59 and the Newey-West t-statistics are 7.21, 5.28, and 3.74, respectively, for aggregative growth, growth, and growth-and-income funds. In particular, a one standard deviation increase in market liquidity increases the market betas of aggressive growth, growth, and growth-and-income fund portfolios by 6.70%, 4.98%, and 4.02%, respectively. In contrast, income funds do not demonstrate significant liquidity-timing ability. The estimated timing coefficient for income funds is 0.33 with the Newey-West t-statistic of 1.51. Since aggressive growth funds tend to tilt more heavily towards small-cap stocks and thus hold more illiquid assets (Chen, Hong, Huang, and Kubik, 2004), the results suggest that funds with more illiquid holdings are more likely to successfully time market liquidity. In addition, although both surviving and non-surviving funds exhibit significant and positive timing ability with similar timing coefficients, the

[3]To streamline notations, we omit the subscript t for QUOTE in Eq. (9). We also experiment with alternative proxies of the mean of liquidity (e.g., the average liquidity estimate over the previous three or ten years). The results are consistent with our findings reported in the paper.

Table 3
Tests of liquidity timing.
Time series regression results of the four-factor liquidity-timing model:

$$R_{pt} = \alpha_p + \beta_{0mp} R_{mt} + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \beta_{UMD,p} UMD_t + \gamma_{mp} \left(L_{mt} - \overline{L}_m \right) R_{mt} + \epsilon_{pt},$$

where R_{pt} is the month-t return on portfolio p in excess of the 1-month T-bill return; R_{mt} is the month-t excess return on the CRSP value-weighted market portfolio; SMB_t, HML_t, and UMD_t are the month-t returns on factor-mimicking portfolios for size, book-to-market equity, and 1-year momentum in stock returns, respectively; L_m is the Pastor and Stambaugh (2003) market liquidity measure for month t; and $\overline{L}_m$ is the time series mean of market liquidity. Each month we use the average liquidity estimate over the previous 60 months as a proxy for the mean of liquidity. We report results for equal-weighted portfolios of aggregative growth, growth, growth-and-income, income, surviving, non-surviving, and all equity funds, respectively, for the period of 1/1974–12/2009. The t-statistics (in parentheses) are calculated using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with one lag. ** and * indicate significance at the 5% and 10% levels, respectively.

Fund group	α (%)	β_{0m}	β_{SMB}	β_{HML}	β_{UMD}	γ_m	Adj. R^2
Aggressive growth	−0.12**	0.99**	0.43**	−0.08**	0.06**	1.10**	0.96
	(−2.48)	(65.93)	(12.66)	(−2.64)	(2.93)	(7.21)	
Growth	−0.09**	0.94**	0.08**	−0.08**	0.00	0.78**	0.98
	(−2.76)	(80.86)	(2.85)	(−4.25)	(0.35)	(5.28)	
Growth & income	−0.06*	0.88**	0.00	0.07**	−0.02*	0.59**	0.98
	(−1.94)	(89.82)	(0.18)	(4.36)	(−1.81)	(3.74)	
Income	0.01	0.58**	−0.05**	0.16**	−0.05**	0.33	0.90
	(0.15)	(37.14)	(−2.73)	(7.67)	(−3.17)	(1.51)	
Survivors	−0.02	0.91**	0.14**	−0.00	0.02	0.84**	0.98
	(−0.69)	(90.67)	(6.37)	(−0.17)	(1.29)	(5.69)	
Non-survivors	−0.20**	0.91**	0.15**	−0.04**	0.00	0.83**	0.97
	(−5.33)	(76.98)	(6.10)	(−2.30)	(0.39)	(3.59)	
All equity funds	−0.09**	0.91**	0.14**	−0.02	0.01	0.84**	0.98
	(−2.76)	(86.32)	(6.35)	(−1.16)	(0.86)	(4.64)	

t-statistic associated with surviving funds is larger (5.69 vs. 3.59). Overall, the results provide strong evidence of liquidity-timing ability at the portfolio level.

3.2. Tests of market liquidity timing: impact of 1987 market crash and 2008 financial crisis

To ensure that our results are not driven by the 1987 market crash and the 2008 financial crisis, we exclude the data from September 1987 to February 1988 and from July to December 2008, and investigate the impact of these crisis periods on liquidity timing.

We repeat the tests in Eq. (9) and report the results in Table 4. Compared to the results in Table 3, the evidence of liquidity timing is slightly weaker but still significant when we exclude the market crash of 1987 and the financial crisis of 2008. For example, for the all-equity fund portfolio, the liquidity-timing coefficient is 0.84 with a Newey-West t-statistic of 4.64 when we include the 1987 crash and the 2008 crisis, but when we exclude these crisis periods, the liquidity-timing coefficient is 0.50 with the Newey-West t-statistic of 3.60. A similar pattern arises for aggressive growth, growth, growth-and-income, income, surviving, and non-surviving funds. Overall the results suggest that liquidity timing is especially valuable during a market crash. Further, our results are not driven by the 1987 market crash and the 2008 financial crisis periods.

Table 4
Tests of liquidity timing: excluding the 1987 crash and the 2008 crisis.
Time series regression results of the four-factor liquidity-timing model:

$$R_{pt} = \alpha_p + \beta_{0mp} R_{mt} + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \beta_{UMD,p} UMD_t + \gamma_{mp} (L_{mt} - \overline{L}_m) R_{mt} + \epsilon_{pt},$$

where R_{pt} is the month-t return on portfolio p in excess of the 1-month T-bill return; R_{mt} is the month-t excess return on the CRSP value-weighted market portfolio; SMB_t, HML_t, and UMD_t are the month-t returns on factor-mimicking portfolios for size, book-to-market equity, and 1-year momentum in stock returns, respectively; L_mt is the Pastor and Stambaugh (2003) market liquidity measure for month t; and $\overline{L}_m$ is the time series mean of market liquidity. Each month we use the average liquidity estimate over the previous 60 months as a proxy for the mean of liquidity. We report results for equal-weighted portfolios of aggregative growth, growth, growth-and-income, income, surviving, non-surviving, and all equity funds, respectively, for the period of 1/1974–12/2009 (excluding the 1987 market crash and the 2008 financial crisis). The t-statistics (in parentheses) are calculated using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with one lag. ** and * indicate significance at the 5% and 10% levels, respectively.

Fund group	α (%)	β_{0m}	β_{SMB}	β_{HML}	β_{UMD}	γ_m	Adj. R^2
Aggressive growth	−0.12**	0.99**	0.43**	−0.07**	0.06**	0.89**	0.96
	(−2.41)	(60.06)	(12.36)	(−2.15)	(2.92)	(4.01)	
Growth	−0.09**	0.94**	0.08**	−0.07**	0.01	0.51**	0.98
	(−2.65)	(75.68)	(2.85)	(−3.47)	(0.47)	(3.28)	
Growth & income	−0.06*	0.88**	0.00	0.08**	−0.02	0.34**	0.98
	(−1.81)	(87.95)	(0.32)	(4.61)	(−1.53)	(2.86)	
Income	0.01	0.59**	−0.05**	0.18**	−0.05**	−0.00	0.89
	(0.21)	(35.03)	(−2.47)	(7.53)	(−2.81)	(−0.01)	
Survivors	−0.02	0.92**	0.14**	0.01	0.02	0.60**	0.98
	(−0.74)	(84.62)	(6.29)	(0.35)	(1.38)	(4.24)	
Non-survivors	−0.18**	0.91**	0.15**	−0.03	0.01	0.35**	0.97
	(−4.98)	(73.46)	(5.91)	(−1.55)	(0.74)	(2.35)	
All equity funds	−0.09**	0.91**	0.15**	−0.01	0.01	0.50**	0.98
	(−2.71)	(80.80)	(6.22)	(−0.49)	(1.08)	(3.60)	

3.3. Sub-period tests

To check whether our results are robust across time, we divide our sample into two equal sub-periods—1974–1991 and 1992–2009—and repeat the tests. The results in Table 5 provide strong evidence of liquidity timing in both sub-periods. For example, in the first sub-period, all the fund categories exhibit significant and positive timing ability. In the second sub-period, the liquidity-timing coefficients are significant for all fund categories except for income funds. Comparing estimated liquidity-timing coefficients (γ_{mp}) from both sub-periods, we note that the timing coefficients from the first sub-period are more than twice as large as those from the later sub-period.

3.4. Tests of liquidity timing: Amihud's illiquidity measure

Because liquidity is not readily observable, the documented evidence of liquidity- timing might be subject to the use of a particular liquidity measure. To address this concern, we repeat our analysis using an alternative liquidity measure derived by Amihud (2002). Since the Amihud measure is a proxy for market illiquidity, we multiply this measure by negative one so that the liquidity-timing coefficients $(\hat{\gamma}_{mp})$ from Eq. (9) have the same

Table 5
Sub−period tests of liquidity timing.
Time series regression results of the four-factor liquidity-timing model:

$$R_{pt} = \alpha_p + \beta_{0mp} R_{mt} + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \beta_{UMD,p} UMD_t + \gamma_{mp} \left(L_{mt} - \overline{L}_m\right) R_{mt} + \epsilon_{pt},$$

where R_{pt} is the month-t return on portfolio p in excess of the 1-month T-bill return; R_{mt} is the month-t excess return on the CRSP value-weighted market portfolio; SMB_t, HML_t, and UMD_t are the month-t returns on factor-mimicking portfolios for size, book-to-market equity, and 1-year momentum in stock returns, respectively; L_{mt} is the Pastor and Stambaugh (2003) market liquidity measure for month t; and $\overline{L}_m$ is the time series mean of market liquidity. Each month we use the average liquidity estimate over the previous 60 months as a proxy for the mean of liquidity. We report results for equal-weighted portfolios of aggregative growth, growth, growth-and-income, income, surviving, non-surviving, and all equity funds, respectively, for the two sub-periods: 1/1974–12/1991 and 1/1992–12/2009. The t-statistics (in parentheses) are calculated using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with one lag. ** and * indicate significance at the 5% and 10% levels, respectively.

