Funding Liquidity Implied by S&P 500 Derivatives

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Abstract

We derive a funding liquidity measure based on synthetic borrowing in the S&P 500 derivative markets. Our measure captures funding constraints of option liquidity providers and affects importantly the returns of leveraged managed portfolios. Hedge funds with negative exposure to changes in the funding liquidity earn high returns in normal times and low returns in crises periods when funding liquidity deteriorates. The results are not driven by the existing measures of funding or market liquidity. To an extent, our funding liquidity measure also affects leveraged closed-end mutual funds and asset classes where leveraged investors are marginal investors.

Key Words: funding liquidity, hedge funds, risk premium, return prediction
JEL: G10, G11, G12

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I. Introduction

Arbitrage is one of the most fundamental forces in financial markets. Theoretically, any mispricing in financial assets can be arbitraged away by creating a zero-cost portfolio: proceeds from short-selling overpriced assets are used to purchase underpriced assets. In practice, however, trading requires capital; buying (on margin) and short-selling both involve putting money in the margin account. Arbitrage forces are thus restricted by the availability of borrowed capital, the so-called funding liquidity (Shleifer and Vishny 1997). Moreover, because availability of funding tightens in bad times when market conditions deteriorate and margin requirements become binding, arbitrageurs are often forced to deleverage at fire sale prices. Shocks to funding liquidity therefore present an important source of risk for arbitrageurs who use leverage (e.g. hedge funds). Evaporating funding liquidity and the related sell-offs also drive prices away from fundamentals, especially in assets where arbitrageurs are marginal investors (Brunnermeier and Pedersen 2009; Garleanu and Pedersen 2011; Aragon and Strahan 2012).

The empirical measurement of funding liquidity, however, is challenging because “real-world financing contracts are complex, opaque, negotiated privately and hence unobservable” (Brunnermeier and Pedersen 2009). The literature has devised two types of proxies for funding liquidity (risk). The first type is based directly on stated interest rates, such as the spread between the Libor and the T-bill rate (TED spread) or the spread between the Libor and the repo rate (Garleanu and Pedersen 2011). The stated interest rates, however, may underestimate the effective cost of funding. For example, during the recent financial crisis, interest rates were low but credit rationing was prohibitive, and the spreads thus understated the ease with which investors were able to obtain financing.[1] An additional problem with the spread measures is their reliance on the Libor, which was often subject to manipulation (Gandhi et al. 2015).

The second type of measures generally overcome the problems of relying on the stated interest rates, but require additional assumptions and are indirectly related to funding liquidity. They include the amount of arbitrage violations in the Treasury market (Fontaine and Garcia, 2012), violations of the CAPM implications (Frazzini and Pedersen, 2014), changes in margin requirements (Garleanu and Pedersen, 2011; Dudley and Nimalendran, 2011), and the broker-dealer leverage (Adrian, Etula, and Muir, 2014).

In this paper, we derive a new direct measure for funding liquidity based on synthetic rates in the derivative markets. One can synthetically borrow or lend in the derivative markets by simultaneously trading a future and a pair of a put and a call. Using these no-arbitrage relations and relying on the most liquid market for derivatives – the S&P 500 derivatives – we define funding liquidity as the difference between the implied borrowing rate and the implied midpoint rate. The borrowing rate involves buying options at the bid price and selling at the ask price. Thus, it is the rate an investor would need to pay to borrow money in the derivatives market. The midpoint rate is based on the options bid-ask midpoint and captures the general time-series variation in interest rates, which empirically is close to Libor.[2]

[1] As captured very well by Sir Mervyn King in testimony to the Treasury Select Committee in late November 2008, "It [Libor] is in many ways the rate at which banks do not lend to each other…." Access to borrowing during the crisis was also affected by bankruptcies of some of the major primer brokers, e.g. Lehman Brothers (Aragon and Strahan 2012).

[2] Our results are largely unaffected if we instead use the spread between the implied borrowing rate and the Libor rate, or the implied borrowing rate and the T-bill rate.

Our measure draws simultaneously on two aspects of funding liquidity. For one, we measure the effective cost borrowing, while circumventing the problems of relying on stated interest rates. In particular, because derivatives are traded on exchanges, the estimated rate is not prone to credit rationing or manipulation.[3] Second, we measure funding cost by relying on bid and ask option prices, which depend on the cost of making the market by liquidity providers. Because continuous hedging of liquidity providers depends on their funding, the ease at which they can obtain financing will in turn be reflected in the implied borrowing rates. All these features make the difference between the implied borrowing rate and the midpoint rate an appealing measure of funding liquidity.

We estimate the rates implied in the S&P 500 derivatives from no-arbitrage relations. As in Golez (2014), we combine the option put-call parity and the future's cost-of-carry. In this way, we can estimate implied rates purely from the observed prices of derivatives without the need to estimate future dividends.

We use end-of-day prices for S&P 500 options from Market Data Express and S&P 500 futures from the Chicago Merchandise Exchange (CBOE) for the period from 1994 through 2012.[4] We estimate a constant three month maturity monthly time-series of funding liquidity. As expected, our funding liquidity measure is relatively persistent, with an autocorrelation coefficient of 0.55, and it spikes around the crisis periods, especially during the global financial crisis in 2008. Our measure is also positively related to the spreads in the observed interest rates and other proxies for credit conditions and market uncertainty.

[3] It also is not prone to counterparty risk as guaranteed by options settlement procedures.

[4] Our funding liquidity measure is not prone to non-synchronicity between end-of-day option prices and the index prices because we substitute the index value with the futures prices through the use of two no-arbitrage relations.

We are interested in the cross-sectional and time-series effects of funding liquidity shocks. We define shocks in funding liquidity, the funding liquidity *factor*, by taking the first differences in our funding liquidity measure. An increase in the factor implies worsening of funding conditions.

We first analyze how funding liquidity shocks affect managed portfolio. We focus on hedge funds, which often use leverage in order to exploit arbitrage opportunities. Using a rolling windows approach of 36 months, we sort hedge funds into ten portfolios according to their exposure to funding liquidity shocks. We note that the portfolio with the most negative exposure to funding liquidity on average earns higher returns than the portfolio with the most positive exposure to funding liquidity. The spread is 34 basis points per month and significant with a *t*-statistic of 2.17. This confirms that funds are compensated for bearing the funding liquidity risk.

Because our sample period includes two crises periods, including the global financial crisis starting in 2008, the full sample results are likely downward biased. In particular, if funding liquidity shocks are a source of risk, then funds that are most exposed to funding liquidity risk should earn a positive return in normal times, but would be hit with negative return in times of tight funding as they may be forced to liquidate their positions at fire sale prices. Aligned with this argument, and as a further confirmation that funding liquidity is a source of risk for hedge funds, we show that the spread is high and positive during normal times and negative during crisis periods when funding is limited and funding costs are high. Using recessions as identified by the NBER, we find a spread of 51 basis points per month (*t*-statistic of 3.50) in normal times, and minus 68 basis points during crisis periods (*t*-statistic of -3.49 for the difference with respect to the normal times).

The documented spread is not driven by the existing factors known to affect hedge fund returns. In particular, results weaken only marginally when we account for the seven Fung and Hsieh (2001) factors or the ten factors proposed by Namvar, Phillips, Pukthuanthong, and Rau (2013). The spread is also robust to survivorship bias.

We also show that the same results cannot be obtained using options bid-ask spread in place of our measure. The two measures are weekly correlated, and our main results are robust, and even improve, when we use the options bid-ask spread (and/or bid-ask squared) as additional control variables when sorting funds into funding liquidity beta portfolios.

Next, we conduct a comparison to other existing measures of funding liquidity. Because our measure is effectively based on the borrowing rates, we find, as expected, that our results weaken somewhat when we control for other interest-rate-based funding liquidity measures (TED spread and the spread between LIBOR and the repo rate). The return spread between the most negative and the most positive funding liquidity portfolios, however, drops only by one third, implying that the information beyond the spread measures is the more important part of our funding liquidity measure. Furthermore, results remain largely unchanged when we control for the above indirect measures of funding liquidity. Finally, our results are robust to controlling for different measures of market wide liquidity in forming the funding liquidity sorted portfolios, such as the aggregate liquidity factor of Pastor and Stambaugh (2003), the transitory and permanent liquidity factors of Sadka (2006), and the noise measure of Hu, Pan, and Wang (2013).

Given that the effect of funding liquidity should be stronger for more leveraged funds, we attempt to distinguish between leveraged and unleveraged hedge funds. While the data on hedge fund leverage is incomplete, using the available information, we find that leveraged hedge funds have a higher spread among the funding liquidity sorted portfolios (0.40 with a *t*-statistic of 2.17) than the unleveraged hedge funds (0.23 with a *t*-statistic of 1.35). Probing further into the effect of leverage, we look at closed-end mutual funds, which also use leverage and where the data on leverage has better coverage. Because closed-end funds generally use less leverage than hedge funds, the effect of funding liquidity on closed-end funds is overall weaker and insignificant. We note, however, an economically important difference in funding liquidity spreads between leveraged and unleveraged closed-end funds. In particular, the spread is on average 30 basis points per month for leveraged closed-end funds and merely 4 basis points per month for unleveraged closed-end funds. We take this as a further confirmation that funding liquidity affects only leveraged funds.

Finally, we analyze funding liquidity risk in asset classes where leveraged investors are likely to be marginal investors. We look at carry trades, CDS-bond basis trades, and S&P 500 option portfolios. Using the Fama and MacBeth (1973) approach, we find a significant effect of funding liquidity risk for CDS-bond basis trades of financial institutions and S&P 500 option portfolios and a weak effect for carry trades. CDS-bond basis trades of industrial firms do not seem to be affected by funding liquidity risk.

In summary, we derive a new funding liquidity measure, which has economically and statistically significant power in explaining returns from leveraged managed funds. Funds with the most negative exposure to funding liquidity shocks earn higher return during normal periods and underperform in crises periods, consistent with funding liquidity presenting a source of risk for leveraged investors. The evidence also suggests that funding liquidity plays a role for asset classes where leveraged investors are among the marginal investors.

The paper continues with Section II where we introduce our measure of funding liquidity. We report our main results concerning delegated portfolios in Section III and concerning other asset classes in Section IV. Robustness results follow in Section V before we conclude in Section VI.

