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Can hedge funds time market liquidity? ☆

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ABSTRACT

We explore a new dimension of fund managers' timing ability by examining whether they can time market liquidity through adjusting their portfolios' market exposure as aggregate liquidity conditions change. Using a large sample of hedge funds, we find strong evidence of liquidity timing. A bootstrap analysis suggests that top-ranked liquidity timers cannot be attributed to pure luck. In out-of-sample tests, top liquidity timers outperform bottom timers by 4.0–5.5% annually on a risk-adjusted basis. We also find that it is important to distinguish liquidity timing from liquidity reaction, which primarily relies on public information. Our results are robust to alternative explanations, hedge fund data biases, and the use of alternative timing models, risk factors, and liquidity measures. The findings highlight the importance of understanding and incorporating market liquidity conditions in investment decision making.

1. Introduction

Can sophisticated investors forecast and exploit changes in market conditions? Academic investigations of this fascinating question have a long history, dating back over seven decades to Cowles (1933). Since then, an extensive literature on market-timing ability has emerged, in which various linear and nonlinear measures with and without conditioning information have been proposed to detect the presence of timing skills. In their pioneering work, Treynor and Mazuy

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(1966) develop a framework to measure market timing by examining whether fund managers adjust their market exposure based on a market return forecast. Subsequently, many other measures have been proposed for identifying market return-timing and volatility-timing skills, e.g., Henriksson and Merton (1981), Jagannathan and Korajczyk (1986), Grinblatt and Titman (1989), Ferson and Schadt (1996), Busse (1999), Jiang, Yao, and Yu (2007), and Chen, Ferson, and Peters (2010).

In this paper, we explore a new dimension of fund managers' timing ability—their ability to time market liquidity.[1] In particular, we ask the following questions: Can hedge fund managers, among the most sophisticated of investors, time market liquidity by strategically adjusting fund betas based on their forecasts of future market liquidity conditions? If so, how much economic value does liquidity-timing skill bring to fund investors? These issues are essential to an understanding of the role of market liquidity in professional fund management.

Market-wide liquidity represents an important dimension of market conditions. Pástor and Stambaugh (2003) and Acharya and Pedersen (2005) show that market liquidity, which captures the aggregate ease of transacting a large quantity of assets in a short time without incurring high costs, is a priced state variable important for asset pricing. As underscored by the 2008–2009 financial crisis, market liquidity deteriorates when many investors exit the market at the same time, which causes more liquidation that further reduces market liquidity through so-called liquidity spirals. Therefore, a savvy manager who can correctly forecast market-wide liquidity deterioration would naturally wish to reduce his fund's market exposure before the event occurs.

We examine hedge funds' liquidity-timing ability for several reasons. First, hedge funds are managed by highly sophisticated managers and have experienced dramatic growth in the past two decades.[2] Over that period, many talented managers have joined the industry and hence, it is natural to ask whether hedge fund managers have the skills to time market conditions.[3] Second, liquidity is crucial to hedge funds. Since the collapse of Long-Term Capital Management (LTCM) in 1998, the interaction between liquidity at various levels (asset, funding, and market liquidity) and traders such as hedge funds has become better understood. Though other levels of liquidity (e.g., funding liquidity) perhaps are equally important (e.g., Aragon and Strahan, 2012), we focus on market-wide liquidity because timing strategies are essentially about aggregate market conditions. Third, hedge funds often employ dynamic strategies and have time-varying market exposure (e.g., Fung and Hsieh, 1997, 2001; and Patton and Ramadorai, forthcoming). The combination of time-varying market exposure and the importance of market liquidity implies that hedge funds provide an ideal platform to study liquidity-timing ability. Finally, given the evidence of positive risk-adjusted performance among hedge funds (e.g., Ackermann, McEnally, and Ravenscraft, 1999; Brown, Goetzmann, and Ibbotson, 1999; Fung, Hsieh, Naik, and Ramadorai, 2008; and Jagannathan, Malakhov, and Novikov, 2010), it is reasonable to ask whether liquidity timing is one source of the superior performance.

We build on the Treynor-Mazuy framework to explore the dynamics of hedge funds' market exposure in relation to market liquidity conditions, which is based on the relation between a fund's beta determined in month t and the market's return in month $t+1$. We estimate a regression model to evaluate how a fund's beta in month t changes with market liquidity realized in month $t+1$ (e.g., proxied by the Pástor-Stambaugh liquidity measure), while controlling for the fund's exposures to other relevant factors. If fund beta varies positively with market liquidity conditions, it indicates successful liquidity timing, i.e., the fund has relatively high (low) market exposure in anticipation of conditions where market liquidity is good (poor). Given the increasing importance of liquidity concerns in asset management, our investigation makes an important contribution to the hedge fund and timing literatures.

Using a large sample of 5,298 equity-oriented hedge funds (including funds of funds) over the period 1994–2009, we evaluate liquidity-timing ability at the individual fund level, which allows us to distinguish top liquidity-timing funds from the rest. We focus on fund managers' ability to time aggregate equity market liquidity because most hedge funds bear significant exposure to equity markets. For funds with at least 36 consecutive non-missing monthly observations, we estimate the timing skill using the fund's monthly returns. To assess statistical significance of timing ability and to separate timing skill from luck, we conduct a bootstrap analysis. For each cross-sectional statistic of the timing coefficients (e.g., the 10th percentile of t-statistics across all funds), we compare the actual estimate with the corresponding distribution of the statistics based on bootstrapped pseudo-funds that share similar risk exposure as actual funds but, by construction, have no timing skill. The findings strongly suggest that liquidity timing ability exists among hedge funds, and top-ranked liquidity timers cannot be attributed to pure luck.

Next, we explore the economic significance of liquidity timing by examining out-of-sample alphas (i.e., risk-adjusted returns) for the portfolios of funds at different levels of liquidity-timing skill. Specifically, in each month we sort funds into ten decile portfolios based on their liquidity-timing coefficients estimated from the previous 36 months. Then, we measure out-of-sample alphas of the portfolios for different holding periods ranging from three to 12 months. The results suggest that liquidity-timing skill generates significant abnormal returns. For example, over a six-month holding period, the decile portfolio consisting of top liquidity timers delivers an out-of-sample alpha of 0.63% per month (or 7.6% per year), which is more than three times the alpha of the portfolio of bottom timers (0.19% per month). The spread in out-of-sample alphas between the top and bottom liquidity timers remains significant even 12 months after forming the portfolios. We also find evidence of persistence in liquidity-timing skill, consistent with Jagannathan,

[1] In this paper, we refer to aggregate equity market liquidity simply as “market liquidity.”

[2] According to estimates of Hedge Fund Research Inc., the hedge fund industry has grown from a few hundred funds managing less than $50 billion in the early 1990s to more than 9,000 funds managing more than $2 trillion by the end of 2010.

[3] We use “hedge funds” and “hedge fund managers” interchangeably.

Malakhov, and Novikov (2010), who find performance persistence among superior hedge funds. Taken together, the results suggest that liquidity timing represents managerial skill adding value to fund investors.

Furthermore, we develop a test to distinguish liquidity-timing skill from liquidity reaction that captures fund managers' change in market exposure after observing market liquidity in the previous month. Interestingly, despite strong evidence of liquidity reaction, the test reveals no economic value as top liquidity reactors fail to deliver larger alphas than other funds in out-of-sample tests. This result is intuitive because liquidity reaction, using public information solely, does not represent managerial skill. Hence, it is important to distinguish liquidity timing from liquidity reaction.

Given that hedge funds' market exposures can change for other reasons, we conduct a wide array of additional tests to gain deeper insights about liquidity timing among hedge funds. First, under deteriorated market liquidity conditions, some hedge funds face margin calls and investor redemptions, requiring them to reduce market exposure (e.g., Lo, 2008). To address this concern due to funding constraint, we examine liquidity timing among funds that do not use leverage, impose strict redemption restrictions, or have low fund-flow volatility. Second, considering that large funds' simultaneous sales of assets can affect market liquidity (e.g., Khandani and Lo, 2007), we perform tests for small funds whose trades are unlikely to impact overall market liquidity. Finally, we conduct tests using alternative timing model specifications, risk factors, and liquidity measures. Overall, our findings are robust to all these investigations

The seminal works of Fung and Hsieh (1997, 2000) have shown various biases in hedge fund data, including survivorship bias, backfilling bias, and selection bias. We make efforts to minimize the impact of the biases on our inference about liquidity-timing skill. We use both live and defunct funds to mitigate the impact of survivorship bias. Hedge fund data also suffer from backfill bias that arises as a hedge fund could choose not to report to the database from its inception but backfill its historical performance later when it has established a successful record. To evaluate the impact of backfill bias, we discard the return observations before the funds are added to the database and repeat the tests for liquidity timing. Finally, Fund and Hsieh (2000) point out that data of funds of funds in general contain less bias compared with those of hedge funds. In this paper, we examine liquidity timing ability for both hedge funds and funds of funds. The results suggest that the inference about liquidity timing appears robust to the data biases.

The rest of the paper proceeds as follows. In Section 2, we outline our liquidity-timing model, and in Section 3 we describe the data. Section 4 presents the empirical results concerning liquidity-timing ability and distinguishes between liquidity timing and liquidity reaction. Section 5 explores alternative explanations related to funding liquidity and investor redemptions. Section 6 addresses the impact of hedge fund data biases on our inference. In Section 7, we check the robustness of our results to alternative model specifications, risk factors, and market liquidity measures. Finally, Section 8 concludes.

2. Liquidity timing model

Our liquidity-timing model builds on the pioneering work of Treynor and Mazuy (1966). In general, a timing model can be understood based on the capital asset pricing model (CAPM), by assuming that a fund manager generates portfolio returns according to the process

$$r_{p,t+1} = \alpha_p + \beta_{p,t} MKT_{t+1} + u_{p,t+1}, \quad t = 0, \ldots, T-1, \tag{1}$$

where $r_{p,t+1}$ is the return in excess of the risk-free rate (proxied by the one-month Treasury bill rate) for fund p in month t+1 and MKT_{t+1} is the excess return on the market portfolio. In Eq. (1), the fund's market beta varies over time. The timeline in Eq. (1) follows the timing literature, in which the fund beta $\beta_{p,t}$ is set by the manager in month t based on his forecast about market conditions in month t+1. Various timing models differ in the dimensions of the market conditions they concentrate on. Market timing focuses on forecasts of market returns, while volatility timing stresses the importance of forecasts of market volatility. In this paper, we test for liquidity-timing skill and focus on forecasts of market liquidity.

Existing timing models (e.g., Admati, Bhattacharya, Ross, and Pfleiderer, 1986; and Ferson and Schadt, 1996) approximate the timer's market beta as a linear function of his forecast about market conditions. The linear functional form can be justified from a Taylor expansion by ignoring higher-order terms (e.g., Shanken, 1990). Accordingly, the generic form of such a specification is

$$\beta_{p,t} = \beta_p + \gamma_p E(\text{market condition}_{t+1} | I_t), \tag{2}$$

where I_t is the information set available to the fund manager in t. The coefficient γ captures the essence of timing skill, i.e., how market beta varies with forecasts about market conditions. Although prior research on timing skill examines market conditions such as market returns and volatility, we explore a new dimension of timing ability, namely, the ability to time market liquidity. Hence, we specify Eq. (2) as

$$\beta_{p,t} = \beta_p + \gamma_p (L_{m,t+1} - \overline{L}_m + \upsilon_{t+1}), \tag{3}$$

where the expression in parentheses represents the manager's forecast (i.e., timing signal) about market liquidity and $L_{m,t+1}$ is the measure of market liquidity in month t+1. As it is unrealistic for a timer to have a perfect signal, υ_{t+1} denotes a forecast noise unknown until t+1, which we assume to be independent with a zero mean. Following the timing literature (e.g., Ferson and Schadt, 1996; and Busse, 1999), we de-mean the manager's signal by subtracting $\overline{L}_m$ for ease of interpretation. Accordingly, β_p captures the fund's average beta approximately. Our inference about liquidity-timing ability is unaffected with or without de-meaning the liquidity signal.

Pástor and Stambaugh (2003) develop a market-wide liquidity measure and show that market liquidity is an important state variable for asset prices. Liquid markets are generally viewed as accommodating large quantities of transactions in a short time with little impact on asset prices. The Pástor-Stambaugh measure captures market liquidity associated with temporary price fluctuations induced by order flow, which can be interpreted as volume-related price reversals attributable to liquidity effects. The measure is based on the assumption that the less liquid a stock is, the greater the expected price reversal is for a given amount of order flow. In this paper, we mainly use the Pástor-Stambaugh liquidity measure, and we use the Amihud (2002) illiquidity measure to cross-validate our results. The Pástor-Stambaugh and Amihud measures have been shown to capture market-wide liquidity conditions well. The Appendix A provides details on the construction of the two measures.

We obtain the following liquidity-timing model by substituting Eq. (3) in Eq. (1) and incorporating the forecast noise υ within the error term:

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \varepsilon_{p,t+1}. \quad (4)$$

The liquidity-timing model in Eq. (4) is parallel to the existing models of market timing [i.e., $\beta_{p,t} = \beta_p + \gamma_p(MTK_{t+1} + \upsilon_{t+1})$] and volatility timing [i.e., $\beta_{p,t} = \beta_p + \gamma_p(Vol_{t+1} - \overline{Vol} + \upsilon_{t+1})$], except that the market condition considered here is market liquidity. A positive timing coefficient γ indicates that the fund has a high (low) market beta during good (poor) market liquidity conditions.

It is well known that hedge funds often follow dynamic trading strategies (e.g., Fung and Hsieh, 1997, 2001; and Mitchell and Pulvino, 2001) and use derivatives (e.g., Chen, 2011). Hence, traditional factors based on linear payoffs might not be well suited for examining hedge fund performance. In this paper, we estimate liquidity-timing ability for hedge funds using the seven-factor model proposed by Fung and Hsieh (2004) as the main benchmark model. The seven factors include both linear and option-like factors and have been shown to explain the variations in hedge fund returns well. Specifically, the factors are an equity market factor, a size factor, the monthly change in the yield of the ten-year Treasury, the monthly change in the spread between Moody's Baa bond and the ten-year Treasury yields, and three trend-following factors for bonds, currencies, and commodities. Among the factors, equity market exposure is the most important for equity-oriented hedge funds. Thus, we test for liquidity-timing ability by examining the changes in equity market exposure in this paper, and we leave the investigation of potential changes in other market exposures for future research. Our baseline liquidity-timing model has the specification

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}, \quad (5)$$

where f denotes the other factors besides the equity market factor ($J = 6$ in this case). The coefficient γ measures liquidity-timing ability. For robustness, we also use alternative benchmark factor models to measure liquidity-timing skill (see Section 7).

3. The data

In this section, we describe the data on the hedge fund sample, the Pástor-Stambaugh liquidity measure, the Amihud illiquidity measure, and the Fung and Hsieh seven factors.

