Can Hedge Funds Time Market Liquidity?

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Abstract

We explore a new dimension of hedge fund managers' timing ability—their ability to time market liquidity, and examine whether fund managers possess liquidity timing ability by adjusting their portfolios' market exposure as aggregate market liquidity conditions change. Using a large sample of equity-oriented hedge funds over 1994-2009, we find strong evidence of liquidity timing at both the strategy portfolio level and the individual fund level. Liquidity timing ability is most evident among primarily equity-oriented strategies and is concentrated in less liquid and more volatile market conditions. The uncovered liquidity timing skill persists over time and generates investment value in out-of-sample tests. Top liquidity timing funds outperform bottom liquidity timing funds by 3.6%–4.9% annually in post-ranking periods after adjusting for risk. Our results are robust to alternative explanations as well as to the use of alternative timing-model specifications, risk factors, and liquidity measures.

JEL Classification: G23, G11

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Can sophisticated investors forecast market conditions? The academic investigation of this question dates back at least to Cowles (1933). In their pioneering work, Treynor and Mazuy (1966) develop a framework to measure market timing by examining whether fund managers adjust their market exposure based on market return forecast. Ever since there have emerged numerous advances in identifying market timers, e.g., Henriksson and Merton (1981), Admati, Bhattacharya, Pfleiderer, and Ross (1986), Jagannathan and Korajczyk (1986), Ferson and Schadt (1996), Becker, Ferson, Myers, and Schill (1999), Busse (1999), Goetzmann, Ingersoll, and Ivkovich (2000), Bollen and Busse (2001), Chen and Liang (2007), Jiang, Yao, and Yu (2007), and Chen, Ferson, and Peters (2010). Among them, Ferson and Schadt (1996) and Busse (1999) generalize the exploration of timing ability beyond equity market returns by examining the relation between funds' market exposure and other dimensions of market conditions—conditioning information and market volatility, respectively.

In this paper, we explore a new dimension of hedge fund managers' timing ability—their ability to time market liquidity.[1] In particular, we ask the following questions: Can hedge funds, presumably sophisticated money managers, time market liquidity by strategically adjusting fund beta based on their forecast about market liquidity conditions? If they can, how much value does such 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) show that market liquidity, which captures the aggregate market-wide easiness to transact a large quantity of assets in a short time without incurring high costs, is a state variable important for asset prices. The recent 2007–2009 financial crisis further highlights the importance of market liquidity. When many investors exit the market at the same time, market liquidity deteriorates, which through various mechanisms (such as margin calls) causes more liquidation that further reduce market liquidity—so called "liquidity spirals" (e.g., Brunnermeier and Pedersen (2009)). Hence, foreseeing a deterioration of market-wide liquidity, a savvy manager would wish to reduce fund beta before liquidity dry-up actually 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

[1] In this paper, we refer to the aggregate equity market liquidity as "market liquidity."

decades. 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 over 9,000 funds managing more than $2 trillion by the end of 2010. Over that period, many skilled money managers joined the hedge fund industry. Thus, it is important to examine whether such sophisticated fund managers have the skills to time market conditions.[2] 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 liquidity, funding liquidity, and market liquidity) and traders like hedge funds has been better understood. Though other levels of liquidity (e.g., funding liquidity) perhaps are equally important, we focus on market-wide liquidity because timing strategy in essence is about aggregated market conditions. Third, hedge funds often employ dynamic strategies and thus their market exposure varies over time (see, e.g., Fung and Hsieh (2001), Mitchell and Pulvino (2001), Agarwal and Naik (2004), Chen and Liang (2007), and Patton and Ramadorai (2010)). Combining the observation of time-varying market exposure with the importance of market liquidity, hedge funds provide an ideal platform to examine liquidity timing ability. Finally, given the documented evidence of positive risk-adjusted performance of hedge funds (e.g., Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), Liang (1999), Kosowski, Naik, and Teo (2007) and Bali, Brown, and Caglayan (2011)), it is natural to ask what contributes to such performance and whether liquidity timing strategy 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. Specifically, we design a regression model to evaluate how fund beta set in month t changes with market liquidity realized in month $t+1$, while controlling for the fund's exposure 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 when market liquidity is good (poor). Our liquidity timing model is motivated by the previous tests for market timing and volatility timing that examine the relation of fund beta determined in month t with market return or volatility in month $t+1$, except that we focus on market liquidity conditions.

[2] We use "hedge funds" and "hedge fund managers" interchangeably in this paper.

Using a large sample of 6,702 equity-oriented hedge funds (including funds-of-funds) over the period of 1994–2009, we find striking evidence that hedge fund managers demonstrate liquidity timing skill, and that such skills persist over time and generate investment value. We focus on timing ability in equity markets because most hedge funds are equity-oriented and bear significant exposure to equity markets.[3]

At the strategy portfolio level, hedge funds exhibit high (low) market exposure during months of good (poor) market liquidity. The evidence on liquidity timing ability is statistically significant for the overall sample, hedge funds, funds-of-funds, as well as four primarily equity-oriented strategies, namely emerging market, event driven, long/short equity, and multi-strategy, out of the seven strategies considered. The timing skill appears economically significant as well. For the overall sample, a one standard-deviation fluctuation in market liquidity corresponds to a change in fund beta by 20%. Furthermore, liquidity timing ability is especially pronounced during poor market-liquidity conditions (e.g., liquidity crisis) and volatile market conditions. This result highlights the practical value of liquidity timing skill—a skilled manager can avoid or mitigate the impact of unfavorable market states.

Next, we evaluate liquidity timing ability for individual funds. For funds with at least 36 monthly observations, we estimate the timing skill using the fund's monthly returns and observe 21.3% of the sample funds having positive and significant timing coefficients at the 10% level, whereas the fraction of negative timing coefficients is fairly close to the corresponding significance level. To further separate timing skill from luck, we conduct a bootstrap analysis. Specifically, for each cross-sectional statistic of the timing coefficients (say the 10th percentile of the timing coefficient and its t-statistic), we compare its actual estimate with the corresponding distribution of estimates based on bootstrapped pseudo funds, which share similar risk exposure as actual funds but have no timing skill by design. The finding strongly suggests that our results on liquidity timing cannot be attributed to pure luck.

Finally, we address another important question: how much value does liquidity timing skill bring to fund investors? We explore the economic value of liquidity timing by examining the out-of-sample alphas (i.e., risk-adjusted returns) for the portfolios consisting of funds at different levels of

[3] For example, over 85% of hedge funds in TASS database are equity-oriented funds.

the associated liquidity timing skill. Specifically, in each month we sort individual funds into 10 portfolios based on their liquidity timing coefficients estimated from the previous 36 months. Then, we measure out-of-sample alphas of these portfolios against the Fung and Hsieh (2004) seven-factor model for different holding periods ranging from three to 12 months. The results suggest that liquidity timing skill generates significant investment value in out-of-sample tests. For example, for a 6-month holding period, the portfolio consisting of top liquidity timers delivers an out-of-sample alpha of 0.79%/month (9.5%/year), which doubles the alpha from the portfolio of bottom timers (0.40%/month). The spread in out-of-sample alphas between top and bottom liquidity timers remains significant even 12 months after forming the portfolios. Using an approach to the test of economic value, we examine whether the liquidity timing skill persists over time and find significant evidence of persistence. Taken together, these results suggest that liquidity timing represents managerial skill that adds value to fund investors.

There can be alternative explanations for our findings, given that hedge funds' market exposure may change for other reasons and that other aspects of liquidity (e.g., funding liquidity) also affect fund management. The latter part of our paper is devoted to a wide array of tests to gain further insights about liquidity timing among hedge funds. We show that our findings about liquidity timing are robust to all these tests.

First, we examine liquidity timing ability jointly with market return timing and volatility timing ability. Second, we are concerned about the possibility that during low market-liquidity conditions, some hedge funds face margin calls and investor redemptions, so they consequently must liquidate their positions, which may reduce the funds' market exposure (e.g., Lo (2008)). To address this concern, we examine liquidity timing ability among funds that do not use leverage, impose strict redemption restrictions, or have low fund-flow volatility. Third, considering that large hedge funds' simultaneous sales of assets can affect market liquidity (e.g., Khandani and Lo (2007)), we perform tests for a subsample of small funds whose trades are unlikely to affect overall market liquidity. Fourth, we conduct robustness tests using alternative timing-model specifications, risk factors and liquidity measures. Finally, 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 last month. Interestingly, despite strong in-sample evidence of liquidity reaction, it shows no economic value in out-of-sample tests as top liquidity reactors fail to deliver larger future alphas than other funds. This result is intuitive since liquidity reaction, which is solely based on public information, does not represent managerial skill. In summary, our results are robust to alternative explanations as well as to the use of alternative timing-model specifications, risk factors, and liquidity measures.

The rest of the paper proceeds as follows. In Section 1, we outline our liquidity timing model. Section 2 describes the hedge fund data. Section 3 reports the results about liquidity timing ability at the strategy portfolio level. Section 4 examines the timing skill for individual funds, presents evidence from the bootstrap analysis, and evaluates the economic value of liquidity timing skill. Section 5 explores alternative explanations related to funding liquidity and investor redemptions, among others. In section 6, we check the robustness of our results to alternative timing model specifications, risk factors, and market liquidity measures. Section 7 distinguishes liquidity timing skill from liquidity reaction. Finally, Section 8 offers concluding remarks.

1. 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 following process:

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

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

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

$$\beta_{p,t} = \beta_p + \gamma_p E(market\, condition_{t+1} \mid I_t). \tag{2}$$

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 forecast 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, and specify equation (2) as:

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

where the expression in parenthesis represents the manager's forecast (i.e., timing signal) about market liquidity and $L_{m,t+1}$ is the market liquidity in month t+1. In this paper, we mainly use the Pástor-Stambaugh measure that has been shown to capture market-wide liquidity conditions, and then use the Amihud illiquid measure to cross-validate our results. Appendix A provides details about the estimation of the Pástor-Stambaugh market liquidity measure. As it is unrealistic for a timer to have a perfect signal, υ_{t+1} is a forecast noise (or imprecision) unknown until t+1 and is assumed 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 $\bar{L}_m$ for ease of interpretation, since β_p captures the average fund beta roughly. Our inference about liquidity timing ability is unaffected with or without de-meaning the liquidity measure.

We obtain the following liquidity timing model by substituting equation (3) in equation (1) and letting the forecast noise υ join the error term:

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

The liquidity timing model in equation (4) is parallel to previous 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 and use derivatives. Hence, traditional factor models based on the CAPM are not well suited for examining managerial skill among hedge funds. In this paper, we estimate hedge funds' liquidity timing ability using the Fung and Hsieh (2004) seven-factor model as the benchmark model. The seven factors include both linear-payoff factors and option-like factors, and have been shown to explain variation in hedge fund returns well. Specifically, these factors include an equity market factor, a size factor, the change in the constant maturity yield on the ten-year Treasury, the change in the spread between Moody's Baa bond and the ten-year Treasury yields, and three trend-following factors for bonds, currency, and commodities. Therefore, our liquidity timing model for hedge funds has the following specification:

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

where f denotes the other factors besides the equity market factor ($J = 6$ in this case). The coefficient γ measures liquidity timing ability after controlling for the fund's exposure to other factors.

2. The Data

2.1 Hedge fund sample

We employ a sample of hedge funds from the Lipper TASS database, which constitutes one of the most comprehensive 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 before 1994 and data in early period clearly contains survivorship bias (see Liang (2000)). Thus, we focus on the period of January 1994 onward. Following the hedge fund literature, we only include funds that report net-of-fee returns on a monthly basis and with at least \$10 million assets under management.[4] To address the concern that historical returns may be back filled when new funds are added to the database, we exclude the first 12 months of returns for each fund in a robustness test and

[4] Our inference remains unchanged when we use other size filters (e.g., \$0, \$5, \$10 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.

find results consistent with those reported in this paper.[5] After these screenings, 7,275 individual funds remain in the sample over the period of January 1994 to December 2009.

TASS classifies individual hedge funds into ten 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 those equity-oriented strategies and accordingly drop the categories of fixed income arbitrage and managed futures from the analysis. To draw reliable inference, we require each category to contain a sufficient number of individual funds, and consequently the category of dedicated short bias is removed due to small fund number.

Among the seven equity-oriented strategies, we distinguish between primarily equity-oriented and partially equity-oriented. Primarily equity-oriented refers to those strategies primarily focusing on equity markets, whereas partially equity-oriented strategies have substantive exposure to equity markets but simultaneously (perhaps mainly) invest in other markets. The primarily equity-oriented strategies include emerging markets, equity market neutral, event driven, long-short equity, and multi-strategy, while the partially equity-oriented strategies include convertible arbitrage and global macro. Convertible arbitrage funds mainly trade convertible bonds despite substantive equity market exposure, and global macro funds rotate assets across different markets such as foreign bond markets, currency and commodity derivatives markets, in addition to equity markets.

Our final sample contains 6,702 funds, of which 3,543 are still alive as of the end of the sample period and 3,159 become defunct during the period. We construct equal-weighted portfolios of all the funds (including both individual hedge funds and funds-of-funds), all hedge funds, funds-of-funds, and hedge funds in each of the seven strategy categories. Panel A of Table 1 summarizes monthly net-of-fee returns for these portfolios. Over the sample period, the portfolio of all funds realizes an average return of 0.88% per month (about 11% per year) with a monthly standard deviation of 1.87%. Hedge funds have higher average monthly return (1.05%) than funds-of-funds (0.57%). This difference may be due to funds-of-funds' double fee structure or lack of managerial skills rela-

[5] We do not use the dates when hedge funds were added to TASS as the cutoff point to address backfilling bias because hedge funds may have reported to another database before they switched reporting to TASS. We also consider other approaches to control for backfilling bias, and our inference is unchanged.

tive to hedge funds, or both. Among different hedge fund strategies, emerging market has the highest average return of 1.25% per month, whereas convertible arbitrage delivers the lowest average return of 0.69% per month. Meanwhile, equity market neutral strategy has the lowest return volatility, due to the hedging nature of their simultaneous holdings of both long and short positions. The numbers of funds in all strategy categories do not sum up to the total number of hedge funds, because 339 hedge funds are not assigned to any of the categories by TASS.

2.2 Factor data

In Panel B of Table 1, we report summary statistics of the Pástor-Stambaugh market liquidity measure. The mean (median) level of market liquidity is –3.36% (–2.57%) per month over our sample period, suggesting a 3.36% average liquidity cost. The liquidity measure has a standard deviation of 6.68%, indicating considerable variation of market-wide liquidity over time and the 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 Figure 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 dry-ups very well, even beyond the period examined in Pástor-Stambaugh (2003).

