Can Hedge Funds Time Market Liquidity?*

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July 16, 2010

* We thank Andres Almazan, David Bates, Nicole Boyson, Mila Getmansky, Will Goetzmann, Narasimhan Jegadeesh, Bill Kracaw, Lubos Pastor, Andrew Patton, Tarun Ramadorai, Clemens Sialm, Melvyn Teo and seminar participants at Oxford University, Peking University, University of Massachusetts at Amherst, Virginia Tech, the 2010 Florida State University Finance Conference, and the 2010 China International Conference in Finance for helpful comments. Lubomir Petrasek provided excellent research assistance. Research support from the BNP Paribas Hedge Fund Center at SMU and our respective universities is gratefully acknowledged. The views and opinions expressed in this article are those of the authors only, and do not necessarily represent the views and opinions of AlphaSimplex Group, or any of its affiliates and employees.
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Abstract

This paper examines how hedge funds manage their market risk by responding to changes in aggregate liquidity conditions. Using a large sample of equity-oriented hedge funds during the period of 1994-2008, we find strong evidence that hedge-fund managers possess the ability to time market liquidity at both the style category level and the individual fund level. They increase (decrease) their portfolios' market exposure when equity-market liquidity is high (low). This liquidity timing ability is asymmetric, and depends on market liquidity conditions: hedge funds reduce their portfolios' market exposure significantly when market liquidity is extremely low, but they do not increase their market exposure when market liquidity is unusually high. Finally, we find that investing in top liquidity timing funds can generate economically significant profits. Our results persist after controlling for alternative benchmark models, various data biases, and return-timing and volatility-timing abilities.

Keywords: Hedge funds, liquidity risk, market liquidity timing, liquidity crisis, bootstrap, investment value

JEL Classification: G23, G11

1. Introduction

The attempt to generate economic profits through the timing of changes in market conditions such as returns and volatilities is well known.[1] By anticipating such changes, hedge-fund managers can adjust their portfolio exposures up or down to exploit them. In this paper, we address a related but previously unexplored question: can hedge funds time market liquidity? In other words, can fund managers deliver abnormal performance by increasing (decreasing) their portfolios' market exposure when market liquidity is high (low)?

The impact of market-wide liquidity shocks on hedge-fund performance and funding availability is now well-established. Liquidity played a major role in the 1998 Long-Term Capital Management (LTCM) debacle, in which a global flight-to-quality caused LTCM to liquidate large positions in the face of margin calls, triggering a market-wide liquidity crisis. The recent financial crisis also involves liquidity, beginning with the meltdown of the subprime-mortgage market in 2006–2007, which created a dramatic "liquidity squeeze" in the hedge-fund industry that generated cascading losses, forced liquidations, and investor redemptions.[2] Such liquidity-based transmission channels have been documented in a recent study by Boyson, Stahel, and Stulz (2010), who show that large declines in stock-market liquidity can cause contagion in hedge-fund returns. Therefore, liquidity risk management is critical for hedge funds and other financial institutions.

If fund managers can correctly forecast market liquidity, they can adjust their portfolio exposures accordingly to avoid or reduce losses during liquidity squeezes. Hedge funds provide a natural platform to study managers' liquidity timing ability. By trading frequently and moving quickly in between positions, hedge funds are a major provider of liquidity to the markets.[3] However, because they are typically leveraged and trade complex instruments, hedge funds are

[1] See, for example, Treynor and Mazuy (1966), Henriksson and Merton (1981), Ferson and Schadt (1996), Busse (1999), Bollen and Busse (2001), Jiang, Yao, and Yu (2007), and Chen and Liang (2007).

[2] In 2008 alone, total investor redemptions reached nearly $400 billion, and the assets under management by the hedge fund industry have shrunk from a peak of $2.2 trillion in mid-2008 to $1.3 trillion by the end of 2008. See "Hedge Fund Liquidation," *New York Law Journal*, March 2, 2009.

[3] It is estimated that hedge fund related trading accounts for 25% of the NYSE trading volume. See Black (2004).

more easily affected by changes in market liquidity. While the dynamic trading strategies employed by hedge funds suggest time-varying risk exposures, it is not clear whether hedge funds pro-actively change market exposures when market liquidity changes.

Using a large sample of equity-oriented hedge funds from the Lipper TASS database from 1994 to 2008, we find strong evidence that hedge funds exhibit liquidity timing ability at the portfolio level, i.e., fund managers adjust their portfolios' market exposure according to the aggregate liquidity of equity markets. In particular, when market liquidity deviates from its mean level by one standard deviation, we estimate that a typical hedge fund changes its market exposure by approximately 17%. Moreover, liquidity timing ability is asymmetric; hedge-fund managers reduce their portfolios' market exposure significantly when market liquidity is extremely low, but do not increase their market exposure when market liquidity is unusually high. Our evidence is robust to controls for alternative benchmark models, various data biases, and return-timing and volatility-timing abilities.

At the individual fund level, we find that 14% of our sample funds have significant liquidity timing ability (at the 5% significance level), and using bootstrap re-sampling techniques, we confirm that these findings are not attributable to pure luck or sampling variation. We also investigate the cross-sectional relationship between various fund characteristics and liquidity timing ability, and find that a fund's liquidity timing ability is positively associated with the quality of auditing services, leverage usage, and the managers' personal capital co-investment, but negatively associated with management fees. Finally, we gauge the performance implications of funds with superior liquidity timing ability by measuring the average return of a portfolio of top liquidity timers, which is 17 to 45 basis points greater than the average monthly return of an equally weighted portfolio of all hedge funds, depending on the rebalancing interval.

The remaining of the paper is organized as follows. In Section 2, we provide a brief literature review, and present our method for testing hedge funds' liquidity timing ability in Section 3. Section 4 contains a description of the hedge-fund data, the market liquidity measure, and benchmark factors that we use in our empirical analysis. In Section 5, we report evidence of liquidity timing ability at the style category level. Section 6 contains similar results at the individual fund level, and also includes evidence on the profitability of investing in top liquidity timers. We conclude in Section 7.

2. Literature Review

Several recent papers have considered the liquidity risk related to hedge funds. Brunnermeier and Pedersen (2009) model an asset's market liquidity and a trader's funding liquidity jointly, and stress that the two types of liquidity can mutually reinforce each other and even cause market-wide liquidity to dry up. Aragon and Strahan (2009) use the event of the Lehman bankruptcy as an exogenous liquidity shock and show that the Lehman-connected hedge funds lost funding liquidity and failed twice as much as other funds. Thus, although hedge funds, in general, provide market liquidity through heavy trading, the liquidity of hedge-fund portfolios largely depends on market liquidity conditions. Sadka (2009) shows that market liquidity risk explains a significant portion of cross-sectional hedge-fund returns. Khandani and Lo (2009) use cross-sectional regression techniques and autocorrelation-based measures of liquidity to estimate the liquidity premium in a broad sample of equities, mutual funds, and hedge funds. Teo (2010) finds that, for liquid hedge funds (i.e., funds imposing less strict redemption terms), investor redemptions negatively affect fund performance in that funds with high net inflows subsequently outperform funds with low net inflows.

Despite its obvious importance, the liquidity risk of hedge funds has received considerably less attention than systemic, operational, and market risk.[4] Our paper seeks to remedy this gap with its exclusive focus on the ability of hedge-fund managers to time the market-wide liquidity. It should be emphasized that we examine the market-wide liquidity instead of the liquidity of assets held by hedge funds or hedge funds' funding liquidity.

[4] Chan et al. (2005) study systemic risk and conclude that systemic risk is rising while the hedge fund industry is heading into a challenging period of lower expected returns. Brown et al. (2008a, 2008b) examine operational risk and find that this risk is related to leverage, manager ownership, and conflict of interest issues. They also find that operational risk can largely contribute to the failure of hedge funds even after controlling for investment risk.

Second, we present new evidence of hedge funds' time-varying market exposure. Fung and Hsieh (1997) show that hedge funds employ dynamic trading strategies that differ from those used by mutual funds. Agarwal and Naik (2004) find that hedge-fund returns exhibit exposures to factors built on the payoffs of market index options. Chen and Liang (2007) illustrate that the market exposure of self-claimed market-timing hedge funds varies with changes in market return and volatility. Fung, Hsieh, Naik, and Ramadorai (2008) document a structural change in risk exposures of funds of funds over time. Bollen and Whaley (2009) highlight the importance of recognizing hedge-fund risk dynamics in evaluating fund performance. Patton and Ramadorai (2009) characterize time-varying risks using high frequency conditional information. Our work extends this literature by showing that hedge funds adjust their market exposure according to the aggregate liquidity conditions.

Finally, the findings of our paper suggest another source of hedge-fund performance. Given the documented superior performance of hedge funds (e.g., Ackermann, McEnally and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), Liang (1999), and Kosowski, Naik, and Teo (2007)), it is important to identify the sources of fund performance since the findings can help hedge-fund investors and funds of hedge-fund managers locate their investment opportunities. Extant studies find a positive association between hedge-fund performance and incentive fees (Ackermann, McEnally, and Ravenscraft, 1999), redemption restrictions (Aragon, 2007), managerial incentives (Agarwal, Daniel, and Naik, 2009), and the proximity of hedge funds to their investment regions (Teo, 2009). Our results suggest that hedge funds can enhance performance through timing market liquidity.

3. Research Design

In this section we describe the methods to estimate the liquidity timing ability of hedge-fund managers. In Section 3.1, we define the measure of aggregate market liquidity used to test liquidity timing. To control for the effects of other systematic factors, we adopt the Fung and Hsieh (2004) seven-factor model as our benchmark model in Section 3.2. Our liquidity timing test is outlined in Section 3.3, and we derive a nonparametric test for individual funds using bootstrap methods in Section 3.4.

3.1. Measuring Market Liquidity

Liquid markets are generally viewed as those which allow rapid trading with the least impact on asset prices. We use the equity market liquidity measure developed by Pastor and Stambaugh (2003)—a cross-sectional average of individual-stock liquidity measures—to perform our empirical tests. For each stock i listed on the NYSE and AMEX in each month t, we measure its liquidity using its daily returns and volume by estimating the following regression:

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

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 Pastor-Stambaugh liquidity measure, which is the coefficient $\eta_{i,t}$, measures the expected return reversal for a given dollar volume, controlling for lagged stock return. When a stock's liquidity is low, $\eta_{i,t}$ is expected to be negative and large in magnitude. This measure can be interpreted as volume-related price reversals attributable to liquidity effects, and is based on the assumption that the lower the liquidity of the stock, the greater the expected price reversal for a given amount of order flow.[5]

Two filters are imposed in computing the liquidity measure in each month: (1) A stock should have at least 15 observations in any given month; and (2) a stock should have a share price between \$5 and \$1,000 at the end of the previous month. The Pastor-Stambaugh aggregate market liquidity measure in month t is then calculated as the average across the individual stocks' liquidity measures for that month:

$$\overline{\eta}_t = \frac{1}{N_t}\sum_{i=1}^{N_t}\eta_{i,t} \tag{2}$$

[5] The intuition for such a measure is straightforward. According to Campbell, Grossman and Wang (1993), risk-averse market makers accommodate order flow from liquidity motivated traders and are compensated with a higher expected return. In (1), order flow is approximated by signed trading volume according to the contemporaneous excess return of stock i. A larger order flow is expected to be associated with a greater compensation; hence liquidity-induced effects on the stock's expected return are expected to be greater if current volume is higher.

where N_t is the number of stocks available in month t. Since the coefficient $\eta_{i,t}$ measures an individual firm's liquidity cost of trading $1 million of the stock, the market liquidity measure can be interpreted as the cost of a $1 million trade distributed equally across all sample stocks. To take into account the fact that the size of the equity market increases over time, we scale each month's liquidity measure by the total size of the market at the beginning of the CRSP daily sample:

$$L_{m,t} = (m_t / m_1) * \overline{\eta_t} \tag{3}$$

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 and aggregated market liquidity measure, $L_{m,t}$, is used in the subsequent analysis to evaluate hedge funds' liquidity timing ability. To check the robustness of our results, in Section 5.6 we also use an alternative market liquidity measure developed by Hasbrouck (2009).