3.1. Hedge fund sample

We employ a sample of hedge funds from the Lipper TASS (hereafter TASS) database, which constitutes one of the most extensive hedge fund data sources and has been widely used in the hedge fund literature. Although the database contains fund returns back to November 1977, it does not retain dead funds until 1994 and data from the early period contain survivorship bias. Thus, we focus on the period from January 1994 onward. Following the hedge fund literature, we include only funds that report net-of-fee returns on a monthly basis and with average assets under management (AUM) of at least \$10 million.[4] Fung and Hsieh (1997, 2000) provide an excellent summary of biases in hedge fund data, such as survivorship bias, backfill bias, and selection bias. We evaluate the impact of these biases on the inference about liquidity timing in Section 6.

TASS classifies hedge funds into ten strategy categories: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event-driven, fixed income arbitrage, global macro, long-short equity, managed futures, and multi-strategy. Funds of funds are treated as a separate category. As most hedge funds trade primarily in equity markets, we focus our investigation on equity-oriented strategies by dropping fixed income arbitrage and managed futures. To draw reliable inference, we require each category to contain a sufficient number of individual funds. Consequently, dedicated short bias funds are eliminated because of the small number of funds in that category.

Our final sample contains 5,298 equity-oriented funds over the sample period of 1994–2009, of which 2,220 are funds of funds and 3,078 are hedge funds in the strategy categories of convertible arbitrage, emerging market, equity market neutral, event-driven, global macro, long-short equity, and multi-strategy. Among the sample funds, 2,266 are alive as of the end of the sample period and 3,032 became defunct during the period. We require each fund to have at least 36 monthly returns to obtain meaningful results.[5]

Panel A of Table 1 summarizes monthly returns for the sample funds. Over the sample period, the average monthly return for all funds is 0.62% (about 7.4% per year)

[4] Our inference remains unchanged when we impose other AUM filters (e.g., \$5 million or \$20 million). For non-US dollar—denominated funds, we convert their assets under management to US dollar values using exchange rates in the corresponding months. For robustness, we also convert fund returns into US dollar values and our inference about liquidity timing is unaffected.

[5] We experiment with alternative filters (e.g., requiring a minimum of 24-month observations) and find that our inference is robust to this parameter.

with a standard deviation of 0.66%. Hedge funds exhibit higher average monthly return (0.82%) than funds of funds (0.34%). Fung and Hsieh (2000) point out two factors that can explain this difference in average returns: Funds of funds charge investors with operating expenses and management fees on top of the fees charged by underlying hedge funds, and funds of funds often hold some cash to meet potential redemptions. Both factors suggest that funds of funds have lower net-of-fee returns than hedge funds on average. In addition, Fung and Hsieh (2000) argue that funds of funds generally contain less survivorship bias and backfill bias than hedge funds. Among different fund strategies, emerging market has the highest average monthly return of 1.07%, and convertible arbitrage delivers the lowest average monthly return of 0.60%. Meanwhile, convertible arbitrage has the lowest return volatility.

3.2. Liquidity and factor data

In Panel B of Table 1, we report summary statistics of the Pástor-Stambaugh market liquidity measure and the Amihud illiquidity measure during 1994–2009.[6] The time series mean (median) of the Pástor-Stambaugh market liquidity is −3.26% (−2.49%), suggesting a 3.26% average liquidity cost for a $1 million trade in 1962 stock market dollars distributed equally across stocks. For the period 1994–2009, we find that the value of $1 million in 1962 stock market dollars is equivalent to approximately $27 million, and the average daily trading volume is about $29 million for stocks on the NYSE and Amex. Based on this comparison, we interpret the 3.26% average liquidity measure as the cost for a trade size roughly as large as the average daily volume.

The liquidity measure has a standard deviation of 7.80% per month, indicating considerable variation of market-wide liquidity over time and potential importance of taking aggregate liquidity conditions into account in investment management. The time series of the market liquidity measure reveals some interesting patterns. As shown in Fig. 1, substantial downward spikes in market liquidity occur around October 1997 (the Asian financial crisis), September 1998 (the turmoil of the LTCM), April 2000 (the burst of Internet bubble), October 2007 (the beginning of the recent financial crisis), and March 2008 (the bankruptcy of Bear Sterns). Thus, this measure captures well-known market liquidity shocks very well, even beyond the period examined in Pástor and Stambaugh (2003). The mean (median) of the Amihud illiquid measure is 1.09% (1.00%), which suggests an average price impact of 1.09% for a $1 million trade in 1962 stock market dollars distributed equally across stocks. Although the two liquidity measures focus on different aspects of market liquidity, they often identify months corresponding to the well-known low-liquidity episodes.

[6] We thank Lubos Pástor and Robert Stambaugh for making the Pástor-Stambaugh liquidity measure data available at http://faculty.chicagobooth.edu/lubos.pastor/research.

Panel B of Table 1 also presents summary statistics for the Fung and Hsieh seven factors.[7] The average market excess return is 0.45% per month over 1994–2009 with a standard deviation of 4.65%. During the period, the lowest market return (−16.20%) occurs in August 1998, and the highest return (8.18%) occurs in April 2003. The correlation between market returns and the Pástor-Stambaugh market liquidity is 0.23 over the sample period.

4. Empirical results on liquidity timing

In this section, we first present the cross-sectional distribution of *t*-statistics for the liquidity-timing coefficients across individual funds. Then, we use a bootstrap analysis to examine the statistical significance of timing ability. Next, we show that liquidity-timing skill is associated with economically significant risk-adjusted returns in out-of-sample tests and that the liquidity-timing skill is persistent over time. Finally, we show that it is important to distinguish liquidity-timing skill from liquidity reaction that primarily relies on public information and, thus, does not generate investment value.

4.1. Cross-sectional distribution of t-statistics for liquidity timing

We evaluate liquidity-timing skill using regression Eq. (5) for individual funds. To ensure a meaningful regression, we require each fund to have at least 36 monthly observations. Table 2 reports the cross-sectional distribution of *t*-statistics for liquidity-timing coefficients across individual funds. In particular, the table shows the percentage of *t*-statistics exceeding the indicated cutoff values. For example, 20.1% of the sample funds have *t*-statistics greater than 1.28. For the overall sample, the right tails appear thicker than the left tails. We also observe a higher proportion of *t*-statistics greater than the cutoff values for hedge funds than for funds of funds. Meanwhile, about 14.7% of the funds have *t*-statistics smaller than −1.28, which indicates that some funds have negative liquidity timing.[8]

Overall, the distribution of *t*-statistics suggests that there exists liquidity timing skill based on the conventional significance values under the normality assumption. However, the conventional inference can be misleading when we infer the cross section of test statistics for a sample of hedge funds. First, due to their dynamic trading strategies (e.g., Fung and Hsieh, 1997, 2001), hedge fund returns often do not follow normal distributions. Second,

[7] We are grateful to David Hsieh for making the data of bond, currency and commodity trend-following factors available from http://faculty.fuqua.duke.edu/_dah7/DataLibrary/TF-FAC.xls. The data of the other factor are from the Center for Research in Security Prices and the Federal Reserve Bank databases.

[8] Negative timing seems hard to interpret because it suggests that the manager changes fund beta in the opposite direction to what is suggested by successful liquidity timing. However, as shown in Section 4.3, we do not find persistence in negative liquidity timing among hedge funds, despite the evidence of persistence in successful liquidity timing skill. Further, when we control for market and volatility timing, the evidence of negative liquidity timing becomes weaker (see Section 7.2 for details).

Table 1
Summary statistics of the data.

This table presents summary statistics of the data. Panel A summarizes average monthly returns on equity-oriented funds (all funds), hedge funds, funds of funds, and funds in each strategy category. Returns are in percent per month. *N* is the number of funds that exist any time during the sample period. Panel B summarizes the Pástor-Stambaugh market liquidity measure, the Amihud illiquidity measure, and the Fung-Hsieh seven factors, which are the market excess return (MKT), a size factor (SMB), monthly change in the ten-year treasury constant maturity yield (YLDCHG), monthly change in the Moody's Baa yield less ten-year treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). The Pástor-Stambaugh liquidity (the Amihud illiquidity) measure is the average liquidity cost (price impact) in percent for a $1 million trade in 1962 stock market dollars distributed equally across all stocks on the NYSE and Amex. The sample period is from January 1994 to December 2009.

Variables	*N*	Mean	Median	Standard deviation	25%	75%
Panel A: Summary of average fund returns						
Equity-oriented funds (all funds)	5298	0.620	0.533	0.667	0.257	0.892
Hedge funds	3078	0.820	0.748	0.741	0.428	1.143
Funds of funds	2220	0.343	0.343	0.408	0.136	0.538
Convertible arbitrage	142	0.600	0.576	0.430	0.376	0.806
Emerging market	340	1.068	0.947	0.962	0.540	1.543
Equity market neutral	239	0.522	0.470	0.489	0.216	0.780
Event-driven	408	0.793	0.751	0.703	0.485	1.010
Global macro	177	0.774	0.732	0.872	0.438	1.100
Long-short equity	1465	0.890	0.819	0.708	0.508	1.220
Multi-strategy	307	0.614	0.545	0.721	0.185	0.913
Panel B: Summary of liquidity measures and factor data						
Pástor-Stambaughliquidity		−3.262	−2.490	7.796	−6.566	1.188
Amihud illiquidity		1.093	1.001	0.268	0.911	1.194
MKT		0.446	1.155	4.652	−2.330	3.480
SMB		0.194	−0.175	3.743	−2.120	2.360
YLDCHG		−0.010	−0.010	0.283	−2.000	0.160
BAAMTSY		0.003	0.000	0.228	−0.090	0.080
PTFSBD		−1.384	−4.821	14.730	−11.320	3.921
PTFSFX		0.194	−4.306	19.820	−13.380	9.281
PTFSCOM		−0.314	−2.896	13.950	−9.627	5.998

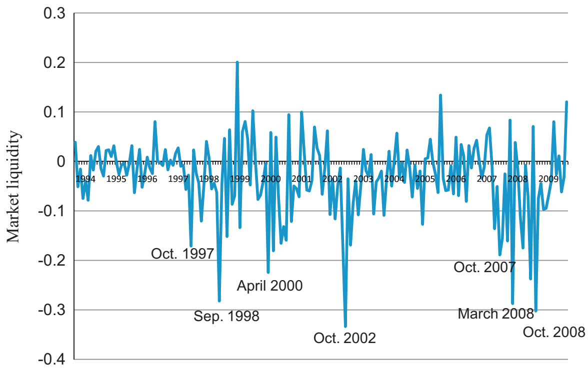

Fig. 1. Time series of monthly market liquidity. This figure plots the time series of monthly market liquidity measure developed by Pástor and Stambaugh (2003). The sample period is from January 1994 to December 2009. The noticeable downward spikes in market liquidity are associated with months of October 1997 (the Asian financial crisis), September 1998 (the height of Russian debt crisis and the collapse of Long-Term Capital Management), April 2000 (the burst of internet bubble), October 2002 (when the market dropped to a five-year low), October 2007 (the beginning of 2008–2009 financial crisis), March 2008 (the Bear Sterns bankruptcy) and October 2008 (the collapse of Lehman Brothers). Anecdotal evidence from financial press has identified these months in which liquidity was extremely low.

when we evaluate managerial skill for a large number of funds, it involves a multiple comparison problem. By random chance, some funds appear to have significant *t*-statistics under the conventional levels even if none of the funds has true timing ability. Third, if fund returns within a strategy are correlated, the timing measures might not be independent across funds. Therefore, we employ a bootstrap analysis to assess the significance of the timing coefficients. The bootstrap technique has the advantage to answer the question of whether the estimated timing coefficients reflect true managerial skill or pure luck.

Before we discuss the bootstrap analysis in detail, we take a look at the magnitude of the estimated timing coefficients. The average γ coefficient of the top 10% liquidity-timing funds is 2.14. To put this number into perspective, we compare it with the average estimated market beta (i.e., the coefficient on *MKT*) of the top 10% timing funds, which is 0.39. A timing coefficient of 2.14 suggests that when market liquidity is 1 standard deviation (i.e., 0.078 from Table 1) above its monthly mean, ceteris paribus, the market beta of a typical top 10% timing fund is higher by 0.17 (2.14×0.078), which translates to about 44% of the average beta of 0.39 when the aggregate liquidity is at its average level.

4.2. Bootstrap analysis

We now describe the bootstrap procedure used to assess the statistical significance of liquidity-timing coefficients for individual hedge funds. Our bootstrap procedure is similar to that of Kosowski, Timmermann, White, and Wermers (2006), Chen and Liang (2007), Jiang, Yao, and Yu (2007), Kosowski, Naik, and Teo (2007), and Fama and French (2010), all building on Efron (1979). The basic idea of the bootstrap analysis is that we randomly resample data (e.g., regression residuals) to generate hypothetical

Table 2
Cross-sectional distribution of t-statistics for the liquidity-timing coefficient across individual funds.

This table summarizes the distribution of t-statistics for the liquidity-timing coefficient. For each fund with at least 36 monthly return observations, we estimate the liquidity-timing model

$$r_{p,t+1} = \alpha_p + \beta_{p,1}MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \beta_{p,2}SMB_{t+1} + \beta_{p,3}YLDCHG_{t+1} + \beta_{p,4}BAAMTSY_{t+1} + \beta_{p,5}PTFSBD_{t+1} + \beta_{p,6}PTFSFX_{t+1} + \beta_{p,7}PTFSCOM_{t+1} + \varepsilon_{p,t+1}.$$

where $r_{p,t+1}$ is the excess return on each individual fund in month t+1. The independent variables are the market excess return (MKT), a size factor (SMB), monthly change in the ten-year Treasury constant maturity yield (YLDCHG), monthly change in the Moody's Baa yield less ten-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). $L_{m,t+1}$ is the market liquidity measure in month t+1, and $\overline{L}_m$ is the mean level of market liquidity. The coefficient γ measures liquidity-timing ability. The t-statistics are heteroskedasticity consistent. The numbers in the table report the percentage of funds with t-statistics of the timing coefficient exceeding the indicated values.

		Percentage of the funds							
Category	Number of funds	$t \le -2.326$	$t \le -1.960$	$t \le -1.645$	$t \le -1.282$	$t \ge 1.282$	$t \ge 1.645$	$t \ge 1.960$	$t \ge 2.326$
All funds	5298	4.27	6.76	9.49	14.65	20.06	13.50	9.31	5.49
Hedge funds	3078	4.81	7.21	10.01	14.68	22.74	15.53	10.43	6.37
Fund of funds	2220	3.51	6.13	8.78	14.59	16.35	10.68	7.75	4.28
Convertible arbitrage	142	8.45	10.56	17.61	24.65	13.38	9.16	3.52	0.70
Emerging market	340	8.53	13.24	19.12	25.00	16.76	12.94	7.35	4.12
Equity market neutral	239	6.70	8.37	10.04	15.48	18.41	14.23	8.37	4.18
Event-driven	408	3.68	6.37	7.84	10.78	28.68	17.89	12.99	8.33
Global macro	177	3.95	4.52	6.78	10.73	24.86	12.43	7.91	3.96
Long/short equity	1465	3.96	5.73	7.85	11.95	24.51	16.86	11.95	7.65
Multi-strategy	307	3.58	7.82	11.40	18.57	19.54	14.66	9.45	6.19

funds that, by construction, have the same factor loadings as the actual funds but have no timing ability, and then we evaluate
if the t-statistics of the estimated timing coefficients for the actual funds are different from the bootstrapped distribution that assumes no timing ability. Our bootstrap procedure has five steps.