Panel C presents summary statistics for the Fung-Hsieh seven factors.[6] 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% happens in August 1998, and the highest 8.18% in April 2003. Furthermore, the correlation between market returns and market liquidity over the sample period is 0.3.

Finally, we examine the relative importance of the equity market factor in explaining hedge fund returns among the seven factors. Table 2 reports the ratios of the adjusted R^2s from a single

[6] The data on the bond, currency and commodity trend-following factors are downloaded from David Hsieh's website at http://faculty.fuqua.duke.edu/_dah7/DataLibrary/TF-FAC.xls. Other data is from CRSP and the Federal Reserve databases.

market-factor model to those from the seven-factor model. The results indicate that equity market exposure is the most important in this context. For example, for the portfolio of hedge funds, the single-factor model produces an adjusted R^2 of 0.63, accounting for 90% of the total explanatory power from the seven factors. A similar result is obtained for all the primarily equity-oriented categories. On the other hand, for the partially equity-oriented strategies (i.e., convertible arbitrage and global macro), the explanatory power of the equity market factor is relatively low (about 50%). This result is intuitive, as these strategies do not exclusively focus on equity markets despite significant market exposure. To summarize, the result in Table 2 confirms that we should test for liquidity timing ability by examining the changes in equity market exposure rather than changes in loadings on the other factors.

3. Liquidity Timing at the Portfolio Level

This section reports the evidence on hedge funds' liquidity timing ability at the portfolio level. We first present results for portfolios consisting of all the funds, hedge funds, funds-of-funds, and hedge funds each of the seven strategy categories. Then we examine liquidity timing ability during extreme market liquidity conditions, such as liquidity crisis and volatile market states.

3.1 Liquidity timing

Based on the liquidity-timing model in (5), Table 3 presents the evidence that hedge funds adjust their market exposure to changes in market liquidity. The liquidity timing coefficient of the equally-weighted portfolio of all funds is 0.62 and significant at the 1% level. To put this coefficient in perspective, we compare it with the estimated market beta, i.e., the coefficient on *MKT*, which is 0.22. When market liquidity fluctuates by one standard deviation (6.68% from Table 1), a typical hedge fund would change its market exposure by 0.042 (0.62×6.68%), which translates to about 20% of the fund's average market beta. The result for the portfolio of all hedge funds is qualitatively similar: the timing coefficient is 0.64 with a t-statistic of 3.50. In addition, the regression coefficients on the seven factors are consistent with the results of Fung and Hsieh (2004).

Table 3 also reveals variation in liquidity timing ability across different fund strategies. Four out of the five primarily equity-oriented strategies (i.e., emerging market, event driven, long/short equity, and multi-strategy) exhibit significant and positive liquidity timing ability.[7] Meanwhile, we observe relatively weak or no evidence of liquidity timing skill for convertible arbitrage, global macro, and equity market neutral funds. This finding is intuitive. As noted previously, convertible arbitrage and global macro funds are partially equity-oriented and mainly trade in markets other than equity markets. Although equity market neutral funds are primarily equity-oriented, they attempt to exploit mispricing and thus have minimal directional exposure to the market. As shown in Table 2, these three strategies bear the lowest equity market exposure among the strategies considered, and hence have less incentive to time equity market liquidity. In fact, funds in the three strategies account for a small portion of our sample—they include 621 individual funds collectively, only about 15% of the 4,020 hedge funds in total. This explains why the overall sample exhibits strong evidence of liquidity timing.

3.2 Liquidity timing during liquidity crisis

Chordia, Roll and Subrahmanyam (2001) and Pástor and Stambaugh (2003) point out that the most salient features of market liquidity are occasional downward spikes corresponding to liquidity crisis. If a fund manager has liquidity timing skill in general, then a particularly important question is whether the manager reduces market exposure during periods of extremely poor liquidity conditions (e.g., a market-wide liquidity crunch).

To better understand liquidity timing ability, we modify the liquidity timing test in (5) by replacing market liquidity measure with a dummy variable $D(Low\_LIQ)_{t+1}$, which indicates whether market liquidity in month t+1 belongs to the bottom quintile during the sample period. Accordingly, the liquidity timing regression model becomes:

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_{p,1} MKT_{t+1} D(Low\_LIQ)_{t+1} + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}, \qquad (6)$$

[7] For emerging market funds, we replace the US equity market factor with the MSCI emerging market index and find the same result about liquidity timing.

where the coefficient γ_1 measures how the manager adjusts fund beta prior to the months of extremely low market liquidity. Note that model (6) is similar in spirit to the Henriksson and Merton (1981) market timing model where they examine the change in fund beta with respect to a dummy variable of whether market excess return is positive in the next month.

Table 4 reports the results. In general, hedge funds dramatically reduce market exposure during months of extremely low liquidity. For the portfolio of all funds, the estimated coefficient (γ_1) on the interaction term of market returns with the dummy of low-liquidity months is -0.10 and statistically significant at the 1% level. This suggests that, when market liquidity in month t+1 belongs to the bottom quintile, a typical fund would cut its market exposure by nearly 50% (given the average beta of 0.22). This finding holds for all the seven strategies except for convertible arbitrage. Since sharp contractions in market liquidity often coincide with market downturns, reducing fund beta before liquidity dry-ups can provide fund investors with a protection against potential, substantial losses.

These results echo the findings of Chen and Liang (2007) that the evidence on market timing and volatility timing for market-timers is particularly strong in bearish and volatile market conditions, as well as the findings of Rapach, Strauss, and Zhou (2010) and Henkel, Martin, and Nardari (2011) that market return predictability is concentrated in recessions and volatile periods. We now examine how liquidity timing ability differs between volatile and stable periods.

3.3 Liquidity timing in volatile vs. stable market conditions

Given the findings that predictability is strong in volatile market conditions in the return forecasting literature, we examine the liquidity timing ability among hedge funds in volatile and stable periods, separately. We define volatile periods as those years when annual market volatility is above the median level (1997–2002 and 2008–2009), and accordingly stable periods are the years with market volatility below the median level (1994–1996 and 2003–2007). The volatile periods appear to correspond to the years during which market liquidity fluctuates greatly, as shown in Figure 1.

We perform liquidity timing test in regression (5) for volatile and stable periods separately and present results in Table 5. Hedge funds' liquidity timing ability appears mostly concentrated in volatile periods rather than in stable periods. Only during volatile periods are the timing coefficients statistically significant for the funds. During stable periods, the timing coefficients are negative for most cases but statistically insignificant at any conventional levels. This is consistent with the evidence in Chen and Liang (2007) that return- and volatility-timing skills are found during volatile periods for self-declared market-timing hedge funds. While prior studies (e.g., Rapach, Strauss, and Zhou (2010) and Henkel, Martin, and Nardari (2011)) find that *return* predictability is strong in bad and volatile times, we show that *liquidity* forecasting is also concentrated in less liquid and more volatile market states.

Consistent with the results in Table 3, the evidence of liquidity timing is particularly strong for the four strategies (i.e., emerging market, event driven, long/short equity, and multi-strategy) that have primary exposure to equity markets. We find little evidence of liquidity timing for those partially equity-oriented strategies (i.e., convertible arbitrage and global macro) and the equity market neutral strategy that, though primarily equity-focused, bears little directional market exposure.

In summary, we find evidence at the portfolio level that hedge funds change their market exposure with market liquidity conditions and that the liquidity timing skill is concentrated in less-liquid and in more-volatile periods. The results are particularly strong for those strategies that bear primary market exposures. We now turn to examine liquidity timing ability for individual funds belonging to each strategy.

4. Liquidity Timing at the Fund Level

In this section, we present the cross-sectional distribution of liquidity timing coefficients across individual funds, and separate the timing skill from pure luck using a bootstrap analysis. More importantly, we show that liquidity timing skill is associated with positive and significant risk-adjusted returns in out-of-sample tests. We finally examine the persistence of liquidity timing skills among individual funds. Our results highlight the practical value of locating liquidity timers in hedge fund investment.

4.1 Cross-sectional distribution of the *t*-statistics for liquidity timing

We evaluate the liquidity timing skill using regression (5) for individual funds. To ensure a meaningful regression, we require each fund to have at least 36 monthly observations.[8] The resulting sample includes 4,874 individual funds (2,883 hedge funds and 1,991 funds-of-funds).[9]

Table 6 reports the cross-sectional distribution of the *t*-statistics for liquidity timing coefficients across funds. The table shows the percentage of the funds with significant timing coefficients at different significance levels. Among all sample funds, 21.3% have positive timing coefficients at the 10% significance level, where the null hypothesis is H_0: γ=0 and the alternative H_a: γ>0.[10] Further, we observe a slightly higher proportion (23.0%) of significant timing coefficients for hedge funds than for funds-of-funds (18.8%).

Across the seven strategies, the four with primary market exposures exhibit stronger results of liquidity timing, with more than 20% of positive timing coefficients significant at the 10% level. Event driven funds display the highest proportion (30.9%) of positive timing coefficients at the 10% level. The two partially equity-oriented strategies and equity market neutral show relatively weak evidence. Meanwhile, for the overall sample, the fraction of negative and significant timing coefficients at the 10% level is only 12.2%, indicating few cases of perverse liquidity timing.

Table 6 also shows the cross-section of liquidity timing ability at other significance levels. Based on those figures, we obtain the same conclusion that the sample funds include a significantly large fraction of successful liquidity timers, whereas the perverse timing evidence is relatively weak. We also examine the magnitude of the timing coefficients across funds. For example, the 10th percentile of timing coefficients is 1.50 for the overall sample and 1.81 for hedge funds. Among various categories, the 10th percentile for emerging market funds has the largest timing coefficient of 2.06. To conserve space, these results are not tabulated but are available from the authors upon request.

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[8] We experiment with alternative filters (e.g., requiring a minimum of 24-month observations) and find that our inferences are unchanged.

[9] Using this restricted sample, we repeat the analysis of Section 3 by re-forming equal-weighted portfolios. The findings are very similar to those reported in Table 3. For example, for the portfolio of all funds, the timing coefficient is 0.64 from the restricted sample versus 0.62 from the full sample.

[10] If we assume that γ's are from an independent Bernoulli distribution, then the 4,874 γ's follow a Binomial distribution. For a critical value of *t*-statistic = 1.282 corresponding to a one-sided test of the 10% significance level, we have a *t*-ratio = $[0.213-0.1] / \sqrt{0.1 \times(1-0.1)/4874} = 26.30$, strongly rejecting the null hypothesis that all γ's are zero. The same result is obtained from using other significance levels.

Overall, the above evidence suggests that a significant portion of hedge funds are able to time market liquidity successfully. However, are such fund managers simply lucky or do they truly process timing skills? This question is important and is the focus of the next subsection.

4.2 Bootstrap analysis

We use a bootstrap procedure to evaluate the statistical significance of the results on liquidity timing ability at the fund level. Details of our bootstrap procedure are described in Appendix B. The bootstrap analysis addresses the following question: how likely is it that we can attribute liquidity timing skills to pure luck? For each cross-sectional statistic of the timing coefficients (or their *t*-statistics), we compare its actual estimate with the corresponding distribution of estimates based on bootstrapped pseudo funds, and determine whether the liquidity timing coefficients are due to random sample variation or fund managers' timing ability. Following Kosowski, Timmermann, White, and Wermers (2006) and others, we focus our discussion on the *t*-statistics ($t_{\hat{\gamma}}$) of the liquidity timing coefficients in the bootstrap analysis, because they possess superior statistical properties in comparison to timing coefficient.

Table 7 reports the results from the bootstrap analysis. We present empirical *p*-values corresponding to the *t*-statistics of liquidity timing coefficients at different extreme percentiles. For all extreme percentiles considered (from 1% to 10%), the evidence suggests that top liquidity timing funds are unlikely to be attributed to random chance. Specifically, for the overall sample, the $t_{\hat{\gamma}}$'s for the top 1%, 3%, 5% and 10% liquidity timing funds are respectively 3.50, 2.78, 2.45 and 1.93 with the empirical *p*-values all close to zero. The same result holds for both samples of hedge funds and funds-of-funds.

We also conduct a bootstrap analysis for individual funds within each strategy. We find low empirical *p*-values for the top-ranked *t*-statistics for most strategies, supporting the notion that top timing coefficients are not from randomness. Thus, the bootstrap evidence is consistent with earlier results from both the portfolio- and fund-level analyses. Once again, four primarily equity-oriented strategies, i.e., emerging market, event driven, long/short equity, and multi-strategy, exhibit relatively strong skills to time market liquidity. On the other hand, the negative timing coefficients cannot be separated from random chance. For example, the empirical *p*-values associated with bottom $t_{\hat{\gamma}}$'s are all above the conventional significance level for the samples of all funds, hedge funds, and funds-of-funds.

For robustness, we implement alternative bootstrap procedures as described in Appendix B. These procedures differ in how we resample regression residuals and factors as well as how we construct pseudo funds. In untabulated tests, we find qualitatively similar results.

The results from the bootstrap analysis reinforce the earlier findings that some hedge fund managers can time market liquidity. Interestingly, the findings about negative timing coefficients suggest that perverse liquidity timing results cannot be distinguished from randomness. To further explore whether liquidity timing truly reflects managerial skill, we now examine the economic value of liquidity timing.

4.3 Economic value of liquidity timing

Given the evidence on liquidity timing, another important question naturally arises: Is liquidity timing skill persistent over time and can such skill add value to fund investors? If it can, 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 of selecting top liquidity timers.

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 hedge fund portfolios based on their liquidity timing coefficients. These portfolios are held subsequently for a 3-, 6-, 9- or 12-month holding period, and the process is repeated.[11] This yields four distinct time series of returns on each portfolio of various levels of liquidity timing skill. Thus, for each holding period, we have a time series of monthly returns on the ten portfolios from 1997 to 2009. Whenever a fund disappears over the holding period, its returns are included in calculating the portfolio returns until it disappears, and the portfolio is rebalanced going forward. Next we estimate the Fung and Hsieh (2004) seven-

[11] We use the minimum of 3-month holding period since the average lock-up period for our sample hedge funds is about three months.

factor model and report each portfolio's alpha. Since such investment strategies are most relevant to fund-of-funds managers, we apply it to two samples: (1) all sample funds, and (2) all hedge funds.

Table 8 presents striking evidence on the economic value of liquidity timing ability. Specifically, the portfolio consisting of the top 10% past liquidity timers delivers economically significant alphas in the post-ranking periods. As reported in Panel A, for a 12-month holding period, the portfolio's alpha is 0.63% per month (7.5% per year) with a *t*-statistic of 4.50 based on the overall sample. Top liquidity-timing funds also generate significantly higher out-of-sample alphas than the other funds. For the overall sample, the spread in alpha between top and bottom timing funds ranges from 0.31% to 0.41% per month, depending on holding periods, and remains significant even one year after the ranking period. That is, top liquidity-timing funds outperform bottom timing funds by 3.6%–4.9% per year subsequently after adjusting for risk. This result is both economically and statistically significant. An analysis focusing on hedge funds produces the same result—top liquidity-timing funds realize an average alpha that are twice as large as 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 alpha of 7.5%, which suggests that liquidity timing reflects managerial skill and is one important source of fund alphas.