II. A Funding Liquidity Measure Implied by S&P 500 Derivative Markets

The intuition behind the funding liquidity measure implied by S&P 500 options and futures markets derives from the no-arbitrage relations. One can synthetically borrow or lend in the derivative markets by simultaneously trading a future and a pair of a put and a call. The put and the call have the same strike prices; all instruments expire simultaneously and are written on the same underlying asset.

To illustrate, consider the following portfolio. At $t = 0$, we sell the future $F_0(\tau)$, sell the put $P_0(K, \tau)$, and buy a call $C_0(K, \tau)$ where the put and the call have the same strike price K. All instruments expire at time $t = \tau$. Since it does not cost anything to trade the future, at $t = 0$, we only pay for the difference between the price of a call and a put, $C_0(K, \tau) - P_0(K, \tau)$. At the expiration date $t = \tau$, the payoff from the portfolio is always $F_0(\tau) - K$.[5]

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[5] To see this, write the payoff of the strategy first in general terms:

$$\text{Payoff}(\tau) = -(S_\tau - F_0) - (K - S_\tau)^+ + (S_\tau - K)^+$$

Note that there are three specific cases regarding the value of S_τ:

- if $S_\tau = K$ then $\text{Payoff}(\tau) = -(S_\tau - F_0) = F_0(\tau) - K$,
- if $S_\tau < K$ then $\text{Payoff}(\tau) = -(S_\tau - F_0) - (K - S_\tau) = F_0(\tau) - K$ and
- if $S_\tau > K$ then $\text{Payoff}(\tau) = -(S_\tau - F_0) + (S_\tau - K) = F_0(\tau) - K$.

Because the payoff is known at time t, the difference between the payment today and the payoff at maturity, by the no-arbitrage argument, reflects only the time value of money. Assuming continuous compounding, the general expression for the interest rate implied by options and futures is (see also Golez 2014):

$$r_t(\tau) = \frac{1}{\tau} log\left[\frac{F_t(\tau) - K}{C_t(K,\tau) - P_t(K,\tau)}\right]\ if\ C_t(K,\tau) - P_t(K,\tau) \neq 0 \tag{1}$$

While index futures are very liquid and have negligible bid-ask spreads, transaction costs in the index options market are important. Using the midpoint of the bid-ask spread for options in Eq. (1) gives a midpoint implied interest rate r_t^{mid}. To calculate the borrowing rate, we need to account for the bid-ask spread. If the call price is higher than the put price, one can borrow from the derivative markets by selling the call at the bid, buying the put at the ask and buying the future. If the call price is lower than the put price, however, one can borrow from the derivatives market by buying the call at the ask, selling the put at the bid, and selling the future.

$$r_t^b(\tau) = \begin{cases} \frac{1}{\tau} log\left[\frac{F_t(\tau)-K}{C_t^{Bid}(K,\tau)-P_t^{Ask}(K,\tau)}\right]\ if\ C_t^{Bid}(K,\tau) > P_t^{Ask}(K,\tau)\ and\ F_t(\tau) > K \\ \frac{1}{\tau} log\left[\frac{F_t(\tau)-K}{C_t^{Ask}(K,\tau)-P_t^{Bid}(K,\tau)}\right]\ if\ C_t^{Ask}(K,\tau) < P_t^{Bid}(K,\tau)\ and\ F_t(\tau) < K \end{cases} \tag{2}$$

We define the level of funding liquidity as $FL_t = r_t^b - r_t^{mid}$, where r_t^{mid} is the midpoint rate. We use the change of funding liquidity $\Delta FL_t = FL_t - FL_{t-1}$ as our funding liquidity factor in our main specifications.

Note that our measure for funding liquidity does not require that investors actually borrow in the derivative markets. We only conjecture that the borrowing rate in the derivative markets is correlated with the actual funding rates of investors.

A. Data and Estimation

We use end-of-day prices of SPX options on the S&P 500 index from Market Data Express for the period 1990-2012 and end-of-day prices of SP futures on the S&P 500 index from the CME for the period 1981-2012. Given the low liquidity of the SPX options (and low coverage of hedge funds) during the initial years, we restrict the sample to January 1994 through December 2012.

In estimating implied rates, we follow closely Golez (2014). We first eliminate options that violate the basic arbitrage relations. Next, to match expirations for options and futures, we keep only options that expire on a quarterly cycle (note, options trade on a monthly expiration cycle whereas futures trade on a quarterly expiration cycle). Focusing on quarterly expirations has an additional advantage in that, due to the simultaneous expiration of options and futures, no-arbitrage violations are less frequent (Kamara and Miller 1995). Note also that both index options and index futures trade daily until 15:15 PM, so our measure is not prone to non-synchronicity between options and the underlying assets (which trade until 15:00PM).

Based on Eq. (2), we estimate the midpoint rate and the borrowing rate at the end of each month. Because liquidity of index options is skewed towards options with strike prices below the index value, in the main analysis, we restrict the moneyness level (K/S) to be below 0.99 and calculate implied borrowing rates in our main analysis from observations where the bid price for the call is higher than the ask price for put and the futures price is higher than the strike price (first line of Eq. (2)). For consistency, we calculate midpoint implied rates r_t^{mid} using the same observations. To minimize effects of microstructure noise, each end-of-month, we use the last 10 days of data and all options with positive volume or open interest greater than 200 contracts. We discard observations where $\frac{F_t(\tau)-K}{C_t(K,\tau)-P_t(K,\tau)}$ (based on the bid-ask mid-point) is lower than 0.5 or higher than 1.5.

This matching procedure results in a total of 113,680 estimated rates in our sample period. The number of estimates increases over time and declines with maturity. We aggregate these estimates at the end of each month by taking the median across all rates with the same maturity. To obtain monthly rates with constant maturities, we interpolate linearly between yields with the closest maturities. In the main analysis we base our funding liquidity measure on the implied rates with constant three-month maturity. In total we have 228 monthly observations.

For comparison, we keep track of the option bid-ask spread across the same set of options that we use for the calculation of our funding liquidity measure. For each call and put, we define the bid-ask spread as the difference between the ask price and the bid price over the mid-quote. We then aggregate those spreads following the exact same procedure we use for our funding liquidity measure.

B. Summary Statistics

Figure 1 plots our funding liquidity measure; the corresponding summary statistics are reported in Table 1 in Panel A. The mean for our funding liquidity measure is 8.45%. It has a standard deviation of 5.21%, and it is relatively persistent with an autocorrelation coefficient of 0.55. As one expects, during the global financial crisis, our funding liquidity measure shoots up substantially and reaches its maximum in October 2008 at 33.38%. Other spikes appear in May

2012 at 32.47%, January 2008 at 24.63%, June 2002 at 22.80%, and September 2001 at 13.57%. These spikes can be associated with the stock market dropping precipitously in January and October of 2008 due to the financial crisis and the worries over the European debt crisis in May 2012. The June of 2002 spike is due to the long downward move after the dotcom bubble and the September 2001 spike coincides with the terrorist attacks of 9/11.

<< Figure 1 about here >>

Funding liquidity should be related to the effective cost of financing and the availability of credit. For this reason, we next compare our funding liquidity measure to the TED spread (3-month LIBOR over 3-month T-bill), the LIBOR-repo spread (spread between 3-month LIBOR and the repo rate), and other variables related to credit conditions and overall market uncertainty, such as the Default spread (spread between BAA and AAA rated corporate bonds), the Term spread (spread between the yield on 10-year Treasury bonds and the 3-month T-bill rate), and the CBOE VIX index (S&P 500 options implied volatility index). Furthermore, we also compare our funding liquidity measure with the option Bid-ask spread, which plays an important role in the estimation of our funding liquidity measure.

We obtain the VIX index from Chicago Board of Options Exchange (CBOE). The repo rate is from Datastream, and the rest of the interest rate variables are from Federal Reserve Bank of St. Louis (FRED, H.15).[6] The option Bid-ask spread is calculated as the average spread for all options included in the calculation of the funding liquidity measure, as explained above.

We start by analyzing the summary statistics for the variables reported in Panel A of Table 1. Our funding liquidity measure is positively related to the TED spread (0.21), the LIBOR-repo spread (0.28), and to other variables related to credit conditions and market uncertainty, with pairwise correlations ranging from 0.26 for Term spread to 0.65 for Default spread. At the same time, our measure of funding liquidity is only weakly related to the option bid-ask spread (0.08), which is a first indication that the funding liquidity measure captures information beyond the simple options bid-ask spread.

In the main empirical tests, we use changes in our funding liquidity measure (funding liquidity factor), rather than levels. Therefore, Panel B of Table 1 also reports the summary statistics for the first differences of all variables. The mean change of our funding liquidity factor is zero, with a standard deviation of 4.97. Interestingly, by taking differences, the AR(1) coefficient goes from positive 0.55 to negative -0.40. Similarly, the AR(1) for the TED spread and the LIBOR-repo spread change from positive 0.82 and 0.78 to -0.17 and -0.21. Thus, the mean reversion in our funding factor is not simply due to noise in derivative prices. In untabulated results we also find that all the main results are robust (or even stronger), if we use the contemporaneous and lagged funding liquidity factor, rather than just the contemporaneous factor. Finally, once we take changes, the correlations of our funding liquidity factor with the

[6] The repo rate starts only in October 1999. As it is highly correlated with the discount window borrowing rate from the H.15 reports (correlation above 0.9), we first regress the repo rate on the discount rate from October 1999 through December 2002. Based on that regression we then reconstruct the earlier repo rate back to January 1994.

other variables decrease substantially, and they are between -0.19 and 0.15 (the only exception is the options bid-ask spread where the correlation increases from 0.08 to 0.36).

<< Table 1 about here >>

Next, we compare our factor (changes in our funding liquidity measure) to other funding liquidity factors proposed in the literature. In particular, we obtain the monthly treasury market arbitrage measure of Fontaine and Garcia (2012) from January 1994 through March 2012 from Jean-Sebastien Fontaine's webpage.[7] We obtain the "Betting against beta" factor for the U.S. equities of Frazzini and Pedersen (2014) from January 1994 through December 2012 from AQR's webpage.[8] We also obtain the broker-dealer leverage factor of Adrian, Etula, and Muir (2014) from January 1994 through December 2009 from Tyler Muir's webpage.[9] Because the data on the broker-dealer leverage factor are quarterly, we define monthly observations by the last available quarterly observation. Finally, we reconstruct the Dudley and Nimalendran (2011) margin requirement measure using their method and margin data starting in January 2000, which we downloaded from the Chicago Mercantile Exchange (CME).[10] Because the margin and treasury market arbitrage data demonstrate a high AR(1) of 0.90 and 0.93 respectively, we use first differences instead of levels in our analysis.

