Funding Liquidity Risk and Hedge Fund Performance

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Abstract

This paper provides evidence on the interaction between hedge funds' performance and their *market liquidity* risk and *funding liquidity* risk. We demonstrate that funding liquidity risk is an important determinant of hedge fund performance. Hedge funds with high loadings on the funding liquidity factor *underperform* low-loading funds by about 2.47% (11.67%) annually in the high (low) liquidity regime, during 1994-2012; with liquidity regimes identified using a 2-state Markov regime switching model. We further confirm that market liquidity and funding liquidity interact with each other, potentially leading to negative liquidity spirals. These results provide support for the Brunnermeier-Pedersen model that rationalizes the link between market liquidity and funding liquidity. We also document that hedge fund managers are not entirely successful in timing shifts in market liquidity, and lockup provisions are only effective during high liquidity states.

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I. Introduction

The financial crisis of 2008 provided a dramatic illustration of the importance of liquidity in financial markets. In addition to this recent episode, a number of other prior events including the October 1987 market crash, the 1998 Russian debt crisis, and the 2007 Quant (hedge fund) Crisis have underscored the role of liquidity, or lack thereof, in market downturns.[1] Furthermore, the potential for negative liquidity spirals and the contagious nature of (il)liquidity across asset classes, can both magnify and prolong the severity of financial crises. For example, Brunnermeier and Pedersen (2009) develop a model that rationalizes the link between an asset's *market liquidity* reflecting the ease with which it can be traded, and traders' *funding liquidity* which reflects the ease/cost of obtaining funding.[2] An important implication of the model is that negative liquidity spirals can arise under certain conditions. Specifically, according to the model, adverse funding shocks can lead to portfolio liquidations that hurt asset values and market liquidity, leading to tighter funding constraints due to increased margin requirements which could further depress market liquidity.

Hedge funds represent an increasingly important group of investors that are exposed to both *market liquidity* risk stemming from the relatively illiquid nature of their portfolio holdings, and *funding liquidity* shocks due in large part to their reliance on leverage. As a result, in the wake of several high profile hedge fund failures in recent years there is increasing concern among regulators and market participants about the potential systemic risk posed by hedge funds.[3] The relation between market liquidity risk and hedge fund performance has been well established in

[1] Examples of academic studies that discuss some of these episodes include Roll (1988), Brunnermeier (2009), Khandani and Lo (2007), and Billio, Getmansky, and Pelizzon (2010).
[2] Drehmann and Nikolaou (2013) define funding liquidity risk as the possibility that over a particular horizon a financial intermediary will be unable to "settle obligations with immediacy."
[3] See, for example, GAO report number GAO-08-200 entitled *'Hedge Funds: Regulators and Market Participants Are Taking Steps to Strengthen Market Discipline, but Continued Attention Is Needed'* dated February 25, 2008.

the literature. For example, Sadka (2010) documents that hedge funds with high market liquidity risk loadings outperform low-loading funds by about 6% per year on average during 1994-2008. Similarly, Khandani and Lo (2011) document an average illiquidity premium of 3.96% for a sample of hedge funds during 1986-2006. As noted above, funding liquidity conditions also play a critical role in the success or failure of hedge fund strategies given the typically high degree of leverage employed by hedge funds. Accordingly, in this study we examine the relation between the funding liquidity risk exposure of hedge funds and their performance, with a particular focus on the interaction between the funds' market liquidity risk and funding liquidity risk.

Our paper contributes to the existing literature in several ways. First, we demonstrate that funding liquidity risk as measured by the sensitivity of a hedge fund's return to a measure of market-wide funding costs, is an important determinant of hedge fund performance. Furthermore, funding liquidity risk plays a critical role in the variation of hedge fund market illiquidity premia across liquidity regimes identified using a 2-state Markov regime switching model.

Our second contribution follows from the above finding. Specifically, we document the combined impact of both market liquidity and funding liquidity on hedge fund performance. We show that hedge fund returns are the highest (lowest) for the funds with high (low) market liquidity exposure and low (high) funding liquidity exposure. We further confirm that market liquidity and funding liquidity interact with each other, potentially leading to liquidity spirals, especially in the low liquidity regime. These results provide empirical evidence in support of the Brunnermeier and Pedersen's (2009) theoretical model.

Third, we extend the findings of Cao, et al. (2013) who provide suggestive evidence that hedge funds can time market liquidity by adjusting their holdings in response to changes in liquidity conditions. In this paper, we argue that market liquidity has state dependent implications and provide evidence that hedge fund managers are not entirely successful in timing shifts in market liquidity.[4] We show that hedge funds do lower their market liquidity exposure in the low liquidity regime; however their performance is significantly lower when liquidity dries up. This finding suggests that funds are likely to engage in asset fire sales when faced with margin calls, resulting in poor performance. Finally, this paper extends the findings of Aragon (2007) who shows that lockup restrictions help hedge funds improve their performance. We extend this result by showing that while lockup provisions enhance hedge fund returns in the high liquidity state; they fail to improve hedge fund performance during low liquidity periods.

We begin our analysis by confirming the earlier results in the literature regarding the link between market liquidity risk and hedge fund performance. We first identify hedge funds' market liquidity exposure across different liquidity regimes using a sample of hedge funds from the Lipper TASS hedge fund database. A number of recent studies have emphasized the systematic nature of the risk posed by market-wide liquidity fluctuations (see, e.g., Chordia, Roll, and Subrahmanyam (2000)). Using various measures of market-wide liquidity, Pástor and Stambaugh (2003), Acharya and Pedersen (2005), and Sadka (2006) provide evidence that systematic liquidity risk is priced in the cross section of asset returns. Furthermore, Sadka (2010) shows that most hedge fund strategies exhibit significant exposure to a market-wide liquidity factor. Moreover, as discussed above, recent market episodes suggest that market liquidity conditions can change dramatically over time with adverse implications for asset values during periods of low liquidity. Accordingly, we use a market-wide liquidity measure and a 2-state Markov regime switching model to identify periods with high and low liquidity. We identify market liquidity regimes using the Sadka (2006) permanent (variable) price impact liquidity measure. Consistent with previous findings in the

[4] Sadka (2010) and Khandani and Lo (2011) provide evidence of time variation in market (il)liquidity premia.

literature, we show that while most hedge funds exhibit positive loadings on the market liquidity factor in the *high liquidity* regime, they appear to decrease their liquidity exposure in the *low liquidity* regime.

One explanation for the variation in the market liquidity betas of hedge funds across the high and low liquidity regimes is that they are able to successfully time market-wide liquidity changes (see, for example, Cao, et al. (2013)). Another possibility is that binding funding constraints during periods of low liquidity lead to forced liquidations of assets, thereby lowering the funds' liquidity betas during such periods. Based on the extended Fung-Hsieh 8-factor model, we find that funds with high market liquidity risk loadings outperform low-loading funds by about 5.80% annually during the *high* liquidity regime. However, the performance difference between the high- and low-liquidity loading funds is -11.50% during the *low* liquidity regime. These results suggest that hedge funds may not be entirely successful in timing liquidity changes – particularly during periods of low liquidity.

Further analysis of the performance of the market liquidity sorted portfolios shows that their alphas display an upward trend across the liquidity beta-sorted deciles in the high liquidity regime. By contrast, in the low liquidity regime, the performance of hedge funds exhibits a downward trend as the funds' exposure to market liquidity increases. The latter result hints at the potential role played by funding liquidity during the low liquidity regime. In particular, it suggests that liquidity spirals originating via shocks to funding liquidity could potentially lead to a negative relation between hedge fund returns and market liquidity during crisis periods.

To investigate this issue we next explore the relation between hedge fund performance and funding liquidity risk. We employ the TED spread, i.e., the spread between the three-month

LIBOR rate and the three-month U.S. Treasury bill rate, as a proxy measure of funding liquidity.[5] Since the TED spread in its original form is an illiquidity measure, we employ the negative of the TED spread as a measure of funding liquidity. Therefore, a positive shock to this measure reflects an improvement in funding liquidity conditions. Henceforth, for the sake of brevity we refer to the measure as simply the 'TED spread.' We measure a hedge fund's funding liquidity risk as the sensitivity of the fund's returns to the innovations in the TED spread measure using a regression specification that incorporates the market index return in addition to the TED spread. Our results show that the hypothetical high-minus-low *funding liquidity* risk portfolio strategy earns an annualized performance of -2.47% in the high market liquidity regime during the period 1994-2012. Interestingly, the strategy's performance is negative even in the high market liquidity state, compared to a performance of 5.50% for a similar strategy based on *market liquidity* sorted portfolios as mentioned earlier. Furthermore, the strategy has an annualized performance of -11.67% in the low liquidity regime. These results show that a high funding liquidity risk exposure is detrimental to hedge fund returns, especially during the low market liquidity state. This result is also consistent with the dynamic margin-based asset pricing model proposed by Gârleanu and Pedersen (2011). According to their model, during periods of adverse funding conditions there is an increase in liquidity-driven risk premia and subsequent decline in asset prices, especially for assets subject to higher margin requirements.

We further examine the role of the interaction between funding liquidity and market liquidity in determining the performance of hedge funds. We double-sort funds into quintiles based on their market liquidity and their funding liquidity exposures and examine the performance of the resulting 25 (5x5) fund portfolios. Our results show that market liquidity exposure is the driver of

[5] The TED spread is a commonly used measure of funding liquidity in the literature (e.g., Boyson, Stahel, and Stulz (2010), and Teo (2011)).

the favorable performance in the high liquidity regime. On the other hand, both market liquidity and funding liquidity exposures are detrimental to hedge fund performance during the low liquidity regime, hinting at the existence of negative liquidity spirals.

Finally, we examine whether share restrictions in the form of lockup periods allow hedge funds to manage the investor flow-related funding liquidity risk. Our results suggest that longer lockup periods are effective only in the high liquidity states in terms of their ability to mitigate the flow-induced funding liquidity risk. On the other hand, lockup period restrictions do not help improve fund performance in the low liquidity state, pointing once again to the dominant effect of negative liquidity spirals.

We further confirm the robustness of our results to several variations in our primary test design. These include the use of a TED spread-based funding liquidity measure that is orthogonal to the market liquidity factor, to assess the funding liquidity betas of hedge funds. Our findings are also robust to the use of an alternative measure of funding liquidity based on the REPO rate, as well as a traded funding liquidity measure proposed by Chen and Lu (2017) that is based on return spreads for "betting-against-beta" (BAB) portfolios of stocks with high- and low-margin requirements. The results are also robust to an alternative definition of liquidity regimes based on the realized hedge fund returns. Collectively, our results confirm the role of funding liquidity risk in explaining the performance of hedge funds.

This study is related to a number of recent studies in the literature. Our results regarding the interaction between market and funding liquidity are broadly consistent with the findings of Aragon and Strahan (2012) who document that stocks held by Lehman Brothers' hedge fund clients experienced unexpectedly large declines in market liquidity after Lehman's bankruptcy in 2008. Our findings also complement those of Boyson, Stahel, and Stulz (2010) who find that shocks to asset liquidity and funding liquidity increase the probability of contagion across hedge fund styles. Their study focuses on return co-movements in the left tails of the return distributions for various hedge fund styles. Reca, Sias, and Turtle (2014) also focus on the tails of the hedge fund return distributions and document that liquidity shock-induced contagion is not the primary factor driving the correlation across hedge fund styles. This suggests that hedge fund returns at the extreme tails may be driven by other factors, in addition to liquidity shocks.[6] By contrast, rather than focusing on the tails of hedge fund return distributions, in this study our objective is to analyze the impact of market and funding liquidity risk on hedge fund performance in different liquidity regimes that are endogenously determined. This framework allows us to explicitly focus on the dynamics of hedge fund illiquidity premia, and in particular on the interaction between market and funding liquidity.

