A Market-Based Funding Liquidity Measure

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Abstract

In this paper, we construct a traded funding liquidity measure from stock returns. Using a stylized model, we show that the expected return of a beta-neutral portfolio, which exploits investors' borrowing constraints (Black (1972)), depends on both the market-wide funding liquidity and stocks' margin requirements. We extract the funding liquidity shock as the return spread between two beta-neutral portfolios constructed using stocks with high and low margin. Our return-based measure is correlated with other funding liquidity proxies derived from various markets. It delivers a positive risk premium, which cannot be explained by existing risk factors. Positive correlation also exists between the funding liquidity measure and market liquidity measures. Using our measure, we find that while hedge funds in general are inversely affected by funding liquidity shocks, some funds exhibit funding liquidity management skill and thus earn higher returns.

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1 Introduction

Since the 2007-2009 financial crisis, funding liquidity, one form of market frictions that measures the easiness for investors to finance their portfolio positions, is understood to be an important factor in determining asset prices. Researchers have done tremendous work on the relation between market frictions and risk premia, including restricted borrowing (Black (1972)), assets' margin constraints (Garleanu and Pedersen (2011)), and an intermediary's capital constraint (He and Krishnamurthy (2013)). Empirically, researchers and practitioners have adopted a number of proxies for funding liquidity, such as the difference between three-month Treasury-bill rate and the three-month LIBOR (TED spread), market volatility measured by VIX, and so forth. However, there is no single agreed upon measure of funding liquidity. In this paper, we construct a theoretically motivated and traded measure of funding liquidity using both the time series and cross-section of stock returns, as well as study its attributes.

Different from existing funding liquidity proxies, our measure is based on a model's prediction that funding liquidity is a valid risk factor and affects assets' risk premia. Moreover, the proposed funding liquidity measure is traded by construction, sharing the same benefits of other traded risk factors. First, a traded factor allows us to evaluate funding liquidity risk adjusted performance of various anomalies and managed portfolios. Second, investors can hedge against funding liquidity risk using the traded factor. Third, a traded factor can be constructed with return data of different frequencies.

The intuition behind our construction rests on the idea of capturing restricted borrowing from stock returns, similar to the "betting against beta" (BAB) portfolio of Frazzini and Pedersen (2014). They show that a market-neutral strategy of buying low-beta and selling high-beta assets delivers significant risk-adjusted returns. One puzzling observation however with their BAB portfolio is that it appears uncorrelated with other proxies for funding liquidity. Although it is possible that other proxies do not pick up the market-wide funding liquidity while the BAB portfolio does, this seems unlikely. This raises a puzzle of strong BAB performance and its weak linkage with the underlying driving force.

We show that the time series variation in returns of a BAB portfolio depends on both the market-wide funding condition and assets' sensitivities to the funding condition, where the latter is governed by margin requirements. We extract the funding liquidity shocks using the return difference of two BAB portfolios that is constructed with high- and low-margin stocks, respectively. Empirical evidence suggests that our traded measure is more likely to capture the market-wide funding liquidity shocks: correlation between our measure and other funding liquidity proxies is high; the funding liquidity factor cannot be explained by existing risk factors; a positive relation exists between our funding liquidity measure and market liquidity measures, supporting the liquidity spiral story. We further apply our measure to study the determinants of hedge fund performance. We find that while the aggregate hedge fund returns comove with funding liquidity in the time series, some funds are able to time funding liquidity risk and deliver higher returns than others in the cross section.

The construction of our funding liquidity measure is guided by a stylized model with both leverage constraints and asset-specific margin constraints. The model is in line with the margin-based CAPM (Ashcraft, Garleanu, and Pedersen (2010)): borrowing-constrained investors are willing to pay higher prices for stocks with larger market exposures, and this effect is stronger for stocks with higher margin requirements. Therefore, a market-neutral portfolio of longing low-beta stocks and shorting high-beta stocks should have a higher expected return for stocks with higher margin. More importantly, our model suggests that a difference-in-BAB series isolates the aggregate funding liquidity shocks from the impact of individual stocks' margin requirements.

Due to data limitation on individual stocks' margin requirements, we adopt five proxies, including size, idiosyncratic volatility, the Amihud illiquidity measure, institutional ownership, and analyst coverage. The selection of these proxies is based on real world margin rules and theoretical prediction of margin's determinants. Brokers typically set higher margin for smaller or more volatile stocks. On the theory side, Brunnermeier and Pedersen (2009) show that price volatility and market illiquidity could have a positive impact on assets' margin. We validate our proxies using a cross section of stock-level margin data obtained from Interactive Brokers LLC. We find that stocks with larger size, smaller idiosyncratic volatility, better liquidity, higher institutional ownership, and higher analyst coverage, are indeed more likely to be marginable. Together, those five proxies can explain 57% of the cross-sectional variation in stocks' marginability. While not perfect, the chosen proxies are likely to capture the determinants of stocks' margin to some extent.

We sort all stocks into five groups based on margin proxies and construct a BAB portfolio for each margin group. Consistent with model prediction, the BAB premium increases as margin increases. The monthly return spread between two BAB portfolios for high- and low-margin stocks ranges from 0.62% (the Amihud illiquidity measure proxy) to 1.21% (idiosyncratic volatility proxy).

The traded funding liquidity factor is constructed as the first principal component of the five BAB spreads, each of which is based on a margin proxy. Several properties of the funding liquidity factor are studied. First, our traded factor is significantly correlated with 11 of the 14 funding liquidity proxies used in the literature. Second, while the factor is constructed from stock returns, it cannot be absorbed by existing risk factors, including the Fama-French three factors, Carhart's momentum factor, the market liquidity factor, and the short-term reversal factor. Third, positive correlation exists between the constructed funding liquidity factor and market liquidity measures, especially during market downturns, supporting the liquidity spiral story (Brunnermeier and Pedersen (2009)). In addition, we show that while related, our funding liquidity measure is different from market liquidity. Fourth, our funding liquidity factor is robust to other specifications of margin proxies, including proxies orthogonalized to size and market beta, and fitted margin requirements from stocks' characteristics. All results suggest that the proposed traded factor is likely to capture the market-wide funding liquidity condition.

Having validated our funding liquidity measure, we investigate its asset pricing implications on hedge funds. We analyze hedge funds for two reasons. First, as major users of leverage (Ang, Gorovyy, and van Inwegen (2011)), their returns are expected to be more subject to funding liquidity shocks than other asset classes (Mitchell and Pulvino (2012)). Time series regression validates our conjecture. The aggregate hedge fund index loads positively and significantly on the funding liquidity factor, after controlling for the market factor. The loading implies a 2% per year decline in the aggregate hedge fund return when a one standard deviation of funding liquidity shock hits.

Second, one feature that differentiates hedge funds from other asset classes is that they are managed portfolios. Fund managers can change the exposures of their holdings to funding liquidity risk and therefore hedge funds might exhibit non-linear exposures (Glosten and Jagannthan (1994)). In the cross-section, we find that funds with small sensitivities to funding liquidity shocks outperform those with large sensitivities by 10.7% per year. This return spread is much larger during market downturns or bad funding liquidity periods. While the return spread cannot be explained by funds' risk taking, age, or strategies, it seems to be attributed to some funds' skill in timing funding liquidity risk. We show that low-sensitivity funds manage funding liquidity risk by reducing their exposures during bad funding periods.

Our paper is related to several strands of literature. First, it is related to the research on implications of funding liquidity for financial markets. On the theoretical side, Black (1972) uses investors' restricted borrowing to explain the empirical failure of CAPM. More recently, Garleanu and Pedersen (2011) derive a margin-based CAPM and Brunnermeier and

Pedersen (2009) model the reinforcement between market liquidity and funding liquidity.[1] On the empirical side, researchers provide evidence from various angles. Frazzini and Pedersen (2014) develop a trading strategy by exploiting assets' implicit leverage.[2] Adrian, Etula, and Muir (2014) investigate the cross-sectional pricing power of financial intermediary's leverage. To the best of our knowledge, we are the first to construct a traded funding liquidity factor from stock returns and study its attributes.[3]

Second, our paper furthers the debate on the risk-return relation in the presence of market frictions. Several explanations have been proposed for the empirical failure of the CAPM (Black, Jensen, and Scholes (1972)), including restricted borrowing (Black (1972); Frazzini and Pedersen (2014)), investors' disagreement and short-sales constraints (Miller (1977); Hong and Sraer (2015)), limited participation (Merton (1987)), fund managers' benchmark behavior (Brennan (1993); Baker, Bradley, and Wurgler (2011)), and behavioral explanation (Antoniou, Doukas, and Subrahmanyam (2014); Wang, Yan, and Yu (2014)). Our empirical evidence favors the leverage constraint explanation. On the other hand, our paper complements those studies in the sense that disagreement, restriction of market participation, and other frictions are likely to be more severe during periods with tighter funding liquidity. All mechanisms could contribute to the flattened security market line.

Finally, our study contributes to the literature that examines the impact of liquidity

[1] Other theoretical papers include Shleifer and Vishny (1997), Gromb and Vayanos (2002), Geanakoplos (2003), Ashcraft, Garleanu, and Pedersen (2010), Acharya and Viswanathan (2011), Chabakauri (2013), He and Krishnamurthy (2013), and Rytchkov (2014).

[2] Several papers further their study: Jylha (2014) finds that the security market line is more flattened during high-margin periods; Malkhozov et al. (2015) find that the BAB premium is larger if the portfolio is constructed in countries with low liquidity; Huang, Lou, and Polk (2014) link the time variation of the BAB returns with arbitrageurs' trading activities.

[3] Adrian and Shin (2010) use broker-dealers' asset growth to measure market level leverage. Comerton-Forde et al. (2010) use market-makers' inventories and trading revenues to explain time variation in liquidity. Nagel (2012) shows that the returns of short-term reversal strategies can be interpreted as expected returns for liquidity provision. Fontain and Garcia (2012) and Hu, Pan, and Wang (2013) extract liquidity shocks from Treasury bond yields. Lee (2013) uses the correlation difference between small and large stocks with respect to the market as a proxy for funding liquidity. Boguth and Simutin (2015) propose the aggregate market beta of mutual funds' holdings as a measure of leverage constraint tightness. Other studies include Boudt, Paulus, and Rosenthal (2014), Acharya, Lochstoer, and Ramadorai (2013), Drehmann and Nikolaou (2013), and Goyenko (2013).

on hedge fund performance and the skill in active asset management. Some researchers find that market liquidity is an important determinant in the cross section of hedge fund returns (Sadka (2010); Hu, Pan, and Wang (2013)). Others focus on funds' locked-up and redemption terms ((Aragon (2007); Teo (2011); Ben-David, Franzoni, and Moussawi (2012); Mitchell and Pulvino (2012))). We find that while the aggregate hedge fund performance is inversely affected by funding liquidity shocks, some fund managers exhibit skill in managing funding liquidity risk. Our results complement other papers that document hedge funds' market liquidity timing skill (Cao et al. (2013)), hedge funds' rare disaster management skill (Gao, Gao, and Song (2015)), and mutual funds' market liquidity management skill (Dong, Feng, and Sadka (2015)).

The rest of the paper is organized as follows. In Section 2, we present a stylized model that guides the construction of our funding liquidity measure. We test the model's predictions in Section 3. We construct the measure and study its properties in Section 4. In Section 5, we examine how the measure helps to explain hedge fund returns in both the time series and cross-section. We conclude in Section 6.

2 The Motivation of the Empirical Strategy through a Stylized Model

Our procedure of extracting the traded funding liquidity measure is motivated by a simple stylized model. Following Frazzini and Pedersen (2014), we consider a simple overlapping-generations economy in which agents (investors) are born in each time period t with exogenously given wealth W_t^i and live for two periods. $n+1$ assets are in the market. The first n assets $R_{k,t+1}$, $k = 1, \ldots, n$, are risky assets with positive net supply. A risk-free asset $R_{n+1,t}$ has a deterministic return of R with zero net supply.

An investor makes her portfolio choice to maximize the utility given in Equation 1:

$$U_t^i = E_t[R_{t+1}^i W_t^i] - \frac{\gamma^i}{2W_t^i}\, VAR_t[R_{t+1}^i W_t^i]. \tag{1}$$

W_t^i is investor i's wealth, $R_{t+1}^i = \Sigma_{k=1}^{n+1}\omega_{k,t}^i R_{k,t+1}$ is the portfolio return, $\omega_{k,t}^i$ is the portfolio weight in asset k, and γ^i is the risk aversion parameter.

Investor i's funding constraint can be written in Equation 2:

$$\Sigma_{k=1}^n m_{k,t} I_{k,t} \omega_{k,t}^i \leq \frac{1}{M_t}, \text{ where } I_{k,t} = \begin{cases} 1, & \text{if } \omega_{k,t}^i \geq 0 \\ -1, & \text{if } \omega_{k,t}^i < 0 \end{cases} \tag{2}$$

Following the literature (Geanakoplos (2003); Ashcraft, Garleanu, and Pedersen (2010)), we assume that investors are subject to asset-specific margin requirements (haircuts) $m_{k,t}$. The restriction on risk-free borrowing M_t imposes an upper bound on investors' total available capital. The indicator variable $I_{k,t}$ takes value of 1 (-1) for long (short) positions, both of which consume capital.

There are two types of investors in the market. We assume homogeneity in wealth and risk aversion within investor type. Type A investors have a high level of risk aversion. Their funding constraints are not binding and therefore do not affect their optimal portfolio choices. Their portfolio choice problem can be summarized in Equation 3, where $E_t[R_{t+1}^n] = (E_t[R_{1,t+1}] - R, \ldots, E_t[R_{n,t+1}] - R)'$ is the vector of risky assets' expected excess returns and Ω is their variance-covariance matrix:

$$\max_{\{\omega_t^A\}} \; U_t^A = \omega_t^{A\prime} E_t[R_{t+1}^n] - \frac{\gamma^A}{2}\omega_t^{A\prime}\Omega\omega_t^A. \tag{3}$$

Type B investors are more risk loving and their portfolio choices are subject to the funding constraints. To simplify the problem, we redefine asset k's effective haircut to be $\hat{m}_{k,t} = m_{k,t}M_t$. Type B investors' portfolio choice problem is summarized in Equation 4:

$$\begin{aligned} \max_{\{\omega_t^B\}} \; U_t^B &= \omega_t^{B\prime} E_t[R_{t+1}^n] - \frac{\gamma^B}{2}\omega_t^{B\prime}\Omega\omega_t^B, \\ s.t. \;\; &\Sigma_{k=1}^n \hat{m}_{k,t} I_{k,t}\omega_{k,t}^B \leq 1. \end{aligned} \tag{4}$$

Define η_t as the Lagrange multiplier that measures the shadow cost of the borrowing constraint, and $\tilde{m}_t = (\hat{m}_{1,t}I_{1,t}, \ldots, \hat{m}_{n,t}I_{n,t})'$ as the margin vector. Lemma 1 gives investors' optimal portfolio choices (All proofs are in Appendix B).

Lemma 1 (*Investors' Optimal Portfolio Choices*)
Type A and type B investors' optimal portfolio choices are given by:

$$\omega_t^A = \frac{1}{\gamma^A}\Omega^{-1}E_t[R_{t+1}^n]. \tag{5}$$

$$\omega_t^B = \frac{1}{\gamma^B}\Omega^{-1}(E_t[R_{t+1}^n] - \eta_t\tilde{m}_t). \tag{6}$$

Note that type B investors' portfolio choice $\omega_{k,t}^B$ is affected by the average shadow cost of borrowing η_t and the asset-specific margin requirement $\tilde{m}_{k,t}$. When the borrowing condition tightens (larger η_t), type B investors allocate less capital in the risky asset k. In addition, this reallocation effect is stronger for the asset with a higher haircut $\tilde{m}_{k,t}$. For simplicity, we assume that each type of investors has a unit of one, and thus their total wealth are W_A and W_B, respectively. Let $P = (P_1, \ldots, P_n)'$ be the market capitalization vector, the market clearing conditions can be summarized by Equation 7, where $X = (\frac{P_1}{P'e^n}, \ldots, \frac{P_n}{P'e^n})'$ is the relative market capitalization vector and $\rho_A = \frac{W_A}{W_A+W_B}$ is the relative wealth of type

A investors.

$$\rho_A \omega_t^A + (1-\rho_A)\omega_t^B \quad = \quad X. \tag{7}$$

We further define the aggregate risk aversion γ in terms of $\frac{1}{\gamma} = \frac{\rho_A}{\gamma_A} + \frac{1-\rho_A}{\gamma_B}$, levered investors' effective risk aversion $\tilde{\gamma} = \gamma\frac{1-\rho_A}{\gamma_B}$, and asset k's market beta $\beta_{k,t} = \frac{COV(R_{k,t+1},R_{M,t+1})}{VAR(R_{M,t+1})}$. Using market clearing condition, we obtain the equilibrium risk premia in Lemma 2.[4]

Lemma 2 (*Assets' Risk Premia*)

In equilibrium, the risk premium for the risky asset k, $k = 1, 2, ..., n$, is given by:

$$E_t[R_{k,t+1}] - R = \beta_k(E_t[R_{m,t+1}] - R) + \psi_t(\hat{m}_{k,t} - \beta_k \hat{m}_{M,t}). \tag{8}$$

$\psi_t = \tilde{\gamma}\eta_t$ measures the shadow cost of the borrowing constraint, and $\hat{m}_{M,t} = X'\hat{m}_t$ is the market size-weighted average margin requirement. Lemma 2 shares the same vein as the margin-based CAPM where an asset's risk premium depends on both the market premium and the margin premium (Ashcraft, Garleanu, and Pedersen (2010); Garleanu and Pedersen (2011)). Different from the standard CAPM, the security market line (SML) is flattened in the presence of borrowing constraints. The intercept of the SML measures the asset-specific cost of funding constraint $\psi_t m_{k,t}$. The slope of the SML, $E_t[R_{m,t+1}] - R - \psi_t m_{M,t}$, is lowered by the aggregate cost of funding constraint $\psi_t \hat{m}_{M,t}$.

Under Assumption 1, Proposition 1 gives the risk premium of a market-neutral BAB portfolio that is constructed in a class of stocks with the same margin requirement.

Assumption 1

Market risk exposures β_k are heterogeneous within a class of stocks that have the same

[4]Lemma 2 is derived under the scenario when the optimal portfolio choice is positive. Since we only have two types of homogeneous investors in our model, it is not an unreasonable assumption that both types allocate a positive fraction of wealth in all the risky assets.

margin requirement $\hat{m}_{BAB,t}$. The distributions of β_k across different classes of stocks are the same.

Proposition 1 (*The BAB Premium with Margin Effect*)

For a given level of margin requirement $\hat{m}_{BAB,t}$, the BAB premium is:

$$E_t R_{t+1}^{BAB} = \psi_t \hat{m}_{BAB,t} (\frac{\beta_H - \beta_L}{\beta_H \beta_L}).$$

Different from Frazzini and Pedersen (2014), we show that the BAB premium monotonically increases in both the aggregate funding tightness ψ_t and stocks' margin requirement $\hat{m}_{BAB,t}$. The explanation is intuitive: the BAB premium comes from the price premium, paid by borrowing-constrained investors, for the embedded leverage of high-beta stocks, therefore such effect should be stronger for high-margin stocks that are difficult to invest with borrowed capital. Both the market-wide funding liquidity shock and stocks' margin requirements could contribute to the observed time series variation in the BAB returns.

Assumption 2

The class-specific margin requirement $\hat{m}_{BAB,t}$ is given by:

$$\hat{m}_{BAB,t} = a_{BAB} + f_t.$$

Under Assumption 2, stocks' margin is determined by two components: one is a time-varying common shock and the other is a asset-specific constant. The common component f_t can be thought of those factors that affect all stocks' margin requirements, such as market condition, technology advancement, or regulation change. The idiosyncratic component a_{BAB} applies to a class of stocks that share similar characteristics. It is not unrealistic to assume that some stocks could be charged with higher margin than others when the two groups of stocks have different properties.

Proposition 2 (*Extraction of Funding Liquidity Shocks from Two BAB Portfolios*) Under Assumption 2, the spread of the risk premia between two BAB portfolios, which are constructed over stocks with high and low margin requirements, respectively, is given by:

$$E_t R_{t+1}^{BAB^1} - E_t R_{t+1}^{BAB^2} = \frac{\beta_H - \beta_L}{\beta_H \beta_L} c\psi_t$$

where $c = a_{BAB}^1 - a_{BAB}^2$ is the difference in the stock characteristics a_{BAB} between these two classes of stocks.