The summary statistics are reported in Panel A of Table 2. All the funding liquidity factors described above have low correlations with our funding liquidity factor, ranging from

[7] Http://jean-sebastienfontaine.com.

[8] Https://www.aqr.com/library/data-sets/betting-against-beta-equity-factors-monthly.

[9] Http://faculty.som.yale.edu/tylermuir/documents/LEVERAGEFACTORDATA_000.xlsx.

[10] Http://www.cmegroup.com/clearing/risk-management/historical-margins.html.

-0.06 to 0.13. The high AR(1) of the broker-dealer factor is due to our monthly use of the originally quarterly observations.

Finally, because funding liquidity and market liquidity may mutually reinforce each other in "liquidity spirals," as shown theoretically by Brunnermeier and Pedersen (2009), we also relate our funding liquidity factor to market wide liquidity factors. We obtain the monthly innovations in the aggregate liquidity of Pastor and Stambaugh (2003) from Lubos Pastor's webpage.[11] We download the monthly transitory and permanent components for the Sadka (2006) liquidity factor from Ronnie Sadka's webpage.[12] Finally, we obtain the monthly Noise measure of Hu, Pan, and Wang (2013) from Jun Pan's webpage.[13] Their measure derives from no-arbitrage violations in the Treasury market. As the Noise factor is highly autocorrelated (0.92), we use differences again. All the liquidity measures are available for the full period from January 1994 through December 2012.

The summary statistics are reported in Panel B of Table 2. Market liquidity factors have low correlations with our funding liquidity factor, ranging from -0.13 to 0.14. Also, all factors have low serial autocorrelations, between -0.13 and 0.11.

<< Table 2 about here >>

III. Funding Liquidity Risk and Delegated Portfolios

[11] Http://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2014.txt.

[12] Http://www2.bc.edu/~sadka/Sadka-LIQ-factors-1983-2012-WRDS.xlsx.

[13] Http://www.mit.edu/~junpan/.

Next, we test whether shocks to funding liquidity are a source of risk for delegated portfolio management. Theoretically, funding liquidity should affect only leveraged investors. The obvious candidates here are hedge funds because they often use high leverage to exploit arbitrage opportunities. We also analyze closed-end funds, which also use leverage, although to a smaller extend. In all our tests, we sort funds into portfolios based on their exposure to funding liquidity risk.

A. Funding Liquidity and Hedge Fund Returns

As emphasized by Joenvaara, Kosowski, and Tolonen (2014), a common issue in hedge fund studies is that the sample coverage is usually restricted by using a particular database. Moreover, different hedge funds have little overlap in terms of coverage of hedge funds. In some cases, certain empirical regularities are prevalent in one database, while not in other databases. As a result, these authors suggest researchers deploy as many hedge fund databases as possible. A unique aspect of our data is that we combine together six hedge fund databases, which include Altvest (now part of Morningstar), BarclayHedge, CISDM Morningstar, HFR, Eureka, and TASS hedge fund databases, and create a comprehensive dataset. For details, see Hodder, Jackwerth, and Kolokolova (2014).

We take care of the main biases contained in hedge fund databases in a way similar to Titman and Tiu (2011). Our merged database provides information on dead and alive funds which decreases survivorship bias. To mitigate the backfilling bias we delete the first 12 monthly observations. When estimating the MA(2) model of Getmansky, Lo, and Makarov (2004), we find that around 70% of all hedge funds within our database exhibit significant smoothing coefficients. To adjust for the downward bias in the volatility of returns resulting from smoothing, we use the correction proposed in Getmansky, Lo, and Makarov (2004). In our statistical tests we require hedge funds to have at least 36 months of observations. After applying these data filters, there are 14,320 funds with summary statistics presented in Table 3.

<< Table 3 about here >>

Returns of a typical hedge fund from our sample are 0.51 basis points per month on average and are non-normally distributed with fat tails (average kurtosis in the sample 6.45) and negative skewness (-0.21). The average life span of a hedge fund is around 7 years. Among other characteristics we find in the database are the management fee (1.50% on average) and the performance fee (18.59% on average); 90% of hedge funds are open to new investments, and 82% use a high-water mark. For a subset of funds that provide data on leverage, 48% are leveraged.

A.1. Hedge Fund Portfolios Formed by Funding Liquidity Betas

To test the sensitivity of hedge fund returns to funding liquidity, we proceed as follows. Let R_{it} be the excess return in month t of hedge fund i, and $R_{Mkt,t}$ be the market excess return factor. We estimate exposure of fund i to the change in the funding liquidity measure ($\Delta FL_t = FL_t - FL_{t-1}$) by the following regression:

$$R_{it} = \beta_{i0} + \beta_i R_{Mkt,t} + \beta_i^{FL} \Delta FL_t + \varepsilon_{it}, \tag{3}$$

where fund i's exposure to the change in funding liquidity is captured by the funding liquidity beta, $\beta^{FL} = \beta_i^{FL}$.

At the end of each month t, based on the regression model in Eq. (3), we first estimate the pre-ranking β^{FL} for each fund i using its previous 36 months excess returns between months $(t-35)$ and (t). Then, we sort all hedge funds at the end of month t by their pre-ranking β^{FL} into decile portfolios. We obtain each fund's return next month and compute equally-weighted average returns for each of these decile portfolios. If any of the hedge funds was delisted from the database, we put a zero instead of missing return.[14] We then compute the return spread between the portfolio consisting of funds with the most negative β_{Low}^{FL} (portfolio 1) and the portfolio consisting of funds with the most positive β_{high}^{FL} (portfolio 10),

$$\frac{1}{N_1}\sum_{i=1}^{N_1} R_{it}^{Bottom\ 10\%} - \frac{1}{N_{10}}\sum_{i=1}^{N_{10}} R_{it}^{Top\ 10\%}. \tag{4}$$

By repeating the previous two steps month by month, we obtain the whole time-series of hedge fund returns for each of the ten portfolios, as well as return spreads between the lowest and the highest β^{FL} sorted portfolio.

Recall that the funding liquidity measure in the above regression is defined as $\Delta FL_t = FL_t - FL_{t-1}$, and Figure 1 clearly illustrates that the funding liquidity measure increases during downturns of the economy. Thus, if funding liquidity shocks are a source of risk, portfolio 1, consisting of hedge funds with the most negative exposure to the funding liquidity measure,

[14] Hodder, Jackwerth, and Kolokolova (2014) show that the estimated mean delisting return is insignificantly different from the average monthly return for live hedge funds. Since average hedge fund returns are positive, we are being conservative by setting missing returns to zero.

should earn higher returns on average as a compensation for bearing funding liquidity risk. By the same logic, portfolio 10, consisting of hedge funds with the most positive exposure to the funding liquidity measure, should earn lower returns. In other words, portfolio 1 bears a higher funding liquidity risk than portfolio 10 and consequently the spread between portfolio 1 and portfolio 10 returns should be positive.

Table 4 reports the basic characteristics of the portfolios sorted by funding liquidity beta. The first three columns report the funding liquidity betas during the portfolio formation period, the funding liquidity betas in the month after portfolio formation, and the returns associated with funding liquidity beta sorted portfolios. Portfolio 1 has a pre-ranking beta of -0.53, whereas portfolio 10 has a pre-ranking beta of 0.30. By construction, the difference between portfolio 1 and 10 is negative at -0.83 and highly significant. Importantly, the post-ranking liquidity beta difference between portfolios 1 and 10 remains negative and significant, although it is more modest, as expected. It amounts to -0.09 with a *t*-statistic of -2.22.[15] Turning to the portfolios' excess returns, we note that portfolio 1 earns 80 basis points in excess returns per month (*t*-statistic of 2.34) whereas portfolio 10 on average earns 46 basis points in excess returns per month (*t*-statistic of 2.11). The return spread between portfolio 1 and portfolio 10 is positive at 34 basis points and statistically significant with a *t*-statistic of 2.17. Thus, exposure to our funding liquidity shocks impacts hedge fund returns in the cross-section, as predicted by the theory.

In the last columns of Table 4, we also see some differences in hedge fund characteristics across funding liquidity beta sorted portfolios. However, they are economically small and do not necessary line up with the returns. For example, there is no difference between low versus high

[15] In our calculations we use Newey-West standard errors with 35 lags (Newey and West 1987).

funding liquidity beta sorted portfolios' performance fees. Low funding liquidity beta sorted portfolios on average charge slightly higher management fees, and are less likely to be open to new investments. We also do not observe any statistically significant differences in the percent of delisted hedge funds among different decile portfolios.

<< Table 4 about here >>

The four models of sorted portfolio returns

To further examine the return spreads between the lowest and the highest β^{FL} sorted portfolios, we run four additional tests. First, we run a standard *t*-test on returns, which is equivalent to the estimation of the following model (**Model Constant**):

$$R_{it} = \alpha_{i0} + \varepsilon_{it} \tag{5}$$

Next, we examine returns of liquidity-beta sorted portfolios during normal and crises periods. Our motivation is as follows. If funding liquidity shocks are a source of risk, then funds that are most exposed to funding liquidity risk should earn a positive return in normal times, but would be hit with negative return in times of tight funding as they may be forced to liquidate their positions at fire sale prices. We investigate this by estimating the following regression model (**Model Crisis**):

$$R_{it} = \alpha_{i0} + I_t(Crisis) \times \alpha_{i0}^{Crisis} + \varepsilon_{it}, \tag{6}$$

where α_{i0} is the intercept term for the full-sample, and $I_t(Crisis)$ is a dummy variable that takes the value one during crisis periods, and zero otherwise. Thus, the non-crisis period alpha of the funding liquidity beta-sorted portfolios is α_{i0}, and the crisis period alpha of the funding liquidity beta-sorted portfolios is $(\alpha_{i0} + \alpha_{i0}^{Crisis})$. We approximate crisis periods by recessions as identified by the NBER.