3.2. Factors in the Benchmark Model

We employ the seven-factor model proposed by Fung and Hsieh (2004) as our benchmark model for evaluating hedge-fund liquidity timing ability. Among these factors are two equity-oriented, two bond-oriented, and three primitive trend-following strategy (PTFS) factors. These factors include: (1) the excess return on the Center for Research in Security Prices (CRSP) value-weighted market portfolio of all NYSE, AMEX and NASDAQ stocks (MKT); (2) the Fama-French size factor (SMB);[6] (3) the change in the constant-maturity yield on the U.S. 10-year Treasury bond (YLDCHG); (4) the change in the credit spread between Moody's Baa and U.S. 10-year Treasury bonds (BAAMTSY); (5) the return of PTFS bond lookback straddles (PTFSBD); (6) the return of PTFS currency lookback straddles (PTFSFX); and (7) the return of PTFS commodity lookback straddles (PTFSCOM).[7] We use our sample of fund returns to

[6] We consider alternative size factors, such as the spread between the Wilshire Small Cap 1750 index return and the Wilshire Large Cap 750 index return. All our inferences are unchanged.

[7] We thank David Hsieh for making the trend-following (PTFS) factor data available on his website http://faculty.fuqua.duke.edu/~dah7/. See Fung and Hsieh (2001) for a description of these factors.

estimate the seven-factor model, and confirm Fung and Hsieh (2004)'s finding that these factors explain a significant portion of the variation in hedge-fund returns.

3.3. Tests of Liquidity Timing Ability

Among the Fung and Hsieh seven factors, the most important factor for equity-oriented hedge funds is the excess return on the market portfolio (MKT). For the equally-weighted portfolio consisting of all 3,156 sample funds, we show that the adjusted R^2 from the one-factor model with the MKT factor is 0.59, which is 85% of the adjusted R^2 of 0.69 from the full seven-factor model (these results are reported in Table 2 and will be discussed more fully in Section 4). In fact, the ratios of R^2s between the one- and seven-factor models are above 70% for portfolios of all investment strategies except for Global Macro. These results suggest that the majority of hedge funds have large exposures to equity market risk. Since market returns and market liquidity are correlated, we focus our tests on the ability of hedge-fund managers to adjust their portfolio's market exposure through timing equity-market liquidity. This test is implemented with and without controlling hedge funds' ability to directly time the market.

The starting point of our liquidity timing analysis is the Fung and Hsieh (2004) seven-factor model for hedge-fund returns. We assume that hedge funds' exposure to the market (MKT) is time varying and we specify hedge-fund returns as the following:

$$\begin{aligned} r_{p,t} &= \alpha_p + \beta_{p,1,t-1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t \\ &\quad + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \upsilon_{p,t}, \end{aligned} \tag{4}$$

where $r_{p,t}$ is excess return on fund p in month t. The fund's market exposure $\beta_{p,1,t-1}$ is chosen by the manager at $t-1$ and varies with her forecast about market liquidity at t if the manager times market liquidity. In the spirit of Shanken (1990) and Ferson and Schadt (1996), we use a Taylor series expansion and specify a fund's time-varying market beta as a linear function of the difference between market liquidity and its time-series mean:

$$\beta_{p,1,t-1} = \beta_{p,1} + \gamma_p (L_{m,t} - \overline{L}_m + u_t), \tag{5}$$

where $L_{m,t}$ is market liquidity in month t and $\overline{L}_m$ is the mean level of market liquidity, $\beta_{p,1}$ is the fund's average market beta over time, and u_t is a zero-mean independent noise term which is orthogonal to each risk factor. Following the market timing literature (e.g., Admati et al., 1986; Ferson and Schadt, 1996), we assume that a liquidity timer sets the market beta at *t-1* based on her market-liquidity forecast, equal to the future market liquidity plus noise. While market beta can be a non-linear function of market liquidity, the linear specification captures the first-order effect of timing ability. Combining Equations (4) and (5) and letting the noise in market-liquidity forecast join the error term, we obtain the liquidity timing model:

$$\begin{aligned} r_{p,t} &= \alpha_p + \beta_{p,1} MKT_t + \gamma_p (L_{m,t} - \bar{L}_m) MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t \\ &\quad + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t}. \end{aligned} \tag{6}$$

The liquidity-timing measure is the coefficient γ from the above model. We perform our main test of hedge-fund liquidity timing ability using both portfolio-level and individual fund-level returns.

3.4. Bootstrap Analysis for Fund-Level Tests

To capture liquidity timing ability at the individual fund level, we need to make inferences on the cross-sectional statistics (e.g., the top 10th percentile) of individual-fund timing measures. However, standard parametric inferences do not apply for several reasons. First, hedge-fund returns of a given strategy are highly correlated thus the timing measures are not independent in the cross section. Next, for majority of our sample funds, the distribution of the residuals from the liquidity-timing model and the distribution of estimated timing coefficients are non-normal. Finally, the number of hedge funds in the sample changes over time and many funds do not have complete return histories, making it difficult to estimate the covariance matrix of fund returns. Hence, to assess the significance of cross-sectional statistics of liquidity timing measures, we employ a bootstrap analysis as in Bollen and Busse (2001), Kosowski, Timmermann, White, and Wermers (2006), Jiang, Yao and Yu (2007), Kosowski, Naik and Teo (2007), and Fama and French (2010). In particular, we implement the following bootstrap procedure to assess the statistical significance of specific liquidity timing percentiles and corresponding *t*-statistics for individual funds:

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

$$r_{p,t} = \hat{\alpha}_p + \hat{\beta}_{p,1} MKT_t + \hat{\beta}_{p,2} SMB_t + \hat{\beta}_{p,3} YLDCHG_t + \hat{\beta}_{p,4} BAAMTSY_t + \hat{\beta}_{p,5} PTFSBD_t + \hat{\beta}_{p,6} PTFSFX_t + \hat{\beta}_{p,7} PTFSCOM_t + \hat{\varepsilon}_{p,t}, \quad (7)$$

and store the estimated coefficients { $\hat{a}_p$, $\hat{\beta}_{p,1}$, …….} and the time series of residuals { $\hat{\varepsilon}_{p,t}$, $t=1$, …..T_p}, 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 { $\hat{\varepsilon}^b_{p,t}$ }, where b is the index for the bootstrap iteration, b=1,2,…,B. Then calculate the monthly excess returns of a pseudo fund that, by construction, has no liquidity timing ability (e.g., $\hat{\gamma}_p = 0$ in (6)):

$$r^b_{p,t} = \hat{\alpha}_p + \hat{\beta}_{p,1} MKT_t + \hat{\beta}_{p,2} SMB_t + \hat{\beta}_{p,3} YLDCHG_t + \hat{\beta}_{p,4} BAAMTSY_t + \hat{\beta}_{p,5} PTFSBD_t + \hat{\beta}_{p,6} PTFSFX_t + \hat{\beta}_{p,7} PTFSCOM_t + \hat{\varepsilon}^b_{p,t}, \quad (8)$$

Step 3: Estimate the liquidity timing model of (6) using the pseudo-fund returns for fund p.

Step 4: Repeat Steps 1–3 for all 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 the timing coefficients and their t-statistics by repeating Steps 1–4. In our bootstrap analysis, we set the number of iterations B to be 1,000. Although the pseudo fund has no liquidity timing ability, the estimated timing coefficient based on its returns can differ from zero due to sampling variation. Using the bootstrap procedure, we evaluate the distribution of timing measures of the actual sample funds against that of pseudo funds to calculate the appropriate empirical p-values.

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 the pseudo funds, and determine whether the liquidity timing coefficients for our sample funds are due to random sampling variation or fund managers' timing ability. To conserve space, we focus exclusively on the *t*-statistics in our discussion of the bootstrap results in Section 6.

For robustness, we implement three 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 (6) in Step 1, and then remove the liquidity timing term (i.e., the interaction term between market return and market liquidity condition) in Step 2 to ensure the pseudo funds possess no liquidity timing skill.

4. The Data

We use two databases to assess hedge-fund liquidity timing ability: the Lipper TASS hedge-fund database and, for our aggregate liquidity measure, the CRSP daily return file. TASS constitutes one of the most comprehensive hedge-fund databases and provides data on both active and defunct funds beginning in 1994. The hedge-fund literature has identified several biases associated with hedge-fund databases, including self-selection bias, survivorship bias, and backfilling bias (e.g., Brown, Goetzmann and Ibbotson (1999), Fung and Hsieh (2000), and Liang (2000)). To minimize the impact of these biases, we select the sample funds based on a few criteria as explained below.

4.1 TASS Data

We start our sample from 1994 and analyze both live and defunct funds. The inclusion of defunct funds mitigates the impact of survivorship bias. To address the concern that database vendors may backfill funds' performance when new funds are added—instead of only including their returns going forward—we exclude the first 12 months of return data for each fund. This criterion ensures that our findings are robust to backfilling bias.[8] Finally, we include funds that report monthly net-of-fee returns in U.S. dollars and have assets under management (AUM) of at

[8] We do not use the dates when hedge funds were added to TASS data as the cutoff point since funds may be in other databases before they were transferred to TASS.

least \$10 million. Smaller funds with AUM less than \$10 million are of less concern from an institutional investor's perspective, and they have less impact on the market as well.[9] Our sample period extends from January 1994 through September 2008, and the selection criteria yields 3,156 equity-oriented hedge funds, comprised of 1,703 live funds and 1,453 defunct funds.

TASS divides funds into the following 11 categories designed to reflect the primary hedge-fund investment styles: convertible arbitrage, dedicated short bias, event driven, emerging markets, equity market neutral, fixed income arbitrage, funds of funds, global macro, long-short equity, managed futures, and multi-strategy. Since our focus is on hedge-fund managers' ability to time equity market liquidity, we exclude fixed-income arbitrage and managed-futures funds from our sample, and also drop funds in the dedicated short-bias strategy because this category contains only a small number of funds. As a result, there are eight categories in our analyses.

We construct equally-weighted portfolios of: (1) all 3,156 hedge funds (ALL); (2) all funds excluding funds of hedge funds (ALL-FoF); (3) funds of hedge funds (FoF) only; and (4) funds in each of the style categories. We evaluate hedge funds' liquidity timing ability at the portfolio level as well as at the individual-fund level.

4.2 Summary Statistics

Panel A of Table 1 provides the descriptive statistics of the portfolios' returns. Over the period from 1994 to 2008, all hedge funds, including funds of hedge funds, realized an average return of 0.89% per month (about 11% per year) with a monthly standard deviation of 1.98%. Typical hedge funds have higher average monthly return (0.98%) in comparison to funds of hedge funds (0.65%), attributed to the double-fee structure of funds of hedge funds (See Brown, Goetzmann, and Liang (2004)). Among the different hedge-fund strategies, long/short equity has the highest average monthly return of 1.11% while convertible arbitrage delivers the lowest average monthly return of 0.62%.

[Insert Table 1 about here.]

[9] For robustness, we also consider other fund size criteria such as \$5 million, and the empirical inferences are unaffected.

According to Getmansky, Lo and Makarov (2004), the first-order autocorrelation of a hedge fund's returns can be used as a proxy for the illiquidity of a fund's assets. Panel A also reports the first-order autocorrelation of each portfolio's monthly returns. It reveals that convertible arbitrage, event driven, and emerging market strategies exhibit a relatively high level of first-order autocorrelation in monthly returns. This result is consistent with the well-documented fact that these strategies invest in relatively illiquid securities. We call these strategies "illiquid strategies". In contrast, the strategies of global macro and long/short equity have relatively low first-order autocorrelations, implying that they invest in relatively liquid securities.[10] We call these strategies "liquid strategies". The remaining three strategies such as equity market neutral, fund of funds, and multi-strategy carry intermediate-level first-order autocorrelations, which makes sense as fund of funds and multi-strategy funds have diversified positions.

Panel B of Table 1 reports summary statistics of our monthly aggregate liquidity measure. The mean (median) level of market liquidity is −3.22% (−2.38%) per month over the period of 1994-2008, indicating a 3.22% average liquidity cost. To confirm that our measure of market liquidity is similar to previous measures, we overlay our time series for the 1962–2008 period on the top of the Pastor and Stambaugh (2003) measure which runs from 1962 to 2000 and find consistent patterns.[11] The correlation between our liquidity measure and the Pastor and Stambaugh (2003) measure is 0.98 for the overlapping time period from 1962 to 2000.

Summary statistics and the correlation matrix of the Fung-Hsieh seven factors are presented in Panels C and D, respectively. The average market portfolio return is 0.77% per month over the 1994–2008 period, with a standard deviation of 4.25%; the lowest monthly market excess return is −15.77% in August 1998, and the highest is 8.39% in April 2001.

