# A Market-Based Funding Liquidity Measure

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First draft: June 2013
This draft: May 2014

**Abstract**

In this paper, we construct a tradable funding liquidity measure from stock returns. Using a stylized model, we show that the returns of a beta-neutral portfolio, which exploits investors' borrowing constraints (Black (1972)), depend on both the market-wide funding liquidity shock and stocks' sensitivities to such shock, where the latter are governed by margin requirements. We extract the funding liquidity shock as the return spread between two beta-neutral portfolios constructed using stocks with high and low margins. Our return-based measure is correlated with funding liquidity proxies derived from other markets but has the benefit of being tradable. It delivers a positive risk premium, which cannot be explained by existing risk factors. Using our measure, we find that while hedge funds in general are inversely affected by funding liquidity shocks, some funds exhibit funding liquidity management skill and thus earn higher returns. In addition, adverse shocks affect the real economy by lowering investment.

*JEL Classification*: G10, G11, G23
*Keywords*: Funding liquidity, Leverage, Margin requirements

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# 1 Introduction

Since the 2007-2009 financial crisis, financial frictions are understood to be an important factor in determining asset prices. Researchers have done tremendous work on the relation between market frictions and risk premia, including restricted borrowing (Black (1972)), limits of arbitrage (Shleifer and Vishny (1997)), and an intermediary's capital constraint (He and Krishnamurthy (2013)). Brunnermeier and Pedersen (2009) model market liquidity and funding liquidity jointly through the channel of margin requirements.[1] Garleanu and Pedersen (2011) present a model in which constraints on investors' ability to take on leverage (funding liquidity constraints) affect equilibrium prices. Empirically, researchers have explored many proxies for funding liquidity, such as the difference between three-month Treasury-bill rate and the three-month LIBOR (TED spread), market volatility (measured by, for example, the VIX), and broker-dealers' asset growth. However, there is no single agreed upon measure of funding liquidity. In this paper, we construct a theoretically motivated measure of funding liquidity using both the time series and cross-section of stock returns, as well as study its attributes. Our measure is most closely related to the "betting against beta" (BAB) factor of Frazzini and Pedersen (2014). Frazzini and Pedersen develop a theoretical model in which the leverage constraints of investors are reflected in the return spread between leveraged low-beta stocks and de-leveraged high-beta stocks. They empirically demonstrate that a BAB portfolio has a high Sharpe ratio and highly significant risk-adjusted returns, which compensate for the shadow cost of leverage constraints. One shortcoming however with their BAB factor is that it appears uncorrelated with other possible proxies for funding liquidity. Although it is possible that this finding indicates that other proxies do not pick up the market-wide funding liquidity while the BAB factor does, this seems unlikely.

[1]Market liquidity refers to how easily an asset can be traded, while funding liquidity refers to the ease with which investors can finance their positions.

We show that the time variation in a BAB factor depends on both the market-wide funding condition and an asset's sensitivity to the funding condition, where the latter is governed by margin requirements. We isolate funding liquidity shocks using the return difference of a BAB portfolio that is constructed with high-margin stocks and a BAB portfolio that is constructed with low-margin stocks, where a BAB portfolio itself captures the return difference between low-beta and high-beta stocks. Our methodology has three advantages. First, taking the return difference between two BAB portfolios enables us to smooth out the possible time variation in margins and maintain time-varying funding liquidity shocks. Second, empirically it is possible that the returns of a BAB portfolio also depend on other omitted factors. We can mitigate the impacts of such noise with a difference-in-BAB approach. Third, because our measure is constructed from stock returns and thus has the benefit of being tradable, it could be used to hedge against funding liquidity risk and to understand stock market anomalies. We believe that our measure captures underlying funding liquidity shocks since correlations between our measure and other possible funding liquidity proxies are high. We observe positive relations between our funding liquidity measure and market liquidity proxies, and such positive correlations are higher during declining markets, supporting the liquidity spiral story. In addition, we use the funding liquidity measure to examine hedge fund performance and find different implications on the time series and cross-section of hedge fund returns. In the time series, a one standard deviation shock to funding liquidity results in a 2% per year decline in the aggregate hedge fund return. In the cross-section, funds with small sensitivities to our funding liquidity measure outperform those with large sensitivities by 10.7% per year. This performance difference could possibly be due to the actively managed nature of hedge funds: some fund managers have the ability to manage funding liquidity risk and thus earn higher returns. We also examine the relation between funding liquidity risk and the real economy and find that adverse funding liquidity shocks lead to less private fixed investment in the future.

The construction of our funding liquidity measure is guided by a simple model with both leverage constraints (Black (1972); Frazzini and Pedersen (2014)) and asset-specific margin constraints (Garleanu and Pedersen (2011)). The reduced form of the model is in line with the margin-based capital asset pricing model (CAPM) (Ashcraft, Garleanu, and Pedersen (2010)): borrowing-constrained investors are willing to pay a higher price for large market-exposure stocks for their embedded leverage, and this effect is stronger for stocks with higher margin requirements because they are more difficult to lever. As a direct model extension, a market-neutral BAB portfolio should have higher returns when it is constructed over stocks with higher margins. Moreover, our model shows how a difference-in-BAB method enables us to isolate funding liquidity shocks from the impact of time-varying margins, which also contribute to the observed BAB returns.

Due to the lack of margin data for individual stocks, we adopt five proxies for margin requirements: size, idiosyncratic volatility, the Amihud illiquidity measure, institutional ownership, and analyst coverage. The selection of these proxies is based on real world margin rules and theoretical prediction of margin's determinants. We choose size because brokers typically set a higher margin for small stocks. The brokerage firm Interactive Brokers, for example, sets 100% initial margins for stocks with less than $250 million in market capitalization. On the theory side, Brunnermeier and Pedersen (2009) suggest that price volatility and market illiquidity may have a positive impact on margins. We measure price volatility using *idiosyncratic* volatility instead of *total* volatility to minimize the impact of the market beta as the construction of a BAB portfolio involves sorting stocks based on the market beta. The market illiquidity of stocks is measured with the commonly-used Amihud measure, as well as institutional ownership and analyst coverage. Researchers have found that stocks with less institutional ownership (Gompers and Metrick (2001); Rubin (2007); Blume and Keim (2012)) or less analyst coverage (Irvine (2003); Roulstone(2003)) are less liquid. While not perfect, our five proxies capture the determinants of stocks' margins to some extent.

We first sort all the AMEX, NASDAQ, and NYSE stocks into five groups based on their margin proxies. Within each margin group, we further sort stocks into two groups with high and low market betas. The BAB portfolio is then constructed by taking a long position in leveraged low-beta stocks and a short position in de-leveraged high-beta stocks such that the portfolio has a beta of zero. We find that the BAB premium decreases as we move from high-margin stocks to low-margin stocks. The monthly return difference between two BAB portfolios constructed over stocks with the highest and lowest margins using different proxies ranges from 0.62% (the Amihud measure), to 1.21% (idiosyncratic volatility). The finding supports our model's prediction that borrowing-constrained investors are willing to pay an even higher price for the embedded leverage of high-beta stocks if those stocks are more difficult to lever.

Our extracted funding liquidity factor is significantly correlated with 11 of the 14 funding liquidity proxies used in the literature (see Appendix A.1 for a list of the 14 proxies). In contrast, a simple BAB factor is significantly correlated with only two proxies. While our tradable factor is constructed from stock returns, it cannot be absorbed by many other known risk factors, including the Fama-French three factors, Carhart's momentum factor, the market liquidity factor, the short-term reversal factor, and the BAB factor. In addition, our funding liquidity factor helps to explain both the size premium and the market liquidity premium. We also find positive correlations between our extracted funding liquidity measure and market liquidity proxies, especially during periods with negative market returns, supporting our theoretical prediction of a close relation between funding liquidity and market liquidity. These results indicate that our measure is likely to capture the market-wide funding liquidity condition.

Having validated our funding liquidity measure, we investigate its asset pricing implications using hedge funds as testing assets. We analyze hedge funds for two reasons. First, as major users of leverage (Ang, Gorovyy, and van Inwegen (2011)), their returns are expected to be more subject to funding liquidity shocks than other asset classes (Mitchell and Pulvino (2012)). Time series regressions validate our conjecture. Using hedge fund return indices from Hedge Fund Research, Inc., we find that the Fund Weighted Composite Index (FWCI) has a positive beta loading on our funding liquidity measure ($t$-statistic=2.03), after controlling for the market factor. This magnitude of loading implies a 2% per year decline in the aggregate hedge fund return when a one standard deviation funding liquidity shock hits. Second, one feature that differentiates hedge funds from other asset classes is that they are managed portfolios. Fund managers can change their holdings' exposures to funding liquidity risk and therefore the funds might exhibit option-like non-linear exposures (Glosten and Jagannthan (1994)). In the cross-section, we find that funds with small sensitivities to funding liquidity shocks outperform those with large sensitivities by 10.7% per year. The return spread could be explained by low-sensitivity funds' ability to manage funding liquidity risk: they reduce their exposures during bad funding periods, resulting in even larger outperformance during those periods.

Finally, we discuss the relation between financial market funding liquidity and the real economy. Funding liquidity matters because it affects financial assets, and it could have a real impact on macroeconomic fluctuations. We find that our funding liquidity measure can be used to predict private investment for up to two years: adverse funding shocks lead to less investment in the future. To understand the sources of funding liquidity risk, we identify several systemic risk measures (Giglio, Kelly, and Pruitt (2013)) that might result in the tightening of market-wide funding liquidity. Our findings suggest that there seems to have interactions between the funding liquidity risk and real economic activities.

The rest of the paper is organized as follows. In Section 2, we review the related literature. In Section 3, we present a stylized model that guides the construction of our funding liquidity measure. We test the model's predictions in Section 4. We construct the measure and study its properties in Section 5. In Section 6, we examine how the measure helps to explain hedge fund returns in both the time series and cross-section. In Section 7, we discuss the relation between funding liquidity risk and the real economy. We conclude in Section 8. Data details are in Appendix A. All proofs are in Appendix B. Additional tables are in Appendix C.

# 2 Literature Review

Our paper is related to several strands of literature. First, it is related to the burgeoning research on funding liquidity and its implications for financial markets. On the theoretical side, Black (1972) shows that restricted borrowing could cause distortion of the risk-return relationship of assets and the empirical failure of the CAPM. Shleifer and Vishny (1997) show how the shortage of arbitrageurs' capital may lead to a price deviation far from an asset's fundamental value. More recently, Brunnermeier and Pedersen (2009) model the reinforcement between market liquidity and funding liquidity. Garleanu and Pedersen (2011) derive a margin-based CAPM in which an asset's expected return depends on both the market beta and the margin requirement. He and Krishnamurthy (2013) model a financial intermediary's equity capital constraint and study its implication on risk premia.[2] Many researchers provide empirical evidence for theoretical predictions. Some examine the implications of leverage constraints by studying the low-beta anomaly: Frazzini and Pedersen (2014) find that a market-neutral BAB portfolio earns a positive significant premium across various markets and asset classes; Malkhozov et al. (2014) find that the BAB premium is larger if the portfolio is constructed using illiquid stocks and in high illiquidity countries; Huang, Lou, and Polk (2014) link the time variation of the BAB returns with arbitrageurs'

[2]Other theoretical papers include Gromb and Vayanos (2002), Geanakoplos (2003), Ashcraft, Garleanu, and Pedersen (2010), Acharya and Viswanathan (2011), Chabakauri (2013), and Rytchkov (2014).

trading activities. Comerton-Forde et al. (2010) find supportive evidence for liquidity spirals using data on market-makers' inventories and trading revenues. Adrian, Etula, and Muir (2013) find that a single financial intermediary leverage factor has an extraordinary cross-sectional pricing power over multiple sets of assets. Recent papers that emphasize Treasury bond illiquidity and its impact on asset prices include Goyenko (2013), Hu, Pan, and Wang (2013), and Goyenko and Sarkissian (2014). To the best of our knowledge, we are the first to measure the market-wide funding liquidity shocks from both the time series and cross-section of stock returns.[3] By investigating stock market reactions as funding conditions change, we provide a return-based tradable measure of funding liquidity, and study its implications on financial markets.