The economic value of liquidity timing skill can be seen from Figures 2 and 3 as well. Figure 2 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 twice as large as that of bottom timing funds in post-ranking periods. Figure 3 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 would yield a cumulative return of 611% from January 1997 to December 2009, whereas holding the bottom-decile liquidity timers generates a cumulative return of 367% over the same period.

Using portfolio returns from the post-ranking periods, we further examine the persistence of the liquidity timing skills. Specifically, after forming the ten portfolios based on past liquidity timing coefficients, we estimate the liquidity timing model in regression (5) and evaluate fund managers' subsequent timing ability. We find significant evidence for the persistence of liquidity timing skills. For example, the portfolio consisting of the top 10% of timing funds in the past 36 months generates an out-of-sample timing coefficient of 1.02 (t-statistic = 2.06) for the 12-month holding period. In contrast, the portfolio of bottom timing funds in the past 36 months exhibits a subsequent timing coefficient of -0.36 (t-statistic = -0.69) for the same holding period. When we run the liquidity timing regression (5) for the time series of the return spread between top and bottom timing funds, the timing coefficient is 1.38 (t-statistic = 3.14) for a 12-month holding period. To conserve space, these results are not tabulated but are available upon request.

To summarize, we find strong evidence that liquidity timing skill adds value to fund investors, which further confirms that liquidity timing reflects managerial skill. We also show that such skill persists over time in out-of-sample tests. Our results demonstrate the practical value of liquidity timing in hedge fund management, which can be particularly relevant to managing a fund of hedge funds.

5. Addressing Alternative Explanations

In this section, we examine the robustness of our results to alternative explanations. We start with an examination of liquidity timing ability with controls for market timing and volatility timing. Then, we address concerns related to hedge funds' funding liquidity and funding constraints. We also consider the possibility that large funds' trades may affect future market liquidity. Finally, we show that our results are robust to the exclusion of the 2007-2009 financial crisis period.

5.1 Can market- and volatility-timing explain the results?

Our liquidity timing model (5) focuses on the adjustment of fund beta in relation to market liquidity. However, fund managers may time market returns and volatility as well. Because market liquidity is positively correlated with market returns and negatively correlated with market volatility, the documented evidence on liquidity timing may reflect fund managers' market- or volatility-timing ability. To address this concern, we include the controls for market timing and volatility timing in our liquidity timing model as follows.

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \bar{L}_m) + \lambda_p MKT_{t+1}^2 + \delta_p MKT_{t+1}(Vol_{t+1} - \overline{Vol}) + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}, \quad (7)$$

where Vol_{t+1} is the market volatility in month t+1 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.[12] The coefficients γ, λ, and δ measure liquidity timing, market timing, and volatility timing ability, respectively. Funds with market timing (volatility timing) skills should exhibit positive λ (negative δ).

Table 9 reports the results. After controlling for market- and volatility-timing, we still observe strong evidence of liquidity timing. For the overall sample, the liquidity timing coefficient is 0.62 (t-statistic = 2.65), and is close to that reported in Table 3. This result also holds for hedge funds, funds-of-funds, as well as four primarily equity-oriented strategy categories. Again, at the strategy level, emerging market funds exhibit the largest timing coefficient of 1.64 (t-statistic = 2.17). In untabulated tests, we run the regression model (7) for individual hedge funds, perform the bootstrap analysis, and find that our inference is unchanged. Table 9 also presents results of market timing and volatility timing skills. Consistent with Chen (2007), we observe that hedge fund managers cannot successfully time market returns. While Chen and Liang (2007) document positive market timing ability among hedge funds, they focus on a special group of self-declared market timing hedge funds. Meanwhile, there is some evidence of volatility timing mainly with strategies such as global macro and long/short equity.

These results suggest that our evidence on liquidity timing ability among hedge funds is not driven by market timing or volatility timing skill. Therefore, market liquidity is an important consideration, in addition to market returns and volatility, when fund managers adjust their portfolios' market exposure.

5.2 Leverage and funding constraints

We are concerned about the possibility that our results on liquidity timing might be driven by the 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 dry-ups. Hence, one might wonder if the reduction of market exposure in poor market liquidity condi-

[12] The correlation between the VIX and market liquidity is -0.4 over our sample period.

tions merely reflects deterioration of funding liquidity because prime brokers have cut funding or increased borrowing costs. We explore this possibility in four ways.

First, we have shown that liquidity timing skill is associated with subsequent superior performance. Such 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 since 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 would perceive. 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.[13] They further find that equity-oriented hedge funds, which are the focus of our study, have lower leverage ratios compared to non-equity-oriented funds such as fixed income arbitrage and managed futures funds.[14] Hence, their finding suggests that the effect of the changes in leverage is not large for most 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 fund managers have no timing skill and the changes in fund beta are caused by fluctuations in leverage, hedge funds that do not use leverage should not exhibit evidence of liquidity timing ability.

Table 10 reports the evidence for liquidity timing for funds that do not use leverage. Among the sample funds, 3,381 report not to use leverage while 3,321 report a use of leverage.[15] For the portfolio of funds that do not use leverage, the timing coefficient is 0.65 (t-statistic = 3.44), which is comparable to the coefficient for funds that use leverage (0.60). When examining individual hedge funds that do not use leverage, we find a timing coefficient of 0.69 (t-statistic = 3.78), which is also

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

[14] In addition, Van Hedge Study (2003) reports that more than one-third of hedge funds do not use leverage at all and about 50% use only a mild level of leverage with leverage ratios between one and two. Thus, only a minority of funds have leverage ratios greater than two.

[15] We examine the leverage-use dummy variable from TASS data downloaded in different years from 1998–2009. 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.

close to its counterpart (0.61) of leverage users. Furthermore, consistent with the evidence for the full sample, we find strong results of liquidity timing for four primarily equity-oriented strategies (e.g., emerging market, event driven, long/short equity, and multi-strategy) for both leverage users and non-users. The results from the fund-level and bootstrap analyses deliver a similar conclusion. Since funds that do not use leverage still exhibit significant timing coefficients, our evidence on liquidity timing ability is unlikely due to the impact of fund leverage.

Finally, we explicitly control for the impact of funding constraints, measured by the TED spread, on the inference about liquidity timing. The TED spread, which is the difference between the three-month LIBOR and the three-month T-bill rate, indicates perceived counterparty default risk. When the risk of counterparty default is considered to be decreasing, the TED spread goes down and a hedge fund's prime broker inclines to provide greater leverage. Hence, we include an additional interaction term between the TED spread and market returns in the liquidity timing model (5):

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \bar{L}_m) + \lambda_p MKT_{t+1}\, TED_{t+1} + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}, \qquad (8)$$

Table 11 reports the results. The coefficient λ on the interaction term between market returns and TED appears insignificant for the overall sample, but is significant for the strategies of emerging market and global macro. After controlling for the impact of funding constraints, we still find significant liquidity timing coefficients for the portfolios of all funds, hedge funds, and funds of funds.

Taken together, these results do not support the view that hedge fund leverage drives our findings about the 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. Quite differently, though leverage changes can affect funds' market exposure, they do not reflect managerial skill.

5.3 Investor redemptions

Besides leverage, funding constraints can be caused by investor redemptions. Thus, another possible argument is that rapid changes in fund capital affect funds' market exposure. As investors withdraw their capital, fund managers have to unwind positions, leading to a decrease in market exposure (e.g., Khandani and Lo (2007)). Indeed, during the recent financial crisis, many hedge funds experienced heavy investor redemptions and were forced to liquidate positions. We conduct three tests to address this concern.[16]

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. Table 12, the first column, reports liquidity timing coefficients for this subsample of funds (3,171 funds, or 47% of the overall sample). Overall, the evidence is consistent with those results in Table 3. For example, the timing coefficient is 0.76 (*t*-statistic = 4.28) for hedge funds with low redemption frequency, which is close to 0.64 (*t*-statistic = 3.50) in Table 3 for all hedge funds. Further analysis for individual funds provides results consistent with those in Section 4. Intuitively, investor redemptions are more likely to have an effect on funds with a shorter redemption frequency (e.g., a month). Hence the finding that funds with longer redemption frequency exhibit equally strong timing ability as funds with shorter redemption frequency suggests that liquidity timing is mostly derived from managers' timing ability rather than investors' redemption decisions.

Second, we examine liquidity timing ability for funds requiring a redemption notice period of 30 days (4,553 funds, or 68% of the overall sample) or 60 days (1,841 funds, or 27% of the sample). The redemption notice period allows more time for the fund manager to adjust positions to meet investors' withdrawal requests, and so money withdrawal has less impact. The second and third columns in Table 12 report the results. Once again, we find that our inference about liquidity timing skill remains unchanged, in that the timing coefficients are both statistically and economically significant for the overall sample, hedge funds, funds-of-funds, and most of the strategy categories.

Finally, we examine a subsample of funds having low fund-flow volatility. The two rightmost columns in Table 12 report the results. We first examine funds whose monthly flow volatility is below the median level of peer funds. Following prior research (e.g., Sirri and Tufano (1998)), we

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[16] Unlike open-ended mutual funds that stand ready to redeem capital for their investors, many hedge funds set restrictions for money withdrawal through several provisions, such as redemption frequency, lock-up period, advance notice period, and redemption gate. 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 actual redemption–redemption notice period. Furthermore, a redemption gate grants the fund manager with discretion to restrict redemption above a percentage of the fund's total assets.

measure fund flows as the percentage change in assets under management (AUM) after adjusting for fund returns. The subsample includes 3,283 funds (or 49% of the overall sample), which is not exactly 50% of the overall sample because some funds do not report information about their AUM. Here, we find a timing coefficient of 0.63 (t-statistic = 3.21) for funds with lower-than-median flow volatility, which is again very similar to the evidence from the overall sample (i.e., a timing coefficient of 0.62 in Table 3). We also examine funds whose flow volatility is below the 25th percentile, and find a similar result. Funds with low flow volatility should be less affected by investor flows and thus better able to implement the manager's strategies. The results suggest that investor flows cannot explain our evidence on the liquidity timing ability.

Collectively, funds that are subject to longer redemption frequencies, longer redemption notice periods, or with lower fund-flow volatility still show liquidity timing ability. These findings indicate that our evidence on liquidity timing is unlikely to be a consequence of investor redemptions.

5.4 The impact of hedge fund trades on market liquidity

Next, we consider another possible explanation 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 fund beta set in month t and market liquidity observed in month t+1. However, one may 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 in turn may deteriorate in the next month and accordingly we observe a positive link between funds' market exposure and 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 (3,333 funds, collectively accounting for 7% of total AUM of the sample funds), less than \$100 million (4,571 funds, or 15% of total AUM), and less than \$150 million (5,208 funds, or 21% of total AUM). The Dodd-Frank Act of 2010 introduces significant regulation of hedge funds, but the regulation applies only to fund advisors with AUM of \$150 million or more. Thus, \$150 million is chosen as the maximum size to define small funds. In addition, 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% funds, and the resulting subsample include 3,056 funds (this number is slightly smaller than 50% of the total number of funds, because we run the regressions only for funds with at least 12 monthly observations).

Table 13 reports the 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 less than $150 million, the timing coefficient for all small funds is 0.62 (*t*-statistic = 3.19), which is similar to that in Table 3. Consistent with the results in previous tables, we find most significant evidence of liquidity timing for the primarily equity-focused strategies of emerging market, event driven, long-short equity, and multi-strategy. Hence, after examining 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 due to the impact of hedge fund trades on market liquidity.

5.5 Excluding the 2007-2009 crisis period

It is worth noting that most of these alternative explanations in Sections 5.2–5.4 should be especially relevant during market liquidity crises, because the impact of leverage, funding constraints and investor redemptions is the greatest during these periods. In another effort to address the concern related to fund liquidity and funding constraints, we examine the liquidity timing ability using the sample period of 1994–2006, excluding the recent 2007–2009 financial crisis period.

Focusing on the period of 1994–2006, we find stronger evidence for the liquidity timing skill. Based on the portfolio level analysis, the liquidity timing coefficient for the overall sample is 0.86 (*t*-statistic = 4.90) over the subperiod of 1994-2006, vs. 0.62 (*t*-statistic = 3.29) in Table 3 for the entire sample period of 1994–2009. For hedge funds, the subperiod analysis yields a timing coefficient of 0.90 (*t*-statistic = 5.37), vs. 0.64 (*t*-statistic = 3.50) for the whole sample period.

Based on the fund level analysis, we also document stronger evidence. For the overall sample, untabulated results show that 28.6% of funds exhibit positive timing ability at the 10% significance level over the 1994–2006 period, which is higher than the 21.3% in Table 6 for the whole sample period. We obtain a similar result for hedge funds, funds-of-funds, and individual funds in the strategy categories.

In summary, the analysis presented in this section strongly suggests that our findings of the liquidity timing ability among hedge funds are not driven by the mechanisms related to funding liquidity and funding constraints. Although funding liquidity and funding constraints play an important role in hedge fund investment, they are not materially related to liquidity timing which is an important component of fund managers' asset allocation strategies.

6. Alternative Timing Model Specifications, Risk Factors, and Liquidity Measure

In this section, we further check the robustness of our findings along four dimensions: (1) alternative timing model specifications, including a conditional version of the liquidity timing model and a timing model with the control for systematic stale pricing; (2) inclusion of the Pástor-Stambaugh liquidity risk factor as an additional factor; (3) using alternative factors in the benchmark model; and (4) using an alternative measure of market liquidity.

6.1 Conditional liquidity timing model

Ferson and Schadt (1996) and Becker, Ferson, Myers, and Schill (1999) emphasize that it is important to distinguish asset allocation decisions based on publicly available information (i.e., conditioning information) from that based on managers' forecast or signal about market conditions. Fund managers who rely on public information to make asset allocation decisions do not possess timing ability. We now examine liquidity timing ability using a conditional version of the timing model in equation (5). Following Ferson and Schadt (1996) and others, we employ four conditioning variables, including one-month lagged values of the three-month T-bill rate, the term premium between the 10-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. We specify the conditional version of our liquidity timing model as the following:

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \overline{L}_m) + \sum_{l=1}^{L} \delta_l MKT_{t+1}(Z_{l,t} - \overline{Z}) + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}, \qquad (9)$$

where $Z_{l,t}$ is a conditioning variable that is publically known in month t, and L = 4 since we use four conditioning variables. As explained previously, the conditioning information is de-meaned for ease of interpretation. In regression (9), we still use the Fung-Hsieh factors as the benchmark.