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[10] However, global macro funds can invest in securities of both developed and developing countries. In the latter case, fund assets could be illiquid.

[11] Data of the original Pastor and Stambaugh (2003) liquidity measure are available on the Wharton Research Data Services (WRDS).

4.3 Adjusted R^2s

In Table 2, we present ratios of adjusted R^2s from the one- to seven-factor models for hedge-fund returns. The market factor (MKT) stands out as the most significant; for all hedge funds excluding funds of funds, the adjusted R^2 from the one-factor model is 0.64, which is 87% of the adjusted R^2 from the seven-factor model. For funds of funds, the adjusted R^2 from the one- and seven-factor models are 0.36 and 0.49, respectively. These results motivate us to study liquidity timing through changes in the equity market beta rather than changes in risk exposures to the other factors.

[Insert Table 2 about here.]

5. 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 the overall portfolio as well as the portfolios of various hedge-fund strategies. Then we examine liquidity timing ability in extreme market liquidity conditions. Finally, we check the robustness of the results by employing alternative benchmark models, controlling for the impact of illiquid holdings, and so forth.

5.1. Liquidity Timing Ability

Table 3 presents the evidence based on the liquidity-timing model in (6). Overall, hedge funds seem to be able to adjust their market exposure to changes in market liquidity. The liquidity timing coefficient of the equally-weighted portfolio of all funds (ALL) is 0.81 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, from the seven-factor model, which is 0.31.[12] If the market liquidity is above (below) its mean level by one standard deviation (i.e., 0.066 from Table 1), then a typical hedge fund would increase (decrease) its market exposure accordingly by about 0.053 (0.81×0.066), which is approximately 17% of the fund's overall market beta based on the seven-factor model. The result for the portfolio of all hedge funds

[12] To conserve space, we do not report detailed estimation results from the seven-factor model.

excluding funds of hedge funds (ALL-FoF) is qualitatively similar: the timing coefficient is 0.91 with a t-statistic of 3.51. Table 3 also reveals that the liquidity timing coefficient is positive and significant for all strategies except for equity market neutral. These results provide strong evidence that hedge funds have liquidity timing ability and that liquidity timing is economically significant. In particular, the three illiquid strategies we identified in Section 4—convertible arbitrage, event driven, and emerging markets—are among the strategies with both statistically and economically significant timing coefficients at the 5% level. This indicates that there is a need to manage liquidity risk in these illiquid strategies and the managers of these strategies seem to be able to do so. The lack of liquidity timing with equity-market-neutral funds is also intuitive, since such funds bear minimal exposure to the market and hence have little incentive to time market liquidity.

[Insert Table 3 about here.]

In the Appendix, we consider whether hedge-fund managers react to lagged market liquidity conditions by replacing the market liquidity regressor of time t in (6) with its one-period lagged value. We find that hedge funds do react to recent market liquidity conditions by changing their market exposure (see Table A.1). However, in contrast to the results of Table 3, hedge funds holding liquid assets tend to react to *past* market liquidity strongly, whereas funds with illiquid holdings seem to time market liquidity actively, due to their need to manage liquidity risk.

5.2. Liquidity Timing in Extreme Market-Liquidity Conditions

If a hedge-fund manager possesses liquidity timing ability and changes the fund's market exposure based on her forecast of market liquidity, then a related question is whether it is more important for the fund manager to reduce market exposure during time periods with extremely poor liquidity conditions (e.g., a market-level liquidity crunch) than to increase market exposure when the market liquidity level is high. Our next test is designed to examine whether hedge funds show differential timing ability under extreme liquidity conditions (e.g., bad versus good liquidity conditions).

We create two indicator variables, $D(Low\_LIQ)_t$ and $D(Hi\_LIQ)_t$ and include interactive terms between the market return and each indicator variable in our tests. $D(Low\_LIQ)_t$ ($D(Hi\_LIQ)_t$) indicates whether market liquidity in month t belongs to the bottom (top) quintile during the sample period. Hence, the liquidity-timing regression model is:

$$\begin{aligned} r_{p,t} = {} & \alpha_p + \beta_{p,1} MKT_t + \gamma_{p,1} MKT_t * D(Low\_LIQ)_t + \gamma_{p,2} MKT_t * D(Hi\_LIQ)_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t \\ & + \beta_{p,4} BAAMTSY_t + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t}, \end{aligned} \quad (9)$$

where the coefficients γ_1 and γ_2 measure timing ability during extremely low and high liquidity months.

The results reported in Table 4 suggest that hedge-fund managers adjust their market exposure asymmetrically. For the equally-weighted portfolio of all sample funds, the estimated coefficient on the interactive term of the market return with the dummy of low-liquidity months (γ_1) is −0.16 and significant at the 1% level. When market liquidity in month t belongs to the bottom quintile, a typical fund decreases its market exposure significantly, and the net market beta is roughly 0.15 ($=\beta_1 - \gamma_1$ = 0.31 − 0.16).[13] This finding holds both for overall portfolios and all of the eight category portfolios. The coefficient on the interactive term of market return with the dummy of high-liquidity months (γ_2), however, is not significant (except for fund of funds that has a negative sign on the coefficient). This result is consistent with the finding of Chen and Liang (2007) that self-proclaimed market-timing hedge funds display better timing skills when market conditions deteriorate, which reflects a need to hedge against adverse market circumstances. Therefore, on average hedge funds tend to reduce market exposure when market liquidity is especially poor, and such adjustments provide investors with some protection against downside losses from negative liquidity shocks.

[Insert Table 4 about here.]

5.3. Evidence from Alternative Benchmark Models

In this section, we check the robustness of our findings by using an alternative to the Fung and Hsieh (2004) seven-factor benchmark model. Specifically, we consider the model

[13] To keep the table parsimonious, we do not report the beta coefficients, but they are available upon request.

proposed by Agarwal and Naik (2004), who construct option-based factors using liquid at-the-money and out-of-the-money options on the S&P 500 index, and find that these option factors, together with the Fama-French three factors (e.g., market, size, and value) and a momentum factor by Carhart (1997), explain the returns on equity-oriented hedge funds quite well. Our liquidity timing model based on the Agarwal and Naik (2004) benchmark factors is given by:

$$\begin{aligned} r_{p,t} &= \alpha_p + \beta_{p,1} MKT_t + \gamma_p (L_{m,t} - \bar{L}_m) MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} HML_t + \beta_{p,4} UMD_t \\ &\quad + \beta_{p,5} OTMCALL_t + \beta_{p,6} OTMPUT_t + \varepsilon_{p,t}, \end{aligned} \tag{10}$$

where $r_{p,t}$ is the excess return in month *t* on portfolio *p*, SMB_t, HML_t and UMD_t are the returns of the value-weighted, zero-net-investment, factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns, $OTMCALL_t$ is the out-of-the-money call-option return factor, and $OTMPUT_t$ is the out-of-the-money put-option return factor. The option factors constructed from the at-the-money and out-of-the-money options are highly correlated; hence we only employ out-of-the-money option factors to avoid multi-collinearity among these factors.[14]

The results reported in Table 5 suggest that our main inference for liquidity timing remains unchanged when using the alternative benchmark model. The liquidity timing coefficient is 0.93 and significant at the 1% level for the equally-weighted portfolio of all sample funds. This estimate is comparable to that reported in Table 3 (0.81) that relies on the Fung and Hsieh (2004) seven-factor model. The timing coefficient on the equally-weighted portfolio of all hedge funds excluding funds of hedge funds is 1.04 with a *t*-statistic of 3.34. Among the eight category portfolios, six of them have significant γ coefficients and demonstrate liquidity timing ability after we control for the option-related risk factors. We also experiment with other risk factors (e.g., a commodity return index and the Agarwal and Naik at-the-money option factors) that have been used in the literature to explain hedge-fund returns and find qualitatively similar results to those presented based on the Fung and Hsieh seven-factor model. Therefore, our subsequent analysis relies only on the Fung and Hsieh seven-factor model.

[14] We are grateful to Vikas Agarwal and Narayan Naik for providing their option return factors.

[Insert Table 5 about here.]

5.4. The Impact of Illiquid Holdings

Asness, Krail and Liew (2001), Getmansky, Lo, and Makarov (2004), and Aragon (2007) point out that many hedge funds hold illiquid assets. These illiquid securities do not necessarily trade at the end of each month and can lead to non-synchronous price reaction. In the absence of end-of-month security transaction prices, fund managers may use the last transaction price of the month, or have the flexibility of marking their portfolio for month-end reporting. According to Scholes and Williams (1977), non-synchronous trading can bias the estimate of a fund's market beta downwards. If the bias is systematically related to the market liquidity condition, it could also bias our inferences about managers' liquidity timing ability.

To alleviate this potential bias, we incorporate two lagged market excess returns, MKT_{t-1} and MKT_{t-2}, as additional control variables in the spirit of Scholes and Williams (1977), and estimate the following regression model:

$$\begin{aligned} r_{p,t} = {} & \alpha_p + \beta_{p,11} MKT_t + \gamma_p (L_{m,t} - \overline{L}_m) MKT_t + \beta_{p,12} MKT_{t-1} + \beta_{p,13} MKT_{t-2} + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t \\ & + \beta_{p,4} BAAMTSY_t + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t}, \end{aligned} \tag{11}$$

Table 6 reports the results. For the equally-weighted portfolio of all funds, the estimate of the liquidity timing coefficient is positive and significant, and MKT_{t-1} enters the regression strongly, indicating that hedge funds, in general, do hold relatively illiquid securities. In comparison to the results reported in Table 3, the equally-weighted portfolios of all funds, all funds excluding funds of hedge funds, and funds in six of the eight categories still have significant liquidity timing coefficients. In particular, among the categories, emerging market, event driven, funds of hedge funds, global macro, long/short equity, and multi-strategies still have significant timing coefficients. Overall, our baseline results of liquidity timing ability presented in Table 3 are robust after controlling for non-synchronous trading and illiquid holdings.[15]

[Insert Table 6 about here.]

[15] To check robustness, we use up to 6 lagged market excess returns and re-estimate the liquidity timing model. We find that our conclusion remains unchanged.

5.5. Controlling for Return Timing and Volatility Timing

Our test of liquidity timing allows us to examine how hedge funds' market exposure varies with market liquidity. However, managers may adjust their funds' market exposure based on other information. For example, there is a large literature on the market-timing ability of professional money managers, dating back to Treynor and Mazuy (1966) and Henriksson and Merton (1981). The idea of market timing is that the fund manager strategically adjusts the fund's market exposure based on her forecast about market returns, increasing (decreasing) the portfolio's market exposure when the market goes up (down).

The evidence on mutual fund managers' market timing ability is mixed. Early studies find negative timing ability with mutual fund managers. Employing conditional timing models, Ferson and Schadt (1996) show that mutual funds tend to have neutral market-timing ability. Bollen and Busse (2001), who use daily returns, and Jiang, Yao, and Yu (2007), who use information on portfolio holdings, find some positive evidence of market timing in mutual funds. Moreover, Busse (1999) investigates mutual-fund managers' volatility-timing ability and finds evidence that mutual-funds' market exposures are negatively associated with market volatility. Recently, Chen and Liang (2007) document evidence of successful return- and volatility-timing ability using a sample of self-declared market-timing hedge funds.

We re-evaluate hedge-funds' liquidity timing ability, controlling for both market-return and volatility timing. We follow Treynor and Mazuy (1966) in controlling for market-return timing and Busse (1999) for volatility timing, and use the following regression:

$$\begin{aligned} r_{p,t} = {} & \alpha_p + \beta_{p,1} MKT_t + \gamma_p (L_{m,t} - \overline{L}_m) MKT_t + \lambda_p MKT_t^2 + \delta_p MKT_t * (Vol_t - \overline{Vol}) + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t \\ & + \beta_{p,4} BAAMTSY_t + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t}, \end{aligned} \quad (12)$$

where Vol_t is the market volatility in month t calculated as follows: $Vol_t = \sqrt{\sum (R_{m,d,t} - \overline{R}_{m,t})^2 / N_t}$, $R_{m,d,t}$ is daily CRSP value-weighted market return on day d in month t, and N_t is the number of trading days in month t. $\overline{Vol}$ is the time-series mean of market volatility, and the coefficients γ, λ, and δ measure liquidity timing, market-return timing, and volatility timing, respectively.