Second, our paper furthers the debates on the risk-return relation in the presence of market frictions. Several explanations have been proposed for the empirical failure of the CAPM (Black, Jensen, and Scholes (1972)), including restricted borrowing (Black (1972); Frazzini and Pedersen (2014)), investors' disagreement and short-sales constraints (Miller (1977); Hong and Sraer (2012)), limited participation due to incomplete information (Merton (1987)), and fund managers' benchmark behavior (Brennan (1993)). Our empirical evidence supports the theoretical prediction that investors' funding constraints can distort the risk-return relation and affect asset prices. Moreover, we propose an approach to extract unobserved market-wide funding liquidity from observed asset price dynamics. On the other hand, those studies complement ours in the sense that disagreement and incomplete information are likely to be more severe during periods with tight funding liquidity.

Finally, our study contributes to the literature that examines the impact of liquidity on hedge fund performance. Some researchers (Sadka (2010); Hu, Pan, and Wang (2013))

[3]Adrian and Shin (2010) use broker-dealers' asset growth to measure market level leverage. Nagel (2012) shows that the returns of short-term reversal strategies can be interpreted as expected returns for liquidity provision. Lee (2013) uses the correlation difference between small and large stocks with respect to the market as a proxy for funding liquidity. Other studies include Boudt, Paulus, and Rosenthal (2012), Acharya, Lochstoer, and Ramadorai (2013), and Drehmann and Nikolaou (2013).

find that market liquidity is an important risk factor that affects hedge fund returns and funds with larger exposures to market liquidity earn higher returns. Others (Aragon (2007); Teo (2011); Ben-David, Franzoni, and Moussawi (2012); Mitchell and Pulvino (2012)) focus on how hedge fund performance and trading activities are affected by fund redemptions. In contrast, we find that while hedge funds in general are inversely affected by funding liquidity shocks, some fund managers exhibit skill in managing funding liquidity risk. Our results complement Cao et al. (2013), who find that some hedge funds can time market liquidity and earn superior returns.

# 3 Theory

We consider financial frictions in the form of stocks' margin requirements and restricted risk-free borrowing. Following Frazzini and Pedersen (2014), we assume a simple overlapping-generations economy in which agents (investors) are born in each time period $t$ with exogenously given wealth $W_t^i$ and live for two periods. There are $n+1$ assets. The first $n$ assets are risky assets with positive net supply and one-period returns of $R_{k,t+1}$ ($k = 1, \ldots, n$). There is also a risk-free asset ($k = n+1$) with a deterministic return of $R$. The risk-free asset is an internal security with zero net supply.

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

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

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

Following the literature (Geanakoplos (2003); Ashcraft, Garleanu, and Pedersen (2010)), we assume that investors are subject to asset-specific margin requirements (haircuts) when they trade (either purchase or short sell) an asset. Haircuts limit investors' capacity to invest using borrowed capital against the asset as collateral. The fact that a weighted total haircut can not exceed investors' available capital restricts investors' portfolio choice. The restriction on risk-free borrowing, in addition, imposes an upper bound on their available capital to meet margin requirements. Investors' total available capital depends on both their wealth and their ability to borrow through risk-free security.

These two types of funding restrictions, the margin requirements and the risk-free borrowing, can be summarized in one single constraint on investors' portfolio choices, as given in Equation 2. For fraction $\omega_{k,t}^i$ invested in asset $k$, investor $i$ is required to put down $m_{k,t}$ to meet the margin requirement. We include an indicator variable $I_{k,t}$ that takes the value of 1 (-1) for long (short) positions. It captures the fact that both long and short positions consume capital. On the other hand, the capital available to meet haircuts depends on the market leverage condition, $M_t$. When $M_t < 1$, investors have more capital than their wealth to spend on haircuts through risk-free borrowing. When $M_t > 1$, investors are required to allocate a certain fraction of their wealth in the risk-free asset. Note that while the tightness of risk-free borrowing $M_t$ is the same across all assets, margin requirements $m_{k,t}$ are asset-specific.

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

Although haircuts and the market level easiness of leverage enter into investors' portfolio constraints differently, their impacts are the same: they jointly determine investors' effective leverage. To simplify the problem, we redefine asset $k$'s effective haircut to be $\hat{m}_{k,t} = m_{k,t} M_t$. Intuitively, we can think of a tighter risk-free borrowing (larger $M_t$) being reflected in an upward scaling of haircuts across all assets. With this simplification, the budget constraint in Equation 2 can be expressed as in Equation 3:

$$\Sigma_{k=1}^{n} \hat{m}_{k,t} I_{k,t} \omega_{k,t}^{i} \leq 1, \text{ where } I_{k,t} = \begin{cases} 1, & \text{if } \omega_{k,t}^{i} \geq 0 \\ -1, & \text{if } \omega_{k,t}^{i} < 0 \end{cases} \tag{3}$$

There are two types of investors in the market. First, there are type A investors who have a high level of risk aversion. We can think of type A investors as mutual funds, who choose to hold some risk-free asset.[4] As a result, their funding constraints are not binding and do not affect their optimal portfolio choices. Their optimization problem is to choose the portfolio allocation, $\omega_t^A = (\omega_{1,t}^A, \ldots, \omega_{n,t}^A)'$, to maximize the utility. We assume homogeneity in wealth and risk aversion across type A investors, denoting wealth and risk aversion by $W_A$ and $\gamma^A$, respectively. Their optimization problem can be summarized in Equation 4, where $E_t[R_{t+1}^n] = (E_t[R_{1,t+1}] - R, \ldots, E_t[R_{n,t+1}] - R)'$ is the vector of risky assets' expected excess returns and $\Omega$ is the variance-covariance matrix:

$$\max_{\{\omega_t^A\}} \; U_t^A = \omega_t^{A\prime} E_t[R_{t+1}^n] - \frac{\gamma^A}{2} \omega_t^{A\prime} \Omega \omega_t^A. \tag{4}$$

Type B investors are more risk loving and use leverage for their portfolio construction. We can think of type B investors as hedge funds, whose portfolio choices are subject to the funding constraints in Equation 3. Again, we assume homogeneity across type B investors so that they have the same level of initial wealth $W_B$ and risk aversion $\gamma^B$, where $\gamma^B < \gamma^A$. Each type B investor chooses her portfolio allocation $\omega_t^B = (\omega_{1,t}^B, \ldots, \omega_{n,t}^B)'$ to maximize her

[4]Most mutual funds in practice choose not to borrow, while they are allowed to use leverage under the Investment Company Act of 1940. For example, mutual funds could borrow from a bank with a 300% asset coverage (33% effective leverage); closed-end funds could issue debt with a 300% asset coverage (33% effective leverage), and preferred stock with a 200% asset coverage (50% effective leverage). In addition, closed-end funds may also exceed the 50% leverage restriction through derivative investments, including total return swaps, non-deliverable forward contracts, etc.

utility, subject to the borrowing constraint, as expressed in Equation 5:

$$\max_{\{\omega_t^B\}} \; U_t^B = \omega_t^{B\prime} E_t[R_{t+1}^n] - \frac{\gamma^B}{2}\omega_t^{B\prime}\Omega\omega_t^B, \qquad s.t. \;\; \Sigma_{k=1}^n \hat{m}_{k,t} I_{k,t}\omega_{k,t}^B \leq 1. \tag{5}$$

Define $\eta_t$ as the Lagrange multiplier that measures the shadow cost of the borrowing constraint, and $\tilde{m}_t = (\hat{m}_{1,t}I_{1,t}, \ldots, \hat{m}_{n,t}I_{n,t})'$ as the margin vector. Lemma 1 gives the optimal portfolio choices for two types of investors. See Appendix B for the proof.

**Lemma 1** (*Investors' Optimal Portfolio Choices*)

Type A and type B investors' optimal portfolio choices are given by:

$$\omega_t^A = \frac{1}{\gamma^A}\Omega^{-1}E_t[R_{t+1}^n]. \tag{6}$$

$$\omega_t^B = \frac{1}{\gamma^B}\Omega^{-1}(E_t[R_{t+1}^n] - \eta_t\tilde{m}_t). \tag{7}$$

For the risk-averse type A investors, their asset allocations are simply the optimal portfolio choices with no constraint. However, for the type B investors, the portfolio choice $\omega_{k,t}^B$ also depends on the average shadow cost of borrowing $\eta_t$ and the asset-specific margin requirement $\tilde{m}_{k,t}$. When the borrowing condition tightens (larger $\eta_t$), the type B investors allocate less capital in the risky asset $k$. In addition, this reallocation effect is more severe for the asset with a higher haircut $\tilde{m}_{k,t}$.

We aggregate individual investors' optimal portfolio choices to obtain assets' expected returns in equilibrium. The market clearing condition requires that the net demand for the risk-free asset is zero and the net demands for all the risky assets are equal to their market capitalization. For simplicity, we assume that investors for each type have a unit of one, and thus the total wealth in each group is given by $W_A$ and $W_B$. If we let $P = (P_1, \ldots, P_n)'$ be the market capitalization vector for assets $k = 1, \ldots, n$, the market clearing conditions can be summarized by Equation 8, where $X = (\frac{P_1}{P'e^n}, \ldots, \frac{P_n}{P'e^n})'$ is the relative market cap vector and $\rho_A = \frac{W_A}{W_A + W_B}$ is the relative wealth of type A investors.

$$\rho_A \omega_t^A + (1 - \rho_A)\omega_t^B \quad = \quad X. \tag{8}$$

We further define the aggregate risk aversion $\gamma$ in terms of $\frac{1}{\gamma} = \frac{\rho_A}{\gamma_A} + \frac{1-\rho_A}{\gamma_B}$, leveraged investors' effective risk aversion $\tilde{\gamma} = \gamma \frac{1-\rho_A}{\gamma_B}$, and asset $k$'s market beta $\beta_{k,t} = \frac{COV(R_{k,t+1}, R_{M,t+1})}{VAR(R_{M,t+1})}$. We obtain the equilibrium risk premia for risky assets as presented in Lemma 2.[5]

**Lemma 2** (*Assets' Risk Premia*)
In equilibrium, the risk premium for the risky asset $k$, $k = 1, 2, ..., n$, depends on both its market beta and its margin requirement:

$$E_t[R_{k,t+1}] - R = \beta_k(E_t[R_{m,t+1}] - R) + \psi_t(\hat{m}_{k,t} - \beta_k \hat{m}_{M,t}). \tag{9}$$

$\psi_t = \tilde{\gamma}\eta_t$ measures the shadow cost of the borrowing constraint, and $\hat{m}_{M,t} = X'\hat{m}_t$ is the market cap-weighted average margin requirement. In the standard CAPM, a linear relationship exists between an asset's risk premium and its market exposure $\beta_k$. An asset that is uncorrelated with the market should earn the risk-free return. In other words, the security market line (SML) should have an intercept of zero and a positive slope of $E_t[R_{M,t+1}] - R$. However, in the presence of borrowing constraints, there is no single SML. This is because risk premia also compensate for the asset-specific cost of funding constraints, measured by $\psi_t m_{k,t}$. Meanwhile, the market risk premium $E_t[R_{m,t+1}] - R - \psi_t m_{M,t}$, i.e., the slope of the "hypothetical" SML, is lowered by the weighted cost of the funding constraints, $\psi_t \hat{m}_{M,t}$.

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

Lemma 2 shares the same vein as the margin-based CAPM where an asset's risk premium depends on both the market premium and the margin premium (Ashcraft, Garleanu, and Pedersen (2010); Garleanu and Pedersen (2011)).

Following the spirit of Frazzini and Pedersen (2014), we can construct a zero-beta BAB portfolio for a class of stocks with the same margin requirement. We long leveraged low-beta stocks and short de-leveraged high-beta stocks such that the portfolio beta is zero. Under Assumption 1, we reach an expression for the BAB premium with the effect of margin in Proposition 1.

**Assumption 1**

Market risk exposures $\beta_k$ are heterogeneous within a class of stocks that have the same margin requirement, $\hat{m}_{BAB,t}$. The distributions of $\beta_k$ across different classes of stocks are the same.

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

1. A market-neutral BAB portfolio earns a positive premium. For a given level of margin requirement, $\hat{m}_{BAB,t}$, the BAB premium can be expressed as:

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

2. The BAB premium is higher if the portfolio is constructed within a class of stocks with a higher margin requirement, $\hat{m}_{BAB,t}$.