Proposition 2 shows that by taking the difference of two BAB portfolios with different margin requirements, we can isolate time-varying funding liquidity ψ_t. A higher ψ_t indicates tighter market-wide borrowing condition and therefore raises the return spread of two BAB portfolios. As the current price moves opposite to the future expected return, a contemporaneous decline in the BAB spread suggests adverse funding liquidity shocks. Note that Proposition 2 still holds if we relax a_{BAB} to be time-varying, as long as $a_{BAB,t}$ follows some distribution that has a constant dispersion over time.

The following section provides empirical evidence for Proposition 1. In Section 4, we construct our funding liquidity measure guided by Proposition 2.

3 Margin Constraints and BAB Portfolio Performance

Proposition 1 suggests that the BAB strategy should earn a large premium when it is constructed within stocks that have high margin requirements. To test this proposition, we divide all the AMEX, NASDAQ, and NYSE traded stocks into five groups using proxies for margin requirements, then construct a BAB portfolio within each group.

3.1 Margin Proxies and Methodology

In the U.S., the initial margin is governed by Regulation T of the Federal Reserve Board.[5] According to Regulation T, investors (both individual and institutional) may borrow up to 50% of market value for both long and short positions. In addition to the initial margin, stock exchanges also set maintenance margin requirements. For example, NYSE/NASD Rule 431 requires investors to maintain a margin of at least 25% for long positions and 30% for short positions.[6] While these rules set the minimum boundaries, brokers could set various margin requirements based on a stock's characteristics such as size, volatility, or liquidity.

On the theory side, Brunnermerier and Pedersen (2009) demonstrate that stocks' margin requirements increase with stocks' price volatility and market illiquidity. In their model, funding liquidity providers with asymmetric information raise the margin of an asset when the asset's volatility increases. In addition, market illiquidity may also have a positive impact on assets' margin.[7]

Motivated by the theoretical prediction and how margins are determined in the market, we select five proxies for margin requirements: size, idiosyncratic volatility, the Amihud illiquidity measure, institutional ownership, and analyst coverage.

The first margin proxy is size. Small stocks typically have higher margin requirements. We measure size as the total market capitalization at the last trading day of each month. The sample period is from January 1965 to October 2012.

The second proxy is idiosyncratic volatility. While total volatility is closer to theory's

[5]Regulation T was instituted on Oct 1, 1934 by the Board of Governors of the Federal Reserve System, whose authority was granted by The Securities Exchange Act of 1934. Historically, the initial margin requirement has been amended many times, ranging from 40% to 100%. The Federal Reserve Board set the initial margin to be 50% in 1974 and has kept it since then.

[6]For stocks traded below $5 per share, the margin requirement is 100% or $2.5 per share (when price is below $2.5 per share).

[7]In Proposition 3 of Brunnermerier and Pedersen (2009), margin requirements increase with price volatility as long as financiers are uninformed; margin increases in market illiquidity as long as the market liquidity shock has the same sign (or greater magnitude than) the fundamental shock.

guidance, we choose to use idiosyncratic volatility to eliminate the impact of the market beta. Given that the second stage of BAB portfolio construction involves picking high-beta and low-beta stocks, we want to sort on the pure margin effect instead of creating a finer sorting on beta.[8] Following Ang et al. (2006), we calculate idiosyncratic volatility as the standard deviation of return residuals adjusted by the Fama-French three-factor model using daily excess returns over the past three months. The sample period is from January 1965 to October 2012.

The third proxy is the Amihud illiquidity measure. Following Amihud (2002), we measure stock illiquidity as the average absolute daily return per dollar volume over the last 12 months, with a minimum observation requirement of 150.[9] The sample period is from January 1965 to October 2012.

The fourth proxy is institutional investors' holdings. Previous research finds that institutional investors prefer to invest in liquid stocks (Gompers and Metrick (2001); Rubin (2007); Blume and Keim (2012)). We calculate a stock's institutional ownership as the ratio of the total number of shares held by institutions to the total number of shares outstanding. Data on quarterly institutional holdings come from the records of 13F form filings with the SEC, which is available through Thomson Reuters. We expand quarterly filings into monthly frequency: we use the number of shares filed in month t as institutional investors' holdings in month t, $t+1$, and $t+2$. We then match the institutional holding data with stocks' returns in the next month.[10] Stocks that are not in the 13F database are considered to have no institutional ownership. The sample period is from April 1980 to March 2012.

[8] The average cross-sectional correlation between idiosyncratic volatility and total volatility is 67.8%, indicating that large idiosyncratic volatility stocks also tend to have large total volatility.

[9] The Amihud illiquidity measure is defined as $Illiquidity_{i,m} = \frac{1}{N_{i,m-1,m-12}} \Sigma_{t=1}^{N_{i,m-1,m-12}} \frac{|ret_{i,t}|}{dollarvol_{i,t}}$, where $N_{i,m-1,m-12}$ is the number of trading days in the previous 12 months prior to the holding month.

[10] SEC requires institutions to report their holdings within 45 days at the end of each quarter. Our match using one-month ahead returns may still result in a forward-looking bias. We also use a 2-quarter lag approach to further eliminate the forward looking bias (Nagel (2005)). Results are very similar and available upon request.

Our last proxy is analyst coverage. Irvine (2003) and Roulstone (2003) find that analyst coverage has a positive impact on a stock's market liquidity as it reduces information asymmetry. Based on this relationship, stocks with more analyst coverage may have lower margin requirements. We measure analyst coverage as the number of analysts following a stock in a given month. Data on analyst coverage are from Thomson Reuters' I/B/E/S dataset. The sample period is from July 1976 to December 2011.

We validate these margin proxies by examining whether they affect stocks' marginability in the cross section. Due to the scarce availability of margin data, we are only able to conduct analysis based on the stock-level initial margin data from an online brokerage firm, Interactive Brokers LLC. Interactive Brokers divides all stocks into a marginable group and a non-marginable group. For the marginable stocks, they have the same initial margin requirement, 25% for the long positions and 30% for the short positions, except for very few exceptions.[11] Specifically, among the 4650 observations with matching margin-proxy information, 1573 of them are not marginable, 3056 of them have 30% (25% for short positions) margin requirement, and the rest 121 have other levels of margin. Given the clustered nature of margin requirements, we create a marginability dummy that takes the value of 1 if the stock is marginable, and 0 otherwise. We run probit regressions of marginability dummy on the five margin proxies. Table 1 presents the results. Columns (1) to (5) show that stocks with larger size, lower idiosyncratic volatility, better liquidity, higher institutional ownership, and more analyst coverage, are more likely to be marginable. Column (6) gives the result when all five proxies are included as the explanatory variables. The pattern is similar except that the Amihud measure is no longer significant and analyst coverage has the opposite sign. The adjusted R^2 is 57%, suggesting that the chosen proxies explain a decent fraction of cross sectional variation in stocks' marginability.

We understand that shortcomings of using proxies instead of real margin data still

[11] The initial margin requirements here are intraday-based, and thus can be lower than the end-of-trading-day initial margin requirements set by Regulation T.

remain. First, those proxies could also be associated with stocks' differences in market liquidity, investors' participation, or the level of information asymmetry. However, on the other hand, all of these dimensions could affect stocks' marginability as well. Second, the margin requirement for a single stock could vary across brokers and also across investors. But as long as the patterns of margins' determinants are the same across brokers and for different investors, e.g., a small stock always has higher margin requirements than a large stock, those proxies can still capture the average margin requirement. Third, brokers can require portfolio margin instead of position margin in recent years.[12] Our sample covers more than forty years' data and therefore stock level margin applies in most sample periods except for the most recent five years. Overall, even though our proxies are not perfect substitutes for the actual margin, they are likely to capture the cross-sectional differences in stocks' margin requirements to some extent.

3.2 BAB Performance Across Different Margin Groups

We divide stocks into five groups based on each of the five margin proxies. Group 1 (5) contains stocks with the lowest (highest) margin requirement. Specifically, Group 1 contains stocks with the largest market capitalization, the lowest idiosyncratic volatility, the smallest Amihud illiquidity measure, the highest institutional ownership, and the highest analyst coverage. The opposite is true for the high margin group. We divide stocks using NYSE breaks to ensure our grouping is not affected by small stocks.[13] We then construct a BAB portfolio within each group of stocks sorted by their margin requirements using each of the five proxies. We follow Frazzini and Pedersen (2014) closely on the formation of the BAB

[12]SEC approved a pilot program offered by the NYSE in 2006 for portfolio margin that aligns margin requirements with the overall risk of a portfolio. The portfolio margin program became permanent in August 2008. Under portfolio margin, stock positions have a minimum margin requirement of 15% (as long as they are not highly illiquid or highly concentrated positions).

[13]We assign all stocks with no analyst coverage to Group 5, and all stocks with only one analyst coverage to group 4. For the rest, we use NYSE breaks to sort them into three groups.

portfolios.

Table 2 reports the excess returns and the five-factor model adjusted alphas of the BAB portfolios conditional on margin requirements.[14] Panel A of Table 2 presents BAB portfolio performance within each margin group when size proxy is used. The results show that the BAB portfolio constructed within smaller stocks, thus having higher margin requirement, delivers considerably higher returns. In particular, the BAB portfolio for Group 5 (smallest size) earns an excess return of 1.22% per month and an alpha of 0.76% per month, while the number is 0.34% and 0.16%, respectively, for the BAB portfolio of Group 1 (largest size). The return difference between these two BAB portfolios is highly significant at 1% significance level.

Similar patterns can be found when other margin proxies are used (Panels B to E of Table 2). The monthly return differences between the two BAB portfolios constructed within Group 5 and Group 1 stocks are 1.21% (idiosyncratic volatility proxy), 0.62% (the Amihud illiquidity proxy), 0.97% (institutional ownership proxy), and 0.99% (analyst coverage proxy). Again, such return spreads cannot be explained by commonly used risk factors: monthly alphas are 0.76% (idiosyncratic volatility proxy, t-statistic = 3.63), 0.42% (the Amihud illiquidity proxy, t-statistic = 2.30), 0.67% (institutional ownership proxy, t-statistic = 2.12), and 0.77% (analyst coverage proxy, t-statistic = 2.27).

Overall, we find supporting evidence that the BAB premium is positively related to the margin requirement. More importantly, the results provide us an empirical ground to construct a funding liquidity measure using stock returns.

[14]Alphas are calculated with respect to five risk factors: the Fama-French (1993) three factors, the Carhart's (1997) momentum factor (UMD), and a market liquidity factor proxied by the returns of a long-short portfolio sorted by the Amihud measure.

4 Funding Liquidity Shocks

4.1 The Extraction of the Funding Liquidity Shocks

We extract funding liquidity shocks using the return spread between two BAB portfolios constructed within high-margin (Group 5) stocks and low-margin (Group 1) stocks. We have five time series of return differences as we use five margin proxies. Following the factor extraction method for unbalanced sample proposed by Connor and Korajczyk (1987),[15] we take the first principal component of these five time series as our measure for funding liquidity shocks (FLS hereinafter).

We first check whether there is a factor structure underlying the five series. Panel A of Table 3 presents the adjusted R^2s from time series regressions of the five BAB spreads on the FLS. The adjusted R^2s are 84.1% (size), 35.9% (idiosyncratic volatility), 70.5% (Amihud), 66.2% (institutional ownership), and 78.3% (analyst coverage). Thus the five series have a clear factor structure and their first principal component can explain, on average, 67.0% of their time-series variation. The average adjusted R^2 is 73.0% if quarterly data are used.

Panel B of Table 3 compares the summary statistics of the FLS to existing risk factors. The annualized average of the FLS is 21.05%, much larger than other risk factors. On the other hand, the volatility of the FLS is also larger at 25.84%, resulting an annualized Sharpe ratio of 0.81. Note that while many existing liquidity measures are highly persistent, our traded measure of funding liquidity is not. The autocorrelation coefficient of the FLS is 0.22, suggesting that it is likely to capture unexpected shocks regarding the market-wide funding condition. We plot the time series of the FLS in Figure 1. Large drops in the FLS usually corresponds to the periods with low market-wide funding liquidity such as the bust of internet bubble and the bankruptcy of Lehman Brothers. Similar figure can be drawn

[15]We also construct the funding liquidity shocks using a balanced sample from January 1980 to December 2011. The correlation coefficient between the two series is higher than 99%.

using quarterly data (Appendix Figure C.1).

Panel A of Table 4 presents the correlations of the FLS with 14 funding liquidity proxies that have been proposed in the literature: broker-dealers' asset growth (Adrian and Shin (2010)), Treasury security-based funding liquidity (Fontaine and Garcia (2012)), major investment banks' CDS spread (Ang, Gorovyy, and Van Inwegen (2011)), credit spread (Adrian, Etula, and Muir (2014)), financial sector leverage (Ang, Gorovyy, and Van Inwegen (2011)), hedge fund leverage (Ang, Gorovyy, and Van Inwegen (2011)),[16] investment bank excess returns (Ang, Gorovyy, and Van Inwegen (2011)), broker-dealers' leverage factor (Adrian, Etula, and Muir (2013)), 3-month LIBOR rate (Ang, Gorovyy, and Van Inwegen (2011)), percentage of loan officers tightening credit standards for commercial and industrial loans (Lee (2013)), the swap spread (Asness, Moskowitz, and Pedersen (2013)), the TED spread (Gupta and Subrahmanyam (2000)), the term spread (Ang, Gorovyy, and Van Inwegen (2011)), and the VIX (Ang, Gorovyy, and Van Inwegen (2011)). For data that are originally quoted in quarterly frequency, we convert it into monthly frequency by applying the value at the end of each quarter to its current month as well as the month before and after that month.[17] We sign each proxy such that a small value indicates an adverse funding liquidity shock. We obtain shocks by taking the residuals of each proxy after fitting in an AR(2) model.[18] Additional details on the construction of these 14 proxies are in Appendix A.1.

We find that FLS is significantly correlated with 11 out of 14 existing funding liquidity proxies: the correlation coefficient ranges from 12.9% (broker-dealers' asset growth) to 45.8% (hedge fund leverage). We find a similar pattern for quarterly data, i.e., FLS is positively

[16] The data are provided by the authors.

[17] Proxies originally quoted in quarterly frequency include broker-dealers' asset growth, broker-dealers' leverage factor, and percentage of loan officers tightening credit standards for commercial and industrial loans.

[18] We follow Korajczyk and Sadka (2008) and Asness, Moskowitz, and Pedersen (2013) to define the shock as AR(2) residuals. This adjustment is done to all proxies except for investment banks excess return and broker-dealers' leverage factor. For quarterly frequency data, we fit the data in an AR(1) model. Results are similar if we use other lags.

and significantly correlated with 10 out of 14 proxies.[19] In contrast, the BAB factor has significant correlation with only two funding liquidity proxies: the Treasury security-based funding liquidity proxy and swap spread.

Changes in each of the 14 proxies could result from other shocks instead of funding liquidity shocks. To mitigate such potential noise, we take the first principal component of the 14 proxies (FPC14) and calculate its correlation with the FLS. Panel B of Table 4 presents the results. Correlation coefficients between the FLS and the FPC14 are 35.8% and 50.2%, respectively, for monthly and quarterly data. In contrast, correlation coefficients are not significant for the BAB factor.

Since some of the 14 proxies have quarterly frequency, and some have shorter sample coverage, we also report correlation coefficients between the FLS and the first principal component of two subsets of the 14 proxies. FPC10 is the first principal component of the 10 proxies that have full sample coverage with the first observation starting in January 1986; FPC7 is the first principal component of an even smaller subset with seven proxies that do not have stock return related data or are originally quoted in quarterly frequency.[20] Correlation coefficients between the FLS and these two alternative principal components are still high: 30.5% and 26.8% for monthly data, and 45.9% and 44.8% for quarterly data. Again, insignificant correlation coefficients are found for the BAB factor (except for the correlation between the BAB factor and FPC10 with monthly data, which is marginally significant).

[19]We also calculate the correlation coefficients of each of the five BAB return difference series with the 14 funding liquidity proxies, separately (Appendix Table C.2). The results are similar, indicating that the significant correlation between the FLS and other funding proxies is not caused by the BAB return difference conditional on any single margin proxy.

[20]Four proxies are excluded for FPC10: major investment banks' CDS spread, hedge fund leverage, percentage of loan officers tightening credit standards for commercial and industrial loans, and the swap spread. FPC7, in addition to the ones excluded in FPC10, does not include major investment bank excess returns, broker-dealers' asset growth rate (quarterly frequency), or broker-dealers' leverage factor (quarterly frequency).

4.2 A Traded Measure of Funding Liquidity Risk

One important feature that distinguishes the FLS from other funding liquidity proxies is that the FLS is traded. This feature allows investors to hedge against funding liquidity risk by forming a portfolio following the proposed procedure. In addition, a traded funding liquidity factor can be applied to better understand stock market anomalies and evaluate portfolios' performance.

We first examine whether our traded funding liquidity measure can be absorbed by other traded risk factors. Panel A of Table 5 reports the results of time series regressions in which the FLS is the dependent variable and various risk factors are the explanatory variables. Columns 1 and 2 show that, even though the FLS is derived from the BAB portfolio, the latter cannot fully explain the former: the alphas are still significant with magnitudes of 1.08% and 0.82% per month, depending on whether we control for the market factor. The adjusted R^2 is less than 20% even when both the BAB factor and market factor are included. Columns 3 to 7 present the results when several common risk factors are added sequentially, including the market factor, the size factor, the value factor, the momentum factor, the illiquidity factor (a long-short portfolio constructed based on stocks' Amihud illiquidity measure), and the short-term reversal factor. Alphas are significant after controlling for these risk factors, and adjusted R^2s are less than 15%. Interestingly, similar to Nagel (2012), who finds that returns of short-term reversal strategies are higher when liquidity (proxied by VIX) deteriorates, we find that our funding liquidity factor negatively (though insignificantly) comoves with the short-term reversal factor. After we include all the risk factors (Column 8), the FLS still has a monthly alpha of 0.89% (t-statistic=1.89) and the adjusted R^2 is only 24.4%. The results in Panel A suggest that our traded funding liquidity factor contains information that cannot be fully explained by common risk factors.

On the other hand, the FLS helps to explain these systematic risk factors. Panel B of Table 5 presents the results in which the FLS is used as the single explanatory variable for existing risk factors. We find that the BAB factor, the SMB factor, and the Amihud illiquidity long-short portfolio load significantly on the FLS, while the HML factor, the momentum factor, and the short-term reversal factor seem not to be explained by the funding liquidity risk. The alphas of the SMB factor and the illiquidity factor are not statistically significant, indicating that the funding liquidity risk is an important factor to explain the risk premia of these two factors. We find similar results in Panel C of Table 5 when we include the market portfolio in the regression.

Even though the FLS by construction is traded, a nature question is how implementable it is. The construction of the FLS requires investors to take long and short positions over small and illiquid stocks. Therefore, we need examine to what extent the traded funding liquidity measure is affected by transaction costs. We calculate the average turnover for each difference-in-BAB portfolio sorted by margin proxy. For those portfolios sorted by size, the Amihud illiquidity measure, and institutional ownership, the turnovers are 26, 24, and 29 cents, respectively, for every dollar spent on the long position. Turnovers are higher for those portfolios sorted on idiosyncratic volatility (78 cents) and analyst coverage (70 cents).

We further examine a difference-in-BAB portfolio's vulnerability to transaction costs by computing the round-trip costs that are large enough to cause the average monthly return to be insignificant. Our approach is similar to the one used in Grundy and Martin (2001) but we incorporate the cross-sectional variation in transaction costs associated with stocks' different margin requirements. We assign high-margin stocks a 11.17 bps higher transaction cost to reflect their higher cost to trade.[21] The "tolerable" round-trip cost is a function of the portfolio's turnover and the raw returns. We find that the returns of the difference-in-BAB portfolios (the last column in Table 2) remain significant as long as the monthly

[21]The transaction cost difference is the difference in implementation shortfall (IS) between large- and small-capitalization stocks from Table II in Frazzini, Israel, and Moskowitz (2012). Since we assume the difference in transaction cost across high- and low-margin stocks is constant, we only calculate the round-trip costs for high-margin stocks.

round-trip costs for the high-margin stocks are less than 114 bps for size proxy, 43 bps for the idiosyncratic volatility proxy, 76 bps for the Amihud illiquidity proxy, 60 bps for the institutional ownership proxy, and 45 bps for the analyst coverage proxy. These estimated "tolerable" costs are considerably higher than the realized transaction costs reported in Frazzini, Israel, and Moskowitz (2012). We understand that the actual round-trip costs could be different for various investors and the scalability of our factor could be limited. However, our estimates suggest that the market-based funding liquidity factor could possibly be implemented at a reasonable transaction cost.