In Table 7 the columns labeled “liquidity timing”, “return timing”, and “volatility timing” contain the estimates of each timing coefficient. After controlling for market-return and volatility timing, we find that the coefficient of liquidity timing is still significant for the portfolio of all sample funds, the portfolio of all hedge funds excluding funds of hedge funds, and six out of eight category portfolios. For example, the timing coefficient γ is 0.87 (with t-statistic=2.77) and significant at the 1% level for the portfolio of all funds excluding funds of hedge funds. Hence, the results confirm the existence of liquidity timing ability, even after controlling for market-return and volatility timing.

[Insert Table 7 about here.]

5.6 Additional Robustness Checks

We further check the robustness of our findings along four dimensions: the measure of aggregate liquidity, reverse causality due to the potential impact of changes in funds’ market beta on future market liquidity, inclusion of the Pastor-Stambaugh liquidity risk factor as an additional risk factor in the liquidity-timing regression model, and the impact of other conditioning variables.

Other Liquidity Measures. To ensure that our results are robust to the measure of aggregate liquidity, we re-examine our timing test using Hasbrouck’s (2009) measure of market liquidity (multiplied by −1 to make the results comparable to those using the Pastor-Stambaugh measure).[16] Using the Hasbrouck measure and re-estimating (6), we find that for the portfolio of all sample funds, the liquidity timing coefficient is 0.38 and significant at the 5% level. For the portfolio of all funds excluding funds of funds, the timing coefficient is also statistically significant at the 5% level. Further, the liquidity timing coefficients are significant for five of the eight category portfolios (convertible arbitrage, funds of funds, global macro, long/short equity, and multi-strategies). Therefore, the Hasbrouck measure delivers similar results to those based on the Pastor-Stambaugh liquidity measure.

[16] We thank Joel Hasbrouck for making his illiquidity measure available on his website http://pages.stern.nyu.edu/~jhasbrou/research.

Another issue related to the Pastor-Stambaugh (2003) measure is that the aggregate liquidity measure is equally weighted across individual stocks. For robustness, we compute a value-weighted Pastor-Stambaugh liquidity measure and repeat our tests, and the inferences of liquidity timing ability remain unchanged.

Reverse Causality. Next, we address the concern that the documented liquidity timing ability may be due to reverse causality, that is, the changes in hedge funds' market exposure *affect* future market liquidity conditions. To check such a possibility, we re-estimate (6) but replace $L_{m,t}$, observed at the end of month t, with next month's market liquidity condition $L_{m,t+1}$. This specification allows us to examine the relationship of a fund's market exposure in month t with market liquidity in month t+1. The regression results show that this relationship is not significant for each category portfolio and for the overall portfolio of all the funds. Thus, reverse causality is not likely to explain our findings.

We also examine whether a passive, well-diversified, buy-and-hold portfolio such as the S&P 500 index fund exhibits liquidity timing ability; if so, our liquidity timing model is clearly misspecified. Using the S&P 500 index fund returns to estimate the liquidity timing model (6), we find that the liquidity timing coefficient is not significant at any conventional significance level.

Inclusion of Liquidity Risk Factor. While our focus in this paper is on hedge funds' change in market exposure to aggregate liquidity conditions, we check and show that our findings are robust to including a liquidity risk factor in the benchmark model. In particular, we employ monthly innovation of the Pastor and Stambaugh liquidity measure as the liquidity risk factor, and therefore augment the Fung and Hsieh seven-factor model with one additional factor. With hedge funds' liquidity risk controlled, the liquidity timing coefficient is 0.73 and statistically significant at the 5% level for the overall portfolio of all funds. For the portfolio of all funds excluding funds of funds, the timing coefficient is 0.81 (with t-statistic=3.38). Consistent with the results in Table 3, seven out of the eight category portfolios (with the exception of equity market neutral) have significant liquidity timing coefficients. Therefore, our results remain unchanged when including a liquidity factor as an additional risk factor in our baseline regression of Equation (6).

Conditional Liquidity-Timing Model. The essence of strategic timing is the adjustment of a hedge fund's market exposure to the manager's expectations about market conditions of which liquidity is one important dimension. However, the information set used by the manager to form her expectations may contain other variables besides her market-liquidity forecast. For example, in proposing methods for conditional performance evaluation, Ferson and Schadt (1996) take into account the well-known fact that conditioning information such as aggregate dividend yield can predict market returns and the market risk premium. To check the robustness of our liquidity timing results to such conditioning information, we estimate a conditional liquidity-timing model using four conditioning variables commonly cited in the empirical literature: the U.S. three-month T-bill rate, the term spread between the U.S. 10-year and three-month Treasury securities, the quality spread between Moody's BAA- and AAA-rated corporate bonds, and the dividend yield of the S&P 500 index. The data are obtained from the Federal Reserve Bank of St. Louis and Datastream. Following Ferson and Schadt (1996), we add interaction terms between the lagged values of these conditioning variables and the market return to (6).

$$\begin{aligned} r_{p,t} = {} & \alpha_p + \beta_{p,1} MKT_t + \gamma_p (L_{m,t} - \bar{L}_m) MKT_t + \sum_{l=1}^{q} \beta_p^l MKT_t * Z_{l,t-1} + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t \\ & + \beta_{p,4} BAAMTSY_t + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t}, \end{aligned} \tag{13}$$

where $Z_{l,t-1}$ is the de-meaned conditioning variables and $q = 4$ since we use four conditioning variables in (13). The results from the conditional liquidity-timing regression are similar to those based on the unconditional timing model in (6). For instance, for the portfolio consisting of all sample hedge funds, the liquidity timing coefficient is 0.71 and significant at the 5% level. We also find evidence of significant liquidity-timing coefficient for the portfolio of all funds excluding funds of funds, and for seven out of the eight category portfolios.

Collectively, our robustness checks suggest that the evidence of liquidity timing ability among hedge-fund managers is reliable.

6. Evidence at the Individual Fund Level

So far we have presented evidence of hedge-fund liquidity timing ability at the portfolio level. From the investors' point of view, another important question is whether one can identify individual funds that possess liquidity timing ability. In this section, we turn to the evaluation of liquidity timing at the individual-fund level and show that some hedge funds do possess the skill to time market liquidity. We also examine the cross-sectional relation between liquidity timing ability and fund characteristics, and then explore the investment value of identifying hedge funds with superior liquidity-timing skill. To ensure meaningful estimation of the timing model, we require each hedge fund to have at least 24 consecutive monthly return observations.[17] Since the first 12 returns are eliminated to avoid backfill bias in the first place, each fund effectively has a minimum of 36 monthly observations for the current test. This additional requirement reduces the number of funds in our sample from 3,156 to 2,358.[18]

6.1. Liquidity Timing of Individual Funds

We estimate the liquidity timing model in (6) for each hedge fund and report cross-sectional distributions of the estimated coefficients and their associated *t*-statistics in Table 8. Before discussing these results, we examine the percentage of funds with significant liquidity timing coefficients (γ) to develop intuition for the timing ability of individual funds.

The results in Table 8 suggest that among the 2,358 hedge funds, 14% have positive and significant γ coefficients at the 5% level, where the null hypothesis is H_0: $\gamma=0$ and the alternative hypothesis is H_a: $\gamma>0$. For the sample of all funds excluding funds of funds, a similar percentage of funds show significant timing ability at the 5% level. Across the eight style categories, except for equity market neutral, all categories have about 10% or more funds with significantly

[17] We have also considered the requirement that funds have at least 36 consecutive non-missing monthly returns, and find that our inferences are virtually unchanged.

[18] Using this restricted sample, we form equally-weighted portfolios and re-estimate the liquidity timing model of (6). The findings are similar to those reported in Table 3. For example, when we consider the portfolio of all sample funds and the portfolio of all funds excluding funds of funds, the timing coefficients are 0.81 and 0.91 respectively for the unrestricted sample (see Table 3), and 0.91 and 0.98 respectively for the restricted sample with both coefficients significant at the 5% level.

positive timing coefficients at the 5% level. Emerging market, funds of hedge funds, and long/short equity funds display stronger results, with more than 15% of funds having significant timing coefficients at the 5% level.

[Insert Table 8 about here.]

To examine cross-sectional distribution of the estimated timing coefficients, Table 8 presents the 5th, 10th, 15th and 20th percentiles of individual funds' timing coefficients on both sides of the distribution. The top 5% of funds with liquidity timing ability have large timing coefficients. For example, the 5th percentile of the timing coefficient is 3.29 for the overall sample and 3.78 for the sample excluding funds of funds. The category of funds of funds contains 652 funds and its top 5% liquidity timers has the smallest timing coefficient (γ =1.35) among the eight style categories, but this result may be explained by the fact that funds of hedge funds charge two-tier fees (see Brown, Goetzmann, and Liang (2004)). Among various categories' top 5% timing funds, the emerging-market category has the largest timing coefficient (γ =6.92). This category also contains the largest percentage of funds with significantly positive timing coefficients (16%). Overall, about 10% or more funds across various categories (except for equity market neutral) have positive and significant timing coefficients at the 5% level and these coefficients reveal significant timing ability.

In the Appendix, we show that a large proportion (39%) of individual funds also react to lagged market liquidity conditions. However, in contrast to the results in Table 8, the percentage of funds showing significantly negative coefficients for lagged market liquidity is low (3%). The reaction to lagged market liquidity is particularly strong for funds of funds: 64% of them have positive and significant θ coefficients, suggesting that fund-of-funds managers hold funds that passively react to market liquidity conditions (see Table A.2 for further details).

6.2. Bootstrap Analysis

We now use the bootstrap procedure, described in Section 3.4, to assess the statistical significance of the results at the fund level. Table 9 reports the top 5th, 10th, 15th, and 20th percentiles of t-statistics for timing coefficients and corresponding bootstrapped p-values.

Comparing the actual estimates of the *t*-statistics (t_γ) with their empirical distributions, we find that the top-ranked hedge funds' liquidity timing ability is not due to random sampling variation. For all funds, the top 5$^{\text{th}}$, 10$^{\text{th}}$, 15$^{\text{th}}$ and 20$^{\text{th}}$ percentiles of the t_γ statistic are 2.46, 1.92, 1.56 and 1.28, respectively, and the *p*-values associated with these *t*-statistics are all less than 1%. Significant liquidity timing coefficients are found for funds in categories such as emerging market, event driven, fund of funds, and long/short equity.

[Insert Table 9 about here.]

These results suggest that managers of top-ranked funds—as ranked by the significance of timing coefficients—can time market liquidity. Moreover, for the overall sample and most of the style categories, bottom-ranked funds (namely, funds that time market liquidity poorly) are not likely to be due to sampling variation either. This suggests that the market exposure of some hedge funds mistakenly decreases when market liquidity improves.

For robustness, we implement alternative bootstrap procedures as described in Section 3.4, and find that the results are qualitatively similar to those reported in Table 9. Overall, the results from the bootstrap analysis indicate that the top-ranked and bottom-ranked liquidity timing funds are not due to chance, but are most likely attributed to skill and lack thereof.

In the Appendix, we provide additional bootstrap evidence that hedge funds react to lagged market liquidity in a reasonable way, i.e., fund managers increase market exposure when the previous month's market was liquid. This is true at both the overall portfolio level and the style category level. The large and positive top-ranked *t*-statistics for the reaction coefficients are not due to random sampling variation, whereas the bootstrap results indicate that the incidence of unreasonable reaction to recent liquidity conditions (e.g., fund managers increasing their market exposure when the previous month's market was illiquid) cannot be distinguished from random chance (see Table A.3 for further details).

6.3. Liquidity Timing and Fund Characteristics

Next, we analyze the cross-sectional relation between various fund characteristics and liquidity-timing ability, to determine the types of funds that are more likely to possess timing skill. Specifically, we regress the liquidity-timing coefficients estimated from (6) on fund characteristics and fund category indicator variables.

We consider seven fund attributes that have been shown to be associated with hedge-fund performance (e.g., Brown and Goetzmann (2003) and Liang (2003)): minimum investment requirement, management fee, incentive fee, total redemption restriction (defined as lock-up period plus redemption advanced notice period), an indicator variable for effective auditing services (whether the fund provides its auditor's name and audit date), an indicator for leverage, and an indicator for whether the fund has its manager's personal capital invested, as well as indicators for style categories.[19]

Table 10 reports the results of the cross-sectional regression. We find that liquidity timing coefficients are positively associated with such fund attributes as better auditing services, use of leverage, and the existence of managers' personal capital co-invested, while negatively associated with management fees. Management fees may be interpreted as a dead-weight loss to investment return, so it is not surprising that it is negatively related to timing ability. Effective auditing, leverage, and a manager's personal investment may indicate better manager quality and thus better liquidity-timing skills. In addition, a fund with higher leverage faces more liquidity risk and requires more skill in managing the portfolio's risk exposures.