Fund group	α (%)	β_{0m}	β_{SMB}	β_{HML}	β_{UMD}	γ_m	Adj. R^2
Panel A: 1/1974–12/1991							
Aggressive growth	−0.08	0.96**	0.42**	−0.20**	0.11**	1.26**	0.97
	(−1.30)	(48.52)	(15.48)	(−5.82)	(3.40)	(12.63)	
Growth	−0.10**	0.88**	0.20**	−0.15**	0.05**	1.05**	0.98
	(−1.99)	(59.93)	(8.97)	(−5.66)	(1.99)	(13.13)	
Growth & income	−0.06	0.83**	0.03**	0.02	0.01	0.71**	0.98
	(−1.33)	(89.34)	(2.20)	(1.59)	(1.05)	(8.53)	
Income	−0.03	0.52**	0.02	0.15**	−0.06**	0.45**	0.87
	(−0.45)	(23.87)	(0.61)	(4.52)	(−2.09)	(3.32)	
Survivors	−0.02	0.88**	0.18**	−0.08**	0.05**	1.00**	0.99
	(−0.39)	(69.62)	(10.07)	(−3.81)	(2.41)	(10.44)	
Non-survivors	−0.18**	0.85**	0.23**	−0.10**	0.05**	1.12**	0.97
	(−3.23)	(59.54)	(11.40)	(−4.28)	(2.40)	(9.22)	
All equity funds	−0.09**	0.87**	0.20**	−0.09**	0.05**	1.06**	0.98
	(−2.10)	(65.06)	(11.25)	(−4.02)	(2.42)	(9.95)	
Panel B: 1/1992–12/2009							
Aggressive growth	−0.14**	0.99**	0.48**	0.02	0.04**	0.47*	0.96
	(−1.98)	(48.36)	(12.10)	(0.56)	(1.99)	(1.85)	
Growth	−0.12**	0.97**	0.03	−0.05**	0.00	0.41**	0.98
	(−3.00)	(82.01)	(1.35)	(−3.42)	(0.41)	(2.42)	
Growth & income	−0.09*	0.92**	−0.00	0.10**	−0.01	0.32**	0.98
	(−1.94)	(60.59)	(−0.00)	(4.31)	(−1.06)	(2.16)	
Income	0.03	0.67**	−0.10**	0.15**	−0.02	0.32	0.94
	(0.42)	(33.30)	(−5.60)	(5.61)	(−1.23)	(1.14)	
Survivors	−0.02	0.93**	0.14**	0.05**	0.01	0.44**	0.98
	(−0.53)	(62.24)	(6.17)	(2.05)	(0.86)	(2.60)	
Non-survivors	−0.25**	0.96**	0.12**	−0.01	0.01	0.33*	0.98
	(−6.01)	(74.55)	(5.29)	(−0.51)	(0.53)	(1.95)	
All equity funds	−0.10**	0.94**	0.13**	0.02	0.01	0.40**	0.98
	(−2.28)	(67.08)	(5.83)	(0.95)	(0.69)	(2.46)	

interpretation as those using the Pastor and Stambaugh (2003) liquidity measure. In other words, if mutual fund managers demonstrate liquidity-timing ability, the timing coefficients should be significant and positive.

Table 6
Tests of liquidity timing using the Amihud measure.
Time series regression results of the four-factor liquidity-timing model:

$$R_{pt} = \alpha_p + \beta_{0mp}R_{mt} + \beta_{SMB,p}SMB_t + \beta_{HML,p}HML_t + \beta_{UMD,p}UMD_t + \gamma_{mp}(L_{mt} - \overline{L}_m)R_{mt} + \epsilon_{pt},$$

where R_{pt} is the month-t return on portfolio p in excess of the 1-month T-bill return; R_{mt} is the month-t excess return on the CRSP value-weighted market portfolio; SMB_t, HML_t, and UMD_t are the month-t returns on factor-mimicking portfolios for size, book-to-market equity, and 1-year momentum in stock returns, respectively; L_m is the Amihud (2002) market liquidity measure for month t (we multiply this measure by negative one such that it is a proxy for market liquidity instead of market illiquidity); and $\overline{L}_m$ is the time series mean of market liquidity. Each month we use the average liquidity estimate over the previous 60 months as a proxy for the mean of liquidity. We report results for equal-weighted portfolios of aggregative growth, growth, growth-and-income, income, surviving, non-surviving, and all equity funds, respectively, for the period of 1/1974–12/2009. The t-statistics (in parentheses) are calculated using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with one lag. ** and * indicate significance at the 5% and 10% levels, respectively.

Fund group	α (%)	β_{0m}	β_{SMB}	β_{HML}	β_{UMD}	γ_m	Adj. R^2
Aggressive growth	−0.09*	0.98**	0.42**	−0.08**	0.07**	0.22**	0.96
	(−1.86)	(55.62)	(11.58)	(−2.42)	(3.56)	(2.72)	
Growth	−0.08**	0.92**	0.07**	−0.08**	0.01	0.17**	0.97
	(−2.13)	(68.29)	(2.39)	(−3.84)	(1.01)	(2.56)	
Growth & income	−0.05	0.87**	−0.00	0.07**	−0.01	0.14**	0.98
	(−1.56)	(75.79)	(−0.27)	(3.87)	(−1.16)	(2.17)	
Income	0.05	0.57**	−0.06**	0.17**	−0.06**	−0.03	0.90
	(0.94)	(34.51)	(−2.83)	(7.71)	(−3.17)	(−0.30)	
Survivors	−0.00	0.90**	0.13**	−0.00	0.02*	0.19**	0.98
	(−0.01)	(73.68)	(5.52)	(−0.17)	(1.89)	(2.39)	
Non-survivors	−0.18**	0.90**	0.14**	−0.04**	0.01	0.17**	0.97
	(−4.75)	(61.95)	(5.28)	(−2.08)	(1.07)	(2.20)	
All equity funds	−0.07**	0.90**	0.13**	−0.02	0.02	0.18**	0.98
	(−2.11)	(69.33)	(5.49)	(−1.06)	(1.53)	(2.35)	

Table 6 presents robust evidence of liquidity timing using the Amihud (2002) measure. For example, the liquidity-timing coefficient for the all equity fund portfolio is significantly positive at the 5% level with a Newey-West t-statistic of 2.35. Among funds with different investment objectives, aggressive growth funds display the most significant liquidity-timing ability, followed by growth and growth-and-income funds. Income funds, however, do not exhibit liquidity-timing ability. The results indicate that the documented evidence of liquidity timing is not driven by the use of a particular liquidity measure.

3.5. Returns timing, volatility timing and liquidity timing

While market liquidity is *positively* correlated with contemporaneous market returns, it is *negatively* correlated with market volatility (Pastor and Stambaugh, 2003). Given these relations, it might be the case that funds successfully time market returns or volatility, but the timing manifests itself in the liquidity-timing coefficients. To explore this possibility, we examine liquidity-timing ability in the presence of market timing and volatility timing, and express market beta as a linear function of market excess return, market volatility, and market liquidity. The specification then becomes:

$$R_{pt} = \alpha_p + \beta_{0mp} R_{mt} + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \beta_{UMD,p} UMD_t$$
$$+\gamma_{mp}\left(L_{mt} - \overline{L}_m\right) R_{mt} + \lambda_{mp} R_{mt}^2 + \delta_{mp}(V_{mt} - V_m) R_{mt} + \epsilon_{pt} \tag{10}$$

where V_{mt} is the month-t market volatility estimate and $\overline{V}_m$ is the time series mean of market volatility estimates. We calculate time-varying market volatility as the realized market volatility, which is the standard deviation of daily demeaned excess market returns within month t. In each month t, we use the average volatility estimate over the previous 60 months ([$t-60$, $t-1$]) as a proxy for the mean of volatility ($\overline{V}_m$). The coefficients λ_{mp} and δ_{mp} measure market timing and volatility timing, respectively.

Table 7 reveals several interesting patterns. First, consistent with the traditional timing literature (e.g., Treynor and Mazuy, 1966), the market-timing coefficients are either insignificant or significantly negative, suggesting that there is no evidence of market timing at the aggregate level. Secondly, the volatility-timing coefficients are significant and negative for the all-equity fund portfolio, aggregative growth, growth, growth-and-income portfolios, survivors, and non-survivors. This result is consistent with Busse's (1999)

Table 7
Tests of liquidity timing, return timing, and volatility timing.

