A Market-Based Funding Liquidity Measure

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We construct a traded funding liquidity measure from stock returns. Guided by a model, we extract the measure as the return spread between two beta-neutral portfolios constructed using stocks with high and low margins, to control for their sensitivity to the aggregate funding shocks. Our measure of funding liquidity is correlated with other funding liquidity proxies. It delivers a positive risk premium that cannot be explained by existing risk factors. A model augmented by our funding liquidity measure has superior pricing performance for various portfolios. Despite evident comovement, this measure contains additional information that is not subsumed by market liquidity. (*JEL* G10, G11, G23)

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Since the 2007–2009 financial crisis, funding liquidity, one form of market frictions that measures investors' ability to finance their portfolios, is understood to be an important factor in determining asset prices. Researchers have examined the relation between market frictions and risk premiums, including restricted borrowing (Black 1972), the margin constraints of assets (Garleanu and Pedersen 2011), and the capital constraints of financial intermediaries

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(He and Krishnamurthy 2013). Empirically, researchers and practitioners have adopted a number of proxies for funding liquidity, such as the difference between the 3-month Treasury-bill rate and the 3-month LIBOR (TED spread), CBOE's VIX, and so forth. However, currently there is no agreed on measure of funding liquidity. In this paper, we use time-series and cross-sectional stock returns to construct a theoretically motivated and traded measure of funding liquidity and study its attributes.

One important feature that distinguishes our funding liquidity factor from previous funding liquidity proxies is that it is traded. This feature allows investors to hedge against funding liquidity risk by forming a portfolio following the factor construction procedure. In addition, a traded funding liquidity factor can be applied to better understand cross-sectional stock return variations and evaluate performance of portfolios. Furthermore, a stock-market-based funding liquidity factor can be constructed at different frequencies with broad empirical applications.

The intuition behind our construction of a funding liquidity measure rests on the idea of capturing restricted borrowing from stock returns. Borrowing-constrained investors prefer high-beta to low-beta stocks for their embedded leverage. Such friction lowers (increases) the required returns for high (low) beta stocks in equilibrium. Therefore, the return spread between low-beta and high-beta stocks could contain information on the funding condition of market participants.

Based on the similar intuition, Frazzini and Pedersen (2014) propose a market-neutral "betting-against-beta" (BAB) strategy of buying low-beta assets and selling high-beta assets that 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. Thus, there is an apparent paradox between strong BAB performance and its weak linkage to the underlying driving force.

We show that the time-series variation in the returns of a BAB portfolio depends on both the market-wide funding liquidity condition and assets' sensitivities to the funding condition, where the latter is governed by margin requirements. We measure the funding liquidity shocks using the return difference of two BAB portfolios that are constructed with high- and low-margin stocks, respectively. The findings suggest that our traded funding liquidity measure captures the market-wide funding liquidity shocks: correlation between our measure and other funding liquidity proxies is high. Our funding liquidity factor cannot be explained by existing risk factors. We find a positive relation between our funding liquidity measure and market liquidity measures, especially during a market downturn when market liquidity and funding liquidity move more in tandem. We apply our measure to study asset pricing implications and find that a model that includes the funding liquidity factor has stronger pricing power for various multiple-asset portfolios.

The construction of our funding liquidity measure is guided by a stylized model that includes investors' leverage constraints and asset-specific margin constraints. Our model is in line with the margin-based capital asset pricing model (Ashcraft et al. 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 a higher margin. More importantly, our model suggests that a difference-in-BAB portfolio can isolate the aggregate funding liquidity shocks from the impact of individual stocks' margin requirements.

Because of the data limitation on individual stocks' margin requirements, we employ five margin proxies: stock size, idiosyncratic volatility, the Amihud illiquidity measure, institutional ownership, and analyst coverage. The selection of these proxies is based on real real-world margin rules and theoretical predictions of margin's determinants. Brokers typically set higher margin for smaller or more volatile stocks. Brunnermeier and Pedersen (2009) theoretically show that price volatility and market illiquidity could have a positive impact on assets' margin. We validate our five proxies using a cross-section of stock-level margin data obtained from Interactive Brokers LLC. We find that larger stocks with smaller idiosyncratic volatility, better liquidity, higher institutional ownership, and higher analyst coverage are more likely to be marginable.

We sort all stocks into five groups based on our five margin proxies and construct a BAB portfolio for each margin group. Consistent with our model's 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), with an average return spread of 0.90%.

We construct the traded funding liquidity factor (FLS) using the equally weighted portfolio of our five margin proxies based BAB spreads. We examine several properties of the factor. First, our traded factor is significantly correlated with 11 of the 14 funding liquidity proxies used in the literature. Second, while this factor is constructed from stock returns, it cannot be absorbed by existing risk factors. Third, there is a positive correlation between our FLS factor and the market liquidity measures, especially during market downturns. Nevertheless, we show that while related, our funding liquidity measure is different from market liquidity. Fourth, our FLS factor is robust to other specifications, including proxies orthogonalized to size and market beta, and the BAB return spread adjusted for beta spread. Lastly, the time-series variation in the BAB spread is unlikely to be driven by the limits-to-arbitrage effect. All results suggest that our traded FLS factor captures the market-wide funding liquidity condition.

Next, we investigate the asset pricing implications of our FLS factor. First, we find that the FLS factor helps explain various stock portfolios, including the 25 Fama-French portfolios formed on size and book-to-market, 10 portfolios formed on momentum, 10 industry portfolios, and 11 anomaly portfolios. A pricing model augmented by the FLS factor has better pricing power than the one without it under all criterions. Further, similar pricing improvement can be extended to portfolios of multiple asset classes, including equity, bond, option, currency, commodity, and CDS. Second, the FLS factor passes the Barillas and Shanken (2017) "exclude-factor test" that FLS' time-series alphas are economically and statistically significant after controlling for other traded factors, suggesting that FLS provides additional information to the pricing model. Overall, the evidence indicates that our FLS factor provides explanatory power for assets' returns.

Our paper is related to several strands of literature. First, it is related to the research on the implications of funding liquidity risk in financial markets. On the theoretical side, Black (1972) uses investors' restricted borrowing to explain the empirical failure of the capital asset pricing model (CAPM). More recently, Garleanu and Pedersen (2011) derived a margin-based CAPM, and Brunnermeier and Pedersen (2009) modeled 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 et al. (2014) investigate the cross-sectional pricing power of financial intermediaries' 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 et al. 1972), including restricted borrowing (Black 1972; Frazzini and Pedersen 2014), investors' disagreement

1 Other theoretical papers include Shleifer and Vishny 1997, Gromb and Vayanos 2002, Geanakoplos 2003, Ashcraft et al. 2010, Acharya and Viswanathan 2011, Chabakauri 2013, He and Krishnamurthy 2013, and Rytchkov 2014.

2 Several papers further their study: Jylha 2018 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; and Huang et al. 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. Fontaine and Garcia 2012 and Hu et al. 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. Fontaine et al. 2015 study the cross-sectional pricing power of a Treasury-based funding liquidity measure on stock portfolios. Boguth and Simutin 2018 propose the aggregate market beta of mutual funds' holdings as a measure of leverage constraint tightness. Other studies include Acharya et al. 2013, Drehmann and Nikolaou 2013, Goyenko 2013, and Boudt et al. 2017.

and short-sales constraints (Miller 1977; Hong and Sraer 2016), limited participation (Merton 1987), fund managers' benchmark behavior (Brennan 1993; Baker et al. 2011), and behavioral explanations (Antoniou et al. 2016; Bali et al. 2017; Shen et al. 2017; Wang et al. 2017). Although our evidence favors the leverage constraint explanation, all mechanisms could contribute to the flattened security market line.

1. A Stylized Model

Our construction of 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 investors are born in each time period t with exogenously given wealth W_t^i and live for two periods. There are $n+1$ assets in the market. The first n assets, $R_{k,t+1}$, $k = 1, \ldots, n$, are risky assets with a positive net supply. A risk-free asset, $R_{n+1,t}$, has a deterministic return of r_f with zero net supply.

An investor makes a portfolio choice to maximize utility as follows:

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

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. We also define $E_t[R_{t+1}^n] = (E_t[R_{1,t+1}] - r_f, \ldots, E_t[R_{n,t+1}] - r_f)'$ to be the vector of the risky assets' expected excess returns and Ω to be their variance-covariance matrix.

Investor i's funding constraint can be written as

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

Following the literature (Geanakoplos 2003; Ashcraft et al. 2010), we assume that investors are subject to an asset-specific effective margin requirement, $\hat{m}_{k,t}$, which determines the amount of leverage that could be achieved from borrowing against risky asset k. The indicator variable $I_{k,t}$ takes the value of 1 (-1) for long (short) positions, reflecting the fact that both long and short positions using margin consume capital.[4]

Two types of investors are present in the market: A and B. We assume homogeneity in wealth and risk aversion within each investor type.