Finally, we consider two benchmark factor models. The first one is the traditional Fung and Hsieh (2001) seven-factor model that includes two equity-oriented factors, three trend-following factors, and two bond-oriented factors downloaded from David Hsieh's Hedge Fund Data Library.[16] The second benchmark model is a ten-factor model recently developed by Namvar, Phillips, Pukthuanthong, and Rau (2014; NPPR hereafter). NPPR extracts the first 10 return-based principal components (PCs) from 251 global assets across different countries and asset classes and shows that these 10 PCs explain approximately 99% of the variability in the returns of the considered assets, on average.[17] The exact specification of our regression model is:

$$R_{it} = \alpha_{i0} + I_t(Crisis) \times \alpha_{i0}^{Crisis} + \sum_{k=1}^{K} \beta_{ik} F_{kt} + \varepsilon_{it}, \tag{7}$$

where factors F_k are either the seven Fung and Hsieh (2001) factors (**Model FH**) or the ten NPPR factors (**Model NPPR**).

<< Table 5 about here >>

[16] Https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm.

[17] We thank Kuntara Pukthuanthong for sharing data on the benchmark factors.

The baseline result

Column (1) of Table 5 presents our baseline results. As noted above, in the full sample period, hedge funds with the most negative exposure to funding liquidity outperform funds with the most positive exposure to funding liquidity by 34 basis points per month (*t*-statistic of 2.17). However, the full-sample evidence masks important time-series variation of funding liquidity beta sorted portfolios of hedge funds. In particular, during the normal periods, the funding liquidity spread is positive at 51 basis points per month (*t*-statistic of 3.50). In sharp contrast, during the crisis periods, the funding liquidity spread is negative at -68 basis points per month, a difference of 1.19% per month (*t*-statistic for the difference of -3.49). This confirms that the extra return is a compensation for bearing funding liquidity risk. Using the Fung-Hsieh (2001) seven-factor model as the benchmark model, we find that the spread is only partially driven by the existing hedge fund pricing factors. During the normal periods, the spread is 28 basis points per month (*t*-statistic of 2.27), whereas it is negative at -36 basis points per month during the crises periods when funding liquidity is low (the difference is significant with a *t*-statistic of -2.21). A similar picture emerges for the NPPR model. During the normal periods, the spread is 36 basis points per month (*t*-statistic of 2.34), while it is negative at -61 basis points per months during times of low funding liquidity (*t*-statistic for the difference of -3.22).

Above, we already documented that, on average, the percent of delisted hedge funds is similar across hedge fund portfolios. If funding liquidity shocks are a source of risk for hedge funds, however, we may expect to observe more delistings among the hedge funds most sensitive to those shocks when funding liquidity evaporates. Indeed, we observe a spike in the delistings for portfolio with hedge funds most sensitive to funding liquidity at the end of 2008.[18] The overall monthly average delistings among the hedge funds with most negative and most positive exposure to funding liquidity, nevertheless, are very similar across all the crises months (1.85% and 1.89%) and across all non-crises months (0.93% and 1.05%). Thus, delistings do not importantly affect our results. In column (2), we also show that the results remain largely unchanged if we set delisting returns to minus 10% rather than zero.

Controlling for bid-ask spreads

One may wonder if our funding liquidity measure provides information beyond the simple options bid-ask spread. To test this, when we estimate individual hedge fund's exposure to the funding liquidity measure, we use changes in S&P 500 options Bid-ask spread as an additional control variable in the first stage regression in Eq. (3):

$$R_{it} = \beta_{i0} + \beta_i R_{Mkt,t} + \beta_i^{FL} \Delta FL_t + \beta_i^{BA} \Delta BA_t^{Option} + \varepsilon_{it}, \tag{8}$$

In the second stage, we then repeat all four tests based on funding liquidity sorted portfolios of hedge funds. Results are reported in column (3) of Table 5 and are comparable to results in Column (1). We also consider adding bid-ask spread squared as the additional control variable and report results in column (4). All the results are robust and become even stronger. These tests highlight that our funding liquidity measure contains information that is different from the option bid-ask spread. In untabulated results, we also find that sorting hedge funds on the options bid-

[18] In December 2008, delistings among the hedge funds with most negative exposure to funding liquidity are 16.8%, in comparison to 11.7% for hedge funds with the most positive exposure to funding liquidity.

ask spread does not lead to a return spread between the decile portfolios. In particular, the return spread is close to zero and insignificant.

Controlling for other *direct* measures of funding liquidity

We motivate our funding liquidity measure by the notion that funding liquidity should capture information beyond the variation in the interest rate and include credit availability. To verify that, we next re-run all the tests by adding the interest-rate-based funding liquidity measures, such as the TED spread and the spread between the Libor and repo rate as additional control variables. In particular, as above, when we estimate individual hedge funds' exposure to the funding liquidity measure, we use changes in the interest-rate-based funding liquidity measures as additional control variables in the first stage regression in Eq. (3):

$$R_{it} = \beta_{i0} + \beta_i R_{Mkt,t} + \beta_i^{FL} \Delta FL_t + \beta_i^{\Delta X} \Delta X_t + \varepsilon_{it}, \tag{9}$$

where ΔX is either the change in the TED spread or the change in the spread between the Libor and repo rate. In the second stage, we then repeat all four tests based on funding liquidity sorted portfolios of hedge funds. Results are reported in columns (5) and (6) of Table 5. Because of the overlap in the information between our funding liquidity measure and the interest-rate-based funding liquidity measures, we expect our results to weaken somewhat. Indeed, when we control for the TED spread, the average return spread becomes insignificant. However, the return spread decreases only by one third, from 34 basis points to 22 basis points per month. Also, the spread remains positive and significant at 36 basis points in normal periods (*t*-statistic of 1.77) and negative and significant at -58 basis points per month during crisis periods (*t*-statistic for the difference of -2.58). The return spread is also always positive in normal times and negative in times of distress in our factor models, and the difference between the normal and crises periods remains significant in the NPPR model. We observe a similar pattern when we control for the spread between Libor and repo, except that now the crisis dummy is always significant. Thus, our funding liquidity measure captures information for the cross-section of hedge fund returns beyond the interest-rate-based funding liquidity measures.[19]

Controlling for other *indirect* measures of funding liquidity

Next, we control for other funding liquidity measures proposed in the literature, such as changes in the treasury market arbitrage measure from Fontaine and Garcia (2012), the leverage of broker-dealers from Adrian, Etula, and Muir (2014), changes in the margin requirements from Dudley and Nimalendran (2011), and the betting against beta factor of Franzzini and Pedersen (2014). As above, we use these measures as additional control variables in the first stage regression in Eq. (3):

$$R_{it} = \beta_{i0} + \beta_i R_{Mkt,t} + \beta_i^{FL} \Delta FL_t + \beta_i^X X_t + \varepsilon_{it}, \tag{10}$$

where X is now either of the alternative funding liquidity factors. Note that these measures are already defined as factors. Results are reported in columns (1) though (4) of Table 6 and remain largely unchanged with respect to our main run in column (1) of Table 5. The average return spread is always above 30 basis points per month. With the exception of the crisis dummy when

[19] In the robustness analysis, we also redefine funding liquidity by subtracting from the implied borrowing rate the T-bill rate or LIBOR (rather than the mid-point implied rate).

we control for the treasury market arbitrage, the results for normal times and crisis periods in Model Crisis remain significant in all four models. When we control for additional risk factors, the constant is always positive and the crisis dummy is always negative, although not always significant. Overall, these results suggest that there may be some overlap between the different funding liquidity measures, but our funding liquidity measure provides additional information about the cross-section of hedge fund returns.

<< Table 6 about here >>

Controlling for other measures of *market* liquidity

Finally, funding liquidity is related to market liquidity, and both may mutually reinforce each other in times of distress (Brunnermeier and Pedersen 2009). Although funding liquidity is fundamentally different from market wide liquidity, it is empirically challenging to disentangle one from the other. Above we have shown that our funding liquidity measure differs from option liquidity and other measures of funding liquidity. Now, we check how our funding liquidity relates to other frequently used measures of market wide liquidity, such as the Pastor and Stambaugh (2003) liquidity measure, the transitory and permanent components of liquidity from Sadka (2006), and changes in the Noise measure of Hu, Pan, and Wang (2013). As before, we use these liquidity measures as additional control variables in the first stage regression in Eq. (3):

$$R_{it} = \beta_{i0} + \beta_i R_{Mkt,t} + \beta_i^{FL} \Delta FL_t + \beta_i^X X_t + \varepsilon_{it}, \tag{11}$$

where X is now either of the market wide liquidity factors. In the second stage, we then repeat all four tests based on funding liquidity sorted portfolios of hedge funds. Results are reported in columns (5) through (8) of Table 6. Because of the common characteristics of market liquidity and funding liquidity, we expect our results to weaken. Indeed, the average hedge fund spread decreases to 26 and 23 basis points and turns insignificant when controlling for the Sadka (2006) permanent liquidity component and the Noise measure. The average spread remains marginally significant, however, when controlling for Pastor and Stambaugh (2003) liquidity and even increases to 38 basis points when controlling for the Sadka (2006) transitory liquidity component. Moreover, the hedge fund return spread remains positive and significant in normal times and is negative and significantly different in times of crises (Model Crisis). Also, with the exception of only a few cases, the spread remains significant in our factor models. All in all, this indicates that our funding liquidity measure is also different from the existing market wide liquidity measures.

B. Funding Liquidity and Leverage

Theoretically, the importance of funding liquidity increases with the investors' leverage. Unfortunately, data on hedge fund leverage is often incomplete. In particular, the definition of leverage depends on a particular database, and the information on leverage is often missing.[20] Despite these data shortcomings, we can identify 3,580 funds as leveraged and 3,403 as unleveraged (for 7,337 funds the information on leverage is missing). We then form funding

[20] The variable leverage is fully populated only in TASS hedge fund database. In other databases, a substantial part of observations has missing values for leverage (75% for Altvest, 59% for BarclayHedge, 57% for CISDM Morningstar, 59% for HFR, and 5% for Eureka).

liquidity sensitive portfolios and calculate the average spread for extreme portfolios, separately for leveraged and unleveraged hedge funds. Results are reported in Table 7. As expected, the spread is larger for leveraged and smaller for unleveraged funds. It is 0.40 basis points per month and significant (*t*-statistic of 2.17) for leveraged hedge funds and 0.23 and insignificant (*t*-statistic of 1.35) for unleveraged hedge funds. Thus, although there are many missing observations for hedge fund leverage, we do find evidence consistent with funding liquidity being more important for leveraged hedge funds.