Time series regression results of the four-factor liquidity, return, and volatility timing model:

$$R_{pt} = \alpha_p + \beta_{0mp} R_{mt} + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \beta_{UMD,p} UMD_t$$
$$+\gamma_{mp}\left(L_{mt} - \overline{L}_m\right) R_{mt} + \lambda_{mp} R_{mt}^2 + \delta_{mp}\left(V_{mt} - \overline{V}_m\right) R_{mt} + \epsilon_{pt},$$

where R_{pt} is the month-t return on portfolio p in excess of the 1-month T-bill return; R_{mt} is the month-t excess return on the CRSP value-weighted market portfolio; SMB_t, HML_t, and UMD_t are the month-t returns on factor-mimicking portfolios for size, book-to-market equity, and 1-year momentum in stock returns, respectively; L_{mt} is the Pastor and Stambaugh (2003) market liquidity measure for month t; and $\overline{L}_m$ is the time series mean of market liquidity; V_{mt} is the month-t realized market volatility; and $\overline{V}_m$ is the time series mean of market volatility estimates. Each month we use the average liquidity (volatility) estimate over the previous 60 months as a proxy for the mean of liquidity (volatility). We report results for equal-weighted portfolios of aggregative growth, growth, growth-and-income, income, surviving, non-surviving, and all equity funds, respectively, for the period of 1/1974–12/2009. The t-statistics (in parentheses) are calculated using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with one lag. ** and * indicate significance at the 5% and 10% levels, respectively.

Fund group	α (%)	β_{0m}	β_{SMB}	β_{HML}	β_{UMD}	γ_m	λ_m	δ_m	Adj. R^2
Aggressive growth	−0.12*	1.00**	0.43**	−0.07**	0.06**	0.94**	−0.05	−0.27**	0.97
	(−1.65)	(65.58)	(11.80)	(−2.21)	(2.98)	(3.99)	(−0.16)	(−3.34)	
Growth	−0.04	0.95**	0.07**	−0.07**	0.00	0.59**	−0.35*	−0.21**	0.98
	(−0.79)	(89.42)	(2.77)	(−3.76)	(0.03)	(3.30)	(−1.83)	(−2.92)	
Growth & income	−0.02	0.89**	−0.00	0.07**	−0.02**	0.48**	−0.27**	−0.14**	0.98
	(−0.45)	(96.28)	(−0.04)	(4.35)	(−2.04)	(3.04)	(−2.06)	(−1.96)	
Income	0.10*	0.60**	−0.06**	0.17**	−0.06**	0.14	−0.53**	−0.09	0.90
	(1.74)	(40.72)	(−3.24)	(7.77)	(−3.74)	(0.56)	(−2.78)	(−1.47)	
Survivors	0.00	0.92**	0.14**	0.00	0.01	0.68**	−0.16	−0.13**	0.98
	(0.05)	(93.44)	(6.07)	(0.11)	(1.13)	(4.25)	(−0.92)	(−2.30)	
Non-survivors	−0.15**	0.93**	0.14**	−0.04*	0.00	0.60**	−0.31*	−0.22**	0.97
	(−3.12)	(81.32)	(5.99)	(−1.75)	(0.13)	(2.76)	(−1.82)	(−2.46)	
All equity funds	−0.05	0.93**	0.14**	−0.01	0.01	0.62**	−0.24	−0.19**	0.98
	(−1.21)	(91.03)	(6.15)	(−0.69)	(0.65)	(3.64)	(−1.38)	(−2.90)	

evidence of volatility timing using daily fund returns. Lastly, we find that including market-timing and volatility-timing terms does not materially affect the significance of the liquidity-timing coefficients. Comparing the results reported in Table 3 with those in Table 7, we can see that after controlling for market timing and volatility timing, the liquidity-timing coefficients, although slightly smaller, remain significant and positive. For example, aggressive growth, growth, and growth-and-income funds demonstrate liquidity-timing ability at the 1% level. Income funds do not show liquidity-timing ability in either Tables 3 or 7.

Taken together, these results indicate that the significant liquidity-timing coefficients are not due to the positive correlation between market returns and liquidity or the negative correlation between market volatility and liquidity. Liquidity timing is therefore an important component of the strategies of actively managed mutual funds.

3.6. Tests of liquidity timing: control for liquidity risk factor

In the previous tests, we utilize the standard Carhart (1997) four-factor model to explain the time series of mutual fund returns. Although the literature has identified liquidity risk as an important determinant of stock returns, it is not clear whether a liquidity risk factor is useful in explaining the time series of mutual fund returns. To examine whether our results are driven by a potentially omitted liquidity risk factor, we consider a five-factor liquidity-timing model as follows:

$$\begin{aligned} R_{pt} = \alpha_p + \beta_{0mp} R_{mt} + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t \\ + \beta_{UMD,p} UMD_t + \beta_{LIQ,p} LIQ_t + \gamma_{mp}\left(L_{mt} - \overline{L}_m\right) R_{mt} + \epsilon_{pt} \end{aligned} \tag{11}$$

where LIQ is the Pastor and Stambaugh (2003) liquidity risk factor, measured as the innovations in market liquidity from an AR (2) model.[4]

Table 8 reports regression estimates of Eq. (11). Comparing the results in Table 8 with those in Table 3, we find that the evidence of liquidity timing remains materially unchanged after we control for the liquidity risk factor. For example, the liquidity-timing coefficients remain significantly positive for all fund portfolios except for the income fund portfolio. In fact, the liquidity factor is not useful in explaining the time series of mutual fund returns because none of the liquidity beta estimates are significant. We also control for the liquidity risk factor and rerun all the robustness tests in Sections 3.2–3.5. In general, the results suggest that adding the liquidity factor does not materially affect the significance of liquidity-timing coefficients. For brevity, these results are not reported but are available upon request.

4. Individual fund-level analysis

In this section, we first investigate the liquidity-timing ability of fund managers at the individual fund level using a bootstrap approach and evaluate the out-of-sample performance of liquidity-timing funds by sorting funds by liquidity-timing coefficients. Then we examine the cross-sectional relationship between liquidity-timing ability and fund characteristics. Finally, we

[4]Specification tests suggest that an AR (2) process is sufficient to model the time series of Pastor and Stambaugh's (2003) market liquidity measure. We also use an alternative risk factor, i.e., the Pastor and Stambaugh (2003) traded liquidity factor measured as the return spread of the top and bottom value-weighted decile portfolios of stocks from a sort on historical liquidity betas. The results are qualitatively similar.

Table 8
Tests of liquidity timing: controlling for liquidity risk.
Time series regression results of the five-factor liquidity-timing model:

$$R_{pt} = \alpha_p + \beta_{0mp}R_{mt} + \beta_{SMB,p}SMB_t + \beta_{HML,p}HML_t + \beta_{UMD,p}UMD_t + \beta_{LIQ,p}LIQ_t + \gamma_{mp}(L_{mt} - \overline{L}_m)R_{mt} + \epsilon_{pt}$$

where R_{pt} is the month-t return on portfolio p in excess of the 1-month T-bill return; R_{mt} is the month-t excess return on the CRSP value-weighted market portfolio; SMB_t, HML_t, and UMD_t are the month-t returns on factor-mimicking portfolios for size, book-to-market equity, and 1-year momentum in stock returns, respectively; LIQ_t is the Pastor and Stambaugh (2003) liquidity risk factor for month t, measured as the innovations in market liquidity from an AR (2) model; L_{mt} is the Pastor and Stambaugh (2003) market liquidity measure for month t; and $\overline{L}_m$ is the time series mean of market liquidity. Each month we use the average liquidity estimate over the previous 60 months as a proxy for the mean of liquidity. We report results for equal-weighted portfolios of aggregative growth, growth, growth-and-income, income, surviving, non-surviving, and all equity funds, respectively, for the period of 1/1974–12/2009. The t-statistics (in parentheses) are calculated using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with one lag. ** and * indicate significance at the 5% and 10% levels, respectively.

Fund group	α (%)	β_{0m}	β_{SMB}	β_{HML}	β_{UMD}	β_{LIQ}	γ_m	Adj. R^2
Aggressive growth	−0.12**	0.99**	0.43**	−0.08**	0.06**	−0.00	1.09**	0.96
	(−2.47)	(61.51)	(12.62)	(−2.62)	(2.91)	(−0.22)	(7.17)	
Growth	−0.09**	0.94**	0.08**	−0.08**	0.00	−0.00	0.78**	0.97
	(−2.75)	(76.54)	(2.84)	(−4.23)	(0.35)	(−0.16)	(5.31)	
Growth & income	−0.06*	0.87**	0.00	0.07**	−0.02*	0.01	0.61**	0.98
	(−1.93)	(90.38)	(0.20)	(4.41)	(−1.86)	(1.49)	(3.61)	
Income	0.01	0.58**	−0.05**	0.16**	−0.05**	0.01	0.34	0.89
	(0.15)	(35.15)	(−2.76)	(7.71)	(−3.19)	(0.47)	(1.50)	
Survivors	−0.02	0.91**	0.14**	−0.00	0.02	0.00	0.84**	0.98
	(−0.69)	(86.25)	(6.40)	(−0.18)	(1.29)	(0.21)	(5.62)	
Non-survivors	−0.20**	0.91**	0.15**	−0.04**	0.00	0.00	0.84**	0.97
	(−5.31)	(74.17)	(6.12)	(−2.31)	(0.39)	(0.19)	(3.60)	
All equity funds	−0.09**	0.91**	0.14**	−0.02	0.01	0.00	0.85**	0.98
	(−2.75)	(82.48)	(6.39)	(−1.17)	(0.87)	(0.26)	(4.61)	

conduct several tests to ensure that the documented liquidity-timing ability is not attributed to a passive timing effect.