4.3 Relation with Market Liquidity

Brunnermeier and Pedersen (2009) show that there is a mutual reinforcement between funding liquidity tightness and market illiquidity. We find supporting evidence for their argument using the extracted funding liquidity measure. Panel A of Table 6 reports the pairwise correlation coefficients between the FLS and four market liquidity measures, including returns of a long-short portfolio sorted by the Amihud illiquidity measure, the Pastor and Stambaugh (2003) market liquidity innovation measure, the variable component of Sadka (2006) market liquidity factor, and the innovation of the noise measure in Hu, Pan, and Wang (2013). The FLS is correlated with all four market liquidity measures, with correlation coefficients ranging from 17.0% (the Pastor and Stambaugh's measure) to 23.9% (the Amihud illiquidity measure). The positive and significant correlation provides supportive evidence for the comovement between market liquidity and funding liquidity.

Moreover, Brunnermeier and Pedersen (2009) also predict that the liquidity spiral is stronger when negative shocks hit asset prices. Based on their theoretical prediction, we would expect to see asymmetric comovements between funding liquidity and market liquidity during up and down markets. We find confirming evidence in our data that supports this prediction. Panels B and C of Table 6 present pairwise correlation coefficients in the months with positive and negative market returns, respectively. The correlation between the FLS and market liquidity is much higher during declining markets than during rising markets. In addition, the correlation among various market liquidity proxies also increases when the market experiences negative returns. Such asymmetry complements Hameed, Kang, and Viswanathan (2010) who find that negative market returns decrease stock liquidity more severely than the positive effect from positive market returns, and the commonality in liquidity increases dramatically with negative market returns.

While overlaps might exist between the informational contents captured by the FLS and market liquidity, we find that the FLS clearly contains information on funding liquidity risk that is not purely driven by market liquidity. We orthogonalize FLS with respect to the market liquidity (proxied by an Amihud illiquidity measure sorted long-short portfolio) and examine its correlation with existing funding liquidity measures. The second row of Panel A of Table 7 reports the correlation coefficients between the market liquidity orthogonalized $\mathrm{FLS}_{\perp ml}$ and 14 funding liquidity proxies. The results are quite similar to the ones when the FLS is used. The six-factor adjusted alpha is 0.92% per month and significant with a t-statistic of 1.81. Our findings indicate that the orthogonalized component is where the funding liquidity related information lies.

Because the construction of FLS involves first grouping stocks based on their characteristics such as size, it is possible that what we extract is the return premium associated with these characteristics, which could well be related to market liquidity. We examine this possibility using two portfolios that are constructed based on the five margin proxies. The first portfolio intends to capture the margin-proxy spread. Specifically, for each margin proxy, we construct a simple long-short portfolio using quintile portfolio sorting. We take the first principal component of the returns of the five long-short portfolios and denote it by FPC_{single}. The second portfolio intends to capture the difference of margin-proxy spreads. We first sort stocks into a low-beta group and a high-beta group. Within each beta group, we construct a long-short portfolio by sorting stocks into five groups according to a margin proxy. Then we take the return difference between two long-short portfolios constructed within low- and high-beta groups. We extract the first principal component of the five return differences and denote it by FPC_{double}. If the FLS captures the market liquidity instead of funding liquidity, we expect the results to be similar if we replace FLS with FPC_{single} and FPC_{double}. It is not the case. The FPC_{single} (FPC_{double}) are only significantly correlated with 5 (4) out of 14 funding liquidity proxies, as shown in Panel A of Table 7. Moreover, the risk-adjusted alphas of FPC_{single} and FPC_{double} are no longer positive or significant. Common risk factors can explain 94.8% and 53.9% of the time series variations of FPC_{single} and FPC_{double}, respectively. The results indicate that portfolios sorted by the margin proxies provide limited information on the funding condition, even though such proxy-sorted long-short portfolios might capture market liquidity.

In sum, what we find so far indicates that even though market liquidity and funding liquidity are closely related, they are not the same. The extracted FLS is more likely to capture the time variation in funding liquidity instead of market liquidity.

4.4 Other Specifications of Margin Proxies

In this section, we explore whether our funding liquidity construction is robust to other specifications of margin proxies.

First, probit regression shows that size contributes the most in explaining the cross section of stock marginability and all the other margin proxies are closely related to size. Thus it is possible that sorting on those proxies does not provide additional benefit than sorting on size. But we find that it is not the case. We orthogonalize other margin proxies with respect to market capitalization, and use the regression residuals in the construction of the size-orthoganlized funding liquidity measure $\text{FLS}_{\perp size}$. We do not include analyst coverage proxy as it has very limited cross-sectional variation. The correlation coefficients and time series regression results are reported in Table 8. $\text{FLS}_{\perp size}$ is significantly correlated with 9 out of 14 funding liquidity proxies. The seven-factor alpha is 0.68% (t-statistic=1.77) and the adjusted R^2 of the time series regression is only 16.25%. The findings suggest that properties of being a valid funding liquidity factor remain after controlling for the size effect.

Second, the chosen margin proxies might be related to stocks' market betas. First-step sorting on margin proxies could result in finer sorting on market beta. To address this issue, we orthogonalize margin proxies with respect to beta first before using them in the construction of the funding liquidity measure. Again, we do not include analyst coverage proxy as it has very limited cross-sectional variation. Results in Table 8 show that the beta-orthogonalized $\text{FLS}_{\perp beta}$ is significantly correlated with 9 out of 14 funding liquidity proxies and cannot be explained by existing risk factors. Furthermore, our results are not driven by different beta spreads $\frac{\beta_H - \beta_L}{\beta_H \beta_L}$ across margin groups. We adjust returns of each BAB portfolio by dividing its beta spread $\frac{\beta_H - \beta_L}{\beta_H \beta_L}$. $\text{FLS}_{\Delta beta}$ is the first principal component of five adjusted BAB spreads between high- and low-margin stocks. We find that $\text{FLS}_{\Delta beta}$ is still significantly correlated with 10 out of 14 funding liquidity proxies. The time series alpha of $\text{FLS}_{\Delta beta}$ is 1.04% per month while insignificant and the adjusted R^2 is 23.01%.

Third, we sort stocks into five margin groups based on the fitted margin requirement. Specifically, a stock's fitted margin requirement over time is calculated using the five time-varying margin proxies and the estimated coefficients from the cross sectional probit regression as reported in Table 1. $\text{FLS}_{\hat{margin}}$ is the first principal component of five adjusted BAB spreads between high- and low-margin stocks. We find similar results as the benchmark case: $\text{FLS}_{\hat{margin}}$ is significantly correlated with 8 out of 14 funding liquidity proxies and cannot be explained by other risk factors (Table 8).

5 Funding Liquidity and Hedge Fund Returns

In this section, we investigate the implications of funding liquidity shocks on hedge fund returns. We apply the FLS to study hedge funds for two reasons. First, hedge funds are major users of leverage and their performance may potentially be more sensitive to shocks of funding conditions. Therefore, we expect to see that the performance of hedge funds in aggregate comoves with the funding liquidity conditions. Second, hedge funds are different from other asset classes in the sense that individual funds are managed portfolios. Some fund managers may be able to manage funding liquidity risk ex-ante if they foresee that adverse funding shocks could result in poor returns. As a result, we may observe cross-sectional difference for funds' performance conditional on funds' sensitivities to funding liquidity shocks.

5.1 Funding Liquidity Shocks and Time Series Hedge Fund Performance

To examine whether the aggregate hedge fund performance is affected by the funding condition, we run time series regressions of hedge fund indices' returns on the FLS and the market factor. Monthly time series of 28 hedge fund indices (HFRI) are from Hedge Fund Research, Inc. These include the HFRI Fund Weighted Composite Index (FWCI), a composite index for fund of funds, return indices for five primary strategies, and return indices for 21 sub-strategies. See Appendix Table A.1 for the full list of the sub-strategies.

We plot the funding liquidity beta and the Newey-West (1987) four-lag adjusted t-statistic for each hedge fund return index in Figure 2. Figure 2.A plots the results for the aggregate hedge fund index and the six primary indices. The overall composite index (FWCI) has a positive loading on the FLS with a t-statistic above 2. The magnitude of this beta loading implies that the aggregate hedge fund return declines by 2% per year if a one standard deviation negative shock hits. Five out of the other six aggregate hedge fund indices comove with the FLS, except for the macro strategy. The observed insensitivity of the macro strategy to funding liquidity risk complements Cao, Rapach, and Zhou (2014), who find that the macro strategy provides investors with valuable hedges against bad times. The positive and significant beta loadings are also seen for 12 out of 21 sub-strategies, as shown in Figure 2.B. Strategies with more significant positive loadings are: equity hedging strategy that aims to achieve equity market neutral (t-statistic=3.48), relative valuation strategy in corporate fixed income (t-statistic=2.99), and the event-driven strategy of distressed securities (t-statistic=2.69). Our results support the conjecture that on average hedge funds are exposed to the FLS. When funding conditions deteriorate, hedge funds in general perform poorly.

5.2 Funding Liquidity Shocks and Cross-Sectional Hedge Fund Returns

In order to examine the cross-sectional hedge fund performance as funding liquidity changes, we construct hedge fund portfolios based on their sensitivities to our funding liquidity measure.[22] Specifically, at the end of each month, we sort hedge funds into ten decile portfolios according to their sensitivities to the extracted FLS, and hold the equal-weighted hedge fund portfolios for one month. Following recent studies (Hu, Pan, and Wang (2013); Gao, Gao, and Song (2013)), funding liquidity sensitivities are estimated using a 24-month rolling-window regression of individual hedge fund excess returns on the FLS and the market factor,

[22]Data on individual hedge funds are from the Center for International Securities and Derivatives Markets (CISDM) database. We only include hedge funds that use USD as their reporting currency for assets under management (AUM), or with the country variable being United States, in cases when the currency variable is missing. Funds are required to have at least \$10 millions in AUM (Cao et al. (2013); Gao, Gao, and Song (2013); Hu, Pan, and Wang (2013)). We eliminate hedge funds that have less than 18 months of return history. We choose our sample to start from January 1994 to mitigate survivorship bias. Our sample period is from January 1994 to April 2009. Appendix Table C.3 presents descriptive statistics of the CISDM hedge fund dataset.

with a minimum observation requirement of 18 months. Decile 1 (10) indicates the portfolio with the lowest (highest) funding liquidity sensitivities. The model used to estimate funding liquidity sensitivities is:

$$R_t^i = \alpha^i + \delta_{fls}^i FLS_t + \delta_{mkt}^i R_{M,t} + \epsilon_t^i. \tag{9}$$

Panel A in Table 9 reports the excess returns and the Fung-Hsieh seven-factor adjusted alphas for 10 equal-weighted FLS-sensitivity sorted portfolios, as well as the spread between the low- and high-sensitivity portfolios. Hedge funds in Decile 1 (those with the lowest sensitivities to the FLS) earn an average excess return of 0.94% per month (t-statistic=3.76). On the other hand, hedge funds in Decile 10 (those with the highest sensitivities to the FLS) earn an almost zero excess return on average (5 bps per month). The spread between these two portfolios is 0.89% per month (t-statistic=3.31). This spread cannot be explained by the Fung-Hsieh seven hedge fund risk factors (α=0.89% per month, t-statistic=3.02).[23] The difference in performance is also reflected in their Sharpe ratios: the lowest FLS-sensitivity portfolio has a Sharpe ratio of 1.03, while the highest-sensitivity portfolio has a Sharpe ratio close to 0.[24]

Panel B in Table 9 presents the characteristics of FLS-sensitivity sorted hedge fund portfolios. Both pre-ranking and post-ranking loadings on the FLS monotonically decrease as we move from the high-beta portfolio to the low-beta portfolio. Meanwhile, the average AUM does not have a monotonic relationship across FLS-sensitivity sorted portfolios. In

[23]Hedge fund portfolio loadings on the Fung-Hsieh seven factors and adjusted R^2s can be found in Appendix Table C.4. We also replace the two non-traded factors, the bond market factor and the credit spread factor, with two traded factors as used in Sadka (2010). The results are very similar and available upon request.

[24]The cumulative return for the lowest FLS-sensitivity portfolio is four times than the cumulative return for the highest-sensitivity portfolio (Appendix Figure C.2.A). The maximum drawdowns are 50% and 16%, respectively, for the two extreme portfolios (Appendix Figure C.2.B). The return spread is also robust to longer holding horizons (Appendix Figure C.3).

addition, all portfolios have a similar average age.[25]

We also investigate the relationship between investment styles of hedge funds and their FLS sensitivities. First, we examine the distribution over the 10 FLS-sensitivity sorted portfolios for each investment style. Conditional on an investment style, we calculate the percentages of hedge funds that belong to those 10 portfolios. Panel C of Table 9 presents the results. We find that 21.6% of Multi-Strategy funds have low FLS sensitivities and 22.5% of Emerging Market funds have high FLS sensitivities. In addition, only 1.3% of Global Macro funds exhibit low FLS sensitivities, while 1.5% of Convertible Arbitrage funds show up in the high FLS-sensitivity portfolio. Second, we calculate the likelihood distribution of the 11 investment styles within each FLS-sensitivity portfolio. Panel D of Table 9 reports the results. We find that Global Macro funds are more likely to be assigned to the low FLS-sensitivity group (17.3%), while the Emerging Market funds are more likely to show up in the high FLS-sensitivity group (21.9%). Overall, investment style concentration does not seem to explain the observed hedge fund portfolio spread.

This seemly puzzling finding of an inverse relationship between hedge funds' FLS loadings and their returns could be due to the manageable nature of hedge funds. Researchers (Glosten and Jagannathan (1994); Fung and Hsieh (1997)) find that actively managed portfolios (including hedge funds) with dynamic trading strategies have option-like feature, i.e., returns of these managed portfolios exhibit non-linearity as the market condition changes. Therefore, the high return of low-sensitivity hedge funds could indicate fund managers' skills: they are able to ride on positive funding liquidity shocks and avoid negative shocks.

If the outperformance of low-sensitivity hedge funds is caused by fund managers' ability to manage the funding liquidity risk, such active portfolio management should be rewarded

[25] Due to the voluntary reporting nature of hedge fund data, young hedge funds with superior recent performance and with incentive to attract investors may start self-reporting, while established funds or funds with poor performance/liquidation may stop reporting (Ackerman, McEnally, and Ravenscraft (1999); Liang (2000); Fung and Hsieh (2002)). We cannot check the former backfill bias due to the limitations of our data, although we do conduct robustness tests to check the potential impact of funds that stop reporting.

more during bad periods. Figure 3 plots the returns of hedge fund portfolios conditional on various market conditions. In Figure 3.A, the sample is divided into normal months and NBER recessions. The return differences between the lowest- and highest-sensitivity hedge fund portfolios are 0.65% and 2.10% per month during normal months and NBER recessions, respectively. Similar pattern is found if we divide the sample into three equal sub-samples according to the FLS: the outperformance of low-sensitivity hedge funds is 1.29% per month when funding liquidity is bad, while high-sensitivity hedge funds actually earn higher returns during good funding liquidity months (Figure 3.B).

We next examine whether the outperformance of low-sensitivity hedge funds arises from their ability to time funding liquidity shocks. We evaluate the potential timing ability for the 10 hedge fund portfolios following Henriksson and Merton (1981) and Jagannathan and Korajczyk (1986). Specifically, we estimate the following nonlinear model:

$$R_t^p = \alpha^p + \beta_{mkt} R_{M,t} + \beta_1 FLS_t + \beta_2 max\{0, -FLS_t\} + \epsilon_t^p. \tag{10}$$

When the funding condition is good (FLS > 0), $\beta^{up} = \beta_1$; when the funding condition is poor (FLS < 0), $\beta^{down} = \beta_1 - \beta_2$. We expect the low FLS-sensitivity portfolio to have $\beta^{up} > \beta^{down}$ (or equivalently $\beta_2 > 0$) if they can time funding liquidity risk. Figure 4.A shows that the low FLS-sensitivity portfolio has a positive β_2, suggesting that fund managers reduce loadings on funding liquidity risk when the FLS is negative. Figure 4.B shows that the inclusion of $max\{0, -FLS_t\}$ into the regression reduces the alpha of the low FLS-sensitivity portfolio from 0.87% to 0.60% per month. Thus, low FLS-sensitivity hedge funds are likely to have the ability to time the funding liquidity risk and deliver higher returns.

However, other sources could also contribute to the outperformance of low-sensitivity funds and managers' ability to time funding liquidity risk is just one dimension of their superior portfolio management skills. For example, some funds may have better relationships with brokers that allow them to secure financing even during market downturns when others cannot. Another possibility is that some funds might adjust their loadings on funding liquidity risk, as well as change their portfolio compositions before adverse funding shocks hit so they might actually ride on negative shocks and generate abnormal returns. Due to data limitations, we cannot test all the hypotheses. Nevertheless, the timing ability of fund managers provides one explanation of how hedge funds, as managed portfolios, could dynamically adjust their exposures to the funding liquidity risk.

5.3 Robustness Tests of the Cross-Sectional Hedge Fund Returns

We examine other possible reasons that could also lead to the observed return spread of two hedge fund portfolios. Reported hedge fund returns may exhibit strong serial correlation because of stale prices and managers' incentives to smooth returns (Asness, Krail, and Liew (2001); Getmansky, Lo, and Makarov (2004); Jagannathan, Malakhov, and Novikov (2010)). To control for the effect of serial correlations, we remove the first- and second-order autocorrelations of reported hedge fund returns following the procedure proposed by Loudon, Okunev, and White (2006).[26] We construct the FLS-sensitivity sorted hedge fund portfolios using these unsmoothed "true" returns. The return spread (0.83%) and the risk-adjusted alpha spread (0.75%) are slightly smaller but still significant, suggesting that serial correlation of reported hedge fund returns may not be the major driver.

We also construct the FLS-sensitivity sorted hedge fund portfolios under several other scenarios: forming value-weighted portfolios, correcting for the potential forward-looking bias, controlling for delisting, controlling for change of VIX, controlling for the variance risk premium, excluding the financial crisis period, selecting funds with AUM denominated in USD, and excluding funds of funds. We find that the results are similar to those re-

[26]Details of the autocorrelation removal procedure can be found in Appendix A.3. Appendix Figures C.4 and C.5 plot the histograms of individual hedge funds' first- and second-order autocorrelation coefficients for observed returns and for unsmoothed raw returns, respectively.

ported in Panel A of Table 9: low FLS-sensitivity hedge funds outperform the high FLS-sensitivity hedge funds. The results of the these robustness tests are available in Appendix Table C.5.

While we find that some hedge fund managers are likely to actively manage funding liquidity risk and deliver higher returns, mutual fund managers do not exhibit such skill. We do not see any significant return spread between mutual funds with low- and high-FLS loadings.[27] This finding is not unexpected because mutual funds usually use little or very limited leverage, and the ability to manage funding liquidity risk is less likely to be a key factor that can effectively distinguish good and bad mutual fund managers.

6 Conclusion

Funding liquidity plays a crucial role in financial markets. Academic researchers, practitioners, and policy makers are interested in how to correctly measure funding liquidity. In this paper, we construct a traded funding liquidity measure from the time series and cross-section of stock returns. We extract the funding liquidity shocks from the return spread of two market-neutral "betting against beta" portfolios that are constructed with high- and low-margin stocks, where the margin requirements are proxied by stocks' characteristics. The traded funding liquidity factor is highly correlated with funding liquidity proxies derived from other markets and cannot be explained by existing risk factors. Our measure is positively correlated with market liquidity measures, supporting the theoretical prediction of a close relation between market liquidity and funding liquidity.

[27]Monthly mutual fund returns are obtained from CRSP Mutual Fund Database. The sample spans from January 1991 to December 2010. Index funds and funds with an AUM less than 20 million USD are excluded. Multiple shares of a single fund are merged using the link table used in Berk, van Binsbergen, and Liu (2014). We do not use WFICN of WRDS MFLINKS because it concentrates on equity funds, while our objective is to evaluate whether some mutual funds, regardless of whether or not they are equity-based funds, can manage funding liquidity risk. Results can be found in Appendix Table C.6

We use the constructed FLS to study hedge fund returns. In the time series, the aggregate hedge fund performance comoves with funding liquidity risk: a one standard deviation of adverse shock to the FLS results in a 2% per year decline in hedge fund returns. In the cross-section, hedge funds that are less sensitive to the FLS can actually earn higher returns. We find that those low-sensitivity funds may have ability to manage funding liquidity risk and thus generate superior returns.