The rest of the paper is organized as follows. Section II describes the data. Section III outlines the Markov regime switching model employed in the analyses. Section IV analyzes the performance of market liquidity risk-sorted portfolios in the high and low liquidity regimes. Section V provides evidence on the impact of funding liquidity risk on hedge fund performance. Section VI analyzes the impact of share restrictions on the performance of funding liquidity risk-sorted fund portfolios in the two liquidity regimes. Section VII describes a number of robustness tests, while Section VIII concludes.

II. Data

This section describes the sample of hedge funds, the Fung and Hsieh factors, and the liquidity factors employed in the empirical analysis.

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[6] Reca, Sias, and Turtle (2014) conclude that the prior evidence of liquidity shock induced contagion (e.g., Boyson, Stahel, and Stulz (2010), and Dudley and Nimalendran (2011)) is largely explained by model misspecification and time-varying market volatility.

A. Hedge Fund Sample

Our sample of hedge funds is obtained from the Lipper TASS database. The original sample extends from January 1994 to May 2012. The Lipper TASS database includes hedge fund data from the following vendors: Cogendi, FinLab, FactSet (SPAR), PerTrac, and Zephyr.

It is well known that hedge fund data suffer from a number of biases. In order to address the backfilling bias we delete the first 24 observations of a fund. Another common bias in hedge fund data is the survivorship bias. To guard against this issue we restrict our sample to the post–1994 period during which "graveyard" funds are retained in the Lipper TASS database. We restrict our sample to funds with at least 24 months of consecutive return observations. Only funds that report their returns on a monthly basis and net of all fees are included and a currency code requirement of "USD" is imposed. All returns are expressed in excess of the risk-free rate. In addition, we unsmooth hedge fund returns following the procedure recommended by Getmansky, Lo, and Makarov (2004). We include hedge funds in the following investment styles: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, fund of funds, global macro, long/short equity hedge, managed futures, and multi strategy. The final sample includes 5,599 funds.

Table I reports summary statistics for the sample described above. Panel A reports statistics (number of funds, average monthly return, standard deviation, skewness, and excess kurtosis) for all hedge funds. The figures within a category are equally weighted averages of the statistics across the funds. The cross-sectional average monthly excess return and the average standard deviation are 29 basis points and 43 basis points, respectively. As may be seen, the sample funds have negatively skewed returns and thick tails in the return distributions.

Panel B reports the statistics by investment style. The Dedicated short bias category exhibits the lowest performance among all strategies, at -25 basis points. The average monthly performance of the Fund of Funds category is 10 basis points, which is low compared to other investment styles. Most of the investment styles display negative skewness. The fixed income arbitrage strategy exhibits the highest kurtosis, which is largely influenced by the Russian debt crisis in 1998 – an episode that famously led to the collapse of the fund, Long Term Capital Management (LTCM).

B. Fung and Hsieh Factors

The Fung and Hsieh (2004) seven-factor model is widely used in the literature on hedge fund performance. The domestic equity factors used in the model are the excess return on the CRSP value-weighted index and the Fama-French size factor. The fixed-income factors include the change in the term spread (the difference between the 10-year Treasury constant maturity yield and Treasury bill yield) and the change in the credit spread (Moody's Baa yield minus 10-year Treasury constant maturity yield). The model also includes three factors designed to mimic trend following strategies employed by certain hedge funds that trade in bond (PTFSBD), commodity (PTFSCOM), and currency (PTFSFX) markets. Recently, Fung and Hsieh have added an eighth factor to the model, namely, the emerging market factor (MSCI emerging market index). We compute fund alphas based on the 8-factor model with the above factors.

Table II (Panels A to D) displays the summary statistics for the Fung and Hsieh factors. Most notably, the trend-following factors have the highest standard deviations with negative average returns, which confirms the riskiness of these strategies. The credit spread factor has the highest kurtosis which reflects the widening in credit spreads during crisis periods.

C. Liquidity Factors

Liquidity is an important factor affecting asset prices. However, there are several dimensions to liquidity and it is not easily captured by a single measure. There has been several liquidity proxies proposed in the literature. In this study we employ two primary liquidity measures: the Sadka (2006) permanent-variable liquidity measure[7], and the 3-month TED spread. The two measures capture different aspects of liquidity. The Sadka (2006) liquidity factor is a measure of *market liquidity* which is typically defined as the ability to trade large quantities quickly, at low cost, and with minimal price impact. Specifically, Sadka's (2006) measure is related to permanent price movements induced by the information content of a trade. On the other hand, the TED spread is a measure of *funding liquidity* which essentially reflects the ability to borrow against a security. The TED spread is calculated as 3-month US LIBOR minus 3-month Treasury yield. Since this is a measure of illiquidity, to be consistent with the other measure, we add a negative sign to make it a liquidity measure for which a positive shock represents an enhancement to (funding) liquidity.

Panel E of Table II reports the summary statistics for the liquidity measures. The measures display negative skewness and high excess kurtosis, which is more pronounced for the TED spread. It is of interest to examine the interactions among the factors discussed above. In Table III, we display the pairwise correlations among the factors used in this study. The correlations among the liquidity factors are low in general. The only notable correlation is between the liquidity factors and the credit spread: -0.45, and -0.36 for the TED Spread, and the Sadka (2006) measure, respectively. This shows that credit conditions worsen during periods of low liquidity.

[7] For examples of other market liquidity measures employed in the literature, see Hu, Pan, and Wang (2013), Pástor and Stambaugh (2003), Amihud (2002), Acharya and Pedersen (2005), and Getmansky, Lo, and Makarov (2004). Kruttli, Patton, and Ramadorai (2013) construct a measure based on the illiquidity of hedge fund portfolios and show that it has predictive ability for asset returns.

III. Methodology

The purpose of this paper is to study the relationship between the liquidity exposure of hedge funds and their performance. Hedge funds often employ dynamic strategies which they adjust depending on the state of the economy and trade a variety of financial securities with non-linear payoffs, including equity and fixed income derivatives. On the other hand, based on prior research there is some evidence that the impact of market liquidity on the performance of hedge funds is state-dependent. For example, Sadka (2010) shows that hedge funds that significantly load on market liquidity risk outperform low-loading funds by 6% per year, on average. Focusing on nine months during the recent financial crises (September-November 1998, August-October 2007, and September-November 2008), he also shows that the performance of this strategy is negative during the crisis period.

Accordingly, in this study, we employ a 2-state Markov regime switching model[8] to endogenously identify the different liquidity regimes. The regimes are identified based on the liquidity factors. Our simple regime switching model for the liquidity factor can be expressed as:

$$L_t = \mu_{S_t} + \varepsilon_t \tag{1}$$

$$\varepsilon_t \sim \mathrm{N}\left(0, \sigma_{S_t}^2\right),$$

where L_t is the liquidity factor, and S_t represents a 2-state Markov chain with transition matrix, Π_s:

$$\Pi_s = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix},$$

and p_{ij} denotes probability of transitioning from state i to state j. Note that the model has two key regime-specific parameters - the mean of the liquidity factor, μ_{S_t}, and its variance, $\sigma_{S_t}^2$. Therefore,

[8] Markov regime switching models are widely used in the literature, e.g., Hamilton (1989, 1990), Ang and Bekaert (2002), Bekaert and Harvey (1995), Guidolin and Timmermann (2008), and Gray (1996).

Markov regime switching model is superior to a methodology which determines the liquidity regimes by simply segregating the data above and below the median of the liquidity measure.

We determine the high and low liquidity regimes based on a particular liquidity factor by estimating the above model using maximum likelihood. The model provides us with a time series of filtered probabilities. For each month in the sample period, the estimated filtered probabilities for the two states add up to one. The state with the highest filtered probability is identified as the state of the economy for that month. Accordingly, based on the 2-state model, the state with filtered probability higher than 50% in a given month is identified as the state of the economy for that particular month.

Table IV displays the estimation results of the 2-state Markov regime switching model based on the Sadka (2006) liquidity measure[9] during the period April 1983 to December 2012.[10] Panel A reports the estimated means of the liquidity factor for the high and low liquidity regimes. Panel B displays the expected duration for the high and low liquidity regimes. Panel C reports the transition matrix. Note that the high liquidity regime is more persistent and has a longer duration compared to the low liquidity regime. We also note that the low liquidity regime identified by the model based on the Sadka (2006) liquidity measure includes the three recent liquidity crises/episodes considered in Sadka (2010).

Figure 1 depicts the filtered probabilities from the Markov regime switching model for the low liquidity regime. Note that high values of filtered probabilities displayed in Figure 1 indicate the low liquidity episodes in U.S. financial markets which includes the Russian debt crisis

[9] Even though Sadka (2006) measure is an equity based liquidity factor, it measures market-wide liquidity. Therefore, this measure is suitable in identifying liquidity regimes as it is a systematic risk factor which is priced across various asset classes.
[10] Note that our hedge fund sample covers the period from January 1994 to May 2012. However, in order to correctly determine the liquidity states we employ the available time series for the Sadka (2006) liquidity measure.

(September 1998), the 2001 recession, the recent financial crisis (August 2007 to October 2009) which includes the period of turmoil related to the Quant (hedge fund) crisis and the bankruptcy of Lehman Brothers, and the Greek crisis (2011). In all, 34 months are identified as belonging to the low liquidity regime while the remaining 187 months belong to the high liquidity regime, during the period January 1994 to May 2012.

IV. Compensation for Market Liquidity Risk and Liquidity Timing

While funding liquidity is the primary focus of this study, we first confirm the results regarding market liquidity and hedge fund performance documented in the literature (e.g., Sadka (2010)) in our Markov regime switching framework. The subsequent sections document the main findings of this study regarding the impact of funding liquidity risk on hedge fund performance.

We begin by first estimating the market liquidity loading of each hedge fund by regressing the fund returns on the market excess return and the liquidity factor during the prior 24-month period:

$$R_t^i - r_{f,t} = \alpha_t^i + \beta_m^i R_t^m + \beta_L^i L_t + \varepsilon_t^i, \tag{2}$$

where R_t^i is a fund's return in month *t*, $r_{f,t}$ is the risk free rate, R_t^m is the market excess return, and L_t is Sadka's (2006) liquidity factor for month *t*. The first set of estimates is obtained using the data for the two-year period prior to January 1996. We only include funds with at least 18 months of non-missing observations. We then sort hedge funds into 10 portfolios based on their estimated market liquidity exposures, β_L^i, with equal number of funds in each decile. We implement this process on a rolling basis each month from January 1996 to May 2012. Funds are kept in the decile portfolios for one month. Following this procedure we obtain a time series of portfolio returns for each of the ten market liquidity deciles.