4.1. Bootstrap tests

The large sample in the CRSP database enables us to perform a fund-by-fund analysis not only for the entire domestic equity fund group, but also within each fund subgroup of different investment objectives. Because the investment objective codes for some funds change over time, we follow Pastor and Stambaugh (2002) and assign a fund to the category into which it is classified most often. For example, if a fund with a 5-year history is classified as a long-term growth fund for four years and as an aggressive growth fund for 1 year, it is assigned to the long-term growth fund group. We also exclude funds that have existed for less than 2 years. The resulting sample contains 4,173 funds.[5]

[5]In unreported tests, we require a fund to have a minimum of 36 or 60 monthly return observations to be included in the sample and find that our main conclusion remains unchanged.

We adopt a bootstrap approach to derive statistical inferences for liquidity timing at the individual fund level, following the methodology of Kosowski, Timmermann, Wermers, and White (2006) and Jiang, Yao, and Yu (2007). The bootstrap approach addresses two issues associated with the statistical inference based on the cross-sectional distributions of liquidity-timing measures and their t-statistics: (1) violation of the *i.i.d.* assumption across fund returns, which is due to correlated returns of funds that follow the same objective and similar strategies, and (2) poor finite sample properties of the test statistics for estimated timing coefficients.

To implement the bootstrap procedure, we first estimate the Carhart (1997) four-factor model in Eq. (7) for each fund p and retain the parameter estimates, $\left\{\hat{\alpha}_p, \hat{\beta}_{mp}, \hat{\beta}_{SMB,p}, \hat{\beta}_{HML,p}, \hat{\beta}_{UMD,p}\right\}$, as well as a time series of residuals, $\{\hat{\varepsilon}_{pt}\}$. Resampling the market factor generates a time series of bootstrapped market excess returns, $\{R^b_{mt}\}$, where b is an index for the bootstrap iteration. Next, by imposing the null hypothesis of no liquidity-timing ability, we construct a time series of bootstrapped returns for fund p, $\left\{R^b_{pt}\right\}$, as follows:

$$R^b_{pt} = \hat{\alpha}_p + \hat{\beta}_{mp} R^b_{mt} + \hat{\beta}_{SMB,p} SMB_t + \hat{\beta}_{HML,p} HML_t + \hat{\beta}_{UMD,p} UMD_t + \hat{\varepsilon}_{pt}. \tag{12}$$

We then estimate the bootstrapped liquidity-timing coefficient, $\hat{\gamma}^b_{mp}$, for fund p and its Newey-West t-statistic, $\hat{t}^b_{\hat{\gamma}_{mp}}$, using the liquidity-timing model given in Eq. (9). By construction, the bootstrapped liquidity-timing estimate is zero. Therefore, any positive bootstrapped liquidity-timing estimate ($\hat{\gamma}^b_{mp}$) and its t-statistic ($\hat{t}^b_{\hat{\gamma}_{mp}}$) are purely due to sampling variation.

We repeat this process for all funds, $p=1,\ldots, N$, and obtain the following cross-sectional statistics of bootstrapped liquidity-timing measures and their t-statistics for each of the quartiles, 25% and 75%, as well as the extreme percentiles, 1%, 5%, 10%, 90%, 95%, and 99%. Repeating this procedure for B bootstrapped iterations, we obtain the distributions of cross-sectional statistics of bootstrapped liquidity-timing measures and their Newey-West t-statistics. The bootstrapped p-value is then calculated as

$$p = \frac{1}{B}\sum_{b=1}^{B} I_{|\pi^b|>|\pi|} \tag{13}$$

where π and π^b are the cross-sectional statistics of the actual and bootstrapped liquidity-timing measures or their Newey-West t-statistics, respectively; B is the number of bootstrapped iterations (set to be 1,000 in this exercise); and $I_{|\pi^b|>|\pi|}$ is an indicator function defined as

$$I_{|\pi^b|>|\pi|} = \begin{cases} 1, & |\pi^b| > |\pi|, \\ 0 & \text{otherwise.} \end{cases} \tag{14}$$

Under the null hypothesis of no liquidity-timing ability, we expect the distributions of bootstrapped statistics to approximate the empirical distributions of actual statistics. If the actual positive liquidity-timing measure or its Newey-West t-statistic for a ranked fund is consistently higher than the corresponding bootstrapped value (i.e., if the bootstrapped p-value for a positive gamma or t-statistic is close to zero), this fund is said to exhibit positive liquidity-timing ability that is not purely due to luck. Similarly, if the estimated negative liquidity-timing measure or its Newey-West t-statistic for a ranked fund is lower than the corresponding bootstrapped value (i.e., if the bootstrapped p-value for a negative gamma or t-statistic is close to zero), we infer that this fund has significantly negative liquidity-timing ability.

Panel A of Table 9 reports the cross-sectional summary statistics of liquidity-timing coefficients for individual funds and their bootstrapped p-values. The table indicates that the positive liquidity-timing coefficients produced by the top percentile funds (e.g., funds ranked as 75%, 90%, 95%, and 99%) are not purely due to luck, except in the case of income funds or extreme percentile funds ranked as 99%. For example, all domestic equity funds that have liquidity-timing coefficients in the 75th, 90th, and 95th percentiles of the empirical distribution of timing coefficients exhibit significant timing ability since the p-values associated with these funds' timing coefficients are close to zero. Similar patterns emerge for the aggressive growth, growth, growth-and-income, surviving, and non-surviving fund groups. Top-ranked income funds do not show liquidity-timing ability as the p-values associated with their timing coefficients are greater than 10%.

While the results reported in Panel A of Table 9 are encouraging, we perform another test in which we sort funds by the t-statistics of their timing coefficients. According to the bootstrap literature (e.g., Kosowski, Timmermann, Wermers, and White, 2006; Jiang, Yao, and Yu, 2007), the pivotal t-statistics possess superior statistical properties. We report this set of bootstrap results in Panel B of Table 9. Consistent with the evidence in Panel A, Panel B indicates the strong liquidity-timing ability of mutual fund managers and this ability varies with fund investment objectives. For example, top-ranked funds in the aggressive growth, growth, and growth-and-income style categories show significant liquidity-timing ability based on the p-values associated with the t-statistics of the timing coefficients. Income funds, on the other hand, do not exhibit timing ability in general. Finally, according to ranked timing coefficients or ranked t-statistics for the liquidity-timing coefficients, we note that bottom-ranked funds (e.g., funds ranked as 5%, 10%, and 25%) demonstrate negative liquidity-timing skills that cannot be attributed to random sampling variation.

We check the robustness of these results by repeating the above experiment using the Amihud (2002) illiquidity measure. As in Table 6, we multiply the Amihud measure by negative one so that the results have the same interpretation as those using the Pastor and Stambaugh (2003) liquidity measure. Table 10 shows that using the Amihud measure produces qualitatively similar results to those reported in Table 9. The only exception is that income funds exhibit significant timing ability when we examine the top-ranked t-statistics of the timing coefficients.

Furthermore, we perform a bootstrap test by including both market timing and volatility timing as in Eq. (10) and report the results in Table 11. The results remain qualitatively similar to those in Table 9. Overall, the fund-level analysis suggests that the evidence in favor of liquidity-timing ability is robust.

We note that there are many ways to perform the bootstrap analysis. To ensure that our results are robust to bootstrap procedures, we experiment with three alternative bootstrap methods: (1) Instead of bootstrapping the market factor, we resample all four risk factors (e.g., R_m, SMB, HML, and UMD) jointly; (2) we bootstrap the residuals from the Carhart four-factor model instead of the risk factors; and (3) we bootstrap the risk factors and residuals jointly. These tests produce qualitatively similar results to those in Table 9.

Table 9
Tests of liquidity timing: fund-level analysis.

Cross-sectional distributions of liquidity-timing coefficients and their t-statistics from the four-factor liquidity-timing model:

$$R_{pt} = \alpha_p + \beta_{mp}R_{mt} + \beta_{SMB,p}SMB_t + \beta_{HML,p}HML_t + \beta_{UMD,p}UMD_t + \gamma_{mp}\left(L_{mt} - \overline{L}_m\right)R_{mt} + \epsilon_{pt},$$

where R_{pt} is the month-t return on portfolio p in excess of the 1-month T-bill return; R_{mt} is the month-t excess return on the CRSP value-weighted market portfolio; SMB_t, HML_t, and UMD_t are the month-t returns on factor-mimicking portfolios for size, book-to-market equity, and 1-year momentum in stock returns, respectively; L_{mt} is the Pastor and Stambaugh (2003) market liquidity measure for month t; and $\overline{L}_m$ is the time series mean of market liquidity. Each month we use the average liquidity estimate over the previous 60 months as a proxy for the mean of liquidity. We estimate the model for each fund and report cross-sectional statistics of liquidity-timing coefficients (γ_{mp}) and their Newey-West t-statistics in Panels A and B, respectively. The bootstrapped p-values (in parentheses) are calculated in a way similar to Jiang, Yao, and Yu (2007). We only include funds with a minimum of 24 monthly observations during the 1/1974–12/2009 period. Results are reported for aggregative growth, growth, growth-and-income, income, surviving, non-surviving, and all equity funds, respectively.