Table 14 presents the results from the conditional liquidity timing model, and shows that our inference about liquidity timing ability remains strong. For the portfolio consisting of all sample funds, the liquidity timing coefficient is 0.56 (t-statistic = 3.21). The timing coefficient is also statistically significant for the portfolios of hedge funds, funds-of-funds, and the four primarily equity-focused strategies of emerging market, event driven, long/short equity, and multi-strategy funds. We also repeat the fund-level analysis using the conditional timing model, and find that our inference is unchanged.

6.2 Controlling for systematic stale pricing

Getmansky, Lo, and Makarov (2004) show that hedge fund returns exhibit serial correlations. One reason for this result is that hedge funds hold relatively illiquid assets that do not trade frequently. Such thin or nonsynchronous trading can bias estimates of fund beta (e.g., Scholes and William (1977)). Recently, 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*, the inference about timing ability can also be biased. They address this problem when measuring timing ability for bond mutual funds, and find that controlling for this bias is important. Now we re-examine the liquidity timing skill using a model including two lagged market excess returns, MKT_t and $MKT_{t\text{-}1}$, as well as two interaction terms between lagged market returns and market liquidity measures. The liquidity timing model with the controls for systematic stale pricing is the following:

$$\begin{aligned} r_{p,t+1} = \alpha_p + \beta_{p,1} MKT_{t+1} + \beta_{p,2} MKT_t + \beta_{p,3} MKT_{t-1} + \gamma_{p,1} MKT_{t+1}(L_{m,t+1} - \overline{L}_m) \\ + \gamma_{p,2} MKT_t (L_{m,t} - \overline{L}_m) + \gamma_{p,3} MKT_{t-1}(L_{m,t-1} - \overline{L}_m) + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}. \end{aligned} \tag{10}$$

The portfolio level analysis shows that MKT_t and $MKT_{t\text{-}1}$ enter the regression significantly, indicating illiquid holdings in hedge fund portfolios. Nonetheless, the regression coefficients on MKT_t and $MKT_{t\text{-}1}$ are rather small (0.08 and 0.05) compared to the coefficient on MKT_{t+1} (0.22). More importantly, similar to the results in Table 3, the portfolios of all funds, hedge funds, funds-of-funds, primarily equity-oriented strategies still exhibit statistically and economically significant liquidity timing ability. The fund level tests, including a bootstrap analysis, lead to the same conclusion as before. Finally, we find similar evidence when using up to 6 lags of market returns and interaction terms between market returns and market liquidity measures. To conserve space, these results are not tabulated.

6.3 Including a liquidity risk factor

The Fung-Hsieh seven factors explain hedge fund returns well, nonetheless, the model does not include an equity market liquidity risk factor. Recently, Sadka (2010) and Teo (2011) show that liquidity risk factor is one important determinant of hedge fund returns in the cross-section. Here, we examine the timing skill by augmenting our timing model (5) with a liquidity risk factor. Accordingly, the timing model becomes:

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \bar{L}_m) + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \beta_{p,liq} Liq_{t+1} + \varepsilon_{p,t+1}, \quad (11)$$

where *Liq* denotes the liquidity risk factor, proxied by monthly innovations in the Pástor-Stambaugh liquidity measure based on an AR(2) process.

Table 15 reports the results from this augmented liquidity timing model. For the portfolio of all funds, we find a liquidity timing coefficient 0.52 (*t*-statistic = 3.10) after controlling for the funds' liquidity risk exposure. For the portfolio of hedge funds, the timing coefficient is 0.54 (*t*-statistic = 3.33). Similar to results in Table 3, four primarily equity-focused strategies have significantly positive timing coefficients. Untabulated bootstrap results from the fund level analysis yield a similar conclusion. Consistent with Sadka (2010) and Teo (2011), hedge fund returns exhibit significant exposure to the liquidity risk factor. Therefore, our main results in Sections 3 and 4 remain unchanged after including a liquidity risk factor in our baseline regression.

6.4 Alternative factors

As an alternative to the seven-factor model, we consider a factor model including 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 (we thank Vikas Agarwal for providing us with the data for option return factors). Thus, we replace the seven factors in equation (5) with these alternative factors to re-examine the liquidity timing skill.

Our inference about liquidity timing ability remains unchanged. The liquidity timing coefficient is significant for the portfolios of all sample funds, hedge funds, funds-of-funds, as well as primarily equity-focused strategy categories. For example, the timing coefficient on the portfolio of all sample funds is 0.58 (*t*-statistic = 2.80). We also obtain the same result from the regression (6) as before when focusing on low-liquidity months. At the fund level, the bootstrap results are consistent with the evidence presented in Section 4. For all funds as well as all hedge funds, top-ranked *t*-statistics of the timing coefficients, such as those at the top 1%, 3%, 5% and 10% levels, have empirical *p*-values below the conventional significance level.

6.5 Alternative liquidity measure

Liquidity is a broad concept, which can be measured in different ways. The Pástor-Stambaugh (2003) 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 price impact of $1 million dollar volume. Now, we repeat our portfolio- and fund-level analyses of liquidity timing skill using the Amihud measure of market illiquidity (see his Section 2 for construction of the measure). For convenience of reporting, we multiply the Amihud illiquidity measure by minus one so that the timing coefficient based on this measure has the same interpretation as that from the Pástor-Stambaugh liquidity measure.

Using the liquidity timing model in equation (5) and the Amihud measure, we find results qualitatively similar to those based on the Pástor-Stambaugh liquidity measure. For the portfolio of hedge funds, the timing coefficient is significant at the 1% level and has a *t*-statistic of 2.21. The result from the regression (6) indicates that hedge funds reduce their market exposure significantly during the months of low market liquidity. For example, for the portfolio of hedge funds, the change in the portfolio's market beta is -0.07 (*t*-statistic = -2.29) during the low-liquidity months. Though somewhat weaker than the result in Table 4 where the change in market beta is -0.1 for hedge funds, the result conveys the same message. At the fund level, we find 24.4% of individual funds have significant liquidity timing coefficient at the 10% level using the Amihud measure, which is similar to the finding of 21.3% in Table 6 based on the Pástor-Stambaugh measure. Furthermore, the bootstrap analysis suggests that the evidence for top-ranked liquidity timers cannot be attributed to pure luck.

Finally, although the two liquidity measures focus on different aspects of market liquidity, they often identify months corresponding to the well-known low-liquidity episodes. To utilize information contained in both measures, we replace the dummy variable in regression (6) with a new dummy of low-liquidity months that belong to the bottom 20% of low-liquidity months according to both the Pástor-Stambaugh and Amihud measures. Consistent with the result in Section 3, we find a significant reduction in fund beta during such low-liquidity months. The coefficient on the dummy variable is -0.09 with a *t*-statistic of -2.66. In summary, we find similar results when using alternative market liquidity measures.

7. Liquidity Timing versus Liquidity Reaction

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

The Pástor-Stambaugh liquidity measure has mild serial correlation. Its first-order autocorrelation is 0.2 over the period of 1962–2009, but is only 0.05 during our sample period of 1994–2009. Fund managers may use observed liquidity in month t to derive a predictable component of liquidity and adjust fund beta accordingly. Such managers have no timing skill, but simply react to past liquidity conditions.

There is an important difference between liquidity timing and liquidity reaction. That is, liquidity reactors adjust fund beta based on observed market liquidity in month t, whereas liquidity timers manage market exposure using their forecast about market liquidity in month t+1. To distinguish liquidity timing skill from liquidity reaction, we estimate the following model where both liquidity timing and liquidity reaction terms are included:

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}\tilde{L}_{m,t+1} + \varphi_p MKT_{t+1}(L_{m,t} - \bar{L}_m) + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}. \tag{12}$$

In this specification, $L_{m,t}$ is one-month lagged market liquidity and represents a predictable component of liquidity based on public information. $\tilde{L}_{m,t+1}$ is the innovation in market liquidity from an AR(1) process and the unpredictable component of market liquidity.[17] In equation (12), the coefficients γ and φ measure liquidity timing ability and liquidity reaction, respectively. If fund managers only react to past liquidity conditions, we expect the timing coefficient to be insignificant once we take liquidity reaction into account.

Table 16 presents the evidence at the portfolio level. The most important result is that liquidity timing ability remains significant even after controlling for liquidity reaction simultaneously. For the portfolio of all funds, the timing coefficient is 0.50 (t-statistic = 2.59). Again, we observe significant liquidity timing coefficients associated with the four primarily equity-focused strategies of emerging market, event driven, long/short equity, and multi-strategy.

This table also provides evidence that fund managers react to past liquidity conditions to change their funds' market beta. The regression coefficient on the interaction term between market returns and lagged market liquidity is 0.73 (t-statistic = 4.15) for the portfolio of all funds. Of particular interest is that even market neutral funds exhibit a pattern of reactions to past market liquidity conditions, though we document no timing skill for this category. Ben-David, Franzoni, and Moussawi (2010) examine hedge funds' quarterly holdings and find evidence that hedge funds reduce their equity positions during the 2007-2008 financial crisis. Hence, their evidence is broadly consistent with the notion that fund managers react to recent market liquidity conditions. As reported in Section 5.5, our results about liquidity timing ability are even stronger when we exclude the 2007-2009 period from the analysis. The monthly hedge fund data used in this study allows us to distinguish liquidity timing skill from liquidity reaction at monthly frequency. Overall, our main results about liquidity timing ability remain unchanged after including a predictable component of market liquidity in the timing model.

To further understand the implication of liquidity reaction, we examine its economic value using the same approach as measuring the economic value of liquidity timing ability. We replace

[17] Using an AR(2) process to obtain innovations in market liquidity does not change our results, since the higher-order autocorrelations of the Pástor-Stambaugh measure are very small.

$L_{m,t+1}$ with $L_{m,t}$ in the equation (5) and then repeat our analysis of our-of-sample risk-adjusted returns following the procedure described in Section 4.3. Table 17 presents out-of-sample alphas of the ten liquidity-reactor portfolios as well as the spread in alphas between the top and bottom portfolios. The results show that liquidity reaction does not generate economic values for fund investors. For the sample of all funds (Panel A), the out-of-sample alpha for the portfolio consisting of top 10% liquidity reactors is 0.43% for a 12-month holding period, while the alpha for bottom 10% liquidity-reactors is 0.41%. In fact, the spread of out-of-sample alphas between the top and bottom liquidity reactors is small and insignificant for all the holding periods considered. These results are in sharp contrast with those reported in Section 4.3 where liquidity timing skills add significant economic values for investors in out-of-sample tests.

We can draw a few conclusions from these findings. First, investing in top liquidity reactors does not generate investment profits in comparison to investing in other funds. Second, the group of top liquidity-timing funds reported in Table 8 is not the same as the group of top liquidity reactors in Table 17. Finally, liquidity timing reflects managerial skill and is one important source of hedge fund alphas. Liquidity timing ability and the corresponding fund performance cannot be easily replicated by reacting to past liquidity conditions.

8. Conclusions

In this paper, we explore a new dimension of hedge fund managers' timing ability—their ability to time market liquidity, and examine whether 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 6,702 equity-oriented hedge funds over the sample period from 1994 to 2009, we find strong evidence of liquidity timing at both the style-category level and the individual-fund level.

In particular, hedge-fund managers increase (decrease) their market exposure when the equity market liquidity is high (low), and this effect is both economically and statistically significant. Liquidity timing ability is most evident among primarily equity-oriented strategies such as emerging market, event driven, long/short equity, and multi-strategy. The liquidity timing skill is especially pronounced when market liquidity is low. Hedge-fund managers tend to reduce their portfolios' market exposures correctly when market liquidity is low and when market volatility is high, which helps to prevent or alleviate investment losses in unfavorable market states. This is important as institutional investors pay particular attention to preserving capital in such scenarios. Our bootstrap analysis provides additional evidence for liquidity timing ability at the individual-fund level. The timing ability of top-ranked liquidity timers cannot be attributed to sampling variation in our samples of all funds, hedge funds, funds of funds, and funds in four style categories.

In addition, the liquidity timing ability persists over time and generates investment value in out-of-sample tests. Though hedge funds exhibit positive alphas, top liquidity timing funds stand out by delivering out-of-sample alphas that are twice as large as those of other funds. In particular, top liquidity timing funds subsequently outperform bottom liquidity timing funds by 3.6%–4.9% per year, depending on holding periods, after adjusting for risk. This result suggests that liquidity timing represents managerial skill and is one important source of hedge fund alphas.

Finally, we conduct a wide array of sensitivity tests and show that our inference about liquidity timing holds in all these tests. For example, our findings are robust to alternative explanations related to funding liquidity or investor redemption, alternative timing model specifications, risk factors, and liquidity measures. Further, we distinguish liquidity timing skills from liquidity reaction, and show that liquidity reaction is not persist over time and does not generate investment value. To conclude, our examination of hedge funds' liquidity timing ability highlights the importance of understanding and incorporating market liquidity conditions in hedge fund management.

Appendix A: The Pástor-Stambaugh Market Liquidity Measure

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. Their measure is based on the assumption that the less liquid a stock is, the greater the expected price reversal for a given amount of order flow. Below are some details about the market liquidity measure.

For each stock i listed on the NYSE and AMEX in each month t, its liquidity is measured by the following regression:

$$r_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + \eta_{i,t} sign(r_{i,d,t}) \times v_{i,d,t} + \varepsilon_{i,d+1,t}, \qquad d = 1,\ldots,D_t, \qquad \text{(A1)}$$

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 aggregate market liquidity measure in month t is then calculated as the average liquidity measure across individual stocks $\bar{\eta}_t = \sum_{i=1}^{N_t} \eta_{i,t} / N_t$, where N_t is the number of stocks available in that month. As $\eta_{i,t}$ measures the liquidity cost of trading \$1 million of stock i, the market liquidity measure can be interpreted as the cost of trading \$1 million distributed equally across all stocks. Since the equity market size increases over time, the liquidity measure is scaled by the market size at the beginning of the CRSP daily sample, i.e., $L_{m,t} = (m_t / m_1) * \bar{\eta}_t$, 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. The scaled aggregate market liquidity measure, $L_{m,t}$, is used in our evaluation of liquidity timing skill for hedge funds.[18]

Appendix B: Bootstrap Analysis of Liquidity Timing Ability

This appendix describes the procedure of our bootstrap analysis of liquidity timing ability. When we infer the cross-sectional statistics (e.g., the top 5th percentile) of timing ability for individual funds, standard parametric inferences may not apply for a few reasons. First, hedge fund returns within a strategy may be highly correlated, and thus timing measures are not independent cross funds. Second, for many funds in our sample, the distribution of their residuals from the timing model is non-normal. Furthermore, the number of funds in the sample changes over time (i.e., not all funds operate during the whole sample period), making it difficult to estimate the covariance matrix of fund returns. Hence, to assess the significance of cross-sectional statistics of the timing coefficients, we employ a bootstrap analysis similar to that used by Kosowski, Timmermann, White, and Wermers (2006), Chen and Liang (2007), Jiang, Yao, and Yu (2007), and Fama and French (2010), built on the work of Efron (1979). In particular, we implement the following procedure to assess the statistical significance of specific percentiles of liquidity-timing coefficients and corresponding *t*-statistics for individual funds:

Step 1: Estimate the Fung-Hsieh factor model for each fund *p*:

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \sum_{j=1}^{K} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}, \tag{B1}$$

and store the estimated coefficients $\{\hat{a}_p, \hat{\beta}_p, \ldots\ldots\}$ as well as the time series of residuals $\{\hat{\varepsilon}_{p,t+1}, t=0, \ldots..T_p\text{-}1\}$, where T_p is the number of monthly observations for fund *p*.