<< Table 7 about here >>

Hedge funds, however, are not the only leveraged investors. Elton, Gruber, Blake, and Shachar (2013) suggest leverage also plays an important role for closed-end mutual funds. We therefore use closed-end funds to develop additional tests. There are two important differences between hedge funds and closed-end funds. First, compared to hedge funds, closed-end funds usually rely on intermediate-term and long-term debt rather than short-term debt. We thus expect a smaller impact of funding liquidity for closed-end funds than for hedge funds. Second, for closed-end funds, we have reliable data on the use of leverage. Thus, we can better separate leveraged from unleveraged closed-end funds.

We obtain the data on closed-end funds and their use of leverage from the Morningstar mutual fund database. Table 8 reports the summary statistics separately for leveraged closed-end funds (Panel A) and unleveraged closed-end funds (Panel B). There are in total 2,209 closed-end funds in our sample in the period between January 1994 and December 2012; 655 are leveraged funds and 1,441 are unleveraged funds; for 113 funds information on leverage is missing.

Interestingly, the monthly average return is somewhat lower for leveraged funds (30 basis points per month) than for unleveraged funds (40 basis points per month) and comes with a lower standard deviation of returns (5.03% versus 6.94%). Leveraged closed-end funds in our sample are also older on average (11.78 year versus 7.04 year) and charge slightly lower management fees (71 versus 88 basis points per year).

<< Table 8 about here >>

Like in the hedge fund analysis, we next form funding liquidity sensitive portfolios and calculate the average spread for extreme portfolios, separately for leveraged and unleveraged closed-end funds. Results are reported in Table 9.

<< Table 9 about here >>

For leveraged closed-end funds, the basic empirical regularities from hedge funds carry over. The difference in post-ranking betas between the portfolio with the most negative exposure to the funding liquidity risk (portfolio 1) and the portfolio with the most positive exposure to the funding liquidity risk (portfolio 10) is as expected negative at -0.20 and highly significant (*t*-statistic of -4.00). Moreover, portfolio 1 earns on average 81 basis points per month (*t*-statistic of 2.00) whereas portfolio 10 earns on average 51 basis points per month (*t*-statistic of 1.58). Thus, the full-sample average return spread between portfolio 1 and portfolio 10 is 30 basis points per month. This spread is marginally insignificant (*t*-statistic of 1.57) but close to the 34 basis points spread that we find for hedge funds.

In comparison, for unleveraged funds, the difference between post-ranking betas between portfolio 1 and portfolio 10 is much smaller at -0.10 and insignificant (*t*-statistic of -0.87). Also, the spread between returns for portfolio 1 and portfolio 10 is very close to zero (0.04) and insignificant (*t*-statistic of 0.07). Thus, as suggested by the theory, we find that funding liquidity risk affects leveraged closed-end funds more than unleveraged.

IV. Funding Liquidity and Returns from Other Asset Classes

Funding liquidity may affect not only portfolio returns of leveraged investors, but also the underlying asset prices, especially of securities where leveraged investors are likely to be marginal investors. For example, Brunnermeier, Nagel, and Pedersen (2009) show that unwinding of carry trades by speculators due to funding liquidity shocks may lead to sudden changes in exchange rates unrelated to fundamentals. Bai and Collin-Dufresne (2013) and Fontana (2011) attribute the negative CDS-bond basis puzzle during the recent financial crisis to the deterioration of funding liquidity.

In this section, we test whether our funding liquidity measure bears a risk premium in the cross-section of these assets. Besides carry trades and CDS bond basis portfolios, we also include S&P 500 options portfolios. We include the options portfolios for two reasons. First, many leveraged investors use options either to hedge their positions or to speculate. Second, our funding liquidity measure derives from the option prices and is thus interesting to see whether it also explains returns of different option portfolios.

A. Data for Carry Trade Portfolios, CDS-Bond Basis, and S&P Option Portfolios

We obtain monthly excess returns for 6 carry trade portfolios from February 1994 till December 2012 from Hanno Lustig's webpage.[21] The construction of the data is described in Lustig, Roussanov, and Verdelhan (2011). The portfolios are sorted by their forward discount. The first portfolio is built on the lowest interest rate currencies, and the last portfolio is built on the highest interest rate currencies.

We obtain credit default swap (CDS) spread from Datastream and Bloomberg. We primarily rely on the information from Datastream. When the pricing information is not available from Datastream, we then use the data from Bloomberg. We winsorize the data by limiting the lowest and highest 10% values to mitigate the effect of possibly spurious outliers, although using all the data yields very similar results.

Additionally, we use monthly returns on 54 portfolios of S&P 500 European-style options between February 1994 and January 2012 from Constantinides, Jackwerth, and Savov (2013). These are portfolios of either calls or puts targeting the following moneyness ratios: 0.90, 0.925, 0.95, 0,975, 1.00, 1.025, 1.05, 1.075, or 1.10; and one of the three maturities: 30, 60, or 90 days.

Table 10 reports the summary statistics. The CDS-bond basis has negative returns on average (minus 30 basis points per month for financial institutions and minus 2.36% per month for industrial companies). The average returns for option portfolios and carry trades are positive on average; 25 basis point per month for options and 17 basis points per month for carry trades.

<< Table 10 about here >>

[21] Https://sites.google.com/site/lustighanno/data.

B. Empirical Models and Results

To test the impact of funding liquidity risk on the portfolios of different asset classes, we now depart from the previous methodology, and rely on Fama-MacBeth regressions. This choice is driven by the rather limited number of portfolios for some of the asset classes (e.g. there are only 6 carry trade portfolios) and the short time-series of the individual CDS-bond basis returns, rendering the rolling-window and sorting approach infeasible. We thus proceed as follows. In the first stage time-series regression, we regress each individual asset's return in excess of the risk free rate on the market excess return and the funding liquidity factor:

$$R_{it} = \beta_i + \beta_{i,Mkt} R_{Mkt,t} + \beta_{i,FL} \Delta FL_t + \varepsilon_{it}. \tag{12}$$

In the second stage cross-sectional regression, we regress asset returns on the estimated risk loadings, separately for each month *t*:

$$R_{it} = c_{t0} + \gamma_{Mkt,t} \hat{\beta}_{iMkt} + \gamma_{FL,t} \hat{\beta}_{iFL} + \varepsilon_{it}, \tag{13}$$

where $\hat{\beta}_{iMkt}$ and $\hat{\beta}_{iFL}$ are the beta estimates from the first-stage time-series regression. Finally, we obtain the time-series averages of the risk-premia on the market and on funding liquidity, $\hat{\gamma}_{Mkt,t}$ and $\hat{\gamma}_{FL,t}$.

Results are reported in Table 11. We first note that the market risk premium is negative and marginally significant for the CDS-bond basis of financial firms at -1.43% per month, and is positive and significant for carry trades at 2.97% per month. The market risk premium for the CDS-bond basis of industrial firms and option portfolios is insignificant.

Regarding funding liquidity, we find a high funding liquidity risk premium for the CDS-bond basis of financial institutions and for option portfolios. In both cases, the risk premium is negative, as expected, and highly significant. It amounts to as much as -7.20% per month for the CDS-bond basis of financial firms and -8.43% per month for option portfolios. In comparison, we do not find evidence for the funding liquidity risk premium in the CDS-bond basis of industrial firms. Also, in contrast to Brunnermeier, Nagel, and Pedersen (2009), the funding liquidity risk premium for carry trades is insignificant, albeit economically important at -1.82% per month and of the correct sign.

<< Table 11 about here >>

Econometrically, Kan, Robotti, and Shanken (2013) voice concerns that model misspecification as well as estimation errors in the betas from the first-pass time series regressions might affect the standard errors of $\hat{\gamma}$. We add an errors-in-variables adjustment term and a misspecification adjustment term to correct the standard errors. While all *t*-statistics shrink somewhat, the funding liquidity premia remain significant for the CDS-bond basis of financial firms and for option portfolios.

V. Robustness

In this section, we analyze the sensitivity of our results to changes in methodology and the measurement of funding liquidity. All robustness checks are reported in Table 12 and refer to our main results reported in column (1) of Table 5, which we duplicate for convenience in column (1) of Table 12.

Our first robustness check entails estimation of all regressions on 48 months instead of 36 months. As we show in column (2), all point estimates stay close to the main results. Trying samples below 36 months weakens the results due to the larger standard errors caused by the shorter regression samples.

In the main analysis, we impose constant loadings for factors. Next, we allow the factor loadings to vary over the business cycle by interacting factors with the crisis dummy. Results are reported in column (3) and are comparable to the results in the main analysis, except for the crisis dummy in the Fung and Hsieh (2001) model which preserves the right sign, but becomes insignificant.

Furthermore, in the main analysis, we define our funding liquidity measure as the implied borrowing rate minus the average (mid-point) implied rate. Instead, we now re-define funding liquidity as the implied borrowing rate minus Libor in column (4) or as the implied borrowing rate minus T-bill rate in column (5). All rates are based on the 3-month maturity. Results are comparable to the main analysis. This is reassuring and confirms that the main driver for our results is the implied borrowing rate rather than the mid-point rate.

In the main analysis, we argue that options liquidity is skewed and concentrated in options with strike prices below the index value. We thus estimate our implied rates using only option pairs where the call price is lower than the put price (second part of Eq. (2)). Also, we only use options with open interest greater than 200 or volume greater than 0. To further analyze the effect of liquidity, we consider two variations to our measure of funding liquidity. First, we re-estimate funding liquidity using a stricter filter for options liquidity and include only put-call pairs where both options have open interest greater than 200 (that is, options with open interest smaller than 200 are excluded even if they have positive volume). In line with options activity being important for our measurement, we note in column (6) that the results improve slightly and all the coefficients are significant at the one percent level. Second, we re-estimate our funding liquidity using options across all moneyness levels (both sides of the Eq. (2)). In this case, the results in column (7) deteriorate, further confirming the importance of options activity. Nevertheless, the distinction between the crisis and non-crisis periods is preserved, and the coefficients in our basic model (Model Crisis) remain significant.