In contrast to Frazzini and Pedersen (2014) where a BAB premium only depends on the aggregate funding tightness, we show that the BAB premium also depends on the margin requirement for the class of stocks that the portfolio is constructed over. The explanation is quite intuitive: the source of a BAB premium comes from the fact that borrowing-constrained investors are willing to pay a higher price for the embedded leverage of high-beta stocks.

This effect should be larger for high-margin stocks that are difficult to invest with borrowed capital.

It is not unrealistic to assume that the haircut for a given class of stocks, $\hat{m}_{BAB,t}$, is positively related to the market-wide funding liquidity, which is captured by the shadow cost of borrowing constraints, $\psi_t$, in our model. In addition, the heterogeneity of haircuts arises from the difference in assets' characteristics. Based on this intuition, we impose a simple functional form for the haircut such that it is monotonically increasing in the funding liquidity tightness, as presented in Assumption 2.

**Assumption 2**

The class-specific margin requirement, $\hat{m}_{BAB,t}$, can be expressed as a function of the shadow cost of funding constraints and class-specific characteristics:

$$\hat{m}_{BAB,t} = a_{BAB,t} - \frac{b_{BAB}}{\psi_t}.$$

The shadow cost of funding constraints, $\psi_t$, reflects the market-wide funding liquidity. An increase in $\psi_t$, i.e., a negative funding liquidity shock, results in an increase in the effective haircut, $\hat{m}_{BAB,t}$, for a class of stocks. Here $b_{BAB}$ captures the sensitivity for a class of stocks' margin requirement to funding liquidity shocks. We allow $a_{BAB,t}$ to be time-dependent to reflect that the characteristics affecting the haircut may also change over time. This provides one possible explanation for why a simple BAB factor cannot isolate the funding liquidity shock $\psi_t$: time variation in the BAB return can also be driven by time-varying $a_{BAB,t}$. Suppose that the characteristic parameter $a_{BAB,t}$ across stock classes comes from a distribution. We assume the time variation in this distribution is from the mean, while the dispersion remains fixed, as described in Assumption 3.

**Assumption 3**

A class of stocks' characteristic parameter $a_{BAB,t}$ follows some distribution that has a constant dispersion over time.

Proposition 2 proposes that, by taking the difference of two BAB portfolios with different margin requirements, we can isolate time-varying funding liquidity shocks.

**Proposition 2** (*Extraction of Funding Liquidity Shocks from Two BAB Portfolios*)
Under Assumptions 2 and 3, the return spread between two BAB portfolios, which are constructed over stocks with high and low margin requirements, respectively, measures the funding liquidity shock $\psi_t$:

$$BAB^1 - BAB^2 = \frac{\beta_H - \beta_L}{\beta_H \beta_L} c\psi_t$$

where $c$ is the dispersion between the stock characteristics, $a_{BAB,t}$, across these two classes of stocks, i.e., $a^1_{BAB,t} - a^2_{BAB,t} = c$.

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

# 4 Margin Constraints and BAB Portfolio Performance

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

### 4.1 Margin Proxies and Methodology

In the U.S., the initial margin is governed by Regulation T of the Federal Reserve Board.[6] 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. They also require higher margins for low price stocks.[7] While these rules set the minimum boundaries for margins, brokers could set various requirements based on a stock's characteristics: they may set higher margin requirements for stocks with high volatility, small market capitalization, or low liquidity.

On the theory side, Brunnermerier and Pedersen (2009) demonstrate that stocks' margin requirements increase with stocks' price volatility and market illiquidity. In their model, funding liquidity providers with asymmetric information raise the margin of an asset when the asset's volatility increases. In addition, market illiquidity may also have a positive impact on margins.[8] Motivated by the theoretical prediction and how margins are determined, we select five proxies for margin requirements: size, idiosyncratic volatility, the Amihud illiquidity measure, institutional ownership, and analyst coverage. We understand that the margin requirement for a single stock could vary across brokers and also across investors. However, as long as the patterns of margins' determinants are the same, e.g., a small stock always has higher margins than a large stock while the margin levels could be different for different

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

[7]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).

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

investors, those proxies can still capture an average margin requirement for a stock.[9]

The first margin proxy is size. Small stocks typically have higher margin requirements. For example, one brokerage firm sets the initial margin as 100% for stocks with a market capitalization of less than $250 million.[10] We measure size as the total market capitalization at the last trading day of the pre-holding month. The sample period is from January 1965 to October 2012.

The second proxy is idiosyncratic volatility. We use idiosyncratic volatility to capture the role of volatility in determining margins. While total volatility in theory should be a more comprehensive proxy, we choose to use idiosyncratic volatility to eliminate the impact of the market beta. This is because a higher market beta could also lead to a larger total volatility. Given that the second stage of BAB portfolio construction involves picking high-beta and low-beta stocks, we want to sort on the pure margin effect, instead of creating a finer sorting on beta.[11] Following Ang et al. (2006), we calculate idiosyncratic volatility as the standard deviation of return residuals adjusted by the Fama-French three-factor model using daily excess returns over the past three months. The sample period is from January 1965 to October 2012.

The third proxy is the Amihud illiquidity measure. Following Amihud (2002), we measure stock illiquidity as the average absolute daily return per dollar volume over the last 12 months, with a minimum observation requirement of 150 trading days.[12] The sample

[9]We consider position-based margin requirements. SEC approved a pilot program offered by the NYSE in 2006 for portfolio margin that aligns margin requirements with the overall risk of a portfolio. The portfolio margin program became permanent in August 2008. Under portfolio margin, stock positions have a minimum margin requirement of 15% (as long as they are not highly illiquid or highly concentrated positions). Based on our conversation with a major U.S. broker, margin requirements are higher for more volatile or concentrated portfolios such as portfolios with small, volatile stocks within the same industry.

[10]http://ibkb.interactivebrokers.com/article/2011.

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

[12]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.

period is from January 1965 to October 2012.

The fourth proxy is institutional investors' holdings. Previous research (Gompers and Metrick (2001); Rubin (2007); Blume and Keim (2012)) finds that institutional investors prefer to invest in liquid stocks. We follow the standard approach to calculate a stock's institutional ownership as the ratio of the total number of shares held by institutions to the total number of shares outstanding (Arbel, Carvell, and Strebel (1983), and Falkenstein (1996)). Data on quarterly institutional holdings come from the records of 13F form filings with the SEC, which is available through Thomson Reuters. We expand quarterly filings into monthly frequency: we use the number of shares filed in month $t$ as institutional investors' holdings in month $t$, $t+1$, and $t+2$. We then match the institutional holding data in month $t$ with the month $t+1$ return data to eliminate potential forward-looking bias.[13] 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 last proxy is analyst coverage. Irvine (2003) and Roulstone (2003) find that analyst coverage has a positive impact on a stock's market liquidity as it reduces information asymmetry. Based on this relationship, stocks with more analyst coverage may have lower margin requirements. We measure analyst coverage as the number of analysts following a stock in a given month. Data on analyst coverage are from Thomson Reuters' I/B/E/S dataset. The sample period is from July 1976 to December 2011.

We divide stocks into five groups based on each of the five margin proxies. Group 1 contains stocks with the lowest margin requirement, while Group 5 contains stocks with the highest margin requirement. In terms of sorting based on proxies, Group 1 corresponds to stocks with the largest market capitalization, the lowest idiosyncratic volatility, the small-

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

est Amihud illiquidity measure, the highest institutional ownership, and the most analyst coverage. The opposite is true for Group 5. We divide stocks using NYSE breaks to ensure our grouping is not affected by small-cap 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 (2013, p16-p19) closely on the formation of the BAB portfolios. Specifically, within each margin group, we long leveraged low-beta stocks and short de-leveraged high-beta stocks such that the overall portfolio beta in each group is zero.[15]

## 4.2 BAB Performance Across Different Margin Groups

We first test whether the Proposition 1 holds, i.e., the BAB premium increases as the margin requirement increases. Table 1 reports the BAB portfolio performance (excess returns and risk-adjusted alphas) conditional on five margin proxies. Alphas are calculated with respect to five risk factors: the Fama-French (1993) three factors, Carhart's (1997) momentum factor (UMD), and a market liquidity factor proxied by the returns of a long-short portfolio based the Amihud measures. We choose to use the Amihud measure sorted long-short portfolio as our market liquidity proxy because, similar to the other four risk factors, it is also a tradable factor. Our results are very similar if we replace the tradable Amihud long-short portfolio with Pastor and Stambaugh's (2003) market liquidity factor.

Panel A of Table 1 presents BAB portfolio performance within each group when size proxy is used. The results show that the BAB portfolio that is constructed within stocks with smaller size, thus higher margin requirement, delivers considerably higher returns. The BAB premium increases monotonically as the market capitalization decreases. In particular,

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

[15]We lever up the low-beta stocks by investing $\frac{1}{\beta_L}$; on the short sale side, we de-lever the high-beta stocks by selling $\frac{1}{\beta_H}$. All positions have a zero cost as we first use risk-free borrowing to finance each position.

the BAB portfolio for Group 5 (smallest size) earns an excess return of 1.22% per month and has a five-factor adjusted alpha of 0.76%, while the BAB portfolio for Group 1 (largest size) earns an excess return of 0.34% and has an insignificant alpha of 0.16%. The return difference between these two BAB portfolios is highly significant at 1% significance level.

Similar patterns can be found when other margin proxies are used (Panels B-E in Table 1). There is a clear monotonic relation between the margin requirement and the BAB premium: the monthly return differences between the two BAB portfolios constructed within Group 5 and Group 1 stocks are highly significant at 1.21% (idiosyncratic volatility proxy), 0.62% (the Amihud illiquidity proxy), 0.97% (institutional ownership proxy), and 0.99% (analyst coverage proxy). Again, such return spreads cannot be explained by commonly used risk factors as the monthly alphas are 0.76% ($t$-statistic = 3.63, idiosyncratic volatility proxy), 0.42% ($t$-statistic = 2.30, the Amihud illiquidity proxy), 0.67% ($t$-statistic = 2.12, institutional ownership proxy), and 0.77% ($t$-statistic = 2.27, analyst coverage proxy).

To better understand the properties of stocks that are used to construct the BAB portfolios, we report stocks' characteristics for each margin proxy group in Appendix Table C.1. Three points are worth emphasizing. First, the return spread between two BAB portfolios is not driven by sorting on margin proxies. Only the long-short portfolios sorted by size proxy and the Amihud proxy deliver significant returns, and the magnitude is much smaller than the spread between two BAB portfolios. Second, even though the number of stocks in the high-margin group is much larger than that in the low-margin group, the market faction of high-margin stocks is small. This finding suggests that the scalability of the BAB strategy is limited. Third, while there is some level of relation between the average beta and each margin proxy, the relation is not monotonic across five margin proxies. For example, the average beta decreases from large stocks (the low-margin group) to small stocks (the high-margin group) when size proxy is used, but the average beta increases from less volatile stocks (the low-margin group) the volatile stocks (the high-margin group) when idiosyncratic volatility proxy is used. To further examine whether the BAB spread is caused by different levels of beta across margin groups, we construct double-sorted BAB portfolios based on orthogonalized margin proxies. Specifically, for each month in the sample period, we run a cross-sectional regression of stocks' margin proxies on their betas, and use the residuals to sort stocks into different margin groups. We find similar results as shown in Appendix Table C.2. Our results suggest that the concern of thinner sorting on beta has, at most, a minor effect on the observed BAB spread.

Overall, we find supporting evidence for Proposition 1, which proposes that the BAB premium is positively related to the margin requirement. More importantly, they provide us an empirical ground to construct a measure of funding liquidity using stock returns.

# 5 Funding Liquidity Shocks

## 5.1 The Extraction of the Funding Liquidity Shocks

We extract funding liquidity shocks using the return spread between two BAB portfolios constructed within high-margin (Group 5) stocks and low-margin (Group 1) stocks. We construct five time series of return differences as we have five margin proxies. We take the first principal component of these five time series as our measure for funding liquidity shocks. We follow the factor extraction method in Connor and Korajczyk (1987). This algorithm is robust to unbalanced samples (the institutional ownership and analyst coverage series are shorter than the other three series). We also construct the funding liquidity shocks using a balanced sample from January 1980 to December 2011. The correlation between the two extracted series is higher than 99%.