While beyond the scope of this paper, we expect the financial market funding liquidity shocks to have some impact on the real economy. In a preliminary test, we discover that adverse FLS lowers private fixed investment. We leave careful examination in this direction to future studies.

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Figure 1: Time Series of the Extracted Funding Liquidity Shocks (Monthly)

The figure presents monthly time series of the extracted funding liquidity shocks. Small values indicate tight funding conditions. The sample period is from January 1965 to October 2012.

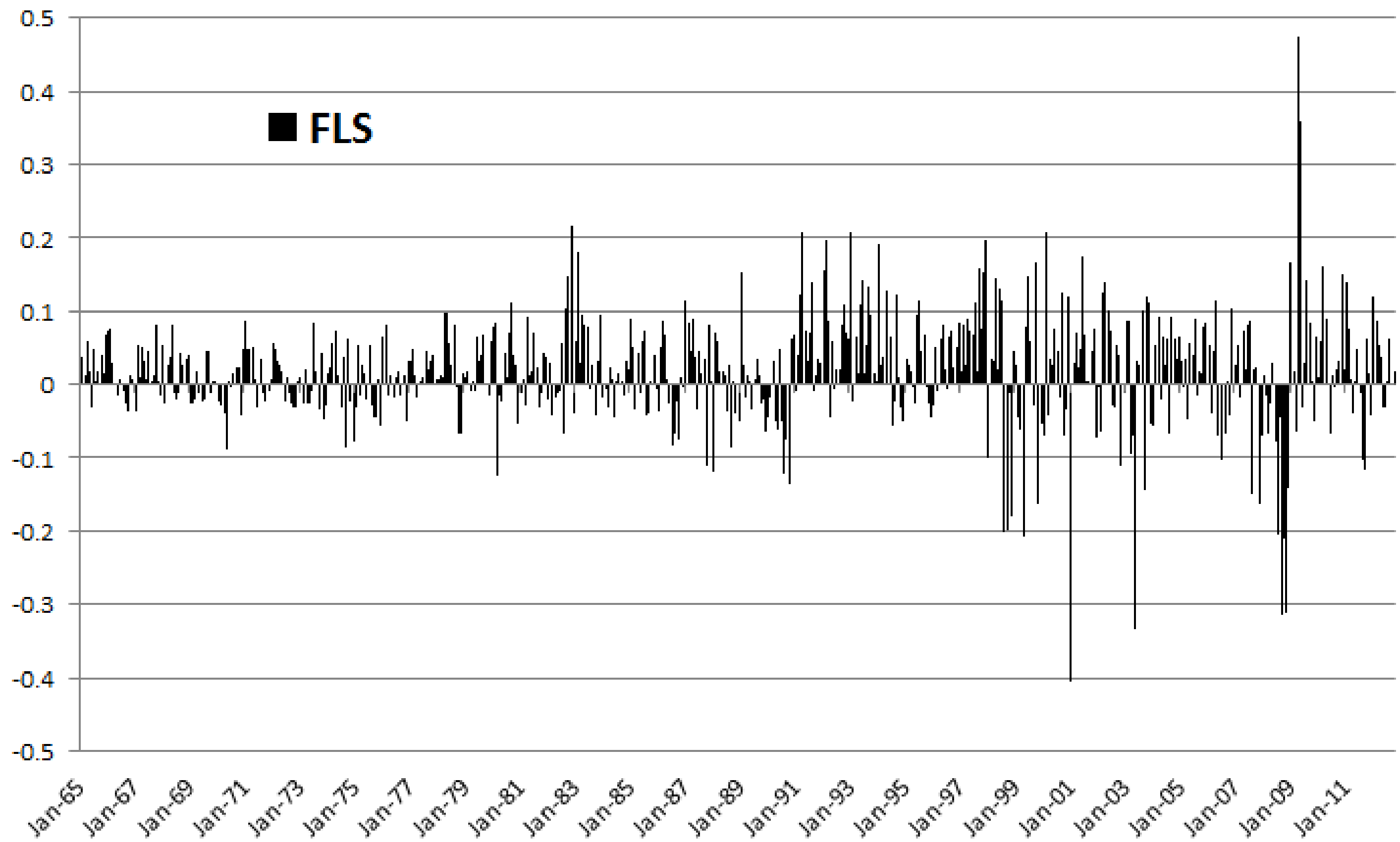

Figure 2: The Funding Liquidity Betas of Hedge Fund Indices

The figures present beta loadings and the Newey-West (1987) 4-lag adjusted t-statistics from regressing hedge fund indices' returns on the extracted funding liquidity shocks, controlling for the market factor. Figure A plots results for the HFRI fund weighted composite index (FWCI), aggregate indices of five primary strategies, and a composite index for fund of funds. Figure B plots results for indices of 21 sub-strategies.

Figure A: FWCI and Indices of Primary Strategies

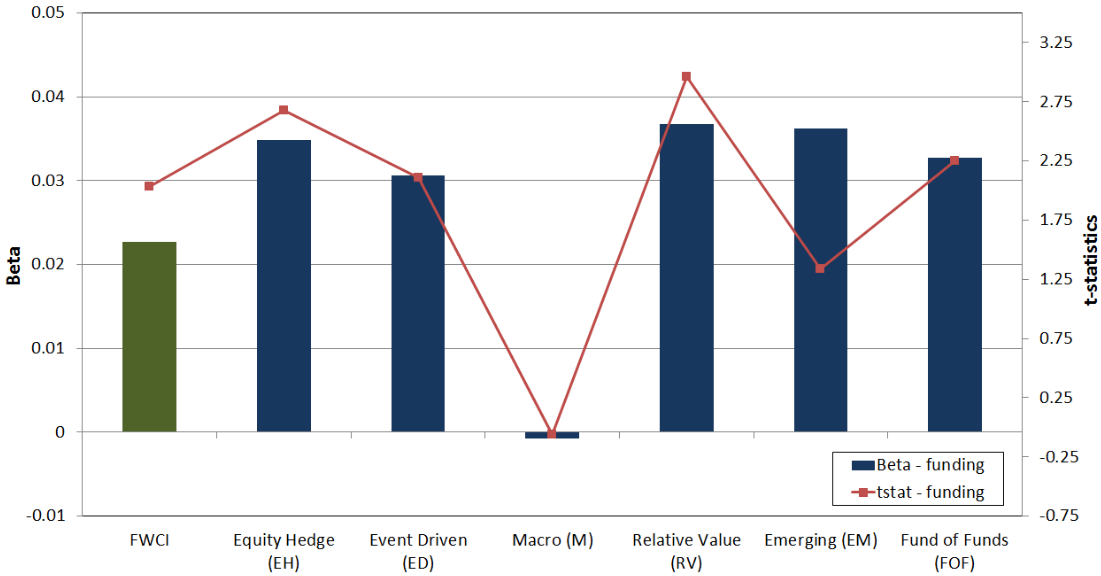

Figure B: Indices of Sub-strategies

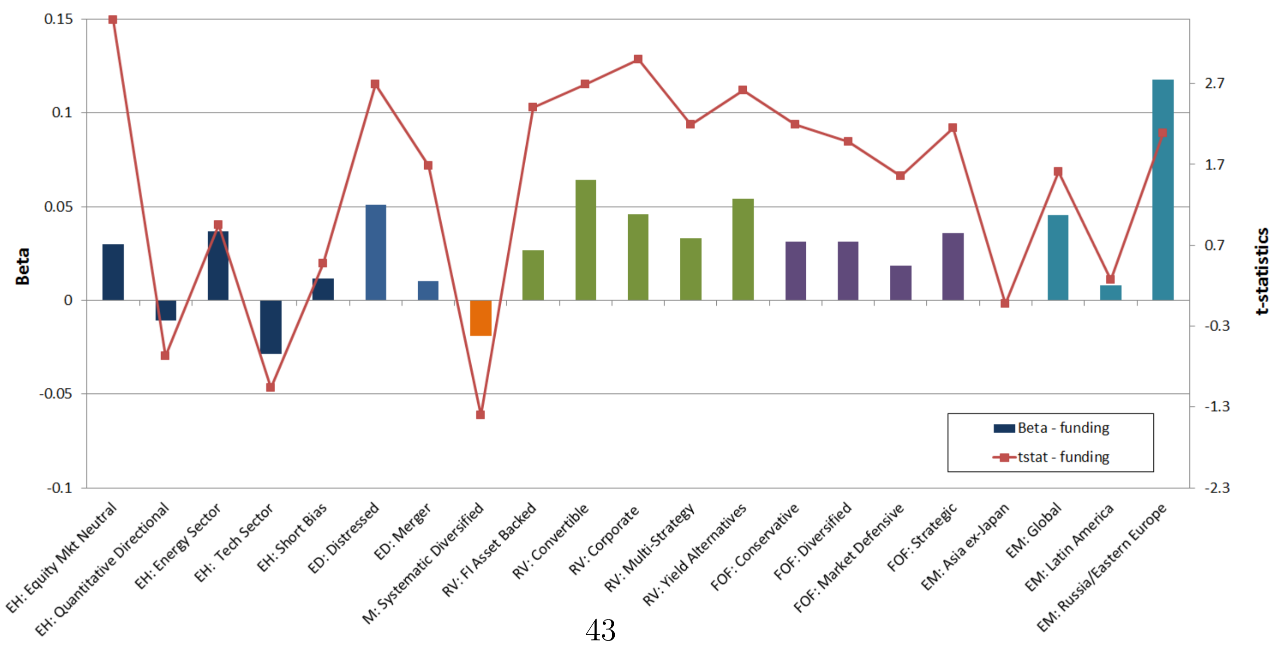

Figure 3: Returns of Hedge Fund Portfolios during Different Periods

The figures present average monthly returns of hedge fund portfolios during different periods. Figure A plots the monthly excess returns of hedge fund portfolios sorted by FLS sensitivities during normal months and NBER recessions. Figure B plots the monthly excess returns of hedge fund portfolios sorted by FLS sensitivities during good, normal, and bad funding liquidity periods

Figure A: Returns of hedge fund portfolios during normal months and NBER recessions

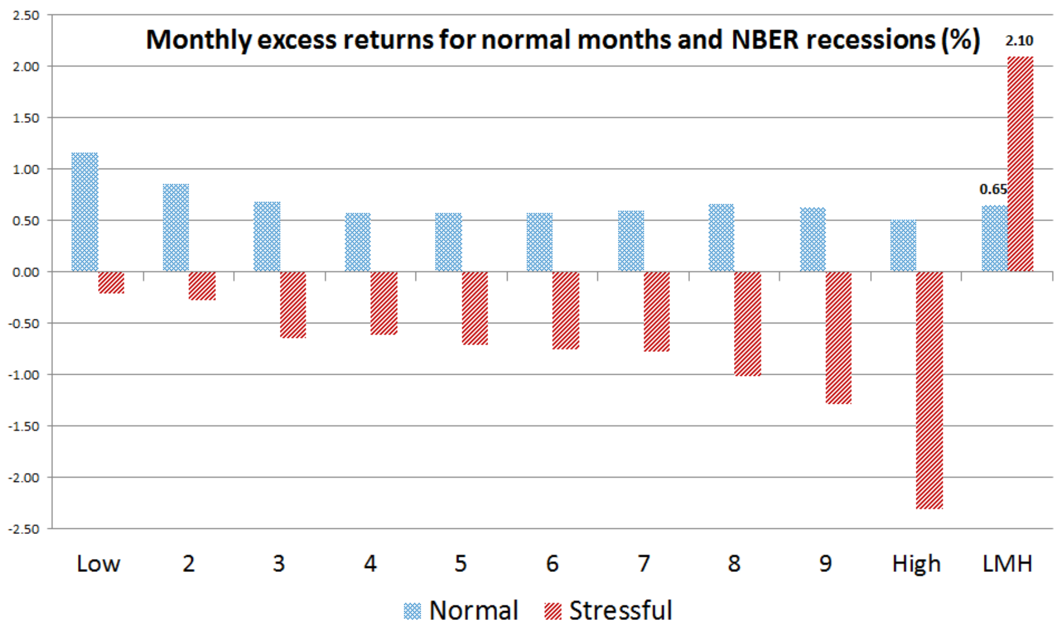

Figure B: Returns of hedge fund portfolios during months with different FLS

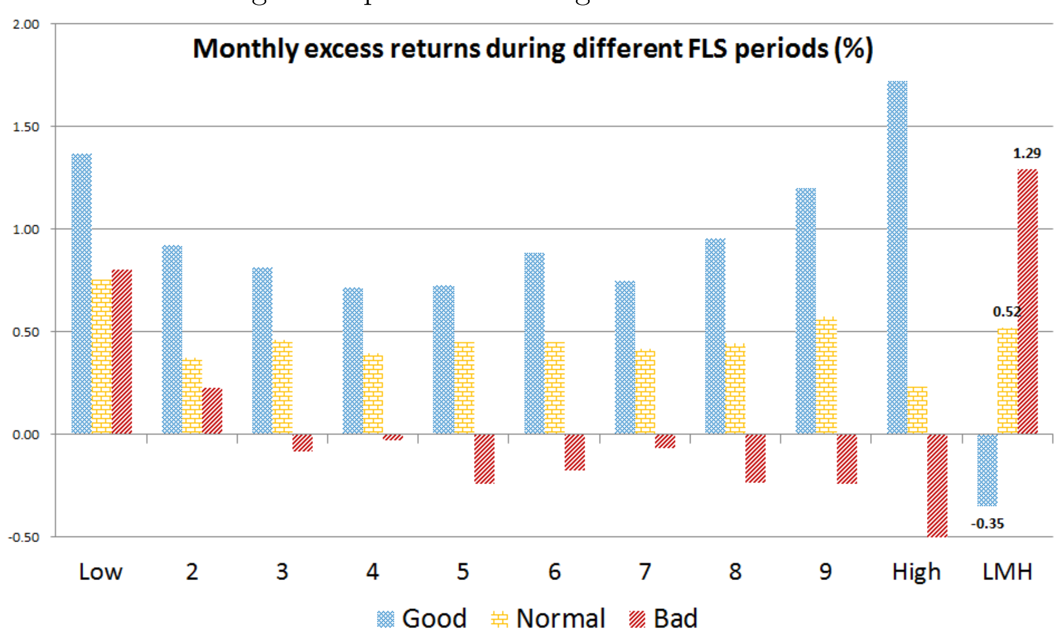

Figure 4: Hedge Fund Ability to Time Funding Liquidity Shocks

Figures A and B plot hedge fund portfolios' nonlinear loadings on the negative funding liquidity shocks and the timing ability-adjusted alphas. We run the following regression for each portfolio: $R_t^p = \alpha^p + \beta_{mkt} R_{M,t} + \beta_1 FLS_t + \beta_2 max\{0, -FLS_t\} + \epsilon_t^p$. Panel A shows the nonlinear loadings β_2, where $\beta^{up} > \beta^{down}$ is equivalent to $\beta_2 > 0$. Panel B shows the alphas for models with and without the timing ability term $max\{0, -FLS_t\}$.

Figure A: Nonlinear loading (β_2) of hedge fund portfolios

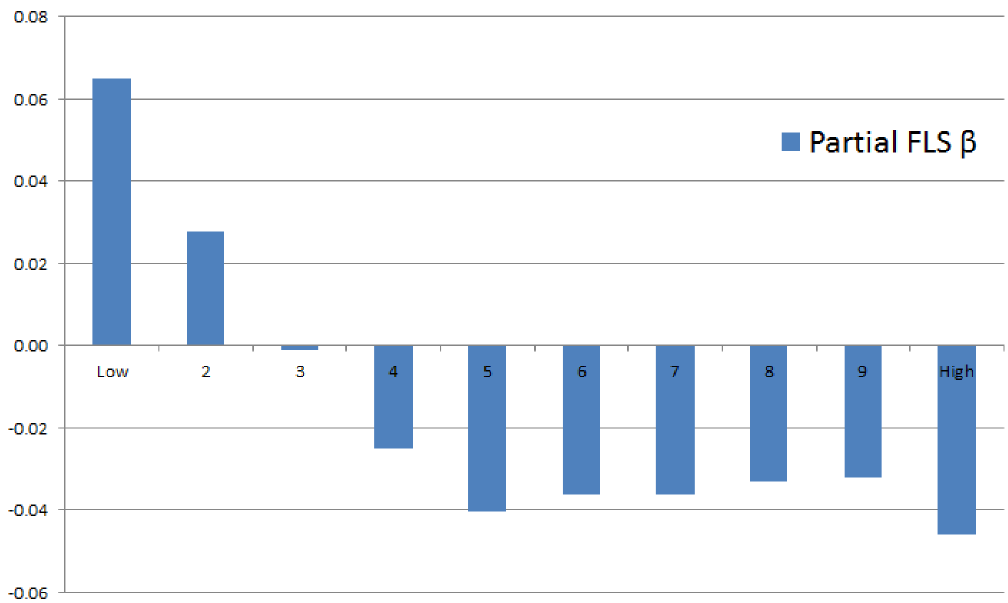

Figure B: Alphas of hedge fund portfolios with/without controlling for the timing ability

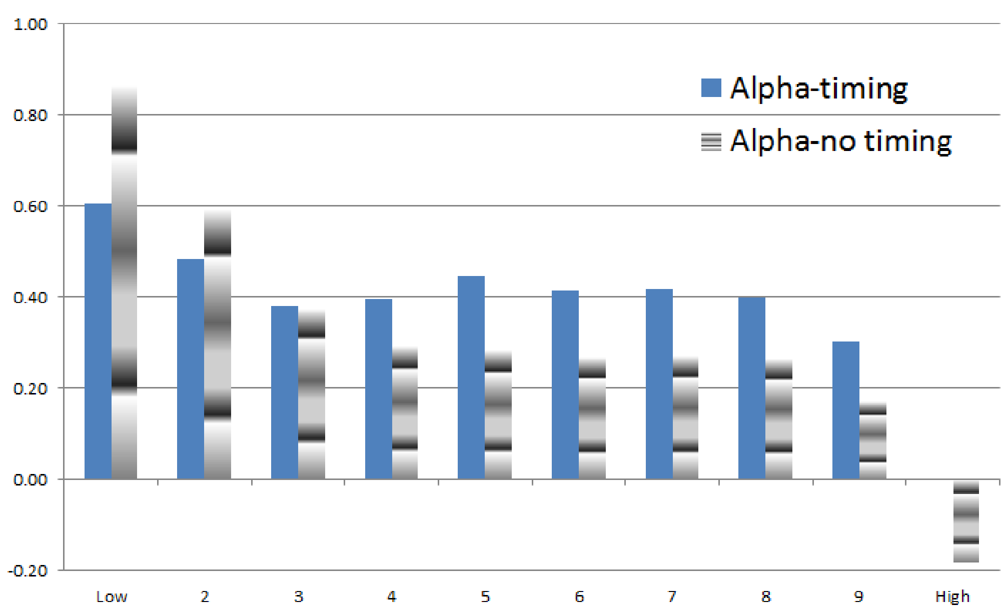

Table 1: Probit Regressions of Stock-level Margin Requirements

This table presents regression coefficients from probit regressions with margin requirement dummy as the dependent variable, and size, idiosyncratic volatility, Amihud illiquidity measure, institutional ownership, and analyst coverage as explanatory variables. Margin requirement dummy is constructed using the initial margin requirements on U.S. stocks obtained from Interactive Brokers LLC. The dummy variable takes the value of 1 (marginable) if the initial margin requirement is under 100% of the stock value, and 0 (non-marginable) otherwise. Probit regressions are conducted for each of the five explanatory variables, as well as for all five. Regression coefficients are reported with standard errors in parentheses, as well as the Pseudo R^2s. *** denotes 1% significance level and ** denotes 5% significance. Coefficients on size and IO ratio are scaled by 1,000,000. The number of observation is 4650.