The purpose of this exercise is to compare the performance of the high market liquidity loading portfolio to the low market liquidity loading portfolio for different states of the economy, namely for the high and low liquidity regimes. To do this we follow a strategy that takes a long position in the high market liquidity decile portfolio and a short position in the low market liquidity decile portfolio. The performance of the strategy is evaluated using the Fung-Hsieh 8–factor model described below:

$$R_t^D - r_{f,t} = \alpha_s^D + \sum_{k=1}^{8} \beta_{k,s}^D F_{k,t} + \varepsilon_t^D, \; s = H, L, \qquad (3)$$

where R_t^D is the liquidity decile portfolio return and $r_{f,t}$ is the risk free rate during month *t*. The subscript *s* denotes the high and low liquidity regimes. In the above specification, we incorporate the 8 Fung-Hsieh factors described previously in Section II.B. However, two of the Fung and Hsieh factors, namely, the change in the term spread and the change in the credit spread, are non-traded factors. We replace these two factors by the returns to tradable portfolios so that the intercept or the alpha of the model represented by Equation (3) can be interpreted as an excess return. As a proxy for the term spread we use the difference between Barclay's 7-10 year Treasury index return and the one-month Treasury bill rate. Similarly, we employ the return difference between Barclay's 7-10 year Corporate Baa index return and Barclay's 7-10 year Treasury Index as a proxy for the credit spread.

Sadka (2010) documents that, on average, the high liquidity-loading funds outperform low liquidity-loading funds by about 6% annually.[11] However, as noted earlier, hedge funds' performance might suffer during the low liquidity states. In this section we analyze the performance of the high-minus-low liquidity strategy in different states of the economy. As previously noted, we identify liquidity regimes using the 2-state Markov regime switching model

[11] In unreported results, we find that the Hu, Pan, and Wang (2013) market (il)liquidity measure (*Noise*) is priced across hedge fund returns and provides a 6.12% premium annually in our dataset. However, we also find that the Pástor and Stambaugh (2003) market liquidity measure is not priced across hedge fund returns. These results are consistent with Hu, Pan, and Wang (2013).

estimated based on the Sadka (2006) liquidity measure. Table V presents the results. Panel A of the table reports the Fung-Hsieh eight factor alpha[12] of the decile portfolios and the performance of the high-minus-low liquidity beta strategy for the entire sample during the period January 1994 to May 2012. The high-minus-low liquidity beta strategy earns an annualized alpha of 3.76%.[13]

Panel B of Table V presents the results for the *high liquidity regime* in which the performance for the high-minus-low portfolio is 5.80%. However, as shown in panel C of the table, in the *low liquidity regime* the high-minus-low portfolio's performance is much lower: -11.50%. Furthermore, comparing the alphas for the decile portfolios reported in Panels B and C, we can see that with the exception of the lowest liquidity beta decile portfolio, the estimated alphas are consistently lower in the low liquidity state.[14]

The evidence presented in Table V confirms that the performance of liquidity beta-sorted hedge fund portfolios is significantly lower during the low liquidity state. This is consistent with the view that the profitability of many hedge fund strategies seeking to exploit mispricing of securities is sensitive to market liquidity conditions. In periods of low liquidity, asset prices may fail to converge to fundamental values leading to the poor performance of many convergence/arbitrage trading strategies.

Figure 2 displays the average market liquidity betas and annualized 8-factor Fung and Hsieh alphas for ten decile portfolios presented in Table V. Note that while hedge funds with positive exposure to market liquidity risk lower their liquidity betas in the low liquidity state, their corresponding performance is significantly lower in the low liquidity regime. This suggests that

[12] In unreported results, we show that our findings are qualitatively similar when based on average monthly excess returns, in addition to fund alphas, throughout the paper.
[13] The 6% Premium reported by Sadka (2010) is calculated for the period 1994 to 2008 using the Fung and Hsieh (2004) 7-factor model. In our analyses that cover the period 1994 to 2012 we employ the Fung and Hsieh 8-factor model that includes the emerging market factor in addition to the original Fung and Hsieh (2004) 7 factors.
[14] The lowest liquidity beta decile portfolio (Portfolio 1) has negative liquidity exposures in both the high liquidity state (liquidity beta = -4.06), and the low liquidity state (liquidity beta = -2.40).

the reduction in hedge funds' market liquidity exposure during periods of liquidity crises is not due to successful liquidity timing, but potentially due to involuntary liquidation of assets, possibly in order to meet funding requirements. Such forced liquidations could potentially explain the significantly lower performance in the low liquidity states. Collectively, these results help extend the earlier findings of Cao, et al. (2013) and provide a more nuanced view of the liquidity timing ability of hedge funds. In particular, our results suggest that hedge funds are not entirely successful in timing liquidity changes – particularly during periods of low liquidity.

Furthermore, our results also strongly hint at the potential role played by funding liquidity during the low liquidity regime. In particular, they suggest that liquidity spirals originating via shocks to funding liquidity could potentially lead to a negative relation between hedge fund returns and market liquidity during crisis periods. We investigate the role of funding liquidity in more detail in the next section.

V. Funding Liquidity Risk

In this section we analyze the performance of the high-minus-low liquidity beta strategy in the context of the funds' funding liquidity exposure. As mentioned earlier, we employ the TED spread[15] as a proxy for funding liquidity. Note also that instead of using the TED spread levels, we employ the innovations in the TED spread to calculate liquidity betas. The innovations are calculated as the residuals from an AR(1) model for the TED spread. We estimate the funding liquidity exposures in a framework in which hedge fund returns are regressed on the market excess return and the funding liquidity measure, i.e., the innovations in the TED spread. Subsequently, we form the funding liquidity decile portfolios following the same procedure employed in Section IV for constructing market liquidity decile portfolios.

[15] Recall that since the TED spread is an illiquidity measure, we employ the negative of the TED spread as a measure of funding liquidity.

Table VI reports the eight factor Fung and Hsieh alphas for the funding liquidity deciles, as well as for the performance of the high-minus-low funding liquidity beta strategy. Panel A presents the results for the whole sample. Panels B and C of the table report results for the high and low liquidity regimes, respectively. For the entire sample, over the period January 1994 to May 2012, the high-minus-low liquidity beta strategy earns an annualized performance of -3.40%. Note that in contrast to the results reported in Table V for *market liquidity* beta sorted portfolios, the performance of the high-minus-low strategy based on *funding liquidity* beta sorted portfolios is negative. It is evident that the funds with high exposure to funding liquidity underperform funds with low funding liquidity exposure. This result highlights the importance of funding liquidity risk exposure in determining the performance of hedge funds.

In panels B and C of Table VI we report the results separately for the two liquidity regimes. In the high liquidity state, the high-minus-low strategy's annualized alpha is -2.47%. In the low liquidity state the results are dramatic, as the strategy's annualized alpha is -11.67%. These results show that while funding liquidity exposure hurts hedge fund performance in general; its impact is severe in the low liquidity regime. One of the reasons for this poor performance is the fact that hedge funds typically employ high leverage which magnified the impact of the recent crises on their performance. When combined with high exposure to funding liquidity, highly levered hedge funds suffered when they faced margin calls in periods of low liquidity. Note that unlike the results related to market liquidity beta sorted strategy presented in Table V, the performance of the high-minus-low funding liquidity strategy is negative in both liquidity regimes.

Next, we graphically display the results reported in Table VI. Figure 3 depicts the Fung and Hsieh 8-factor alphas across the funding liquidity deciles. Panels A and B of the figure show that hedge funds' performance declines as their funding liquidity exposure increases, not only in the entire sample but also in the high liquidity regime. Moreover, as seen in Panel C, the impact of funding liquidity exposure is more pronounced in the low liquidity regime; hedge funds with high funding liquidity exposure significantly underperform the funds that have low exposure to funding liquidity risk.

A. Liquidity Spirals

In the model considered by Brunnermeier and Pedersen (2009), under certain conditions market liquidity and funding liquidity are mutually reinforcing which creates liquidity spirals. In the model, an adverse shock to speculators' funding liquidity forces them to lower their leverage and reduce the liquidity they provide to the market, which in turn leads to diminished overall market liquidity. When funding liquidity shocks are severe, the decrease in market liquidity makes funding conditions even more restrictive, which leads to a liquidity spiral. We investigate the implications of their model in this section.

In Tables V and VI, we reported the fund alphas for each liquidity decile portfolio based on market liquidity and funding liquidity exposure, respectively. We now jointly consider the two liquidity scenarios and sequentially sort funds, first by their market liquidity betas, followed by the funding liquidity betas. The fund alphas are displayed in the form of a two-way matrix in Table VII. The table shows the annualized fund alphas for a total of 25 (5x5) portfolios. Note that we divide the sample of hedge funds into quintiles (rather than deciles) based on both the market and funding liquidity betas, in order to obtain sufficient number of hedge funds in each portfolio. Panel A (B) displays the results for the high (low) liquidity regime. Along with the performance of each of the 25 portfolios, the performance of the high-minus-low liquidity beta strategy is also reported.

It is clear from Panel A that, in the high liquidity regime, the fund alphas are the highest for funds with a high market liquidity exposure (quintiles 4 & 5). On the other hand, the lowest annualized alpha (-3.77%) is recorded by funds with low market liquidity exposure and high funding liquidity exposure.[16] Also note that the performance of the high-minus-low *market liquidity* strategy is positive for four of the five funding liquidity quintiles, with annualized alphas ranging from -1.22% to 11.81% per year. However, the performance of the high-minus-low *funding liquidity* strategy is negative in four of the five market liquidity quintiles, with annualized performances ranging from -7.20% to 3.37% per year. This shows that while having high exposure to market liquidity helps hedge funds in the high liquidity regime, exposure to funding liquidity hurts hedge fund performance.

Panel B of Table VII displays the results for the low liquidity regime. First, note that most of the annualized alphas of the 25 portfolios are negative (16 out of 25) and generally lower compared to their corresponding alphas in the high liquidity regime. The performance of the high-minus-low *funding liquidity* strategy is strikingly lower in the low liquidity regime with the annualized performance ranging from -16.30% to -6.41% per year. Further, in contrast to Panel A, the market liquidity strategies also perform poorly in the low liquidity regime. The performance of the high-minus-low *market liquidity* strategy is negative in all funding liquidity quintiles, ranging from -11.97% to -0.92% per year. These results show that while funding liquidity risk seems more dominant in the low liquidity regime; both market liquidity and funding liquidity risk exposure result in negative hedge fund performance in the low liquidity state. This result is consistent with the negative liquidity spirals hypothesized by Brunnermeier and Pedersen (2009).

[16] In unreported results we confirm that a similar pattern holds for monthly excess returns of hedge fund portfolios.

Next, we graphically display the annualized fund alphas for the high and low liquidity regimes in Figures 4 and 5, respectively. The figures shows that in general funds with high exposure to market liquidity risk in the high liquidity regime (Figure 4) have higher alphas compared to the low liquidity regime alphas depicted in Figure 5. Moreover, funds with high exposure to funding liquidity and low exposure to the market liquidity perform poorly in the high liquidity regime. On the other hand, Figure 5 shows that, in the low liquidity regime, funds with low exposure to funding liquidity perform better regardless of the level of market liquidity exposure. Similarly, the funds with high exposure to funding liquidity perform poorly regardless of the level of market liquidity exposure.

Figures 4 and 5 demonstrate that hedge fund performance varies significantly across different quintiles of market and funding liquidity. It is clear from the figures that the impact of market liquidity and funding liquidity on hedge fund performance varies across different liquidity regimes. Under certain market conditions, reflected in the low liquidity regime, the two liquidity characteristics mutually reinforce each other. Note that in the high liquidity state (Figure 4), the best performance is obtained when exposure to funding liquidity and market liquidity is the highest, hinting at a positive liquidity spiral. In addition, in the low liquidity state (Figure 5), the worst performance is obtained when exposure to funding liquidity and market liquidity is the highest which indicates a negative liquidity spiral. These results provide support for a key prediction of the Brunnermeier and Pedersen (2009) model.