<< Table 12 about here >>

VI. Summary and Conclusion

One can borrow or lend in the derivative markets by simultaneously trading a future and a pair of a put and a call. Applying this fundamental relationship, we derive a simple, yet novel funding liquidity measure based on the most liquid segment of the derivative markets: S&P 500 options and futures. We show that our funding liquidity measure importantly affects the returns of leveraged hedge funds. In particular, hedge funds with negative exposure to changes in funding liquidity earn high returns in normal times and low returns in crises periods when funding liquidity deteriorates. The results are not driven by existing measures of funding or market liquidity. Our funding liquidity measure also affects leveraged closed-end funds and asset classes where leveraged investors are marginal investors (option portfolios and CDS-bond basis trades of financial firms). Collectively our evidence suggests that funding liquidity risk is an important source of risk for assets which are sensitive to funding liquidity.

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Table 1: Summary statistics of the funding liquidity measure and other variables

This table reports the summary statistics for the funding liquidity measure derived from the derivative markets and other variables of interest. Panel A describes levels and Panel B summarizes changes of these variables. The construction of the Funding liquidity measure derived from the S&P 500 derivative markets is described in Section II. Other variables include the TED spread, the LIBOR-repo spread, the Default spread, the Term spread, the CBOE VIX index, and the Bid-ask spread for S&P 500 options. The sample period is from January 1994 through December 2012.

Panel A: Summary statistics – levels

	Funding liquidity	TED	LIBOR-repo	Default	Term	VIX	Bid-ask
Mean	8.45	0.54	0.35	0.99	1.73	42.68	10.62
Std. Deviation	5.21	0.41	0.35	0.47	1.16	37.83	3.23
AR(1)	0.55	0.82	0.78	0.96	0.96	0.80	0.54
Correlation matrix							
Funding liquidity	1.00	0.21	0.28	0.65	0.26	0.49	0.08
TED		1.00	0.66	0.30	-0.25	0.43	-0.32
LIBOR-repo			1.00	0.39	0.16	0.30	-0.21
Default				1.00	0.36	0.68	-0.11
Term					1.00	0.18	0.01
VIX						1.00	-0.30
Bid-ask							1.00

Panel B: Summary statistics – changes

	Funding liquidity	TED	LIBOR-repo	Default	Term	VIX	Bid-ask
Mean	0.00	0.00	0.00	0.00	0.00	0.08	-0.03
Std. Deviation	4.97	0.25	0.23	0.14	0.31	24.10	3.10
AR(1)	-0.40	-0.17	-0.21	0.29	0.06	0.05	-0.35
Correlation matrix							
Funding liquidity	1.00	-0.05	-0.19	0.15	-0.03	0.14	0.36
TED		1.00	0.47	0.12	0.28	0.20	-0.16
LIBOR-repo			1.00	0.16	0.03	0.10	-0.11
Default				1.00	-0.09	0.32	-0.10
Term					1.00	0.00	-0.03
VIX						1.00	-0.09
Bid-ask							1.00

Table 2: Summary statistics of the alternative funding liquidity and market liquidity factors

This table compares the summary statistics for our funding liquidity factor (changes in our funding liquidity measure) and either the alternative measures for funding liquidity factors (Panel A) or market liquidity factors (Panel B). Alternative funding liquidity factors include changes in the treasury market arbitrage factor from Fontaine and Garcia (2012), the broker-dealer leverage factor from Adrian, Etula, and Muir (2014), changes in the margin requirements factor from Dudley and Nimalendran (2011) and the Betting against beta factor of Frazzini and Pedersen (2014). Market liquidity measures include the Pastor and Stambaugh (2003) liquidity factor, the transitory and permanent components of liquidity factor from Sadka (2006), and the changes in Noise measure of Hu, Pan, and Wang (2013). The data availability for each factor is denoted separately for each factor in the table. The full period is from January 1994 through December 2012.

Panel A: Funding liquidity factors

	Funding liquidity 94/01-12/12	Treasury market arbitrage 94/01-12/03	Broker-dealer leverage 94/01-09/12	Margin requirements 00/01-12/12	Betting against beta 94/01-12/12
Mean	0.00	0.01	0.31	0.00	0.01
Std. Deviation	4.97	0.36	15.35	0.03	0.04
AR(1)	-0.40	0.05	0.64	0.01	0.14
Correlations					
Funding liquidity	1.00	0.13	0.09	0.02	-0.06
Treasury market arbitrage		1.00	0.02	0.05	-0.09
Broker-dealer leverage			1.00	-0.24	0.19
Margin requirements				1.00	0.15
Betting against beta					1.00

Panel B: Market liquidity factors

	Funding liquidity 94/01-12/12	Pastor and Stambaugh (2003) 94/01-12/12	Sadka (2006) transitory liquidity 94/01-12/12	Sadka (2006) permanent liquidity 94/01-12/12	Noise (Hu, Pan, and Wang 2013) 94/01-12/12
Mean	0.00	0.00	0.00	0.00	-0.01
Std. Deviation	4.97	0.07	0.00	0.01	0.95
AR(1)	-0.40	-0.13	0.11	0.09	0.05

Correlation matrix

Funding liquidity	1.00	-0.13	0.04	-0.08	0.14
Pastor and Stambaugh (2003)		1.00	0.02	0.19	-0.20
Sadka (2006) transitory liquidity			1.00	0.13	-0.01
Sadka (2006) permanent liquidity				1.00	-0.23
Noise (Hu, Pan, and Wang 2013)					1.00

Table 3: Hedge fund sample summary statistics

This table reports the summary statistics for hedge funds. For each fund, we first calculate its time-series average return, return standard deviation, minimum, and maximum returns. Then we report the cross-sectional distribution of the statistics. Summary statistics for fund age, management fees, and performance fees are calculated from the cross-sectional observations. We also report the percentage of funds using leverage (Leverage {0,1}), the percentage of funds opened to new investments (Open to new investment {0,1}), and the percentage of funds using high-water-mark. The sample covers 14,320 hedge funds in the period from January 1994 through December 2012.

	N	Mean	Std. Deviation	5% Quintile	95% Quintile
Mean (%)	14,320	0.51	0.74	-0.46	1.66
Std.Dev. (%)	14,320	4.86	3.99	1.18	11.70
Minimum (%)	14,320	-15.03	12.75	-39.90	-2.61
Maximum (%)	14,320	15.27	16.32	3.11	39.66
Skewness (%)	14,320	-0.21	1.20	-2.03	1.39
Kurtosis (%)	14,320	6.45	6.98	2.55	16.55
Age (years)	14,320	7.44	3.85	3.25	15.33
Management fee (%)	12,030	1.50	0.94	0.90	2.00
Performance fee (%)	12,091	18.59	5.42	2.00	22.50
Leverage {0,1}	6,983	0.48	0.48	0.00	1.00
Open to new investment {0,1}	11,990	0.90	0.30	0.00	1.00
High-water-mark{0,1}	12,210	0.82	0.38	0.00	1.00

Table 4: Returns from funding liquidity beta sorted hedge fund portfolios

This table reports the summary statistics for ten funding liquidity beta β^{FL} sorted hedge fund portfolios. Funding liquidity beta is estimated month by month in a regression of fund excess returns on market excess returns and our funding liquidity factor over the previous 36 months. The reported values are average pre-ranking funding liquidity beta, average post-ranking funding liquidity beta, average excess returns associated with each of the funding liquidity beta sorted portfolio, average management fee, average performance fee, average open to new investment {0,1}, high water mark {0,1}, and percent of delisted hedge funds. The last row reports the difference for each variable between portfolio 1 and 10. Newey-West *t*-statistics are reported in parentheses below the estimated parameters. The sample period is from February 1994 through December 2012. The time-series for portfolio spreads is February 1997 through December 2012. The average number of unique hedge funds in each portfolio is 689, ranging between 111 in February 1997 and 1,104 in August 2008.

FL-Beta Rank	Pre-ranking FL-Beta	Post-ranking FL-beta	Excess Return (%)	MGMT Fee (%)	PERF Fee (%)	Open to new investment	High Water Mark	Delistings (%)
1	-0.53	-0.15	0.80	1.55	18.73	0.86	0.80	1.07
	(-35.47)	(-3.12)	(2.34)					
2	-0.24	-0.09	0.57	1.49	18.07	0.87	0.77	1.08
	(-31.50)	(-2.62)	(2.43)					
3	-0.16	-0.06	0.49	1.45	18.07	0.87	0.77	1.07
	(-28.13)	(-2.83)	(2.78)					
4	-0.10	-0.06	0.44	1.47	18.05	0.86	0.77	1.09
	(-24.12)	(-3.17)	(2.91)					
5	-0.06	-0.05	0.38	1.46	17.95	0.86	0.75	1.10
	(-18.93)	(-3.23)	(2.90)					
6	-0.03	-0.06	0.39	1.43	18.09	0.86	0.75	1.17
	(-11.46)	(-3.95)	(3.40)					
7	0.00	-0.05	0.38	1.42	18.15	0.88	0.76	1.12
	(1.29)	(-3.54)	(3.50)					
8	0.04	-0.04	0.39	1.44	18.13	0.89	0.77	1.11
	(17.53)	(-2.38)	(3.33)					
9	0.10	-0.04	0.47	1.46	18.59	0.89	0.79	1.10
	(32.39)	(-2.08)	(3.24)					
10	0.30	-0.06	0.46	1.51	18.77	0.89	0.79	1.17
	(46.74)	(-2.16)	(2.11)					
1-10	-0.83	-0.09	0.34	0.04	-0.04	-0.03	0.01	-0.11
	(-46.26)	(-2.22)	(2.17)	(2.85)	(-0.55)	(-7.83)	(1.15)	(0.66)

Table 5: Returns from funding liquidity beta sorted hedge fund portfolios, main tests

This table reports results for regressions of the low-minus-high funding-liquidity beta-sorted hedge fund portfolios on a constant (Model Constant); a constant and a Crisis Dummy (Model Crisis); a constant, Crisis Dummy, and the seven Fung and Hsieh (2001) factors (Model FH); a constant, Crisis Dummy, and the ten Namvar, Phillips, Pukthuanthong, and Rau (2013) factors (Model NPPR). Crisis Dummy takes a value one for recession periods identified by NBER, and zero otherwise. Newey-West t-statistics are reported in parentheses below the estimated parameters. In Column (1), funds are sorted into high and low funding liquidity sorted portfolios by regressing fund excess returns over the previous 36 months on market excess returns and our funding liquidity factor. In Column 2, we set delisting returns to -10%, rather than 0%. In Columns 3 through 6, we use additional control variables in our sorting regressions: the S&P 500 options Bid-ask spread, the options Bid-ask spread squared, the TED spread, and the spread between the Libor and repo rate. The sample period for hedge funds is February 1994 through December 2012. The time-series for portfolio spreads is February 1997 through December 2012.