	(1)	(2)	(3)	(4)	(5)	(6)
Size	2.87***					3.12***
	(0.10)					(0.13)
Idiovol		-1.88***				-1.34***
		(0.11)				(0.13)
Amihud			-0.21***			-0.01
			(0.02)			(0.01)
IO ratio				2.03***		0.25***
				(0.07)		(0.07)
Analyst					0.14***	-0.07***
					(0.01)	(0.01)
Constant	-1.11***	0.92***	0.49***	-0.63***	-0.22***	-0.72***
	(0.04)	(0.03)	(0.02)	(0.04)	(0.03)	(0.06)
Pseudo R^2	0.53	0.10	0.05	0.17	0.20	0.57

Table 2: BAB Portfolio Performance Conditional on Margin Requirements

This table presents BAB portfolio returns conditional on five proxies for the margin requirements of stocks as in Panels A to E. Size refers to a stock's market capitalization. Idiosyncratic volatility is calculated following Ang et al. (2006). The Amihud illiquidity measure is calculated following Amihud (2002). Institutional ownership refers to the fraction of common shares held by institutional investors. Analyst coverage is the number of analysts following a stock. Stocks are sorted into five groups based on NYSE breaks, where 1 indicates the low-margin group and 5 indicates the high-margin group. The high-margin group includes stocks that have small market cap, large idiosyncratic volatility, low market liquidity, low institutional ownership, and low analyst coverage. "Diff" indicates the return difference between two BAB portfolios constructed with high-margin and low-margin stocks. We report raw returns (indicated by "Exret") and risk-adjusted alphas. Alphas are calculated using a five-factor model: the Fama-French (1993) three factors, the Carhart (1997) momentum factor, and a liquidity factor proxied by the returns of a long-short portfolio based on stocks' Amihud measures. Returns and alphas are reported in percentage per month. The Newey-West five-lag adjusted t-statistics are in parentheses.

	1 (Low)	2	3	4	5 (High)	Diff
Panel A: Size [1965:M1-2012:M10]						
Exret	0.34	0.41	0.59	0.76	1.22	0.88
	(2.11)	(2.28)	(3.33)	(4.55)	(6.64)	(4.86)
Alpha	0.16	0.13	0.30	0.37	0.76	0.60
	(1.05)	(0.87)	(1.89)	(2.42)	(3.02)	(2.39)
Panel B: Idiosyncratic volatility [1965:M1 - 2012M:10]						
Exret	0.23	0.62	0.50	0.83	1.44	1.21
	(1.73)	(4.87)	(3.99)	(5.98)	(8.13)	(6.08)
Alpha	0.19	0.44	0.22	0.50	0.95	0.76
	(1.32)	(3.12)	(1.72)	(3.76)	(5.11)	(3.63)
Panel C: Amihud [1965:M1 - 2012M:10]						
Exret	0.27	0.40	0.41	0.46	0.88	0.62
	(2.03)	(2.84)	(2.91)	(3.24)	(5.73)	(4.17)
Alpha	0.09	0.16	0.12	0.12	0.51	0.42
	(0.69)	(1.28)	(0.8)	(0.78)	(2.60)	(2.30)
Panel D: Institutional ownership [1980:M4 - 2012:M3]						
Exret	0.40	0.56	0.53	0.85	1.37	0.97
	(1.99)	(2.64)	(2.31)	(3.63)	(5.16)	(4.12)
Alpha	0.15	0.23	0.24	0.55	0.82	0.67
	(0.77)	(1.19)	(1.18)	(2.49)	(2.49)	(2.12)
Panel E: Analyst coverage [1976:M7 - 2011:M12]*						
Exret	0.29	0.56	0.51	0.89	1.27	0.99
	(1.22)	(2.49)	(2.32)	(3.37)	(4.79)	(3.88)
Alpha	0.04	0.24	0.11	0.38	0.81	0.77
	(0.22)	(1.28)	(0.5)	(1.29)	(2.28)	(2.27)

* 5 - no coverage; 4 - one analyst coverage; for the rest, divided into 1-3.

Table 3: Summary Statistics

This table presents the summary statistics of the FLS. Panel A shows the adjusted R^2s from time series regressions of five BAB return spreads on their first principal component FLS. A BAB return spread is defined as the difference between two BAB portfolios that are constructed with stocks that have high-margin and low-margin requirements. The margin requirement is proxied by five measures: size, idiosyncratic volatility, the Amihud illiquidity measure, institutional ownership, and analyst coverage. The sample period is January 1965 to October 2012 for size, idiosyncratic volatility, and the Amihud illiquidity measure. April 1980 to March 2012 for institutional ownership, and July 1976 to December 2011 for analyst coverage. Panel B shows the summary statistics (mean, volatility, Sharpe ratio, and first-order autocorrelation coefficient) of the FLS and other risk factors, including betting against beta factor, the Fama-French three factors, the momentum factor, and the short-term reversal factor. Factor mean and volatility are presented in annualized percentage.

Panel A: Adjusted R^2 (%)

	Monthly	Quarterly
Size	84.1	86.4
Idiosyncratic volatility	35.9	54.8
Amihud	70.5	77.5
Institutional ownership	66.2	66.9
Analyst coverage	78.3	79.5
Average	67.0	73.0

Panel B: Summary statistics of various risk factors

	FLS	BAB	MKT	HML	SMB	MOM	STR
Mean	21.05	10.82	5.21	3.26	4.44	8.55	6.26
	(5.63)	(6.64)	(2.27)	(2.05)	(3.02)	(3.91)	(3.86)
Vol	25.84	11.28	15.88	11.01	10.18	15.13	11.20
SR	0.81	0.96	0.33	0.30	0.44	0.57	0.56
ρ_1	0.22	0.13	0.09	0.06	0.16	0.06	-0.02

Table 4: Correlation Between the Extracted Funding Liquidity Measure and Existing Funding Liquidity Proxies

This table presents correlation coefficients of 14 commonly used funding liquidity proxies with our extracted funding liquidity measure and the Frazzini and Pedersen (2014) BAB factor. Fourteen funding liquidity proxies are filtered with AR(2) for monthly data and AR(1) for quarterly data, except for the investment bank excess returns. We sign all funding liquidity proxies such that smaller values indicate tighter funding conditions. FLS is the funding liquidity shocks (the first principal component) extracted from five BAB portfolio return differences. BAB is the Frazzini and Pedersen (2014) "betting against beta" portfolio returns. Panel A reports correlation coefficients using monthly data and quarterly data, respectively. Panel B presents correlation coefficients between the first principal component of commonly used funding liquidity proxies and our funding liquidity measure (and the BAB factor). FPC14 is the first principal component of all 14 proxies; FPC10 is the first principal component of 10 proxies, excluding investment banks' CDS, hedge fund leverage, fraction of loan officers tightening credit standards, and the swap spread; FPC7 is the first principal component of seven proxies, further excluding investment banks' excess returns, broker-dealers' leverage, and broker-dealers' asset growth. Correlation coefficients are reported, with 5% statistical significance indicated with $*$. funding liquidity proxy. The sample period in Panel A depends on the specific funding liquidity proxy. The sample period for Panel B is March 1986 to October 2012.

Panel A: Correlations with 14 funding liquidity proxies

	Asset growth	Bond liquidity	CDS	Credit spread	Financial leverage	HF leverage	IB exret	Broker leverage	LIBOR	Loan	Swap spread	TED spread	Term spread	VIX
Monthly														
FLS	12.9*	12.9*	41.1*	22.9*	23.1*	45.8*	26.4*	-2.5	-9.8	17.9*	18.5*	16.1*	-7.4	25.0*
BAB	6.9	13.4*	9.3	3.6	-5.5	-16.8	-18.2	-0.1	-10.2	6.3	26.0*	11.0	10.9	-1.6
Quarterly														
FLS	23.3*	26.9*	43.1*	42.1*	47.1*	57.9*	40.7*	10.9	-16.3	43.3*	19.6	24.9*	-10.1	37.7*
BAB	28.4*	23.0*	20.0	17.4	15.9	-24.1	-0.4	25.3*	-6.5	30.9*	27.7	17.0	7.6	9.2

Panel B: Correlations with first principal components

	FPC14	FPC10	FPC7
Monthly			
FLS	35.5*	30.5*	26.8*
BAB	-2.8	11.7*	0.5
Quarterly			
FLS	50.2*	45.9*	44.8*
BAB	14.1	11.5	13.3

Table 5: Time Series Regressions of the Extracted Funding Liquidity Measure

This table presents the results of time series regressions. Panel A reports the time series alphas, beta loadings, and adjusted R^2 when the funding liquidity shock (FLS) is regressed on commonly used traded risk factors. Panel B (C) reports the time series alphas, beta loadings, and adjusted R^2 when common risk factors are regressed on the FLS (and the market factor). Traded risk factors include the BAB factor, the size factor, the value factor, the Carhart momentum factor, the market liquidity factor constructed by forming a long-short portfolio based on stocks' Amihud measures, and the short-term reversal (STR) factor. Newey-West five-lag adjusted t-statistics are in parentheses. The sample period is January 1965 to October 2012.

Panel A: Time series regressions of FLS on common risk factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α	1.08	0.82	1.57	1.39	1.21	1.22	1.39	0.89
	(2.40)	(1.99)	(4.22)	(3.93)	(2.65)	(2.71)	(2.75)	(1.68)
β_{bab}	0.77	0.83						0.90
	(4.69)	(5.29)						(5.52)
β_{mkt}		0.47	0.42	0.36	0.40	0.44	0.49	0.40
		(5.24)	(4.45)	(3.52)	(4.17)	(4.07)	(4.05)	(3.24)
β_{smb}				0.45	0.45	-0.33	-0.34	0.33
				(4.03)	(4.11)	(-0.67)	(-0.71)	(0.78)
β_{hml}				0.22	0.28	0.00	0.00	-0.23
				(1.63)	(2.05)	(0.02)	(0.01)	(-1.41)
β_{umd}					0.20	0.23	0.18	-0.02
					(0.89)	(1.12)	(0.83)	(-0.09)
β_{amihud}						0.65	0.68	0.13
						(1.54)	(1.66)	(0.35)
β_{str}							-0.31	-0.31
							(-1.46)	(-1.41)
adj. R^2 (%)	11.08	19.21	6.35	9.60	10.72	11.73	13.08	24.40

Panel B: Time series regressions of risk factors on FLS

	BAB	SMB	HML	UMD	Amihud	STR
α	0.64	0.09	0.39	0.64	0.18	0.55
	(4.27)	(0.61)	(2.72)	(3.49)	(1.00)	(3.60)
β_{fls}	0.16	0.10	-0.01	0.04	0.12	-0.02
	(4.66)	(3.60)	(-0.47)	(0.47)	(3.86)	(-0.51)
adj. R^2 (%)	11.08	5.70	-0.11	0.26	5.56	-0.01

Panel C: Time series regressions of risk factors on FLS and MKT

	BAB	SMB	HML	UMD	Amihud	STR
α	0.66	0.06	0.42	0.67	0.17	0.52
	(4.25)	(0.43)	(3.00)	(3.78)	(0.96)	(3.57)
β_{fls}	0.17	0.07	0.02	0.06	0.11	-0.05
	(5.15)	(2.64)	(1.08)	(0.79)	(3.45)	(-1.71)
β_{mkt}	-0.14	0.19	-0.20	-0.15	0.07	0.23
	(-2.28)	(5.77)	(-3.96)	(-1.94)	(1.44)	(5.25)
adj. R^2 (%)	14.31	12.43	9.05	2.45	6.06	9.61

Table 6: Pairwise Correlation

This table presents pairwise correlation coefficients between the extracted funding liquidity shocks (FLS) and market liquidity measures. We sign all liquidity measures such that small values indicate illiquidity. FLS is the first principal component extracted from five BAB portfolio return differences. Amihud is the long-short equity portfolio sorted by individual stocks' Amihud illiquidity measure. PS is the Pastor and Stambaugh (2003) market liquidity innovation measure. Sadka is the variable component of Sadka (2006) market liquidity factor. HPW is the Hu, Pan, and Wang (2013) monthly change of the noise illiquidity measure. Panels A, B, and C report pairwise correlation coefficients calculated over the full sample, the months with positive market returns, and the months with negative market returns, respectively. 5% statistical significance is indicated with $*$.

Panel A: Pairwise correlations - unconditional

	FLS	Amihud	PS	Sadka
Amihud	23.9*			
PS	17.0*	9.1*		
Sadka	17.7*	12.2*	23.1*	
HPW	17.7*	5.3	22.1*	20.2*

Panel B: Pairwise correlations - MKT>=0

	FLS	Amihud	PS	Sadka
Amihud	14.6*			
PS	12.7*	-0.5		
Sadka	11.1	10.1	8.3	
HPW	3.4	-1.3	9.1	-0.5

Panel C: Pairwise correlations - MKT<0

	FLS	Amihud	PS	Sadka
Amihud	36.5*			
PS	14.8*	15.2*		
Sadka	24.9*	14.8	35.2*	
HPW	29.3*	11.3	27.6*	34.0*

Table 7: Correlation and Time Series Regressions - Market Liquidity Effect

This table presents the results for three alternative funding liquidity measures in consideration of the market liquidity effect. $FLS_{\perp ml}$ is the residual after projecting the funding liquidity shock (FLS) on the long-short portfolio sorted by the Amihud illiquidity measure. FPC_{single} is the first principal component of five long-short portfolios sorted by margin proxies. FPC_{double} is the first principal component of five return difference series, where each return difference is calculated between a margin-proxy sorted long-short portfolio within low-beta stocks and a margin-proxy sorted long-short portfolio within high-beta stocks. Panel A reports the correlation coefficients between $FLS_{orth}/FPC_{single}/FPC_{double}$ and 14 funding liquidity proxies with 5% statistical significance indicated with $*$. Panel B reports the results of time series regressions where $FLS_{orth}/FPC_{single}/FPC_{double}$ are regressed on common risk factors, including the BAB factor, the Fama-French three factors, the Carhart momentum factor, the market liquidity factor proxied by a long-short portfolio based on stocks' Amihud measures, and the short-term reversal (STR) factor. Newey-West five-lag adjusted t-statistics are in parentheses. The sample period in Panel A depends on the specific funding liquidity proxy. The sample period for Panel B is January 1965 to October 2012.

Panel A: Correlation coefficients with 14 funding liquidity proxies

	Asset growth	Bond liquidity	CDS	Credit spread	Financial leverage	HF leverage	IB exret	Broker leverage	LIBOR	Loan	Swap spread	TED spread	Term spread	VIX
$FLS_{\perp ml}$	12.7*	11.6*	40.8*	20.7*	22.0*	46.4*	27.2*	-2.1	-8.2	18.1*	18.4*	15.5*	-4.1	23.1*
FPC_{single}	-0.5	8.5	21.2*	19.1*	18.8*	22.8	17.7*	-5.2	-8.3	4.1	-1.7	8.0	-21.9	24.4*
FPC_{double}	5.6	-0.3	33.4*	-3.9	-6.3	44.3*	-5.7	-0.5	-7.6	8.2	17.8*	3.5	11.5*	-5.9

Panel B: Time series regressions

	α	β_{bab}	β_{mkt}	β_{smb}	β_{hml}	β_{umd}	β_{amihud}	β_{str}	adj. R^2 (%)
$FLS_{\perp ml}$	0.92	0.86	0.43	-0.06	-0.35	0.00	-	-0.32	19.63
	(1.81)	(5.63)	(3.95)	(-0.60)	(-2.72)	(0.02)	-	(-1.47)	
FPC_{single}	-0.07	-0.16	0.18	0.13	-0.28	-0.23	1.68	0.06	94.82
	(-0.72)	(-3.98)	(6.80)	(1.26)	(-4.03)	(-8.36)	(20.94)	(1.50)	
FPC_{double}	-0.35	0.92	-0.01	0.50	0.27	0.03	-1.66	-0.16	53.91
	(-0.87)	(6.02)	(-0.13)	(1.08)	(1.30)	(0.18)	(-3.82)	(-1.08)	

Table 8: Correlation and Time Series Regressions - Other Specifications

This table presents the results for four funding liquidity measures constructed using other specifications. $\text{FLS}_{\perp size}$ is the first principal component of return differences between high- and low-margin BAB portfolios, where stocks are sorted into high- and low-margin groups according to the size-orthogonalized margin proxies. $\text{FLS}_{\perp beta}$ is the first principal component of return differences between high- and low-margin BAB portfolios, where stocks are sorted into high- and low-margin groups according to the beta-orthogonalized margin proxies. $\text{FPC}_{\Delta beta}$ is the first principal component of adjusted return differences between high- and low-margin BAB portfolios, where the returns of BAB portfolios are divided by $\frac{\beta_H-\beta_L}{\beta_H\beta_L}$ for adjustment. $\text{FLS}_{\hat{margin}}$ is the first principal component of return differences between high- and low-margin BAB portfolios, where stocks are sorted into high- and low-margin groups according to fitted margin requirements. Panel A reports the correlation coefficients between various specifications of FLS and 14 funding liquidity proxies with 5% statistical significance indicated with $*$. Panel B reports the results of time series regressions where FLS are regressed on common risk factors, including the BAB factor, the Fama-French three factors, the Carhart momentum factor, the market liquidity factor proxied by a long-short portfolio based on stocks' Amihud measures, and the short-term reversal (STR) factor. Newey-West five-lag adjusted t-statistics are in parentheses. The sample period in Panel A depends on the specific funding liquidity proxy. The sample period for Panel B is January 1965 to October 2012.

Panel A: Correlation coefficients with 14 funding liquidity proxies

	Asset growth	Bond liquidity	CDS	Credit spread	Financial leverage	HF leverage	IB exret	Broker leverage	LIBOR	Loan	Swap spread	TED spread	Term spread	VIX
$\text{FLS}_{\perp size}$	14.1*	8.9	23.2*	20.0*	17.3*	35.0*	14.7*	3.0	-3.9	19.5*	15.3	11.1*	-5.1	13.3*
$\text{FLS}_{\perp beta}$	7.6	14.5*	38.3*	23.7*	25.5*	51.4*	25.3*	-6.7	-9.4	20.1*	20.0*	22.3	-2.3	23.8*
$\text{FLS}_{\Delta beta}$	11.1*	7.9	44.4*	21.4*	28.9*	38.9*	36.9*	-4.9	-8.3	15.1*	15.6	13.4*	-11.0	28.7*
$\text{FLS}_{\hat{margin}}$	4.7	6.8	33.7*	25.7*	19.6*	43.6*	29.9*	-1.8	-4.3	16.4*	3.2	16.8*	-11.1	25.9*

Panel B: Time series regressions

	α	β_{bab}	β_{mkt}	β_{smb}	β_{hml}	β_{umd}	β_{amihud}	β_{str}	adj. R^2 (%)
$\text{FLS}_{\perp size}$	0.68	0.58	0.25	-0.16	-0.25	-0.07	0.18	-0.26	16.24
	(1.77)	(4.96)	(2.82)	(-0.55)	(-2.06)	(-0.47)	0.69	(-1.65)	
$\text{FLS}_{\perp beta}$	1.00	0.97	0.40	-0.07	-0.24	0.03	0.39	-0.19	37.61
	(2.59)	(8.14)	(4.48)	(-0.21)	(-2.24)	(0.19)	(1.39)	(-1.27)	
$\text{FLS}_{\Delta beta}$	1.04	0.26	0.74	0.66	-1.08	0.07	0.50	-0.53	23.01
	(1.08)	(0.89)	(3.05)	(0.85)	(-3.67)	(0.18)	(0.75)	(-1.29)	
$\text{FLS}_{\hat{margin}}$	0.87	0.24	0.45	-0.48	-0.76	-0.04	1.04	-0.21	32.33
	(2.64)	(1.91)	(5.25)	(-1.49)	(-5.84)	(-0.32)	(3.24)	(-1.54)	

Table 9: Hedge Fund Decile Portfolios: Performance and Characteristics

This table presents performance and characteristics of hedge fund decile portfolios. At the end of each month, we sort hedge funds into ten decile portfolios according to their funding liquidity sensitivities. Funding liquidity sensitivities are computed using a 24-month rolling-window regression of monthly excess returns on the funding liquidity shock (FLS) and the market factor with a minimum observation requirement of 18 months. Panel A reports monthly portfolio excess returns, the Fung-Hsieh 7-factor adjusted alphas, portfolio volatilities, and Sharpe ratios. Panel B reports portfolio pre-ranking betas (cross-sectional average of funds' betas within each rolling window and then time series average over all months), post-ranking betas (estimated from regressing monthly portfolio returns on the market factor and the FLS over the full sample), average AUM, and average age (number of months from inception to portfolio formation). Panel C presents the allocation (%) of hedge fund portfolios conditional on an investment style. For each style, we calculate the fractions of funds that belong to 10 hedge fund portfolios. Panel D presents the likelihood distribution (%) of hedge fund investment styles conditional an FLS-sensitivity portfolios. The likelihood distribution is calculated as the normalized ratio between realized and expected number of funds. The realized number of funds is the number of funds (for an investment style) for each FLS-sensitivity portfolio at portfolio formation. The expected number of funds is the total number of funds (for an investment style) divided by 10 at portfolio formation. The Newey-West four-lag adjusted t-statistics are reported in parentheses. The sample period is from January 1996 to April 2009.