Our funding liquidity extraction strategy has three advantages. First, as suggested by Proposition 2, the time-varying BAB return could be driven by both market-wide funding liquidity shocks and time-varying margin requirements that are related to asset characteristics. By taking the return difference between two BAB portfolios based on different margin levels, we can smooth out the potential time-varying margin effect while maintain the time-varying funding liquidity shocks. Second, empirically it is possible that the simple BAB return is driven by both funding liquidity and other omitted variables. Our approach can eliminate the impacts of other factors as long as they are similar across the five margin groups. Third, using the first principal component, we are able to extract the common underlying driving force, the funding liquidity shock, out of the five series of return differences, even though each series might be partially driven by their own specific factor.

We check whether there is a factor structure underlying the five series. Table 2 presents the adjusted $R^2$s from time series regressions of the five BAB series on the extracted funding liquidity shock. The first principal component can explain, on average, 67.0% of the time-series variation for the five series with adjusted $R^2$s ranging from 35.9% (idiosyncratic volatility) to 84.1% (size). The average adjusted $R^2$ is 73.0% if quarterly data are used. The results show that the five series have a clear factor structure and a single factor, the extracted funding liquidity shock, is able to explain most variation. For convenience, we refer to the extracted funding liquidity shock as the FLS, from this point forward.

Panel A of Table 3 presents the correlations of the FLS with 14 funding liquidity proxies that have been proposed in the literature: broker-dealers' asset growth (Adrian and Shin (2010)), Treasury security-based funding liquidity (Fontaine and Garcia (2012)),[16] major investment banks' CDS spread (Ang, Gorovyy, and Van Inwegen (2011)), credit spread (Adrian, Etula, and Muir (2013)), financial sector leverage (Ang, Gorovyy, and Van Inwegen (2011)), hedge fund leverage (Ang, Gorovyy, and Van Inwegen (2011)),[17] investment bank excess returns (Ang, Gorovyy, and Van Inwegen (2011)), broker-dealers' leverage factor

[16]The data are downloaded from Jean-Sébastien Fontaine's website.
[17]The data are kindly provided by the authors.

(Adrian, Etula, and Muir (2013)), 3-month LIBOR rate (Ang, Gorovyy, and Van Inwegen (2011)), percentage of loan officers tightening credit standards for commercial and industrial loans (Lee (2013)), the swap spread (Asness, Moskowitz, and Pedersen (2013)), the TED spread (Gupta and Subrahmanyam (2000)), the term spread (Ang, Gorovyy, and Van Inwegen (2011)), and the VIX (Ang, Gorovyy, and Van Inwegen (2011)). For data that are originally quoted in quarterly frequency, we convert it into monthly frequency by applying the value at the end of each quarter to its current month as well as the month before and after that month.[18] We sign each proxy such that a small value indicates an adverse funding liquidity shock. To remove potential autocorrelation, we take the residual of each proxy after fitting in an AR(2) model.[19] Additional details on the construction of these 14 proxies are in Appendix A.1.

We find that FLS is significantly, at a significance level of 5%, correlated with most existing funding liquidity proxies: among the 14 proxies we consider, FLS has positive and significant correlations with 11; correlations range from 12.9% (broker-dealers' asset growth) to 45.8% (hedge fund leverage). We find a similar pattern when we use quarterly data, i.e., FLS is positively and significantly correlated with 10 of 14 proxies. In Appendix Table C.3, we also report the correlations of the five BAB return difference series with the 14 funding liquidity proxies. The results are similar, indicating that the significant correlations between the FLS and other funding proxies are not caused by the BAB return difference conditional on one margin proxy. In contrast, the BAB factor has significant correlations with only two funding liquidity proxies: the Treasury security-based funding liquidity proxy and swap spread.

[18]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.

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

It is possible that other shocks, in addition to funding liquidity shocks, may also lead to changes in the 14 proxies. To mitigate such potential noise, we take the first principal component of the 14 proxies (FPC14) and calculate its correlation with the extracted FLS. Panel B of Table 3 presents the results. Correlations between our FLS and the FPC14 are 35.8% and 50.2%, respectively, for monthly and quarterly data. In contrast, correlations are not significant for the BAB factor. Since some of the 14 proxies have quarterly frequency, and some are shorter than others in terms of sample length, we also report correlations between our FLS and the first principal component of two subsets of the 14 proxies. FPC10 is the first principal component of 10 proxies that have full sample coverage with the first observation starting in January 1986; FPC7 is the first principal component of an even smaller subset with seven proxies that do not have stock return related data and are originally quoted in monthly frequency.[20] Correlations between the FLS and these two alternative principal components are still high: 30.5% and 26.8% for monthly data, and 45.9% and 44.8% for quarterly data. Again, insignificant correlations are found for the BAB factor (except for the correlation between the BAB factor and FPC10 with monthly data, which is marginally significant).

Figure 1 shows the time series of the FLS from January, 1965 to October, 2012. From the figure, we can see that when the FLS experiences large drops, it usually corresponds to the months when the market-wide funding liquidity is also low. Similar figure can be drawn using quarterly data (Appendix Figure C.1). It is important to point out that while many existing liquidity measures are highly persistent, our measure of funding liquidity is not. The autocorrelation coefficient of the FLS is 0.22. In other words, our measure is likely to capture unexpected shocks regarding the market-wide funding condition.

[20]Four proxies are excluded for FPC10: major investment banks' CDS spread, hedge fund leverage, percentage of loan officers tightening credit standards for commercial and industrial loans, and the swap spread. FPC7, in addition to the ones excluded in FPC10, does not include major investment bank excess returns, broker-dealers' asset growth rate (quarterly frequency), or broker-dealers' leverage factor (quarterly frequency). We exclude investment bank excess returns because the FLS is extracted from equity market data and we want to rule out the possibility that these two are correlated by construction.

## 5.2 A Tradable Measure of Funding Liquidity Risk

Since FLS is a linear combination of five tradable portfolios, FLS itself is also tradable. Being tradable in the stock market is one feature that distinguishes the FLS from other funding liquidity proxies. This feature allows investors to hedge against funding liquidity risk by forming a portfolio following the procedure described in the previous section. In addition, a tradable funding liquidity factor can be applied to help us to understand stock market anomalies and evaluate portfolio performance.

We examine whether our tradable funding liquidity measure can be absorbed by other tradable risk factors. Panel A of Table 4 reports the results of time series regressions in which the FLS is the dependent variable and various stock market factors are the explanatory variables. Columns 1 and 2 show that, even though the FLS is derived from the BAB portfolio, the latter cannot fully explain the return spread of our factor: the alphas are still significant with magnitudes of 1.08% and 0.82% per month, depending on whether we control for the market factor. The adjusted $R^2$ is less than 20% even when both the BAB factor and market factor are included. Columns 3 to 7 present the results when several common risk factors are added sequentially, including the market factor, the size factor, the value factor, the momentum factor, the illiquidity factor (a long-short portfolio constructed based on stocks' Amihud illiquidity measure), and the short-term reversal factor. Alphas are significant after controlling for these risk factors, and adjusted $R^2$s are less than 15%. Although the FLS has a significant loading on the market factor, its loadings on other factors are less obvious. FLS loads positively and significantly on the size factor before we include the illiquidity factor. This observation could possibly be caused by the high correlation between the size factor and the illiquidity factor. Interestingly, similar to Nagel (2012), who finds that returns of short-term reversal strategies are higher when liquidity (proxied by VIX) deteriorates, we find that our funding liquidity factor negatively (though insignificantly) comoves with the short-term reversal factor. In the column 8, we include all the risk factors: the FLS has positive and significant loadings on the BAB and market factors, the monthly alpha is 0.89% ($t$-statistic=1.89), and the adjusted $\mathrm{R}^2$ is 24.4%. The results in Panel A indicate that our tradable funding liquidity factor contains information that cannot be fully explained by common risk factors.

On the other hand, the FLS helps us to explain these systematic risk factors. Panel B of Table 4 presents the results in which the FLS is used as the single explanatory variable. We find that the BAB factor, the SMB factor, and the Amihud illiquidity long-short portfolio load significantly on the FLS, while the HML factor, the momentum factor, and the short-term reversal factor cannot be explained by the funding liquidity risk. The alphas of the SMB factor and the illiquidity factor are not statistically significant, indicating that the funding liquidity risk is an important factor to explain the risk premia of these two systematic factors. We find similar results in Panel C of Table 4 when we include the market portfolio as a control variable.

Even though the FLS by construction is tradable, a valid concern is how implementable it is. The construction of the FLS requires investors to take long and short positions over small and illiquid stocks. Therefore, we need examine, to what extent, the tradable funding liquidity measure is affected by transaction costs. The FLS is essentially the return difference of two BAB portfolios with high- and low-margin stocks, where the margin level is captured by five proxies. As a result, the turnover for the difference-in-BAB portfolio varies across margin proxies. We calculate the average turnover for each difference-in-BAB portfolio sorted by margin proxy. For those portfolios sorted by size, the Amihud illiquidity measure, and institutional ownership, the turnovers are 26, 24, and 29 cents, respectively, for every dollar spent on the long position. Turnovers are higher for those portfolios sorted on idiosyncratic volatility (78 cents) and analyst coverage (70 cents).

We examine a difference-in-BAB portfolio's vulnerability to transaction costs by computing the round-trip costs that are large enough to cause the average monthly return to be insignificant. Our approach is similar to the one used in Grundy and Martin (2001) but we incorporate the cross-sectional variation in transaction costs associated with stocks' different margin requirements. Specifically, low-margin stocks and the risk-free asset are typically less costly to trade than high-margin stocks. We assign low-margin stocks a 11.17 bps lower transaction cost to reflect this difference.[21] The "tolerable" round-trip cost is a function of the portfolio's turnover and the raw return before transaction costs. We find that the returns of the difference-in-BAB portfolios (the last column in Table 1) remain significant as long as the monthly round-trip costs for the high-margin stocks are less than 114 bps for size proxy, 43 bps for the idiosyncratic volatility proxy, 76 bps for the Amihud illiquidity proxy, 60 bps for the institutional ownership proxy, and 45 bps for the analyst coverage proxy. These estimated "tolerable" costs are considerably higher than the realized transaction costs reported in Frazzini, Israel, and Moskowitz (2012). We understand that the actual round-trip costs could be much smaller than our estimates for various investors and the scalability of our measure could be limited (Panel C of Appendix Table C.1). However, our market-based funding liquidity factor could be implemented at a reasonable transaction cost level.

Last, we discuss two alternative approaches to construct a tradable funding liquidity measure from the 14 funding liquidity proxies. In the first approach, we construct a funding factor mimicking portfolio (FMP) by projecting the first principal component (FPC14) of those 14 proxies on the six Fama-French benchmark portfolios. However, by doing this we implicitly assume that the funding liquidity risk is a linear combination of the six benchmark portfolios, which are supposed to capture other aspects of systematic risk, such as size premium and value premium. In fact, while the correlation between FMP and FPC14 is

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

64.8%, the correlation between FMP and the market return is 96.6%, casting doubt on whether FMP measures funding liquidity risk or merely captures the market risk. A second approach to construct a tradable funding liquidity measure is to form a long-short portfolio based on stocks' pre-ranking loadings on the FPC14. The pre-ranking FPC14 loadings are estimated using past 24-month rolling window regressions with at least 18 observations. We drop the 10% smallest stocks at the formation date and form five value-weighted portfolios according to pre-ranking FPC14 betas. The high-minus-low portfolio has a low correlation of 2.6% with FPC14 and an insignificant spread of 26 bps per month ($t$-statistic=0.91). The results are disappointing but not surprising. As shown in Adrian, Etula, and Muir (2013), the procedure of sorting on past non-tradable factor covariances is a noisy way to measure future conditional covariances. Therefore, the long-short portfolio is unlikely to capture the underlying funding liquidity risk.