	(1)	(2)	(3)	(4)	(5)	(6)
Additional controls in sorting regressions						
Bid-ask spread	No	No	Yes	Yes	No	No
Bid-ask spread squared	No	No	No	Yes	No	No
TED spread	No	No	No	No	Yes	No
Libor minus repo rate	No	No	No	No	No	Yes
Model Constant						
Constant	0.34	0.34	0.46	0.41	0.22	0.22
t-stat.	(2.17)	(2.20)	(2.51)	(2.83)	(1.14)	(1.09)
Model Crisis						
Constant	0.51	0.52	0.60	0.60	0.36	0.45
t-stat.	(3.50)	(3.57)	(3.28)	(4.27)	(1.77)	(2.60)
Crisis Dummy	-1.19	-1.19	-0.96	-1.32	-0.94	-1.54
t-stat.	(-3.49)	(-3.61)	(-2.41)	(-4.10)	(-2.58)	(-3.21)
Model FH						
Constant	0.28	0.29	0.28	0.35	0.18	0.24
t-stat.	(2.27)	(2.36)	(1.70)	(2.59)	(0.86)	(1.51)
Crisis Dummy	-0.64	-0.66	-0.13	-0.86	-0.43	-0.95
t-stat.	(-2.21)	(-2.31)	(-0.44)	(-2.82)	(-1.39)	(-2.87)
Model NPPR						
Constant	0.36	0.37	0.42	0.48	0.18	0.27
t-stat.	(2.34)	(2.38)	(2.62)	(2.97)	(0.98)	(1.59)
Crisis Dummy	-0.97	-0.98	-0.66	-1.12	-0.59	-1.26
t-stat.	(-3.22)	(-3.25)	(-2.74)	(-3.44)	(-2.41)	(-3.92)

Table 6: Returns from funding liquidity beta sorted hedge fund portfolios, additional tests

This table reports results for regressions of the low-minus-high funding-liquidity beta-sorted hedge fund portfolios on a constant (Model Constant); a constant and a Crisis Dummy (Model Crisis); a constant, Crisis Dummy, and the seven Fung and Hsieh (2001) factors (Model FH); a constant, Crisis Dummy, and the ten Namvar, Phillips, Pukthuanthong, and Rau (2013) factors (Model NPPR). Crisis Dummy takes a value one for recession periods identified by NBER, and zero otherwise. Newey-West t-statistics are reported in parentheses below the estimated parameters. Funds are sorted into high and low funding liquidity sorted portfolios by regressing fund excess returns over the previous 36 months on market excess returns, our funding liquidity factor, and additional control variables. Control variables include changes in the treasury market arbitrage from Fontaine and Garcia (2012), the leverage of broker-dealer from Adrian, Etula, and Muir (2014), changes in margin requirements from Dudley and Nimalendran (2011), betting against beta factor of Franzzini and Pedersen (2014), Pastor and Stambaugh (2003) liquidity measure, the transitory and permanent components of liquidity from Sadka (2006), and changes in the Noise measure of Hu, Pan, and Wang (2013).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Additional controls in sorting regressions								
Treasury market arbitrage	Yes	No	No	No	No	No	No	No
Leverage of broker-dealers	No	Yes	No	No	No	No	No	No
Margin requirements	No	No	Yes	No	No	No	No	No
Betting against beta	No	No	No	Yes	No	No	No	No
Pastor and Stambaugh (2003)	No	No	No	No	Yes	No	No	No
Sadka (2006) transitory liquidity	No	No	No	No	No	Yes	No	No
Sadka (2006) permanent liquidity	No	No	No	No	No	No	Yes	No
Noise (Hu, Pan, and Wang 2013)	No	No	No	No	No	No	No	Yes
Model Constant								
Constant	0.33	0.31	0.50	0.35	0.31	0.38	0.26	0.23
t-stat.	(2.32)	(1.70)	(2.10)	(1.87)	(1.83)	(2.32)	(1.54)	(1.14)
Model Crisis								
Constant	0.40	0.53	0.73	0.47	0.47	0.52	0.42	0.48
t-stat.	(2.54)	(3.11)	(3.81)	(2.67)	(2.50)	(3.62)	(2.46)	(3.47)
Crisis Dummy	-0.47	-1.25	-1.45	-0.82	-1.09	-0.99	-1.08	-1.72
t-stat.	(-1.43)	(-4.17)	(-3.01)	(-2.00)	(-3.12)	(-2.47)	(-3.27)	(-3.98)
Model FH								
Constant	0.25	0.38	0.42	0.23	0.18	0.30	0.23	0.30
t-stat.	(1.76)	(2.49)	(1.72)	(1.24)	(0.91)	(2.62)	(1.65)	(2.62)
Crisis Dummy	-0.16	-0.92	-0.45	-0.39	-0.48	-0.45	-0.64	-1.23
t-stat.	(-0.50)	(-3.90)	(-1.06)	(-1.00)	(-1.39)	(-1.39)	(-2.05)	(-4.13)
Model NPPR								
Constant	0.28	0.29	0.53	0.38	0.35	0.38	0.29	0.35
t-stat.	(1.91)	(2.04)	(2.87)	(2.31)	(1.63)	(2.37)	(1.77)	(2.29)
Crisis Dummy	-0.42	-1.15	-0.96	-0.51	-0.93	-0.79	-0.91	-1.43
t-stat.	(-1.30)	(-4.44)	(-2.23)	(-1.14)	(-2.71)	(-2.97)	(-2.77)	(-4.87)

Table 7: Returns from funding liquidity beta sorted leveraged and unleveraged hedge fund portfolios

This table reports the summary statistics for the ten funding liquidity beta β^{FL} sorted hedge fund portfolios, separately for leveraged hedge funds and unleveraged hedge funds. Funding liquidity beta is estimated month by month in a regression of fund excess returns on market excess returns and our funding liquidity factor over the previous 36 months. The reported values include average pre-ranking funding liquidity beta, average post ranking funding liquidity beta, and average excess returns associated with each of the funding liquidity beta sorted portfolio. The last row reports the differences in the variables between portfolio 1 and portfolio 10. Newey-West *t*-statistics are reported in parentheses below the estimated parameters. The sample period is from January 1994 through December 2012. The time-series for portfolio spreads is February 1997 through December 2012. For leveraged hedge funds, the time-series average number of funds in each portfolio is 184, ranging between 15 in February 1997 and 318 in June 2007. For unleveraged hedge funds, the time-series average number of funds in each portfolio is 206, ranging between 58 in February 1997 and 303 in January 2008.

	Leveraged Hedge Funds			Unleveraged Hedge Funds		
FL-Beta Rank	Pre-ranking FL-Beta	Post-ranking FL-beta	Excess Return (%)	Pre-ranking FL-Beta	Post-ranking FL-beta	Excess Return (%)
1	-0.53	-0.18	0.84	-0.53	-0.13	0.71
	-40.61	-3.57	2.19	-34.20	-2.72	2.15
2	-0.24	-0.10	0.56	-0.25	-0.08	0.60
	-32.73	-2.82	2.14	-30.72	-2.33	2.58
3	-0.15	-0.07	0.56	-0.16	-0.05	0.45
	-28.46	-3.02	2.90	-28.06	-2.16	2.54
4	-0.10	-0.07	0.43	-0.11	-0.05	0.46
	-24.55	-3.26	2.62	-24.31	-2.71	3.20
5	-0.06	-0.06	0.39	-0.06	-0.05	0.40
	-19.74	-3.58	2.81	-18.98	-3.03	3.05
6	-0.03	-0.05	0.40	-0.03	-0.07	0.41
	-11.83	-3.67	3.23	-11.85	-4.12	3.47
7	0.00	-0.05	0.37	0.00	-0.04	0.42
	1.38	-3.92	3.07	0.81	-2.80	3.68
8	0.04	-0.04	0.36	0.04	-0.04	0.41
	17.61	-2.93	2.84	17.31	-2.17	3.36
9	0.09	-0.03	0.41	0.10	-0.05	0.51
	32.31	-1.83	2.76	32.58	-2.24	3.39
10	0.29	-0.06	0.44	0.30	-0.06	0.48
	47.65	-2.28	1.94	42.10	-1.93	2.17
1-10	-0.82	-0.12	0.40	-0.83	-0.07	0.23
	-53.73	-2.28	2.17	-44.01	-1.11	1.35

Table 8: Closed-end fund sample summary statistics

This table reports the summary statistics for leveraged closed-end mutual funds (Panel A) and unleveraged closed-end mutual funds (Panel B). For each fund, we first calculate its time-series average return, return standard deviation, minimum, and maximum returns. Then we report the cross-sectional distribution of the statistics. Summary statistics for fund age and management fees are calculated from the cross-sectional observations. The sample covers 655 leveraged and 1,441 unleveraged closed-end funds in the period from January 1994 through July 2011. The time-series for portfolio spreads is February 1997 through July 2011.