Panel A: Hedge fund decile portfolio performance

	Low	2	3	4	5	6	7	8	9	High	LMH
Exret	0.94	0.68	0.47	0.38	0.37	0.36	0.37	0.39	0.32	0.05	0.89
	(3.76)	(3.88)	(3.29)	(3.14)	(2.94)	(2.87)	(2.66)	(2.3)	(1.53)	(0.15)	(3.31)
Alpha	0.75	0.53	0.36	0.32	0.30	0.30	0.30	0.31	0.19	-0.14	0.89
	(4.03)	(3.48)	(3.26)	(3.89)	(3.34)	(3.22)	(3.02)	(2.65)	(1.56)	(-0.59)	(3.02)
Vol	10.96	7.66	6.29	5.29	5.51	5.51	6.11	7.39	9.03	14.86	11.79
SR	1.03	1.06	0.90	0.86	0.80	0.79	0.73	0.63	0.42	0.04	0.91

Panel B: Hedge fund decile portfolio characteristics

	Low	2	3	4	5	6	7	8	9	High
Pre-ranking β_{Mkt}	0.44	0.28	0.24	0.22	0.22	0.22	0.25	0.31	0.39	0.60
Pre-ranking β_{FLS}	-0.14	-0.04	-0.01	0.01	0.02	0.03	0.05	0.07	0.10	0.23
Post-ranking β_{Mkt}	0.49	0.32	0.26	0.22	0.23	0.22	0.24	0.30	0.40	0.64
Post-ranking β_{FLS}	-0.03	0.01	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.07
AUM (million)	161.1	214.3	221.8	230.3	226.8	245.2	228.3	209.3	188.5	170.6
Age (month)	73.4	74.9	75.5	77.2	77.6	78.8	78.1	76.9	74.4	73.1

Table 8 (cont.): Hedge Fund Decile Portfolios: Performance and Characteristics

Panel C: Allocation of hedge fund portfolios conditional on an investment style (%)

	Low	2	3	4	5	6	7	8	9	High
Convertible Arbitrage	10.5	14.7	14.2	15.2	15.3	11.6	9.0	5.3	2.7	1.5
Distressed Securities	10.6	12.2	10.8	10.3	7.9	8.5	10.9	10.3	10.7	7.8
Emerging Market	17.4	10.9	8.9	5.4	4.9	4.3	6.1	7.3	12.2	22.5
Equity Long/Short	14.1	12.5	9.2	7.3	6.2	6.0	6.6	9.5	13.0	15.7
Equity Market Neutral	13.6	16.9	12.3	8.6	7.4	6.4	7.9	9.1	12.1	5.8
Event Driven	11.0	13.3	14.3	10.2	8.0	8.2	10.3	9.4	9.3	6.0
Fixed Income	9.7	16.9	14.8	11.9	10.6	9.7	8.8	7.3	6.6	3.9
Global Macro	1.3	4.6	9.4	13.7	15.6	16.4	15.1	12.4	8.1	3.5
Multi-Strategy	21.6	12.3	8.2	6.0	6.0	5.7	5.1	8.5	11.8	14.8
Fund of Funds	10.1	9.2	10.5	10.7	10.2	10.7	11.2	10.6	8.9	7.8
Other	16.6	10.4	8.6	6.3	6.3	6.5	7.4	9.0	11.2	17.9

Panel D: Likelihood distribution of investment styles conditional on an FLS-sensitivity portfolio (%)

	Convertible Arbitrage	Distressed Securities	Emerging Market	Equity Long Short	Equity Market Neutral	Event Driven	Fixed Income	Global Macro	Multi Strategy	Fund of Funds	Other
Low	6.3	7.0	16.2	11.3	9.0	6.6	5.7	17.3	7.0	1.5	12.1
2	10.8	9.0	9.0	10.5	10.1	8.9	10.5	10.0	8.3	4.7	8.3
3	11.2	7.6	6.7	8.2	10.6	11.2	13.1	7.0	8.7	8.5	7.2
4	14.4	8.7	4.5	6.9	9.6	9.3	12.1	5.2	10.6	12.6	6.1
5	14.5	7.3	4.8	6.1	8.0	8.7	11.3	5.7	12.2	15.2	6.0
6	12.0	9.2	4.1	6.6	7.2	9.6	11.4	5.6	10.1	17.8	6.5
7	8.5	11.0	5.0	7.5	7.2	11.5	9.1	5.3	11.7	16.1	7.0
8	4.8	11.4	7.0	10.3	8.7	10.7	6.9	8.3	9.6	12.8	9.5
9	3.7	10.5	10.5	12.4	10.7	9.0	5.3	12.1	6.0	7.4	12.4
High	1.5	8.3	21.9	15.4	5.3	5.4	3.2	13.3	5.2	2.8	17.7

Internet Appendix to "A Market-Based Funding Liquidity Measure"

This Internet Appendix consists of three sections. In Section A, we provide details of data construction. Section B presents mathematical proofs of lemmas and propositions. In Section C, we present additional empirical analyses and results.

A Data Appendix

A.1 Funding liquidity proxies

We construct 14 funding liquidity measures by following previous papers closely.

Broker-dealers' asset growth rate (Asset growth): the quarterly growth rate of total financial asset. We obtain the quarterly data from the Federal Reserve Board Flow of Funds Table L.127. We calculate the growth rate and implement seasonal adjustment using quarterly dummy. The sample period is 1986:Q1-2012:Q3.

Treasury security-based funding liquidity (Bond liquidity): Fontaine and Garcia (2012) measure funding liquidity from the cross section of U.S. Treasury securities, including bills, notes, and bonds. We obtain the their funding liquidity factor from Jean-Sebastien Fontaine's website. The sample period is 1986:M1-2013:M3.

Major investment banks' senior 10-year debt CDS spread (CDS): We follow Ang et al. (2011) and calculate the market cap-weighted major investment banks' CDS spread on 10-year senior bonds (Bear Stearns, Citibank, Goldman Sachs, JP Morgan, Lehman Brothers, Merrill Lynch, Morgan Stanley, Credit Suisse, HSBC). We obtain CDS data from Datastream. The sample period is 2004:M1-2013:M3.

Credit spread between AAA and BAA bond yield (Credit spread): Credit spread is the difference between Moody's BAA bond yield and AAA bond yield at monthly frequency. Bond yields are from the Federal Reserve's FRED database. The sample period is 1986:M1-2013:M4.

Financial sector leverage (Financial leverage): We define the financial sector as companies with SIC codes between 6000-6999, and the leverage is defined as the total sector asset divided by total sector market value $\frac{\Sigma_{i \in fin} A_{i,t}}{\Sigma_{i \in fin} MV_{i,t}}$. Total assets data are from Compustat with quarterly frequency, and market value is calculated at the end of each month using CRSP data. We assume total assets in month $t-1$ and $t+1$ are the same as total assets in month t, where t is the month with quarterly Compustat observation. The sample period is 1986:M1-2012:M12.

Hedge fund leverage (HF leverage): We get the hedge fund leverage data from Andrew Ang. Details for this data can be found in Ang et al. (2011). The sample period is 2004:M12-2009:M9.

Major investment banks' excess return (IB exret): We calculate the nine major investment banks' value-weighted monthly excess return. The sample period is 1986:M1-2012:M10.

Broker-dealers' leverage factor (Broker leverage)): We follow the procedure in Adrian et al. (2013) and construct the broker-dealers leverage factor. The sample period is 1986:Q1-2012:Q4.

3-month LIBOR rate (LIBOR): We obtain the 3-month LIBOR data based on USD (USD3MTD156N) from the Federal Reserve's FRED database. The sample period is 1986:M1-2013:M4.

Percentage of loan officers tightening credit standards for commercial and industrial loans (Loan): We obtain the Senior Loan Officer Opinion Survey on Banking Lending Practices-Large and medium firms seeking commercial and industrial loans, from the Federal Reserve Bank dataset. The sample period is 1990:Q2-2013:Q1.

Swap T-bill spread (Swap spread): We calculate the spread between the 1-year interest rate swap (the shortest maturity swap available in the FRED database) and the 3-month

T-bill. Data are obtained from the FRED data library. The sample period is 2000:M7-2013:M4.

TED spread (TED spread): The TED spread is the difference between three-month Eurodollar deposits yield (LIBOR) and three-month US T-bills. LIBOR and T-bills yields are from the FRED data library at monthly frequency. The sample period is 1986:M1-2013:M4.

Treasury bond term spread (Term spread): The yield spread between the 10-year Treasury bond (constant maturity) and the 3-month T-bill. Data are obtained from the FRED data library. The sample period is 1986:M1-2013:M4.

VIX (VIX): Chicago Board Options Exchange Market Volatility Index, which measures the implied volatility of S&P 500 Index options (for the period before 1990, we use VXO data due to the unavailability of VIX). We obtain the data from CBOE. The sample period is 1986:M1-2013:M4.

A.2 Hedge Fund Data

Table A.1: List of Hedge Fund Strategies

Primary Strategy	Sub-strategy
Equity Hedge	Equity Market Neutral Quantitative Directional Sector - Energy/Basic Materials Sector - Technology/Healthcare Short Bias
Event-driven	Distressed/Restructuring Merger Arbitrage
Macro	Systematic Diversified
Relative Valuation	Fixed Income-Asset Backed Fixed Income-Convertible Arbitrage Fixed Income-Corporate Multi-Strategy Yield Alternatives
Relative Valuation	Conservative Diversified Market Defensive Strategic
Emerging Markets	Asia ex-Japan Global Latin America Russia/Eastern Europe

Table A.2: The Fung-Hsieh Seven Hedge Fund Risk Factors

Factor	Construction	Source
PTFSBD	Return of PTFS Bond Lookback straddle	David Hsieh's website
PTFSFX	Return of PTFS Currency Lookback Straddle	David Hsieh's website
PTFSCOM	Return of PTFS Commodity Lookback Straddle	David Hsieh's website
Equity market factor	Standard & Poor's 500 Index monthly total return	Datastream (code: S&PCOMP(RI))
Size spread factor	Russell 2000 index monthly total return less Standard & Poor's 500 monthly total return	Datastream (code: FRUSS2L(RI), S&PCOMP(RI))
Bond market factor	The monthly change in the 10-year Treasury constant maturity yield (month end-to-month end)	FRB Data H15
CS factor	The monthly change in the Moody's Baa yield less 10-year Treasury constant maturity yield	FRB Data H15

A.3 Removal of Hedge Fund Returns' First- and Second-Order Autocorrelations

We follow the procedure proposed by Loudon, Okunev, and White (2006) to remove the first- and second-order autocorrelations for the returns of individual hedge funds. We assume that for each hedge fund i, its manager smooths reported return $r^0_{i,t}$ in the following manner:

$$r^0_{i,t} = (1 - \Sigma^l_{j=1}\alpha_{i,j})r^m_{i,t} + \Sigma^l_{j=1}\alpha_{i,j}r^0_{i,t-j},$$

where $r^m_{i,t}$ is the unobserved true return and l is the time period that hedge fund managers choose to smooth their returns. Following the literature (Getmansky, Lo, and Makarov (2004);, Jagannathan, Malakhov, and Novikov (2010)), we choose $l = 2$ such that the reported returns are smoothed up to two lags. We remove the first- and second-order autocorrelations using a three-step approach: in the first step, we remove observed hedge fund returns' first-order autocorrelation; in the second step, we remove the second-order autocorrelations from the first-step unsmoothed returns $r^1_{i,t}$; finally, we remove the first-order autocorrelations from the second-step unsmoothed returns $r^2_{i,t}$. The following equations give these three steps, where $\rho^m_{i,n}$ is the n^{th} order autocorrelation for hedge fund i after m adjustments:

$$\begin{aligned}
r^1_{i,t} &= \frac{r^0_{i,t} - c^1_i r^0_{i,t-1}}{1 - c^1_i}, \quad where \;\; c^1_i = \rho^0_{i,1}. \\
r^2_{i,t} &= \frac{r^1_{i,t} - c^2_i r^1_{i,t-2}}{1 - c^2_i}, \quad where \;\; c^2_i = \frac{1 + \rho^1_{i,4} - \sqrt{(1 + \rho^1_{i,4})^2 - 4{\rho^1_{i,2}}^2}}{2\rho^1_{i,2}}. \\
r^3_{i,t} &= \frac{r^2_{i,t} - c^3_i r^2_{i,t-1}}{1 - c^3_i}, \quad where \;\; c^3_i = \rho^2_{i,1}.
\end{aligned}$$

B Mathematics Appendix

B.1 Proof of Lemma 1

For type A investors who do not have funding constraints (or in other words, whose funding constraints are not binding at optimal), and type B investors who face funding constraints as in Equation **??**, we have two Lagrange problems:

$$
\begin{aligned}
Ł_t^A &= \omega_t^{A\prime} E_t R_{t+1}^n - \frac{\gamma^A}{2} \omega_t^{A\prime} \Omega \omega_t^A. \\
Ł_t^B &= \omega_t^{B\prime} E_t R_{t+1}^n - \frac{\gamma^B}{2} \omega_t^{B\prime} \Omega \omega_t^B - \eta_t (\tilde{m}_t' \omega_t^B - 1).
\end{aligned}
$$

Taking the first order condition with respect to ω_t^A and ω_t^B gives us the optimal portfolio choice for type A and type B investors.$\square$

B.2 Proof of Lemma 2

Insert the optimal portfolio choices ω_t^A and ω_t^B into the market clearing condition $\rho_A \omega_t^A + (1-\rho_A)\omega_t^B = X$ and using the definition $\frac{1}{\gamma} = \frac{\rho_A}{\gamma_A} + \frac{1-\rho_A}{\gamma_B}$, we have the following result:

$$
\begin{aligned}
(\frac{\rho_A}{\gamma_A} + \frac{1-\rho_A}{\gamma_B}) E_t R_{t+1}^n &= \Omega_R X + \frac{1-\rho_A}{\gamma_B} \eta_t \tilde{m}_t. \\
\frac{1}{\gamma} X' E_t R_{t+1}^n &= X' \Omega_R X + \frac{1-\rho_A}{\gamma_B} \eta_t X' \tilde{m}_t. \\
(E_t R_{M,t+1} - R) &= \gamma VAR(R_M) + \gamma \frac{1-\rho_A}{\gamma_B} \eta_t X' \tilde{m}_t.
\end{aligned}
$$

For an asset k, we have the following relationship using the market clearing condition:

$$
\frac{1}{\gamma}(E_t R_{k,t+1} - R) = \Omega_{s=1}^n COV(R_{k,t+1}, R_{s,t+1}) X_s + \frac{1-\rho_A}{\gamma_B} \eta_t \tilde{m}_{k,t}.
$$

Using definitions $\beta_k = \frac{COV(R_{k,t+1}, R_{M,t+1})}{VAR(R_{M,t+1})}$, $\tilde{m}_{M,t} = X'\tilde{m}_t$, $\tilde{\gamma} = \gamma\frac{1-\rho_A}{\gamma_B}$, and $\psi_t = \tilde{\gamma}\eta_t$, and under the case when both type A and type B investors take long positions in all assets, i.e., $\tilde{m}_t = \hat{m}_t$, we have the expression in Lemma 2.$\square$

B.3 Proof of Proposition 1

Under Assumption 1, we can calculate the premium of a zero-beta BAB portfolio following Frazzini and Pedersen (2014) conditional on the margin requirement $\hat{m}_{BAB,t}$:

$$\begin{aligned} E_t R_{t+1}^{BAB} &= \frac{E_t R_{L,t+1} - R}{\beta_L} - \frac{E_t R_{H,t+1} - R}{\beta_H} \\ &= E_t R_{M,t+1} - R + \psi_t \frac{\hat{m}_{BAB,t}}{\beta_L} - \psi_t \hat{m}_{M,t} - (E_t R_{M,t+1} - R + \psi_t \frac{\hat{m}_{BAB,t}}{\beta_H} - \psi_t \hat{m}_{M,t}) \\ &= \frac{\beta_H - \beta_L}{\beta_H \beta_L} \hat{m}_{BAB,t} \psi_t . \square \end{aligned}$$

B.4 Proof of Proposition 2

Suppose we construct two BAB portfolios within two groups of stocks with different margin requirements, denoted by $\hat{m}_{1,t}$ and $\hat{m}_{2,t}$. The BAB premia are given by $E_t R_{t+1}^{BAB^1} = \frac{\beta_H - \beta_L}{\beta_H \beta_L} \hat{m}_{1,t} \psi_t$ and $E_t R_{t+1}^{BAB^2} = \frac{\beta_H - \beta_L}{\beta_H \beta_L} \hat{m}_{2,t} \psi_t$. Under Assumptions 1 and 2, we can rewrite the return difference between the two BAB portfolios as:

$$E_t R_{t+1}^{BAB^1} - E_t R_{t+1}^{BAB^2} = \frac{\beta_H - \beta_L}{\beta_H \beta_L} (a_{BAB}^1 - a_{BAB}^2) \psi_t .$$

Even a_{BAB} is time-varying, as long as it is drawn from some distribution with a time-invariant dispersion, we have the difference between $a_{BAB,t}^1$ and $a_{BAB,t}^2$ across two groups of stocks as a constant. We conclude that the source of time series variation in the $E_t R_{t+1}^{BAB^1} - E_t R_{t+1}^{BAB^2}$ spread is the time-varying funding liquidity shock ψ_t.$\square$

C Additional Results

C.1 Additional Figures and Tables

Figure C.1: Time Series of the Extracted Funding Liquidity Shocks (Quarterly)

The figure presents quarterly time series of the extracted funding liquidity shocks. Small values indicate tight funding conditions. The sample period is from 1965Q1 to 2012Q3.

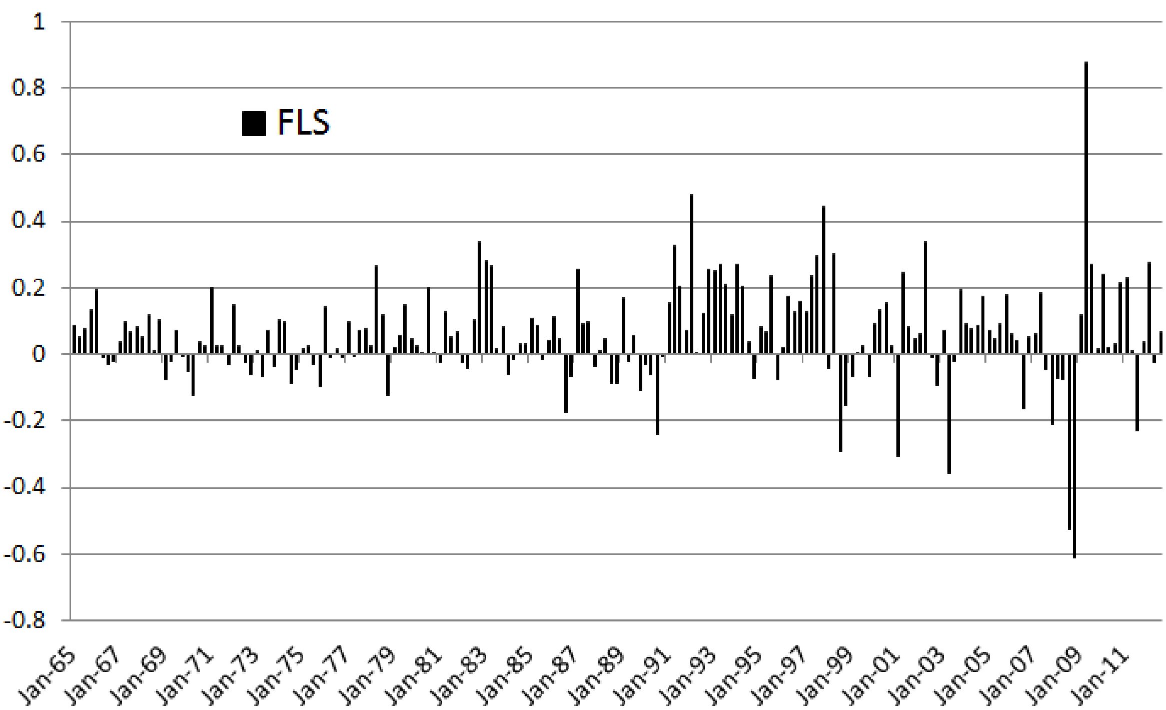

Figure C.2: Hedge Fund Portfolios' Performance

Figures A and B plot the cumulative returns and maximum drawdowns for hedge fund decile portfolios with the lowest sensitivity to funding liquidity shocks (solid line), and with the highest sensitivity to funding liquidity shocks (dashed line). The sample period is from January 1996 to April 2009.