Fund group	1%	5%	10%	25%	75%	90%	95%	99%
Panel A: Cross-section statistics of liquidity-timing coefficients								
Aggressive growth	−3.04	−1.02	−0.54	−0.07	0.87	1.60	2.13	3.73
	(0.15)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.26)
Growth	−2.88	−0.84	−0.42	−0.02	0.83	1.42	1.93	3.74
	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.14)
Growth & income	−2.27	−0.78	−0.45	−0.14	0.57	1.07	1.38	2.93
	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.05)
Income	−2.57	−1.12	−0.66	−0.33	0.26	0.66	1.06	2.04
	(0.83)	(0.37)	(0.02)	(0.17)	(0.94)	(0.94)	(0.80)	(0.78)
Survivors	−1.26	−0.55	−0.37	−0.10	0.56	1.00	1.27	2.08
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.63)
Non-survivors	−3.79	−1.53	−0.79	−0.15	1.00	1.83	2.47	4.63
	(0.41)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
All equity funds	−2.73	−0.84	−0.47	−0.12	0.71	1.28	1.84	3.47
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
Panel B: Cross-section statistics of t-statistics for liquidity-timing coefficients								
Aggressive growth	−3.27	−1.63	−1.04	−0.20	1.77	2.76	3.50	5.34
	(0.67)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Growth	−2.78	−1.50	−0.88	−0.04	2.03	2.99	3.83	6.82
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Growth & income	−3.35	−2.05	−1.49	−0.50	1.45	2.63	3.36	4.73
	(0.69)	(0.13)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Income	−3.53	−2.90	−2.53	−1.53	0.70	1.73	2.26	4.71
	(0.42)	(1.00)	(1.00)	(1.00)	(0.90)	(0.26)	(0.40)	(0.02)
Survivors	−3.26	−2.10	−1.45	−0.32	1.73	2.67	3.28	4.48
	(0.49)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Non−survivors	−3.27	−1.77	−1.22	−0.26	1.74	3.04	3.90	6.83
	(0.18)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
All equity funds	−3.27	−1.93	−1.36	−0.28	1.74	2.81	3.58	5.69
	(0.23)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 10
Tests of liquidity timing using the Amihud measure: fund-level analysis.

Cross-sectional distributions of liquidity-timing coefficients and their t-statistics from the four-factor liquidity-timing model:

$$R_{pt} = \alpha_p + \beta_{mp}R_{mt} + \beta_{SMB,p}SMB_t + \beta_{HML,p}HML_t + \beta_{UMD,p}UMD_t + \gamma_{mp}\left(L_{mt}-\overline{L}_m\right)R_{mt} + \epsilon_{pt}\ ,$$

where R_{pt} is the month-t return on portfolio p in excess of the 1-month T-bill return; R_{mt} is the month-t excess return on the CRSP value-weighted market portfolio; SMB_t, HML_t, and UMD_t are the month-t returns on factor-mimicking portfolios for size, book-to-market equity, and 1-year momentum in stock returns, respectively; L_{mt} is the Amihud (2002) market liquidity measure for month t (we multiply this measure by negative one such that it is a proxy for market liquidity instead of market illiquidity); and $\overline{L}_m$is the time series mean of market liquidity. Each month we use the average liquidity estimate over the previous 60 months as a proxy for the mean of liquidity. We estimate the model for each fund and report cross-sectional statistics of liquidity-timing coefficients (QUOTE and their Newey-West t-statistics in Panels A and B, respectively. The bootstrapped p-values (in parentheses) are calculated in a way similar to Jiang, Yao, and Yu (2007). We only include funds with a minimum of 24 monthly observations during the 1/1974–12/2009 period. Results are reported for aggregative growth, growth, growth-and-income, income, surviving, non-surviving, and all equity funds, respectively.

Fund group	1%	5%	10%	25%	75%	90%	95%	99%
Panel A: Cross-section statistics of liquidity-timing coefficients								
Aggressive growth	−1.07	−0.41	−0.25	−0.08	0.26	0.48	0.71	1.58
	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)
Growth	−1.27	−0.38	−0.19	−0.02	0.25	0.47	0.67	1.29
	(0.57)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.35)
Growth & income	−0.92	−0.31	−0.22	−0.07	0.16	0.32	0.47	1.04
	(0.51)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.20)
Income	−0.71	−0.41	−0.25	−0.15	0.16	0.33	0.43	0.56
	(0.13)	(0.40)	(0.21)	(0.99)	(0.13)	(0.10)	(0.62)	(1.00)
Survivors	−0.53	−0.28	−0.19	−0.06	0.18	0.32	0.44	0.84
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.80)
Non-survivors	−1.46	−0.54	−0.30	−0.09	0.31	0.57	0.81	1.75
	(0.74)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
All equity funds	−1.08	−0.37	−0.23	−0.07	0.22	0.43	0.59	1.27
	(0.24)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)
Panel B: Cross-section statistics of t-statistics for liquidity-timing coefficients								
Aggressive growth	−3.65	−1.92	−1.40	−0.52	1.50	2.61	3.22	4.51
	(1.00)	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Growth	−3.16	−1.73	−1.10	−0.21	1.91	2.97	3.64	5.01
	(0.45)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Growth & income	−3.58	−2.20	−1.62	−0.65	1.33	2.51	3.06	4.58
	(0.99)	(0.93)	(0.65)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Income	−5.23	−3.70	−2.80	−1.94	1.48	2.72	3.54	5.06
	(1.00)	(1.00)	(1.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)
Survivors	−4.10	−2.39	−1.67	−0.55	1.58	2.63	3.31	4.62
	(1.00)	(1.00)	(0.98)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Non−survivors	−3.34	−2.03	−1.40	−0.48	1.68	2.79	3.49	5.37
	(0.77)	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
All equity funds	−3.79	−2.27	−1.58	−0.54	1.61	2.71	3.37	4.94
	(1.00)	(1.00)	(0.15)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 11
Tests of liquidity timing, return timing, and volatility timing: fund-level analysis.

Cross-sectional distributions of liquidity-timing coefficients and their t-statistics from the four-factor liquidity, return, and volatility timing model:

$$R_{pt} = \alpha_p + \beta_{0mp}R_{mt} + \beta_{SMB,p}SMB_t + \beta_{HML,p}HML_t + \beta_{UMD,p}UMD_t \\ +\gamma_{mp}\left(L_{mt}-\overline{L}_m\right)R_{mt} + \lambda_{mp}R_{mt}^2 + \delta_{mp}\left(V_{mt}-\overline{V}_m\right)R_{mt} + \epsilon_{pt},$$

where R_{pt} is the month-t return on portfolio p in excess of the 1-month T-bill return; R_{mt} is the month-t excess return on the CRSP value-weighted market portfolio; SMB_t, HML_t, and UMD_t are the month-t returns on factor-mimicking portfolios for size, book-to-market equity, and 1-year momentum in stock returns, respectively; L_{mt} is the Pastor and Stambaugh (2003) market liquidity measure for month t; and $\overline{L}_m$ is the time series mean of market liquidity; V_{mt} is the month-t realized market volatility, and $\overline{V}_m$ is the time series mean of market volatility estimates. Each month we use the average liquidity (volatility) estimate over the previous 60 months as a proxy for the mean of liquidity (volatility). We estimate the model for each fund and report cross-sectional statistics of liquidity-timing coefficients (γ_{mp}) and their Newey-West t-statistics in Panels A and B, respectively. The bootstrapped p-values (in parentheses) are calculated in a way similar to Jiang, Yao, and Yu (2007). We only include funds with a minimum of 24 monthly observations during the 1/1974–12/2009 period. We report results for aggregative growth, growth, growth-and-income, income, surviving, non-surviving, and all equity funds, respectively.

Fund group	1%	5%	10%	25%	75%	90%	95%	99%
Panel A: Cross-section statistics of liquidity-timing coefficients								
Aggressive growth	−3.24	−1.52	−0.86	−0.25	0.84	1.53	2.18	4.05
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.58)
Growth	−3.92	−1.40	−0.74	−0.20	0.77	1.50	2.09	4.24
	(0.45)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.29)
Growth & income	−3.00	−1.04	−0.65	−0.20	0.60	1.21	1.70	3.11
	(0.43)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.39)
Income	−3.51	−1.36	−0.79	−0.24	0.33	0.78	1.39	3.25
	(0.86)	(0.34)	(0.03)	(0.00)	(0.80)	(0.89)	(0.46)	(0.29)
Survivors	−1.64	−0.77	−0.47	−0.16	0.59	1.07	1.41	2.26
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.98)
Non-survivors	−4.90	−2.25	−1.29	−0.39	0.93	1.96	2.66	5.61
	(0.78)	(0.58)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
All equity funds	−3.62	−1.33	−0.74	−0.22	0.71	1.36	2.01	3.72
	(0.39)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.45)
Panel B: Cross-section statistics of t-statistics for liquidity-timing coefficients								
Aggressive growth	−2.76	−1.66	−1.20	−0.40	1.25	1.98	2.54	3.78
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Growth	−2.80	−1.62	−1.17	−0.40	1.31	2.10	2.68	3.79
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
Growth & income	−3.24	−1.86	−1.33	−0.50	1.17	2.01	2.51	3.48
	(0.43)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.20)
Income	−2.53	−1.74	−1.17	−0.66	0.84	1.61	2.33	4.68
	(0.00)	(0.00)	(0.00)	(0.00)	(0.46)	(0.65)	(0.25)	(0.02)
Survivors	−2.92	−1.63	−1.11	−0.41	1.26	2.03	2.54	3.90
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Non-survivors	−2.80	−1.82	−1.38	−0.56	1.17	2.01	2.61	3.60
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)
All equity funds	−2.88	−1.72	−1.22	−0.45	1.22	2.03	2.57	3.76
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

4.2. Liquidity timing and future fund performance

It is natural to ask whether liquidity-timing ability translates into superior performance. In this section, we study whether liquidity timing predicts the future risk-adjusted performance of mutual funds. For each year, we run the four-factor liquidity-timing regression in Eq. (9) for all funds using the previous 2 years of data. Based on the liquidity-timing coefficients, $\hat{\gamma}_{mp}$, we form ten decile portfolios and evaluate their out-of-sample performance using five measures: raw returns, Sharpe ratio, CAPM alpha, Fama and French (1993) three-factor model alpha, and Carhart (1997) four-factor model alpha.