Boyson, Stahel, and Stulz (2010) document that large adverse shocks to market and funding liquidity increase the probability of worst return contagion across hedge fund styles. The results presented in Panel B of Table VII and Figure 5 support the findings of Boyson, Stahel, and Shulz

(2010), as we document that during poor market liquidity conditions hedge fund returns suffer severely from exposures to both market and funding liquidity.

B. Discussion

Our results regarding the significance of funding liquidity risk exposure, and the mutually reinforcing impact of funding liquidity risk and market liquidity risk in the low liquidity regime, have important implications for understanding the dynamics of hedge fund performance. In contrast to mutual funds, most hedge fund strategies invest in relatively illiquid assets and employ significant leverage. This makes them particularly vulnerable to adverse shocks to funding liquidity conditions as evidenced by the above results that highlight the key role played by funding liquidity risk exposure. These results also have broader implications in the context of the evolving market environment. During the past decade, non-traditional intermediaries like hedge funds and proprietary trading desks of banks have come to play an increasingly prominent role – as liquidity suppliers and counterparties in transactions in several markets. In recent years hedge funds have also become important participants in several less developed financial markets. In contrast to traditional market makers or banking intermediaries that face mandatory capital requirements, hedge funds are largely unregulated. Further, as highlighted by the events of August 2007 when a number of hedge funds employing quantitative strategies suffered substantial losses, return correlations across hedge funds have increased markedly in recent years.[17] Our results suggest that a better understanding of the funding liquidity risk exposure of hedge funds is particularly relevant for a broader assessment of the robustness of the evolving market ecosystem.

[17] See Khandani and Lo (2007) for a fuller discussion of these issues.

VI. Impact of Share Restrictions on Fund Performance Across Liquidity Regimes

In order to cope with funding problems related to investor fund flows, many hedge funds adopt share restrictions. These restrictions may be in the form of a lockup provision specifying a minimum lockup period during which no redemptions are allowed, or a redemption notice period specifying a minimum notice that the investor is required to provide before redeeming shares, or a redemption frequency which sets the time intervals at which investors are allowed to withdraw their holdings. Funds with share restrictions are likely less funding restricted than otherwise similar funds. A number of recent studies suggest that such share restrictions have a significant impact on the ability of hedge funds to manage their funding liquidity risk. For example, Aragon (2007) shows that funds with lockup restrictions outperform funds without such restrictions by 4-7% annually suggesting that share restrictions enable funds to efficiently manage illiquid assets. On the other hand, Aiken, Clifford, and Ellis (2015) show that hedge funds with discretionary liquidity restrictions are unable to avoid sale of illiquid assets and underperform the funds without discretionary liquidity restrictions. Teo (2011) examines the performance of liquid hedge funds that grant favorable redemption terms (i.e., redemptions at monthly, or more frequent intervals) to investors and finds that high net inflow funds outperform low net inflow funds by 4.79% per year. Furthermore, he documents that within the group of liquid hedge funds the performance impact of fund flows is stronger when market liquidity is low and when funding liquidity is tight.

Given the aforementioned unconditional results in the literature, it is of interest to examine how the presence or absence of share restrictions affects the funding liquidity risk and performance of hedge funds in the high as well as the low liquidity regimes.[18] Accordingly, in this section we analyze the impact of lockup restrictions on the performance of funding liquidity sorted decile

[18] Recall that liquidity regimes are determined using the Sadka (2006) market liquidity measure.

portfolios in the two regimes. Following Aragon (2007), we define liquid hedge funds as funds with no lockup restrictions.[19] Similarly, we define illiquid hedge funds as funds with lockup periods. Tables VIII and IX report the performance of the funding liquidity sorted decile portfolios for the liquid and illiquid hedge funds, respectively. Portfolio excess returns are reported in the form of 8-factor Fung-Hsieh alphas.

First consider the performance of the respective fund decile portfolios in the high liquidity state reported in Panel B of Tables VIII and IX. It can be seen that in the high liquidity state the performance of the decile portfolios of liquid hedge funds (Panel B, Table VIII) is lower compared to the illiquid hedge funds' decile portfolios (Panel B of Table IX) in all ten deciles. Furthermore, in the case of *illiquid funds* the high-minus-low funding liquidity risk portfolio strategy has a performance equal to -0.39% per year in the high liquidity regime. By contrast, in the case of *liquid funds* the high-minus-low funding liquidity risk portfolio strategy has an annualized performance of -2.66%. These results suggest that having protection against investor flow-related funding liquidity risk in the form of lockup restrictions helps hedge funds improve their performance in the high liquidity state.

On the other hand, as seen in Panel C of Tables VIII and IX, in the low liquidity state the pairwise comparison between decile portfolios of liquid and illiquid hedge funds is ambiguous. Furthermore, the performance of the high-minus-low funding liquidity risk portfolio strategy is actually lower for illiquid funds, with an annualized performance of -16.97% vs. -9.82% for liquid funds.[20] This shows that imposing lockup periods does not improve fund performance in the low liquidity state. This finding extends the results presented in Aragon (2007) by documenting that

[19] Liquid funds are identified using the 'lockup period' variable in the Lipper TASS database with values equal to 0. This results in 75.5% of the funds in our sample being classified as 'liquid' funds.
[20] The results presented in this section are robust to identifying liquid and illiquid hedge funds using redemption frequency and redemption notice periods, in addition to lockup periods.

funds with lockup restrictions outperform funds without such restrictions only in the high liquidity state. Evidently, the negative impact of funding liquidity risk on performance in the low liquidity state (and the impact of negative liquidity spirals) far outweighs any benefits offered by having lockup restrictions in place. This result also reflects the possibility that funds with lockup restrictions endogenously choose to invest in relatively less liquid assets which contributes to their poor performance in the low liquidity state. Furthermore, this finding confirms that the underperformance of illiquid hedge funds documented by Aiken, Clifford, and Ellis (2015) stems from the poor performance in the low liquidity state, possibly due to forced asset fire sales. These findings also contribute to the recent literature by documenting the effectiveness of share restrictions in different liquidity states. In particular, our results suggest that lockup periods are effective only in the high liquidity states in terms of their ability to mitigate the flow-induced funding liquidity risk.

VII. Robustness Tests

In this section we provide additional tests to support the robustness of our results. We begin by adjusting the funding liquidity measure to account for the potential correlation between measures of market liquidity and funding liquidity.

A. Correlation between Market and Funding Liquidity Measures

Since funding liquidity conditions and market liquidity measures are positively correlated, it would be useful to isolate the impact of funding liquidity risk that is orthogonal to market liquidity.[21] To this end, we project the innovations in the TED spread on the market liquidity measure (i.e., the Sadka (2006) liquidity factor) and use the orthogonal component to compute the funding liquidity betas and form liquidity beta sorted portfolios. We display the performance of

[21] The Pearson correlation coefficient between the Sadka (2006) liquidity factor and the TED spread is 0.39.

the new liquidity decile portfolios in Table A.1 in the Appendix. Note that the performance of the high-minus-low liquidity strategy is negative across the board and the results are consistent with the results displayed in Table VI. Therefore, our results are robust to the use of the orthogonal component of the TED spread as a measure of funding liquidity.

B. Alternative Funding Liquidity Measures

One of the main contributions of this paper is to provide evidence on the interaction between hedge funds' performance and their funding liquidity risk. The primary funding liquidity measure employed in this study is the (innovations in) TED spread. In this section we assess the robustness of our results to alternative funding liquidity measures, namely, the REPO rate[22] , a traded funding liquidity measure proposed by Chen and Lu (2017), and a funding liquidity measure proposed by Fontaine and Garcia (2012).

REPO Rate

The REPO rate (i.e., the difference between overnight repurchase rate and the 3-month treasury rate) reflects the actual funding cost experienced by banks and investors, and is available through DataStream starting in November 1996. Since our hedge fund data starts in January 1994, we use the FED Funds Rate as a proxy during the period from January 1994 to October 1996.[23] Note that the REPO rate is an illiquidity measure. To be consistent with the methodology employed for the TED spread, we first add a negative sign to the REPO rate. Secondly, we employ the innovations in the REPO rates, instead of the levels, when calculating the liquidity betas of hedge funds. The innovations in the REPO rates are estimated as the residuals from an AR(1) model fitted to the modified REPO data.

[22] The REPO rate is employed as a funding liquidity measure in several studies, including Kambhu (2006), Adrian and Fleming (2005), and Boyson et al. (2010).
[23] Nath (2003) shows that the overnight repurchase rate is of the same order of magnitude as the FED Funds rate.

We repeat the analysis performed in Table VI using the REPO data. Table A-2 in the Appendix presents the results. Note that the performance of the high-minus-low liquidity strategy is negative in both liquidity states. Specifically, the strategy's estimated performance is -0.83% and -10.78% in the high and low liquidity states, respectively. These results confirm that having exposure to funding liquidity significantly hurts the funds' performance in the low liquidity state.

Traded Funding Liquidity Measure

Next we repeat the above analysis using a theoretically motivated traded funding liquidity measure recently proposed by Chen and Lu (2017). The measure is based on return spreads for "betting-against-beta" (BAB) portfolios of stocks with high- and low-margin requirements.[24] We note that this measure is a funding *liquidity* factor; therefore we do not add a negative sign as we did for the TED spread and the REPO rate which are both measures of funding *illiquidity*. We repeat the analysis related to funding liquidity exposure of hedge funds by employing the aforementioned traded funding liquidity measure. Table A-3 presents the results. We note that the funds which the highest exposure to the traded funding *liquidity* factor (decile 10) underperform funds with the lowest exposure in both the high and the low liquidity states. The annualized 10-1 decile portfolio performance is -5.55% and -8.50% in the high and low liquidity states, respectively. As seen in Panel A of the table, the corresponding unconditional performance (-5.84% per year) is negative as well.[25] These results are consistent with our primary funding liquidity results presented in Table VI.

[24] The trading liquidity factor is the first principal component of five BAB spread portfolios, which are constructed using five different margin proxies.

[25] Chen and Lu (2017) attribute the superior performance of low-sensitivity hedge funds to fund managers' funding liquidity timing skills which allows them to capitalize on positive funding liquidity shocks and avoid negative shocks.

Fontaine and Garcia Measure

Fontaine and Garcia (2012) estimate a funding liquidity factor based on fitting a term structure model to a panel of pairs of U.S. treasury securities. The estimation relies on the assumption that price differences between pairs of treasury securities that are similar in their cash flows but differ in their maturities, can be attributed to a latent liquidity factor. We now repeat the analysis performed in Table VI using the Fontaine and Garcia (2012) liquidity factor to estimate the funding liquidity exposure of hedge funds.

Table A-4 presents the results of this analysis. Note that since the Fontaine and Garcia (2012) factor is an illiquidity measure, we add a negative sign, as we did for the TED spread and the REPO rate, in order to obtain the relevant liquidity measure. We then calculate hedge fund betas with respect to this liquidity measure. Panel A of Table A-4 shows that, unconditionally, the annualized performance of the high-minus-low liquidity strategy is negative, -1.32%, in the overall sample. This result is qualitatively similar to our unconditional results in Panel A of Table VI which are based on the use of the TED spread as a funding liquidity measure.