[Insert Table 10 about here.]

6.4. Investment Value of Liquidity Timing

To gauge the practical significance of our liquidity timing measure, we investigate the investment value of selecting top liquidity timers. To that end, in each month we estimate the liquidity timing coefficient for each fund using the past 36-month estimation period and rank hedge funds based on their timing coefficients. We then form a portfolio consisting of the top liquidity timers (e.g., the 90th percentile and better) that have timing coefficients with *t*-statistic

[19] We do not include fund age and size variables in this test in order to avoid look-ahead bias.

greater than 1.65.[20] Such a portfolio is then held for a 3-, 6-, 9- or 12-month holding period, and the process is repeated.[21] This yields four distinct time series of returns on portfolios of liquidity timing managers. Next, we estimate the Fung and Hsieh (2004) seven-factor model and report each portfolio's alpha in Table 11, together with the alpha from the corresponding equally-weighted portfolio of all funds.[22] If the portfolio of top liquidity timers has an alpha significantly larger than that from the equally-weighted portfolio of all funds, it indicates strong investment value associated with liquidity timing ability. Since this investment strategy is most relevant to funds of funds managers, we apply it to two samples: (1) all funds in our sample; and (2) all funds excluding funds of hedge funds.

[Insert Table 11 about here.]

Two patterns emerge from the risk-adjusted performance statistics, as measured by alpha, in Table 11. First, for a given timer portfolio (say the portfolio consisting top 10% timers), the alphas are stable and only decrease slightly when the holding period becomes longer. Second, the strategy of investing in top liquidity timers generates an alpha greater than the one from a simple strategy of holding an equally-weighted portfolio of all funds. This result holds regardless of whether or not funds of funds are included. For example, for all hedge funds excluding funds of funds, the alpha is 0.70% per month (*t*-statistic=3.90) for the top-10% timers portfolio with a 12-month holding period, while the alpha is 0.61% (*t*-statistic=3.98) for the equally-weighted portfolio consisting all funds.

To test if the difference between the two alphas is significant, we compute a simple *t*-statistic defined as $t=(\hat{\alpha}_1-\hat{\alpha}_2)/\sqrt{\hat{s}_1^2+\hat{s}_2^2-2\hat{s}_1\hat{s}_2\hat{\rho}_{\alpha_1\alpha_2}}$, where $\hat{\alpha}_1$ and $\hat{s}_1$ are the estimated alpha and its standard error for a given timer portfolio, $\hat{\alpha}_2$ and $\hat{s}_2$ are the parameter estimates for the corresponding equally-weighted portfolio, and $\hat{\rho}_{\alpha_1\alpha_2}$ is the correlation between the two alphas.

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[20] This hypothetical portfolio starts from January 1997 because we need to use return information from the past three years, and our hedge fund sample begins in January 1994.

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

[22] The results are robust to employing alternative benchmark models as considered in the previous section.

We consider a plausible range of correlations from 0.7 to 0.9 and then compute the corresponding *t*-statistics, and we also attempt to empirically estimate the correlation between the two alphas using the estimated alphas from a 36-month rolling window. The estimated correlation between the alpha of top-10%-timer portfolio and that of the overall portfolio of all hedge funds is 0.84, which provides some reassurance that the range of correlations we consider is reasonable.

Using the sample of all hedge funds and assuming a 12-month holding period for the timer portfolio, we find that the seven-factor model alphas are 0.61% and 0.40% per month, with standard errors of 0.15 and 0.09, respectively, for the top 10% liquidity timer portfolio and the equally-weighted portfolio of all funds. The *t*-statistics for their differences in alphas—assuming correlations of 0.7, 0.8, and 0.9—are 1.90, 2.18, and 2.63, respectively. For the sample of all hedge funds excluding funds of funds, the *t*-statistics for the difference in alphas between the top-10% timers and the overall portfolios are also significant at the 5% level, indicating a performance difference between liquidity timers and the overall portfolio.

In summary, we find a significant difference in alphas between liquidity timers and the equally-weighted portfolio of all funds. Interestingly, when the same investment strategy is applied to funds that are top liquidity reactors—funds with the largest market-beta adjustment to lagged market liquidity—the differences in alphas vanish (see Table A.4 of the Appendix for further details). These results may be particularly relevant to managers of funds of hedge funds seeking to improve their investment process with respect to liquidity characteristics.

7. Conclusions

In this paper, we examine whether hedge-fund managers possess liquidity timing ability by adjusting their portfolios' market exposure as aggregate market liquidity conditions change. We focus on hedge funds because they are among the most dynamic investment vehicles and their performance is strongly affected by market liquidity conditions. Using a large sample of equity-oriented hedge funds over the sample period from 1994 to 2008, 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. Our evidence indicates that funds investing in illiquid securities (such as emerging market, event driven, and convertible arbitrage funds) and funds with relatively liquid holdings (such as global macro and long/short equity funds) both demonstrate liquidity timing skills. However, funds holding liquid assets also react to the past liquidity conditions strongly—their market exposure is significantly associated with lagged market liquidity.

Also, liquidity timing ability is asymmetric: it is more pronounced when market liquidity is especially low than when it is especially high. Hedge-fund managers tend to reduce their portfolios' market exposures correctly when the market liquidity condition is extremely poor, which helps to protect investors from losses during liquidity crisis. This is important as institutional investors pay particular attention to preserving capital in such scenarios.

Our bootstrap analysis provides additional evidence of 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 hedge funds, all funds excluding fund of funds, and funds in four style categories.

Finally, we find that an investment strategy of investing in top liquidity-timers significantly outperforms the equally-weighted portfolio of all hedge funds, and apparently generates economically significant profits, but investing in top liquidity-reactors (those funds that react to past liquidity conditions) does not. This finding suggests an additional source of hedge-fund performance, in addition to other sources documented in the literature, such as incentive structure, share restrictions, and market-return and volatility timing. These empirical results confirm and extend the common intuition among hedge-fund managers and investors that liquidity plays a critical role in the dynamics of the hedge-fund industry.

Appendix

In this Appendix, we examine whether hedge-fund managers react to lagged market liquidity conditions. Specifically, we use the following regression to test whether fund managers react to the previous month's market liquidity:

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \theta_p (L_{m,t-1} - \overline{L}_m) MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t}, \tag{A.1}$$

where $L_{m,t-1}$ is the one-month lagged market liquidity measure and the coefficient θ measures reaction to past liquidity conditions. One important difference between this specification and the specification in (6) is that we use lagged market liquidity in the above equation, instead of market liquidity of month t. The logic is that the manager may react to recently observed market liquidity conditions, and such reaction does not need superior information about future market liquidity, but rely on observing recent market-wide liquidity. Another interpretation is that $L_{m,t-1}$ belongs to the manager's conditioning information set, and the manager changes the portfolio's market beta with conditioning information (see Ferson and Schadt, 1996).

Table A.1 presents evidence at the portfolio level that hedge funds react to recent market liquidity conditions by changing their market exposure. The regression coefficient of the interaction term between the market return and lagged market liquidity is 0.87 for the equally-weighted portfolio of all funds, with a t-statistic of 3.31. In comparison to the results reported in Table 3, none of the three illiquid categories (convertible arbitrage, emerging market, and event driven) shows significant reaction to the previous month's market liquidity. The two liquid categories (global macro and long/short equity) display large and significant coefficients of 1.53 and 0.96 that are significant at the 5% level, which indicates that hedge funds holding liquid assets tend to react to past market liquidity strongly. In contrast, funds with illiquid holdings tend to time the current market liquidity actively, due to their need to manage liquidity risk.

[Insert Table A.1 about here.]

In Table A.2, we report evidence of individual funds' reaction to lagged market liquidity conditions. A large proportion (39%) of the funds shows the ability to respond to past market liquidity conditions. In contrast, the percentage of funds showing significantly negative coefficients is low (3%). The evidence of reacting to market liquidity is particularly strong for funds of funds, among which 64% of funds have positive and significant coefficients of θ, suggesting that fund of funds managers invest in funds that passively react to market liquidity conditions. The cross-sectional distribution of the estimated reaction coefficients shows that the global macro category has the largest top 5% reaction coefficient (θ =8.55).

[Insert Table A.2 about here.]

The bootstrap results in Table A.3 provide additional evidence that hedge funds react to recent market liquidity in a reasonable way, namely, fund managers increase market exposure when the previous month's market was liquid. This is true at both the overall portfolio level and the style category level. The large and positive top-ranked t-statistics for the reaction coefficients are not due to random sampling variation. The bootstrap results suggest that the incidence of unreasonable reaction to recent liquidity conditions (e.g., fund managers increasing their market exposure when the previous month's market was illiquid) cannot be distinguished from random chance.

[Insert Table A.3 about here.]

Having observed that hedge-fund managers react to the previous month's market liquidity, we consider whether investing in top-ranked liquidity *reactors* can produce abnormal performance. To answer this question, we examine the alphas of portfolios that invest in top liquidity reactors by following a procedure similar to that discussed in Section 6.4. Table A.4 presents the alpha of each top-liquidity-reactor portfolio and the alpha of a corresponding equally-weighted portfolio of all funds in the same category.

[Insert Table A.4 about here.]

Even though hedge-fund managers respond to past liquidity conditions strongly, the portfolios of top liquidity reactors do not outperform their corresponding overall portfolios. For the sample of all hedge funds, the portfolios of top-10% liquidity reactors with holding periods of 3, 6, 9, and 12 months have alphas of 0.27%, 0.27%, 0.30% and 0.33%, respectively, while the alpha of an equally-weighted portfolio of all funds is 0.40%. These results are in sharp contrast with those reported in Table 11, which shows that investing in top liquidity timers can generate significantly higher alpha.

We can draw a few conclusions from these findings. First, by identifying and investing in top liquidity reactors instead of top liquidity timers, an investor cannot outperform the equally-weighted portfolio of all funds. Second, the group of top liquidity timing funds in Table 11 is not the same as the group of top liquidity reacting funds in Table A.4. Finally, these results reconfirm our earlier finding that liquidity timing ability is attributable to fund managers' skill and is a source of hedge-fund alpha. Liquidity timing ability and the corresponding fund performance cannot be easily replicated by reacting to past liquidity conditions.

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Table 1
Summary Statistics

Panel A presents summary statistics of monthly hedge-fund returns for equally-weighted portfolios of all 3,156 hedge funds (ALL), all hedge funds excluding funds of funds (ALL-FoF), and funds in each style category. Returns are in percent per month, and ρ_1 is the first-order autocorrelation in returns. Among the 3,156 hedge funds in our sample, 1,703 are live and 1,453 are defunct funds. Panel B reports summary statistics of the Pastor-Stambaugh (2003) market liquidity measure. In Panel C, we present summary statistics of the Fung and Hsieh (2004) benchmark factors. MKT is the Center for Research in Security Prices (CRSP) value-weighted market portfolio excess return, SMB is the Fama-French size factor, YLDCHG is change in the constant maturity yield on the 10-year Treasury bond, BAAMTSY is change in the credit spread between Moody's Baa and the 10-year Treasury bond, PFTSBD is return of PTFS bond lookback straddle, PFTSFX is return of PTFS currency lookback straddle, and PFTSCOM is return of PTFS commodity lookback straddle (PTFS refers to primitive trend following strategy). Panel D presents correlation matrix of the benchmark factors. The hedge-fund data are from the Lipper TASS database and the sample period extends from 1994 through 2008.