## 5.3 Relation with Market Liquidity

Brunnermeier and Pedersen (2009) suggest that there is a positive relation between funding liquidity tightness and market illiquidity. They show that as funding liquidity tightens, arbitrageurs' ability to provide market liquidity is diminished, and this process eventually leads to liquidity spirals. We examine whether this positive relation between market liquidity and funding liquidity exists using the extracted funding liquidity measure. Panel A of Table 5 reports the pairwise correlations between FLS and other liquidity measures, including the return of a long-short portfolio sorted by the Amihud illiquidity measure, the Pastor and Stambaugh (2003) market liquidity innovation measure, the variable component of Sadka (2006) market liquidity factor, and the innovation of the noise measure in Hu, Pan, and Wang (2013). We find that the FLS is correlated with all four liquidity measures, with correlation coefficients ranging from 17.0% (the Pastor and Stambaugh's measure) to 23.9% (the Amihud measure). The positive and significant correlations provide some supportive evidence for the comovement between market liquidity and funding liquidity.

Moreover, Brunnermeier and Pedersen (2009) also predict that the liquidity spiral is stronger when negative shocks hit asset prices. If their story is true, we would expect to see asymmetric comovements between funding liquidity and market liquidity during up and down markets. Panels B and C of Table 5 present pairwise correlations in the months with positive market returns and in the months with negative market returns, respectively. Interestingly but not surprisingly, the correlations between FLS and market liquidity proxies are much higher during declining markets than during rising markets. In addition, the correlations among various market liquidity proxies also increase when the market experiences negative returns. Such asymmetry complements Hameed, Kang, and Viswanathan (2010) who find that negative market returns decrease stock liquidity more severely than the positive effect from positive market returns, and the commonality in liquidity increases dramatically after negative market returns. This observation of asymmetric correlations further confirms the theoretical prediction on the relation between market liquidity and funding liquidity.

Given the significant correlations, one would then wonder whether the FLS captures only the market liquidity information, rather than the time-varying funding liquidity shocks. While the small magnitudes of correlations suggest it is unlikely to be the case, to answer this question, we project FLS on market liquidity proxies, and examine the properties of the residuals. We use the Amihud measure sorted long-short portfolio as the market liquidity proxy due to its tradable feature, but the results are similar when other proxies are used. The second row of Panel A of Table 6 reports the correlations between the orthogonalized FLS ($\text{FLS}_{orth}$) and 14 funding liquidity proxies. The results are quite similar to the ones when the FLS is used. Panel B of Table 6 shows that the time series alpha (0.92% per month) of ($\text{FLS}_{orth}$) is significant ($t$-statistic=1.81) when we control for the BAB factor, the Fama-French three factors, the momentum factor, and the short-term reversal factor. Our findings indicate that while there are possibly some overlaps between the informational contents that FLS and market liquidity capture, our extracted factor clearly contains information on funding liquidity risk that is not purely driven by market liquidity.

Because the construction of FLS involves first sorting stocks into groups based on their characteristics such as size, idiosyncratic volatility, and so forth, it is possible that what we extract is the return premium associated with these characteristics, which could well be related to stocks' market liquidity. We examine this possibility using two portfolios that are constructed based on the five margin proxies. The first portfolio intends to capture the margin-proxy spread. Specifically, conditional on each margin proxy, we construct a simple long-short portfolio by sorting stocks into five groups according to that proxy. We take the first principal component of the returns of the five long-short portfolios and denote it by $\text{FPC}_{single}$. The second portfolio intends to capture the difference of margin-proxy spreads. We first sort stocks into a low-beta group and a high-beta group. Within each beta group, we construct a long-short portfolio by sorting stocks into five groups according to a margin proxy. Then we take the return difference between two long-short portfolios constructed within low- and high-beta groups. We extract the first principal component of the five return differences, each of which corresponds to a margin proxy, and denote it by $\text{FPC}_{double}$. Both $\text{FPC}_{single}$ and $\text{FPC}_{double}$ track the return spread of portfolios sorted by margin proxies and could possibly be related to market liquidity. If the FLS captures the market liquidity instead of funding liquidity, we expect the results to be similar if we replace FLS with $\text{FPC}_{single}$ and $\text{FPC}_{double}$; however, we find that it is not the case. $\text{FPC}_{single}$ ($\text{FPC}_{double}$) are only significantly correlated with 5 (4) out of 14 funding liquidity proxies, as shown in Panel A of Table 6. Moreover, the risk-adjusted alphas of $\text{FPC}_{single}$ and $\text{FPC}_{double}$ are no longer positive or significant, and common risk factors can explain 94.8% and 53.9% of the time series variations of $\text{FPC}_{single}$ and $\text{FPC}_{double}$, respectively. The results indicate that portfolios sorted by the margin proxies provide limited information on the funding condition, even though such proxy-sorted long-short portfolios might capture market liquidity.

In sum, we cannot and do not want to rule out the possibility that FLS could be driven by both funding liquidity and market liquidity shocks, given the close relation of these two. However, what we find so far indicates that even though market liquidity and funding liquidity are related, they are still different. The extracted FLS is more likely to capture funding liquidity, which measures the market-wide easiness of raising external capital, instead of market liquidity, which measures the easiness to sell assets without large price impacts.

# 6 Funding Liquidity and Hedge Fund Returns

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

## 6.1 Funding Liquidity Shocks and Time Series Hedge Fund Performance

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

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

## 6.2 Funding Liquidity Shocks and Cross-Sectional Hedge Fund Returns

In order to examine the cross-sectional hedge fund performance as funding liquidity changes, we construct hedge fund portfolios based on their sensitivities to our funding liquidity measure.[22] Specifically, at the end of each month, we sort hedge funds into ten decile portfolios according to their sensitivities to the extracted FLS, and hold the equal-weighted hedge fund portfolios for one month. Following recent studies (Hu, Pan, and Wang (2013); Gao, Gao, and Song (2013)), funding liquidity sensitivities are estimated using a 24-month rolling-window regression of individual hedge fund excess returns on the FLS and the market factor, with a minimum observation requirement of 18 months. Decile 1 indicates the portfolio with the lowest funding liquidity sensitivities, and Decile 10 indicates the portfolio with the highest funding liquidity sensitivities. The model used to estimate funding liquidity sensitivities is:

$$R_t^i = \alpha^i + \delta_{fls}^i FLS_t + \delta_{mkt}^i R_{M,t} + \epsilon_t^i. \tag{10}$$

Panel A in Table 7 reports the excess returns and the Fung-Hsieh seven-factor[23] adjusted alphas for 10 equal-weighted FLS-sensitivity sorted portfolios, as well as the spread between the low-sensitivity and high-sensitivity portfolios. Hedge funds with higher sensitivities to the FLS earn lower returns, while those with lower sensitivities earn higher returns. Hedge funds in Decile 1 (those with the lowest sensitivities to the FLS) earn an average

[22]Data on individual hedge funds are from the Center for International Securities and Derivatives Markets (CISDM) database. We only include hedge funds that use USD as their reporting currency for assets under management (AUM), or with the country variable being United States, in cases when the currency variable is missing. Funds are required to have at least $10 millions in AUM (Cao et al. (2013); Gao, Gao, and Song (2013); Hu, Pan, and Wang (2013)). We eliminate hedge funds that have less than 18 months of return history. We choose our sample to start from January 1994 to mitigate survivorship bias. Our sample period is from January 1994 to April 2009. Appendix Table C.4 presents descriptive statistics of the CISDM hedge fund dataset.

[23]We follow Fung and Hsieh (2004) to construct the seven hedge fund risk factors. Details about factor construction are in Table A.2.

excess return of 0.94% per month ($t$-statistic=3.76). On the other hand, hedge funds in Decile 10 (those with the highest sensitivities to the FLS) earn an almost zero excess return on average (5 bps per month). The spread between these two portfolios is 0.89% per month ($t$-statistic=3.31). This spread cannot be explained by the Fung-Hsieh seven hedge fund risk factors ($\alpha$=0.89% per month, $t$-statistic=3.02).[24] The difference in performance is also reflected in their Sharpe ratios: the lowest FLS-sensitivity portfolio has a Sharpe ratio of 1.03, while the highest-sensitivity portfolio has a Sharpe ratio close to 0.[25]

Panel B in Table 7 presents the characteristics of FLS-sensitivity sorted hedge fund portfolios. Both pre-ranking and post-ranking loadings on the FLS monotonically decrease as we move from the high-beta portfolio to the low-beta portfolio. Meanwhile, the average AUM does not have a monotonic relationship across FLS-sensitivity sorted portfolios. In addition, all portfolios have a similar average age, meaning that we are not constructing portfolios with different ages.[26]

We also investigate the relationship between investment styles of hedge funds and their FLS sensitivities. First, we examine the distribution over the 10 FLS-sensitivity sorted portfolios for each investment style. Conditional on an investment style, we calculate the percentages of hedge funds that belong to 10 portfolios. Panel C of Table 7 presents the results. We find that 21.6% of Multi-Strategy funds have low FLS sensitivities and 22.5% of Emerging Market funds have high FLS sensitivities. In addition, only 1.3% of Global

[24]Hedge fund portfolio loadings on the Fung-Hsieh seven factors and adjusted $R^2$s can be found in Appendix Table C.5. We also replace the two non-tradable factors, the bond market factor and the credit spread factor, with two tradable factors as used in Sadka (2010). The results are very similar and available upon request.

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

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

Macro funds exhibit low FLS sensitivities, while 1.5% of Convertible Arbitrage funds show up in the high FLS-sensitivity portfolio. Second, we calculate the likelihood distribution of the 11 investment styles within each FLS-sensitivity portfolio. Panel D of Table 7 reports the results. We find that Global Macro funds are more likely to be assigned to the low FLS-sensitivity group (17.3%), while the Emerging Market funds are more likely to show up in the high FLS-sensitivity group (21.9%). Overall, investment style concentration does not seem to explain the observed hedge fund portfolio spread.

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

If the outperformance of low-sensitivity hedge funds is caused by fund managers' ability to manage the funding liquidity risk, such active portfolio management should be rewarded more during bad economic periods. Table 8 reports the performance of hedge fund portfolios during NBER recession months and "normal" months. During normal periods, low FLS-sensitivity funds earn an average excess return of 1.16% per month, while high FLS-sensitivity funds earn 0.51% per month, resulting in a spread of 0.65% per month ($t$-statistic=2.50). During stressful periods, the Decile 10 portfolio, which has the largest loading on the FLS, experiences a loss of 2.31% per month, while the Decile 1 portfolio experiences an insignificant 0.21% loss per month. That is, by managing funding liquidity risk, managers could potentially reduce the loss in stressful periods by over 2.10% per month

($t$-statistic=2.10).[27]

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

$$R_t^p = \alpha^p + \beta_{mkt} R_{M,t} + \beta_1 FLS_t + \beta_2 max\{0, -FLS_t\} + \epsilon_t^p. \tag{11}$$

When the funding condition is good (FLS is positive), we have $\beta^{up} = \beta_1$; when the funding condition is poor (FLS is negative), we have $\beta^{down} = \beta_1 - \beta_2$. We expect the low FLS-sensitivity portfolio to have $\beta^{up} > \beta^{down}$ (or equivalently $\beta_2 > 0$) if they can time funding liquidity risk. Panel A of Figure 3 shows that the low FLS-sensitivity portfolio has a positive $\beta_2$, indicating that fund managers reduce loadings on funding liquidity risk when the FLS is negative. Panel B of Figure 3 shows that the inclusion of $max\{0, -FLS_t\}$ into the regression reduces the alpha of the low FLS-sensitivity portfolio from 0.87% to 0.60% per month. Thus, low FLS-sensitivity hedge funds, as managed portfolios, are likely to have the ability to time the funding liquidity risk, and therefore they can deliver higher returns.

However, other sources could also contribute to the outperformance of low-sensitivity funds and managers' ability to time funding liquidity risk is just one dimension of their superior portfolio management skills. For example, some funds may have better relationships with brokers that allow them to secure financing even during market downturns when others cannot. Another possibility is that some funds might adjust their loadings on funding liquidity risk, as well as change their portfolio compositions before adverse funding shocks

[27] The risk-adjusted spread is not significant. The loss of statistical significance is very likely to be due to the limited number of observations: we have 26 recession months but 7 risk factors in the time series regression.

hit so they might actually ride on negative shocks and generate abnormal returns. Due to data limitations, we cannot test all the hypotheses. Nevertheless, the timing ability of fund managers provides one explanation of how hedge funds, as managed portfolios, could dynamically have their exposures adjusted to the funding liquidity risk.