However, as seen in Panel B of Table A-4, in the high liquidity regime the performance of the high-minus-low funding liquidity strategy is actually positive at 2.31%. This result contrasts with the corresponding result in Panel B of Table VI which showed a negative performance for the high-minus-low funding liquidity strategy. A potential reason for the positive performance of the high-minus-low funding liquidity strategy noted in Panel B of Table A-4 may be the manner of construction of the Fontaine and Garcia (2012) measure. To see this, note that Hu, Pan, and Wang (2013) propose a similar illiquidity measure which is also derived from the deviations of observed treasury prices from their no-arbitrage model-implied prices. Hu, Pan, and Wang (2013) interpret their measure as a *market illiquidity* measure and find that the measure is a priced risk factor for a broad set of assets. Hence, we conjecture that the Fontaine and Garcia

(2012) measure might share some elements of market liquidity which may help explain the positive performance of the high-minus-low funding liquidity strategy in the high liquidity state.

Panel C of Table A-4 presents results for the low liquidity state. The high-minus-low funding liquidity strategy has an annualized alpha of -16.60 percent which is qualitatively consistent with our main result presented in Table VI.

C. Liquidity Regimes Determined by Hedge Fund Returns

In this study we identify the high and low liquidity states based on a market liquidity factor, i.e., the Sadka (2006) market liquidity measure. Alternatively, the regimes can be identified by the hedge fund returns under the assumption that low hedge fund returns coincide with low liquidity periods. To this purpose we calculate the average hedge fund returns for each month in the sample period, and assign the bottom 20% of the returns as belonging to the low liquidity regime. This procedure results in 55 months of the sample being classified in the low liquidity regime, compared with the 34 months allocated to the low liquidity regime previously.

Table A.5 exhibits the results obtained by the new liquidity regimes suggested in this section. First, note that the performance of the decile portfolios is now more pronounced. While the aforementioned performance is consistently positive in the high liquidity state, it is highly negative in the low liquidity state, compared to the original results reported in Table VI. Moreover, the annualized performance of the high-minus-low liquidity strategy is -30.66% in the low liquidity state, compared to the performance of -11.67% reported in Table VI. Therefore, the results displayed in Table A.5 are sharper compared to our original results. However, note that identifying the liquidity regimes using the hedge fund returns mechanically allocates the high and low performing hedge funds in the high and low liquidity regimes, respectively. Hence, the sharper results obtained by this methodology are not surprising. On the other hand, the regimes identified based on liquidity factors correctly deliver high and low liquidity periods, and they do not necessarily perfectly coincide with high and low hedge fund returns. Therefore, the Markov regime switching methodology employed in this paper is more conservative and successfully isolates the effects of liquidity exposure in different regimes.

In summary, the results of this section confirm that our primary results are robust to the use of alternative funding liquidity measures as well to an alternative definition of liquidity regimes.

VIII. Concluding Remarks

This paper provides evidence on the relation between the funding liquidity risk exposure of hedge funds and their performance. The analysis focuses in particular on the interaction between the funds' market liquidity risk and their funding liquidity risk. A key result of the paper is that funding liquidity risk as measured by the sensitivity of a hedge fund's return to a measure of market-wide funding costs, is an important determinant of fund performance. Furthermore, funding liquidity risk is a critical determinant of the variation in hedge fund illiquidity premia across liquidity regimes.

Our results contribute to the literature in several ways. First, we demonstrate that funding liquidity risk as measured by the sensitivity of a hedge fund's return to a measure of market-wide funding costs, is an important determinant of hedge fund performance. Second, we examine the combined impact of both market liquidity risk and funding liquidity risk on hedge fund performance. We show that hedge fund returns are the highest (lowest) for the funds with high (low) market liquidity exposure and low (high) funding liquidity exposure. We also show that market liquidity and funding liquidity interact with each other, potentially leading to liquidity spirals, especially in the low liquidity regime. These results provide empirical evidence in support of the Brunnermeier and Pedersen's (2009) theoretical model which rationalizes the link between market liquidity and funding liquidity.

Third, this paper contributes to the liquidity timing literature. Cao, et al. (2013) document that hedge funds can time market liquidity by adjusting their holdings as liquidity conditions change. In this paper, we argue that liquidity has state dependent implications and provide evidence that hedge fund managers are not entirely successful in timing liquidity changes. We show that hedge funds do lower their market liquidity exposure in the low liquidity regime; however their performance is significantly lower when liquidity dries up. This finding suggests that funds are likely to engage in asset fire sales when faced with margin calls, resulting in poor performance. Finally, this paper extends the findings by Aragon (2007) who shows that lockup provisions help hedge funds improve their performance. We extend this result by showing that while lockup provisions enhance hedge fund returns in the high liquidity state; they fail to improve hedge fund performance during low liquidity periods.

Given the critical importance of funding liquidity for hedge funds demonstrated in this paper, investors clearly need to pay attention to the funding liquidity risk exposure of funds. In order to identify the funding liquidity risk exposure an investor would need to track a hedge fund's leverage and the quality of assets held in its portfolio. However, this is not an easy task given the absence of reporting requirements for hedge funds. The framework adopted in this paper provides a convenient way to analyze a fund's funding liquidity exposure from an investment management perspective.

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Table I: Summary Statistics for Monthly Excess Hedge Fund Returns

Panel A reports statistics (average monthly percentage return, monthly standard deviation in percent, skewness, and excess kurtosis) for the full sample of hedge funds, and Panel B reports statistics by category. The figures within a category are equally weighted averages of the statistics across the funds in the category. The sample includes funds in the Lipper TASS database with at least 24 months of consecutive return data. Only funds that report their returns on a monthly basis and net of all fees are included and a currency code of "USD" is imposed. The sample period is January 1994 to May 2012.

Category	Funds	Mean	St. Dev.	Skewness	Kurtosis
Panel A: Full Sample					
All Funds	5599	0.29	4.26	-0.36	3.51
Panel B: By Hedge Fund Category					
Directional Funds					
Dedicated Short Bias	34	-0.25	6.11	0.28	3.08
Emerging Markets	444	0.42	7.00	-0.36	3.67
Global Macro	223	0.33	4.03	0.10	2.50
Managed Futures	412	0.43	5.19	0.20	2.23
Non-Directional Funds					
Convertible Arbitrage	136	0.23	3.50	-0.68	7.05
Equity Market Neutral	202	0.26	2.55	-0.15	3.05
Fixed Income Arbitrage	151	0.24	3.01	-1.02	9.97
Semi-Directional Funds					
Event Driven	421	0.37	3.56	-0.49	4.55
Long/Short Equity Hedge	1529	0.43	5.21	-0.09	2.35
Multi Strategy	320	0.36	4.02	-0.44	4.56
Fund of Funds					
Fund of Funds	1727	0.10	3.06	-0.70	3.70

Table II: Summary Statistics for Factors

The table lists the Fung and Hsieh hedge fund factors and the liquidity factors employed in this paper and reports average monthly percentage returns, monthly standard deviation in percent, skewness, and excess kurtosis of the factors. The factors are described in the text. The sample period for all factors is January 1994 to May 2012.

Factor	Description	Mean	St. Dev.	Skewness	Kurtosis
	Panel A: Domestic Equity Factors				
MKTXS	Excess return of CRSP value-weighted index	0.49	4.64	-0.68	0.93
SMB	Fama-French size factor	0.20	3.56	0.87	7.98
	Panel B: Fixed Income Factors				
D10YR	Change in the 10YR Treasury yield	-0.02	0.24	-0.17	1.56
DSPRD	Change in Moody's Baa yield minus 10YR Treasury yield	0.01	0.20	1.22	15.23
	Panel C: Trend Following Factors				
PTFSBD	Primitive trend follower strategy bond	-1.15	15.55	1.39	2.53
PTFSFX	Primitive trend follower strategy currency	-0.20	19.68	1.34	2.53
PTFSCOM	Primitive trend follower strategy commodity	-0.53	13.69	1.16	2.28
	Panel D: Global Factors				
EM	MSCI emerging markets	0.70	7.28	-0.49	1.57
	Panel E: Liquidity Factors				
Sadka	Sadka (2006) permanent-variable liquidity measure	0.04	0.59	-0.92	6.23
TED Spread	-(3 month US LIBOR - 3 month Treasury yield)	-0.48	0.40	-3.03	13.03

Table III: Correlations

The table reports the Pearson correlations of the Fung and Hsieh factors, the TED spread, and the Sadka (2006) liquidity measure as described in Table II. P-values are reported in square brackets. The sample period is January 1994 to May 2012.

	PTFSBD	PTFSFX	PTFSCOM	SMB	MKT_RF	MSCI	ΔTERM	ΔCREDIT	TED
PTFSFX	0.26								
	[0.00]								
PTFSCOM	0.21	0.39							
	[0.00]	[0.00]							
SMB	-0.09	-0.02	-0.06						
	[0.18]	[0.75]	[0.39]						
MKT-RF	-0.26	-0.20	-0.18	0.24					
	[0.00]	[0.00]	[0.01]	[0.00]					
MSCI	-0.25	-0.18	-0.16	0.30	0.78				
	[0.00]	[0.01]	[0.02]	[0.00]	[0.00]				
ΔTERM	-0.19	-0.19	-0.12	0.09	0.10	0.11			
	[0.00]	[0.00]	[0.07]	[0.18]	[0.13]	[0.11]			
ΔCREDIT	0.19	0.28	0.19	-0.21	-0.30	-0.30	-0.52		
	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]		
TED	-0.13	-0.19	-0.20	0.08	0.22	0.22	0.12	-0.45	
	[0.05]	[0.01]	[0.00]	[0.21]	[0.00]	[0.00]	[0.08]	[0.00]	
Sadka	-0.03	-0.11	-0.08	0.08	0.13	0.16	0.08	-0.36	0.39
	[0.67]	[0.10]	[0.27]	[0.25]	[0.06]	[0.02]	[0.26]	[0.00]	[0.00]

Table IV: Estimation Results from the 2-State Markov Regime Switching Model

The table exhibits the estimation results from the 2-state Markov regime switching model. Regimes are identified using the Sadka (2006) liquidity measure. Panel A reports the estimated means of the liquidity measure in the high and the low liquidity states. The associated p-values are reported in square brackets. Panel B reports the expected duration of each state in months. Panel C reports the estimated transition probabilities.