4 Margins are set in this way so that the levered investors' counterparties are relatively immune to investors' possible losses. Specifically, for long positions, levered investors need to put their own capital into the margin account to cover possible price decreases for assets that they purchased with borrowed money. Similarly, investors who short assets also need to put their own capital into the margin account so the counterparty has enough collateral in case of an asset price increase.

Type A investors have risk aversion γ^A. Their funding constraints are not binding and thus do not affect their portfolio choices ω_t^A. Their portfolio choice problem is simply maximizing the utility function as described in Equation (1). Type B investors have risk aversion γ^B, and their portfolio choices ω_t^B are additionally subject to the funding constraints of Equation (2).

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

Lemma 1. (*Investors' optimal portfolio choices*). The optimal portfolio choices of type A and type B investors are given by

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

$$\omega_t^B = \frac{1}{\gamma^B}\Omega^{-1}(E_t[R_{t+1}^n] - \eta_t\tilde{m}_t). \tag{4}$$

Note that type B investors' portfolio choice of asset k, $\omega_{k,t}^B$, is affected by the average shadow cost of borrowing constraint η_t and the asset-specific margin requirement $\hat{m}_{k,t}$. When the borrowing condition tightens (larger η_t), type B investors allocate less capital to the risky asset k. In addition, this reallocation effect is stronger for the asset k with a higher haircut $\hat{m}_{k,t}$.

For simplicity, we assume that each type of investors has one unit of wealth and thus their total wealth is 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 (5), where $X = \left(\frac{P_1}{P'e^n}, \ldots, \frac{P_n}{P'e^n}\right)'$ is the relative market capitalization vector and e^n is an $n \times 1$ vector of ones. We also denote $\rho_A = \frac{W_A}{W_A + W_B}$ as the relative wealth of type A investors:

$$\rho_A\omega_t^A + (1-\rho_A)\omega_t^B = X. \tag{5}$$

Next, we define aggregate risk aversion γ such that $\frac{1}{\gamma} = \frac{\rho_A}{\gamma_A} + \frac{1-\rho_A}{\gamma_B}$, levered investors' effective risk aversion as $\tilde{\gamma} = \gamma\frac{1-\rho_A}{\gamma_B}$, and asset k's market beta as $\beta_{k,t} = \frac{COV(R_{k,t+1}, R_{M,t+1})}{VAR(R_{M,t+1})}$. Using the market-clearing condition, we obtain the equilibrium risk premiums in Lemma 2.[5]

[5] 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 of investors allocate a positive fraction of wealth in all the risky assets.

Lemma 2. (***Assets' risk premiums***). In equilibrium, the risk premium for the risky asset k, $k = 1, 2, \cdots, n$, is given by

$$E_t[R_{k,t+1}] - r_f = \beta_k(E_t[R_{m,t+1}] - r_f) + \psi_t(\hat{m}_{k,t} - \beta_k \hat{m}_{M,t}). \qquad (6)$$

$\psi_t = \tilde{\gamma}\eta_t$ measures the shadow cost of the borrowing constraint, and $\hat{m}_{M,t}{}' = X'\hat{m}_t$ is the market-capitalization-weighted average margin requirement. Lemma 2 follows the same trajectory as the margin-based CAPM, where an asset's risk premium depends on both the market premium and the margin premium (Ashcraft et al. 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 the funding constraint, $\psi_t \hat{m}_{k,t}$. The slope of the SML, $E_t[R_{m,t+1}] - r_f - \psi_t \hat{m}_{M,t}$, is lowered by the aggregate cost of the 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 margin requirement $\hat{m}_{BAB,t}$. The distributions of β_k across different classes of stocks are the same.

Proposition 1. (BAB premium with margin effect). For a given margin requirement, $\hat{m}_{BAB,t}$, the BAB premium is

$$E_t[R_{t+1}^{BAB}] = \psi_t \hat{m}_{BAB,t}\left(\frac{\beta_H - \beta_L}{\beta_H \beta_L}\right). \qquad (7)$$

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

Assumption 2. The class-specific margin requirement $\hat{m}_{BAB,t}$ is given by

$$\hat{m}_{BAB,t} = a_{BAB} + f_t. \qquad (8)$$

Under Assumption 2, a stock's margin is determined by two components: one is a time-varying common shock, and the other is an asset-specific constant. The common component f_t can be thought of as 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 a higher margin than others when the two groups of stocks have different properties. Under Assumption 2, Proposition 2 shows that funding liquidity can be measured with two market-neutral BAB portfolios.

Proposition 2. (Construction of the funding liquidity measure from two BAB portfolios). The spread of the risk premiums between two BAB portfolios, which are constructed using stocks with high and low margin requirements, respectively, is given by

$$E_t[R_{t+1}^{BAB^1}] - E_t[R_{t+1}^{BAB^2}] = \frac{\beta_H - \beta_L}{\beta_H \beta_L} c\psi_t, \tag{9}$$

where $c = a_{BAB}^1 - a_{BAB}^2$ is the difference in the stock's 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 the time-varying funding liquidity ψ_t. A higher ψ_t indicates a tighter market-wide borrowing condition, which raises the return spread of two BAB portfolios. As the current price moves opposite 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 it follows some distribution that has a constant dispersion over time.[6]

2. 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.

[6] An implicit assumption of our model is that margin requirements are not correlated with betas. While empirically stock margin may be possibly correlated stock beta (e.g., volatile stocks usually have a high margin and a large beta), the model's prediction holds even with this assumption violated. For example, suppose that margin requirements are different for high- and low-beta stocks, Proposition 1 would become $E_t[R_{t+1}^{BAB}] = \psi_t(\frac{\hat{m}_{BAB,t}^{\beta_L}}{\beta_L} - \frac{\hat{m}_{BAB,t}^{\beta_H}}{\beta_H})$. Furthermore, according to Assumption 2, we will have $\hat{m}_{BAB^1,t}^{\beta_L} = a_L^1 + f_t$, $\hat{m}_{BAB^1,t}^{\beta_H} = a_H^1 + f_t$, $\hat{m}_{BAB^2,t}^{\beta_L} = a_L^2 + f_t$, and $\hat{m}_{BAB^2,t}^{\beta_H} = a_H^2 + f_t$. Under Proposition 2, the spread between two BAB portfolios becomes $E_t[R_{t+1}^{BAB^1}] - E_t[R_{t+1}^{BAB^2}] = \psi_t(\frac{a_L^1 - a_L^2}{\beta_L} - \frac{a_H^1 - a_H^2}{\beta_H})$, which still measures time-varying ψ_t.

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.

2.1 Margin proxies and methodology

In the United States, the initial stock margin is governed by Regulation T of the Federal Reserve Board.[7] 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.[8] 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.

Brunnermeier and Pedersen (2009) demonstrate that stocks' margin requirements increase with price volatility and market illiquidity. In their model, funding liquidity providers with asymmetric information raise the margin of an asset when the price volatility increases. In addition, market illiquidity may also have a positive impact on the asset's margin.[9]

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, 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, not a finer sorting on beta.[10] Following Ang et al. (2006), we calculate idiosyncratic volatility as the standard deviation of return residuals

[7] Regulation T was instituted on October 1, 1934, by the Board of Governors of the Federal Reserve System, whose authority was granted by The Securities Exchange Act of 1934. 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.

[8] 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).

[9] In Proposition 3 of Brunnermeier 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.

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

adjusted by the Fama-French three-factor model using daily excess returns over the past 3 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.[11] 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 2017; Blume and Keim 2012). We calculate a stock's institutional ownership as the ratio of the total number of shares held by institutions divided by the total number of shares outstanding. Data on quarterly institutional holdings come from the records of 13F form filings with the SEC, which are 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.[12] 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.

Our fifth 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 data set. The sample period is from July 1976 to December 2011.

We validate our five margin proxies by examining whether they affect stocks' marginability in the cross-section. Because of the scarce availability of margin data, we are only able to conduct analysis based on a snapshot of stock-level initial margin data from an online brokerage firm, Interactive Brokers LLC, as of January 2015. Interactive Brokers divides all U.S. stocks into two groups: a marginable group and a nonmarginable group. For the marginable stocks, they have the same initial margin requirement, 25% for the long positions and 30% for the short positions, with very few exceptions. Specifically, among the 4,650 stocks that are publicly traded on the three exchanges, 1,573 are not marginable, 3,056 have a 25% (30% for short positions) margin requirement, and the remaining 121 have other levels of

[11] 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.

[12] The SEC requires that institutions report their holdings within 45 days of the end of each quarter. Our match using 1-month-ahead returns may still result in a forward-looking bias. We also use a two-quarter lag approach to further eliminate the forward-looking bias (Nagel 2005). The results are very similar and available on request.