Step 2: Resample the residuals with replacement and obtain a randomly re-sampled residual time-series $\{\hat{\varepsilon}^b_{p,t+1}\}$, where *b* is the index of bootstrap iteration, *b* = 1, 2, …, *B*. In our analysis, we

[18] We are grateful to Lubos Pástor for providing their market liquidity data up to December 2008, and we replicate and extend their measure to December 2009 to match our hedge fund sample.

set the number of iterations B to be 1,000. Then we calculate 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:

$$r_{p,t+1}^{b} = \hat{\alpha}_p + \hat{\beta}_p MKT_{t+1} + \sum_{j=1}^{K} \hat{\beta}_j f_{j,t+1} + \hat{\varepsilon}_{p,t+1}^{b}, \tag{B2}$$

Step 3: Estimate the liquidity timing model (5) using the pseudo-fund returns for fund p.

Step 4: Repeat Steps 1–3 for each of the sample funds and store the cross-sectional statistics of timing coefficients and their t-statistics.

Step 5: Generate the distributions of the relevant cross-sectional statistics of timing coefficients and their t-statistics by repeating Steps 1–4 for B iterations. Although a pseudo fund possess no timing skill, the estimated timing coefficient can differ from zero due to sampling variation. Using the bootstrap procedure, we calculate the empirical p-values by comparing the distribution of timing coefficients from the actual funds with that from pseudo funds.

Following Kosowski et al. (2006) and others, we mainly conduct bootstrap analysis for the t-statistics of timing coefficient (i.e., t_γ), because the t-statistic is a pivotal statistic and has some favorable sampling properties. For robustness, we implement additional bootstrap procedures. In one experiment, we re-sample the seven factors together but not residuals. In another experiment, we re-sample the factors and residuals jointly. Finally, we first estimate the liquidity timing regression in (5) in Step 1, and then remove the liquidity timing term (i.e., the interaction term between market return and market liquidity) in Step 2 to ensure the pseudo funds possess no liquidity timing skill.

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Table 1
Summary statistics

Panel A presents summary statistics of monthly returns on the equal-weighted portfolios of all funds, hedge funds, funds-of-funds, and hedge 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 reports summary statistics of the Pástor-Stambaugh market liquidity measure. Panel C summarizes the Fung-Hsieh seven factors, including the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-year treasury constant maturity yield (BAAMTSY), and three trend-following factors: PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). The sample period is from January 1994 to December 2009.

	N	Mean	Median	STD	25%	75%
Panel A: Hedge fund Returns (%)						
All funds	6702	0.878	0.946	1.867	-0.323	1.982
Hedge funds	4020	1.050	1.290	2.042	-0.066	2.200
Funds of funds	2682	0.570	0.623	1.603	-0.213	1.518
Convertible arbitrage	161	0.693	0.943	2.147	0.029	1.587
Emerging market	441	1.253	1.871	4.436	-1.713	3.980
Equity market neutral	299	0.868	0.856	0.932	0.396	1.326
Event driven	490	0.941	1.255	1.612	0.203	1.839
Global macro	161	0.917	0.853	1.960	-0.352	1.928
Long/short equity	1685	1.189	1.253	2.519	-0.386	2.528
Multi-strategy	444	0.894	0.940	1.453	0.116	1.855
Panel B: Liquidity Measure (%)						
PS liquidity measure		-3.356	-2.572	6.678	-6.546	1.236
Panel C: Fung-Hsieh Factors (%)						
MKT		0.447	1.155	4.653	-2.330	3.480
SMB		0.191	-0.175	3.739	-2.150	2.320
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

Table 2
Why focus on exposure to the equity market?

This table reports ratios of adjusted R^2s from the single-factor model to the Fung-Hsieh seven-factor model. Time-series regressions of the single-factor and seven-factor models are as follows.

$$r_{p,t+1} = \alpha_p + \beta_{p,1} MKT_{t+1} + \varepsilon_{p,t+1}, \qquad t = 0,...,T-1.$$

$$r_{p,t+1} = \alpha_p + \beta_{p,1} MKT_{t+1} + \beta_{p,2} SMB_{t+1} + \beta_{p,3} YLDCHG_{t+1} + \beta_{p,4} BAAMTSY_{t+1} + \beta_{p,5} PTFSBD_{t+1} + \beta_{p,6} PTFSFX_{t+1} + \beta_{p,7} PTFSCOM_{t+1} + \varepsilon_{p,t+1}.$$

$r_{p,t+1}$ is the excess return in month t+1 on the equal-weighted portfolio of all funds, hedge funds, funds-of-funds, or hedge funds in each strategy category. The independent variables include the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-year treasury constant maturity yield (BAAMTSY), and three trend-following factors PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). The *t*-statistics are heteroskedasticity consistent.

Portfolio	β_1 (1-factor model)	*t*-stat.	Adj. R^2 (1-factor model)	Ratio of R^2s (1-factor/7-factor)
All funds	0.236	14.10	0.554	0.88
Hedge funds	0.259	16.80	0.626	0.90
Fund of funds	0.193	9.02	0.382	0.80
Convertible arbitrage	0.159	4.99	0.248	0.52
Emerging market	0.388	14.50	0.402	0.92
Equity market neutral	0.069	5.49	0.181	0.99
Event driven	0.205	10.00	0.498	0.76
Global macro	0.137	5.81	0.172	0.51
Long/short equity	0.336	16.30	0.657	0.90
Multi-strategy	0.174	12.70	0.469	0.91

Table 3
Liquidity timing at the portfolio level

This table presents results from the liquidity timing regression model:

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

where $r_{p,t+1}$ is the excess return in month t+1 on the equal-weighted portfolio of all funds, hedge funds, funds-of-funds, or hedge funds in each strategy category. The independent variables include the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-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 $\bar{L}_m$ is the mean level of market liquidity. The coefficient γ measures liquidity timing ability. Heteroskedasticity-consistent t-statistics are reported in parentheses.

Portfolio	α	β_1	γ	β_2	β_3	β_4	β_5x100	β_6x100	β_7x100	R^2
All funds	0.371	0.223	0.624	0.087	-0.469	-1.030	-0.742	0.411	0.721	0.634
	(5.51)	(12.70)	(3.29)	(5.14)	(-1.69)	(-2.36)	(-1.75)	(1.14)	(1.35)	
Hedge Funds	0.510	0.250	0.643	0.093	-0.289	-0.745	-0.632	0.405	0.564	0.701
	(8.09)	(15.40)	(3.50)	(5.88)	(-1.12)	(-1.74)	(-1.59)	(1.14)	(1.13)	
Fund of funds	0.133	0.171	0.570	0.079	-0.817	-1.570	-1.060	0.493	1.130	0.481
	(1.70)	(8.43)	(2.70)	(3.55)	(-2.34)	(-2.97)	(-2.05)	(1.22)	(1.85)	
Convertible arbitrage	0.414	0.083	0.357	0.032	-1.320	-3.810	-0.947	-0.185	-0.430	0.481
	(5.25)	(3.28)	(1.37)	(1.39)	(-4.55)	(-5.79)	(-2.13)	(-0.53)	(-0.71)	
Emerging market	0.563	0.362	0.957	0.118	-0.142	-1.650	-1.010	-0.082	1.520	0.440
	(3.51)	(10.50)	(2.17)	(2.80)	(-0.25)	(-2.12)	(-0.98)	(-0.10)	(1.22)	
Equity market neutral	0.512	0.067	0.235	0.004	-0.408	-0.522	-0.216	0.249	-0.070	0.185
	(10.60)	(5.24)	(1.45)	(0.31)	(-2.16)	(-1.65)	(-0.79)	(1.05)	(-0.20)	
Event driven	0.478	0.168	0.698	0.064	-0.193	-1.950	-1.440	0.311	-0.140	0.667
	(8.23)	(10.50)	(3.75)	(3.91)	(-0.63)	(-4.60)	(-3.66)	(1.02)	(-0.37)	
Global macro	0.382	0.163	0.560	0.026	-1.440	-0.802	-0.690	2.200	1.650	0.350
	(4.14)	(6.50)	(1.70)	(1.21)	(-3.35)	(-1.32)	(-0.91)	(3.96)	(1.93)	
Long/short equity	0.564	0.338	0.662	0.134	-0.051	0.049	-0.316	0.470	0.573	0.728
	(7.38)	(15.90)	(2.69)	(7.40)	(-0.17)	(0.09)	(-0.64)	(1.08)	(1.01)	
Multi-strategy	0.487	0.166	0.626	0.052	-0.429	-1.120	-0.002	0.222	0.401	0.537
	(8.04)	(12.10)	(3.68)	(2.23)	(-1.86)	(-2.84)	(0.01)	(0.66)	(0.83)	

Table 4
Liquidity timing in low market-liquidity conditions

This table presents results of hedge funds' liquidity timing ability in low market-liquidity conditions based on the following regression model:

$$r_{p,t+1} = \alpha_p + \beta_{p,1}MKT_{t+1} + \gamma_{p,1}MKT_{t+1}D(Low\_LIQ)_{t+1} + \beta_{p,2}SMB_{t+1} + \beta_{p,3}YLDCHG_{t+1} + \beta_{p,4}BAAMTSY_{t+1}$$
$$+ \beta_{p,5}PTFSBD_{t+1} + \beta_{p,6}PTFSFX_{t+1} + \beta_{p,7}PTFSCOM_{t+1} + \varepsilon_{p,t+1}.$$

where $r_{p,t+1}$ is the excess return in month t+1 on the equal-weighted portfolio of all funds, hedge funds, funds-of-funds, or hedge funds in each strategy category. The independent variables include the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-year treasury constant maturity yield (BAAMTSY), and three trend-following factors PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). $D(Low\_LIQ)_{t+1}$ is a dummy variable indicating whether market liquidity in month t+1 belongs to the bottom quintile over the sample period. The coefficient γ_1 measures liquidity timing ability during low market-liquidity months. The last column reports the ratio of γ_1 to the average market beta. The t-statistics are heteroskedasticity consistent.

Portfolio	γ_1	t-stat	γ_1/*avg. beta (%)*
All funds	-0.100	-3.54	-48.78
Hedge funds	-0.096	-3.71	-41.37
Funds of funds	-0.106	-3.09	-68.39
Convertible arbitrage	-0.009	-0.19	-8.11
Emerging market	-0.125	-2.35	-37.20
Equity market neutral	-0.048	-1.93	-81.36
Event driven	-0.097	-3.63	-65.99
Global macro	-0.110	-2.92	-75.34
Long/short equity	-0.105	-2.97	-32.71
Multi-strategy	-0.084	-3.46	-56.38

Table 5
Liquidity timing in volatile vs. stable market conditions

This table presents results of hedge funds' liquidity timing ability during volatile and stable periods separately based on the following regression model:

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

where $r_{p,t+1}$ is the excess return in month t+1 on the equal-weighted portfolio of all funds, hedge funds, funds-of-funds, or hedge funds in each strategy category. The independent variables include the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-year treasury constant maturity yield (BAAMTSY), and three trend-following factors PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). The coefficient γ measures liquidity timing ability. We define volatile periods as the years when annualized market volatility is higher than the median level, and stable periods as the years when market volatility is lower than the median level. Accordingly, the volatile years are 1997–2002 and 2008–2009, whereas stable years are 1994–1996 and 2003–2007. The *t*-statistics are heteroskedasticity consistent.

	Volatile periods		Stable periods	
Portfolio	γ	*t*-stat	γ	*t*-stat
All funds	0.595	2.79	-0.394	-0.68
Hedge funds	0.600	2.96	-0.303	-0.57
Funds of funds	0.566	2.37	-0.674	-1.00
Convertible arbitrage	0.288	1.07	-0.617	-0.90
Emerging market	0.977	2.11	-0.597	-0.48
Equity market neutral	0.289	1.61	-0.615	-1.43
Event driven	0.670	3.38	-0.380	-0.90
Global macro	0.461	1.59	0.220	0.32
Long/short equity	0.567	2.09	-0.272	-0.45
Multi-strategy	0.611	3.28	-0.126	-0.22

Table 6
Cross-sectional distribution of *t*-statistics for liquidity timing coefficients across individual funds

This table presents the cross-sectional distribution of *t*-statistics for liquidity-timing coefficients. 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), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-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 significance level of a one-sided test is in parentheses.

		Percentage of the funds							
	# of funds	t≤-2.326 (1%)	t≤-1.960 (2.5%)	t≤-1.645 (5%)	t≤-1.282 (10%)	t≥1.282 (10%)	t≥1.645 (5%)	t≥1.960 (2.5%)	t≥2.326 (1%)
All funds	4874	2.59	4.53	7.22	12.19	21.30	13.93	9.48	5.99
Hedge funds	2883	2.71	4.65	7.15	11.72	23.03	15.05	10.44	6.49
Fund of funds	1991	2.41	4.37	7.33	12.86	18.78	12.31	8.09	5.27
Convertible arbitrage	122	1.64	3.28	4.92	9.02	18.03	13.93	7.38	4.92
Emerging market	292	3.08	4.11	8.90	14.73	20.21	15.41	9.25	4.11
Equity market neutral	200	4.50	7.00	10.00	14.50	18.50	8.50	5.50	3.50
Event driven	385	2.60	3.64	4.42	9.61	30.91	22.34	16.88	11.95
Global macro	163	1.84	2.45	4.29	9.20	14.11	7.36	4.29	2.45
Long/short equity	1298	2.77	5.09	7.09	11.09	24.73	16.02	11.17	7.09
Multi-strategy	284	2.11	5.99	10.21	15.85	20.07	12.32	9.51	5.99

Table 7
Bootstrap analysis of liquidity timing

This table presents 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 include the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-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 1000.