Panel A: Mean		
High Liquidity State	0.0005	
	[0.01]	
Low Liquidity State	-0.0016	
	[0.19]	
Panel B: Expected Duration (months)		
High Liquidity State	27.14	
Low Liquidity State	8.01	
Panel C: Transition Probabilities		
	High LS	Low LS
High Liquidity State	0.96	0.04
Low Liquidity State	0.12	0.88

Table V: Performance of Market Liquidity Beta Sorted Portfolios

Hedge funds are sorted into 10 equally weighted portfolios each month according to their historical market liquidity betas. The market liquidity beta is calculated by a regression of monthly hedge fund returns on the market portfolio and a market liquidity factor (Sadka (2006)), using the 24 months prior to portfolio formation. Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the annualized fund alphas (in percent) of the decile portfolios and the performance of the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. Newey-West t-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the unconditional results in the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

	Market Liquidity Beta Deciles										
Panel A: All Observations											
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	0.21	0.80	1.47	1.96	2.06	2.67	2.02	3.40	3.01	3.97	3.76
	[0.39]	[2.38]	[4.54]	[6.97]	[7.39]	[10.15]	[7.59]	[9.63]	[9.79]	[6.55]	[4.67]
Panel B: High Liquidity State											
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	0.04	1.18	1.67	2.64	2.85	3.40	3.01	5.07	3.99	5.83	5.80
	[0.06]	[3.21]	[5.02]	[9.65]	[11.15]	[14.30]	[12.21]	[13.31]	[13.18]	[8.54]	[6.36]
Panel C: Low Liquidity State											
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	3.80	-0.09	0.40	-1.86	-1.68	-1.00	-2.89	-4.81	-1.38	-7.70	-11.50
	[2.91]	[-0.10]	[0.52]	[-3.19]	[-2.68]	[-1.53]	[-4.35]	[-5.58]	[-1.81]	[-5.35]	[-5.92]

Table VI: Performance of Funding Liquidity Beta Sorted Portfolios

Hedge funds are sorted into 10 equally weighted portfolios each month according to their historical funding liquidity betas. The funding liquidity beta is calculated by a regression of monthly hedge fund returns on the market portfolio and a funding liquidity factor (innovations in TED spread), using the 24 months prior to portfolio formation. Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the annualized fund alphas (in percent) of the decile portfolios and the performance of the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. Newey-West t-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the unconditional results in the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

	Funding Liquidity Beta Deciles										
Panel A: All Observations	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	4.59	3.30	2.68	2.71	1.42	1.13	1.44	1.65	1.45	1.19	-3.40
	[9.06]	[9.84]	[9.48]	[9.94]	[4.94]	[3.98]	[5.14]	[6.06]	[4.17]	[1.97]	[-4.30]
Panel B: High Liquidity State	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	5.29	3.81	2.89	3.26	2.21	1.80	2.28	2.36	2.98	2.81	-2.47
	[9.29]	[11.20]	[9.75]	[12.34]	[8.21]	[7.11]	[8.52]	[9.24]	[8.08]	[4.41]	[-2.89]
Panel C: Low Liquidity State	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	3.73	1.03	2.08	-0.59	-2.22	-2.40	-2.27	-2.40	-6.26	-7.94	-11.67
	[4.37]	[1.73]	[3.88]	[-0.99]	[-3.19]	[-3.04]	[-2.59]	[-2.57]	[-4.35]	[-4.28]	[-5.71]

Table VII: Market Liquidity Beta and Funding Liquidity Beta Sorted Portfolios

Hedge funds are sequentially sorted into 25 (5 by 5) equally weighted portfolios each month according to their historical market and funding liquidity betas. The market liquidity beta (funding liquidity beta) is calculated by a regression of monthly hedge fund returns on the market portfolio and a liquidity factor, Sadka (2006) liquidity measure (innovations in TED spread), using the 24 months prior to portfolio formation. Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the annualized fund alphas (in percent) of the quintile portfolios and the performance of the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. Newey-West t-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A and B report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

Panel A: Fund Alphas in High Liquidity State

		Funding Liquidity Beta Quintiles					
		1	2	3	4	5	5-1
Market Liquidity Beta Quintiles	1	3.43	3.41	0.01	0.02	-3.77	-7.20
		[5.27]	[7.16]	[0.01]	[0.03]	[-5.39]	[-7.53]
	2	3.88	2.64	1.51	1.79	1.02	-2.87
		[7.89]	[8.53]	[5.80]	[6.58]	[2.44]	[-4.44]
	3	3.29	3.71	2.46	3.11	3.07	-0.22
		[9.14]	[15.58]	[8.30]	[12.64]	[8.14]	[-0.42]
	4	6.04	3.97	2.99	2.57	4.67	-1.37
		[8.77]	[14.98]	[11.33]	[9.67]	[9.80]	[-1.64]
	5	4.67	2.19	4.39	5.30	8.04	3.37
		[9.87]	[5.75]	[9.73]	[7.22]	[7.81]	[2.98]
	5-1	1.23	-1.22	4.39	5.28	11.81	
		[1.53]	[-2.00]	[6.55]	[5.87]	[9.49]	

Panel B: Fund Alphas in Low Liquidity State

		Funding Liquidity Beta Quintiles					
		1	2	3	4	5	5-1
Market Liquidity Beta Quintiles	1	4.83	3.81	4.88	3.49	-7.28	-12.11
		[3.13]	[3.86]	[4.14]	[3.41]	[-2.50]	[-3.68]
	2	5.78	1.18	-3.68	-1.92	-4.93	-10.71
		[7.29]	[2.02]	[-3.93]	[-2.19]	[-3.57]	[-6.73]
	3	2.27	-0.94	-1.59	-2.13	-4.14	-6.41
		[5.09]	[-1.95]	[-2.82]	[-3.17]	[-3.15]	[-4.63]
	4	-0.67	-3.27	-3.46	-4.39	-7.51	-6.84
		[-0.72]	[-4.90]	[-5.67]	[-6.46]	[-6.25]	[-4.51]
	5	3.91	0.75	-7.08	-8.20	-12.39	-16.30
		[3.58]	[0.90]	[-5.49]	[-5.25]	[-8.15]	[-8.71]
	5-1	-0.92	-3.06	-11.97	-11.69	-5.11	
		[0.65]	[-0.95]	[2.51]	[2.83]	[3.60]	

Table VIII: Performance of Funding Liquidity Beta Sorted Portfolios of Liquid Hedge Funds

Hedge funds with no lockup restrictions (liquid hedge funds) are sorted into 10 equally weighted portfolios each month according to their historical funding liquidity betas. The funding liquidity beta is calculated by a regression of monthly hedge fund returns on the market portfolio and a funding liquidity factor (innovations in TED spread), using the 24 months prior to portfolio formation. Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the annualized fund alphas (in percent) of the decile portfolios and the performance of the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. T-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

	Panel A: All Observations										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	4.03	2.89	2.65	2.23	1.48	1.01	0.63	1.51	1.29	0.86	-3.18
	[7.36]	[8.35]	[8.90]	[7.71]	[5.50]	[3.56]	[2.13]	[5.56]	[3.25]	[1.44]	[-3.93]
	Panel B: High Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	4.91	3.23	2.81	2.87	2.31	1.69	1.27	2.38	2.97	2.25	-2.66
	[7.94]	[9.29]	[8.99]	[10.11]	[9.52]	[6.47]	[4.47]	[9.18]	[6.68]	[3.53]	[-2.99]
	Panel C: Low Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	3.63	1.38	2.57	-1.03	-2.26	-1.86	-2.34	-3.22	-6.39	-6.19	-9.82
	[3.82]	[2.06]	[4.81]	[-1.46]	[-2.97]	[-2.60]	[-2.43]	[-3.09]	[-4.63]	[-3.51]	[-4.90]

Table IX: Performance of Funding Liquidity Beta Sorted Portfolios of Illiquid Hedge Funds

Hedge funds with lockup rectrictions (illiquid hedge funds) are sorted into 10 equally weighted portfolios each month according to their historical funding liquidity betas. The funding liquidity beta is calculated by a regression of monthly hedge fund returns on the market portfolio and a liquidity factor (innovations in TED spread), using the 24 months prior to portfolio formation. Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the annualized fund alphas (in percent) of the decile portfolios and the performance of the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. T-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

	Panel A: All Observations										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	6.32	5.06	3.23	3.94	2.88	2.45	3.05	3.43	2.20	3.70	-2.62
	[11.19]	[10.60]	[9.05]	[13.55]	[8.33]	[7.20]	[7.87]	[9.15]	[4.70]	[5.00]	[-2.82]
	Panel B: High Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	6.50	5.98	3.55	4.46	3.34	3.38	4.20	3.99	3.39	6.11	-0.39
	[10.10]	[12.75]	[9.03]	[14.64]	[9.79]	[9.90]	[11.55]	[11.76]	[7.85]	[8.40]	[-0.40]
	Panel C: Low Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	4.77	-2.02	2.15	-0.53	0.38	-3.64	-4.63	0.59	-6.60	-12.20	-16.97
	[6.12]	[-1.98]	[4.00]	[-0.90]	[0.68]	[-5.86]	[-3.75]	[0.67]	[-4.69]	[-5.40]	[-7.10]

Figure 1: Filtered Probabilities for the Low Liquidity State

The figure exhibits the filtered probabilities from the Markov regime switching model for the low liquidity state. The data covers the period from January 1994 to May 2012.

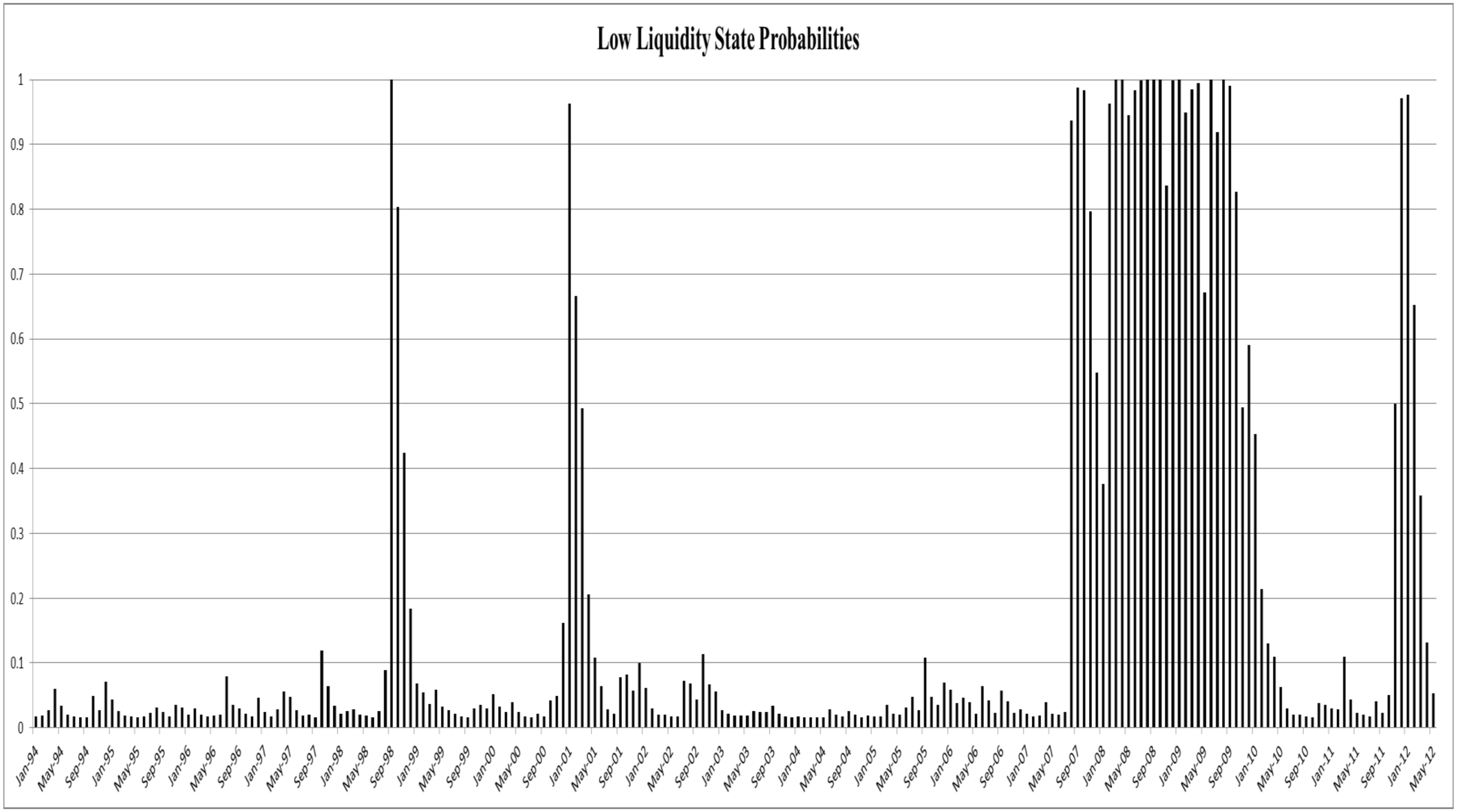
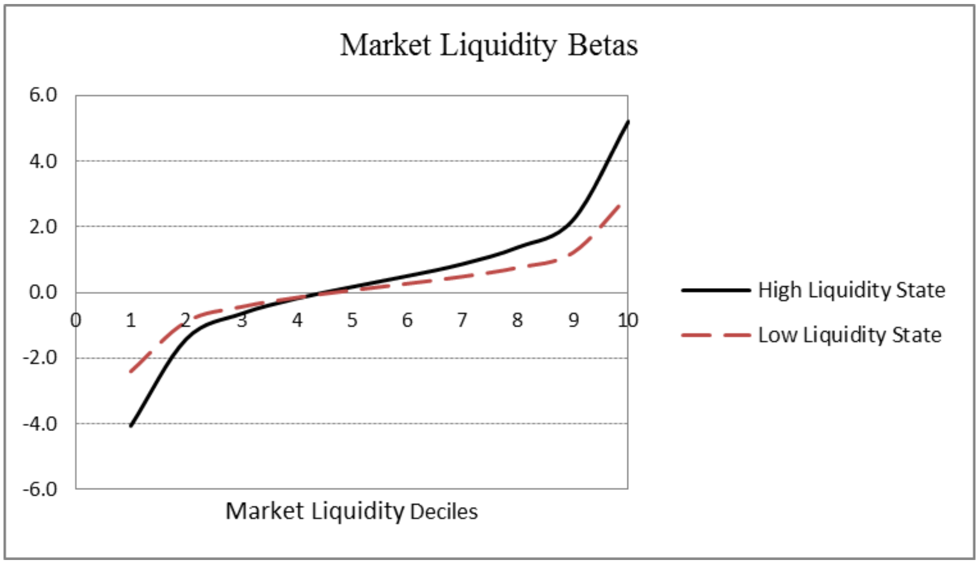