Panel A: Hedge-fund Returns (% per month)

Portfolio	Mean	Median	STD	Min	Max	ρ_1
ALL	0.89	1.04	1.98	-8.98	7.33	0.25
ALL-FoF	0.98	1.23	2.17	-10.43	7.95	0.25
Convertible arbitrage	0.62	0.86	1.76	-10.04	5.47	0.35
Emerging market	1.09	1.77	4.60	-26.54	15.68	0.30
Equity market neutral	0.94	0.81	1.11	-2.47	6.65	0.25
Event driven	0.89	1.15	1.42	-6.70	3.82	0.35
Fund of funds	0.65	0.67	1.57	-6.00	5.52	0.26
Global macro	0.91	0.73	2.21	-5.79	8.68	0.05
Long/short equity	1.11	1.27	2.60	-9.63	9.36	0.19
Multi-strategy	0.85	0.93	1.51	-5.95	5.92	0.27

Table 1 (Continued)

Panel B: Liquidity Measure (%)

	Mean	Median	STD	Min	Max
P-S liquidity measure	-3.22	-2.38	6.56	-27.44	19.24

Panel C: Fung and Hsieh Benchmark Factors

	Mean	Median	STD	Min	Max
MKT	0.77	1.41	4.25	-15.77	8.39
SMB	0.17	-0.17	3.78	-16.79	21.96
YLDCHG	-0.01	-0.04	0.23	-0.53	0.65
BAAMTSY	0.01	-0.02	0.21	-0.47	1.57
PTFSBD	-1.22	-3.86	14.53	-25.36	68.86
PTFSFX	0.41	-2.93	19.34	-30.13	90.27
PTFSCOM	-0.04	-2.54	13.91	-24.20	64.75

Panel D: Correlation Matrix of the Benchmark Factors

MKT	SMB	YLDCHG	BAAMTSY	PFTSBD	PTFSFX	PTFSCOM
1.00						
0.19	1.00					
0.12	0.18	1.00				
-0.21	0.10	0.70	1.00			
-0.15	-0.03	0.04	0.15	1.00		
-0.12	0.02	-0.11	0.06	0.19	1.00	
-0.11	-0.01	-0.02	0.13	0.18	0.33	1.00

Table 2
Ratios of Adjusted R^2s from One-factor and Seven-factor Models for Hedge-Fund Returns

Time series regression of one-factor and seven-factor models for hedge-fund excess returns:

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \varepsilon_{p,t},$$

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t$$
$$+ \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t}.$$

The dependent variable is the monthly excess return on an equally-weighted portfolio of all sample hedge funds (ALL), all hedge funds excluding funds of funds (ALL-FoF), or funds in each style category. The independent variables include the Fung and Hsieh (2004) factors: MKT is the Center for Research in Security Prices (CRSP) value-weighted market portfolio excess return, SMB is the Fama-French size factor, YLDCHG is change in the constant maturity yield on the 10-year Treasury bond, BAAMTSY is change in the credit spread between Moody's Baa and the 10-year Treasury bond, PFTSBD is return of PTFS bond lookback straddle, PFTSFX is return of PTFS currency lookback straddle, and PFTSCOM is return of PTFS commodity lookback straddle (PTFS refers to primitive trend following strategy).

Portfolios	β_1 (1-factor model)	t-statistic	Adj. R^2 (1-factor model)	Ratio of R^2s (1-factor/7-factor)
ALL	0.36	10.90	0.59	0.85
ALL-FoF	0.41	11.43	0.64	0.87
Convertible arbitrage	0.24	5.87	0.34	0.71
Emerging market	0.67	6.33	0.37	0.85
Equity market neutral	0.08	4.70	0.10	0.68
Event driven	0.23	7.38	0.48	0.77
Fund of funds	0.22	7.85	0.36	0.73
Global macro	0.19	5.46	0.13	0.46
Long/short equity	0.51	17.03	0.71	0.87
Multi-strategy	0.26	9.97	0.52	0.89

Table 3
Liquidity Timing Ability: Portfolio-Level Evidence

This table presents results from the liquidity timing regression model:

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p(L_{m,t} - \overline{L}_m)MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}YLDCHG_t + \beta_{p,4}BAAMTSY_t + \beta_{p,5}PTFSBD_t + \beta_{p,6}PTFSFX_t + \beta_{p,7}PTFSCOM_t + \varepsilon_{p,t},$$

where r_{pt} is the excess return in month t on an equally-weighted portfolio of all sample hedge funds (ALL), all hedge funds excluding funds of funds (ALL-FoF), or funds in each style category. The independent variables include the Fung and Hsieh (2004) factors: MKT is the Center for Research in Security Prices (CRSP) value-weighted market portfolio excess return, SMB is the Fama-French size factor, YLDCHG is change in the constant maturity yield on the 10-year Treasury bond, BAAMTSY is change in the credit spread between Moody's Baa and the 10-year Treasury bond, PFTSBD is return of PTFS bond lookback straddle, PFTSFX is return of PTFS currency lookback straddle, and PFTSCOM is return of PTFS commodity lookback straddle (PTFS refers to primitive trend following strategy). $L_{m,t}$ is the Pastor-Stambaugh (2003) market liquidity measure in month t, and $\overline{L}_m$ is the mean level of market liquidity over the sample period. The coefficient γ measures liquidity timing ability. *t*-statistics are in parentheses. *, **, and *** indicate that the liquidity timing coefficients are significant at the 10%, 5%, and 1% levels, respectively.

Table 3 (continued)

Portfolio	α	β_1	γ	β_2	β_3	β_4	β_5x100	β_6x100	β_7x100	R^2
ALL	0.33	0.33	0.81	0.15	1.02	-1.57	-1.60	0.69	0.75	0.71
	(4.03)	(12.80)	(3.34)***	(5.45)	(1.52)	(-1.99)	(-2.35)	(1.53)	(1.14)	
ALL-FoF	0.39	0.38	0.91	0.17	1.02	-1.35	-1.82	0.62	0.47	0.75
	(4.53)	(13.80)	(3.51)***	(5.49)	(1.51)	(-1.75)	(-2.48)	(1.38)	(0.69)	
Convertible arbitrage	0.19	0.18	0.67	0.08	3.05	-4.04	-1.68	-0.08	-0.04	0.50
	(2.07)	(6.12)	(2.26)**	(2.72)	(3.44)	(-3.41)	(-2.15)	(-0.17)	(-0.06)	
Emerging market	0.29	0.61	1.99	0.24	3.90	-2.72	-5.43	-0.06	0.41	0.45
	(1.01)	(7.29)	(2.41)**	(2.98)	(2.29)	(-1.79)	(-2.08)	(-0.05)	(0.21)	
Equity market neutral	0.57	0.07	0.22	0.04	-0.03	-0.97	-0.73	0.44	0.41	0.14
	(7.60)	(3.89)	(1.03)	(2.28)	(-0.06)	(-1.70)	(-1.50)	(1.23)	(0.78)	
Event driven	0.43	0.19	0.72	0.09	1.86	-2.54	-1.78	0.46	0.04	0.64
	(6.41)	(8.50)	(3.03)***	(3.83)	(3.49)	(-3.97)	(-3.32)	(1.33)	(0.08)	
Fund of funds	0.19	0.20	0.59	0.12	1.06	-2.21	-1.03	0.85	1.55	0.50
	(2.34)	(8.06)	(2.59)**	(4.90)	(1.48)	(-2.56)	(-1.71)	(1.74)	(2.34)	
Global macro	0.37	0.22	1.06	0.08	-0.85	-1.56	-1.42	2.96	2.22	0.29
	(2.68)	(5.23)	(2.75)***	(1.84)	(-1.05)	(-2.24)	(-1.45)	(2.90)	(1.75)	
Long/short equity	0.46	0.49	0.72	0.22	0.31	-0.62	-0.95	0.68	0.43	0.81
	(5.50)	(18.30)	(2.53)**	(6.78)	(0.43)	(-0.68)	(-1.74)	(1.39)	(0.66)	
Multi-strategy	0.36	0.24	0.75	0.09	1.13	-1.76	-0.77	0.18	0.62	0.60
	(4.84)	(10.10)	(2.71)***	(3.04)	(1.76)	(-2.50)	(-1.30)	(0.49)	(1.11)	

Table 4
Liquidity Timing in Extreme Market-Liquidity Conditions

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

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_{p,1}MKT_t * D(Low\_LIQ)_t + \gamma_{p,2}MKT_t * D(Hi\_LIQ)_t + \beta_{p,2}SMB_t + \beta_{p,3}YLDCHG_t$$
$$+ \beta_{p,4}BAAMTSY_t + \beta_{p,5}PTFSBD_t + \beta_{p,6}PTFSFX_t + \beta_{p,7}PTFSCOM_t + \varepsilon_{p,t},$$

where r_{pt} is the excess return in month t on an equally-weighted portfolio of all sample hedge funds (ALL), all hedge funds excluding funds of funds (ALL-FoF), or funds in each style category. The independent variables include the Fung and Hsieh (2004) factors: MKT is the Center for Research in Security Prices (CRSP) value-weighted market portfolio excess return, SMB is the Fama-French size factor, YLDCHG is change in the constant maturity yield on the 10-year Treasury bond, BAAMTSY is change in the credit spread between Moody's Baa and the 10-year Treasury bond, PFTSBD is return of PTFS bond lookback straddle, PFTSFX is return of PTFS currency lookback straddle, and PFTSCOM is return of PTFS commodity lookback straddle (PTFS refers to primitive trend following strategy). $D(Low\_LIQ)_t$ (or, $D(Hi\_LIQ)_t$) is a dummy variable indicating whether the liquidity in month t belongs to the bottom (or, the top) quintile over the sample period. The coefficients γ_1 and γ_2 measure liquidity timing ability during high and low market-liquidity months. t-statistics are in parentheses. *, **, and *** indicate that the liquidity timing coefficients are significant at the 10%, 5%, and 1% levels, respectively.

Portfolios	γ_1	t-statistic	γ_2	t-statistic
ALL	-0.16	-3.85***	-0.08	-1.32
ALL-FoF	-0.17	-3.77***	-0.07	-1.08
Convertible arbitrage	-0.10	-1.77*	-0.07	-0.95
Emerging market	-0.40	-2.81***	-0.07	-0.41
Equity market neutral	-0.06	-1.71*	-0.07	-1.31
Event driven	-0.11	-2.65***	-0.03	-0.56
Fund of funds	-0.14	-3.63***	-0.10	-1.73*
Global macro	-0.21	-3.43***	-0.05	-0.50
Long/short equity	-0.14	-2.95***	-0.08	-1.18
Multi-strategy	-0.12	-3.26***	-0.04	-0.73

Table 5
Evidence from the Agarwal-Naik (2004) Factor Model

This table presents results from the following liquidity timing regression model:

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \gamma_p (L_{m,t} - \overline{L}_m) MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} HML_t + \beta_{p,4} UMD_t + \beta_{p,5} OTMCALL_t + \beta_{p,6} OTMPUT_t + \varepsilon_{p,t},$$

where r_{pt} is the excess return in month t on an equally-weighted portfolio of all sample hedge funds (ALL), all hedge funds excluding funds of funds (ALL-FoF), or funds in each style category. The independent variables include the Agarwal and Naik (2004) factors: MKT is the Center for Research in Security Prices (CRSP) value-weighted market portfolio excess return, SMB and HML are the Fama-French size and value factors, UMD is the Carhart momentum factor, OTMCALL is out-of-the-money call option return factor and OTMPUT is out-of-the-money put option return factor. $L_{m,t}$ is the Pastor-Stambaugh (2003) market liquidity measure in month *t,* and $\overline{L}_m$ is the mean level of market liquidity over the sample period. The coefficient γ measures liquidity timing ability. *, **, and *** indicate that the liquidity timing coefficients are significant at the 10%, 5%, and 1% levels, respectively.

Portfolios	γ	*t*-statistic
ALL	0.93	3.22***
ALL-FoF	1.04	3.34***
Convertible arbitrage	0.53	1.32
Emerging market	2.63	2.30**
Equity market neutral	0.09	0.38
Event driven	0.56	2.04**
Fund of funds	0.61	2.45**
Global macro	0.76	1.71*
Long/short equity	0.86	2.85***
Multi-strategy	0.75	2.35**

Table 6
The Impact of Illiquid Holdings

Regression coefficients are from the following liquidity timing model where the lagged market portfolio return is used to control for the impact of illiquid holdings on the results:

$$r_{p,t} = \alpha_p + \beta_{p,11} MKT_t + \gamma_p (L_{m,t} - \overline{L}_m) MKT_t + \beta_{p,12} MKT_{t-1} + \beta_{p,13} MKT_{t-2} + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t$$
$$+ \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t},$$

where r_{pt} is the excess return in month t on an equally-weighted portfolio of all sample hedge funds (ALL), all hedge funds excluding funds of funds (ALL-FoF), or funds in each style category. The independent variables include the Fung and Hsieh (2004) factors: MKT is the Center for Research in Security Prices (CRSP) value-weighted market portfolio excess return, SMB is the Fama-French size factor, YLDCHG is change in the constant maturity yield on the 10-year Treasury bond, BAAMTSY is change in the credit spread between Moody's Baa and the 10-year Treasury bond, PFTSBD is return of PTFS bond lookback straddle, PFTSFX is return of PTFS currency lookback straddle, and PFTSCOM is return of PTFS commodity lookback straddle (PTFS refers to primitive trend following strategy). $L_{m,t}$ is the Pastor-Stambaugh (2003) market liquidity measure in month t, and $\overline{L}_m$ is the mean level of market liquidity over the sample period. The coefficient γ measures liquidity timing ability. *, **, and *** indicate that the liquidity timing coefficients are significant at the 10%, 5%, and 1% levels, respectively.