### 6.3 Robustness Tests of the Cross-Sectional Hedge Fund Returns

We examine other possible reasons that could also lead to the observed return spread of two hedge fund portfolios. Researchers (Asness, Krail, and Liew (2001); Getmansky, Lo, and Makarov (2004); Loudon, Okunev, and White (2006); Jagannathan, Malakhov, and Novikov (2010)) find that reported hedge fund returns may exhibit strong serial correlations because of stale prices and managers' incentives to smooth returns. Panel A in Figure 4 presents the autocorrelation functions of 10 FLS-sensitivity sorted hedge fund portfolios with 1 - 12 lags. All 10 portfolios have significant first-order autocorrelations at the 5% significance levels; several portfolios (3, 4, 6, 7, and 8) also have significant second-order autocorrelations. The serial correlations of hedge fund portfolios suggest that we need check whether the return spread is caused by stale prices and smoothed returns.

We control for the effect of serial correlations by backing out the unobserved raw returns from the observed smoothed returns. We remove the first- and second-order autocorrelations of reported hedge fund returns following the procedure proposed by Loudon, Okunev, and White (2006).[28] We construct the FLS-sensitivity sorted hedge fund portfolios using the unsmoothed "true" returns. Panel B in Figure 4 shows that all the hedge fund portfolios constructed using unsmoothed returns have smaller serial autocorrelations, and most of the autocorrelation coefficients become insignificant. Panel A of Table 9 presents the results.

[28] Details of the autocorrelation removal procedure can be found in Appendix A.3. Appendix Figures C.4 and C.5 show individual hedge funds' first- and second-order autocorrelation coefficients for observed returns, as well as for unsmoothed raw returns. Although the observed returns have large autocorrelation coefficients, the coefficients of the unsmoothed returns are close to zero.

We see that the return spread and the risk-adjusted alpha spread are slightly smaller but still significant when the unsmoothed returns are used.

Table 9 also presents the excess returns and risk-adjusted alphas of the FLS-sensitivity sorted hedge fund portfolios under several other scenarios: forming value-weighted portfolios, correction for the forward-looking bias of the FLS, controlling for delisting, controlling for change of VIX, controlling for the variance risk premium, excluding the financial crisis period, selecting funds with AUM denominated in USD, and excluding funds of funds. We find that the results are similar to those reported in Panel A of Table 7: low FLS-sensitivity hedge funds outperform the high FLS-sensitivity hedge funds in terms of both raw returns and risk-adjusted alphas.

While we find that some hedge fund managers are likely to actively manage funding liquidity risk and deliver higher returns, mutual fund managers do not exhibit such skill. In Appendix Table C.6, we report the performance of FLS-sensitivity sorted mutual fund portfolios.[29] We do not see any significant return spread between mutual funds with low- and high-FLS loadings. This finding is somewhat expected because mutual funds usually use little or very limited leverage, and the ability to manage funding liquidity risk might not be a key factor that can effectively distinguish good and bad mutual fund managers.

# 7 Funding Liquidity Shocks and the Real Economy

In this section, we examine the interaction between funding liquidity risk and the real economy. We first investigate the relation between the extracted funding liquidity shock and

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

future economic activities. Researchers (Levine and Zervos (1998); Næs, Skjeltorp, and Ødegaard (2011)) find that stock market liquidity is a good "leading indicator" for economic conditions such as GDP growth, investment growth, and unemployment rate growth. Because funding liquidity risk affects asset prices in a frictional market and asset prices affect firms' capital structure and investment decisions, shocks to investors' funding conditions could also contain useful information about the future real economy. In the second part of this section, we briefly examine possible determinants of funding liquidity risk. After the recent financial crisis, researchers have become more interested in the systemic risk that could result in instability of the financial system and fluctuations of the macro economy. Our objective is to have an understanding about systemic risk measures that could have an impact on the market-wide funding liquidity risk.

## 7.1 Forecast of Macroeconomic Growth

Following Næs, Skjeltorp, and Ødegaard (2011), we use four variables to proxy for the macroeconomic condition: the growth of real GDP per capita, the growth of real fixed private investments, the growth of the unemployment rate, and the growth of real consumption on nondurable goods and services per capita.[30] Other control variables used in our predictive regressions include the market excess return over one-month Treasury-bill rate, the realized volatility calculated using the market excess daily return over one quarter, the credit spread calculated as the yield difference between BAA- and AAA-rated corporate bonds, and the term spread calculated as the yield difference between ten-year and three-month Treasury bonds. The sample period is from 1965:Q1 to 2012:Q3 (1968:Q1-2012:Q3 for unemployment rate growth) for the regressions without control variables, and from 1986:Q1 to 2012:Q3 for the regressions with control variables.

[30]GDP, consumption, and price index for private fixed investment data are downloaded from the Bureau of Economic Analysis; nominal private fixed investment data are downloaded from the Federal Reserve Economic Data; unemployment rate data are downloaded from the Bureau of Labor Statistics.

Panel A of Table 10 reports the results for the predictive regressions with and without control variables. The dependent variables are quarterly GDP growth, investment growth, unemployment rate growth, and consumption growth. The main predictor of interest is the extracted FLS. The results indicate that the funding liquidity shock has significant predictive power for GDP growth, private investment growth, and unemployment rate growth, even after we include the lagged dependent variable in the regression. This finding indicates that when the market-wide funding liquidity deteriorates, economic growth slows down, firms cut their investment in physical capital, and curtail hiring. If we consider the regression specification with additional control variables that are known to have predictive power for future macroeconomic conditions, only private investment growth can be predicted by using the FLS: adverse current quarter funding shocks are followed by smaller investment growth in the next quarter. In Panels B-D of Table 10, we also report the results when two-quarter, four-quarter, and eight-quarter cumulative growth rates are used as dependent variables. We find that the predictive power of FLS on private investment growth continues to remain significant for longer horizons even when we control for other predictors. The results indicate that funding liquidity is more likely to affect the real economy through the investment channel.

## 7.2 Determinants of Funding Liquidity Risk

We examine various quantitative measures for systemic risk as potential determinants of funding liquidity risk. The time series of the 17 measures we consider are from Giglio, Kelly, and Pruitt (2013). Details on the definition and the construction of those measures can be found in Bisias et al. (2012) and Giglio, Kelly, and Pruitt (2013). We conduct a backward elimination variable selection procedure to identify the systemic risk measures that may have significant impact on the FLS.

Panel A of Table 11 presents the results when the contemporaneous measures of systemic risk are used as the explanatory variables. Seven measures pass the variable selection procedure and have significant coefficients in a regression when FLS is the dependent variable. We find that a higher level of conditional value-at-risk (CoVaR) of the financial system is associated with better funding liquidity, while a larger increase in CoVaR results in worse funding liquidity. Furthermore, when the largest 20 financial institutions are hurt more severely (lower MES-BE), the market-wide funding condition is worse. In addition, when the threat of default of the largest financial firms is larger (higher Size con), the funding liquidity is worse. Lastly, higher return volatility of large financial institutions, higher excess return volatility of large financial institutions, and larger TED spread also lead to worse funding liquidity.

Panel B of Table 11 presents the results when the lagged measures of systemic risk are used as the explanatory variables. Another set of seven systemic risk measures remains significant after the backward elimination of variables. Compared to the case when contemporaneous regressors are used, the lagged CoVaR and lagged return volatility no longer significantly affect funding liquidity. Larger interconnectness of the 20 largest financial institutions, on the other hand, leads to worse funding liquidity. However, it is puzzling that a smaller lagged default spread is associated with lower funding liquidity, as we would usually expect a small default spread to be a signal of good funding conditions.

Panel C of Table 11 presents the results when both the contemporaneous and the lagged measures of systemic risk are used as the explanatory variables. Thirteen of the 34 variables remain significant after implementing the backward elimination procedure of variables. We find that a few findings are worth discussing. First, while higher default spread, larger interdependence of assets across global equity markets (*Intl spill*), and larger threat of default of the largest financial companies (*Size con*) lead to worse funding liquidity in the same month, the lagged values of these three variables have the opposite effect on

FLS. This result could arise from the mean-reverting property of these variables. Second, the higher book leverage of the 20 largest financial institutions is associated with better funding liquidity; however, the higher market leverage leads to worse funding liquidity. Third, a large slope of the yield curve indicates a positive effect on the market-wide funding liquidity.

# 8 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 tradable funding liquidity measure from the time series and cross-section of stock returns. We extract the funding liquidity shocks from the return spread of two market-neutral "betting against beta" portfolios: one is constructed with high-margin stocks and the other is constructed with low-margin stocks, where the margin requirements are proxied by stocks' characteristics. Our measure is highly correlated with funding liquidity proxies derived from other markets. Our funding liquidity risk factor cannot be explained by other stock market risk factors and helps to explain the size premium and the market liquidity premium. Our measure is positively correlated with market liquidity, supporting the theoretical prediction of the close relation between market liquidity and funding liquidity.

We use our tradable funding liquidity measure to study hedge fund returns. In the time series, the aggregate hedge fund performance comoves with funding liquidity risk: a one standard deviation of adverse shock to the market funding liquidity results in a 2% per year decline in hedge fund returns. In the cross-section, hedge funds that are less sensitive to the funding liquidity shock actually earn higher returns, which suggests that some fund managers may have the ability to manage funding liquidity risk and generate superior returns.

Lastly, we examine the relation between funding liquidity risk and the real economy. We find that funding liquidity shocks negatively affect future private fixed investment. We also identify several systemic risk measures that might explain funding liquidity risk. We leave detailed analyses to future research.