Figure 2: Liquidity Timing Ability of Hedge Funds

The figure exhibits the average market liquidity betas and annualized 8-factor Fung and Hsieh alphas (in percent) for ten decile portfolios sorted by market liquidity exposure presented in Table V.

Panel A:



Panel B:

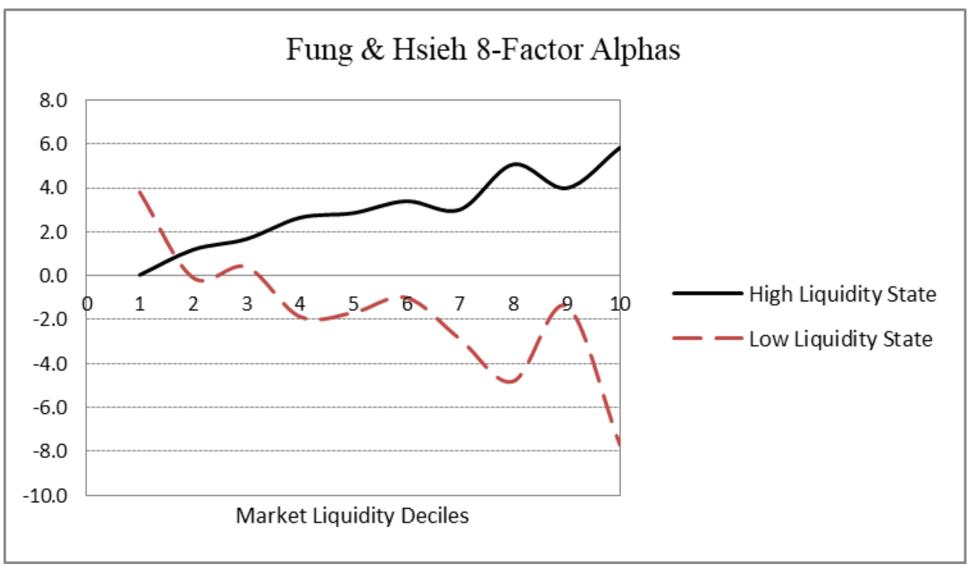
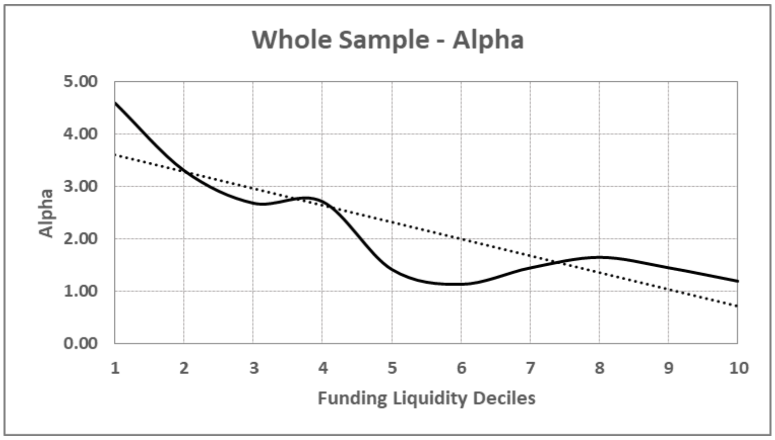


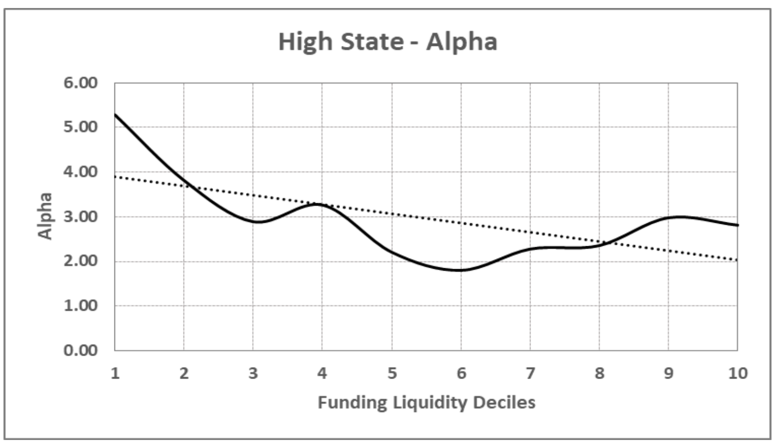
Figure 3: Fund Alphas for Funding Liquidity-Sorted Portfolios

The figure exhibits the annualized fund alphas (in percent) for the funding liquidity deciles described in Table VI, based on the innovations in TED spread. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively.

Panel A:



Panel B:



Panel C:

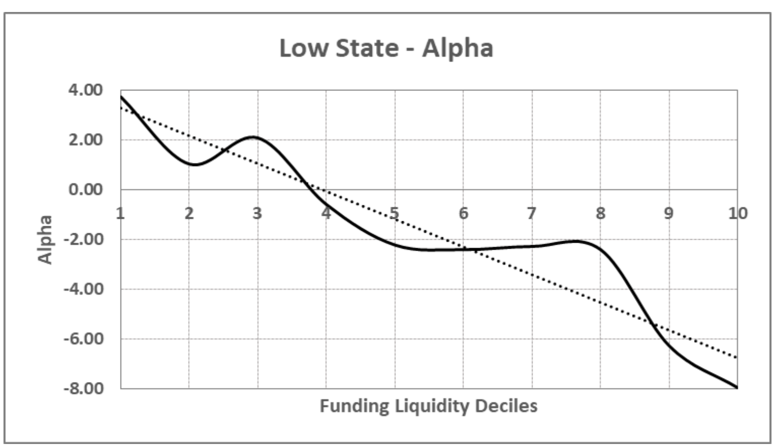


Figure 4: Fund Alphas for Market and Funding Liquidity-Sorted Portfolios (High Liquidity Regime)

The figure exhibits the annualized fund alphas (in percent) for the market and funding liquidity sorted quintile portfolios for the high liquidity regime.

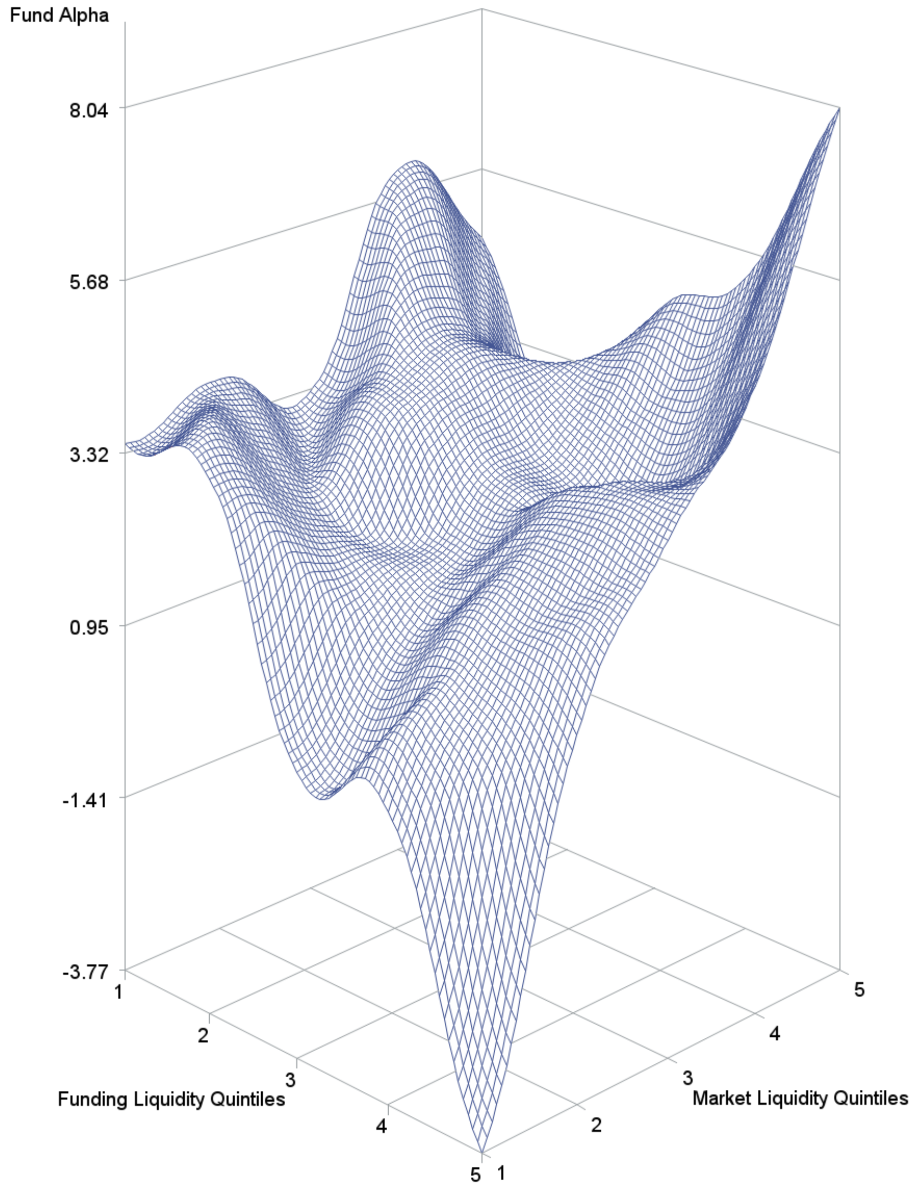


Figure 5: Fund Alphas for Market and Funding Liquidity-Sorted Portfolios (Low Liquidity Regime)

The figure exhibits the annualized fund alphas (in percent) for the market and funding liquidity sorted quintile portfolios for the low liquidity regime.