Table 12
Performance and Liquidity timing.
Each year we form decile portfolios based on the funds' liquidity-timing coefficients estimated from the four-factor liquidity-timing model given in Eq. (9) using the previous 2 years of data and then report the out-of-sample performance of each decile portfolio using five measures: raw returns, Sharpe ratio, CAPM alpha, Fama-French three-factor alpha, and Carhart four-factor alpha in Columns 2–6, respectively. Panels A and B report the results for the equal-weighted and value-weighted portfolios, respectively. "H–L" denotes the performance difference between the highest and lowest deciles. The numbers in parentheses are t-statistics for the null hypothesis that the performance difference between the highest and lowest deciles is zero. ** and * indicate significance at the 5% and 10% levels, respectively.

Decile	Raw returns (%)	Sharpe ratio	CAPM alpha (%)	F-F 3-factor alpha (%)	4-factor alpha (%)
			Panel A: Equal-weighted portfolios		
L	0.87**	0.15**	−0.08	−0.11**	−0.09*
2	0.96**	0.17**	0.01	−0.02	−0.01
3	0.93**	0.16**	−0.03	−0.07	−0.05
4	0.99**	0.17**	0.02	0.01	0.00
5	0.95**	0.17**	−0.02	−0.04	−0.05
6	1.04**	0.18**	0.06	0.02	0.01
7	0.98**	0.17**	0.01	−0.02	−0.03
8	0.98**	0.17**	−0.00	−0.04	−0.05
9	1.01**	0.17**	0.03	0.01	0.01
H	1.05**	0.19**	0.07	0.03	0.03
H-L	0.17**	0.04**	0.15**	0.14**	0.12**
??	(2.77)	(2.06)	(2.42)	(2.30)	(2.02)
			Panel B: Value-weighted portfolios		
L	0.83**	0.15**	−0.11**	−0.09*	−0.10*
2	0.89**	0.15**	−0.08*	−0.07	−0.06
3	0.94**	0.17**	−0.02	−0.01	−0.02
4	1.00**	0.18**	0.03	0.03	0.01
5	0.91**	0.18**	−0.04	−0.03	−0.02
6	1.01**	0.18**	0.06	0.02	0.03
7	0.97**	0.17**	−0.01	0.00	−0.02
8	0.94**	0.17**	−0.03	−0.04	−0.05
9	0.98**	0.17**	−0.01	0.03	0.03
H	1.04**	0.19**	0.07	0.04	0.04
H-L	0.21**	0.04**	0.18**	0.14**	0.14**
??	(3.07)	(2.09)	(2.56)	(2.14)	(2.17)

Panels A and B of Table 12 report the results for the equal-weighted and value-weighted portfolios, respectively. Based on the value-weighted portfolios, the funds with the most significant liquidity-timing ability (decile H) significantly outperform those with the least significant (or the most significantly negative) liquidity-timing ability (decile L) by 21 basis points per month (or 2.5% annually) in terms of raw returns and 18 basis points per month (or 2.2% annually) in terms of CAPM alpha. The difference between the highest and lowest deciles (H–L) is 14 basis points (or 1.7% annually) for the Fama-French three-factor alpha and Carhart four-factor alpha. The results based on the equal-weighted portfolios are similar albeit slightly weaker. For example, the difference between the highest and lowest deciles (H–L) is 17 basis points (or 2.0% annually) for raw returns, 15 basis points (or 1.8% annually) for the CAPM alpha, 14 basis points (or 1.7% annually) for the Fama-French three-factor alpha, and 12 basis points (or 1.4% annually) for the Carhart four-factor alpha. We also calculate the Sharpe Ratio in each month using portfolio returns over the previous 2 years and find that the Sharpe Ratio is significantly higher for the highest decile than for the lowest decile based on either the equal-weighted or value-weighted portfolios. Collectively, the evidence suggests that funds with more significant liquidity-timing ability generate higher future risk-adjusted performance.

4.3. Cross-sectional relationship between liquidity timing and fund characteristics

While we document positive liquidity-timing ability on average, we also observe a wide variation of timing ability across funds. In addition, we observe that funds with certain investment objectives (e.g., aggressive growth funds) are more likely to time market liquidity than others (e.g., income funds). In this section, we examine whether liquidity timing is associated with fund characteristics in the cross-section. For example, are successful liquidity-timing managers found in younger or older funds? Is the size of a fund associated with its timing ability? Do successful liquidity timers tend to charge higher fees and have higher turnover rates? Finally, is there a relationship between liquidity-timing ability and fund flow in the cross-section? These questions would help investors pick successful liquidity timers.

To answer these questions, we examine the cross-sectional relationship between liquidity timing and the following fund characteristics: age, size, expense ratio, turnover rate, and flow. We first estimate the four-factor liquidity-timing model in Eq. (9) and obtain the liquidity-timing coefficients, $\hat{\gamma}_{mp}$, for all equity funds with a minimum of 24 monthly return observations. We then estimate the following cross-sectional regression model using funds within each investment objective category:

$$\hat{\gamma}_{m,i} = a + b_1 AGE_i + b_2 SIZE_i + b_3 EXP_i + b_4 TR_i + b_5 flow_i + \varepsilon_i \tag{15}$$

where AGEi is the fund age, and SIZE_i, EXP_i, TR_i, and FLOW_i are the time series averages of total net assets, expense ratios, turnover ratios, and (normalized) flows of fund i, respectively.

As shown in Table 13, we first find a significant and positive relationship between liquidity-timing coefficients and fund age for all equity funds. We also find that survivors and aggressive growth funds exhibit a strong relationship between liquidity-timing ability and fund age. For example, the coefficient on fund age is 0.10 (0.28) with a t-statistic of 2.59 (3.01) for survivors (aggressive growth funds). Second, funds with higher turnover rates are more likely to time liquidity. This relationship holds not only for all equity funds, but also for aggressive growth, growth, growth-and-income, surviving, and non-surviving funds. This is consistent with our empirical evidence that aggressive growth funds tend to

Table 13
Test for cross-sectional relationship between fund characteristics and liquidity timing.
Cross-sectional regression of liquidity-timing coefficients on fund characteristics:

$$\hat{\gamma}_{m,i} = a + b_1 AGE_i + b_2 SIZE_i + b_3 EXP_i + b_4 TR_i + b_5 flow_i + \epsilon_i,$$

where $\hat{\gamma}_{m,i}$ is the liquidity-timing coefficient of fund i estimated from the four-factor liquidity-timing model given in Eq. (9), AGE_i is the fund age (in years), and $SIZE_i$, EXP_i, TR_i, and $flow_i$ are the time series averages of a fund's total net assets (in $10 billions), expense ratios, turnover rates, and (normalized) flows, respectively. We only include funds with a minimum of 24 monthly observations during the 1/1974–12/2009 period. The results are reported for aggregative growth, growth, growth-and-income, income, surviving, non-surviving, and all equity funds, respectively. ** and * indicate significance at the 5% and 10% levels, respectively.