Table 1
Probit regressions of stock-level margin requirements

	(1)	(2)	(3)	(4)	(5)
Size	2.87***				
	(0.10)				
Idiovol		−1.88***			
		(0.11)			
Amihud			−0.21***		
			(0.02)		
IO ratio				2.03***	
				(0.07)	
Analyst					0.14***
					(0.01)
Constant	−1.11***	0.92***	0.49***	−0.63***	−0.22***
	(0.04)	(0.03)	(0.02)	(0.04)	(0.03)
Pseudo R^2	0.53	0.10	0.05	0.17	0.20

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. The 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 (nonmarginable) otherwise. Probit regressions are conducted for each of the five explanatory variables. Reported are the regression coefficients, with standard errors in parentheses, and the pseudo R^2s. ** $p < .05$; *** $p < .01$. Coefficients on size and IO ratio are scaled by 1,000,000. The number of observations is 4,650.

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 the marginability dummy on our five margin proxies. Table 1 presents the results. Stocks with larger size, lower idiosyncratic volatility, better liquidity, higher institutional ownership, and more analyst coverage, are more likely to be marginable. In addition, all regression coefficients are significant at the 1% level. Overall, the results suggest that our proxies tend to affect the cross-sectional variation in stocks' marginability.

We understand that using proxies instead of real margin data may have some shortcomings. First, our proxies also could be associated with stocks' differences in market liquidity, investors' participation, or the level of information asymmetry. On the other hand, all these dimensions could affect stocks' marginability as well. Second, the margin requirement for a single stock could vary across brokers and investors (e.g., for retail and institutional investors). However, 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 a portfolio margin instead of a position margin in recent years.[13] Our sample covers more than 40 years of data, therefore stock-level margin applies in most sample

[13] The 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

periods, except for the most recent 5 years. Overall, even though our proxies are not perfect substitutes for actual margin data, they are likely to capture the cross-sectional differences in the margin requirements of stocks to some extent.

2.2 BAB performance across different margin groups

We divide stocks into five groups based on each of our 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, group 5. We divide stocks using NYSE breaks to ensure our grouping is not affected by small stocks.[14] 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) on the formation of the BAB portfolios. Specifically, we assign a stock within each margin group to either a low-beta group or a high-beta group and form a beta-neutral portfolio within each group. Stocks in each beta group are weighted by the ranked betas such that lower (higher) beta stocks have greater weights in the low-beta (high-beta) portfolio. Both high- and low-beta portfolios are rescaled to have a market beta of one in the formation month. Portfolios are rebalanced monthly. Betas ($\beta_i = \rho \frac{\sigma_i}{\sigma_m}$) are estimated using past one-year standard deviations and past five-year correlation with daily observations. One-day returns are used for volatility estimation and overlapping three-day returns are used for correlation estimation. A minimum of 120 and 750 trading days are required for volatility and correlation estimations, respectively. Raw betas are shrunk toward one with a shrinkage factor of 0.6.

Table 2 reports the excess returns and the five-factor model adjusted alphas of the BAB portfolios conditional on margin requirements, where the five factors include the Fama and French (2013) three factors, the Carhart (1997) momentum factor (UMD), and a market liquidity factor proxied by the returns of a long-short portfolio sorted by the Amihud measure. Panel A of Table 2 presents BAB portfolio performance within each margin group when the size proxy is used. The results show that the BAB portfolio constructed within smaller stocks, thus having a higher margin requirement, delivers considerably higher returns. In particular, the BAB portfolio for

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.

[14] Given the large number of stocks with either no coverage or one analyst, we apply a different group assignment for analyst coverage. We assign all stocks with no analyst coverage to group 5, and all stocks with only one analyst to group 4. For the rest, we use NYSE breaks to sort them into three groups.

Table 2
BAB portfolio performance conditional on margin requirements

	1 (Low)	2	3	4	5 (High)	Diff
A. Size [1/1965–10/2012]						
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)
B. Idiosyncratic volatility [1/1965– 10/2012]						
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)
C. Amihud [1/1965–10/2012]						
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)
D. Institutional ownership [4/1980–3/2012]						
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)
E. Analyst coverage [7/1976–12/2011]						
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)
F. Average across five margin-sorted portfolios [1/1965–10/2012][a]						
Exret	0.32	0.55	0.52	0.73	1.21	0.90
	(2.30)	(3.87)	(3.73)	(4.98)	(6.97)	(5.77)
Alpha	0.12	0.25	0.17	0.34	0.76	0.64
	(0.97)	(1.92)	(1.31)	(2.38)	(3.31)	(2.93)

This table presents BAB portfolio returns conditional on the five margin proxies and the average portfolio returns across five margin proxies. 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 excess 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 as a percentage per month. The Newey-West five-lag adjusted *t*-statistics are in parentheses. [a] 5, no coverage; 4, one analyst; for the rest, divided into 1–3.

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 0.88% per month and highly significant at the 1% level with a *t*-statistic of 4.86.

Similar patterns can be found when our 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% (t-statistic = 6.08, idiosyncratic volatility proxy), 0.62% (t-statistic = 4.17, the Amihud illiquidity proxy), 0.97% (t-statistic = 4.12, institutional ownership proxy), and 0.99% (t-statistic = 3.88, analyst coverage proxy). In addition, such return spreads cannot be explained by commonly used risk factors as the five-factor (the Fama-French three factors, the Carhart momentum factor, and a liquidity factor) alpha of each one of the five return spreads is economically and statistically significant.

Panel F of Table 2 reports the average portfolio returns for the BAB portfolios constructed across our five margin proxy sorted groups. On average, the high-margin BAB portfolio has a monthly excess return of 1.21% (t-statistic = 6.97) and the low-margin BAB portfolio has a monthly excess return of 0.32% (t-statistic = 2.30). The difference portfolio between the two has a monthly return of 0.90% (t-statistic = 5.77) and a five-factor alpha of 0.64% (t-statistic = 2.93).

Overall, we find supporting evidence in Table 2 that the BAB premium is positively related to the margin requirement. More importantly, the results provide us an empirical framework to construct a funding liquidity measure using stock returns.

3. Funding Liquidity Shocks

3.1 A traded measure of funding liquidity risk

Based on our model's prediction, we measure funding liquidity shocks using the return spread between two BAB portfolios constructed within high-margin (group 5) stocks and low-margin (group 1) stocks (the "Diff" column in panel F of Table 2). We construct an equally weighted portfolio of the five BAB spreads across our five margin proxies and take it as our measure for funding liquidity shocks (FLS).

By construction, the FLS is a traded factor of which the average portfolio return can be interpreted as funding liquidity risk premium. The FLS has an annualized factor mean of 10.8%, an annualized volatility of 12.9%, and a Sharpe ratio of 0.68. In other words, investors need to be compensated for around 11% per year for bearing funding liquidity risk. While many funding liquidity measures are highly persistent, our measure of funding liquidity is not. The autocorrelation coefficient of the FLS is 0.18, 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 correspond to the periods with low market-wide funding liquidity, such as the collapse of Internet bubble and the global financial crisis. This observation is intuitive: when funding conditions tighten, the expected return

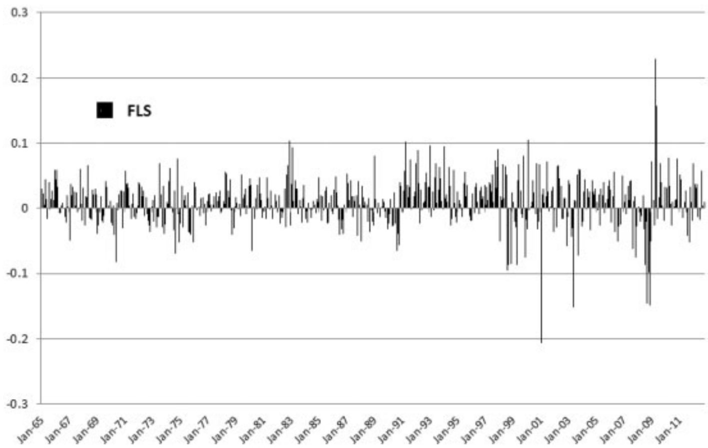

Figure 1
Time series of extracted funding liquidity shocks (monthly)
The figure presents monthly time series of the funding liquidity measure. Small values indicate tight funding conditions. The sample period is from January 1965 to October 2012.

of a portfolio tracking funding liquidity risk must increase, and thus the realized return of this portfolio is negative. A similar pattern can be seen using quarterly data (Figure A1).

We validate that the FLS does capture time-varying funding liquidity conditions by examining its empirical relation with other funding liquidity measures. Panel A of Table 3 presents the correlation coefficients of the FLS with 14 funding liquidity proxies proposed in the literature.[15] For data 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.[16] We sign each proxy such that a small value corresponds to tight funding liquidity condition. We obtain funding liquidity shocks by taking the residuals of each proxy after fitting in an AR(2) model.[17] Appendix B provides the additional construction details.

[15] These 14 funding liquidity proxies are broker-dealers' asset growth (Adrian and Shin 2010), Treasury security-based funding liquidity (Fontaine and Garcia 2012), major investment banks' CDS spread (Ang et al. 2011), credit spread (Adrian et al. 2014), financial sector leverage (Ang et al. 2011), hedge fund leverage (Ang et al. 2011), investment bank excess returns (Ang et al. 2011), broker-dealers' leverage factor (Adrian and Shin 2010), 3-month LIBOR rate (Ang et al. 2011), percentage of loan officers tightening credit standards for commercial and industrial loans (Lee 2013), the swap spread (Asness et al. 2013), the TED spread (Gupta and Subrahmanyam 2000), the term spread (Ang et al. 2011), and the VIX (Ang et al. 2011).