1. Estimate the liquidity-timing model for fund p:

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}, \tag{6}$$

   and store the estimated coefficients $\{\hat{\alpha}_p, \hat{\beta}_p, \hat{\gamma}_p, ...\}$ as well as the time series of residuals $\{\hat{\varepsilon}_{p,t+1},\ t\ 0,\ \ldots,\ T_p-1\}$, where T_p is the number of monthly observations for fund p.
2. Resample the residuals with replacement and obtain a randomly resampled residual time series $\{\hat{\varepsilon}^b_{p,t+1}\}$, where b is the index of bootstrap iteration (b=1, 2,…, B). Then, generate monthly excess returns for a pseudo-fund that has no liquidity-timing skill (i.e., $\gamma_p = 0$ or, equivalently, $t_\gamma = 0$) by construction, that is, set the coefficient on the liquidity-timing term to be zero.

$$r^b_{p,t+1} = \hat{\alpha}_p + \hat{\beta}_p MKT_{t+1} + \sum_{j=1}^{J} \hat{\beta}_j f_{j,t+1} + \hat{\varepsilon}^b_{p,t+1} \tag{7}$$

3. Estimate the liquidity-timing model Eq. (6) using the pseudo-fund returns from Step 2, and store the estimate of the timing coefficient and its t-statistic. Because the pseudo-fund has a true γ of zero by construction, any nonzero timing coefficient (and t-statistic) comes from sampling variation.
4. Complete Steps 1–3 across all the sample funds, so that the cross-sectional statistics (e.g., the top 10th percentile) of the estimates of the timing coefficients and their t-statistics across all of the sample funds can be observed.
5. Repeat Steps 1–4 for B iterations to generate the empirical distributions for cross-sectional statistics (e.g., the top 10th percentile) of t-statistics for the pseudo-funds. In our analysis, we set the number of bootstrap simulations B to 10,000. Finally, for a given cross-sectional statistic, calculate its empirical p-value as the frequency that the values of the bootstrapped cross-sectional statistic (e.g., the top 10th percentile) for the pseudo-funds from B simulations exceed the actual value of the cross-sectional statistic.

The bootstrap analysis addresses the question: How likely is it that a positive (or negative) test result for liquidity-timing skill is the result of pure luck? For each cross-sectional statistic of the timing coefficient (or its t-statistic), we compare the actual estimate with the corresponding distribution of estimates based on bootstrapped pseudo-funds, and we determine whether the liquidity-timing coefficient can be explained by random sampling variation. We conduct our bootstrap analysis mainly for t-statistics of the timing coefficient (i.e., t_γ), because t-statistic is a pivotal statistic and has favorable sampling properties in bootstrap analysis (e.g., Horowitz, 2001).

Table 3 reports the empirical p-values corresponding to the t-statistics of liquidity-timing coefficients at different extreme percentiles from the bootstrap analysis. For all extreme percentiles considered (from 1% to 10%), the evidence suggests that the top liquidity-timing funds are unlikely to be attributed to random chance. Specifically, for the sample of 5,298 funds, the $t_{\hat{\gamma}}$s for the top 1%, 3%, 5%, and 10% liquidity-timing funds are 3.45, 2.72, 2.39, and 1.89, respectively, with empirical p-values all close to zero.

Table 3
Bootstrap analysis of liquidity timing.

This table presents the results of the bootstrap analysis of liquidity timing. For each fund with at least 36 monthly return observations, we estimate the liquidity-timing model

$$r_{p,t+1} = \alpha_p + \beta_{p,1}MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \beta_{p,2}SMB_{t+1} + \beta_{p,3}YLDCHG_{t+1} + \beta_{p,4}BAAMTSY_{t+1} + \beta_{p,5}PTFSBD_{t+1} + \beta_{p,6}PTFSFX_{t+1} + \beta_{p,7}PTFSCOM_{t+1} + \varepsilon_{p,t+1},$$

where $r_{p,t+1}$ is the excess return on each individual fund in month t+1. The independent variables are the market excess return (MKT), a size factor (SMB), monthly change in the ten-year Treasury constant maturity yield (YLDCHG), monthly change in the Moody's Baa yield less ten-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). $L_{m,t+1}$ is the market liquidity measure in month t+1, and $\overline{L}_m$ is the mean level of market liquidity. The coefficient γ measures liquidity-timing ability. In the table, the first row reports the sorted t-statistics of liquidity-timing coefficients across individual funds, and the second row is the empirical p-values from bootstrap simulations. The number of resampling iterations is 10,000.

			Bottom t-statistics for $\hat{\gamma}$				Top t-statistics for $\hat{\gamma}$			
Category	Number of funds		1%	3%	5%	10%	10%	5%	3%	1%
All funds	5,298	t-statistic	−3.47	−2.60	−2.20	−1.60	1.89	2.39	2.72	3.45
		p-value	0.00	0.00	0.00	0.21	0.00	0.00	0.00	0.00
Hedge funds	3,078	t-statistic	−3.50	−2.71	−2.30	−1.65	1.99	2.51	2.86	3.69
		p-value	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00
Fund of funds	2,220	t-statistic	−3.24	−2.49	−2.07	−1.56	1.70	2.25	2.52	3.11
		p-value	0.09	0.12	0.49	0.68	0.01	0.00	0.02	0.19
Convertible arbitrage	142	t-statistic	−4.27	−3.50	−3.17	−2.16	1.63	1.84	2.03	2.13
		p-value	0.01	0.00	0.00	0.00	0.41	0.84	0.83	0.98
Emerging market	340	t-statistic	−3.47	−2.95	−2.68	−2.15	1.80	2.23	2.48	2.68
		p-value	0.09	0.00	0.00	0.00	0.04	0.17	0.28	0.88
Equity market neutral	239	t-statistic	−4.27	−3.38	−2.74	−1.65	1.88	2.28	2.68	3.31
		p-value	0.00	0.00	0.01	0.35	0.02	0.06	0.00	0.15
Event-driven	408	t-statistic	−3.42	−2.71	−2.13	−1.38	2.18	2.73	3.00	3.92
		p-value	0.04	0.01	0.27	0.96	0.00	0.00	0.00	0.00
Global macro	177	t-statistic	−3.05	−2.41	−1.78	−1.35	1.81	2.17	2.54	3.26
		p-value	0.53	0.41	0.93	0.94	0.09	0.34	0.24	0.36
Long-short equity	1,465	t-statistic	−3.32	−2.56	−2.10	−1.44	2.11	2.62	3.08	3.89
		p-value	0.04	0.03	0.28	0.99	0.00	0.00	0.00	0.00
Multi-strategy	307	t-statistic	−3.04	−2.43	−2.25	−1.71	1.94	2.51	2.76	3.00
		p-value	0.39	0.36	0.17	0.16	0.00	0.01	0.03	0.42

The same result holds for both samples of hedge funds and funds of funds (with only one exception for the top 1% fund).

We also conduct a bootstrap analysis for funds in each strategy category. We find low empirical p-values for the top-ranked t-statistics for the following strategies: long-short equity, event-driven, multi-strategy, and equity market neutral, supporting the notion that top-ranked liquidity-timing coefficients are not due to random chance. Meanwhile, the timing coefficients of top-ranked funds in the convertible arbitrage, emerging market, and global macro strategies cannot be distinguished from luck. The negative timing coefficients of some funds cannot be attributed to random chance. For example, the empirical p-values associated with bottom-ranked $t_{\hat{\gamma}}$s are all close to zero for the samples of all funds, hedge funds, and funds in three strategy categories.

Fig. 2 plots the kernel density distributions of bootstrapped 10th percentile t-statistics in shaded areas, as well as the actual t-statistics of the timing coefficients as a vertical line for the sample of all funds, hedge funds, funds of funds, and funds in each strategy category. These graphs indicate that the distributions of bootstrapped t-statistics are non-normal and, thus, the inference drawn from the bootstrapped distributions and that from the conventional significance levels under the normality assumption can be different.

For robustness, we implement additional bootstrap procedures. In one experiment, we control for autocorrelation in fund residuals from regression Eq. (6) when bootstrapping pseudo fund returns. In another experiment, we address the concern that fund residuals can be correlated across funds (see Section 7.1 for details). We also resample the factors and residuals jointly. Although these procedures differ in resampling regression residuals and factors, we find qualitatively similar results.

The evidence from the bootstrap analysis suggests that top-ranked hedge fund managers can time market liquidity, and the results for negative timing coefficients cannot be attributed to randomness either. To further explore whether liquidity timing truly reflects managerial skill, we now examine the economic significance of liquidity timing.

4.3. Economic value of liquidity timing

Is liquidity-timing skill persistent over time? Can this skill add economic value to investors? If so, the evidence would lend additional support to the idea that liquidity timing represents valuable managerial skill. To gauge the practical significance of our liquidity-timing measure, we investigate the investment value based on selecting top liquidity timers.

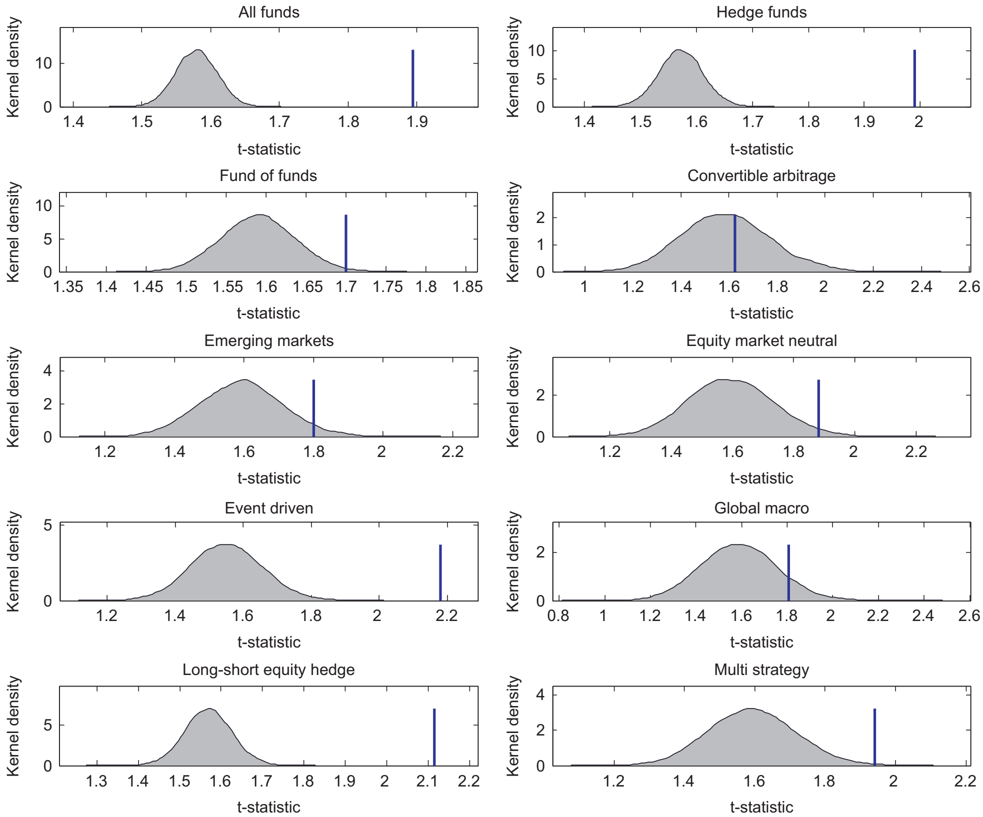

Fig. 2. *T*-statistics of the liquidity-timing coefficient for the top 10th percentile: actual fund verses bootstrapped funds. The shaded area represents the density distribution of *t*-statistics of the liquidity-timing coefficient for 10,000 pseudo-funds that appear at the top 10th percentile in each of 10,000 bootstrap simulations for the cross-section of sample funds. The vertical line corresponds to the actual fund at the top 10th percentile for each fund strategy category. The sample period is from January 1994 to December 2009.

In each month starting from January 1997, we estimate the liquidity-timing coefficient for each fund using the past 36-month estimation period and then form ten decile portfolios based on their liquidity-timing coefficients. These portfolios are held subsequently for a three-, six-, nine-, or 12-month holding period, and the process is repeated.[9] This yields four distinct time series of returns, one for each holding period, for each of the ten portfolios of varying levels of liquidity-timing skill from 1997 to 2009. Whenever a fund disappears over the holding period, its returns are included in calculating the portfolio returns until its disappearance, and the portfolio is rebalanced going forward. Next we estimate the seven-factor model and report each portfolio's alpha. Because this investment strategy is most relevant to fund of funds managers, we apply it to two samples: (1) all funds including funds of funds and (2) hedge funds only.

Table 4 presents striking evidence on the economic value of liquidity-timing ability. Specifically, the portfolio consisting of the top 10% of liquidity timers delivers economically significant alphas in the post-ranking periods. As reported in the Fifth column, for a 12-month holding period, the portfolio's alpha is 0.51% per month (6.1% per year) with a *t*-statistic of 3.48 based on the sample of all funds. Top liquidity-timing funds also generate significantly higher out-of-sample alphas than the other funds. For instance, the spread in alpha between top and bottom timing funds ranges from 0.33% to 0.46% per month, depending on the holding periods, and remains significant even one year after the ranking period. That is, top liquidity-timing funds outperform bottom timing funds by 4.0–5.5% per year subsequently on a risk-adjusted basis. This result is both economically and statistically significant.[10] An analysis focusing on only hedge funds produces the same result, that is, top liquidity-timing funds realize an average alpha that is about three times as large as the alphas of the other portfolios. Although hedge funds with no liquidity-timing ability can still generate alphas through other channels, top liquidity timers stand out by delivering an annualized

[9] We use the minimum three-month holding period because the average lock-up period for our sample of hedge funds is about three months.

[10] For robustness, we estimate alphas using the seven-factor model augmented with two market return lags to adjust for potential serial correlation in portfolio returns. In another robustness test, we estimate seven-factor alphas after unsmoothing portfolio returns to remove serial correlation. The inference about economic value of liquidity timing is unchanged.

Table 4
Economic value of liquidity timing: evidence from out-of-sample alphas.

This table presents the out-of-sample alphas for the portfolios consisting of funds at different levels of liquidity-timing skill. In each month, we form ten decile portfolios based on the funds' liquidity-timing coefficients estimated from the past 36 months (i.e., ranking period) and then hold these portfolios for different periods of K months. The table reports the out-of-sample seven-factor alphas (in percent per month) estimated from the post-ranking returns. T-statistics calculated based on Newey and West heteroskedasticity and autocorrelation-consistent standard errors with two lags are reported in parentheses.