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

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

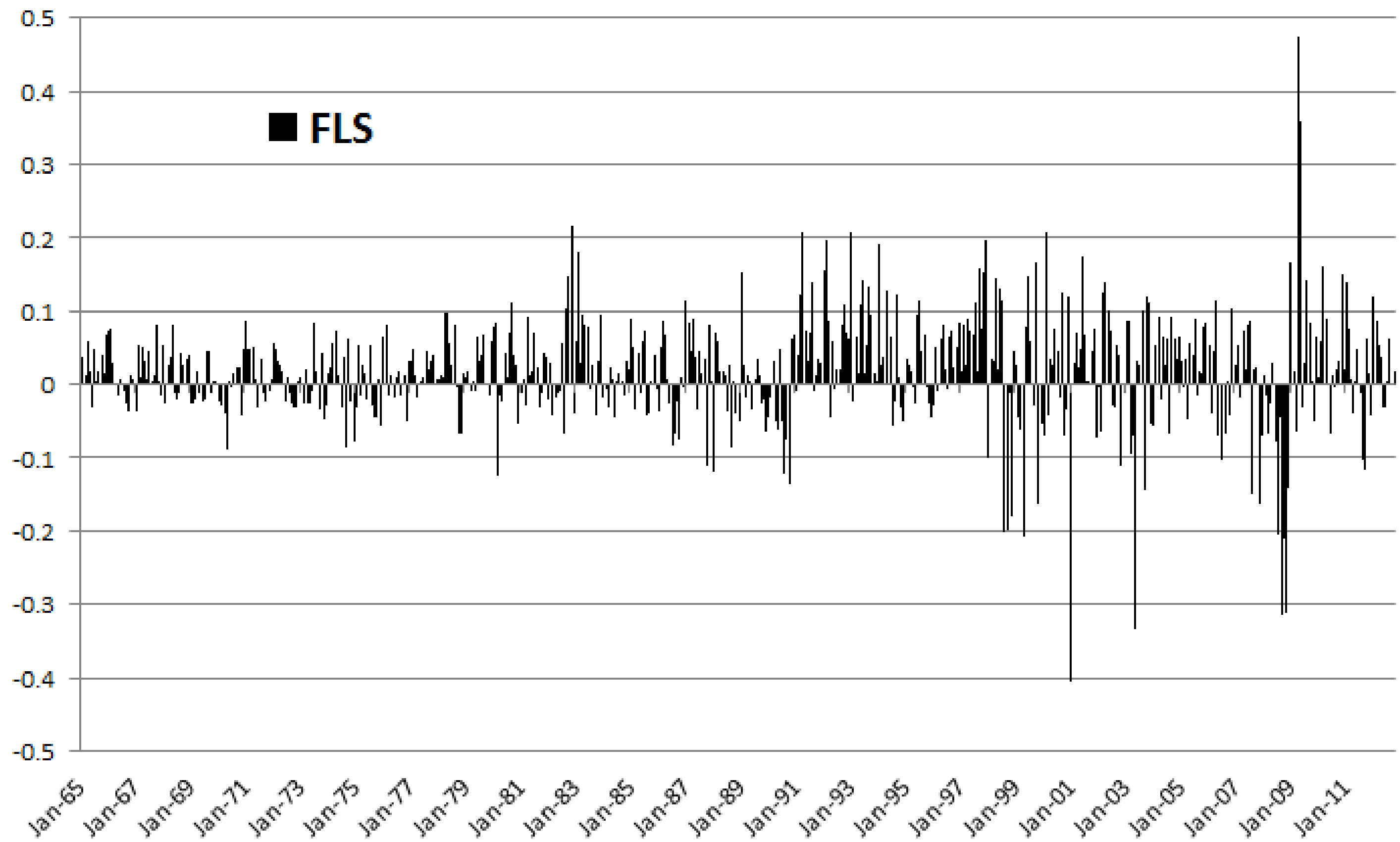
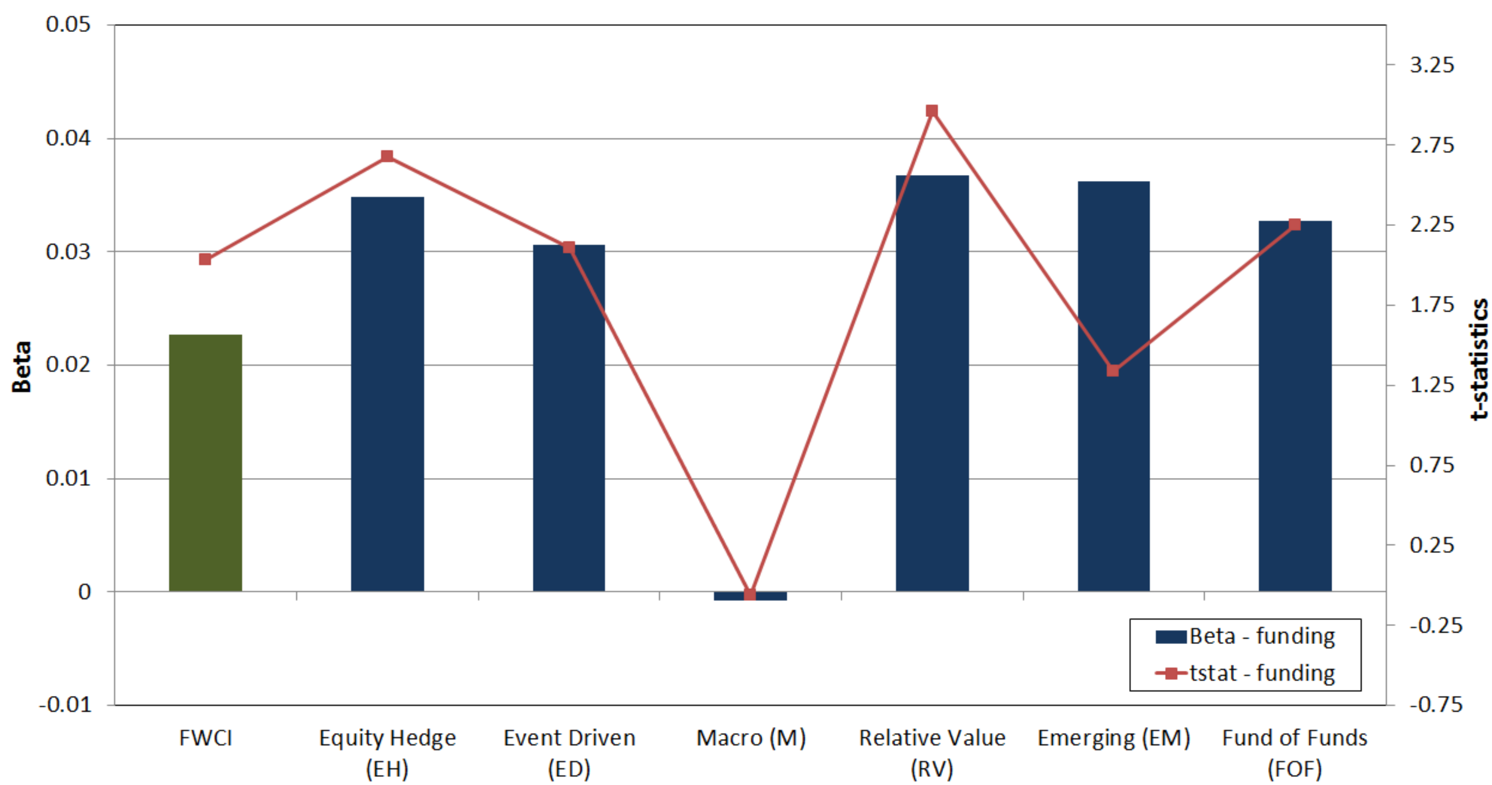


Figure 2: The Funding Liquidity Betas of Hedge Fund Indices

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

Panel A: FWCI and Indices of Primary Strategies



Panel B: Indices of Sub-strategies

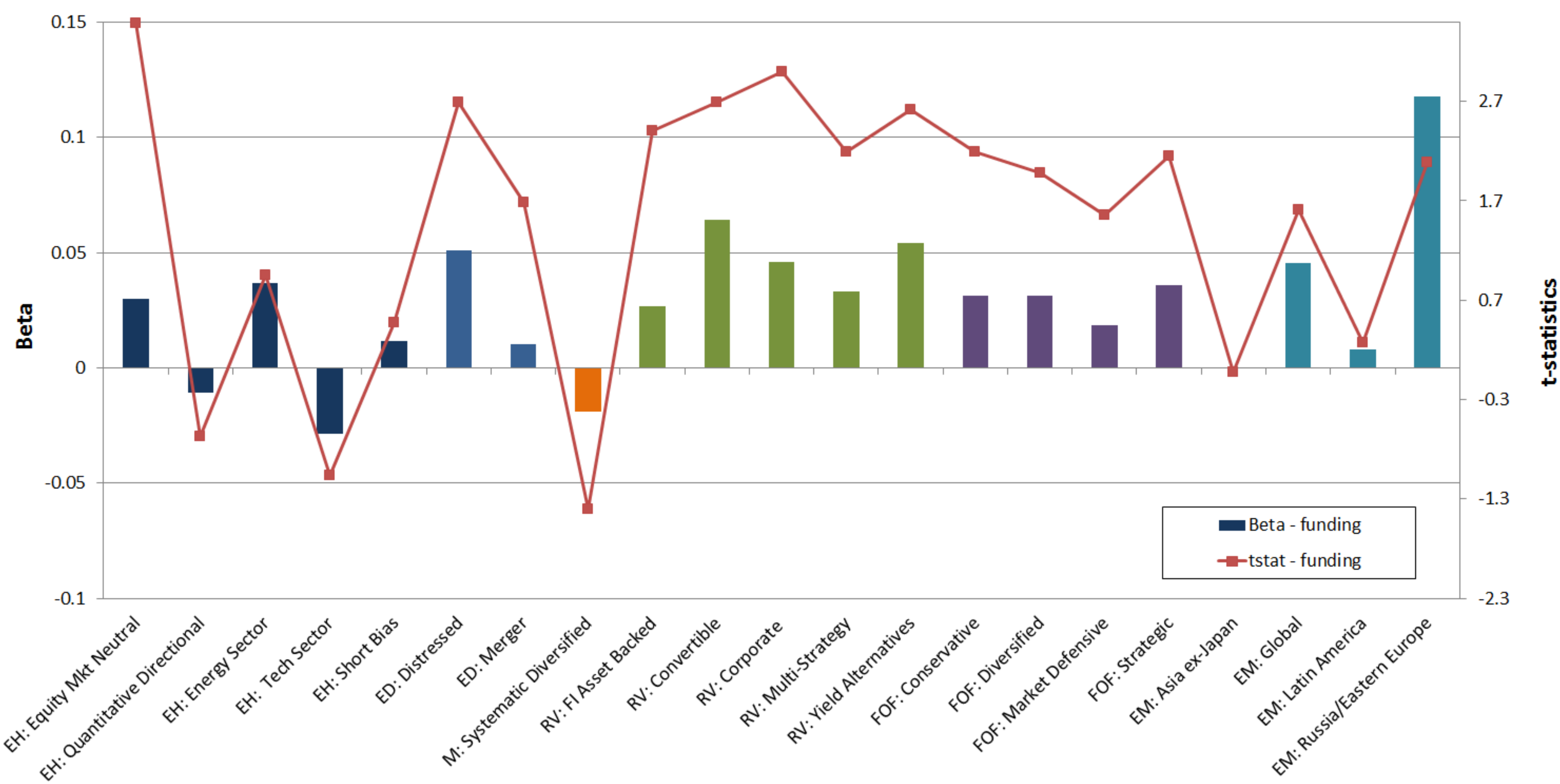
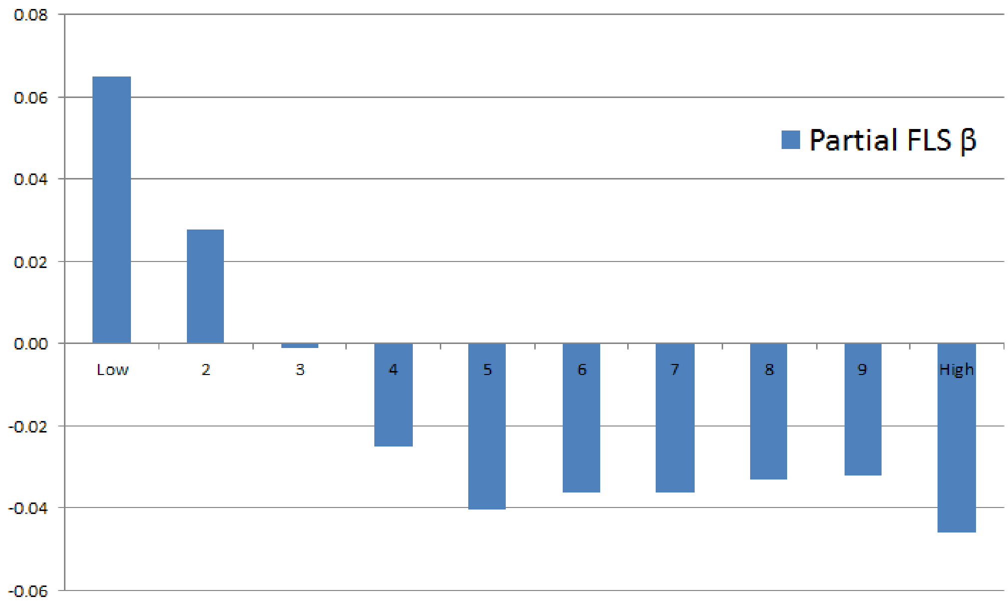