[16] 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.

[17] We follow Korajczyk and Sadka (2008) and Asness et al. (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.

Table 3

Correlation between the extracted funding liquidity measure and existing funding liquidity proxies

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	12.7*	12.6*	40.1*	22.4*	23.7*	44.8*	26.7*	−3.2	−9.1	17.4*	17.7*	15.9*	−5.8	24.9*
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	22.3*	24.4*	28.7*	41.1*	46.9*	−9.4	40.8*	9.8	−16.4	43.1*	−9.7	24.8*	−8.4	37.9*
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

B. Correlations with first principal components

	FPC14	FPC10	FPC7
Monthly			
FLS	34.8*	30.6*	26.9*
BAB	−2.8	11.7*	0.5
Quarterly			
FLS	50.1*	46.2*	44.9*
BAB	14.1	11.5	13.3

This table presents correlation coefficients of 14 commonly used funding liquidity proxies with the extracted funding liquidity factor 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 equally weighted portfolio) extracted from five BAB portfolios' 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 14 funding liquidity proxies and FLS/BAB. 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. *$p < .05$. 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.

We find that FLS is significantly correlated with 11 of 14 funding liquidity proxies: the correlation coefficient ranges from 12.6% (Treasury security-based funding liquidity) to 44.8% (hedge fund leverage). We find a similar pattern for quarterly data: FLS is positively and significantly correlated with 9 of the 14 proxies.[18] In contrast, the monthly BAB factor has significant correlation with only two funding liquidity proxies: the Treasury security-based funding liquidity proxy and swap spread, and the quarterly BAB factor is significantly correlated with four funding liquidity proxies.

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 3 presents the results. Correlation coefficients between the FLS and the FPC14 are 34.8% and 50.1%, respectively, for monthly and quarterly data. In contrast, correlation coefficients are small and insignificant for the BAB factor. As a robustness test, we also examine the correlation between the proposed FLS with the principal component estimated from two subsets of the 14 proxies, denoted by FPC10 and FPC7, respectively.[19] The findings are similar.

In addition, when funding liquidity tightens, the expected return difference of the two BAB portfolios constructed within high-margin stocks and low-margin stocks should increase, resulting in negative realized returns for the FLS factor. We find that changes in funding liquidity measures indeed predict negative realized FLS returns, and detailed results are left to Appendix C.1.

Even though the FLS is traded, a natural concern arises regarding its implementability. 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 per month for each difference-in-BAB portfolio sorted by margin proxy. For the 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. In other words, 20% to 30% of stocks in dollar value in these portfolios are flipped every month. Turnovers are higher for those portfolios sorted on idiosyncratic volatility (78 cents) and analyst coverage (70 cents).

We further examine an FLS portfolio's vulnerability to transaction costs by computing the round-trip costs that are large enough to cause the average

[18] We also calculate the correlation coefficients of each of the five BAB return difference series with the 14 funding liquidity proxies (Table A2). The results are similar, suggesting 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.

[19] Four proxies with shorter sample coverage 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 does not include, in addition to the ones excluded in FPC10, major investment banks' excess returns, broker-dealers' asset growth rate, or broker-dealers' leverage factor.

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 trading cost.[20] 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 round-trip costs for the high-margin stocks are less than 114 bps for the 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 et al. (2012). While the actual round-trip costs could be different for various investors, our estimates still suggest that the market-based funding liquidity factor could possibly be implemented at a reasonable transaction cost.

3.2 Asset pricing implications of the FLS factor

Different from existing funding liquidity proxies, the FLS factor is traded and should help explain assets' return variations. In the previous subsection, we find that FLS is a priced factor with a positive risk premium that measures funding liquidity movement. In this subsection, we investigate the asset pricing implications of the FLS factor.

First, we examine whether the FLS factor helps explain the time-series variation for a cross-section of portfolio returns in the presence of other traded factors. Following Barillas and Shanken (2017) and Stambaugh and Yuan (2017), four pricing error measures are used for model comparison: the average absolute alpha ($A|\alpha_i|$), the average absolute t-statistic of alpha ($A|t_i|$), the average absolute alpha divided by the average absolute value of the average return deviation ($A|\alpha_i|/A|r_i|$), and the Gibbons-Ross-Shanken (GRS) statistic. We examine, after adding the FLS factor to the CAPM or the Fama-French three-factor model, whether we achieve better pricing performance for various sets of testing portfolios.

Table 4 reports the time-series test results. We use different combinations of stock portfolios as testing assets, including the 25 Fama-French size and B/M portfolios, 10 momentum portfolios, 10 industry portfolios, and 11 anomaly portfolios used in Stambaugh et al. (2012). The results in Columns 2 to 5 in panels A to C indicate that the models including the FLS have better pricing power in terms of delivering smaller average absolute alphas, smaller average absolute t-statistics of alphas, smaller average

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

Table 4
Time-series asset pricing tests of FLS using various portfolios

	Exret	Mkt	Mkt+FLS	FF3	FF3+FLS	Mkt+FMP14	FF3+FMP14
A. 25 Fama-French size and B/M portfolios							
$A\|\alpha_i\|$	8.19	3.30	2.77	1.24	1.15	6.53	4.01
$A\|t_i\|$	2.71	1.92	1.64	1.42	1.28	3.64	3.08
$A\|\alpha_i\|/A\|r_i\|$		1.45	1.22	0.55	0.50	4.01	2.46
GRS		4.46	3.79	3.67	3.19	25.46	19.51
p(GRS)		.0000	.0000	.0000	.0000	.0000	.0000
B. 25 Fama-French size and B/M + 10 momentum + 10 industry portfolios							
$A\|\alpha_i\|$	7.08	2.86	2.61	2.01	1.97	5.70	4.46
$A\|t_i\|$	2.46	1.72	1.55	1.70	1.57	3.12	2.75
$A\|\alpha_i\|/A\|r_i\|$		1.20	1.10	0.85	0.83	3.21	2.52
GRS		4.37	3.97	3.89	3.63	17.21	13.59
p(GRS)		.0000	.0000	.0000	.0000	.0000	.0000
C. 25 Fama-French size and B/M + 10 momentum + 10 industry + 11 anomalies portfolios							
$A\|\alpha_i\|$	7.06	3.94	3.77	3.33	3.26	6.40	5.55
$A\|t_i\|$	2.58	2.15	2.00	2.21	2.04	3.13	2.82
$A\|\alpha_i\|/A\|r_i\|$		1.58	1.51	1.34	1.31	3.20	2.78
GRS		5.10	4.82	4.57	4.33	14.74	11.72
p(GRS)		.0000	.0000	.0000	.0000	.0000	.0000
D. 124 multiasset class portfolios							
$A\|\alpha_i\|$	3.05	3.41	3.18	2.92	2.83	4.21	3.66
$A\|t_i\|$	1.22	1.81	1.74	1.64	1.65	2.44	2.17
$A\|\alpha_i\|/A\|r_i\|$		0.81	0.75	0.69	0.67	1.03	0.89
GRS		8.20	8.18	8.82	8.19	12.30	8.70
p(GRS)		.0000	.0000	.0000	.0000	.0000	.0000

This table presents the results of FLS' asset pricing power on stock portfolios and multiasset portfolios. Six factor models are considered: (1) the CAPM; (2) a two-factor model with the market factor and FLS; (3) the Fama-French three-factor model; (4) a four-factor model with the Fama-French three factors and FLS; (5) a two-factor model with the market factor and a mimicking portfolio (FMP14) of the first principal component of the 14 existing funding liquidity proxies (FPC14); (6) a four-factor model with the Fama-French three factors and FMP14. FMP14 is the return spread of decile 10 - decile 1 portfolios sorted by FPC14 betas estimated using 24-month rolling windows. For each model, the table reports the average absolute alpha ($A|\alpha_i|$, measured in terms of annualized percentage), the average absolute t-statistic of alphas ($A|t_i|$), the average absolute alpha over the average absolute value of the average return deviation ($A|\alpha_i|/A|r_i|$) where the average return deviation is computed as the average return on portfolio i minus the cross-sectional average of the time-series average portfolio returns, and the *GRS*-statistic and associated p-value for the Gibbons, Ross, and Shanken (1989) test. The results using four sets of testing portfolios are reported in panel A to E. Data on 25 size and B/M, 10 momentum, and 10 industry portfolios are from Ken French's website. 11 anomaly portfolios are constructed following Stambaugh et al. (2012). The 124 multiple-asset portfolios are from Zhiguo He's website.

absolute alphas over average absolute t-statistics of alphas, and smaller GRS statistics. The improvement is more evident when switching from a single-factor CAPM to a two-factor model that includes both the market factor and the FLS.