	All funds				Hedge funds			
Portfolio	$K=3$	6	9	12	$K=3$	6	9	12
Portfolio 1 (top timers)	0.513	0.522	0.525	0.508	0.620	0.625	0.630	0.608
	(2.96)	(3.26)	(3.46)	(3.48)	(3.34)	(3.53)	(3.75)	(3.73)
Portfolio 2	0.323	0.322	0.310	0.297	0.348	0.354	0.342	0.337
	(3.18)	(3.32)	(3.18)	(3.05)	(2.99)	(3.38)	(3.56)	(3.50)
Portfolio 3	0.257	0.259	0.256	0.249	0.360	0.339	0.333	0.319
	(3.26)	(3.44)	(3.27)	(3.11)	(4.36)	(4.47)	(4.02)	(3.93)
Portfolio 4	0.228	0.239	0.232	0.222	0.302	0.312	0.301	0.292
	(2.29)	(2.96)	(2.92)	(2.65)	(3.72)	(4.41)	(4.22)	(3.95)
Portfolio 5	0.203	0.214	0.216	0.211	0.271	0.292	0.294	0.292
	(2.62)	(2.61)	(2.63)	(2.55)	(4.07)	(4.37)	(4.35)	(3.92)
Portfolio 6	0.195	0.197	0.202	0.198	0.240	0.240	0.247	0.249
	(1.98)	(1.96)	(2.07)	(2.09)	(2.48)	(2.52)	(2.75)	(2.88)
Portfolio 7	0.166	0.172	0.171	0.195	0.169	0.220	0.232	0.247
	(1.68)	(1.75)	(1.71)	(1.90)	(1.94)	(2.36)	(2.51)	(2.67)
Portfolio 8	0.171	0.182	0.197	0.209	0.308	0.294	0.295	0.307
	(1.22)	(1.48)	(1.59)	(1.67)	(2.10)	(2.20)	(2.20)	(2.32)
Portfolio 9	0.155	0.145	0.163	0.171	0.226	0.213	0.233	0.240
	(1.34)	(1.05)	(1.26)	(1.32)	(2.10)	(1.52)	(1.57)	(1.58)
Portfolio 10 (bottom timers)	0.180	0.102	0.070	0.081	0.255	0.192	0.162	0.176
	(1.01)	(0.54)	(0.38)	(0.46)	(1.21)	(0.89)	(0.76)	(0.83)
Spread (Portfolio 1–Portfolio 10)	0.333	0.420	0.455	0.427	0.365	0.433	0.468	0.432
	(1.79)	(2.33)	(2.63)	(2.51)	(1.65)	(2.01)	(2.28)	(2.13)

alpha of 7.3%, which suggests that liquidity timing reflects managerial skill and can be an important source of fund alphas.

The economic value of liquidity-timing skill can be seen more directly from Figs. 3 and 4. Fig. 3 plots out-of-sample alphas for the portfolios of top versus bottom timing funds for different holding periods. It illustrates that top liquidity-timing funds have an average alpha two to four times as large as that of bottom timing funds in post-ranking periods. Fig. 4 plots cumulative returns on the portfolios of top and bottom liquidity-timing funds, respectively, for a 12-month holding period. Holding the top-decile liquidity-timing funds yields a cumulative return of 471% from January 1997 to December 2009, and holding the bottom-decile liquidity timers generates a cumulative return of only 296% over the same period.

Using portfolio returns from the post-ranking periods, we further examine the persistence of liquidity-timing skill. Specifically, after forming ten portfolios based on the past liquidity-timing coefficients, we estimate the liquidity-timing model Eq. (5) and evaluate fund managers' subsequent timing ability. We find significant evidence of persistence in liquidity-timing skill. For example, the portfolio consisting of the top 10% timing funds in the past 36 months generates an out-of-sample timing coefficient of 0.56 (t-statistic$=$2.22) for a 12-month holding period. In contrast, the portfolio of bottom timers in the past 36 months exhibits a subsequent timing coefficient of 0.03 (t-statistic$=$0.03) for the same holding period. When we estimate Eq. (5) for the time series of the return spread between top and bottom timing funds, the timing coefficient is 0.54 (t-statistic$=$2.40) for a 12-month holding period.

To summarize, we find strong evidence that liquidity-timing skill adds economic value to investors, which further confirms that liquidity timing reflects managerial skill and can be one of the sources for hedge fund alpha. We also show that this skill persists over time in out-of-sample tests. This result is consistent with Jagannathan, Malakhov, and Novikov (2010) who find significant persistence in hedge fund alpha.

4.4. *Liquidity timing versus liquidity reaction*

The literature on timing ability examines whether fund managers could forecast the level of market conditions. If market conditions such as market liquidity are serially correlated, their values in month $t+1$ contain information from prior months. Thus, a fund manager may adjust market exposure based on lagged values of market conditions. As noted by Ferson and Schadt (1996), lagged market conditions are public information and adjusting fund betas based on public information does not reflect true timing skill.

The Pástor-Stambaugh liquidity measure has mild serial correlation. If a fund manager uses observed liquidity in month t to derive a predictable component of liquidity and adjusts his fund beta accordingly, he has no timing skill but simply reacts to past liquidity conditions. This

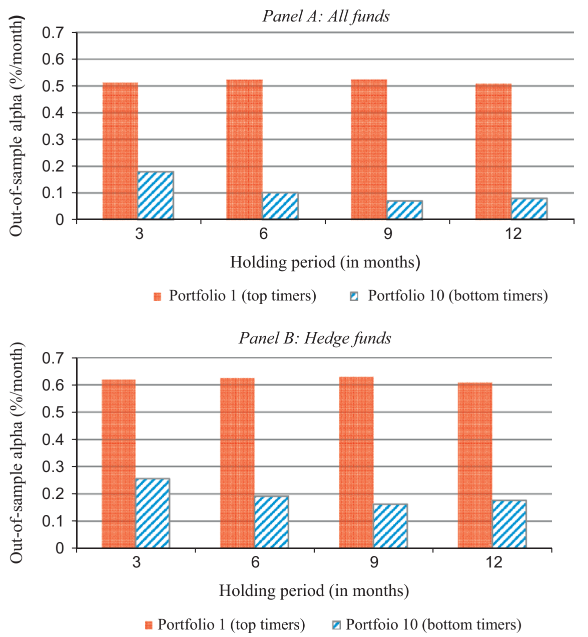

Fig. 3. Out-of-sample alphas for the portfolios of top verses bottom timing funds. This figure plots out-of-sample alphas for the portfolios consisting of top verses bottom timing funds for a holding period of three, six, nine, or 12 months. In each month starting from January 1997, we form the portfolios based on funds' liquidity-timing coefficients estimated from the past 36 months. Panel A reports results for all funds (including hedge funds and funds of funds), and Panel B reports results for hedge funds only.

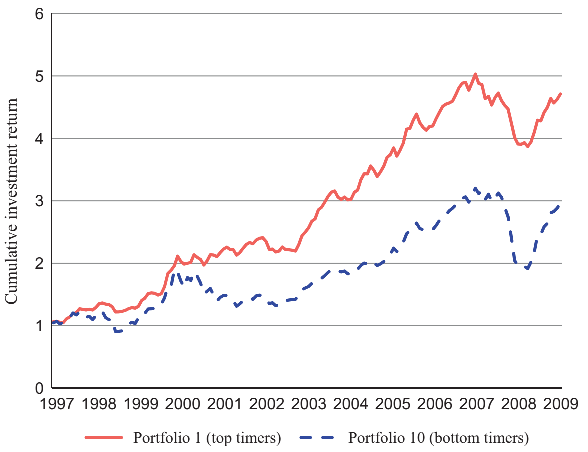

Fig. 4. Cumulative returns of investing in top verses bottom timing hedge funds. This figure plots cumulative returns of the portfolios consisting of top versus bottom liquidity-timing hedge funds for a 12-month holding period. In each month starting from January 1997, we form the portfolios based on hedge funds' liquidity-timing coefficients estimated from the past 36 months. These portfolios are held for 12 months subsequently.

observation highlights an important difference between liquidity timing and liquidity reaction: Liquidity reactors adjust fund betas based on observed market liquidity in month t, and liquidity timers manage market exposure using their forecasts of market liquidity in month t+1. To distinguish liquidity-timing skill from liquidity reaction, we estimate the following model in which both liquidity-timing and liquidity-reaction terms are included:

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}\tilde{L}_{m,t+1} + \varphi_p MKT_{t+1}(L_{m,t} - \bar{L}_m) + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}. \tag{8}$$

In this regression, $L_{m,t}$ is one-month lagged market liquidity and represents a predictable component of liquidity. $\tilde{L}_{m,t+1}$ is the innovation in market liquidity from an AR(2) process and the unpredictable component of market liquidity. In Eq. (8), the coefficients γ and φ measure liquidity-timing ability and liquidity reaction, respectively. If a fund manager reacts only to past liquidity conditions, we expect his timing coefficient to be insignificant once we take liquidity reaction into account.

We find that liquidity-timing ability remains significant after controlling for liquidity reaction simultaneously. A bootstrap analysis based on regression Eq. (8) suggests that $t_{\hat{\gamma}}$s of top-ranked liquidity timers have empirical p-values close to zero. In the bootstrap analysis, top-ranked funds in the strategies of equity market neutral, event-driven, long-short equity, and multi-strategy exhibit timing ability. Overall, the inference about liquidity-timing ability remains unchanged. In untabulated results, we also find significant evidence of liquidity reaction among hedge funds.

To further explore the distinction between liquidity reaction and liquidity timing, we examine the economic value of the former using the same approach applied to valuing the latter. We replace $L_{m,t+1}$ with $L_{m,t}$ in Eq. (5), repeat the analysis of economic value in Section 4.3, and then obtain out-of-sample alphas of the ten liquidity-reaction portfolios as well as the spread in alphas between the top and bottom portfolios. The results in Table 5 show that liquidity reaction does not generate economic value for fund investors. For the sample of all funds, the out-of-sample alpha for the portfolio consisting of top 10% liquidity reactors is 0.24% for a 12-month holding period, and the alpha for the bottom 10% liquidity reactors is 0.34% for the same holding period. In fact, the spread between the out-of-sample alphas of the top and bottom liquidity reactors is small and insignificant for all the four holding periods considered, i.e., three, six, nine, and 12 months. Hence, funds' reaction to past market-liquidity conditions, no matter whether it is fund managers' reaction to changes in leverage or to fund flows (see more discussion in Section 5), does not reflect managerial skill. Clearly, the group of top liquidity timers is different from the group of top liquidity reactors, and liquidity timing cannot be easily replicated by reacting to past liquidity conditions.

5. Alternative explanations

In this section, we examine the robustness of our results to alternative explanations. We address the concern that hedge funds' funding liquidity and redemption constraints could affect the inference about liquidity timing. We also consider the possibility that large funds' trades could impact market liquidity. Finally, we examine liquidity timing by excluding the 2008–2009 financial crisis period.

Table 5
Economic value of liquidity reaction: evidence from out-of-sample alphas.

This table presents the out-of-sample alphas for the portfolios consisting of funds to various extents of reacting to past market liquidity conditions. In each month, we form ten portfolios based on the funds' liquidity reaction coefficients estimated from the past 36 months (i.e., ranking period) and then hold these portfolios for different periods of *K* months. The table reports the out-of-sample seven-factor alphas (in percent per month) estimated from the post-ranking returns. *T*-statistics calculated based on Newey and West heteroskedasticity and autocorrelation-consistent standard errors with two lags are reported in parentheses.

	All funds				Hedge funds			
Portfolio	$K=3$	6	9	12	$K=3$	6	9	12
Portfolio 1 (top reactors)	0.116	0.116	0.174	0.242	0.251	0.255	0.311	0.363
	(0.54)	(0.56)	(0.86)	(1.29)	(1.12)	(1.19)	(1.52)	(1.88)
Portfolio 2	0.230	0.220	0.232	0.238	0.337	0.324	0.340	0.352
	(1.55)	(1.59)	(1.66)	(1.74)	(1.98)	(1.97)	(2.22)	(2.48)
Portfolio 3	0.239	0.226	0.228	0.229	0.324	0.295	0.300	0.303
	(1.82)	(1.92)	(2.05)	(2.06)	(2.19)	(2.62)	(2.68)	(2.85)
Portfolio 4	0.242	0.223	0.214	0.209	0.280	0.282	0.287	0.286
	(2.68)	(2.45)	(2.41)	(2.28)	(3.35)	(3.23)	(3.43)	(3.35)
Portfolio 5	0.189	0.207	0.212	0.208	0.325	0.344	0.348	0.320
	(2.32)	(2.51)	(2.65)	(2.52)	(4.68)	(4.64)	(4.80)	(4.18)
Portfolio 6	0.207	0.219	0.216	0.210	0.315	0.322	0.302	0.300
	(2.36)	(2.44)	(2.42)	(2.38)	(3.39)	(3.83)	(3.58)	(3.52)
Portfolio 7	0.214	0.218	0.214	0.216	0.289	0.298	0.300	0.306
	(2.48)	(2.54)	(2.38)	(2.30)	(3.52)	(3.36)	(3.34)	(3.28)
Portfolio 8	0.295	0.280	0.259	0.254	0.377	0.340	0.305	0.292
	(3.01)	(3.17)	(2.88)	(2.74)	(4.24)	(3.93)	(3.42)	(3.25)
Portfolio 9	0.278	0.293	0.269	0.252	0.286	0.330	0.307	0.288
	(3.37)	(3.22)	(3.12)	(2.91)	(2.68)	(3.33)	(3.16)	(2.87)
Portfolio 10 (bottom reactors)	0.422	0.388	0.366	0.339	0.446	0.380	0.355	0.335
	(3.26)	(2.95)	(2.79)	(2.56)	(2.97)	(2.44)	(2.31)	(2.21)
Spread (Portfolio 1–Portfolio 10)	−0.306	−0.272	−0.192	−0.097	−0.195	−0.125	−0.044	0.028
	(−1.42)	(−1.33)	(−0.97)	(−0.50)	(−0.75)	(−0.45)	(−0.06)	(0.34)

5.1. Leverage and funding constraints

We are concerned about the possibility that our results on liquidity timing might be driven by changes in hedge fund leverage. As discussed in Lo (2008) and Ang, Gorovyy, and van Inwegen (2011), hedge funds' use of leverage, mainly provided by prime brokers through short-term funding, exposes funds to the risk of sudden margin calls that can force them to liquidate positions. Such forced liquidations can occur to many funds at the same time, especially during market liquidity shocks. Hence, one might wonder if the reduction of market exposure in poor market liquidity conditions merely reflects a deterioration of funding liquidity because prime brokers have cut funding or increased borrowing costs. We consider this possibility from four perspectives.

First, we have shown that liquidity-timing skill is associated with subsequent superior performance. This result should be more likely to be attributed to managerial skill rather than to leverage. In fact, theory suggests that funds experiencing fire sales should incur substantial losses because forced liquidations are often associated with distressed asset prices (e.g., Brunnermeier and Pedersen, 2009).