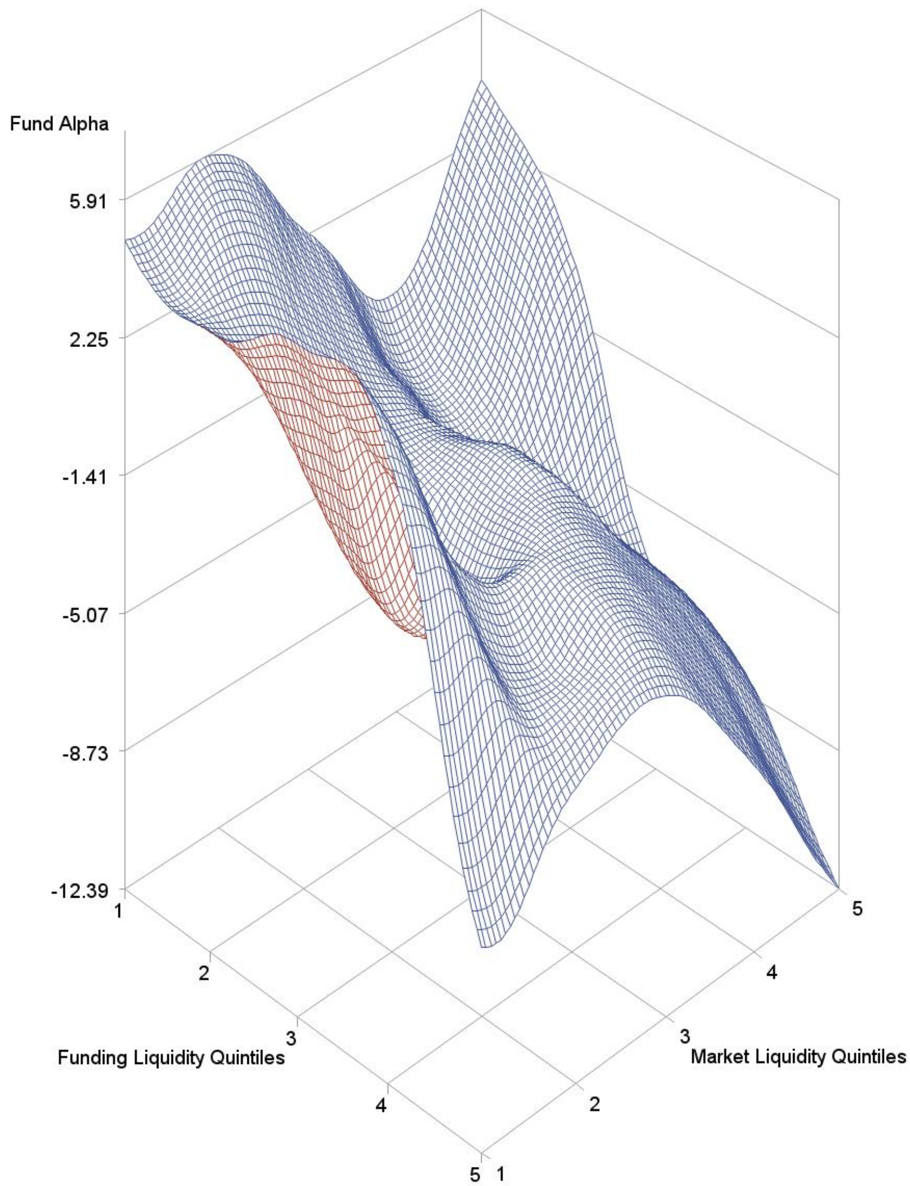


Table A.1: Performance of Funding Liquidity Beta Sorted Portfolios Identified Using the Orthogonal component of the TED spread

Hedge funds are sorted into 10 equally weighted portfolios each month according to historical funding liquidity betas. The funding liquidity betas are calculated based on 24-month rolling regressions of monthly hedge fund returns on the market portfolio and the orthogonal component of the innovations in TED spread when projected onto the Sadka measure. Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the annualized fund alphas (in percent) of the decile portfolios and the performance of the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. T-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

	Panel A: All Observations										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	4.61	3.12	2.86	3.20	1.43	1.99	1.44	1.23	1.40	0.31	-4.29
	[9.07]	[9.17]	[10.43]	[10.88]	[5.19]	[7.58]	[5.41]	[4.27]	[3.89]	[0.54]	[-5.53]
	Panel B: High Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	5.37	3.42	3.39	4.11	2.19	2.76	2.45	2.10	2.47	1.46	-3.91
	[9.76]	[10.37]	[13.00]	[14.79]	[8.88]	[11.76]	[10.05]	[8.04]	[6.23]	[2.54]	[-4.92]
	Panel C: Low Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	2.88	1.88	0.21	-1.30	-2.28	-2.05	-3.34	-3.56	-2.76	-6.81	-9.69
	[3.48]	[2.83]	[0.31]	[-2.39]	[-3.77]	[-2.38]	[-3.24]	[-3.46]	[-2.50]	[-3.59]	[-4.69]

Table A.2: Performance of Funding Liquidity Beta Sorted Portfolios (REPO rate)

Hedge funds are sorted into 10 equally weighted portfolios each month according to historical funding liquidity betas. The funding liquidity betas are calculated based on 24-month rolling regressions of monthly hedge fund returns on the market portfolio and the funding liquidity factor, namely, innovations in the REPO rate, as explained in Section VII.B, Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the annualized fund alphas (in percent) of the decile portfolios and the performance high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. T-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

	Panel A: All Observations										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	3.36	2.48	2.94	2.15	2.45	2.46	2.17	2.33	0.87	0.33	-3.02
	[7.19]	[6.72]	[10.74]	[8.22]	[8.67]	[7.67]	[7.22]	[7.46]	[2.70]	[0.60]	[-4.15]
	Panel B: High Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	3.06	2.55	3.86	2.57	3.39	3.44	3.28	3.34	1.94	2.22	-0.83
	[5.45]	[6.82]	[13.19]	[9.75]	[12.48]	[11.29]	[11.78]	[11.59]	[7.47]	[4.75]	[-1.14]
	Panel C: Low Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	2.87	1.28	-1.55	0.59	-2.09	-2.23	-2.41	-2.29	-3.39	-7.91	-10.78
	[3.17]	[2.06]	[-2.89]	[1.06]	[-3.39]	[-3.27]	[-2.86]	[-2.62]	[-2.58]	[-3.73]	[-4.68]

Table A.3: Performance of Funding Liquidity Beta Sorted Portfolios (Traded Funding Liquidity Measure)

Hedge funds are sorted into 10 equally weighted portfolios each month according to historical funding liquidity betas. The funding liquidity betas are calculated based on 24-month rolling regressions of monthly hedge fund returns on the market portfolio and the traded liquidity factor proposed by Chen and Lu (2017). Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the annualized fund alphas (in percent) of the decile portfolios and performance of the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. T-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

	Panel A: All Observations										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	4.24	3.42	2.32	2.76	2.51	2.43	2.19	1.66	1.63	-1.60	-5.84
	[8.93]	[9.87]	[7.99]	[8.59]	[8.63]	[9.08]	[8.32]	[5.38]	[4.97]	[-2.66]	[-7.62]
	Panel B: High Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	5.03	4.29	3.34	3.66	3.27	3.23	2.97	2.19	2.19	-0.52	-5.55
	[9.23]	[10.75]	[10.40]	[11.44]	[12.19]	[13.10]	[13.41]	[7.90]	[8.90]	[-0.96]	[-7.23]
	Panel C: Low Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	0.61	0.04	-2.02	-1.27	-0.96	-1.05	-2.09	-0.78	-1.87	-7.89	-8.50
	[0.91]	[0.08]	[-3.31]	[-2.54]	[-1.67]	[-1.43]	[-2.25]	[-0.80]	[-1.41]	[-3.47]	[-3.58]

Table A.4: Performance of Funding Liquidity Beta Sorted Portfolios (Fontaine and Garcia (2012) Measure)

Hedge funds are sorted into 10 equally weighted portfolios each month according to historical funding liquidity betas. The funding liquidity betas are calculated based on 24-month rolling regressions of monthly hedge fund returns on the market portfolio and the funding liquidity factor proposed by Fontaine and Garcia (2012). Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the annualized fund alphas (in percent) of the decile portfolios and performance of the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. T-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

	Panel A: All Observations										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	3.05	3.33	2.62	1.89	1.20	1.60	1.36	1.66	3.08	1.74	-1.32
	[5.60]	[10.17]	[11.67]	[7.17]	[3.93]	[5.25]	[3.87]	[5.57]	[7.49]	[2.67]	[-1.55]
	Panel B: High Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	1.94	3.32	2.96	2.79	1.96	2.50	2.55	2.89	4.50	4.25	2.31
	[3.61]	[9.26]	[12.53]	[10.91]	[6.50]	[9.23]	[7.83]	[11.55]	[11.23]	[7.31]	[2.91]
	Panel C: Low Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	6.65	2.36	1.22	-2.72	-1.86	-2.76	-3.90	-3.63	-2.63	-9.95	-16.60
	[2.83]	[1.68]	[1.39]	[-4.11]	[-3.16]	[-4.99]	[-5.62]	[-4.74]	[-2.71]	[-6.38]	[-5.89]

Table A.5: Performance of Funding Liquidity Beta Sorted Portfolios (Regimes determined by hedge fund returns)

Hedge funds are sorted into 10 equally weighted portfolios each month according to historical funding liquidity betas. The funding liquidity beta is calculated by a regression of monthly hedge fund returns on the market portfolio and the liquidity factor (innovations in TED spread), using the 24 months prior to portfolio formation. Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the annualized fund alphas (in percent) of the decile portfolios and the performance of high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. T-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the hedge fund returns.

	Panel A: All Observations										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	4.59	3.30	2.68	2.71	1.42	1.13	1.44	1.65	1.45	1.19	-3.40
	[9.06]	[9.84]	[9.48]	[9.94]	[4.94]	[3.98]	[5.14]	[6.06]	[4.17]	[1.97]	[-4.30]
	Panel B: High Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	8.31	7.08	5.77	5.50	5.86	5.46	5.91	5.88	5.69	5.53	-2.78
	[13.60]	[19.48]	[18.44]	[19.50]	[23.10]	[19.44]	[19.84]	[17.72]	[14.25]	[6.53]	[-2.67]
	Panel C: Low Liquidity State										
	Funding Liquidity Beta Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	-9.48	-7.31	-8.77	-10.31	-9.98	-11.16	-14.03	-18.20	-27.22	-40.14	-30.66
	[-4.50]	[-4.91]	[-6.40]	[-8.82]	[-8.25]	[-7.67]	[-11.48]	[-22.57]	[-23.20]	[-25.98]	[-11.74]