	N	Mean	Std. Deviation	5% Quantile	95% Quantile
Panel A: Leveraged closed-end funds					
Mean (%)	655	0.30	0.72	-0.69	1.04
Std. Dev. (%)	655	5.03	3.68	1.99	10.46
Minimum (%)	655	-20.27	12.61	-46.82	-7.63
Maximum (%)	655	17.49	25.44	6.49	39.28
Age (years)	655	11.78	5.21	4.17	17.50
Management fee (%)	650	0.71	0.41	0.00	1.50
Panel B: Unleveraged closed-end funds					
Mean (%)	1,441	0.40	4.44	-0.81	1.39
Std. Dev. (%)	1,441	6.94	23.85	2.23	11.04
Minimum (%)	1,441	-18.31	11.85	-37.30	-5.74
Maximum (%)	1,441	28.58	176.89	5.78	47.37
Age (years)	1,441	7.04	4.53	3.17	17.50
Management fee (%)	1,088	0.88	0.70	0.00	2.00

Table 9: Returns from funding liquidity beta sorted leveraged and unleveraged closed-end fund portfolios

This table reports the summary statistics for the ten funding liquidity beta β^{FL} sorted closed-end funds, separately for leveraged and unleveraged closed-end funds. Funding liquidity beta is estimated month by month in a regression of fund excess returns on market excess returns and our funding liquidity factor over the previous 36 months. The reported values include average pre-ranking funding liquidity beta, average post ranking funding liquidity beta, and average excess returns associated with each of the funding liquidity beta sorted portfolio. The last row reports the differences in the variables between the portfolio 1 and portfolio 10. Newey-West *t*-statistics are reported in parentheses below the estimated parameters. The sample period is from January 1994 through December 2012. For leveraged closed-end funds, the time-series average number of closed-end funds in each portfolio is 40, ranging between 25 in February 1997 and 64 in December 2010. For unleveraged closed-end funds, the time-series average number of closed-end funds in each portfolio is 39, ranging between 14 in February 1997 and 120 in July 2011.

	Leveraged Closed-End Funds			Unleveraged Closed-End Funds		
FL-Beta Rank	Pre-ranking FL-Beta	Post-ranking FL-beta	Excess Return (%)	Pre-ranking FL-Beta	Post-ranking FL-beta	Excess Return (%)
1	-0.53	-0.25	0.81	-0.63	-0.16	0.93
	(-27.56)	(-4.92)	(2.00)	(-42.73)	(-1.84)	(2.00)
2	-0.16	-0.14	0.64	-0.25	-0.16	0.48
	(-30.49)	(-3.28)	(1.91)	(-43.53)	(-3.21)	(1.42)
3	-0.10	-0.08	0.42	-0.16	-0.14	0.41
	(-21.63)	(-2.22)	(1.41)	(-37.36)	(-3.14)	(1.27)
4	-0.06	-0.05	0.34	-0.10	-0.07	0.58
	(-15.08)	(-1.56)	(1.46)	(-29.35)	(-1.97)	(2.23)
5	-0.03	-0.04	0.22	-0.05	-0.05	0.35
	(-8.42)	(-1.23)	(1.17)	(-19.71)	(-1.57)	(1.60)
6	-0.01	-0.05	0.27	-0.02	-0.06	0.21
	(-2.33)	(-1.41)	(1.70)	(-9.24)	(-2.02)	(1.08)
7	0.00	-0.03	0.29	0.01	-0.05	0.24
	(1.22)	(-0.93)	(1.98)	(2.93)	(-1.85)	(1.38)
8	0.02	-0.03	0.18	0.04	-0.09	0.50
	(5.75)	(-1.00)	(1.04)	(14.97)	(-1.56)	(1.73)
9	0.04	-0.06	0.23	0.11	-0.06	0.45
	(13.75)	(-1.56)	(1.10)	(23.84)	(-1.68)	(1.78)
10	0.18	-0.05	0.51	0.37	-0.06	0.90
	(31.86)	(-1.18)	(1.58)	(32.49)	(-1.08)	(2.37)
1-10	-0.70	-0.20	0.30	-0.99	-0.10	0.04
	(-32.96)	(-4.00)	(1.57)	(-46.68)	(-0.87)	(0.07)

Table 10: Summary statistics for different asset classes

This table reports the summary statistics for the CDS-bond basis returns from July 2002 through March 2010, separately for financial institutions and industrial companies; for the 54 portfolio returns of S&P 500 European-style options from February 1994 through January 2012 from Constantinides, Jackwerth, and Savov (2013), and for the 6 carry trade portfolio returns from February 1994 through December 2012 downloaded from Hanno Lustig's webpage.

	N	Mean	Std. Dev.	5% Quintile	95% Quintile
CDS, Financial	1,492	-0.30	0.72	-1.55	0.83
CDS, Industiral	1,151	-2.36	2,99	-7,75	0.06
Options	54	0.25	4.80	-8.01	6.84
Carry trades	6	0.17	2.17	-3.43	3.59

Table 11: Fama-MacBeth Regression of Funding Liquidity and Asset Class Returns

This table reports the time-series averages of risk-premia on the market and funding liquidity from Fama-MacBeth regressions that relate the funding liquidity measure derived from the derivative markets to monthly returns from several funding liquidity shock sensitive assets: CDS-bond basis trades (separately for financial institutions and industrial companies), S&P 500 options, and carry trades. The sample of options is from February 1994 through January 2012, the sample of carry trades is from February 1994 through December 2012, and the sample of credit default swap (CDS) bond basis is from July 2002 through March 2010. We report *t*-statistics in parentheses below the estimated parameters.

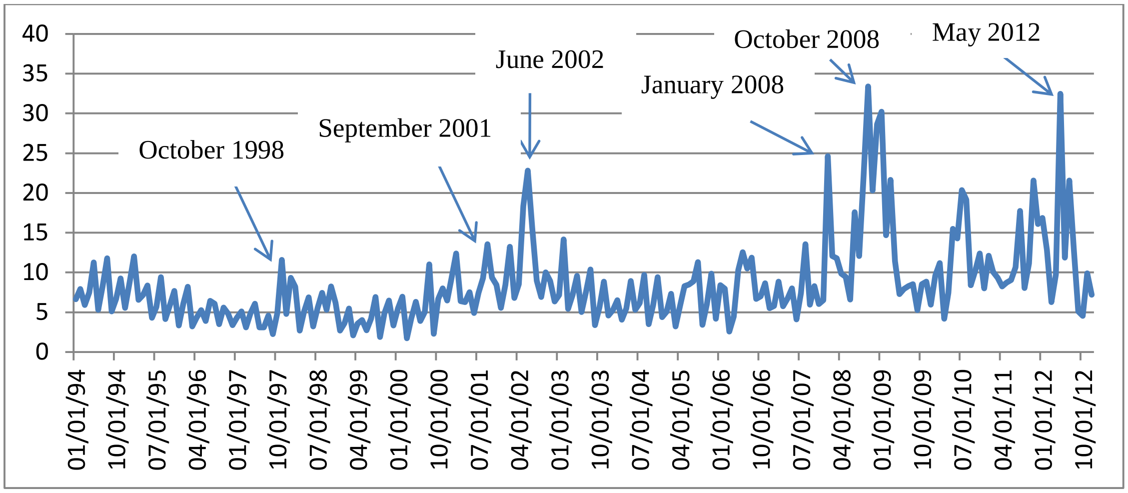
	CDS, Financial	CDS, Industrial	Options	Carry Trades
Intercept	-0.39	-1.77	-0.24	-0.33
t-stat.	(-9.23)	(-6.00)	(-0.45)	(-2.35)
Market	-1.43	-0.61	1.02	2.97
t-stat.	(-1.80)	(-1.11)	(1.50)	(3.76)
Funding liquidity	-7.20	0.51	-8.43	-1.82
t-stat.	(-2.93)	(0.72)	(-6.53)	(-0.85)
Obs.	1,492	1,151	54	6

Table 12: Returns from funding liquidity beta sorted hedge fund portfolios, methodological robustness

This table reports results for regressions of the low-minus-high funding-liquidity beta-sorted hedge fund portfolios on a constant (Model Constant); a constant and a Crisis Dummy (Model Crisis); a constant, Crisis Dummy, and the seven Fung and Hsieh (2001) factors (Model FH); a constant, Crisis Dummy, and the ten Namvar, Phillips, Pukthuanthong, and Rau (2013) factors (Model NPPR). Crisis Dummy takes a value one for recession periods identified by NBER and zero otherwise. Newey-West t-statistics are reported in parentheses below the estimated parameters. Funds are sorted into high and low funding liquidity sorted portfolios by regressing fund excess returns over the previous 36 months on market excess returns and our funding liquidity factor. In column (1), we repeat column (1) of Table 4. In column (2) we estimate all regressions on 48 months instead of 36 months. In column (3) we interact factors with the crisis dummy. Next, we re-define funding liquidity as the implied borrowing rate minus Libor (column 4) or as the implied borrowing rate minus T-bill rate (column 5). In column (6) we use only put-call pairs where both options have open interest greater than 200. In column (7) we use options across all moneyness levels (both sides of the Eq. (2)). The sample period for hedge funds is February 1994 through December 2012. The time-series for portfolio spreads is February 1997 through December 2012.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Controlling for Bid-ask spread	No	No	No	No	No	No	No
Controlling for TED spread	No	No	No	No	No	No	No
Controlling for liquidity (Noise)	No	No	No	No	No	No	No
Model Constant							
Constant	0.34	0.34	0.34	0.31	0.29	0.37	0.15
t-stat.	(2.17)	(2.16)	(2.17)	(1.98)	(1.84)	(2.55)	(0.83)
Model Crisis							
Constant	0.51	0.54	0.51	0.47	0.44	0.53	0.30
t-stat.	(3.50)	(3.99)	(3.51)	(3.04)	(3.00)	(3.51)	(1.82)
Crisis Dummy	-1.19	-1.26	-1.19	-1.09	-1.08	-1.06	-0.97
t-stat.	(-3.49)	(-3.50)	(-3.49)	(-3.46)	(-3.02)	(-3.38)	(-2.66)
Model FH							
Constant	0.28	0.35	0.21	0.29	0.25	0.43	0.13
t-stat.	(2.27)	(1.76)	(1.96)	(2.12)	(1.88)	(3.35)	(0.74)
Crisis Dummy	-0.64	-0.81	-0.42	-0.61	-0.55	-0.83	-0.79
t-stat.	(-2.21)	(-1.86)	(-1.43)	(-2.20)	(-1.93)	(-2.74)	(-2.22)
Model NPPR							
Constant	0.36	0.38	0.30	0.32	0.28	0.40	0.19
t-stat.	(2.34)	(3.12)	(1.80)	(2.08)	(1.87)	(2.58)	(1.48)
Crisis Dummy	-0.97	-0.96	-1.15	-0.93	-0.88	-1.06	-0.66
t-stat.	(-3.22)	(-3.49)	(-4.07)	(-3.46)	(-3.70)	(-3.26)	(-1.47)

Figure 1: The time-series plot of the funding liquidity measure derived from the derivative markets



The construction of the *Funding liquidity* measure derived from the S&P 500 derivative markets is described in Section II. The period is from January 1994 through December 2012.