Since time-varying funding liquidity shocks are likely to affect a broad array of asset markets, we expect that FLS to be useful in explaining multiple-asset portfolios as well. We assess the pricing power of FLS on portfolios used in He et al. (2017), which span seven different markets. These include 25 equity portfolios, 20 bond portfolios, 6 sovereign bond portfolios, 18 option portfolios, 12 currency portfolios, 23 commodity portfolios, and 20 CDS portfolios.[21] Panel D of Table 4 reports the results. Similar to the stock portfolios, we find that FLS reduces pricing errors according to all criterions. For example, a model with both the market factor and the FLS reduces the average absolute alpha of the 124 portfolios from 3.41% to 3.18% compared to the CAPM. Overall, our funding liquidity factor improves the pricing efficiency for both stock portfolios and portfolios formed with other asset classes.

As a comparison, we also examine whether adding a mimicking portfolio of the first principal component of the 14 funding liquidity proxies to the CAPM or the Fama-French three-factor model helps explain assets' returns. The results in the last two columns of Table 4 suggest this is not the case. In fact, all four criterions with the mimicking portfolio worsen compared to the model without the mimicking portfolio. This finding suggests that, despite existing funding liquidity proxies' usefulness in capturing funding liquidity condition in their corresponding markets, these proxies are less helpful in explaining multiple-asset-class portfolios from a pricing perspective.

Barillas and Shanken (2017) show that different sets of testing assets could favor different traded factor models and thus conclusions of model comparison can be testing asset dependent. As a result, we need to examine whether the superior pricing power of the larger factor models that contain the FLS factor is subject to this concern. We run a what they call exclude-factor regression to conduct nested model comparison, which involves assessing whether the FLS factor can be explained by the other nested traded factors in terms of time-series alpha. A statistically significant alpha for the FLS factor in the presence of other factors suggests that a model including the new factor is more superior in explaining cross-sectional return variations, and the conclusion would be independent to the choice of testing assets. We consider 10 factor combinations as candidate right-hand side variables in the exclude-factor regression. These factors including the BAB factor, the Fama-French five factors, the Carhart momentum factor, the Amihud illiquidity factor, the short-term reversal factor, and the Q factors proposed by Hou et al. (2015). Panel A of Table 5 reports the regression results.

A few findings are worth noticing. First, all alphas after controlling for these combinations of factors are economically and statistically significant, with magnitudes ranging from 0.45% to 0.80% per month. Even though the FLS factor is derived from the BAB portfolio, the BAB factor cannot fully explain the FLS factor: the alphas are still significant with magnitudes of 0.59% (t-statistic = 2.69) and 0.45% (t-statistic = 2.23) per month, respectively, depending on whether we control for the market factor. Besides the models including the BAB factor and the market factor, the Q-factor model adjusted alpha is relatively small (0.49%, t-statistic = 2.09) compared to

[21] Returns of multiple-asset portfolios were downloaded from Zhiguo He's website.

Table 5
Time-series regressions of the traded funding liquidity measure

A. Time-series regressions of the FLS factor on common risk factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
α	0.59	0.45	0.80	0.74	0.65	0.64	0.71	0.48	0.66	0.49
	(2.69)	(2.23)	(4.49)	(4.40)	(2.91)	(2.93)	(2.89)	(1.94)	(3.73)	(2.09)
β_{bab}	0.34	0.37						0.40		
	(4.15)	(4.70)						5.57		
β_{mkt}		0.25	0.22	0.18	0.20	0.23	0.25	0.21	0.20	0.21
		(6.26)	(5.28)	(4.07)	(4.67)	(4.89)	(4.92)	(4.24)	(4.29)	(4.42)
β_{smb}				0.24	0.24	0.22	0.23	0.25	0.29	
				(4.28)	(4.21)	(3.66)	(3.71)	(4.34)	(4.94)	
β_{hml}				0.02	0.05	0.02	0.02	−0.14	0.03	
				(0.23)	(0.65)	(0.25)	(0.28)	(−2.31)	(0.29)	
β_{umd}					0.10	0.07	0.05	0.00		
					(0.93)	(0.66)	(0.43)	(−0.01)		
β_{amihud}						0.13	0.13	0.03		
						(2.52)	(2.62)	(0.84)		
β_{str}							−0.13	−0.13		
							(−1.24)	(−1.21)		
β_{rmw}									0.22	
									(2.53)	
β_{cma}									−0.03	
									(−0.18)	
β_{me}										0.31
										(5.80)
β_{ia}										0.10
										(0.80)
β_{roe}										0.24
										(1.75)
Adj. R^2	8.55	17.75	7.43	10.96	12.18	13.67	14.52	23.35	12.33	13.73

B. Time-series regressions of risk factors on FLS and MKT

	BAB	SMB	HML	UMD	Amihud	STR	RMW	CMA	ME	I/A	ROE
α	0.69	0.08	0.44	0.65	0.24	0.51	0.29	0.42	0.11	0.51	0.58
	(4.32)	(0.53)	(3.16)	(3.68)	(1.33)	(3.57)	(2.58)	(4.71)	(0.79)	(6.11)	(5.79)
β_{fls}	0.30	0.17	0.01	0.14	0.21	−0.09	0.04	−0.01	0.18	0.01	0.06
	(4.55)	(3.37)	(0.16)	(0.93)	(3.28)	(−1.52)	(1.11)	(−0.35)	(3.65)	(0.35)	(0.94)
β_{mkt}	−0.14	0.15	−0.18	−0.15	−0.30	0.23	−0.13	−0.18	0.14	−0.17	−0.12
	(−2.27)	(4.42)	(−3.48)	(−1.98)	(−6.24)	(5.29)	(−3.29)	(−5.26)	(3.98)	(−5.45)	(−2.80)
Adj. R^2	11.82	11.27	7.43	2.67	10.95	9.29	5.72	15.73	11.25	15.40	4.18

This table presents the results of time-series regressions. Panel A presents the time-series alphas, beta loadings, and adjusted R^2 when the funding liquidity shock (FLS) is regressed on commonly used traded risk factors, including 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, the short-term reversal (STR) factor, the Q factors, and the Fama-French five factors. Panel B presents the time-series alphas, beta loadings, and adjusted R^2 when various risk factors are regressed on the FLS factor and the market factor. Newey-West five-lag adjusted t-statistics are in parentheses. The sample period is January 1965 to October 2012.

other adjustments. Second, other factors have limited explanatory power for the FLS factor. All the adjusted R^2s are small with the largest one being only 23.4% (generated by a seven-factor model with the BAB factor, the Fama-French three factors, the momentum factor, the Amihud illiquidity factor, and the short-term reversal factor). Third, the FLS factor loads positively and statistically significantly on the BAB factor, the market factor, the SMB factor, the illiquidity factor, and the RMW factor. Overall, these results indicate that the FLS factor cannot be subsumed by other traded factors, thus it should extend the mean variance frontier and provide additional pricing information.

Next, we examine whether any traded factor is still informative in the presence of the FLS factor and the market factor. In panel B of Table 5, we report the results of factors regressed on the FLS factor and the market factor. The alphas of the SMB factor, the liquidity factor, and the ME factor in the *Q*-model are no longer statistically significant, whereas other factors survive with economically and statistically meaningful alphas. The findings suggest that most factors have their own pricing information in addition to the funding liquidity factor. We conclude that a model that includes the FLS factor, along with other traded factors should provide explanatory power for asset returns.

3.3 Relation to market liquidity

Brunnermeier and Pedersen (2009) show that there is a mutual reinforcement between funding liquidity tightness and market illiquidity. Using the FLS factor, we find that market liquidity and funding liquidity do move together empirically. Panel A of Table 6 reports the pairwise correlation coefficients between the FLS factor and four market liquidity measures: the returns of a long-short portfolio sorted by the Amihud illiquidity measure, the Stambaugh and Pastor (2013) market liquidity innovation measure, the variable component of Sadka (2016) market liquidity factor, and the innovation of the noise measure in Hu et al. (2013). The results show that the FLS factor is correlated with all four market liquidity measures, with positive and significant correlation coefficients ranging from 17.3% (Sadka's measure) to 24.0% (Amihud measure). These results provide supportive evidence for the comovement between market liquidity and funding liquidity.

Moreover, the comovement between market liquidity and funding liquidity should be stronger when asset markets experience negative shocks. As a result, we would expect to see asymmetric comovements between funding liquidity factor and market liquidity during up and down markets. 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 market declines. For example, the correlation coefficient between the FLS factor and the Amihud market illiquidity measure is 36.6% during negative return months in contrast to the 12.2% during positive return months. In addition, the correlation among various market liquidity proxies also increases when the market experiences negative returns. Such asymmetry complements Hameed et al. (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 in down markets.