			Bottom t-statistics for $\hat{\gamma}$				Top t-statistics for $\hat{\gamma}$			
	# of funds		1%	3%	5%	10%	10%	5%	3%	1%
All funds	4874	t-stat	-2.93	-2.23	-1.90	-1.43	1.93	2.45	2.78	3.50
		p-value	0.19	0.63	0.91	1.00	0.00	0.00	0.00	0.00
Hedge funds	2883	t-stat	-2.97	-2.27	-1.91	-1.40	1.99	2.49	2.85	3.62
		p-value	0.17	0.42	0.85	1.00	0.00	0.00	0.00	0.00
Fund of funds	1991	t-stat	-2.85	-2.16	-1.86	-1.45	1.83	2.38	2.70	3.32
		p-value	0.47	0.85	0.88	0.84	0.00	0.00	0.00	0.00
Convertible arbitrage	122	t-stat	-2.66	-2.08	-1.73	-1.23	1.83	2.36	2.54	2.88
		p-value	0.48	0.68	0.86	0.95	0.05	0.09	0.17	0.28
Emerging market	292	t-stat	-2.97	-2.38	-1.92	-1.60	1.91	2.31	2.39	3.70
		p-value	0.45	0.31	0.61	0.24	0.00	0.02	0.30	0.03
Equity market neutral	200	t-stat	-4.08	-3.57	-2.31	-1.65	1.54	2.13	2.62	3.00
		p-value	0.02	0.00	0.05	0.21	0.45	0.22	0.10	0.47
Event driven	385	t-stat	-3.25	-2.27	-1.62	-1.28	2.50	3.06	3.35	3.63
		p-value	0.08	0.39	0.99	0.99	0.00	0.00	0.00	0.01
Global macro	163	t-stat	-3.17	-1.88	-1.51	-1.25	1.48	1.94	2.29	2.36
		p-value	0.24	0.96	1.00	0.98	0.64	0.61	0.52	0.92
Long/short equity	1298	t-stat	-2.93	-2.28	-1.97	-1.35	2.07	2.54	2.86	3.83
		p-value	0.42	0.45	0.42	1.00	0.00	0.00	0.00	0.00
Multi-strategy	284	t-stat	-2.93	-2.26	-2.16	-1.66	1.93	2.42	2.69	3.40
		p-value	0.54	0.50	0.15	0.15	0.00	0.01	0.03	0.09

Table 8
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 10 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 holding periods of *K* months. The table reports the out-of-sample seven-factor alphas (in percent per month) estimated from the post-ranking returns. Heteroskedasticity-consistent *t*-statistics are reported in parentheses.

	Panel A: All funds				Panel B: Hedge funds			
	K=3	6	9	12	*K*=3	6	9	12
Portfolio 1 (top timers)	0.627	0.661	0.662	0.629	0.727	0.794	0.804	0.766
	(3.90)	(4.46)	(4.69)	(4.50)	(3.82)	(4.59)	(4.94)	(4.80)
Portfolio 2	0.359	0.367	0.357	0.345	0.367	0.373	0.369	0.366
	(3.64)	(3.89)	(3.79)	(3.67)	(3.49)	(3.84)	(3.81)	(3.81)
Portfolio 3	0.305	0.313	0.310	0.297	0.391	0.399	0.384	0.385
	(3.59)	(3.91)	(3.91)	(3.72)	(4.51)	(4.98)	(4.97)	(4.91)
Portfolio 4	0.261	0.279	0.276	0.267	0.364	0.365	0.392	0.375
	(3.33)	(3.71)	(3.71)	(3.59)	(4.88)	(5.20)	(5.62)	(5.28)
Portfolio 5	0.250	0.227	0.233	0.232	0.362	0.338	0.342	0.347
	(3.63)	(3.17)	(3.30)	(3.25)	(5.42)	(5.13)	(5.38)	(5.46)
Portfolio 6	0.241	0.240	0.237	0.242	0.321	0.305	0.307	0.302
	(2.96)	(2.91)	(2.92)	(3.00)	(4.66)	(4.31)	(4.38)	(4.32)
Portfolio 7	0.218	0.228	0.224	0.239	0.293	0.317	0.299	0.313
	(2.38)	(2.54)	(2.44)	(2.59)	(2.38)	(2.65)	(3.28)	(3.38)
Portfolio 8	0.227	0.232	0.236	0.252	0.298	0.317	0.325	0.345
	(2.32)	(2.29)	(2.30)	(2.48)	(2.88)	(3.09)	(3.08)	(3.41)
Portfolio 9	0.277	0.246	0.262	0.266	0.377	0.327	0.341	0.336
	(2.73)	(2.26)	(2.38)	(2.45)	(3.57)	(2.90)	(3.03)	(3.02)
Portfolio 10 (bottom timers)	0.319	0.281	0.253	0.262	0.444	0.396	0.348	0.360
	(1.96)	(1.77)	(1.63)	(1.73)	(2.32)	(2.13)	(1.92)	(2.02)
Spread (Port. 1– Port. 10)	0.308	0.380	0.409	0.367	0.283	0.398	0.456	0.406
	(1.83)	(2.51)	(2.90)	(2.72)	(1.31)	(2.06)	(2.52)	(2.35)

Table 9
Controlling for market return-timing and volatility-timing

This table presents results from the liquidity timing regression model that controls for market return-timing and volatility-timing:

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

where $r_{p,t+1}$ is the excess return in month t+1 on the equal-weighted portfolio of all funds, hedge funds, funds-of-funds, or hedge funds in each strategy category. The independent variables include the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-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 $\bar{L}_m$ is the mean level of market liquidity. *Vol* is the market volatility measured by the CBOE VIX. The coefficients γ, λ, and δ measure liquidity timing, market timing, and volatility timing ability, respectively. Heteroskedasticity-consistent t-statistics are reported in parentheses.

Portfolio	α	β_1	γ	λ	δ	β_2	β_3	β_4	β_5x100	β_6x100	β_7x100	R^2
All funds	0.455	0.284	0.623	-0.608	-1.140	0.116	-0.620	-1.460	-1.040	0.529	0.337	0.660
	(4.98)	(13.00)	(2.65)	(-1.84)	(-2.21)	(3.92)	(-1.78)	(-2.28)	(-1.88)	(1.24)	(0.54)	
Hedge funds	0.591	0.326	0.605	-0.500	-0.974	0.130	-0.548	-1.480	-1.060	0.538	0.134	0.722
	(6.53)	(15.00)	(2.48)	(-1.53)	(-1.93)	(4.21)	(-1.68)	(-2.28)	(-1.92)	(1.21)	(0.22)	
Fund of funds	0.191	0.199	0.599	-0.602	-1.130	0.086	-0.903	-1.820	-1.100	0.574	0.888	0.500
	(1.99)	(8.79)	(2.61)	(-1.84)	(-2.03)	(3.19)	(-2.26)	(-2.80)	(-1.93)	(1.35)	(1.35)	
Convertible arbitrage	0.316	0.069	0.212	0.568	2.700	0.023	-2.400	-6.100	-1.130	-0.459	-0.599	0.642
	(2.89)	(2.43)	(0.57)	(1.36)	(2.16)	(0.74)	(-4.98)	(-6.25)	(-1.67)	(-1.16)	(-0.77)	
Emerging market	0.823	0.548	1.640	-1.480	-0.742	0.161	-0.010	-2.810	-2.350	0.288	0.026	0.476
	(2.86)	(8.37)	(2.17)	(-1.41)	(-0.44)	(2.23)	(-0.01)	(-1.74)	(-1.28)	(0.23)	(0.01)	
Equity market neutral	0.583	0.076	0.317	-0.338	0.011	0.008	-0.544	-0.693	-0.195	0.215	-0.102	0.252
	(9.58)	(4.54)	(1.53)	(-1.76)	(0.03)	(0.42)	(-2.41)	(-1.63)	(-0.61)	(0.81)	(-0.26)	
Event driven	0.615	0.186	0.845	-0.708	-0.169	0.069	-0.234	-2.360	-1.580	0.301	-0.307	0.713
	(8.62)	(9.56)	(3.89)	(-3.09)	(-0.38)	(3.42)	(-0.64)	(-3.97)	(-3.78)	(0.89)	(-0.70)	
Global macro	0.332	0.247	0.287	0.043	-2.530	0.036	-1.970	-1.780	-1.560	3.040	1.320	0.369
	(2.43)	(7.87)	(0.87)	(0.12)	(-3.52)	(1.16)	(-4.32)	(-2.96)	(-1.73)	(3.62)	(1.39)	
Long/short equity	0.638	0.439	0.355	-0.432	-1.850	0.201	-0.449	-0.770	-0.651	0.591	0.081	0.756
	(6.54)	(17.40)	(1.96)	(-1.13)	(-2.97)	(5.02)	(-1.30)	(-1.05)	(-1.07)	(1.15)	(0.12)	
Multi-strategy	0.499	0.192	0.779	-0.299	-0.134	0.057	-0.575	-1.530	-0.239	0.214	0.214	0.548
	(5.81)	(10.70)	(3.75)	(-1.34)	(-0.32)	(1.88)	(-1.87)	(-2.67)	(-0.56)	(0.53)	(0.36)	

Table 10
Fund leverage and liquidity timing

This table reports the liquidity-timing coefficient (γ) estimated from the regression 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 an equal-weighted portfolio of individual funds in month t+1. We construct portfolios of funds that do not use leverage (3381 funds) and that use leverage (3321), respectively. The independent variables include the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-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. Heteroskedasticity-consistent t-statistics are reported in parentheses.

Portfolio	No use of leverage	Use of leverage
All funds	0.653	0.598
	(3.44)	(3.14)
Hedge funds	0.688	0.609
	(3.78)	(3.21)
Fund of funds	0.573	0.587
	(2.77)	(2.68)
Convertible arbitrage	0.499	0.269
	(1.83)	(1.00)
Emerging market	0.883	0.989
	(1.92)	(2.31)
Equity market neutral	0.269	0.203
	(1.43)	(1.04)
Event driven	0.755	0.635
	(3.85)	(3.31)
Global macro	0.647	0.537
	(1.63)	(1.75)
Long/short equity	0.626	0.692
	(2.77)	(2.64)
Multi-strategy	0.841	0.541
	(4.41)	(3.06)

Table 11
Controlling for a funding-liquidity factor: the TED spread

This table presents results from the liquidity timing regression model that includes the interaction of a funding-liquidity factor (TED) with the market return:

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

where $r_{p,t+1}$ is the excess return in month t+1 on the equal-weighted portfolio of all funds, hedge funds, funds-of-funds, or hedge funds in each strategy category. The independent variables include the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-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. *TED* is the spread between the three-month LIBOR and the three-month T-bill rate. The coefficient γ measures liquidity timing ability. Heteroskedasticity-consistent t-statistics are reported in parentheses.

Portfolio	α	β_1	γ	λ	β_2	β_3	β_4	β_5x100	β_6x100	β_7x100	R^2
All funds	0.368	0.224	0.615	-0.567	0.086	-0.512	-1.130	-0.735	0.400	0.712	0.632
	(5.51)	(13.10)	(3.21)	(-0.47)	(5.03)	(-1.68)	(-2.08)	(-1.74)	(1.11)	(1.33)	
Hedge funds	0.501	0.252	0.614	-1.970	0.090	-0.438	-1.100	-0.606	0.367	0.530	0.703
	(8.09)	(16.30)	(3.39)	(-1.77)	(5.62)	(-1.67)	(-2.30)	(-1.55)	(1.05)	(1.06)	
Fund of funds	0.139	0.170	0.589	1.250	0.081	-0.723	-1.340	-1.070	0.517	1.150	0.480
	(1.78)	(8.35)	(2.76)	(0.90)	(3.66)	(-1.90)	(-2.07)	(-2.06)	(1.26)	(1.89)	
Convertible arbitrage	0.419	0.082	0.371	0.925	0.033	-1.250	-3.650	-0.959	-0.167	-0.414	0.479
	(5.26)	(3.31)	(1.43)	(0.41)	(1.43)	(-3.91)	(-4.01)	(-2.16)	(-0.48)	(-0.70)	
Emerging market	0.541	0.367	0.891	-4.390	0.113	-0.473	-2.440	-0.950	-0.167	1.440	0.442
	(3.37)	(10.70)	(2.12)	(-2.42)	(2.68)	(-0.81)	(-2.88)	(-0.94)	(-0.20)	(1.17)	
Equity market neutral	0.518	0.066	0.254	1.270	0.006	-0.313	-0.295	-0.232	0.274	-0.048	0.187
	(10.80)	(5.12)	(1.59)	(1.29)	(0.42)	(-1.65)	(-0.80)	(-0.86)	(1.13)	(-0.14)	
Event driven	0.478	0.168	0.698	0.018	0.064	-0.192	-1.950	-1.440	0.312	-0.139	0.665
	(8.28)	(10.50)	(3.65)	(0.02)	(3.91)	(-0.58)	(-3.71)	(-3.64)	(1.02)	(-0.37)	
Global macro	0.353	0.169	0.470	-6.060	0.019	-1.890	-1.890	-0.610	2.080	1.550	0.383
	(4.00)	(7.48)	(1.91)	(-4.41)	(0.92)	(-4.59)	(-3.25)	(-0.83)	(3.88)	(1.87)	
Long/short equity	0.551	0.341	0.622	-2.700	0.131	-0.255	-0.435	-0.280	0.418	0.526	0.731
	(7.42)	(17.00)	(2.57)	(-1.86)	(7.14)	(-0.82)	(-0.72)	(-0.57)	(0.98)	(0.93)	
Multi-strategy	0.490	0.166	0.638	0.751	0.053	-0.372	-0.985	-0.012	0.236	0.414	0.536
	(8.02)	(12.10)	(3.76)	(0.72)	(2.27)	(-1.54)	(-2.06)	(-0.03)	(0.70)	(0.86)	

Table 12
Investor redemptions, fund flows, and liquidity timing

This table reports the liquidity-timing coefficient (γ) estimated from the regression 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 an equal-weighted portfolio of individual funds in month t+1. We construct portfolios of funds that have redemption frequency as quarterly or longer (3171 funds), that impose redemption notice period equal or longer than 30 days (4553 funds) or 60 days (1841 funds), that have fund-flow volatility lower than the median level (3283 funds), and that have fund-flow volatility lower than the 25% level (1644 funds). The independent variables include the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-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. Heteroskedasticity-consistent t-statistics are reported in parentheses.