Second, although leverage is sometimes portrayed as a common characteristic of hedge funds, most hedge funds use leverage to a much lesser extent than outsiders believe especially after the LTCM debacle in 1998. Ang, Gorovyy, and van Inwegen (2011) report an average net leverage ratio of 0.58 and an average long-only leverage ratio of 1.36 when examining leverage ratios for 208 hedge funds based on data from a large fund of funds.[11] They further find that equity-oriented hedge funds, which are the focus of our study, have lower leverage ratios compared with non-equity-oriented funds. Hence, their finding suggests that the effect of leverage change is not large for equity-oriented hedge funds.

Third, to further address this concern about hedge fund leverage, we repeat our analysis using a subsample of funds that do not use leverage at all. If the changes in fund beta are merely caused by fluctuations in leverage, hedge funds that do not use leverage should exhibit no evidence of liquidity-timing ability. Table 6 reports the results for funds that do not use leverage. Among the 5,298 funds in our sample, 2,649 of them claim not to use leverage while the other 2,649 report the use of leverage.[12] For the funds that do not use leverage, the bootstrap results are consistent with those in Table 3. The $t_{\hat{\gamma}}$s for the top 1%, 3%, 5%, and 10% liquidity-timing funds are 3.46, 2.76, 2.43, and 1.86, respectively, with empirical p-values all close to zero. Furthermore, consistent with the evidence from the full sample, we find evidence of liquidity timing among both leverage users and non users for the following four

[11] The net leverage ratio is long and short exposure divided by the assets under management, and the long-only leverage ratio is long positions divided by the assets under management.

[12] We examine the leverage-use indicator variable from TASS data downloaded in different years from 1998 to 2010. According to the data, most hedge funds do not change their leverage policy over time. On average, less than 1% of funds change their status of leverage use from one year to another.

Table 6

Fund leverage and liquidity timing.

This table presents the results of the bootstrap analysis of liquidity timing for funds that use leverage and those that do not use leverage, separately. For each fund with at least 36 monthly return observations, we estimate the liquidity-timing model

$$r_{p,t+1} = \alpha_p + \beta_{p,1}MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \beta_{p,2}SMB_{t+1} + \beta_{p,3}YLDCHG_{t+1} + \beta_{p,4}BAAMTSY_{t+1}$$
$$+\beta_{p,5}PTFSBD_{t+1} + \beta_{p,6}PTFSFX_{t+1} + \beta_{p,7}PTFSCOM_{t+1} + \varepsilon_{p,t+1},$$

where $r_{p,t+1}$ is the excess return on each individual fund in month t+1. The independent variables include the market excess return (MKT), a size factor (SMB), monthly change in the ten-year Treasury constant maturity yield (YLDCHG), monthly change in the Moody's Baa yield less ten-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). $L_{m,t+1}$ is the market liquidity measure in month t+1, and $\overline{L}_m$ is the mean level of market liquidity. The coefficient γ measures liquidity-timing ability. In each panel, the first row reports the sorted t-statistics of liquidity-timing coefficients across individual funds, and the second row is the empirical p-values from bootstrap simulations. The number of resampling iterations is 10,000.

			Bottom t-statistics for $\hat{\gamma}$				Top t-statistics for $\hat{\gamma}$			
Category	Number of funds		1%	3%	5%	10%	10%	5%	3%	1%
Panel A: Bootstrap results for funds that do not use leverage										
All funds	2,649	t-statistic	−3.47	−2.60	−2.22	−1.67	1.86	2.43	2.76	3.46
		p-value	0.00	0.00	0.01	0.03	0.00	0.00	0.00	0.00
Hedge funds	1,263	t-statistic	−3.47	−2.69	−2.29	−1.71	2.05	2.59	3.00	3.89
		p-value	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00
Fund of funds	1,386	t-statistic	−3.52	−2.57	−2.18	−1.61	1.64	2.22	2.55	3.05
		p-value	0.01	0.06	0.12	0.38	0.08	0.04	0.05	0.45
Panel B: Bootstrap results for funds that use leverage										
All funds	2,649	t-statistic	−3.50	−2.59	−2.18	−1.53	1.94	2.38	2.70	3.35
		p-value	0.00	0.00	0.01	0.82	0.00	0.00	0.00	0.00
Hedge funds	1,815	t-statistic	−3.56	−2.71	−2.33	−1.59	1.98	2.46	2.79	3.33
		p-value	0.00	0.00	0.00	0.35	0.00	0.00	0.00	0.01
Fund of funds	834	t-statistic	−3.02	−2.18	−1.96	−1.47	1.83	2.26	2.47	3.35
		p-value	0.49	0.96	0.84	0.93	0.00	0.02	0.04	0.04

strategies: equity market neutral, event-driven, long-short equity, and multi-strategy. Because funds that do not use leverage still exhibit significant timing ability, our evidence on liquidity-timing skill is unlikely to be attributed to the impact of fund leverage.

Finally, we explicitly control for the impact of funding constraints, measured by the TED spread, on our liquidity-timing inference. The TED spread, measured by the difference between the three-month LIBOR (London Interbank Offered Rate) and the three-month T-bill rate, indicates market-perceived counterparty default risk. When the risk of counterparty default is considered to be decreasing, the TED spread goes down and a prime broker is inclined to provide greater leverage. Hence, we include an additional interaction term between the TED spread and market returns in the liquidity-timing model Eq. (5):

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m)$$
$$+\lambda_p MKT_{t+1}TED_{t+1} + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}. \quad (9)$$

In untabulated bootstrap analysis, we find significant evidence of liquidity-timing ability even after controlling for the impact of funding constraints. This result holds for all sample funds, hedge funds, and funds of funds.

Taken together, these results suggest that externally driven changes in hedge fund leverage are not driving our findings about liquidity-timing skill among hedge funds. By definition, liquidity timing reflects fund managers' ability to forecast market liquidity and make ex ante adjustment to market exposure. Although external leverage changes can affect a fund's market exposure, they do not reflect managerial skill.

5.2. Investor redemptions

Besides broker-dictated changes in leverage, external funding constraints can be caused by investor redemptions, which present another mechanism by which a fund's market exposure could change rapidly. As investors withdraw their capital, fund managers have to unwind positions, leading to a decrease in market exposure (e.g., Khandani and Lo, 2007). During the recent financial crisis, many hedge funds experienced heavy investor redemptions and were forced to liquidate positions. We conduct three tests to investigate this possibility.[13]

First, we repeat our analysis using funds that impose a redemption frequency of one quarter or longer. A longer redemption frequency blocks rapid capital redemptions, and this provision is especially effective during market crashes or liquidity crises. Thus, funds with low redemption frequency face relatively less pressure from investor redemptions. Panel A of Table 7 contains bootstrap results

[13] Unlike open-ended mutual funds that stand ready to redeem capital for their investors, many hedge funds set redemption restrictions through several provisions such as redemption frequency, lock-up periods, advance-notice periods, and redemption gates. Redemption frequency sets the frequency of capital withdrawals. A lock-up period refers to a time period during which initial investments cannot be redeemed. After the lock-up period, many funds require their investors to submit a notice prior to the actual redemption. Furthermore, a redemption gate grants the fund manager the right to restrict redemptions beyond a percentage of the fund's total assets.

for funds that have redemption frequency equal to or greater than one quarter. Out of all funds, 2,457 funds (or 46% of the sample) meet this criterion, among which 1,488 are hedge funds and 969 are funds of funds.

The evidence is consistent with the results in Table 3. For example, the $t_{\hat{\gamma}}$s for the top 1%, 3%, 5%, and 10% liquidity-timing funds are, respectively, 3.48, 2.79, 2.49, and 2.01, with empirical p-values all below 1% for the sample of all funds. Further analysis for hedge funds in each strategy category yields results consistent with those in Section 4. Intuitively, investor redemptions are more likely to have an effect on funds with a higher redemption frequency (e.g., a month). The fact that funds with lower redemption frequency exhibit equally strong timing ability as funds with higher redemption frequency suggests that liquidity timing is mostly derived from managers' timing ability, not from investors' informed redemption decisions.

Second, we examine liquidity-timing ability for funds requiring a redemption notice period of 60 days; 1,340 funds, including 739 hedge funds and 601 funds of funds, meet this requirement. The redemption notice period allows more time for a fund manager to adjust positions to meet investors' withdrawal requests, reducing the market impact of redemptions. Panel B of Table 7 reports these results. Once again, we find that our inference about liquidity-timing skill remains unchanged, in that top-ranked t-statistics of timing coefficients have p-values less than or equal to 5% for the samples of all funds, hedge funds, and funds of funds (with one exception).

Finally, we examine a subsample of funds having low fund-flow volatility, and we report bootstrap results in Panel C of Table 7. Specifically, we examine funds whose monthly flow volatility is below the median level of peer funds. Funds with low flow volatility should be less affected by investor flows. Following prior research (e.g., Sirri and Tufano, 1998), we measure fund flows as the percentage change in assets under management after adjusting for fund returns. The subsample contains 2,533 funds (or 48% of the overall sample), which is not exactly 50% of the entire sample because some funds do not report AUMs. Here, we find that the $t_{\hat{\gamma}}$s for the top 1%, 3%, 5%, and 10% liquidity-timing funds are 3.43, 2.81, 2.44, and 1.95, respectively, with empirical p-values all close to zero. The same conclusion holds for the samples of 1,270 hedge funds and 1,263 funds of funds that have low fund-flow volatility. These findings are similar to the evidence reported in Table 3, suggesting that fund flows cannot explain our finding of liquidity-timing ability.

Collectively, we find significant evidence of liquidity timing among funds that are subject to lower redemption frequencies or longer redemption notice periods or have lower fund-flow volatility. These findings indicate that our evidence on liquidity timing is unlikely to be merely a consequence of investor redemptions.

5.3. The impact of hedge fund trades on market liquidity

We now consider the possibility that our results are driven by the impact of large funds' trading on market liquidity. By definition, liquidity-timing ability implies a positive relation between a fund's beta set by managers in month t and market liquidity observed in month $t+1$. However, one could argue that hedge fund trading in month t could affect market liquidity in month $t+1$. For example, if large funds liquidate their equity positions simultaneously in one month, market liquidity could deteriorate in the next month, generating a positive link between funds' market exposure and subsequent market liquidity.

To address this concern, we examine liquidity-timing ability using several subsamples of small funds, because these funds' trades are unlikely to have an effect on market liquidity. We employ subsamples of funds with AUM less than \$50 million (2,315 funds, collectively accounting for about 9.2% of the total AUM of the sample funds) and less than \$150 million (3,984 funds, or 28.5% of the total AUM). The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 introduces significant regulation of hedge funds, but the regulation applies only to fund advisers with AUM of \$150 million or more. Hence, we use \$150 million as the threshold of materiality to distinguish small funds from large ones.[14] In addition, we perform a test in which we define small funds as those having lower than median R^2 in a regression of fund returns on the portfolio of the largest 10% of funds. The resulting subsample contains 2,649 funds.

Table 8 reports the bootstrap results of liquidity timing for different subsamples of small funds. Regardless of the definition of small funds, we find evidence of liquidity timing consistent with those reported previously. For example, when small funds are defined as having AUM less than \$150 million, the $t_{\hat{\gamma}}$s for the top 1%, 3%, 5%, and 10% liquidity-timing funds are 3.46, 2.69, 2.36, and 1.86, respectively, and their p-values are close to zero. In sum, among small funds that are unlikely to affect market liquidity materially, we still find significant evidence for liquidity-timing ability, which suggests that our results are not driven by large-fund trading that could affect market liquidity.

5.4. Excluding the 2008–2009 crisis period

Most of the alternative explanations in Sections 5.1–5.3 should be especially relevant during market liquidity crises because the impact of leverage, funding constraints, and investor redemptions are the greatest during these periods. To focus squarely on these alternate explanations, we examine liquidity-timing ability excluding the 2008–2009 financial crisis period.[15] During the 1994–2007 period, we find somewhat stronger evidence for liquidity-timing skill. For example, 25.8% of the funds have t-statistics for the timing coefficient exceeding 2.82, compared with 20.1% reported in Table 2 for the entire sample period. A bootstrap analysis indicates that top-ranked liquidity timers have t-statistics corresponding to empirical values close to zero. We obtain similar results for hedge funds and funds

[14] The AUM requirement of \$150 million in the Dodd-Frank act applies to fund advisers, and a fund adviser could manage multiple funds.

[15] Ben-David, Franzoni, and Moussawi (2012) examine hedge funds' trading patterns in stock markets during this financial crisis period.

Table 7
Investor redemptions, fund flows, and liquidity timing.
This table presents the results of the bootstrap analysis of liquidity timing for funds that have redemption frequency as quarterly or longer, that impose redemption notice period equal or longer than 60 days, and that have fund-flow volatility lower than the median level. For each fund with at least 36 monthly return observations, we estimate the liquidity-timing model:

$$r_{p,t+1} = \alpha_p + \beta_{p,1}MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \beta_{p,2}SMB_{t+1} + \beta_{p,3}YLDCHG_{t+1} + \beta_{p,4}BAAMTSY_{t+1} + \beta_{p,5}PTFSBD_{t+1} + \beta_{p,6}PTFSFX_{t+1} + \beta_{p,7}PTFSCOM_{t+1} + \varepsilon_{p,t+1},$$

where $r_{p,t+1}$ is the excess return on each individual fund in month t+1. The independent variables include the market excess return (MKT), a size factor (SMB), monthly change in the ten-year Treasury constant maturity yield (YLDCHG), monthly change in the Moody's Baa yield less ten-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). $L_{m,t+1}$ is the market liquidity measure in month t+1, and $\overline{L}_m$ is the mean level of market liquidity. The coefficient γ measures liquidity-timing ability. In each panel, the first row reports the sorted t-statistics of liquidity-timing coefficients across individual funds, and the second row is the empirical p-values from bootstrap simulations. The number of resampling iterations is 10,000.

			Bottom t-statistics for $\hat{\gamma}$				Top t-statistics for $\hat{\gamma}$			
Category	Number of funds		1%	3%	5%	10%	10%	5%	3%	1%
Panel A: Bootstrap results for funds that have redemption frequency equal or greater than a quarter										
All funds	2,457	t-statistic	−3.27	−2.57	−2.18	−1.59	2.01	2.49	2.79	3.48
		p-value	0.03	0.01	0.01	0.34	0.00	0.00	0.00	0.00
Hedge funds	1,488	t-statistic	−3.27	−2.58	−2.20	−1.53	2.09	2.64	2.98	3.75
		p-value	0.04	0.01	0.01	0.68	0.00	0.00	0.00	0.00
Fund of funds	969	t-statistic	−3.28	−2.56	−2.19	−1.63	1.72	2.31	2.49	2.98
		p-value	0.16	0.09	0.14	0.27	0.03	0.01	0.05	0.60
Panel B: Bootstrap results for funds that have redemption notice period equal or longer than 60 days										
All funds	1,340	t-statistic	−3.34	−2.58	−2.18	−1.62	1.84	2.44	2.79	3.46
		p-value	0.04	0.01	0.07	0.26	0.00	0.00	0.00	0.01
Hedge funds	739	t-statistic	−3.34	−2.76	−2.32	−1.75	1.89	2.59	2.92	3.76
		p-value	0.10	0.00	0.01	0.02	0.00	0.00	0.00	0.00
Fund of funds	601	t-statistic	−2.82	−2.29	−1.99	−1.44	1.83	2.35	2.49	3.34
		p-value	0.79	0.73	0.77	0.95	0.00	0.01	0.17	0.05
Panel C: Bootstrap results for funds that have fund-flow volatility lower than the median level										
All funds	2,533	t-statistic	−3.23	−2.51	−2.09	−1.55	1.95	2.44	2.81	3.43
		p-value	0.05	0.02	0.19	0.62	0.00	0.00	0.00	0.00
Hedge funds	1,270	t-statistic	−3.05	−2.56	−2.18	−1.60	2.07	2.63	2.98	3.71
		p-value	0.35	0.02	0.03	0.24	0.00	0.00	0.00	0.00
Fund of funds	1,263	t-statistic	−3.28	−2.46	−2.03	−1.50	1.81	2.25	2.60	3.21
		p-value	0.09	0.23	0.62	0.89	0.00	0.01	0.01	0.08

of funds. The details of these results are omitted to conserve space but are available upon request.