Table 6
Pairwise correlation

A. Pairwise correlations - unconditional

	FLS	Amihud	PS	Sadka
Amihud	24.0*			
PS	17.7*	9.1*		
Sadka	17.3*	12.2*	23.1*	
HPW	17.4*	5.3	22.1*	20.2*

B. Pairwise correlations - MKT>=0

	FLS	Amihud	PS	Sadka
Amihud	14.2*			
PS	11.1*	−0.5		
Sadka	9.7	10.1	8.3	
HPW	3.5	−1.3	9.1	−0.5

C. Pairwise correlations - MKT <0

	FLS	Amihud	PS	Sadka
Amihud	36.6*			
PS	17.2*	15.2*		
Sadka	25.7*	14.8	35.2*	
HPW	28.5*	11.3	27.6*	34.0*

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 average portfolio of five BAB return spreads within low- and high-margin groups based on five margin proxies. Amihud is the long-short equity portfolio sorted by individual stocks' Amihud illiquidity measure. PS is Pastor and Stambaugh (2003) market liquidity innovation measure. Sadka is the variable component of Sadka (2006) market liquidity factor. HPW is the Hu et al. 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. $^*p < .05$.

While overlaps might exist between the informational contents captured by the FLS factor and market liquidity, we find that the FLS factor clearly contains information on funding liquidity risk that is not purely driven by market liquidity. Next, we orthogonalize the FLS factor with respect to a traded measure of market liquidity (proxied by the long-short portfolio formed on the Amihud illiquidity measure) and examine whether it still correlates with funding liquidity measures. Panel A of Table 7 reports the correlation coefficients between the market liquidity orthogonalized FLS factor ($\text{FLS}_{\perp ml}$) and 14 funding liquidity proxies. The results are quite similar: $\text{FLS}_{\perp ml}$ is positively and statistically significantly correlated with 11 of the 14 funding liquidity proxies. In panel B of Table 7, we report the time-series alpha controlling for six traded factors.[22] The $\text{FLS}_{\perp ml}$'s alpha is 0.17% per month and significant with a *t*-statistic of 1.81. The decrease in the

[22] We do not include the long-short portfolio formed on the Amihud measure as an additional factor because the residual FLS is orthogonal to the Amihud measure sorted long-short portfolio by construction.

Table 7

Correlation and time-series regressions: Market liquidity effect

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
$FLS_{\perp ml}$	12.3*	13.2*	40.0*	22.8*	25.9*	43.9*	30.0*	−2.9	−8.7	17.3*	17.0*	16.1*	−6.5	26.8*
FLS_{single}	−4.95	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*

B. Time-series regressions

	α	β_{bab}	β_{mkt}	β_{smb}	β_{hml}	β_{umd}	β_{amihud}	β_{str}	Adj. R^2 (%)
$FLS_{\perp ml}$	0.17	0.00	0.25	0.23	0.02	0.05	–	−0.32	19.63
	(1.81)	(5.63)	(3.95)	(−0.60)	(−2.72)	(0.02)	–	(−1.47)	
FLS_{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)	

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. FLS_{single} is the average of the five long-short portfolios sorted by margin proxies. Panel A reports the correlation coefficients between $FLS_{\perp ml}$/FLS_{single} and 14 funding liquidity proxies. *$p < .05$. Panel B reports the results of time-series regressions where $FLS_{\perp ml}$/FLS_{single} 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.

magnitude of the alpha suggests that part of funding liquidity risk premium may also result from bearing some market liquidity risk.

Because the construction of the FLS factor 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 an average portfolio that is constructed based on our five margin proxies. The portfolio is designed to capture the margin-proxy spread. Specifically, for each margin proxy, we construct a simple long-short portfolio according to quintile portfolio sorting. We take an average portfolio of the five long-short portfolios as an alternative funding liquidity measure and denote it by FLS_{single}. If the FLS factor captures the market liquidity instead of funding liquidity, we expect the results to be similar if we replace FLS with FLS_{single}. It is not the case. The FLS_{single} is only statistically significantly correlated with 5 of the 14 funding liquidity proxies with moderate magnitude, as shown in panel A of Table 7. Moreover, the risk-adjusted alpha of FLS_{single} is only -0.07% per month with a t-statistic of -0.72; common risk factors explain 94.8% of the time-series variations of FLS_{single} (panel B of Table 7). The results indicate that portfolios sorted only by the margin proxies provide limited information on the funding liquidity condition, even though these proxies per se may be related to market liquidity.

In sum, our findings indicate that even though market liquidity and funding liquidity are closely related, they are not the same. The FLS factor is more likely to capture the time variation in funding liquidity, not the market liquidity.

3.4 Additional discussions

We also examine whether the properties of the FLS factor are robust to alternative specifications. First, the ability of the FLS factor in capturing funding liquidity shock is not driven by the effect of size, which is known to be an important characteristic that could affect various types of portfolios' returns. We find that the FLS factor still captures funding liquidity shocks after we orthogonalize the margin proxies used in the FLS construction with respect to size. Second, to rule out the possibility of finer sorting on market beta in our double-sort procedure, we use the margin proxies orthogonalized with respect to market beta in the first-step sorting, and the FLS factor constructed from these adjusted margin proxies remains correlated with funding liquidity proxies. Last, our results are not driven by different levels of beta spreads ($\frac{\beta_H-\beta_L}{\beta_H\beta_L}$) across margin groups. We provide the detailed results and discussions in Appendix C.2.

Because the five margin proxies are also commonly used as proxies for limits to arbitrage, we examine whether our construction procedure for the funding liquidity measure results in a measure for capturing time-varying levels of limits to arbitrage. Specifically, we use the average portfolios of other anomaly spreads instead of BAB spreads across different stock characteristics groups as an alternative measure. As expected, while the average portfolios of other anomaly spreads exhibit monotonically increasing returns across the characteristics groups (possibly reflecting different levels of limits to arbitrage), they are not correlated with the 14 funding liquidity measures, thus they do not capture funding liquidity conditions. Appendix C.3 presents the results.

4. 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. The proposed funding liquidity factor is constructed as 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. We find that our traded funding liquidity factor is highly correlated with existing funding liquidity measures and earns a positive risk premium.

Moreover, the FLS factor provides additional cross-sectional pricing power for stock and multiple-asset portfolios in the presence of the market factor or the Fama-French three factors. The FLS factor cannot be absorbed by other traded factors in the time-series regression, suggesting that a pricing model that includes the FLS factor is more superior.

Lastly, although we find a close empirical relation between market liquidity and funding liquidity, the proposed funding liquidity factor and the associated risk premium are not purely driven by market liquidity movement, suggesting that funding liquidity risk contains additional information about the well-documented market liquidity risk.

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Appendix A. Mathematics Appendix

A.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 like in Equation (2), we have two Lagrange problems:

$$L_t^A = \omega_t^{A\prime} E_t[R_{t+1}^n] - \frac{\gamma^A}{2}\omega_t^{A\prime}\Omega\omega_t^A.$$

$$L_t^B = \omega_t^{B\prime} E_t[R_{t+1}^n] - \frac{\gamma^B}{2}\omega_t^{B\prime}\Omega\omega_t^B - \eta_t(\tilde{m}_t{}'\omega_t^B - 1).$$

(A10) 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. ■

A.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:

$$\left(\frac{\rho_A}{\gamma_A} + \frac{1-\rho_A}{\gamma_B}\right) E_t[R_{t+1}^n] = \Omega_R X + \frac{1-\rho_A}{\gamma_B}\eta_t\tilde{m}_t.$$

$$\frac{1}{\gamma}X' E_t[R_{t+1}^n] = X'\Omega_R X + \frac{1-\rho_A}{\gamma_B}\eta_t X'\tilde{m}_t.$$

$$(E_t[R_{M,t+1}] - r_f) = \gamma VAR(R_M) + \gamma\frac{1-\rho_A}{\gamma_B}\eta_t X'\tilde{m}_t.$$

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

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

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, that is, $\tilde{m}_t = \hat{m}_t$, we have the expression in Lemma 2. ■

A.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 $\hat{m}_{BAB,t}$:

$$\begin{aligned} E_t[R_{t+1}^{BAB}] &= \frac{E_t[R_{L,t+1}] - r_f}{\beta_L} - \frac{E_t[R_{H,t+1}] - r_f}{\beta_H} \\ &= E_t[R_{M,t+1}] - r_f + \psi_t \frac{\hat{m}_{BAB,t}}{\beta_L} - \psi_t \hat{m}_{M,t} - \left(E_t[R_{M,t+1}] - r_f + \psi_t \frac{\hat{m}_{BAB,t}}{\beta_H} - \psi_t \hat{m}_{M,t}\right) \\ &= \frac{\beta_H - \beta_L}{\beta_H \beta_L} \hat{m}_{BAB,t} \psi_t. \blacksquare \end{aligned}$$

A.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 premiums 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. ■

Appendix B. Construction of Funding Liquidity Proxies

We construct 14 funding liquidity measures using the following previous papers.

Broker-dealers' asset growth rate (Asset growth): The quarterly growth rate of total financial assets. 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 a 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 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, and 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 and 6999, and 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 obtain the hedge fund leverage data from the authors of Ang et al. (2011). Details for this data can be found in their paper. 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 data set. The sample period is 1990:Q2–2013:Q1.