Figure A: Decile portfolios' cumulative returns

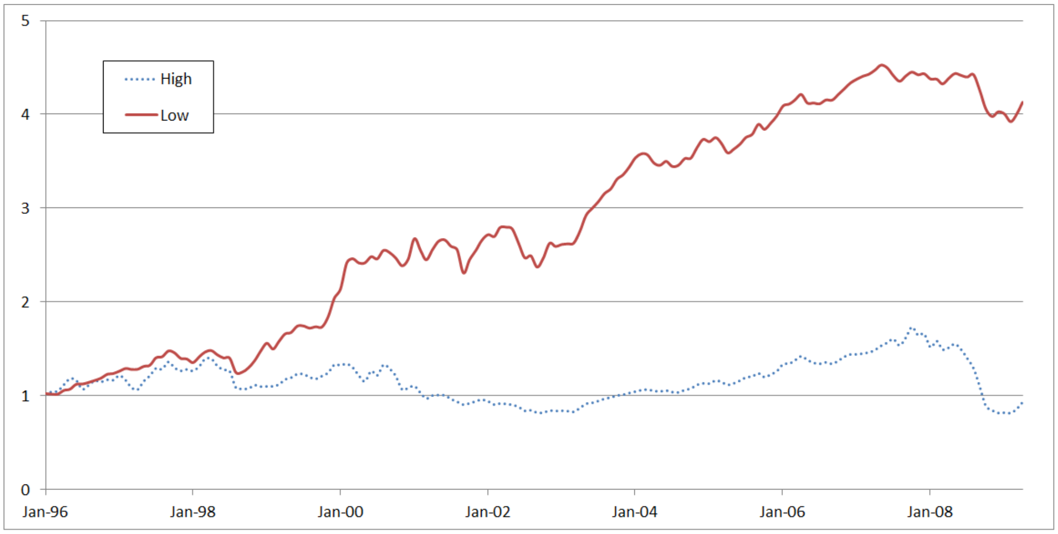

Figure B: Decile portfolios' maximum drawdowns

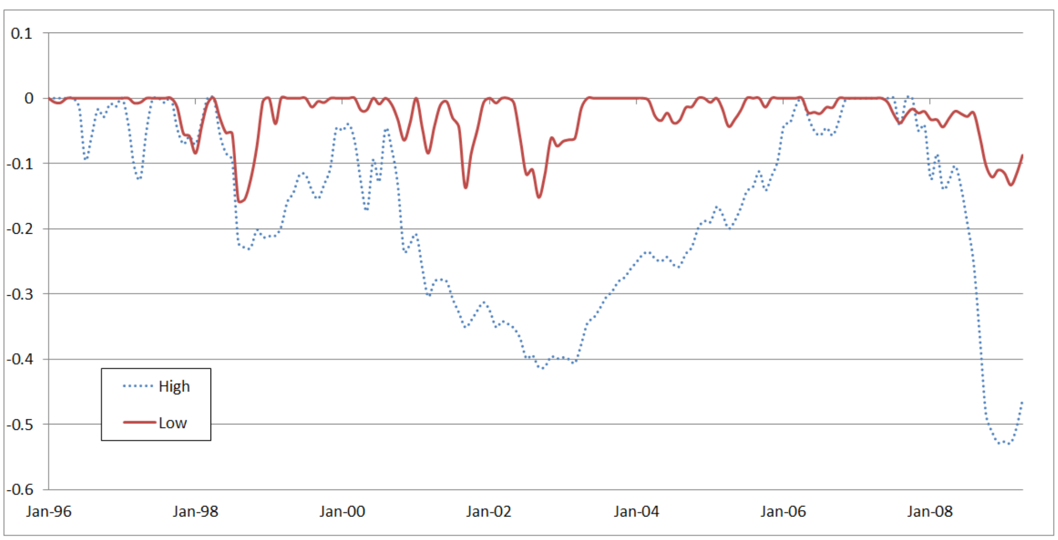

Figure C.3: Hedge Fund Portfolios' Spreads over Different Holding Horizons

The figures show the monthly time series low-minus-high hedge fund portfolio spreads based on their sensitivities to the funding liquidity shocks with different holding horizons. Figure A shows the spread for the one-month holding horizon, Figure B shows the spread for the six-month holding horizon, Figure C shows the spread for the twelve-month holding horizon.

Figure A: One-month holding horizon

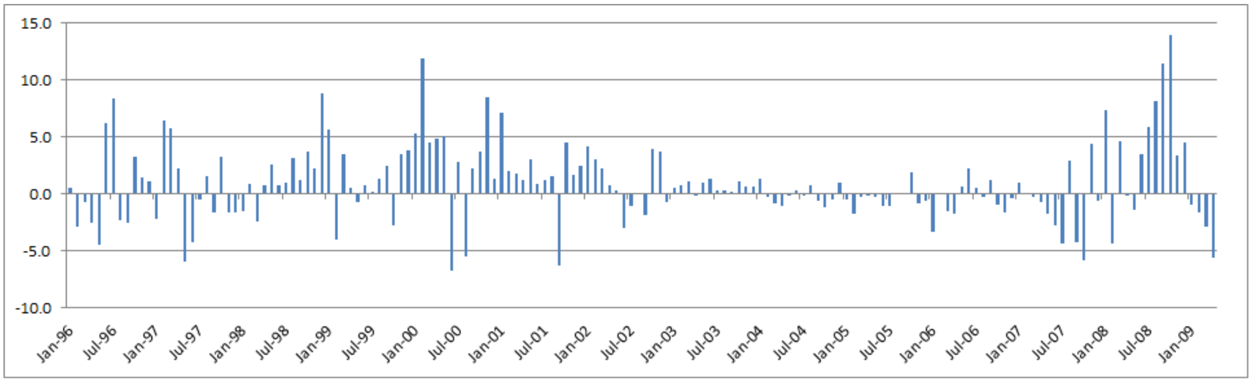

Figure B: Six-month holding horizon

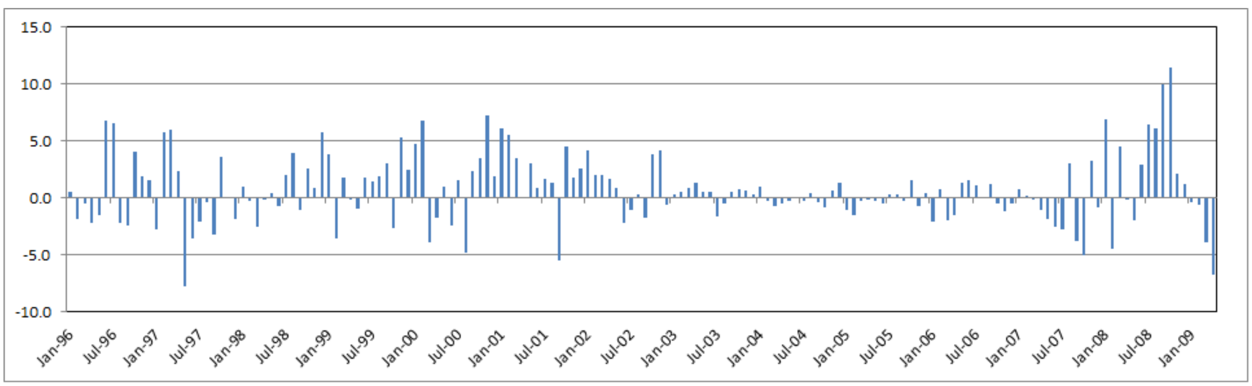

Figure C: Twelve-month holding horizon

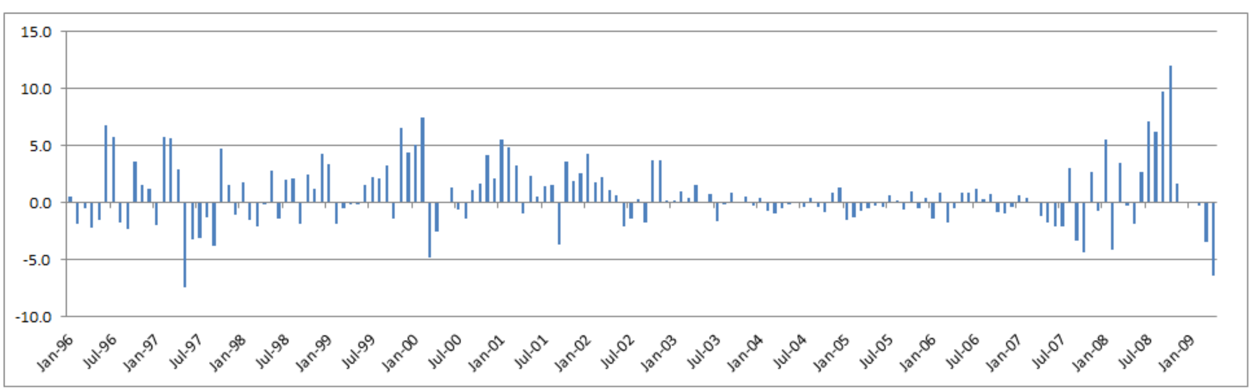

Figure C.4: Histograms of Hedge Fund Returns' First-Order Autocorrelations

The histograms show the first-order autocorrelation coefficients for the returns of all hedge funds with at least 18 months of observations. We follow the three-step procedure proposed in Loudon, Okunev, and White (2006) to remove the first- and second-order autocorrelations of raw hedge fund returns (details about this procedure can be found in Appendix A). We plot the histograms of the first-order autocorrelation coefficients for four types of returns: the raw returns, returns after the first-time removal of the first-order autocorrelations, returns after the first-time removal of the second-order autocorrelations, and returns after the second-time removal of the first-order autocorrelations.

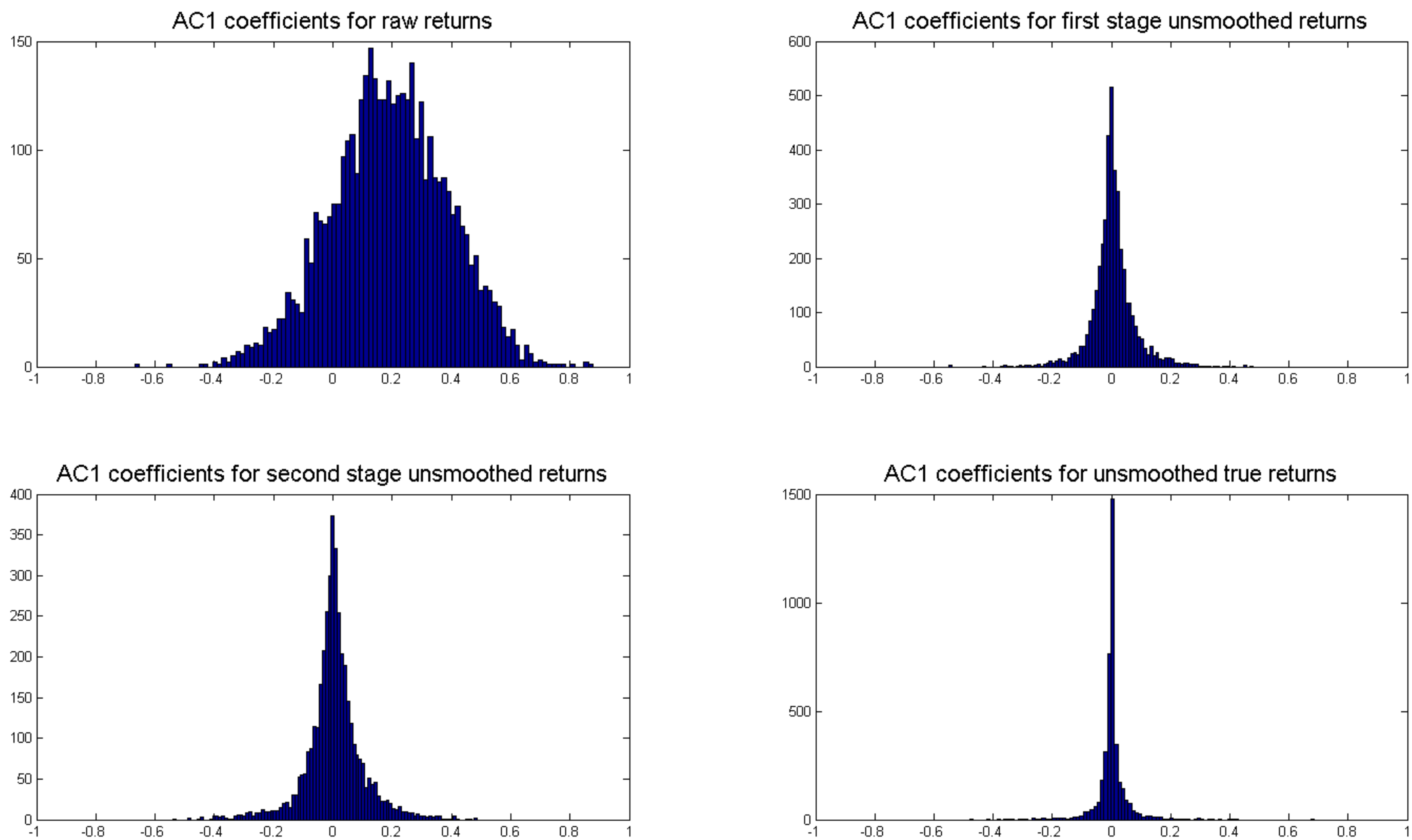

Figure C.5: Histograms of Hedge Fund Returns' Second-Order Autocorrelations

The histograms show the second-order autocorrelation coefficients for the returns of all hedge funds with at least 18 months of observations. We follow the three-step procedure proposed in Loudon, Okunev, and White (2006) to remove the first- and second-order autocorrelations of raw hedge fund returns (details about this procedure can be found in Appendix A). We plot the histograms of the second-order autocorrelation coefficients for four types of returns: the raw returns, returns after the first-time removal of the first-order autocorrelations, returns after the first-time removal of the second-order autocorrelations, and returns after the second-time removal of the first-order autocorrelations.

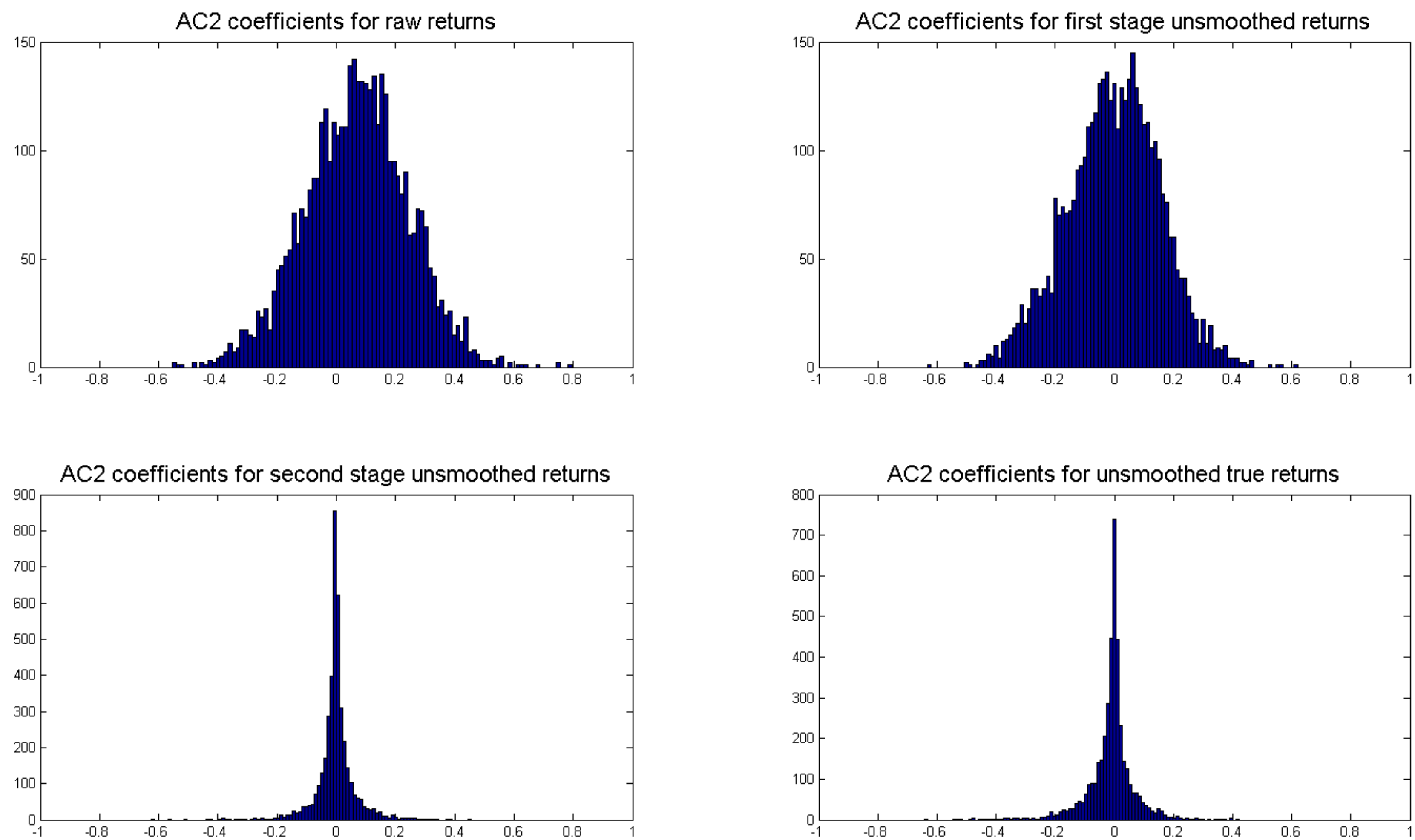

Table C.1: Characteristics of BAB Portfolios

This table presents characteristics of BAB portfolios sorted by margin proxies. Size refers to a stock's market capitalization. σ_{ang} refers to a stock's idiosyncratic volatility calculated following Ang et al. (2006). The Amihud illiquidity measure is calculated following Amihud (2002). Institutional ownership refers to the fraction of common shares held by institutional investors. Analyst coverage is the number of analysts following a stock. Stocks are sorted into five groups based on NYSE breaks: 1 indicates the low-margin group and 5 indicates the high-margin group. The high-margin group includes stocks that have small market cap, large idiosyncratic volatility, low market liquidity, low institutional ownership, and low analyst coverage. Panel A presents excess returns of single sorted portfolios based on five margin proxies. Panel B presents the average number of stocks in each portfolio. Panel C presents the average fraction of market capitalization for each portfolio. Panel D presents the average beta of stocks within each portfolio.

	1 (Low)	2	3	4	5 (High)	Diff
Panel A: Excess returns of single sorted portfolios						
Size	0.39	0.61	0.71	0.75	0.75	0.36
	(2.15)	(2.84)	(3.06)	(2.95)	(2.75)	(1.93)
σ_{ang}	0.47	0.52	0.62	0.62	0.28	-0.20
	(2.98)	(2.68)	(2.77)	(2.34)	(0.84)	(-0.79)
Amihud	0.39	0.60	0.65	0.69	0.79	0.40
	(2.13)	(2.82)	(2.94)	(2.95)	(3.24)	(2.47)
Inst.	0.65	0.64	0.69	0.63	0.49	-0.16
	(2.41)	(2.53)	(2.99)	(2.78)	(2.26)	(-1.13)
Analyst	0.49	0.59	0.61	0.69	0.58	0.09
	(2.28)	(2.42)	(2.5)	(2.68)	(2.45)	(0.69)
Panel B: Average number of stocks						
Size	295	337	417	601	2346	
σ_{ang}	490	445	519	703	1838	
Amihud	306	340	405	533	2052	
Inst.	436	444	514	713	2242	
Analyst	399	536	985	521	2130	
Panel C: Average fraction of market capitalization						
Size	73.3	13.3	6.6	3.9	2.9	
σ_{ang}	43.8	24.0	15.2	10.1	7.0	
Amihud	72.4	13.7	6.7	3.9	3.3	
Inst.	18.5	22.0	24.1	24.2	11.1	
Analyst	62.8	16.5	10.1	3.1	7.5	
Panel D: Average beta						
Size	1.04	0.99	0.98	0.96	0.89	
σ_{ang}	0.93	1.01	1.08	1.15	1.23	
Amihud	1.05	0.99	0.95	0.91	0.84	
Inst.	1.06	1.05	1.03	0.97	0.87	
Analyst	1.06	1.01	0.93	0.84	0.72	

Table C.2: Correlation Between the Extracted Funding Liquidity Shock and Existing Funding Liquidity Proxies

This table presents correlations of 14 commonly used funding liquidity proxies with the BAB spread conditional on each margin proxy. Fourteen funding liquidity proxies are filtered with AR(2) for monthly data and AR(1) for quarterly data, except for the investment bank excess returns. We sign all funding liquidity proxies such that smaller values indicate tighter funding conditions. BAB is the Frazzini and Pedersen (2014) "betting against beta" portfolio returns. The BAB spread is calculated as the return difference between two BAB portfolios, each of which is constructed using stocks with high/low margin requirements. Margin proxies include size, idiosyncratic volatility, Amihud illiquidity measure, institutional ownership, and analyst coverage. Correlation coefficients are reported, with 5% statistical significance indicated with $*$.