Portfolio	Redemption frequency ≥ a quarter	Redemption notice period ≥ 30 days	Redemption notice period ≥ 60 days	Lower 50% in fund-flow volatility	Lower 25% in fund-flow volatility
All funds	0.714	0.613	0.630	0.634	0.628
	(3.79)	(3.52)	(3.65)	(3.21)	(3.15)
Hedge funds	0.763	0.624	0.627	0.658	0.625
	(4.28)	(3.73)	(3.77)	(3.50)	(3.32)
Fund of funds	0.576	0.589	0.638	0.592	0.634
	(2.80)	(2.90)	(3.12)	(2.69)	(2.81)
Convertible arbitrage	0.363	0.353	0.324	0.470	0.460
	(1.41)	(1.29)	(1.27)	(2.14)	(2.76)
Emerging market	1.151	0.867	0.706	0.962	1.020
	(2.46)	(1.94)	(1.58)	(2.20)	(2.27)
Equity market neutral	0.763	0.318	0.472	0.505	0.584
	(3.09)	(1.68)	(2.31)	(2.66)	(2.06)
Event driven	0.786	0.697	0.645	0.662	0.682
	(3.09)	(3.78)	(3.38)	(3.58)	(3.63)
Global macro	0.612	0.476	0.679	0.815	0.721
	(1.64)	(2.08)	(1.80)	(2.38)	(1.54)
Long/short equity	0.732	0.673	0.669	0.620	0.574
	(3.07)	(2.83)	(2.93)	(2.63)	(2.39)
Multi-strategy	0.794	0.505	0.607	0.778	0.769
	(3.82)	(3.29)	(3.06)	(4.32)	(3.35)

Table 13
Evidence of liquidity timing from small funds

This table presents the liquidity-timing coefficient (γ) estimated from the regression 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 an equal-weighted portfolio of individual funds in month t+1. We construct portfolios of funds with assets under management smaller than \$50 million (3333 funds), \$100 million (4571 funds), and \$150 million (5208 funds), as well as 3056 funds that have lower-than-median R^2 (of 0.36) in a regression against returns of the portfolio of top 10% largest funds. The independent variables include the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-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. Heteroskedasticity-consistent t-statistics are reported in parentheses.

Portfolio	AUM < \$50 mil	AUM < \$100 mil.	AUM < \$150 mil.	Low R^2 to large funds
All funds	0.588	0.603	0.621	0.538
	(3.02)	(3.10)	(3.19)	(3.26)
Hedge funds	0.634	0.628	0.641	0.562
	(3.43)	(3.37)	(3.45)	(3.30)
Fund of funds	0.483	0.531	0.561	0.404
	(2.21)	(2.46)	(2.59)	(2.53)
Convertible arbitrage	0.258	0.296	0.302	0.278
	(0.88)	(1.03)	(1.10)	(1.00)
Emerging market	0.920	0.929	0.918	0.871
	(2.16)	(2.11)	(2.10)	(2.41)
Equity market neutral	0.350	0.271	0.285	0.211
	(1.95)	(1.61)	(1.68)	(1.44)
Event driven	0.649	0.611	0.662	0.636
	(3.28)	(3.24)	(3.52)	(3.46)
Global macro	0.583	0.577	0.541	0.316
	(1.94)	(2.24)	(2.11)	(1.07)
Long/short equity	0.650	0.634	0.665	0.623
	(2.76)	(2.65)	(2.76)	(2.64)
Multi-strategy	0.652	0.692	0.677	0.655
	(3.03)	(3.27)	(3.26)	(4.53)

Table 14
Conditional liquidity timing model

This table presents results from the conditional liquidity timing model:

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

where $r_{p,t+1}$ is the excess return in month t+1 on the equal-weighted portfolio of all funds, hedge funds, funds-of-funds, or hedge funds in each strategy category. The independent variables include the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-year treasury constant maturity yield (BAAMTSY), and three trend-following factors PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). The regression also includes the interaction terms between market returns and four lagged conditioning variables: three-month T-bill rate (tb), a term premium (term), a credit premium (credit), and the dividend yield of the S&P 500 index (dy). $L_{m,t+1}$ is the market liquidity measure in month t+1, and $\bar{L}_m$ is the mean level of market liquidity. The coefficient γ measures liquidity timing ability. Heteroskedasticity-consistent t-statistics are reported in parentheses.

Portfolio	α	β_1	γ	δ_1	δ_2	δ_3	δ_4	β_2	β_3	β_4	β_5x100	β_6x100	β_7x100	R^2
All funds	0.337	0.243	0.564	1.560	0.018	-9.700	7.310	0.084	-0.377	-1.370	-0.561	0.394	0.710	0.664
	(5.07)	(15.60)	(3.21)	(0.80)	(0.01)	(-2.18)	(2.04)	(4.93)	(-1.49)	(-3.30)	(-1.44)	(1.07)	(1.39)	
Hedge funds	0.478	0.268	0.571	1.450	0.165	-9.070	7.730	0.091	-0.176	-1.020	-0.450	0.389	0.557	0.721
	(7.63)	(18.60)	(3.30)	(0.76)	(0.06)	(-1.96)	(2.22)	(5.63)	(-0.77)	(-2.49)	(-1.20)	(1.06)	(1.16)	
Fund of funds	0.100	0.191	0.526	1.480	-0.151	-9.680	6.400	0.076	-0.751	-1.940	-0.889	0.478	1.120	0.513
	(1.28)	(9.78)	(2.60)	(0.61)	(-0.05)	(-1.89)	(1.46)	(3.43)	(-2.23)	(-3.75)	(-1.90)	(1.17)	(1.89)	
Convertible arbitrage	0.373	0.099	0.184	0.920	-0.469	-9.360	17.000	0.035	-0.964	-3.710	-0.625	-0.244	-0.382	0.506
	(4.91)	(4.89)	(0.66)	(0.40)	(-0.15)	(-1.26)	(3.52)	(1.41)	(-3.12)	(-5.23)	(-1.43)	(-0.72)	(-0.68)	
Emerging market	0.561	0.367	1.050	0.146	-0.690	-1.490	-5.160	0.114	-0.308	-1.980	-1.070	-0.072	1.490	0.434
	(3.40)	(9.58)	(2.36)	(0.03)	(-0.11)	(-0.16)	(-0.54)	(2.71)	(-0.54)	(-2.50)	(-1.02)	(-0.08)	(1.19)	
Equity market neutral	0.480	0.083	0.143	1.390	-0.180	-7.970	10.200	0.004	-0.227	-0.674	-0.004	0.213	-0.063	0.247
	(9.72)	(6.66)	(0.94)	(0.96)	(-0.09)	(-2.40)	(3.43)	(0.27)	(-1.16)	(-2.24)	(-0.01)	(0.92)	(-0.19)	
Event driven	0.445	0.185	0.647	-3.060	-3.070	-12.400	8.320	0.066	-0.072	-1.840	-1.220	0.295	-0.027	0.674
	(7.43)	(11.40)	(3.25)	(-1.57)	(-0.98)	(-2.52)	(2.02)	(3.84)	(-0.24)	(-4.24)	(-3.19)	(0.94)	(-0.07)	
Global macro	0.376	0.173	0.517	-0.230	1.540	-5.810	-1.080	0.026	-1.470	-0.907	-0.669	2.250	1.650	0.350
	(4.30)	(6.51)	(1.93)	(-0.08)	(0.37)	(-0.88)	(-0.18)	(1.16)	(-3.57)	(-1.57)	(-0.88)	(4.02)	(1.95)	
Long/short equity	0.516	0.366	0.520	3.140	1.280	-13.300	12.900	0.132	0.160	-0.374	-0.026	0.448	0.544	0.764
	(7.00)	(20.60)	(2.37)	(1.35)	(0.40)	(-2.28)	(2.96)	(7.22)	(0.60)	(-0.77)	(-0.05)	(1.02)	(1.04)	
Multi-strategy	0.464	0.176	0.698	-1.930	-4.290	-6.270	3.390	0.050	-0.441	-1.240	0.103	0.166	0.468	0.543
	(7.33)	(12.10)	(3.78)	(-1.09)	(-1.83)	(-1.53)	(0.98)	(2.08)	(-1.91)	(-3.09)	(0.30)	(0.48)	(0.95)	

Table 15
Liquidity timing using the liquidity-factor-augmented model

This table presents results from the liquidity timing regression model augmented with a market liquidity risk factor:

$$r_{p,t+1} = \alpha_p + \beta_{p,1}MKT_{t+1} + \gamma_p MKT_{t+1}(L_{m,t+1} - \bar{L}_m) + \beta_{p,2}SMB_{t+1} + \beta_{p,3}YLDCHG_{t+1} + \beta_{p,4}BAAMTSY_{t+1} + \beta_{p,5}PTFSBD_{t+1} + \beta_{p,6}PTFSFX_{t+1} + \beta_{p,7}PTFSCOM_{t+1} + \beta_{p,8}Liq_{t+1} + \varepsilon_{p,t+1},$$

where $r_{p,t+1}$ is the excess return in month t+1 on the equal-weighted portfolio of all funds, hedge funds, funds-of-funds, or hedge funds in each strategy category. The independent variables include the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-year treasury constant maturity yield (BAAMTSY), three trend-following factors PFTSBD (bond), PFTSFX (currency), PFTSCOM (commodity), and the market liquidity risk factor (Liq). $L_{m,t+1}$ is the market liquidity measure in month t+1, and $\bar{L}_m$ is the mean level of market liquidity. The coefficient γ measures liquidity timing ability. Heteroskedasticity-consistent t-statistics are reported in parentheses.

Portfolio	α	β_1	γ	β_2	β_3	β_4	β_5x100	β_6x100	β_7x100	β_8	R^2
ALL	0.383	0.211	0.519	0.088	-0.506	-0.964	-0.741	0.488	0.621	0.029	0.647
	(6.02)	(12.00)	(3.10)	(5.34)	(-2.00)	(-2.32)	(-1.78)	(1.31)	(1.21)	(2.98)	
ALL-FoF	0.522	0.239	0.541	0.094	-0.325	-0.680	-0.631	0.480	0.465	0.028	0.713
	(8.75)	(14.60)	(3.33)	(6.13)	(-1.36)	(-1.63)	(-1.63)	(1.31)	(0.97)	(3.24)	
Fund of funds	0.144	0.160	0.471	0.080	-0.852	-1.500	-1.060	0.566	1.040	0.027	0.492
	(1.94)	(7.75)	(2.45)	(3.64)	(-2.64)	(-2.98)	(-2.06)	(1.37)	(1.74)	(2.31)	
Convertible arbitrage	0.410	0.087	0.393	0.032	-1.310	-3.840	-0.947	-0.211	-0.396	-0.010	0.480
	(5.26)	(3.36)	(1.49)	(1.38)	(-4.50)	(-5.89)	(-2.13)	(-0.60)	(-0.67)	(-0.84)	
Emerging market	0.590	0.336	0.721	0.121	-0.224	-1.510	-1.000	0.091	1.290	0.064	0.458
	(3.77)	(9.65)	(1.88)	(2.96)	(-0.41)	(-1.96)	(-1.02)	(0.10)	(1.07)	(3.11)	
Equity market neutral	0.513	0.067	0.231	0.004	-0.410	-0.519	-0.216	0.252	-0.074	0.001	0.181
	(10.70)	(5.00)	(1.37)	(0.31)	(-2.17)	(-1.64)	(-0.79)	(1.05)	(-0.22)	(0.14)	
Event driven	0.488	0.158	0.613	0.065	-0.222	-1.900	-1.430	0.374	-0.221	0.023	0.677
	(9.09)	(10.20)	(3.32)	(4.11)	(-0.81)	(-4.64)	(-3.77)	(1.20)	(-0.60)	(2.07)	
Global macro	0.394	0.151	0.457	0.027	-1.470	-0.737	-0.688	2.270	1.550	0.028	0.360
	(4.35)	(5.91)	(1.68)	(1.27)	(-3.49)	(-1.21)	(-0.93)	(4.06)	(1.86)	(2.21)	
Long/short equity	0.578	0.325	0.540	0.136	-0.094	0.126	-0.314	0.560	0.456	0.033	0.739
	(7.97)	(15.00)	(2.43)	(7.68)	(-0.33)	(0.24)	(-0.64)	(1.27)	(0.83)	(3.11)	
Multi-strategy	0.494	0.159	0.561	0.052	-0.452	-1.080	-0.001	0.270	0.338	0.018	0.544
	(8.45)	(11.20)	(3.55)	(2.26)	(-2.05)	(-2.84)	(-0.01)	(0.78)	(0.72)	(1.85)	

Table 16
Distinguishing liquidity timing from liquidity reaction

This table presents the results from the following regression model:

$$r_{p,t+1} = \alpha_p + \beta_{p,1}MKT_{t+1} + \gamma_p MKT_{t+1}\tilde{L}_{m,t+1} + \varphi_p MKT_{t+1}(L_{m,t} - \bar{L}_m) + \beta_{p,2}SMB_{t+1} + \beta_{p,3}YLDCHG_{t+1} + \beta_{p,4}BAAMTSY_{t+1} + \beta_{p,5}PTFSBD_{t+1} + \beta_{p,6}PTFSFX_{t+1} + \beta_{p,7}PTFSCOM_{t+1} + \beta_{p,8}Liq_{t+1} + \varepsilon_{p,t+1},$$

where $r_{p,t+1}$ is the excess return in month t+1 on the equal-weighted portfolio of all funds, hedge funds, funds-of-funds, or hedge funds in each strategy category. The independent variables include the market excess return (MKT), a size factor (SMB), change in the 10-year treasury constant maturity yield (YLDCHG), change in the Moody's Baa yield less 10-year treasury constant maturity yield (BAAMTSY), and three trend-following factors PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). $\tilde{L}_{m,t+1}$ is market liquidity innovation in month t+1 derived from an AR(1) process, and $L_{m,t}$ is one-month lagged market liquidity in month t. The coefficients γ and φ measure liquidity timing ability and liquidity reaction, respectively. Heteroskedasticity-consistent t-statistics are reported in parentheses.