Swap Treasury-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 3-month Treasury bills. 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 3-month eurodollar deposits yield (LIBOR) and 3-month U.S. Treasury bills. LIBOR and Treasury-bill 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 Treasury bills. 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 because of the unavailability of VIX). We obtain the data from CBOE. The sample period is 1986:M1–2013:M4.

Appendix C. Additional Results

C.1 Predictability Tests of FLS

The proposed traded funding liquidity shock (FLS) is the return difference of two "betting-against-beta" portfolios within high margin and low margin stocks. When funding liquidity tightens, the expected return difference of these BAB portfolios should increase, which leads to negative realized returns for the FLS factor. As a result, we expect to see that changes in funding liquidity measures result in negative realized FLS returns while lagged funding liquidity measures predict positive future FLS returns.

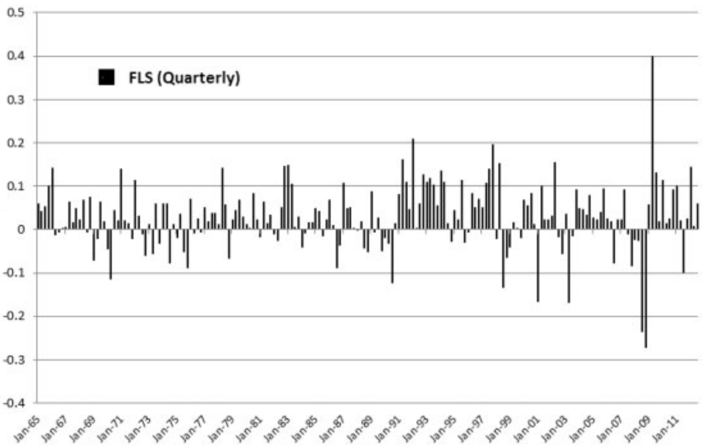

Figure A1
Time series of the extracted funding liquidity shocks (quarterly)
The figure presents quarterly time series of the funding liquidity measure. Small values indicate tight funding conditions. The sample period is from 1965:Q1 to 2012:Q3.

We test this conjecture by running time-series predictive regressions of the FLS factor on various funding liquidity measures. We consider those funding liquidity measures, frequently used in other studies, which have monthly frequency and full sample coverage for the sample period of March 1986 to October 2012. This leaves us with five funding liquidity measures, that is, the TED spread, credit spread, term spread, VIX, and financial sector's market leverage. All measures are signed so that increasing levels indicate tighter funding condition.

Panel A of Table A3 reports the regression results of FLS returns on contemporaneous change in funding liquidity measures. All coefficients, except for the one for term spread, are negative. The coefficients are statistically significant for credit spread, VIX, and financial sector leverage. The finding of FLS' negative coefficients on contemporaneous change in funding liquidity measures is intuitive: when funding conditions are tight, the realized returns of FLS are negative as the expected returns should be higher given that FLS is a good measure of funding liquidity shock.

In panel B of Table A3, we present the results of including both the contemporaneous change and the lagged funding liquidity measure as explanatory variables in the regressions. Again, all coefficients, except for the one for term spread, are negative and significant. While we expect that lagged funding condition predicts positive future FLS returns, only the coefficient of term spread is positive and statistically significant. Overall, our findings suggest that a contemporaneous increase in funding tightness results in negative realized FLS returns, however the predictability of the lagged funding condition on future FLS returns is unclear.

C.2 Other Specifications of Margin Proxies

We explore whether our funding liquidity construction is robust to other specifications of margin proxies. First, size seems to be the most important proxy in explaining the cross-section of stocks' marginability in terms of pseudo R^2 and all the other margin proxies are closely related to size. To control for the size effect, we orthogonalize three other margin proxies (idiosyncratic volatility, the Amihud illiquidity measure, and institutional ownership) with respect to market capitalization and use the regression residuals as margin proxies to construct the size-orthoganlized funding liquidity measure $\text{FLS}_{\perp size}$. We do not include the analyst coverage proxy as it has limited cross-sectional variation. The correlation coefficients and time-series regression results are reported in Table A4. $\text{FLS}_{\perp size}$ is significantly correlated with 9 of the 14 funding liquidity proxies. The seven-factor alpha is 0.62% (t-statistic = 2.91) and the adjusted R^2 of the time-series regression is only

Table A1
Characteristics of BAB portfolios

	1 (Low)	2	3	4	5 (High)	Diff
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)
B. Average number of stocks)						
Size	295	337	417	601	2,346	
σ_{ang}	490	445	519	703	1,838	
Amihud	306	340	405	533	2,052	
Inst.	436	444	514	713	2,242	
Analyst	399	536	985	521	2,130	
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	
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	

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.

8.34%. The findings suggest that the properties of being a valid funding liquidity factor remain after controlling for the size effect.

Second, the chosen margin proxies might be related to the market betas of stocks. Therefore, a 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 in the cross-section. Again, we do not include analyst coverage proxy for the same reason as above. Table A4 shows that the beta-orthogonalized $FLS_{\perp beta}$ is significantly correlated with 11 of the 14 funding liquidity proxies and cannot be explained by other risk factors (alpha = 0.69% and t-statistic = 4.02).

Third, our results are not driven by different beta spreads $\frac{\beta_H-\beta_L}{\beta_H\beta_L}$ across margin groups. We adjust the returns of each BAB portfolio by dividing its beta spread $\frac{\beta_H-\beta_L}{\beta_H\beta_L}$. $FLS_{\Delta beta}$ is the average portfolio of the five adjusted BAB spreads between the high- and low-margin stocks. We find that $FLS_{\Delta beta}$ is still significantly correlated with 9 of the 14 funding liquidity proxies. The time-series alpha of $FLS_{\Delta beta}$ is 0.67% per month (t-statistic = 1.70) and the adjusted R^2 is 23.89%.

Table A2

Correlation between the extracted funding liquidity shock and existing 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*

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.

*p <.05.

Table A3
Predictive regressions of FLS

A. ΔFL

	TED spread	*Credit spread*	*Term spread*	*VIX*	*Finnancial leverage*
ΔFL	−0.017	−0.030	0.005	−0.002	−0.012
	(−1.351)	(−1.774)	(0.381)	(−2.984)	(−4.009)
Constant	0.010	0.010	0.010	0.010	0.010
	(3.324)	(3.471)	(3.308)	(3.428)	(3.635)
Adj. R^2	0.006	0.023	−0.002	0.036	0.070
No. obs	321	321	321	321	321

B. ΔFL and lagged FL

	TED spread	Credit spread	Term spread	VIX	Finnancial leverage
ΔFL	−0.029	−0.036	0.007	−0.002	−0.012
	(−2.22)	(−2.061)	(0.587)	(−3.899)	(−4.018)
Lagged FL	−0.024	−0.011	0.005	−0.001	0.000
	(−2.523)	(−0.723)	(2.068)	(−2.052)	(−0.347)
Constant	0.025	0.021	0.001	0.035	0.012
	(4.399)	(1.511)	(0.202)	(3.221)	(1.84)
Adj. R^2	0.061	0.031	0.012	0.074	0.068
No. obs	321	321	321	321	321

This table presents the results of time-series predictive regressions of the FLS returns on other funding liquidity measures. The FLS is the average portfolio of five BAB spread portfolios that are constructed within high- and low-margin stocks according to five margin proxies. Funding liquidity measures include TED spread, credit spread, term spread, VIX, and financial sector's total market leverage. Panel A reports the regression results of FLS returns on contemporaneous change in funding liquidity measures. Panel B reports the regression results of FLS returns on contemporaneous change in funding liquidity measures and lagged funding liquidity measures. Newey-West four-lag adjusted t-statistics are in parentheses. The sample period is from February 1986 to October 2012.

In summary, our FLS factor is robust to alternative specifications and captures time-varying funding liquidity risk.

C.3 Discussions on Limits to Arbitrage

The five stock characteristics that we use as margin proxies are sometimes also used as proxies for limits to arbitrage. Some researchers argue that the high-beta low-return relation also could be an anomaly caused by investors' behavioral bias, such as reference-dependent preference (Wang et al. 2017) or demand for lottery stocks (Bali et al. 2017). Therefore, the high return of the BAB portfolio within high-margin, also possibly difficult to arbitrage, stocks could be a natural result due to the stronger effects of limits to arbitrage. Moreover, the time-series variation in the BAB portfolio might only reflect the time-varying degree of limits to arbitrage instead of the movement of funding liquidity. In this section, we examine whether the double-sort factor construction produces solely an alternative limits-to-arbitrage measure.

To do so, we form long-short portfolios of anomalies, in place of BAB portfolios, within different margin proxy groups. As anomaly effects are stronger within high limit-to-arbitrage stocks, we expect that anomaly returns are larger in small, large volatility, low liquidity, low institutional ownership, and low analyst coverage stocks. On the other hand, the return difference of two anomaly portfolios across low and high limit-to-arbitrage stocks is not supposed to comove with funding liquidity measures as time-series variations in those anomaly spreads are less clearly related to funding liquidity compared to the BAB strategy.