	Aggressive growth	Growth	Growth & income	Income	Survivors	Non-survivors	All equity funds
a	−0.80**	−0.25*	−0.09	−0.40**	−0.49**	−0.12	−0.32**
	(−3.39)	(−1.66)	(−0.66)	(−3.58)	(−6.85)	(−0.63)	(−4.04)
b_1	0.28**	0.07	0.03	0.11	0.10**	0.10	0.10**
	(3.01)	(1.21)	(0.49)	(1.36)	(2.59)	(1.23)	(2.82)
b_2	0.00	0.02	−0.00	0.02	0.03**	0.00	0.01
	(0.14)	(1.34)	(−0.20)	(0.89)	(2.84)	(0.14)	(1.02)
b_3	15.01	20.07**	9.54	12.18	16.20**	8.87	15.08**
	(1.51)	(2.65)	(1.26)	(0.76)	(3.54)	(1.09)	(3.43)
b_4	0.19**	0.15**	0.22**	0.05	0.17**	0.16**	0.17**
	(4.97)	(2.93)	(3.55)	(0.64)	(6.33)	(2.87)	(6.31)
b_5	0.01	−0.20	−0.10	−0.70	−0.20**	0.05	−0.09
	(0.08)	(−1.16)	(−0.68)	(−1.02)	(−2.13)	(0.46)	(−1.02)
Adj. R^2	0.05	0.03	0.04	0.02	0.07	0.01	0.03

be the most significant liquidity timers, followed by growth and growth-and-income, while income funds do not exhibit liquidity-timing ability. As shown in Table 1, funds in the aggressive growth group have the highest average turnover ratio of 151% per year, followed by growth funds, which have an average turnover ratio of 97% per year. The less aggressive funds, growth-and-income and income funds, are characterized by lower turnover ratios of 88% and 67% per year, respectively. Third, there is some evidence that timing ability is positively related to expense ratios. This is true for the sample of all equity funds, growth funds, and surviving funds. Finally, we do not find a significant relationship between flows and liquidity timing for all equity funds, aggressive growth, growth, growth-and-income, and income funds. Overall, the results suggest that liquidity timers tend to have longer histories, higher expense ratios, and higher turnover rates.

4.4. *Passive liquidity-timing effect*

Our analysis has uncovered the liquidity-timing ability of mutual fund managers. A potential concern is that we have simply identified a "passive" liquidity-timing effect, i.e., if the betas of stocks held by mutual funds increase when market liquidity increases, even a simple buy-and-hold strategy might give the appearance of liquidity timing. To address this concern, we perform four additional tests.[6] For illustrative purpose, we use aggressive growth funds to explain our test procedures. The same test procedures are also applied to growth, growth-and-income, and income funds.

[6]We are grateful to an anonymous referee who suggested these tests.

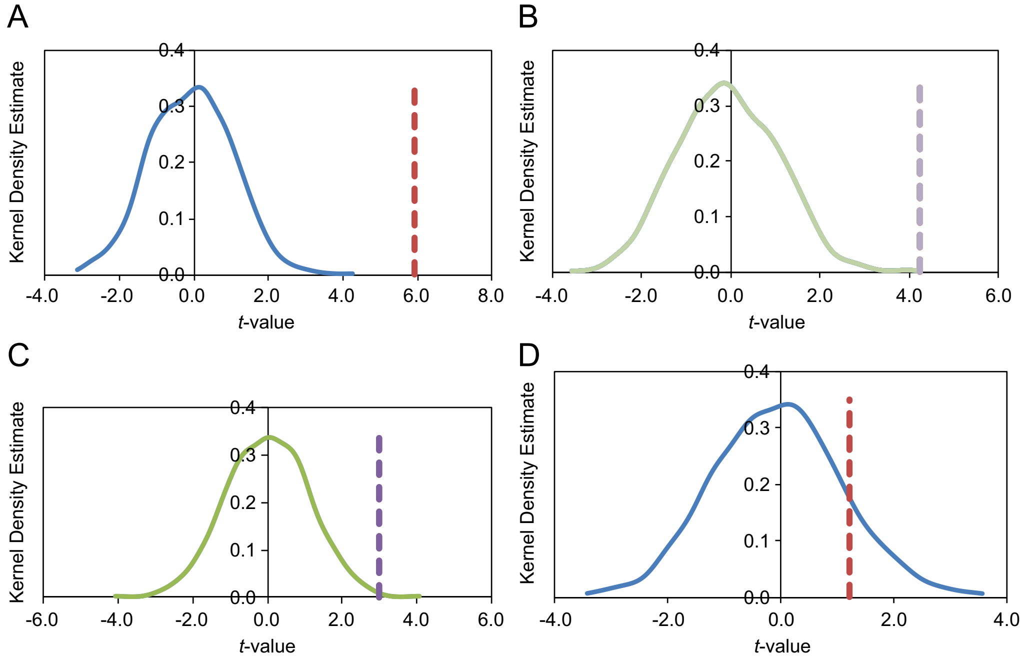

Fig. 1. Actual vs. bootstrapped t-statistics of the liquidity-timing coefficients: bootstrap analysis using fund returns. This figure plots kernel density estimates of the bootstrapped t-statistics of the liquidity-timing coefficients (solid lines), as well as the actual t-statistics of liquidity-timing coefficients (dashed vertical lines) for the aggressive growth portfolio (Panel A), the growth portfolio (Panel B), the growth-and-income portfolio (Panel C), and the income portfolio (Panel D) of our sample funds, respectively. The bootstrap is conducted at the fund level for funds with more than 24 monthly return observations during the 1974–2009 period.

First, we use a bootstrap method similar to the one outlined in Section 4.1 to assess the liquidity-timing ability found in the aggressive growth portfolio of our sample funds. In this test, we construct bootstrapped benchmark portfolios that share similar characteristics with the aggressive growth portfolio of our sample funds and that, by construction, do not have liquidity-timing ability. Specifically, we start with the 1,313 aggressive growth funds and use the 1,063 funds that have more than 24 monthly return observations to construct an equal-weighted aggressive growth portfolio.[7] Then we estimate the liquidity-timing model in Eq. (9) and find that the Newey-West t-statistic of the timing coefficient is 5.93. This result is similar to that reported in Table 3 in which all 1,313 aggressive growth funds are used to construct the aggressive growth portfolio. (The t-statistic of the estimated timing coefficient reported in Table 3 is 7.21.) The question we ask is whether the t-statistic of 5.93 is significant when it is evaluated against the bootstrapped distribution of t-statistics of timing coefficients.

To obtain bootstrapped benchmark portfolios, we use Eq. (12) to generate a time series of a pseudo fund's returns, $\{R^b_{pt}\}$, for each aggressive growth fund p in the bth round bootstrap. The pseudo fund and the fund p should share similar characteristics because

[7]The requirement of 24 monthly observations ensures that our bootstrap results, which rely on the estimation results for each fund using the Carhart (1997) four-factor model, are meaningful.

they have the same exposures (betas) to the market, size, book-to-market, and momentum factors. We then use the returns of all pseudo aggressive growth funds from the bth round bootstrap to obtain returns of an equal-weighed aggressive growth portfolio, $\{R^b_{AG,\ t}\}$. The resulting portfolio is an aggressive growth portfolio with similar characteristics to the aggressive growth portfolio of our sample funds, but by construction the bootstrapped portfolio does not have liquidity-timing ability. Finally, we estimate the timing model in Eq. (9) using the bootstrapped portfolio returns, $\{R^b_{AG,\ t}\}$, and preserve its timing coefficient γ^b_{AG} and corresponding t-statistic, $t^b_{\gamma,\ AG}$. We repeat the above procedure B times (we set B = 1,000) and obtain the empirical distribution of t-statistics associated with 1,000 liquidity-timing coefficients.

Panel A of Fig. 1 presents the bootstrapped distribution of t-statistics for the aggressive growth portfolio. For the estimated t-statistic of 5.93, its bootstrapped p-value is less than 1%, suggesting that the aggressive growth portfolio shows significant liquidity-timing ability.[8] Panels B–D of Fig. 1 report bootstrapped distributions of t-statistics for growth, growth-and-income, and income portfolios. The results show that the bootstrapped p-values associated with the estimated t-statistics of growth (4.22) and growth-and-income portfolios (2.97) are less than 1% while the t-statistic of income portfolio (1.22) is insignificant. These results are consistent with those reported in Table 3.

In the second test, we attempt to circumvent the problem of survivorship bias in our first test by directly bootstrapping the returns of the aggressive growth portfolio used in Section 3 instead of its underlying funds. That is, we estimate the Carhart (1997) four-factor model, retain estimated parameters and residuals for the aggressive growth portfolio, and use Eq. (12) to generate a time series of pseudo returns for the aggressive growth portfolio by imposing the null hypothesis of no liquidity-timing ability. Then we estimate the liquidity-timing coefficient and its Newey-West t-statistic using Eq. (9). Repeating the above steps B times ($B = 1{,}000$), we obtain the empirical distribution of t-statistics associated with bootstrapped timing coefficients.

Panel A of Fig. 2 shows the bootstrapped distribution of the t-statistics and the estimated t-statistic (7.21) for the aggressive growth portfolio from Table 3. When evaluating the estimated t-statistic against the bootstrapped distribution, we find the t-statistic of the aggressive growth portfolio is significant at any conventional level. The findings of the second test suggest that the aggressive growth portfolio has a significant liquidity-timing coefficient when compared with the bootstrapped benchmark portfolios (the bootstrapped p-value is less than 1%). Similarly, using the above bootstrap procedure, we conclude that the timing coefficients reported in Table 3 for the growth and growth-and-income portfolios are significant, but the timing coefficient of income portfolio is insignificant.

In the third test, we use a matching approach to examine whether a passive portfolio from the 125 characteristic-based benchmark portfolios, which is most similar to the aggressive growth portfolio of our sample funds, exhibits liquidity-timing ability. Specifically, we consider the 125 benchmark portfolios formed on size,

[8] We note that there is a difference between the sample of aggressive growth funds here and the sample used in Section 3.1 and Table 3. Dropping funds with less than 24 observations ensures that the estimation of the Carhart (1997) four-factor model and the liquidity-timing model is meaningful because it relies on the time series of each fund's returns. It also introduces survivorship bias, but the bias is in the direction against findings of timing ability.