Portfolio	α	β_1	γ	φ	β_2	β_3	β_4	β_5x100	β_6x100	β_7x100	R^2
All funds	0.382	0.261	0.503	0.725	0.081	-0.347	-0.998	-0.592	0.453	0.792	0.653
	(5.92)	(12.50)	(2.59)	(4.15)	(4.63)	(-1.25)	(-2.48)	(-1.37)	(1.29)	(1.58)	
Hedge funds	0.520	0.283	0.551	0.624	0.088	-0.185	-0.717	-0.496	0.438	0.625	0.715
	(8.61)	(14.90)	(2.98)	(3.86)	(5.38)	(-0.74)	(-1.86)	(-1.23)	(1.26)	(1.33)	
Fund of funds	0.148	0.218	0.391	0.907	0.073	-0.662	-1.530	-0.885	0.553	1.220	0.513
	(1.96)	(8.89)	(1.75)	(4.33)	(3.17)	(-1.86)	(-3.01)	(-1.70)	(1.43)	(2.15)	
Convertible arbitrage	0.419	0.102	0.312	0.369	0.030	-1.260	-3.800	-0.865	-0.166	-0.394	0.484
	(5.32)	(3.84)	(1.12)	(1.12)	(1.24)	(-4.17)	(-5.97)	(-1.96)	(-0.47)	(-0.66)	
Emerging market	0.575	0.373	0.867	0.256	0.115	-0.099	-1.640	-0.934	-0.069	1.550	0.436
	(3.59)	(8.36)	(1.90)	(0.67)	(2.71)	(-0.17)	(-2.13)	(-0.90)	(-0.08)	(1.26)	
Equity market neutral	0.513	0.098	0.222	0.549	0.001	-0.319	-0.499	-0.095	0.272	-0.019	0.239
	(11.40)	(5.80)	(1.37)	(3.67)	(0.06)	(-1.71)	(-1.72)	(-0.35)	(1.15)	(-0.06)	
Event driven	0.482	0.186	0.676	0.346	0.061	-0.138	-1.930	-1.340	0.321	-0.105	0.673
	(8.60)	(9.95)	(3.61)	(1.95)	(3.63)	(-0.45)	(-4.70)	(-3.49)	(1.06)	(-0.29)	
Global macro	0.397	0.198	0.399	0.709	0.021	-1.310	-0.772	-0.555	2.250	1.720	0.364
	(4.38)	(7.28)	(1.43)	(2.55)	(0.97)	(-3.25)	(-1.36)	(-0.71)	(4.22)	(2.11)	
Long/short equity	0.576	0.386	0.533	0.904	0.128	0.101	0.088	-0.128	0.521	0.660	0.748
	(8.09)	(15.60)	(2.26)	(4.27)	(6.83)	(0.35)	(0.19)	(-0.25)	(1.24)	(1.24)	
Multi-strategy	0.495	0.188	0.551	0.427	0.048	-0.358	-1.100	0.096	0.244	0.444	0.545
	(8.30)	(10.80)	(2.97)	(2.80)	(2.04)	(-1.50)	(-2.91)	(0.27)	(0.73)	(0.95)	

Table 17
Economic value of liquidity reaction: Evidence from out-of-sample alphas

This table presents the out-of-sample alphas for the portfolios consisting of hedge funds to various extents of reacting to past market liquidity conditions. In each month since January 1997, we form 10 portfolios based on hedge funds' liquidity reaction coefficients estimated from the past 36 months (i.e., formation period is 36 months) and then hold these portfolios for different holding periods of *K* months. The table reports the out-of-sample seven-factor alphas (in percent per month) estimated from the post-ranking returns. Heteroskedasticity-consistent *t*-statistics are reported in parentheses.

	Panel A: All funds				Panel B: All funds excluding FOFs			
	K=3	6	9	12	*K*=3	6	9	12
Portfolio 1 (top reactors)	0.364	0.353	0.387	0.428	0.446	0.432	0.469	0.503
	(1.87)	(1.83)	(2.08)	(2.44)	(2.06)	(2.06)	(2.31)	(2.61)
Portfolio 2	0.306	0.294	0.305	0.317	0.424	0.415	0.459	0.491
	(2.34)	(2.33)	(2.43)	(2.60)	(3.17)	(3.17)	(3.52)	(3.87)
Portfolio 3	0.271	0.291	0.286	0.280	0.353	0.366	0.351	0.341
	(2.77)	(3.07)	(3.04)	(3.04)	(3.30)	(3.64)	(3.43)	(3.59)
Portfolio 4	0.274	0.256	0.252	0.251	0.369	0.386	0.390	0.384
	(3.21)	(3.08)	(3.11)	(3.15)	(4.07)	(4.56)	(5.07)	(5.03)
Portfolio 5	0.292	0.283	0.261	0.262	0.400	0.367	0.347	0.358
	(3.87)	(3.69)	(3.44)	(3.47)	(5.87)	(5.32)	(5.10)	(5.18)
Portfolio 6	0.246	0.242	0.248	0.240	0.324	0.342	0.357	0.356
	(3.25)	(3.25)	(3.35)	(3.16)	(4.97)	(5.19)	(5.34)	(5.27)
Portfolio 7	0.263	0.276	0.279	0.277	0.364	0.376	0.378	0.355
	(3.28)	(3.55)	(3.62)	(3.51)	(4.80)	(5.38)	(5.46)	(4.97)
Portfolio 8	0.257	0.264	0.266	0.252	0.366	0.367	0.362	0.343
	(2.90)	(3.10)	(3.19)	(2.98)	(4.55)	(4.72)	(4.68)	(4.38)
Portfolio 9	0.311	0.312	0.316	0.317	0.384	0.385	0.362	0.340
	(3.67)	(3.69)	(3.67)	(3.55)	(4.47)	(4.49)	(4.18)	(3.60)
Portfolio 10 (bottom reactors)	0.498	0.489	0.440	0.413	0.526	0.510	0.462	0.445
	(4.15)	(4.08)	(3.70)	(3.39)	(3.99)	(3.82)	(3.51)	(3.35)
Spread (Port. 1– Port. 10)	-0.134	-0.136	-0.052	0.015	-0.079	-0.078	0.007	0.058
	(-0.73)	(-0.80)	(-0.34)	(0.11)	(-0.39)	(-0.43)	(0.04)	(0.36)

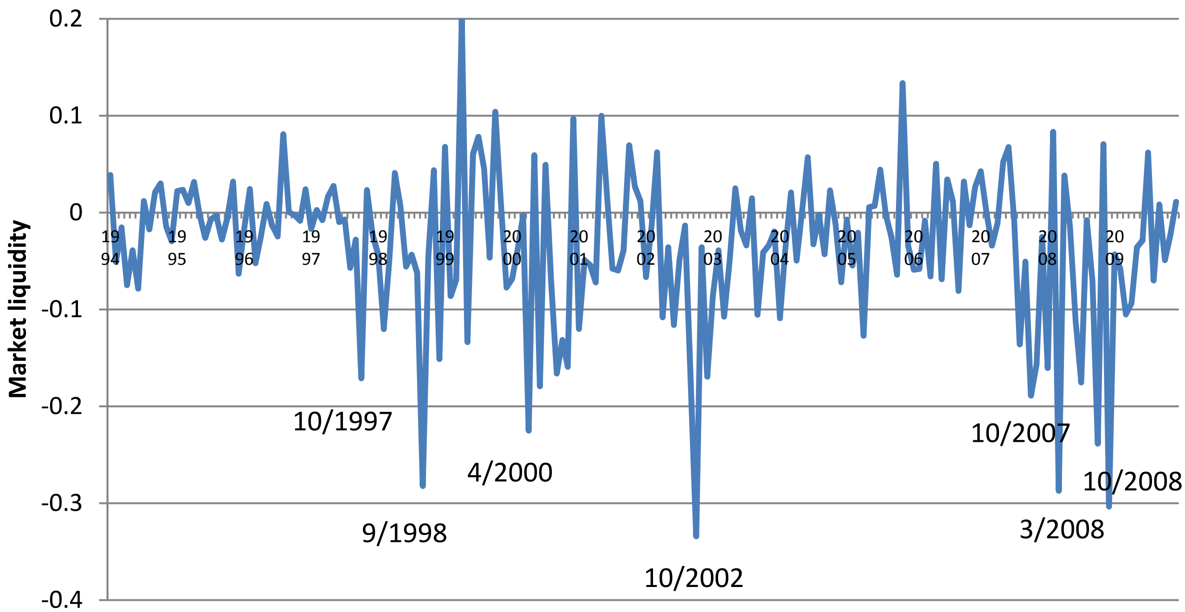
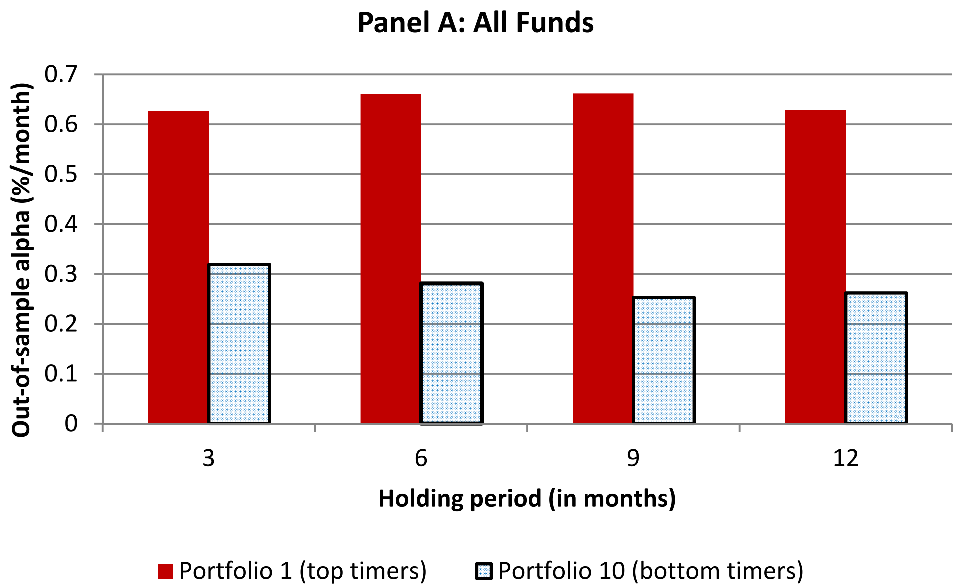


Figure 1
Time series of monthly market liquidity

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 the LTCM), April 2000 (the burst of internet bubble), October 2002 (when the market dropped to a five-year low), October 2007 (the beginning of 2008 financial crisis), March 2008 (the Bear Sterns' bankruptcy) and October 2008 (the collapse of Lehman Brother). Anecdotal evidence from financial press has identified these months in which liquidity was extremely low.



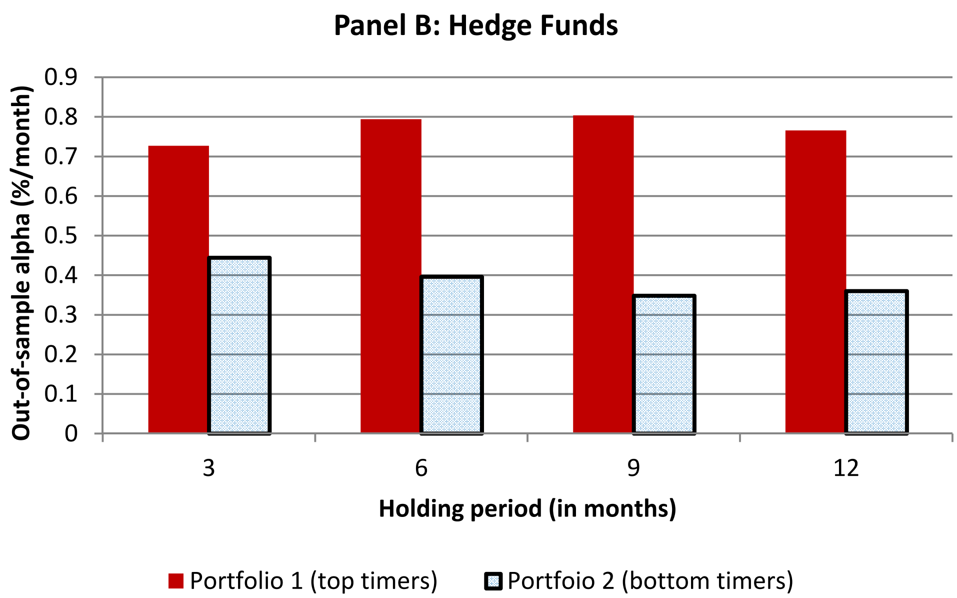


Figure 2
Out-of-sample alphas for the portfolios of top vs. bottom timing funds

This figure plots out-of-sample alphas for the portfolios consisting of top vs. bottom timing funds for a holding period of 3, 6, 9, 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 sample funds, including individual hedge funds and funds-of-funds, while Panel B for hedge funds.

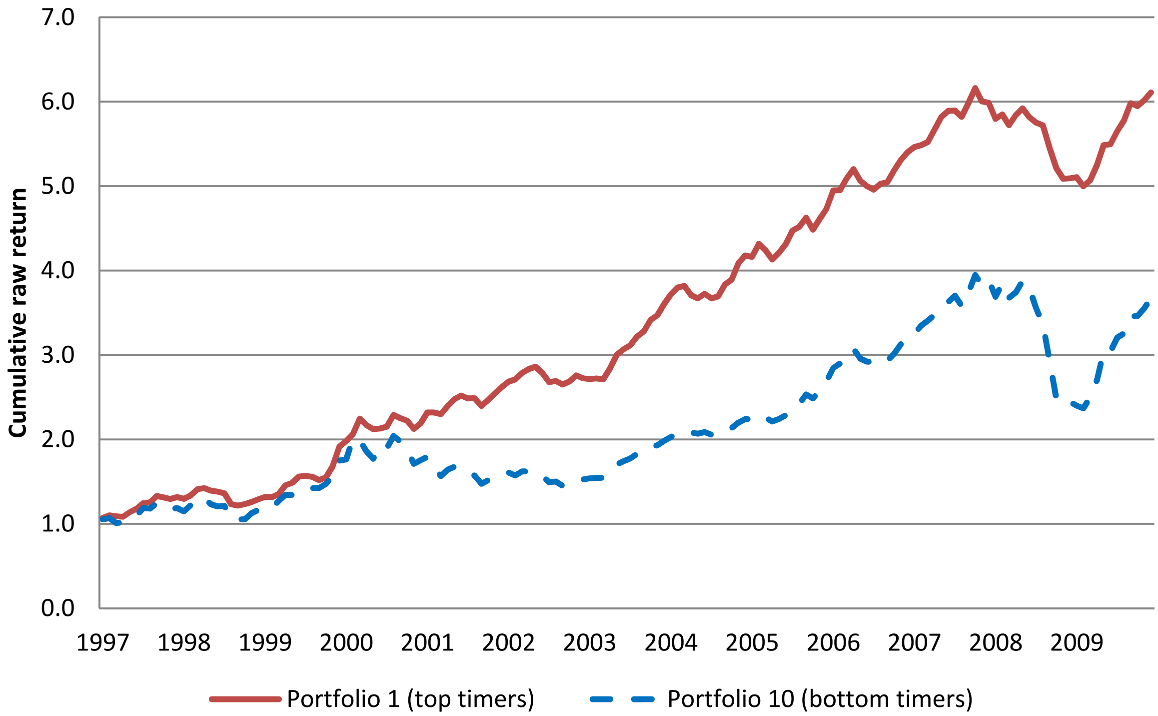


Figure 3
Cumulative returns of investing in top vs. bottom timing funds

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.