Portfolio	γ	t-statistic	β_{12}	t-statistic	β_{13}	t-statistic	R^2
ALL	0.69	2.93**	0.07	3.41	0.06	3.39	0.74
ALL-FoF	0.77	3.16***	0.07	3.55	0.06	3.18	0.77
Convertible arbitrage	0.43	1.43	0.10	4.52	0.02	0.94	0.54
Emerging market	1.62	2.13**	0.15	2.57	0.04	0.69	0.46
Equity market neutral	0.20	0.99	0.03	1.57	0.06	4.13	0.19
Event driven	0.50	2.35**	0.09	6.49	0.04	2.93	0.72
Fund of funds	0.51	2.12**	0.05	2.73	0.07	3.52	0.56
Global macro	1.17	2.74***	0.00	0.03	0.12	2.98	0.33
Long/short equity	0.64	2.20**	0.06	2.57	0.08	3.89	0.84
Multi-strategy	0.63	2.58**	0.05	3.08	0.04	2.14	0.63

Table 7
Market Timing, Volatility Timing and Liquidity Timing

The test of market timing, volatility timing and liquidity timing is based on the following model:

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \gamma_p (L_{m,t} - \overline{L}_m) MKT_t + \lambda_p MKT_t^2 + \delta_p MKT_t * (Vol_t - \overline{Vol}) + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t$$
$$+ \beta_{p,4} BAAMTSY_t + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t},$$

where r_{pt} is the excess return in month t on an equally-weighted portfolio of all sample hedge funds (ALL), all hedge funds excluding funds of funds (ALL-FoF), or funds in each style category. The independent variables include the Fung and Hsieh (2004) factors: MKT is the Center for Research in Security Prices (CRSP) value-weighted market portfolio excess return, SMB is the Fama-French size factor, YLDCHG is change in the constant maturity yield on the 10-year Treasury bond, BAAMTSY is change in the credit spread between Moody's Baa and the 10-year Treasury bond, PFTSBD is return of PTFS bond lookback straddle, PFTSFX is return of PTFS currency lookback straddle, and PFTSCOM is return of PTFS commodity lookback straddle (PTFS refers to primitive trend following strategy). $L_{m,t}$ is the Pastor-Stambaugh (2003) market liquidity measure in month *t*, and $\overline{L}_m$ is the mean level of market liquidity over the sample period. Vol is the market volatility in month t, and $\overline{Vol}$ is the time-series mean of the market volatility. The coefficients γ, λ, and δ measure liquidity timing, market timing and volatility timing, respectively. *, **, and *** indicate that the liquidity timing coefficients are significant at the 10%, 5%, and 1% levels, respectively.

	Liquidity timing		*Return timing*		*Volatility timing*	
Portfolio	γ	*t*-statistic	λ	*t*-statistic	δ	*t*-statistic
ALL	0.75	2.56**	-0.38	-0.84	0.66	0.15
ALL-FoF	0.87	2.77***	-0.45	-0.98	1.25	0.28
Convertible arbitrage	0.90	2.56**	0.03	0.07	9.96	2.26
Emerging market	2.41	2.50**	-2.24	-1.63	6.85	0.54
Equity market neutral	0.17	0.77	0.10	0.33	0.38	0.12
Event driven	0.88	3.27***	-0.64	-2.29	4.01	1.17
Fund of funds	0.44	1.68*	-0.16	-0.38	-1.89	-0.43
Global macro	0.82	1.94*	-0.19	-0.30	-6.44	-1.02
Long/short equity	0.45	1.42	0.02	0.04	-1.29	-0.27
Multi-strategy	0.70	2.28**	-0.35	-1.00	-1.13	-0.29

Table 8
Liquidity Timing Ability: Evidence at the Fund Level

This table presents cross-sectional distribution of individual funds' liquidity timing coefficients. For each fund with at least 24 monthly return observations, we estimate the following liquidity timing model:

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \gamma_p (L_{m,t} - \overline{L}_m) MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t$$
$$+ \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t},$$

where r_{it} is the excess return on fund i in month t. The independent variables include the Fung and Hsieh (2004) factors: MKT is the Center for Research in Security Prices (CRSP) value-weighted market portfolio excess return, SMB is the Fama-French size factor, YLDCHG is change in the constant maturity yield on the 10-year Treasury bond, BAAMTSY is change in the credit spread between Moody's Baa and the 10-year Treasury bond, PFTSBD is return of PTFS bond lookback straddle, PFTSFX is return of PTFS currency lookback straddle, and PFTSCOM is return of PTFS commodity lookback straddle (PTFS refers to primitive trend following strategy). $L_{m,t}$ is the Pastor-Stambaugh (2003) market liquidity measure in month t, and $\overline{L}_m$ is the mean level of market liquidity over the sample period. The coefficient γ measures liquidity timing ability.

# of funds	Bottom of γ coefficient				Top of γ coefficient				% of t-statistic negative and significant at 5%	% of t-statistic positive and significant at 5%
	5%	10%	15%	20%	20%	15%	10%	5%		
					All funds					
2,358	-4.58	-2.89	-2.08	-1.61	1.10	1.42	2.05	3.29	14.72	13.99
					All funds excluding Funds of Funds					
1,706	-5.31	-3.28	-2.19	-1.66	1.37	1.74	2.53	3.78	13.77	13.54
					Convertible arbitrage					
75	-4.81	-2.16	-1.42	-1.00	0.55	0.70	0.91	2.65	9.33	12.00
					Emerging market					
171	-7.74	-4.58	-2.90	-1.98	2.52	2.82	5.10	6.92	12.28	16.37
					Equity market neutral					
133	-3.95	-2.83	-2.26	-1.71	0.58	0.81	1.20	1.46	15.04	3.76
					Event driven					
251	-3.26	-2.09	-1.65	-1.30	0.85	1.03	1.44	2.55	15.14	13.94
					Fund of funds					
652	-3.17	-2.31	-1.89	-1.49	0.65	0.81	1.05	1.35	17.18	15.18
					Global macro					
107	-5.49	-2.66	-1.92	-1.40	2.00	2.47	3.29	4.30	10.28	14.02
					Long/short equity					
789	-6.48	-3.97	-2.80	-1.93	1.57	2.08	2.79	3.83	13.43	15.46
					Multi-strategy					
175	-4.43	-2.84	-2.08	-1.67	0.77	1.00	1.41	2.17	17.14	9.71

Table 9
Bootstrap Analysis of Liquidity Timing

This table presents the evidence from a bootstrap analysis of liquidity timing ability of individual hedge funds. The first row reports the sorted *t*-statistic of liquidity timing coefficient across individual funds, while the second row is the empirical *p*-value from bootstrap simulations. The number of resampling iterations is 1,000.

		Bottom *t*-statistic of γ coefficient						Top *t*-statistic of γ coefficient					
# of funds		1%	3%	5%	10%	15%	20%	20%	15%	10%	5%	3%	1%
							All funds						
2,358	*t*-stat	-3.66	-2.93	-2.59	-1.96	-1.58	-1.28	1.28	1.56	1.92	2.46	2.91	3.49
	p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
							All funds excluding Funds of Funds						
1,706	*t*-stat	-3.63	-2.83	-2.50	-1.94	-1.51	-1.19	1.27	1.54	1.89	2.38	2.84	3.44
	p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
							Convertible arbitrage						
75	*t*-stat	-3.75	-2.62	-2.34	-1.28	-1.13	-0.86	1.19	1.49	1.78	2.19	2.40	3.40
	p-value	0.15	0.14	0.16	0.82	0.73	0.79	0.19	0.16	0.15	0.26	0.29	0.27
							Emerging market						
171	*t*-stat	-3.93	-3.00	-2.31	-1.85	-1.49	-1.24	1.50	1.88	2.27	2.68	3.07	3.89
	p-value	0.05	0.00	0.07	0.03	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.04
							Equity market neutral						
133	*t*-stat	-2.94	-2.65	-2.31	-1.87	-1.64	-1.45	0.84	1.19	1.41	1.56	1.89	2.14
	p-value	0.47	0.24	0.15	0.09	0.01	0.01	0.87	0.69	0.85	0.98	0.97	0.98
							Event driven						
251	*t*-stat	-3.57	-2.83	-2.39	-1.94	-1.66	-1.08	1.27	1.52	2.02	2.63	2.83	3.16
	p-value	0.06	0.01	0.02	0.00	0.00	0.22	0.01	0.01	0.00	0.00	0.01	0.26
							Fund of funds						
652	*t*-stat	-3.66	-3.06	-2.75	-2.10	-1.73	-1.45	1.33	1.65	2.00	2.64	3.17	3.51
	p-value	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02
							Global macro						
107	*t*-stat	-2.67	-2.63	-2.15	-1.65	-1.22	-0.87	1.33	1.58	1.81	2.11	2.18	2.61
	p-value	0.62	0.18	0.50	0.37	0.62	0.84	0.05	0.04	0.12	0.52	0.63	0.65
							Long/short equity						
789	*t*-stat	-3.63	-2.84	-2.47	-1.94	-1.49	-1.14	1.40	1.67	1.97	2.66	3.17	3.95
	p-value	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
							Multi-strategy						
175	*t*-stat	-4.98	-3.02	-2.80	-2.30	-1.99	-1.50	1.09	1.37	1.60	2.08	2.22	2.46
	p-value	0.00	0.01	0.00	0.00	0.00	0.00	0.32	0.23	0.37	0.39	0.60	0.91

Table 10
Cross-Sectional Regression Analysis of Liquidity Timing Ability

This table reports the results from a cross-sectional regression, where the dependent variable is the liquidity timing coefficient for each sample fund and the independent variables include fund characteristics and category dummies. Minimum investment is the minimum required investment from an investor in millions of dollars; Management fee is in percent of assets under management; Incentive fee is in percentage of the profits; Redemption restriction period is the combination of lock-up period during which investors' money is locked up and advanced notice period that is the time needed for investors to notify managers before they can withdraw money; Effective auditing dummy=1 if the fund provides both its auditor's name and audit date and 0 otherwise; Leverage dummy=1 if the fund uses leverage and 0 otherwise; Personal capital dummy=1 if the fund manager invests own money in the fund and 0 otherwise. ** and *** indicate significance at the 5% and 1% levels, respectively. The number of funds in this test is 2,330.

Variable	Coefficient	*t*-statistic
Constant	-0.023	-0.11
Minimum investment ($million)	-0.034	-0.39
Management fee	-0.437	-5.20***
Incentive fee	0.003	0.59
Redemption restriction period (month)	-0.004	-0.60
Effective auditing dummy	0.215	2.45**
Leverage dummy	0.205	3.16***
Personal capital dummy	0.233	3.38***
Category dummies	Yes	
Number of funds	2,330	
Adjusted R^2	0.041	

Table 11
Investment Value of Liquidity Timing

This table presents investment value of liquidity timing ability. In each month since January 1997 we rank hedge funds based on their liquidity timing coefficients in the past three years (i.e., estimation period *J*=36 months). We then form portfolios of top 5%, 10%, and 20% of liquidity timers while requiring their timing coefficients to have a *t*-statistic>1.65. Portfolios are formed and held for different holding periods of *K* months, i.e., *K*=3, 6, 9, and 12 months. We report alphas of these top-timer portfolios as well as the equally-weighted portfolio of all the sample funds (i.e., "Overall portfolio"). Alphas are in percent per month, estimated from the Fung and Hsieh (2004) seven-factor model. *t*-statistics are in parentheses.