Twelve anomalies are considered following Stambaugh et al. 2015, including financial distress, Ohlson's score, net stock issues, composite equity issues, total accruals, net operating assets, past

Table A4

Correlation and time-series regressions: Other specifications

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
$FLS_{\perp size}$	14.3*	9.3	25.1*	19.7*	19.8*	36.2*	16.4*	4.0	−4.4	19.5*	16.2	12.3*	−3.3	14.5*
$FLS_{\perp beta}$	12.2*	14.7*	42.9*	16.9*	27.9*	45.4*	25.7*	0.7	−5.6	18.2*	23.8*	15.4*	3.28	21.2*
$FLS_{\Delta beta}$	10.9*	8.2	28.4*	21.6*	30.9*	−5.2	38.6*	−4.2	−7.6	17.0*	−5.2	14.0*	−11.6*	29.6*

B. Time-series regressions

	α	β_{bab}	β_{mkt}	β_{smb}	β_{hml}	β_{umd}	β_{amihud}	β_{str}	Adj. R^2 (%)
$FLS_{\perp size}$	0.62	0.00	0.21	0.06	0.02	0.02	0.11	−0.12	8.34
	(2.91)	(-2.45)	(4.87)	(0.96)	(0.26)	(0.22)	(2.62)	(-1.42)	
$FLS_{\perp beta}$	0.69	0.00	0.27	0.20	0.07	0.14	0.13	0.01	20.75
	(4.02)	(-0.26)	(6.04)	(3.52)	(1.28)	(2.13)	(2.99)	(0.10)	
$FLS_{\Delta beta}$	0.67	0.00	0.38	0.65	−0.36	0.04	0.03	−0.19	23.89
	(1.70)	(0.35)	(4.13)	(6.43)	(-3.02)	(0.21)	(0.39)	(-1.08)	

This table presents the results for three funding liquidity measures constructed using other specifications. $FLS_{\perp size}$ is the average return difference between high- and low-margin BAB portfolios, where stocks are sorted into high- and low-margin groups according to the three size-orthogonalized margin proxies, including idiosyncratic volatility, the Amihud illiquidity measure, and the institutional ownership. $FLS_{\perp beta}$ is the average return difference between high- and low-margin BAB portfolios, where stocks are sorted into high- and low-margin groups according to the beta-orthogonalized margin proxies. $FLS_{\Delta beta}$ is the average adjusted return difference 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. Panel A reports the correlation coefficients between various specifications of FLS and 14 funding liquidity proxies. *$p<.05$. 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.

Table A5
Anomaly portfolio performance conditional on margin requirements

	1 (Low)	2	3	4	5 (High)	Diff
Distress	0.20	0.39	0.59	0.70	1.28	1.07
	(1.22)	(2.21)	(3.36)	(3.57)	(6.71)	(7.06)
O score	0.29	0.21	0.37	0.57	0.34	0.06
	(2.21)	(1.65)	(2.34)	(3.16)	(1.68)	(0.26)
NSI	0.42	0.45	0.46	0.58	0.73	0.31
	(4.23)	(4.56)	(4.40)	(4.6)	(4.82)	(2.72)
CEI	0.31	0.32	0.37	0.38	0.53	0.22
	(3.05)	(3.44)	(3.77)	(3.53)	(4.26)	(2.22)
Accrual	0.16	0.21	0.33	0.39	0.47	0.32
	(2.10)	(2.8)	(4.13)	(4.71)	(5.22)	(3.31)
NOA	0.39	0.45	0.49	0.51	0.82	0.42
	(4.52)	(4.42)	(4.05)	(3.98)	(5.76)	(3.28)
Momentum	0.24	0.46	0.69	0.96	0.43	0.19
	(1.25)	(2.34)	(3.51)	(4.57)	(1.81)	(1.20)
GP	0.25	0.28	0.33	0.36	0.43	0.18
	(2.15)	(2.20)	(2.70)	(2.88)	(3.58)	(1.24)
AG	0.35	0.35	0.49	0.63	1.27	0.92
	(2.91)	(2.98)	(4.29)	(5.05)	(7.36)	(4.33)
ROA	0.41	0.56	0.77	0.91	0.82	0.41
	(2.43)	(3.07)	(4.07)	(4.04)	(3.04)	(2.05)
IA	0.15	0.24	0.17	0.22	0.34	0.18
	(2.28)	(3.49)	(2.50)	(2.99)	(3.67)	(2.06)
BM	0.20	0.39	0.59	0.70	1.28	1.07
	(1.22)	(2.21)	(3.36)	(3.57)	(6.71)	(7.06)

This table presents average portfolio returns of 12 long-short anomalies conditional on five margin proxies. 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. Average anomaly returns across five margin proxies for 12 anomalies are calculated and "Diff" indicates the return difference between two long-short anomaly portfolios constructed with high-margin and low-margin stocks. Anomalies include financial distress, Ohlson's score, net stock issues (NSI), composite equity issues (CEI), total accruals, net operating assets (NOA), past 12-month momentum, gross profitability (GP), asset growth (AG), return-on-assets (ROA), investment-to-assets (IA), and book-to-market ratio (BM). Monthly excess returns are reported with Newey-West five-lag adjusted t-statistics in parentheses.

12-month momentum, gross profitability, asset growth, return-on-assets, investment-to-assets, and book-to-market ratio. Table A5 reports the average anomaly returns across five stock characteristics within different margin (or limits-to-arbitrage) groups. Except for the O score, momentum, and gross profitability, all other anomalies exhibit monotonic increasing returns from low to high limit-to-arbitrage groups and the return difference is statistically significant.

However, the results in Table A6 show that correlation coefficients between existing funding liquidity measures and the 12 anomaly return spreads are not significant with the correct sign. Among the 12 anomalies, the average return spreads have statistically significant correlation with zero (O score, composite equity issues, net operating assets, momentum, book-to-market ratio) to at most 4 (asset growth) of the 14 funding liquidity measures.

Taking all findings together, the time-varying FLS factor is more likely to be driven by the market-wide funding liquidity shocks due to investors' leverage constraints than by other sources related to limits to arbitrage.

Table A6

Correlation between anomaly spreads and funding liquidity measures

	Asset growth	Bond liquidity	CDS	Credit spread	Financial leverage	HF leverage	IB exret	Broker leverage	LIBOR	Loan	Swap spread	TED spread	Term spread	VIX
Distress	−1.3	−2.7	2.9	−8.4	14.0*	−22.8	1.8	3.7	−7.7	−3.2	−9.1	−14.0	9.4	5.5
O score	−3.3	−8.9	−21.0	−12.6	−10.3	−28.8	−23.1	8.4	−10.8	−7.3	−14.3	−22.0	10.4	−11.5
NSI	8.8	−12.7	−22.0	−12.4	−5.8	−23.6	−20.7	15.7*	−9.2	−7.3	−8.7	−16.8	12.8*	−16.8
CEI	0.9	−8.6	−16.4	−5.2	−9.9	−13.0	−15.5	5.6	−8.3	−12.3	−13.1	−15.4	5.6	−10.7
Accrual	4.4	6.8	10.0	10.1	8.7	0.1	20.6*	−0.5	−4.7	−5.3	−4.1	5.3	−6.3	14.9*
NOA	−2.4	−6.3	−11.5	−3.5	−27.1	−17.2	−13.7	−11.0	6.6	−8.4	11.5	4.7	3.9	−9.8
Momentum	8.4	−7.2	9.3	−2.2	−0.4	−24.0	−8.1	9.1	−9.6	3.1	−7.2	−12.5	8.8	0.2
GP	−1.0	7.5	11.4	3.8	19.8*	19.5	16.7*	7.3	−4.7	−0.5	−16.5	−4.6	−0.7	10.9
AG	1.2	0.6	12.0	16.6*	6.5	16.0	23.6*	−12.7	7.5	1.2	1.2	17.0*	−4.5	14.8*
ROA	8.7	−6.4	−2.8	−10.9	−0.3	−13.7	−16.0	11.5*	−12.0	0.9	−3.0	−13.5	9.0	−2.2
IA	1.1	−0.8	7.8	10.6	0.8	29.4*	11.2*	−3.3	7.8	−7.8	8.9	16.8*	−3.5	10.1
BM	10.9	−5.4	−14.8	1.2	−19.1	−9.9	−16.2	1.5	−9.3	7.9	−5.2	0.1	2.4	−15.6

This table presents the correlation between 12 anomaly spreads across low- and high-margin stocks and 14 funding liquidity measures. Anomalies include financial distress, Ohlson's score, net stock issues (NSI), composite equity issues (CEI), total accruals, net operating assets (NOA), past 12-month momentum, gross profitability (GP), asset growth (AG), return-on-assets (ROA), investment-to-assets (IA), and book-to-market ratio (BM). Anomaly spreads are the return differences of average anomaly returns across five margin proxies. Correlation coefficients are reported with positive value. *$p < .05$. The sample period is March 1986 to October 2012.