In summary, the analysis presented in this section strongly suggests that our findings of the liquidity-timing ability among hedge funds are not explained by mechanisms related to external changes in funding liquidity and constraints. Although these effects do play an important role in the hedge fund industry, they do not seem materially related to liquidity timing.

6. The impact of hedge fund data biases

The pioneering works of Fung and Hsieh (1997, 2000) show various biases in hedge fund data, including survivorship bias, backfilling bias, and selection bias. We make efforts to minimize the impact of these biases on our results about the liquidity-timing ability. First, we follow the convention of hedge fund literature to include both live and defunct funds in this paper. The inclusion of defunct funds alleviates the effect of survivorship bias, if funds exit the database mainly due to poor performance.

Second, we examine the impact of backfill bias (or incubation bias) that arises as a hedge fund could backfill its historical performance when it is added into a database. Fung and Hsieh (2000), using TASS data as of September 1999, find a median backfill period of 343 days for hedge funds. They further report a backfill bias of 1.4% per year in average returns for hedge funds and 0.7% per year for funds of funds. In our sample, the median backfill period is 23 months. To address the concern about backfill bias, we discard the backfill period for each fund and use only fund returns recorded after the date when the fund is added to the TASS database.[16] After we delete the backfill period, the sample size reduces to 2,688 funds (1,815 hedge funds and 873 funds of funds). The average monthly return for hedge funds is 0.65% in this reduced sample compared with 0.82% in the full sample (see Table 1), which indicates a backfill bias about 2.0% per year. Meanwhile, the monthly average return for funds of funds is 0.32% in the reduced sample versus 0.34% in the full sample, implying a backfill bias about 0.24% per year. Thus, the magnitude of backfill

[16] Fung and Hsieh (2009) find that the date when a fund enters a database can sometimes differ from the fund's inception date for reasons unrelated to incubation period. For example, hedge funds could migrate from one database to another, and one database sometimes can be merged into another database. For robustness, we also experiment with deleting the first 12 or 24 months for each fund, and we find that our inference is unchanged.

Table 8
Liquidity timing of small funds.

This table presents the results of the bootstrap analysis of liquidity timing for funds that have assets under management (AUM) below \$50 million, that have AUM below \$150 million, and that have lowerthanmedian R^2 in a regression against returns of the portfolio of top 10% large funds. For each fund with at least 36 monthly return observations, we estimate the liquidity-timing model

$$r_{p,t+1} = \alpha_p + \beta_{p,1}MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \beta_{p,2}SMB_{t+1} + \beta_{p,3}YLDCHG_{t+1} + \beta_{p,4}BAAMTSY_{t+1} + \beta_{p,5}PTFSBD_{t+1} + \beta_{p,6}PTFSFX_{t+1} + \beta_{p,7}PTFSCOM_{t+1} + \varepsilon_{p,t+1},$$

where $r_{p,t+1}$ is the excess return on each individual fund in month t+1. The independent variables include the market excess return (MKT), a size factor (SMB), monthly change in the ten-year Treasury constant maturity yield (YLDCHG), monthly change in the Moody's Baa yield less ten-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). $L_{m,t+1}$ is the market liquidity measure in month t+1, and $\overline{L}_m$ is the mean level of market liquidity. The coefficient γ measures liquidity-timing ability. In each panel, the first row reports the sorted t-statistics of liquidity-timing coefficients across individual funds, and the second row is the empirical p-values from bootstrap simulations. The number of resampling iterations is 10,000.

			Bottom t-statistics for $\hat{\gamma}$				Top t-statistics for $\hat{\gamma}$			
Category	Number of funds		1%	3%	5%	10%	10%	5%	3%	1%
Panel A: Bootstrap results for funds with AUM < \$50 million										
All funds	2,315	t-statistic	−3.38	−2.66	−2.23	−1.61	1.87	2.39	2.72	3.46
		p-value	0.01	0.00	0.00	0.26	0.00	0.00	0.00	0.00
Hedge funds	1,352	t-statistic	−3.38	−2.71	−2.30	−1.62	1.91	2.48	2.82	3.69
		p-value	0.03	0.00	0.00	0.29	0.00	0.00	0.00	0.00
Fund of funds	963	t-statistic	−3.49	−2.59	−2.21	−1.61	1.76	2.27	2.64	3.11
		p-value	0.03	0.10	0.11	0.41	0.01	0.02	0.02	0.36
Panel B: Bootstrap results for funds with AUM < \$150 million										
All funds	3,984	t-statistic	−3.51	−2.70	−2.26	−1.65	1.86	2.36	2.69	3.46
		p-value	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00
Hedge funds	2,300	t-statistic	−3.51	−2.75	−2.33	−1.69	1.94	2.48	2.79	3.49
		p-value	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
Fund of funds	1,684	t-statistic	−3.53	−2.57	−2.18	−1.61	1.66	2.22	2.56	3.18
		p-value	0.01	0.05	0.09	0.33	0.06	0.02	0.02	0.15
Panel C: Bootstrap results for funds that have lower than median R^2 in a regression against returns of the portfolio of top 10% large funds										
All funds	2,649	t-statistic	−3.47	−2.63	−2.22	−1.55	2.08	2.55	2.88	3.69
		p-value	0.00	0.00	0.00	0.69	0.00	0.00	0.00	0.00
Hedge funds	2,151	t-statistic	−3.51	−2.63	−2.22	−1.53	2.07	2.57	2.93	3.74
		p-value	0.00	0.00	0.01	0.84	0.00	0.00	0.00	0.00
Fund of funds	498	t-statistic	−3.11	−2.71	−2.22	−1.76	2.12	2.44	2.81	3.35
		p-value	0.49	0.02	0.10	0.04	0.00	0.00	0.00	0.05

bias for our sample is similar to that shown in Fung and Hsieh (2000).

Table 9 presents the results of liquidity timing after we control for backfill bias. Overall, the bootstrap analysis delivers evidence consistent with the findings reported in Section 4. For hedge funds, the $t_{\hat{\gamma}}$'s for the top 1%, 3%, 5% and 10% liquidity-timing funds are respectively 4.09, 2.82, 2.43 and 1.91 and their empirical p-values are close to zero. Note that though discarding the backfill period mitigates the impact of backfill bias, it tilts the sample towards funds with longer history. Because we require each fund to have at least 36 monthly returns after their backfill periods are discarded, most of the funds that remain in the reduced sample have a track record longer than five years. As a result, younger funds are excluded from the analysis, which could bias against finding timing skills if young funds tend to have better performance.

Another data bias is the selection bias, because reporting to a database is voluntary in the hedge fund industry. It is difficult to examine this bias because we do not observe funds that choose not to report to any database. Fung and Hsieh (1997, 2009) find anecdotal evidence indicating that the selection bias could be limited, as some funds with superior performance deliberately do not disclose their information to data vendors. Recently, Agarwal, Fos, and Jiang (forthcoming) use the mandatory 13F filing data to study hedge fund selection bias and find no performance difference between self-reporting funds and nonreporting funds. One benefit for hedge funds to report to data vendors is to attract potential investors because hedge funds are not allowed to publicly advertise in the US. The upward bias from self-reporting superior performance is offset by the downward bias from hiding inferior performance because some star hedge funds do not need to report to any data vendor for more investors and poorly performed funds have no incentive to report either. In addition, Fung and Hsieh (2000) suggest that data of funds of funds contain less return biases compared with hedge funds. For example, returns on funds of funds are audited to match the performance of underlying hedge funds, irrespective of whether an underlying fund is liquidated or stops reporting to the TASS database. Further, when a new hedge fund is added to the portfolio of a fund of funds, the tracking record of the fund of funds does not change. Fung and Hsieh (2000) conclude that using returns of funds of funds can help avoid biases in hedge fund data. In this study, we find evidence of liquidity timing for both hedge funds and funds of funds.

In summary, we evaluate the impact of biases in hedge fund data, such as survivorship bias and backfill bias, on the inference about the liquidity timing ability. Overall, our

Table 9
Evidence of liquidity timing with controls for backfill bias.

This table presents the results of liquidity timing with controls for backfill bias. To control for backfill bias, we exclude, for each fund, return observations before the date when the fund was added to Lipper TASS. For each fund with at least 36 monthly return observations (after returns in the backfill period are deleted), we estimate the liquidity-timing model

$$r_{p,t+1} = \alpha_p + \beta_{p,1}MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \beta_{p,2}SMB_{t+1} + \beta_{p,3}YLDCHG_{t+1} + \beta_{p,4}BAAMTSY_{t+1} + \beta_{p,5}PTFSBD_{t+1} + \beta_{p,6}PTFSFX_{t+1} + \beta_{p,7}PTFSCOM_{t+1} + \varepsilon_{p,t+1},$$

where $r_{p,t+1}$ is the excess return on each individual fund in month t+1. The independent variables are the market excess return (MKT), a size factor (SMB), monthly change in the ten-yearTreasury constant maturity yield (YLDCHG), monthly change in the Moody's Baa yield less ten-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). $L_{m,t+1}$ is the market liquidity measure in month t+1, and $\overline{L}_m$ is the mean level of market liquidity. The coefficient γ measures liquidity-timing ability. In the table, the first row reports the sorted t-statistics of liquidity-timing coefficients across individual funds, and the second row is the empirical p-values from bootstrap simulations. In the bootstrap test, the number of resampling iterations is 10,000.

			Bottom t-statistics for $\hat{\gamma}$				Top t-statistics for $\hat{\gamma}$			
Category	Number of funds		1%	3%	5%	10%	10%	5%	3%	1%
All funds	2,688	t-statistic	−3.46	−2.54	−2.16	−1.64	1.83	2.30	2.72	3.67
		p-value	0.01	0.08	0.22	0.21	0.00	0.00	0.00	0.00
Hedge funds	1,815	t-statistic	−3.57	−2.64	−2.24	−1.70	1.91	2.43	2.82	4.09
		p-value	0.00	0.01	0.02	0.05	0.00	0.00	0.00	0.00
Fund of funds	873	t-statistic	−2.75	−2.24	−2.00	−1.53	1.69	2.24	2.50	3.09
		p-value	0.98	0.95	0.85	0.86	0.07	0.09	0.05	0.47
Convertible arbitrage	107	t-statistic	−4.04	−3.58	−3.46	−2.62	1.17	1.93	1.99	2.13
		p-value	0.02	0.00	0.00	0.00	0.98	0.82	0.89	0.97
Emerging market	177	t-statistic	−4.12	−3.23	−2.39	−1.94	1.77	2.08	2.13	4.28
		p-value	0.03	0.00	0.09	0.02	0.15	0.52	0.83	0.01
Equity market neutral	155	t-statistic	−4.23	−3.46	−2.71	−2.07	1.80	2.18	2.68	4.44
		p-value	0.04	0.01	0.02	0.01	0.09	0.07	0.02	0.00
Event-driven	277	t-statistic	−3.31	−2.43	−2.09	−1.44	2.08	2.43	2.65	3.60
		p-value	0.31	0.44	0.53	0.90	0.00	0.04	0.05	0.10
Global macro	100	t-statistic	−4.54	−2.30	−2.03	−1.64	1.84	2.64	2.73	4.09
		p-value	0.11	0.73	0.66	0.52	0.18	0.07	0.27	0.15
Long-short equity	897	t-statistic	−3.19	−2.43	−2.06	−1.45	2.08	2.67	3.10	4.38
		p-value	0.48	0.59	0.72	0.99	0.00	0.00	0.00	0.00
Multi-strategy	102	t-statistic	−2.65	−2.59	−2.38	−1.83	1.93	2.42	2.33	3.63
		p-value	0.58	0.18	0.19	0.17	0.00	0.01	0.08	0.05

results about liquidity timing are not driven by these data biases.

7. Alternative bootstrap procedures, timing model specifications, risk factors, and liquidity measures

In this section, we present several robustness checks for our empirical findings, using bootstrap procedures accounting for time series and cross-correlations correlations in regression residuals; alternative timing-model specifications, including a liquidity-timing model that controls for market and volatility timing and another liquidity timing model that controls for systematic stale pricing; alternative factors in the benchmark model; and an alternative measure of market-wide liquidity.

7.1. Bootstrap analysis accounting for time series and cross-sectional correlations in residuals

The bootstrap procedure described in Section 4.2 assumes that the residuals from the liquidity-timing regressions are independently and identically distributed for the funds. Here, we consider the cases in which the residuals can have serial dependence over time or cross-sectional correlation across funds, and we evaluate their effect on the bootstrap results for liquidity-timing skill.

First, we employ a parametric approach, the sieve bootstrap (e.g., Bühlmann, 1997), to control for potential serial correlations in residuals in the bootstrap analysis. Suppose that residuals follow an unknown stationary process. In the sieve bootstrap, we approximate this process using a p-order autoregressive process, i.e., AR (p), with the order p chosen by the Akaike information criterion (AIC) for each fund. The coefficients of the autoregression are estimated for each fund. Then, instead of resampling residuals directly, we first resample the error terms from the autoregression and then generate bootstrap residuals by plugging the resampled error terms back into the AR model. Panel A of Table 10 reports the results from the sieve bootstrap, which suggests the existence of liquidity timing skill among the sample funds.

Second, we use a nonparametric block bootstrap approach (e.g., Hall, Horowitz, and Jing, 1995), to control for potential serial dependence in residuals. Specifically, we resample residual blocks that can be overlapping to preserve serial correlation in the bootstrap analysis. Hall, Horowitz, and Jing (1995) show that the optimal block size is $n^{1/4}$ for estimating a one-sided distribution function, where n is the length of the fund return time series. We follow their procedure to perform a block bootstrap analysis, and the results suggest that top-ranked timers cannot be attributed to pure randomness. For robustness,

Table 10
Bootstrap analysis with controls for time series and cross-sectional correlations in regression residuals.