Correlations with 14 funding liquidity proxies

	Asset growth	Bond liquidity	CDS	Credit spread	Financial leverage	HF leverage	IB exret	Broker leverage	LIBOR	Loan	Swap spread	TED spread	Term spread	VIX
Monthly														
Size	13.9*	11.5*	42.1*	20.2*	19.7*	47.6*	25.0*	-3.3	-10.5	18.4*	19.1*	15.3*	-1.5	23.7*
σ_{ang}	3.3	13.4*	41.8*	16.5*	32.4*	42.0*	30.5*	0.6	-1.3	13.0*	19.9*	19.9*	-5.5	24.6*
Amihud	12.9*	11.9*	48.5*	21.3*	22.8*	49.2*	30.8*	-1.3	-8.6	18.2*	21.6*	18.0*	-10.8	25.1*
Inst.	11.4*	4.4	29.5*	14.9*	9.75	41.1*	6.3	-0.1	-4.5	16.3*	16.5	10.0	-2.6	8.3
Analyst	11.0	13.1*	28.3*	22.7*	17.3*	35.8*	22.5*	-5.0	-13.26*	11.1	7.2	8.3	-10.8	24.7*
Quarterly														
Size	22.4*	20.9*	42.8*	38.8*	41.7*	61.0*	40.9*	11.1	-20.6	40.8*	20.2	22.9*	-2.3	34.4*
σ_{ang}	28.4*	28.4*	39.2*	37.6*	43.9*	50.7*	34.2*	19.3*	-12.2	36.1*	13.4	22.5*	-15.2	32.7*
Amihud	24.1*	29.4*	46.8*	36.9*	43.4*	65.1*	45.6*	7.3	-14.3	43.0*	26.7	27.3*	-12.2	35.6*
Inst.	18.9	15.7	36.8*	38.2*	34.4*	50.9*	24.6*	9.4	-6.0	42.2*	17.4	22.2*	1.6	26.8*
Analyst	10.3	23.5*	39.5*	33.5*	43.3*	54.0*	34.6*	1.6	-16.6	29.9*	11.5	16.2	-15.6	36.0*

Table C.3: Descriptive Statistics of the CISDM Hedge Fund Data

This table presents summary statistics of hedge fund data. Our sample includes hedge funds that report the currency of assets under management (AUM) to be USD, or have the country variable to be United States if the currency variable is missing. We drop hedge funds that have less than 18 months of return history in the dataset. We require hedge funds to have at least $10 million AUM. Panels A and B report summary statistics by year and investment style, respectively. Summary statistics include total number of funds, total number of graveyard funds, average AUM (million), average number of reporting months, the mean and median of the first-order autocorrelation coefficients for hedge funds' monthly returns, the mean, the standard deviation, the maximum, and the minimum of monthly equal-weighted returns of hedge fund portfolios. We merge several original CISDM investment styles to ensure enough number of funds for each style. Fixed Income style includes Fixed Income, Fixed Income-MBS, and Fixed Income Arbitrage; Multi-Strategy style includes Multi-Strategy and Relative Value Multi-Strategy; Other style includes Capital Structure Arbitrage, Equity Long Only, Market Timing, Merger Arbitrage, Other Relative Value, Regulation D, Sector, Short Bias, and Single Strategy. The sample period is from January 1994 to April 2009.

Year	Total NO.	Graveyard NO.	AUM (mm)	Reporting (month)	Auto corr (mean)	Auto corr (median)	EW Ret (mean)	EW Ret (std)	EW Ret (max)	EW Ret (min)
Panel A: Summary statistics by year										
1994	324	0	138.5	119.9	0.191	0.187	0.001	0.016	0.029	-0.025
1995	433	6	104.8	115.6	0.186	0.178	0.016	0.011	0.032	-0.008
1996	607	9	102.6	112.4	0.184	0.178	0.017	0.015	0.038	-0.020
1997	809	19	111.6	107.4	0.187	0.183	0.017	0.020	0.045	-0.010
1998	962	58	132.0	104.9	0.191	0.188	0.004	0.029	0.036	-0.072
1999	1097	72	120.2	105.4	0.188	0.182	0.024	0.023	0.072	-0.009
2000	1272	72	127.2	102.4	0.192	0.188	0.011	0.028	0.072	-0.023
2001	1486	90	121.0	99.6	0.197	0.191	0.006	0.016	0.031	-0.024
2002	1688	128	122.0	96.7	0.210	0.200	0.001	0.012	0.020	-0.021
2003	1906	107	134.9	92.7	0.214	0.207	0.014	0.008	0.031	0.002
2004	2212	153	177.9	86.1	0.215	0.210	0.008	0.011	0.028	-0.009
2005	2615	217	196.0	79.2	0.214	0.211	0.008	0.013	0.021	-0.015
2006	2816	253	212.2	71.2	0.217	0.218	0.010	0.014	0.033	-0.016
2007	2876	347	246.3	66.0	0.223	0.228	0.009	0.015	0.031	-0.018
2008	2538	941	246.3	66.4	0.235	0.243	-0.020	0.031	0.020	-0.078
2009	1600	230	181.3	70.7	0.261	0.270	0.011	0.019	0.036	-0.010
Panel B: Summary statistics by investment style										
Convertible Arbitrage	888	110	148.9	89.5	0.374	0.402	0.007	0.018	0.049	-0.126
Distressed Securities	714	67	293.0	101.4	0.284	0.294	0.008	0.021	0.065	-0.106
Emerging Market	1206	109	145.6	86.0	0.211	0.214	0.012	0.060	0.269	-0.283
Equity Long/Short	6244	703	152.7	81.5	0.136	0.136	0.010	0.026	0.098	-0.074
Equity Market Neutral	723	86	192.4	81.5	0.059	0.058	0.007	0.008	0.031	-0.016
Event Driven	1007	90	190.0	93.9	0.248	0.258	0.009	0.021	0.073	-0.093
Fixed Income	1426	154	227.6	81.9	0.235	0.233	0.006	0.013	0.029	-0.107
Global Macro	807	78	371.0	89.4	0.081	0.065	0.008	0.020	0.087	-0.047
Multi-Strategy	1238	121	244.5	80.6	0.256	0.265	0.009	0.017	0.045	-0.088
Fund of Funds	7980	809	173.0	86.6	0.281	0.281	0.006	0.017	0.064	-0.069
Other	3008	375	107.4	78.9	0.167	0.159	0.011	0.027	0.136	-0.098

Table C.4: Hedge Fund Decile Portfolio Alphas and the Fung-Hsieh Seven-factor Loadings

This table presents the loadings on the Fung-Hsieh seven factors for hedge fund decile portfolios. At the end of each month, we sort hedge funds into 10 decile portfolios according to their funding liquidity betas. Funding liquidity betas are computed using a 24-month rolling-window regression of excess returns on the funding liquidity shocks and the market factor with a minimum observation requirement of 18 months. We require funds to have at least \$10 million AUM. Adjusted R^2s are reported in percentage. The Newey-West four-lag adjusted t-statistics are reported in parentheses. The sample period is from January 1996 to April 2009.

	Low	2	3	4	5	6	7	8	9	High	LMH
Alpha	0.75	0.53	0.36	0.32	0.30	0.30	0.30	0.31	0.19	-0.14	0.89
	(4.03)	(3.48)	(3.26)	(3.89)	(3.34)	(3.22)	(3.02)	(2.65)	(1.56)	(-0.59)	(3.02)
PTFSBD	0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	0.02
	(0.33)	(-0.45)	(-1.2)	(-1.16)	(-1.57)	(-1.37)	(-1.51)	(-1.05)	(-1.15)	(-1.36)	(1.46)
PTFSFX	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
	(0.67)	(2.46)	(1.13)	(1.24)	(0.94)	(0.94)	(0.58)	(0.26)	(0.78)	(0.2)	(0.15)
PTFSCOM	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.02	-0.02
	(-0.37)	(-0.09)	(0.12)	(-0.18)	(0.07)	(0.21)	(0.89)	(0.67)	(0.85)	(0.96)	(-1.02)
Equity market factor	0.43	0.29	0.23	0.18	0.19	0.19	0.21	0.26	0.36	0.56	-0.12
	(8.87)	(7.36)	(9.27)	(10.87)	(8.25)	(8.61)	(8.38)	(9.65)	(11.43)	(9.25)	(-1.71)
Size spread factor	0.34	0.22	0.18	0.13	0.13	0.11	0.12	0.14	0.17	0.30	0.04
	(4.41)	(3.31)	(4.44)	(4.05)	(5.52)	(4.39)	(4.62)	(4.59)	(4.21)	(4.79)	(0.35)
Bond market factor	0.01	0.00	0.00	-0.01	0.00	0.00	0.00	-0.01	-0.01	0.00	0.01
	(1.39)	(0.59)	(-0.07)	(-1.98)	(-1.34)	(-1.01)	(-0.71)	(-1.1)	(-1.73)	(-0.16)	(1.13)
CS factor	-0.01	-0.01	-0.02	-0.03	-0.03	-0.03	-0.03	-0.04	-0.04	-0.06	0.06
	(-0.47)	(-1.08)	(-2.7)	(-7.55)	(-6.75)	(-7.24)	(-6.47)	(-7.02)	(-7.38)	(-5.98)	(3.10)
Adj. R^2 (%)	59.81	56.51	63.43	66.08	65.49	62.79	61.60	62.13	68.01	62.79	10.89

Table C.5: Hedge Fund Decile Portfolios: Robustness Tests

This table presents hedge fund decile portfolios sorted by funds' sensitivities to the funding liquidity shocks. Monthly excess returns and the Fung-Hsieh seven-factor adjusted alphas are reported with the Newey-West four-lag adjusted t-statistics in parentheses. Panel A reports the performance of hedge fund portfolios that are constructed using unsmoothed returns. Panel B presents results for value-weighted hedge fund portfolios. Panel C presents results using the funding liquidity shocks constructed with no forward-looking information. Panel D presents results when we replace the returns of the last month before delisting by -100%. Panel E presents results when funding liquidity betas are estimated in a three-factor model, controlling for the market and ΔVIX. Panel F presents results when funding liquidity betas are estimated in a three-factor model, controlling for the variance risk premium. Panel G presents results using a sample excluding the recent financial crisis (January 1996 to December 2006). Panel H presents results using only hedge funds with AUM denominated in USD. Panel I presents results when funds of funds are excluded. The sample period is from January 1996 to April 2009 (except for the Panel G).

	Low	2	3	4	5	6	7	8	9	High	LMH
Panel A: Removal of the first- and the second-order autocorrelations											
Exret	0.81	0.76	0.56	0.39	0.32	0.32	0.37	0.38	0.20	-0.02	0.83
	(2.71)	(3.63)	(3.09)	(2.98)	(2.11)	(2.24)	(1.87)	(1.65)	(1.06)	(-0.01)	(2.55)
Alpha	0.49	0.57	0.40	0.28	0.22	0.24	0.27	0.26	0.07	-0.25	0.75
	(2.92)	(3.99)	(2.81)	(3.25)	(2.21)	(2.40)	(2.00)	(1.53)	(0.72)	(-0.64)	(2.25)
Panel B: Value-weighted portfolios											
Exret	0.72	0.60	0.35	0.37	0.34	0.32	0.31	0.35	0.32	-0.24	0.97
	(2.57)	(3.64)	(2.45)	(2.81)	(2.69)	(2.78)	(2.23)	(2.13)	(1.70)	(-0.71)	(2.70)
Alpha	0.46	0.47	0.27	0.32	0.30	0.30	0.27	0.30	0.23	-0.32	0.79
	(1.94)	(3.35)	(2.43)	(3.05)	(3.75)	(3.40)	(2.67)	(2.26)	(1.59)	(-1.26)	(1.93)
Panel C: Correction for forward-looking bias in the funding liquidity shocks											
Exret	0.95	0.68	0.49	0.40	0.34	0.35	0.36	0.38	0.37	0.04	0.91
	(3.72)	(3.96)	(3.40)	(3.11)	(2.88)	(2.85)	(2.56)	(2.18)	(1.86)	(0.11)	(3.53)
Alpha	0.74	0.54	0.38	0.33	0.28	0.30	0.30	0.29	0.25	-0.15	0.90
	(3.61)	(3.55)	(3.87)	(3.35)	(3.36)	(3.75)	(3.06)	(2.43)	(2.09)	(-0.66)	(3.10)
Panel D: Delisting											
Exret	-0.53	-0.61	-0.88	-0.68	-0.68	-0.65	-0.74	-0.86	-1.05	-1.53	1.00
	(-1.73)	(-2.49)	(-4.03)	(-3.36)	(-3.35)	(-3.15)	(-3.36)	(-3.24)	(-3.71)	(-3.71)	(2.93)
Alpha	-0.69	-0.70	-0.96	-0.72	-0.78	-0.71	-0.81	-0.91	-1.15	-1.67	0.98
	(-2.94)	(-3.02)	(-4.11)	(-3.31)	(-3.62)	(-3.14)	(-3.17)	(-3.31)	(-4.58)	(-5.34)	(2.68)
Panel E: Control for ΔVIX											
Exret	1.02	0.66	0.54	0.37	0.34	0.40	0.34	0.41	0.38	0.27	0.75
	(3.86)	(3.74)	(4.10)	(3.19)	(2.73)	(3.28)	(2.50)	(2.46)	(1.86)	(0.76)	(2.73)
Alpha	0.84	0.53	0.45	0.33	0.27	0.36	0.32	0.33	0.29	0.07	0.77
	(3.78)	(3.92)	(4.02)	(3.75)	(2.53)	(3.68)	(3.31)	(3.07)	(2.17)	(0.29)	(2.72)
Panel F: Control for the variance risk premium (VRP)											
Exret	1.04	0.70	0.52	0.36	0.41	0.37	0.31	0.37	0.24	0.01	1.03
	(4.21)	(4.40)	(3.61)	(2.81)	(3.46)	(2.90)	(2.28)	(2.16)	(1.08)	(0.04)	(3.99)
Alpha	0.85	0.56	0.43	0.29	0.35	0.32	0.24	0.28	0.10	-0.19	1.03
	(4.52)	(4.85)	(3.51)	(3.43)	(4.08)	(3.43)	(2.38)	(2.49)	(0.71)	(-0.80)	(3.61)

Table C.7 (cont.): Hedge Fund Decile Portfolios: Robustness Tests

	Low	2	3	4	5	6	7	8	9	High	LMH
Panel G: Exclude recent crisis											
Exret	1.17	0.87	0.67	0.57	0.56	0.56	0.56	0.62	0.57	0.35	0.83
	(4.02)	(4.33)	(4.51)	(5.01)	(4.65)	(4.88)	(4.40)	(4.07)	(3.06)	(1.07)	(3.19)
Alpha	0.70	0.53	0.42	0.37	0.34	0.36	0.34	0.35	0.20	-0.24	0.94
	(3.56)	(3.14)	(3.34)	(4.31)	(3.45)	(3.61)	(3.39)	(2.98)	(1.78)	(-1.13)	(3.08)
Panel H: Only funds with AUM denominated in USD											
Exret	1.03	0.67	0.53	0.41	0.38	0.40	0.33	0.38	0.39	0.23	0.80
	(3.81)	(3.76)	(3.61)	(3.5)	(3.18)	(3.07)	(2.31)	(2.37)	(1.89)	(0.67)	(2.78)
Alpha	0.84	0.53	0.45	0.36	0.33	0.33	0.27	0.33	0.28	0.07	0.77
	(3.81)	(3.46)	(3.76)	(3.92)	(4.02)	(3.18)	(2.43)	(2.84)	(2.20)	(0.29)	(2.65)
Panel I: Exclude FOF											
Exret	1.06	0.74	0.61	0.48	0.40	0.47	0.37	0.45	0.23	0.05	1.00
	(3.79)	(3.89)	(4.11)	(3.57)	(3.19)	(3.59)	(2.35)	(2.32)	(0.93)	(0.14)	(3.20)
Alpha	0.84	0.59	0.46	0.39	0.33	0.39	0.29	0.33	0.09	-0.17	1.01
	(4.20)	(3.52)	(3.94)	(3.68)	(4.33)	(4.44)	(2.76)	(2.57)	(0.60)	(-0.62)	(3.01)

Table C.6: Mutual Fund Decile Portfolios

This table presents mutual fund decile portfolios sorted by funds' sensitivities to the funding liquidity shocks. Funding liquidity sensitivities are computed using a 24-month rolling-window regression of monthly returns on the funding liquidity shock (FLS) and the market factor with a minimum observation requirement of 18 months. Monthly returns and the Fama-French three-factor plus Carhart momentum factor adjusted alphas are reported with the Newey-West four-lag adjusted t-statistics in parentheses. Index funds and funds with an AUM less than 20 million USD are excluded. Multiple shares of a single fund are merged using the link table in Berk, van Binsbergen, and Liu (2014). Fund investment styles are classified according to CRSP Style Code. Panel A reports the performance of mutual fund portfolios constructed using all funds. Panel B reports the performance of mutual fund portfolios constructed using domestic equity funds. Panel C reports the performance of mutual fund portfolios constructed using fixed income funds. Panel D reports the performance of mutual fund portfolios constructed using fixed income/equity mixed strategy funds. The sample period is from July 1992 to December 2010.

	Low	2	3	4	5	6	7	8	9	High	LMH
Panel A: All mutual funds											
Exret	0.67	0.50	0.51	0.60	0.62	0.64	0.72	0.81	0.75	0.70	-0.03
	(2.5)	(2.40)	(2.95)	(4.3)	(4.61)	(4.32)	(4.01)	(3.67)	(2.78)	(2.00)	(-0.14)
Alpha	0.19	0.11	0.17	0.28	0.32	0.31	0.37	0.41	0.26	0.13	0.06
	(1.36)	(1.00)	(1.81)	(3.97)	(4.46)	(4.25)	(3.87)	(3.86)	(2.48)	(0.82)	(0.29)
Panel B: Domestic equity mutual funds											
Exret	0.87	0.89	0.89	0.80	0.89	0.84	0.84	0.82	0.75	0.71	0.16
	(2.69)	(3.05)	(3.08)	(2.84)	(3.13)	(2.94)	(2.79)	(2.61)	(2.19)	(1.82)	(0.62)
Alpha	0.27	0.31	0.33	0.24	0.32	0.28	0.24	0.20	0.12	0.05	0.22
	(1.75)	(3.13)	(3.86)	(3.57)	(5.29)	(4.98)	(4.21)	(3.05)	(1.32)	(0.34)	(0.95)
Panel C: Fixed income mutual funds											
Exret	0.38	0.46	0.45	0.45	0.45	0.43	0.42	0.45	0.45	0.52	-0.13
	(3.55)	(5.78)	(5.89)	(6.02)	(5.97)	(5.84)	(5.81)	(6.17)	(5.61)	(5.32)	(-1.28)
Alpha	0.27	0.38	0.39	0.38	0.39	0.37	0.37	0.39	0.37	0.42	-0.16
	(2.57)	(4.63)	(4.74)	(4.97)	(4.84)	(4.76)	(4.64)	(4.4)	(3.59)	(3.17)	(-1.19)
Panel D: Fixed income/equity mixed mutual funds											
Exret	0.53	0.52	0.56	0.58	0.58	0.59	0.59	0.64	0.69	0.73	-0.20
	(2.66)	(3.40)	(4.14)	(4.45)	(4.36)	(4.29)	(3.89)	(3.88)	(3.88)	(3.33)	(-1.46)
Alpha	0.17	0.25	0.30	0.33	0.31	0.31	0.27	0.33	0.34	0.28	-0.12
	(1.47)	(3.44)	(5.09)	(5.08)	(4.45)	(4.49)	(3.48)	(4.50)	(5.21)	(2.23)	(-0.78)