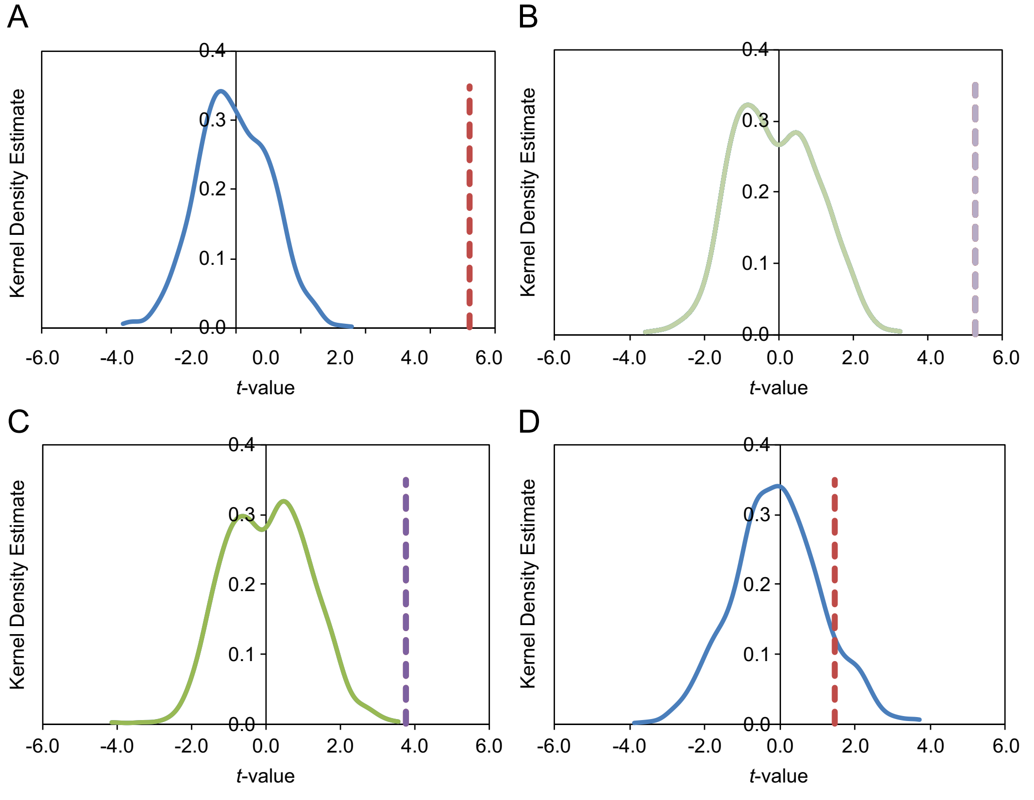

Fig. 2. Actual vs. bootstrapped t-statistics of the liquidity-timing coefficients: bootstrap analysis using portfolio returns. This figure plots kernel density estimates of the bootstrapped t-statistics of the liquidity-timing coefficients (solid lines), as well as the actual t-statistics of liquidity-timing coefficients (dashed vertical lines) for the aggressive growth portfolio (Panel A), the growth portfolio (Panel B), the growth-and-income portfolio (Panel C), and the income portfolio (Panel D) of our sample funds, respectively. The bootstrap is conducted at the portfolio level using portfolio returns during the 1974–2009 period.

book-to-market, and momentum suggested by Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW hereafter) as potential matches of the aggressive growth portfolio. The 125 DGTW portfolios are passive portfolios formed based on stock characteristics (i.e., they should not display any timing ability).[9] Our matching procedure is as follows:

1. For each portfolio j among the 125 portfolios, estimate the Carhart four-factor model and retain betas of SMB ($\beta_{size,j}$), HML($\beta_{B/M,j}$), and UMD ($\beta_{UMD,j}$).
2. Estimate the Carhart four-factor model for the aggressive growth portfolio of our sample funds and obtain betas of SMB ($\beta_{size,\ AG}$), HML ($\beta_{B/M,\ AG}$), and UMD ($\beta_{UMD,AG}$).

[9]The DGTW portfolios are provided by Russ Wermers and are available via http://www.smith.umd.edu/faculty/ rwermers/ftpsite/Dgtw/coverpage.htm. Details about the construction of these portfolios can be found in Wermers (2003).

3. For a potential matching portfolio j, use size, book-to-market, and momentum betas to construct a score statistic:

$$score_j = \left(\frac{\beta_{size,j} - \beta_{size,\ AG}}{0.5(\beta_{size,j} + \beta_{size,\ AG})}\right)^2 + \left(\frac{\beta_{B/M,j} - \beta_{B/M,\ AG}}{0.5\left(\beta_{B/M,j} + \beta_{B/M,\ AG}\right)}\right)^2 + \left(\frac{\beta_{UMD,j} - \beta_{UMD,\ AG}}{0.5(\beta_{UMD,j} + \beta_{UMD,\ AG})}\right)^2 \tag{16}$$

Select the portfolio with the lowest score from the 125 potential matching portfolios as the characteristic-matched benchmark portfolio for the aggressive growth portfolio.

The size, book-to-market, and momentum betas of the aggressive growth portfolio are 0.45, −0.05, and 0.04, respectively. The respective betas of the matched portfolio are 0.64, −0.15, and 0.11. While the aggressive growth portfolio and its matched portfolio share similar characteristics (size, book-to-market, and momentum), the liquidity-timing coefficient of the matched portfolio is insignificant (t-stat. = 1.58). Thus, the passive portfolio with characteristics similar to the aggressive growth portfolio of our sample funds does not demonstrate liquidity-timing ability.

We repeat the above analysis for all four subgroups with different investment objectives and find that none of the matched passive portfolios exhibit liquidity-timing ability. For example, the size, book-to-market, and momentum betas of the growth portfolio of sample funds are 0.07, −0.07, and −0.01, respectively, while the betas of its matched portfolio are 0.23, −0.07, and −0.38, respectively; the t-statistic of the liquidity-timing coefficient for the matched portfolio of growth funds is 1.47. For the growth-and-income portfolio, its matched portfolio has an insignificant t-statistic of the liquidity-timing coefficient of −0.47. The income fund portfolio does not demonstrate timing ability in Table 3 and neither does its matched portfolio (the t-statistic of the timing coefficient is 0.36).

In the last test, we examine the liquidity-timing ability of the 125 DGTW passive, characteristic-based portfolios. Based on conventional t-statistics, 11 (9%) of the 125 portfolios have a significant and positive timing coefficient. Six of the portfolios with a significant timing coefficient fall in the two highest momentum categories, but there is no apparent relation between timing coefficients and the size or book-to-market ratio rankings. Due to the violation of the i.i.d. assumption across portfolios' returns, we base cross-sectional statistical inference on the bootstrapped p-values for the Newey-West t-statistics of liquidity-timing coefficients, following the bootstrap procedure described in Section 4.1.

The bootstrap results show that these passive, characteristic-based portfolios do not show spurious liquidity-timing ability. For example, among the 125 portfolios, portfolios ranked as 75%, 90%, 95%, and 99% have Newey-West t-statistics of 1.34, 1.88, 2.74, and 3.55, respectively, for the liquidity-timing coefficients. Their bootstrapped p-values are all greater than 67%, indicating that the positive liquidity-timing coefficients of the top percentile portfolios are attributable to random sampling variation. Further, we find that none of these 125 passive portfolios have significant liquidity-timing coefficients based on the bootstrapped p-values for the t-statistics. Collectively, the evidence suggests that the documented liquidity-timing ability of mutual fund managers cannot be attributed to a passive liquidity-timing effect.

5. Conclusion

In this paper, we investigate the liquidity-timing ability of mutual funds by studying how fund managers change market exposure when market liquidity changes. We find that fund managers demonstrate the ability to time market liquidity at both the portfolio level and the individual fund level—they increase (reduce) market exposure when the market is more liquid (illiquid). We also find that among funds with different investment objectives, aggressive growth funds demonstrate the most significant liquidity-timing ability, followed by growth and growth-and-income funds, while income funds do not exhibit liquidity-timing ability. The results are robust to the exclusion of the 1987 market crash and the 2008 financial crisis, a sub-period analysis, the use of an alternative liquidity measure, and the inclusion of a liquidity risk factor. In addition, liquidity timing is an important component of the strategies of active mutual fund managers after controlling for volatility timing. We also find that such ability predicts funds' future risk-adjusted performance. Finally, liquidity-timing funds tend to have longer histories, higher expense ratios, and higher turnover rates.

Our paper makes several important contributions to the literature on mutual fund managers' timing ability. First, we examine the traditional timing issue from a new perspective by focusing on liquidity timing rather than return or volatility timing. This new focus enables us to better understand the asset allocation decisions of mutual fund managers. In particular, we show that fund managers increase (reduce) portfolio exposure prior to more liquid (illiquid) markets. As such, actively managed funds could potentially provide investors with valuable protection when market liquidity deteriorates, which is particularly important in times of crisis when liquidity risk is a major concern for investors. Second, we find that liquidity-timing strategies pay off in the form of higher future risk-adjusted performance. As risk-adjusted performance affects fund flows (e.g., Sirri and Tufano, 1998), our results have significant implications for manager compensation. Finally, our evidence reveals the important role that market liquidity plays in the asset allocation decisions active mutual fund managers make.

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