This table presents the bootstrap results with controls for time series and cross-sectional correlations in regression residuals. For each fund with at least 36 monthly return observations, we estimate the liquidity-timing model

$$r_{p,t+1} = \alpha_p + \beta_{p,1}MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \beta_{p,2}SMB_{t+1} + \beta_{p,3}YLDCHG_{t+1} + \beta_{p,4}BAAMTSY_{t+1} + \beta_{p,5}PTFSBD_{t+1} + \beta_{p,6}PTFSFX_{t+1} + \beta_{p,7}PTFSCOM_{t+1} + \varepsilon_{p,t+1},$$

where $r_{p,t+1}$ is the excess return on each individual fund in month t+1. The independent variables include the market excess return (MKT), a size factor (SMB), monthly change in the ten-year Treasury constant maturity yield (YLDCHG), monthly change in the Moody's Baa yield less ten-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). $L_{m,t+1}$ is the market liquidity measure in month t+1, and $\overline{L}_m$ is the mean level of market liquidity. The coefficient γ measures liquidity-timing ability. In Panel A, we control for time series correlation in residuals by imposing an AR(p) process on the regression residuals of each fund, with the order p chosen by the Akaike information criterion (AIC). Instead of resampling the residuals, we first resample the error terms from the AR process and then generate bootstrap residuals using the AR process. In Panel B, we control for cross-sectional correlation in residuals by resampling fund returns in the same month all together. In the table, the first row reports the sorted *t-value* of liquidity-timing coefficients across individual funds, and the second row is the empirical p-values from bootstrap simulations. The number of resampling iterations is 10,000.

			Bottom t-statistics for $\hat{\gamma}$				Top t-statistics for $\hat{\gamma}$			
Category	Number of funds		1%	3%	5%	10%	10%	5%	3%	1%
Panel A: Bootstrap results with controls for time-series correlation in residuals										
All funds	5,298	t-statistic	−3.47	−2.60	−2.20	−1.60	1.89	2.39	2.72	3.45
		p-value	0.00	0.00	0.00	0.27	0.00	0.00	0.00	0.00
Hedge funds	3,078	t-statistic	−3.50	−2.71	−2.30	−1.65	1.99	2.51	2.86	3.69
		p-value	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00
Fund of funds	2,220	t-statistic	−3.24	−2.49	−2.07	−1.56	1.70	2.25	2.52	3.11
		p-value	0.11	0.16	0.57	0.72	0.01	0.00	0.05	0.25
Convertible arbitrage	142	t-statistic	−4.27	−3.50	−3.17	−2.16	1.63	1.84	2.03	2.13
		p-value	0.01	0.00	0.00	0.00	0.42	0.85	0.85	0.99
Emerging market	340	t-statistic	−3.47	−2.95	−2.68	−2.15	1.80	2.23	2.48	2.68
		p-value	0.09	0.00	0.00	0.00	0.05	0.18	0.30	0.89
Equity market neutral	239	t-statistic	−4.27	−3.38	−2.74	−1.65	1.88	2.28	2.68	3.31
		p-value	0.01	0.00	0.00	0.37	0.03	0.07	0.09	0.22
Event-driven	408	t-statistic	−3.42	−2.71	−2.13	−1.38	2.18	2.73	3.00	3.92
		p-value	0.04	0.02	0.28	0.96	0.00	0.00	0.00	0.00
Global macro	177	t-statistic	−3.05	−2.41	−1.78	−1.35	1.81	2.17	2.54	3.26
		p-value	0.55	0.44	0.93	0.93	0.10	0.35	0.25	0.37
Long-short equity	1465	t-statistic	−3.32	−2.56	−2.10	−1.44	2.11	2.62	3.08	3.89
		p-value	0.05	0.04	0.32	0.99	0.00	0.00	0.00	0.00
Multi-strategy	307	t-statistic	−3.04	−2.43	−2.25	−1.71	1.94	2.51	2.76	3.00
		p-value	0.43	0.41	0.21	0.18	0.00	0.01	0.04	0.46
Panel B: Bootstrap results with controls for cross-sectional correlation in residuals										
All funds	5,298	t-statistic	−3.47	−2.60	−2.20	−1.60	1.89	2.39	2.72	3.45
		p-value	0.02	0.03	0.03	0.03	0.01	0.02	0.03	0.03
Hedge funds	3,078	t-statistic	−3.50	−2.71	−2.30	−1.65	1.99	2.51	2.86	3.69
		p-value	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fund of funds	2,220	t-statistic	−3.24	−2.49	−2.07	−1.56	1.70	2.25	2.52	3.11
		p-value	0.06	0.08	0.09	0.09	0.07	0.07	0.08	0.09
Convertible arbitrage	142	t-statistic	−4.27	−3.50	−3.17	−2.16	1.63	1.84	2.03	2.13
		p-value	0.01	0.00	0.00	0.01	0.11	0.24	0.26	0.55
Emerging market	340	t-statistic	−3.47	−2.95	−2.68	−2.15	1.80	2.23	2.48	2.68
		p-value	0.03	0.01	0.00	0.00	0.01	0.03	0.04	0.20
Equity market neutral	239	t-statistic	−4.27	−3.38	−2.74	−1.65	1.88	2.28	2.68	3.31
		p-value	0.00	0.00	0.00	0.01	0.00	0.02	0.02	0.04
Event-driven	408	t-statistic	−3.42	−2.71	−2.13	−1.38	2.18	2.73	3.00	3.92
		p-value	0.03	0.02	0.06	0.13	0.00	0.00	0.01	0.01
Global macro	177	t-statistic	−3.05	−2.41	−1.78	−1.35	1.81	2.17	2.54	3.26
		p-value	0.12	0.03	0.09	0.03	0.00	0.01	0.02	0.07
Long-short equity	1,465	t-statistic	−3.32	−2.56	−2.10	−1.44	2.11	2.62	3.08	3.89
		p-value	0.02	0.01	0.02	0.03	0.00	0.00	0.00	0.00
Multi-strategy	307	t-statistic	−3.04	−2.43	−2.25	−1.71	1.94	2.51	2.76	3.00
		p-value	0.06	0.04	0.02	0.01	0.00	0.01	0.02	0.07

we also experiment with block size of $n^{1/3}$ and $n^{1/5}$, and the inference about liquidity timing is unchanged. The details of the results are not tabulated to conserve space.

Finally, to address possible cross-sectional correlation in the residuals, we follow Kosowski, Timmermann, White, and Wermers (2006) to resample residuals of the same month together for all funds. This way, we preserve cross-sectional correlation in the residuals. However, this procedure has a drawback. As not all funds have observations over the entire sample period, it is likely that some funds

Table 11

Controlling for market return timing and volatility timing.

This table presents the bootstrap results of liquidity timing with controls for market return timing and volatility timing. For each fund with at least 36 monthly return observations, we estimate the liquidity-timing model:

$$r_{p,t+1} = \alpha_p + \beta_{p,1} MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \lambda_p MKT_{t+1}^2 + \delta_p MKT_{t+1}(Vol_{t+1} - \overline{Vol}) + \beta_{p,2} SMB_{t+1} + \beta_{p,3} YLDCHG_{t+1}$$
$$+ \beta_{p,4} BAAMTSY_{t+1} + \beta_{p,5} PTFSBD_{t+1} + \beta_{p,6} PTFSFX_{t+1} + \beta_{p,7} PTFSCOM_{t+1} + \varepsilon_{p,t+1},$$

where $r_{p,t+1}$ is the excess return on each individual fund in month t+1. The independent variables are the market excess return (MKT), a size factor (SMB), monthly change in the ten-year Treasury constant maturity yield (YLDCHG), monthly change in the Moody's Baa yield less ten-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). $L_{m,t+1}$ is the market liquidity measure in month t+1, and $\overline{L}_m$ is the mean level of market liquidity. *Vol* is the market volatility measured by the Chicago Board Options Exchange Market Volatility Index (VIX). The coefficients γ, λ, and δ measure liquiditytiming, market timing, and volatility timing, respectively. Panel A reports the evidence on liquidity timing. For comparison, Panel B reports the evidence on market timing. In the table, the first row reports the sorted t-value of liquidity-timing coefficients across individual funds, and the second row is the empirical p-values from bootstrap simulations. The number of resampling iterations is 10,000.

Panel A: Evidence on liquidity timing

			Bottom t-statistics for $\hat{\gamma}$				Top t-statistics for $\hat{\gamma}$			
Category	Number of funds		1%	3%	5%	10%	10%	5%	3%	1%
All funds	5,298	t-statistic	−3.26	−2.42	−2.11	−1.41	2.04	2.50	2.81	3.65
		p-value	0.13	0.78	0.69	1.00	0.00	0.00	0.00	0.00
Hedge funds	3,078	t-statistic	−3.53	−2.59	−2.23	−1.61	2.00	2.54	2.93	3.77
		p-value	0.00	0.02	0.02	0.59	0.00	0.00	0.00	0.00
Fund of funds	2,220	t-statistic	−2.76	−2.21	−1.81	−1.14	2.07	2.42	2.67	3.26
		p-value	1.00	1.00	1.00	1.00	0.00	0.00	0.02	0.27
Convertible arbitrage	142	t-statistic	−7.13	−3.28	−3.11	−2.60	1.26	1.50	1.83	2.19
		p-value	0.00	0.00	0.00	0.00	0.98	0.99	0.98	0.99
Emerging market	340	t-statistic	−3.37	−2.67	−2.43	−1.96	1.78	2.12	2.49	3.27
		p-value	0.22	0.10	0.03	0.00	0.13	0.55	0.39	0.32
Equity market neutral	239	t-statistic	−4.31	−3.46	−2.66	−1.98	2.07	2.54	2.82	3.32
		p-value	0.01	0.00	0.01	0.02	0.00	0.03	0.06	0.30
Event-driven	408	t-statistic	−2.79	−2.15	−1.86	−0.93	2.52	2.98	3.25	3.84
		p-value	0.80	0.92	0.96	1.00	0.00	0.00	0.00	0.01
Global macro	177	t-statistic	−2.95	−2.32	−2.23	−1.38	1.76	2.00	2.21	2.81
		p-value	0.71	0.64	0.34	0.95	0.21	0.73	0.82	0.80
Long-short equity	1,465	t-statistic	−3.50	−2.51	−2.14	−1.51	2.07	2.54	3.00	4.34
		p-value	0.02	0.31	0.43	0.96	0.00	0.00	0.00	0.00
Multi-strategy	307	t-statistic	−2.73	−2.24	−2.05	−1.69	1.91	2.55	2.93	3.59
		p-value	0.88	0.84	0.75	0.35	0.03	0.02	0.02	0.08

Panel B: Evidence on marketreturn timing

			Bottom t-statistics for $\hat{\lambda}$				Top t-statistics for$\hat{\lambda}$			
Category	Number of funds		1%	3%	5%	10%	10%	5%	3%	1%
All funds	5,298	t-statistic	−4.96	−3.96	−3.45	−2.79	1.30	1.96	2.44	3.50
		p-value	0.00	0.00	0.00	0.00	1.00	1.00	0.83	0.00
Hedge funds	3,078	t-statistic	−4.64	−3.45	−3.08	−2.44	1.69	2.33	2.75	3.93
		p-value	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00
Fund of funds	2,220	t-statistic	−5.16	−4.23	−3.84	−3.15	0.48	0.91	1.30	2.16
		p-value	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Convertible arbitrage	142	t-statistic	−4.28	−1.85	−1.72	−1.34	2.67	3.63	3.75	4.11

Table 11 (*continued*)

Panel B: Evidence on marketreturn timing

Category	Number of funds		Bottom t-statistics for $\hat{\lambda}$				Top t-statistics for$\hat{\lambda}$			
			1%	3%	5%	10%	10%	5%	3%	1%
		p-value	0.01	0.94	0.92	0.91	0.12	0.00	0.00	0.02
Emerging market	340	t-statistic	−5.00	−4.07	−3.63	−2.71	1.49	2.17	2.52	3.17
		p-value	0.00	0.00	0.00	0.00	0.91	0.49	0.39	0.52
Equity market neutral	239	t-statistic	−4.53	−3.36	−3.12	−2.74	1.53	2.17	2.50	3.08
		p-value	0.00	0.00	0.00	0.00	0.74	0.41	0.33	0.50
Event-driven	408	t-statistic	−5.71	−4.35	−3.67	−3.12	0.92	1.34	1.74	2.47
		p-value	0.00	0.00	0.00	0.00	1.00	1.00	1.00	0.99
Global macro	177	t-statistic	−3.22	−2.44	−2.17	−1.72	2.10	2.74	2.83	3.49
		p-value	0.51	0.51	0.47	0.33	0.00	0.01	0.10	0.31
Long-short equity	1,465	t-statistic	−4.28	−3.17	−2.74	−2.21	1.67	2.23	2.76	3.90
		p-value	0.00	0.00	0.00	0.00	0.12	0.04	0.00	0.00
Multi-strategy	307	t-statistic	−4.92	−3.81	−3.39	−2.43	1.80	2.56	2.90	4.76
		p-value	0.00	0.00	0.00	0.00	0.18	0.03	0.04	0.00

have resampled residuals from months when they do not have a return observation (e.g., before they started operating or after they became defunct) and, thus, the resampled residuals for these months are set as missing values. To run meaningful regressions, we require each fund to have at least 36 non-missing resampled observations and, accordingly, the number of bootstrap funds in each simulation is smaller than the number of actual funds. As reported in Panel B of Table 10, the results from this procedure still suggest existence of liquidity-timing skill.

7.2. Controlling for market and volatility timing

Our liquidity-timing model (5) focuses on the adjustment of fund beta in response to market liquidity. However, fund managers could time market returns and volatility as well. Because market liquidity is positively correlated with market returns and negatively correlated with market volatility, the evidence on liquidity timing could partially reflect fund managers' market- or volatility-timing ability. To address this concern, we explicitly control for market timing and volatility timing in our liquidity-timing model in the specification

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \lambda_p MKT_{t+1}^2 + \delta_p MKT_{t+1}(Vol_{t+1} - \overline{Vol}) + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}, \quad (10)$$

where Vol_{t+1} is the market volatility in month t+1 as measured by the CBOE S&P 500 index option implied volatility (i.e., the VIX) and $\overline{Vol}$ is the time series mean of market volatility. The correlation between market returns and the Pástor-Stambaugh liquidity measure is 0.23 over the sample period 1994–2009, and the correlation between the VIX and the liquidity measure is −0.33 over the same period. The coefficients γ, λ, and δ measure liquidity-timing, market-timing, and volatility-timing ability, respectively.

In Panel A of Table 11, we present empirical p-values associated with t-statistics of liquidity-timing coefficients at different tail percentiles from the bootstrap analysis. With controls for market and volatility timing, we still observe significant evidence of liquidity-timing skill. For the overall sample, $t_{\hat{\gamma}}$s for the top 1%, 3%, 5%, and 10% liquidity-timing funds are 3.65, 2.81, 2.50, and 2.04, respectively, and their empirical p-values are all close to zero. This result holds for hedge funds and funds of funds as well. Among seven strategy categories, most top-ranked funds in the categories of equity market neutral, event-driven, long-short equity and multi-strategies have empirical p-values less than 5%. Interestingly, after we control for market and volatility timing, the evidence of negative liquidity timing becomes much weaker.