Panel A: All Funds

Overall	Top 5% timers				Top 10% timers				Top 20% timers			
portfolio	*K*=3	6	9	12	*K*=3	6	9	12	*K*=3	6	9	12
0.40	0.82	0.85	0.82	0.76	0.62	0.67	0.64	0.61	0.58	0.61	0.59	0.57
(4.25)	(3.56)	(3.80)	(3.75)	(3.48)	(3.73)	(4.10)	(4.12)	(3.98)	(4.71)	(5.11)	(5.13)	(5.01)

Panel B: All Funds Excluding Funds of Funds

Overall	Top 5% timers				Top 10% timers				Top 20% timers			
portfolio	*K*=3	6	9	12	*K*=3	6	9	12	*K*=3	6	9	12
0.46	0.89	0.95	0.93	0.86	0.68	0.73	0.73	0.70	0.61	0.66	0.64	0.62
(4.68)	(3.09)	(3.47)	(3.55)	(3.38)	(3.52)	(3.91)	(3.99)	(3.90)	(4.25)	(4.66)	(4.73)	(4.63)

Table A.1
Reaction to Past Liquidity Conditions: Portfolio-Level Evidence

This table presents results from the following regression model:

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \theta_p (L_{m,t-1} - \overline{L}_m) MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} YLDCHG_t + \beta_{p,4} BAAMTSY_t + \beta_{p,5} PTFSBD_t + \beta_{p,6} PTFSFX_t + \beta_{p,7} PTFSCOM_t + \varepsilon_{p,t},$$

where r_{pt} is the excess return in month t on an equally-weighted portfolio of all sample hedge funds (ALL), all hedge funds excluding funds of funds (ALL-FoF), or funds in each style category. The independent variables include the Fung and Hsieh (2004) factors: MKT is the Center for Research in Security Prices (CRSP) value-weighted market portfolio excess return, SMB is the Fama-French size factor, YLDCHG is change in the constant maturity yield on the 10-year Treasury bond, BAAMTSY is change in the credit spread between Moody's Baa and the 10-year Treasury bond, PFTSBD is return of PTFS bond lookback straddle, PFTSFX is return of PTFS currency lookback straddle, and PFTSCOM is return of PTFS commodity lookback straddle (PTFS refers to primitive trend following strategy). $L_{m,t-1}$ is the Pastor-Stambaugh (2003) market liquidity measure in month t-1, and $\overline{L}_m$ is the mean level of market liquidity over the sample period. The coefficient θ measures reaction to past liquidity conditions. t-statistics are in parentheses. *, **, and *** indicate that the liquidity reaction coefficients (θ) are significant at the 10%, 5%, and 1% levels, respectively.

Table A.1 (continued)

Portfolio	α	β_1	θ	β_2	β_3	β_4	β_5x100	β_6x100	β_7x100	R^2
ALL	0.42	0.32	0.87	0.15	1.17	-1.46	-1.50	0.79	0.72	0.71
	(5.42)	(11.70)	(3.31)***	(4.86)	(1.71)	(-1.93)	(-2.19)	(1.83)	(1.17)	
ALL-FoF	0.48	0.37	0.81	0.16	1.17	-1.26	-1.74	0.73	0.43	0.74
	(6.02)	(12.40)	(2.96)***	(4.88)	(1.69)	(-1.68)	(-2.32)	(1.65)	(0.67)	
Convertible arbitrage	0.26	0.16	0.02	0.08	3.12	-4.07	-1.69	-0.02	-0.09	0.48
	(2.75)	(5.07)	(0.07)	(2.50)	(3.43)	(-3.42)	(-2.09)	(-0.04)	(-0.14)	
Emerging market	0.50	0.56	1.00	0.22	4.18	-2.65	-5.35	0.14	0.30	0.44
	(1.88)	(6.01)	(1.17)	(2.71)	(2.31)	(-1.59)	(-2.01)	(0.11)	(0.15)	
Equity market neutral	0.59	0.08	0.44	0.03	0.03	-0.90	-0.67	0.47	0.41	0.15
	(8.21)	(4.14)	(2.18)**	(1.95)	(0.05)	(-1.65)	(-1.40)	(1.33)	(0.77)	
Event driven	0.50	0.18	0.36	0.08	1.96	-2.52	-1.75	0.53	0.00	0.62
	(7.56)	(7.44)	(1.57)	(3.34)	(3.53)	(-3.89)	(-3.13)	(1.57)	(0.00)	
Fund of funds	0.26	0.20	1.07	0.11	1.19	-2.06	-0.90	0.93	1.54	0.53
	(3.35)	(8.14)	(3.63)***	(4.49)	(1.72)	(-2.54)	(-1.51)	(2.14)	(2.54)	
Global macro	0.48	0.22	1.53	0.06	-0.64	-1.35	-1.25	3.09	2.19	0.31
	(3.67)	(5.24)	(2.59)**	(1.52)	(-0.77)	(-1.81)	(-1.19)	(3.28)	(1.86)	
Long short equity	0.54	0.48	0.96	0.21	0.45	-0.50	-0.85	0.76	0.41	0.82
	(6.97)	(18.50)	(3.41)***	(6.17)	(0.64)	(-0.59)	(-1.56)	(1.64)	(0.67)	
Multi-strategy	0.44	0.23	0.63	0.08	1.25	-1.69	-0.71	0.26	0.59	0.60
	(6.46)	(8.78)	(2.64)***	(2.70)	(1.86)	(-2.40)	(-1.10)	(0.78)	(1.11)	

Table A.2
Reaction to Past Liquidity Conditions: Evidence at the Fund Level

This table presents cross-sectional distribution of individual funds' reactions to past liquidity conditions. For each fund with at least 24 monthly return observations, we estimate the following regression model:

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \theta_p(L_{m,t-1} - \overline{L}_m)MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}YLDCHG_t + \beta_{p,4}BAAMTSY_t + \beta_{p,5}PTFSBD_t + \beta_{p,6}PTFSFX_t + \beta_{p,7}PTFSCOM_t + \varepsilon_{p,t},$$

where r_{it} is the excess return on fund i in month t. The independent variables include the Fung and Hsieh (2004) factors: MKT is the Center for Research in Security Prices (CRSP) value-weighted market portfolio excess return, SMB is the Fama-French size factor, YLDCHG is change in the constant maturity yield on the 10-year Treasury bond, BAAMTSY is change in the credit spread between Moody's Baa and the 10-year Treasury bond, PFTSBD is return of PTFS bond lookback straddle, PFTSFX is return of PTFS currency lookback straddle, and PFTSCOM is return of PTFS commodity lookback straddle (PTFS refers to primitive trend following strategy). $L_{m,t-1}$ is the Pastor-Stambaugh (2003) market liquidity measure in month t-1, and $\overline{L}_m$ is the mean level of market liquidity over the sample period. The coefficient θ measures reaction to past liquidity conditions.

# of funds	Bottom of θ coefficient				Top of θ coefficient				% of t-statistic negative and significant at 5%	% of t-statistic positive and significant at 5%
	5%	10%	15%	20%	20%	15%	10%	5%		
					All funds					
2358	-1.94	-0.84	-0.28	-0.04	2.81	3.26	4.11	5.75	3.10	38.63
					All funds excluding Funds of Funds					
1706	-2.36	-1.15	-0.60	-0.26	2.77	3.22	4.22	6.09	4.10	28.78
					Convertible arbitrage					
75	-2.47	-1.56	-1.39	-1.13	1.80	2.27	3.32	4.41	10.67	17.33
					Emerging market					
171	-1.18	-0.35	-0.09	0.04	4.23	4.88	5.98	7.86	0.58	31.58
					Equity market neutral					
133	-2.77	-1.17	-0.84	-0.42	1.64	2.39	2.90	3.72	6.77	24.81
					Event driven					
251	-1.16	-0.48	-0.29	-0.13	1.98	2.28	2.55	3.99	2.79	26.69
					Fund of funds					
652	-0.17	0.22	0.39	0.51	2.92	3.35	3.96	5.23	0.46	64.42
					Global macro					
107	-4.13	-2.02	-1.32	-0.73	4.91	5.51	6.60	8.55	6.54	28.97
					Long short equity					
789	-3.09	-1.41	-0.85	-0.27	2.89	3.31	4.14	6.21	3.68	29.53
					Multi-strategy					
175	-2.01	-0.74	-0.47	-0.16	2.89	3.38	4.34	5.50	5.14	33.71

Table A.3
Bootstrap Analysis of Liquidity Reaction

This table presents the evidence from a bootstrap analysis of liquidity reaction of individual hedge funds. The first row reports the sorted t-statistic of liquidity reaction coefficient across individual funds, while the second row is the empirical p-value from bootstrap simulations. The number of resampling iterations is 1,000.

		Bottom t-statistic of θ coefficient						Top t-statistic of θ coefficient					
# of funds		1%	3%	5%	10%	15%	20%	20%	15%	10%	5%	3%	1%
							All funds						
2358	t-stat	-2.48	-1.66	-1.26	-0.69	-0.31	-0.05	2.40	2.70	3.07	3.61	3.95	4.72
	p-value	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
							All funds excluding Funds of Funds						
1706	t-stat	-2.67	-1.80	-1.47	-0.88	-0.52	-0.27	1.99	2.26	2.61	3.13	3.48	4.02
	p-value	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
							Convertible arbitrage						
75	t-stat	-3.58	-2.03	-1.86	-1.65	-1.43	-1.29	1.37	1.85	2.19	2.89	2.99	3.52
	p-value	0.25	0.69	0.69	0.31	0.24	0.11	0.04	0.01	0.00	0.01	0.04	0.26
							Emerging market						
171	t-stat	-1.63	-1.15	-0.95	-0.36	-0.15	0.04	2.05	2.20	2.70	3.26	3.73	4.58
	p-value	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.01
							Equity market neutral						
133	t-stat	-2.59	-2.08	-1.75	-1.11	-0.59	-0.39	1.83	2.11	2.49	3.07	3.36	3.84
	p-value	0.83	0.91	0.92	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.02	0.09
							Event driven						
251	t-stat	-2.67	-1.30	-1.11	-0.64	-0.33	-0.21	2.00	2.14	2.49	3.10	3.32	4.12
	p-value	0.84	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.01
							Fund of funds						
652	t-stat	-1.30	-0.63	-0.15	0.34	0.76	1.02	3.10	3.42	3.72	4.28	4.72	5.77
	p-value	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
							Global macro						
107	t-stat	-2.86	-2.17	-2.13	-1.08	-0.75	-0.46	2.26	2.84	3.09	3.91	3.95	4.24
	p-value	0.52	0.71	0.58	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.01
							Long/short equity						
789	t-stat	-2.68	-1.71	-1.47	-0.83	-0.52	-0.24	1.99	2.27	2.58	3.12	3.33	3.89
	p-value	0.98	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
							Multi-strategy						
175	t-stat	-2.63	-1.81	-1.70	-1.00	-0.48	-0.25	2.18	2.51	2.94	3.74	3.85	4.31
	p-value	0.88	0.99	0.96	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.04

Table A.4
Investment Value of Liquidity Reaction

This table presents investment value of liquidity reaction. In each month since January 1997 we rank hedge funds based on their liquidity reaction coefficients in the past three years (i.e., estimation period *J*=36 months). We then form portfolios of top 5%, 10%, and 20% of liquidity reactors while requiring their reaction coefficients to have a *t*-statistic>1.65. Portfolios are formed and held for different holding periods of *K* months, i.e., *K*=3, 6, 9, and 12 months. We report alphas of these top-reactor portfolios as well as the equally-weighted portfolio of all the sample funds (i.e., "Overall portfolio"). Alphas are in percent per month, estimated from the Fung and Hsieh (2004) seven-factor model. *t*-statistics are in parentheses.

Panel A: All Funds

Overall	Top 5% reactors				Top 10% reactors				Top 20% reactors			
portfolio	*K*=3	6	9	12	*K*=3	6	9	12	*K*=3	6	9	12
0.40	0.34	0.28	0.28	0.28	0.27	0.27	0.30	0.33	0.28	0.29	0.31	0.33
(4.25)	(1.56)	(1.29)	(1.34)	(1.39)	(1.55)	(1.67)	(1.93)	(2.13)	(1.87)	(2.13)	(2.40)	(2.57)

Panel B: All Funds Excluding Funds of Funds

Overall	Top 5% reactors				Top 10% reactors				Top 20% reactors			
portfolio	*K*=3	6	9	12	*K*=3	6	9	12	*K*=3	6	9	12
0.46	0.35	0.29	0.26	0.26	0.28	0.28	0.29	0.30	0.31	0.31	0.33	0.34
(4.68)	(1.39)	(1.20)	(1.13)	(1.16)	(1.44)	(1.49)	(1.63)	(1.74)	(2.01)	(2.13)	(2.35)	(2.52)