For comparison, Panel B of Table 10 provides bootstrap results for t-statistics of market-timing coefficients. For individual hedge funds, strong evidence exists of positive market-timing ability as well as negative timing. The cutoff t-statistics at extreme percentiles and the associated empirical p-values are similar to those for liquidity timing. No evidence exists of successful market timing for funds of funds. Funds of funds are essentially indices of hedge funds and, thus, represent a mixture of real timers and other funds, which could explain why the results for funds of funds differ from those for individual hedge funds.[17]

7.3. Controlling for systematic stale pricing

Getmansky, Lo, and Makarov (2004) show that hedge fund returns often exhibit significant serial correlation. One reason for this result is that hedge funds hold relatively illiquid assets that do not trade frequently. This thin or nonsynchronous trading can bias estimates of fund beta (e.g., Scholes and Williams, 1977; and Dimson, 1979). Chen, Ferson, and Peters (2010) show that if the extent of stale pricing is related to the market factor (a case they call systematic stale pricing), then the inference about timing ability can also be biased. They address this problem when measuring timing ability for bond mutual funds, and they find that controlling for this bias is important. In the same spirit of Chen, Ferson, and Peters (2010), we reexamine liquidity-timing skill using a model including two lagged market excess returns and two interaction terms between lagged market returns and market liquidity measures:

$$\begin{aligned} r_{p,t+1} = {} & \alpha_p + \beta_{p,1} MKT_{t+1} + \beta_{p,2} MKT_t + \beta_{p,3} MKT_{t-1} \\ & + \gamma_{p,1} MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \gamma_{p,2} MKT_t (L_{m,t} - \overline{L}_m) \\ & + \gamma_{p,3} MKT_{t-1}(L_{m,t-1} - \overline{L}_m) + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}. \end{aligned} \tag{11}$$

The results show that MKT_t and MKT_{t-1} in general enter the regression significantly for most of the sample funds, indicating illiquid holdings in hedge fund portfolios. However, we still observe significant evidence of liquidity timing for the groups of all funds, hedge funds, funds of funds, equity market neutral, event driven, long-short equity, and multi-strategy funds. We omit the details of these results to conserve space, but they are available upon request.

7.4. Alternative factors

Fung and Hsieh (1997, 2001) find evidence that some hedge fund strategies can generate option-like returns. Jagannathan and Korajczyk (1986) show that if funds invest in options and stocks with option-like payoffs, artificial market-timing evidence can arise for these funds that have no real timing skill. Similarly, spurious liquidity timing could exist if hedge funds hold some assets (including options) whose market exposure varies with market liquidity conditions. Although it is a priori unclear what types of assets have such dynamic market exposure, we conduct a few experiments to address this concern about model misspecification.

We consider an alternative factor model that includes the market factor, a size factor, a value factor, a momentum factor, and two of the Agarwal and Naik (2004) option factors constructed from out-of-the-money options on the S&P 500 index.[18] That is, we use these alternative factors in regression Eq. (5) to reexamine liquidity-timing skill. After including option factors in the benchmark model, we find that the bootstrap results are consistent with the evidence presented in Section 4. For the samples of all funds, hedge funds, and funds of funds, top-ranked t-statistics of the timing coefficients have empirical p-values below the conventional significance level.[19] Collectively, the findings do not suggest that our liquidity-timing model is misspecified.

7.5. Alternative liquidity measures

Liquidity is a complex and multi-faceted concept that can be measured in different ways. The Pástor-Stambaugh measure focuses on market-wide liquidity related to temporary price impact. Because it captures well-known episodes of low market liquidity, the measure is particularly appealing to our study of liquidity-timing ability. As an alternative measure, the Amihud (2002) illiquidity measure is based on the ratio of absolute return to trading volume and captures the average price impact of $1 million trade in 1962 stock market dollars distributed equally across stocks. We repeat our fund-level analyses of liquidity-timing skill using the Amihud measure of market illiquidity. For convenience, we multiply the Amihud illiquidity measure by −1 so that the timing coefficient based on this measure has the same interpretation as that from the Pástor-Stambaugh liquidity measure.

As shown in Table 12, the bootstrap results based on the Amihud measure are consistent with those based on the Pástor-Stambaugh measure in Table 3. Take the sample of all funds as an example. The $t_{\hat{\gamma}}$s for the top 1%, 3%, 5%, and 10% liquidity-timing funds are 4.98, 3.64, 3.00, and 2.29, respectively, and their empirical p-values are close to zero. The bootstrap analysis suggests that the evidence for top-ranked liquidity-timing funds cannot be attributed to pure luck for the samples of all funds, hedge funds, and funds of funds or funds in equity market neutral, event-driven, global macro, long-short equity, and multi-strategy categories. Overall, we find consistent results when using the Amihud measure.

We recognize that there are other proxies for liquidity. The Pástor-Stambaugh and Amihud measures, designed to capture the price-impact dimension of liquidity, are estimated using daily stock returns and volumes. The estimation of other measures such as effective bid-ask spread often requires intraday trade-and-quote data and is computationally intensive. For example, Goyenko, Holden, and Trzcinka (2009) compute spread-based and price impact—based liquidity measures using intraday data of only 400 stocks due to computational limit. In this paper, we do not

[17] See, e.g., Chen (2007) and Chen and Liang (2007) for additional discussion about market-timing ability in hedge funds. In the paper, we also examine liquidity-timing ability using a conditional timing model. Following Ferson and Schadt (1996), we proxy for public information by one-month lagged values of the three-month T-bill rate, the term premium between the ten-year and three-month Treasury yields, the credit premium between Moody's BAA- and AAA-rated corporate bonds yields, and the dividend yield of the S&P 500 index. With the conditional timing model, the inference about liquidity-timing skill is unchanged.

[18] We thank Vikas Agarwal for providing us with the data for the option-return factors.

[19] To further check the robustness of our results to the choice of benchmark models, we augment the liquidity-timing model Eq. (5) with a liquidity risk factor proxied by monthly innovations in the Pástor-Stambaugh liquidity measure from an AR(2) process. The results are consistent with those reported in Table 3.

Table 12
Liquidity timing using the Amihud liquidity measure.

This table presents the results of the bootstrap analysis of liquidity timing using the Amihud (2002) market liquidity measure. For each fund with at least 36 monthly return observations, we estimate the liquidity-timing model

$$r_{p,t+1} = \alpha_p + \beta_{p,1} MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \beta_{p,2} SMB_{t+1} + \beta_{p,3} YLDCHG_{t+1} + \beta_{p,4} BAAMTSY_{t+1} \\ + \beta_{p,5} PTFSBD_{t+1} + \beta_{p,6} PTFSFX_{t+1} + \beta_{p,7} PTFSCOM_{t+1} + \varepsilon_{p,t+1},$$

where $r_{p,t+1}$ is the excess return on each individual fund in month t+1. The independent variables are the market excess return (MKT), a size factor (SMB), monthly change in the ten-year Treasury constant maturity yield (YLDCHG), monthly change in the Moody's Baa yield less ten-year Treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). $L_{m,t+1}$ is the Amihud market liquidity measure (multiplied by −1) in month t+1, and $\overline{L}_m$ is the mean level of market liquidity. We multiply the Amihud illiquidity measure by −1 so that the liquidity-timing coefficient has the same interpretation as that based on the Pástor-Stambaugh liquidity measure. The coefficient γ measures liquidity-timing ability. In the table, the first row reports the sorted *t-value* of liquidity-timing coefficients across individual funds, and the second row is the empirical *p*-values from bootstrap simulations. The number of resampling iterations is 10,000.

			Bottom t-statistics for $\hat{\gamma}$				Top t-statistics for $\hat{\gamma}$			
Category	Number of funds		1%	3%	5%	10%	10%	5%	3%	1%
All funds	5,298	*t*-statistic	−3.84	−3.12	−2.68	−2.01	2.29	3.00	3.64	4.98
		p-value	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hedge funds	3,078	*t*-statistic	−4.02	−3.40	−2.86	−2.23	2.07	2.75	3.29	4.79
		p-value	0.11	0.00	0.02	0.62	0.00	0.00	0.00	0.00
Fund of funds	2,220	*t*-statistic	−3.44	−2.75	−2.24	−1.63	2.60	3.31	3.92	5.09
		p-value	0.08	0.00	0.11	0.13	0.00	0.00	0.00	0.01
Convertible arbitrage	142	*t*-statistic	−4.74	−4.42	−3.96	−2.13	1.41	1.96	2.14	3.15
		p-value	0.00	0.01	0.00	0.11	0.49	0.33	0.37	0.18
Emerging market	340	*t*-statistic	−4.93	−4.01	−3.71	−2.60	1.52	2.19	2.51	3.63
		p-value	0.03	0.01	0.01	0.04	0.51	0.23	0.41	0.27
Equity market neutral	239	*t*-statistic	−3.62	−3.24	−2.70	−1.96	2.19	2.79	3.31	4.02
		p-value	0.18	0.01	0.01	0.02	0.00	0.00	0.00	0.05
Event-driven	408	*t*-statistic	−3.52	−2.35	−1.92	−1.47	2.60	3.27	3.80	4.21
		p-value	0.06	0.46	0.82	0.79	0.00	0.00	0.00	0.00
Global macro	177	*t*-statistic	−4.09	−2.93	−2.72	−1.57	2.87	3.55	3.82	4.85
		p-value	0.13	0.22	0.05	0.82	0.02	0.04	0.09	0.11
Long-short equity	1,465	*t*-statistic	−3.08	−2.38	−1.92	−1.37	2.71	3.31	3.85	4.90
		p-value	0.47	0.55	0.97	0.99	0.00	0.00	0.00	0.00
Multi-strategy	307	*t*-statistic	−3.91	−2.75	−2.61	−1.81	2.38	3.05	3.82	4.43
		p-value	0.06	0.09	0.01	0.08	0.00	0.00	0.00	0.00

use liquidity measures constructed from intraday data to study liquidity timing, and we leave this subject for future research.

8. Conclusions

In this paper, we explore a new dimension of fund managers' timing ability—their ability to time market liquidity—and examine whether hedge fund managers possess liquidity timing ability by adjusting their portfolios' market exposure as aggregate market liquidity conditions change. We focus on hedge funds because they are among the most dynamic investment vehicles and their performance is strongly affected by market liquidity conditions. Using a large sample of 5,298 equity-oriented hedge funds (including funds of funds) from 1994 to 2009, we evaluate liquidity-timing ability at the individual fund level and find strong evidence of liquidity timing among the funds.

In particular, hedge fund managers increase (decrease) their market exposure when equity market liquidity is high (low), and this effect is both economically and statistically significant. Our bootstrap analysis suggests that top-ranked liquidity timers cannot be attributed to sampling variation. In addition, liquidity-timing skill persists over time and adds value to fund investors. In particular, top liquidity-timing funds subsequently outperform bottom liquidity-timing funds by 4.0%–5.5% per year on a risk-adjusted basis. This result suggests that liquidity timing represents managerial skill and can be one important source of hedge fund alphas. We also distinguish liquidity-timing skills from liquidity reaction that primarily relies on public information, and we show that the latter does not generate investment value.

Finally, we conduct a wide array of sensitivity tests and show that our inference about liquidity timing holds in all these tests. Our findings are robust to alternative explanations related to funding liquidity and investor redemptions, alternative timing model specifications, risk factors, and liquidity measures. Our results are also robust to hedge fund data biases, such as survivorship bias and backfill bias. To conclude, our examination of fund managers' liquidity-timing ability highlights the importance of understanding and incorporating market liquidity conditions in asset management and investment decision making.[20]

[20] Recently, Cao, Simin, and Wang (2013) study the liquidity-timing ability of mutual fund managers.

Appendix A. The Pástor-Stambaugh (2003) and Amihud (2002) liquidity measures

The Pástor-Stambaugh (2003) liquidity measure captures market liquidity associated with temporary price fluctuations induced by order flows, which can be interpreted as volume-related price reversals attributable to liquidity effects.

For each stock i listed on the NYSE and Amex in each month t, its liquidity $\eta_{i,t}$ is measured by the regression

$$r_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + \eta_{i,t}\text{sign}(r_{i,d,t}) * v_{i,d,t} + \varepsilon_{i,d+1,t}, \quad d = 1, \ldots, \text{D}, \tag{12}$$

where $r_{i,d,t}$ is the excess return of stock i (in excess of the market return) on day d in month t, $v_{i,d,t}$ is the dollar volume (in millions of dollars) for stock i on day d in month t, and D_t is the number of trading days in month t. The coefficient $\eta_{i,t}$ measures the expected return reversal for a given dollar volume, controlling for lagged excess stock returns. For a less liquid stock, $\eta_{i,t}$ is expected to be negative and large in magnitude.

Two filters are imposed when computing the liquidity measure in each month: A stock has at least 15 observations in any given month; and a stock has a share price between \$5 and \$1,000 at the end of the previous month. The market liquidity measure in month t is then calculated as the average liquidity measure across individual stocks $\overline{\eta}_t = \sum_{i=1}^{N_t} \eta_{i,t}/N_t$, where N_t is the number of stocks available in that month. Because the size of the equity market increases over time, the liquidity measure is scaled by market size at the beginning of the Center for Research in Security Prices daily sample, i.e., $L_{m,t} = (m_t/m_1) * \overline{\eta}_t$, where m_t is the total market value of all sample stocks at the end of month t–1 and month 1 refers to August 1962.

As $\eta_{i,t}$ measures the liquidity cost of trading \$1 million of stock i, the scaled market liquidity measure $L_{m,t}$ can be interpreted as the average liquidity cost at time t of trading \$1 million in 1962 stock market dollars distributed equally across all stocks. Pástor and Stambaugh (2003) find that the average (median) value of market liquidity during 1962–1999 is –0.03 (–0.02), suggesting the cost of such a trade is 2–3%. The scaled aggregate market liquidity measure, $L_{m,t}$, is used in our evaluation of liquidity-timing skill for hedge funds.

Amihud (2002) measures stock illiquidity as the average ratio of the daily absolute return to the dollar trading volume. This measure can be interpreted as the price impact per million dollars of daily trading volume, or the daily price impact of the order flow, and is expected to be positive. The illiquidity of stock i in month t, $ILLIQ_t^i$,is defined as

$$ILLIQ_t^i = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|R_{td}^i|}{v_{td}^i}, \tag{13}$$

where D_t is the number of trading days in month t, and R_{td}^i and v_{td}^i are the return and dollar volume (in millions) of stock i on day d in month t. We follow Acharya and Pedersen (2005) to construct a normalized Amihud measure of illiquidity, c_t^i,using the equation

$$c_t^i = \min(0.25 + 0.30(m_t/m_1) * ILLIQ_t^i, \ 30.00), \tag{14}$$

where m_t/m_1 is the scaling factor defined in the same way as in the Pástor and Stambaugh measure; 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 Amex:

$$c_t = \frac{1}{N_t} \sum_{i=1}^{N_t} c_t^i, \tag{15}$$

where N_t is the number of stocks in month t. We interpret the Amihud market illiquidity measure as the average price impact of \$1 million trade in 1962 stock market dollars distributed equally across stocks.

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