Figure 3: Hedge Fund Ability to Time Funding Liquidity Shocks

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

Panel A: Nonlinear loading ($\beta_2$) of hedge fund portfolios




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

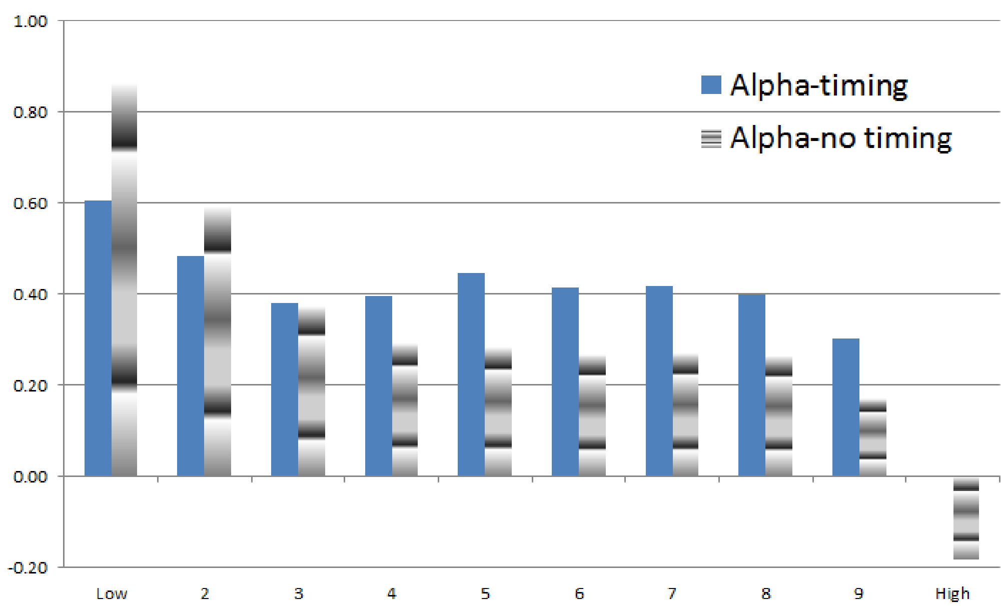
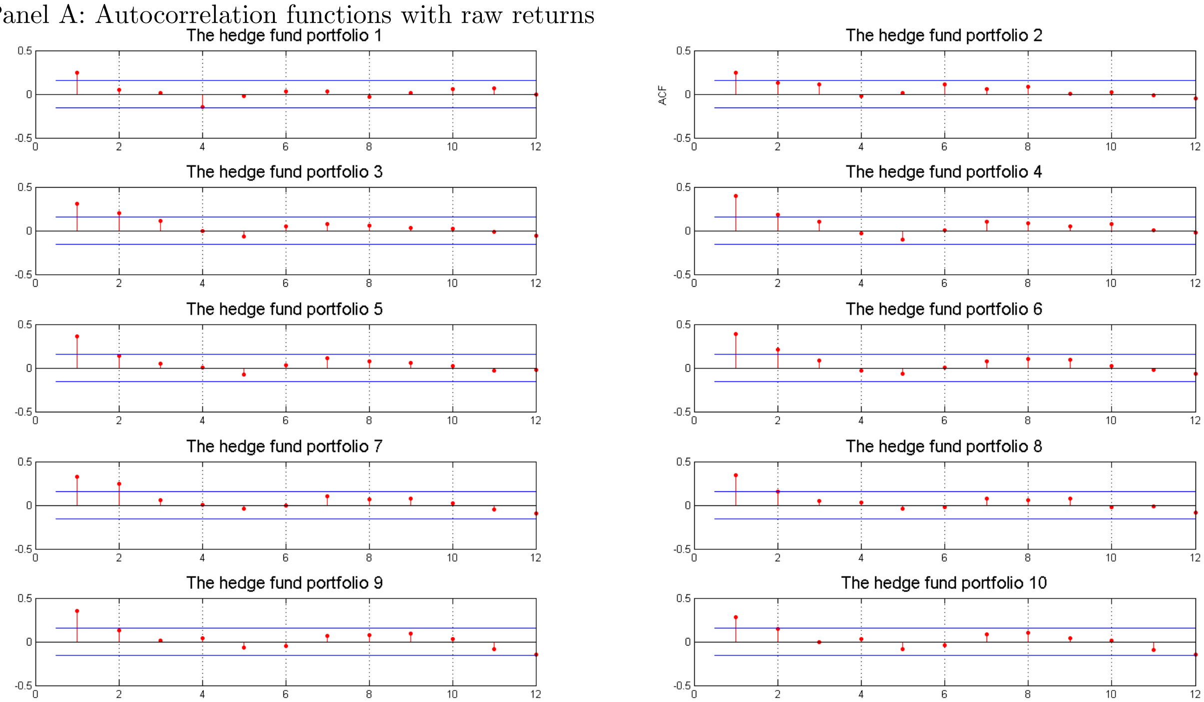


Figure 4: Hedge Fund Portfolios' Autocorrelation Functions

Panels A and B show the autocorrelation functions for ten hedge fund decile portfolios. The autocorrelation coefficients are computed for lags from 1 to 12. The 95% confidence intervals are indicated by the horizontal lines around the x axes. Panel A presents the autocorrelation functions for hedge fund portfolios that are constructed using raw returns. Panel B presents the autocorrelation functions for hedge fund portfolios that are constructed using unsmoothed returns. We follow the procedure in Loudon, Okunev, and White (2006) to remove the first- and second-order autocorrelations for individual hedge funds returns.

Panel A: Autocorrelation functions with raw returns




Panel B: Autocorrelation functions with unsmoothed returns

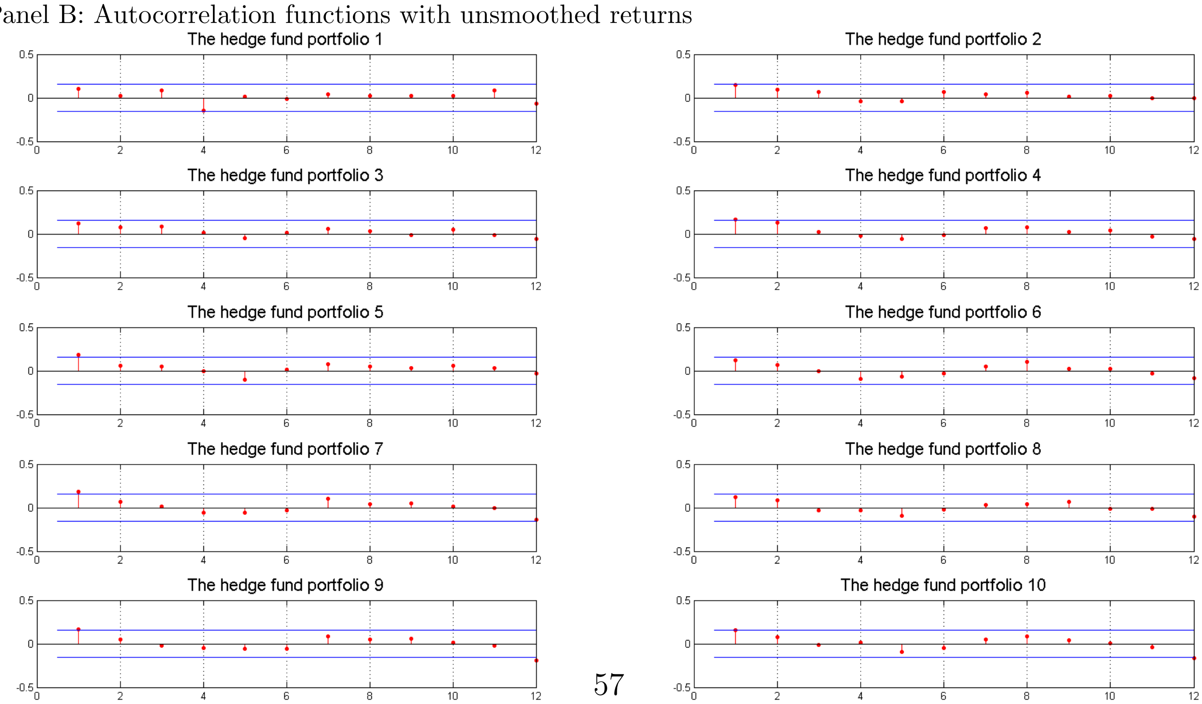


Table 1: BAB Portfolio Performance Conditional on Margin Requirements

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

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

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

Table 2: Factor Structure of the BAB Return Difference Series

This table presents the adjusted $R^2$s from time series regressions of five BAB return differences on their first principal component. A BAB return difference is calculated as the difference between two BAB portfolios that are constructed with stocks that have high-margin and low-margin requirements. The margin requirement is proxied by five measures: size, idiosyncratic volatility, the Amihud illiquidity measure, institutional ownership, and analyst coverage. The sample period is January 1965 to October 2012 for size, idiosyncratic volatility, and the Amihud illiquidity measure. The sample period is April 1980 to March 2012 for institutional ownership, and July 1976 to December 2011 for analyst coverage.

| | Adjusted $R^2$ (%) | |
|---|---|---|
| | Monthly | Quarterly |
| Size | 84.1 | 86.4 |
| Idiosyncratic volatility | 35.9 | 54.8 |
| Amihud | 70.5 | 77.5 |
| Institutional ownership | 66.2 | 66.9 |
| Analyst coverage | 78.3 | 79.5 |
| Average | 67.0 | 73.0 |

## Table 3: Correlations Between the Extracted Funding Liquidity Measure and Existing Funding Liquidity Proxies

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

Panel A: Correlations with 14 funding liquidity proxies

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

Panel B: Correlations with first principal components

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

Table 4: Time Series Regressions of the Extracted Funding Liquidity Measure

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

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

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

Panel B: Time series regressions of risk factors on FLS

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

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

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

Table 5: Pairwise Correlations

This table presents pairwise correlations between the extracted funding liquidity shocks (FLS) and other liquidity measures. We sign all liquidity measures such that small values indicate illiquidity. FLS is the first principal component extracted from five BAB portfolio return differences. FPC14 is the first principal component of 14 funding liquidity proxies. Amihud is the long-short equity portfolio sorted by individual stocks' Amihud measure. PS is the Pastor and Stambaugh (2003) market liquidity innovation measure. Sadka is the variable component of Sadka (2006) market liquidity factor. HPW is the Hu, Pan, and Wang (2013) monthly change of the noise illiquidity measure. BAB is the Frazzini and Pedersen (2014) "betting against beta" factor. MKT is the market risk premium. Panels A, B, and C report pairwise correlations calculated over the full sample, the months with positive market returns, and the months with negative market returns, respectively. Monthly correlations are reported with 5% statistical significance indicated with ∗.

Panel A: Pairwise correlations - unconditional

| | FLS | FPC14 | Amihud | PS | Sadka | HPW | BAB |
|---|---|---|---|---|---|---|---|
| FPC14 | 35.5* | | | | | | |
| Amihud | 23.9* | 8.2 | | | | | |
| PS | 17.0* | 28.4* | 9.1* | | | | |
| Sadka | 17.7* | 24.8* | 12.2* | 23.1* | | | |
| HPW | 17.7* | 20.4* | 5.3 | 22.1* | 20.2* | | |
| BAB | 33.5* | -2.8 | 11.5* | 14.8* | 17.9* | 8.2 | |
| MKT | 25.5* | 64.1* | 14.0* | 33.5* | 16.6* | 35.5* | -9.2* |

Panel B: Pairwise correlations - MKT>=0

| | FLS | FPC14 | Amihud | PS | Sadka | HPW | BAB |
|---|---|---|---|---|---|---|---|
| FPC14 | 27.8* | | | | | | |
| Amihud | 14.6* | -0.5 | | | | | |
| PS | 12.7* | 18.4* | -0.5 | | | | |
| Sadka | 11.1 | -1.1 | 10.1 | 8.3 | | | |
| HPW | 3.4 | 9.7 | -1.3 | 9.1 | -0.5 | | |
| BAB | 31.2* | -6.3 | -2.0 | 18.4* | 13.5 | -3.5 | |
| MKT | 5.8 | 43.4* | -1.4 | -0.7 | -10.9 | 21.4* | -19.5* |

Panel C: Pairwise correlations - MKT<0

| | FLS | FPC14 | Amihud | PS | Sadka | HPW | BAB |
|---|---|---|---|---|---|---|---|
| FPC14 | 40.5* | | | | | | |
| Amihud | 36.5* | 17.3 | | | | | |
| PS | 14.8* | 24.6* | 15.2* | | | | |
| Sadka | 24.9* | 44.9* | 14.8 | 35.2* | | | |
| HPW | 29.3* | 14.5 | 11.3 | 27.6* | 34.0* | | |
| BAB | 44.2* | 21.7* | 35.8* | 18.0* | 26.5* | 28.5* | |
| MKT | 38.6* | 47.9* | 20.3* | 43.9* | 38.9* | 41.1* | 18.2* |

Table 6: Correlations and Time Series Regression Results for Alternative Measures

This table presents the results for three alternative funding liquidity measures in consideration of the market liquidity effect. $FLS_{orth}$ is the residual after projecting the funding liquidity shock (FLS) on the long-short portfolio sorted by the Amihud illiquidity measure. $FPC_{single}$ is the first principal component of five long-short portfolios sorted by margin proxies. $FPC_{double}$ is the first principal component of five return difference series, where each return difference is calculated between a margin-proxy sorted long-short portfolio within low-beta stocks and a margin-proxy sorted long-short portfolio within high-beta stocks. Panel A reports the correlations between $FLS_{orth}$/$FPC_{single}$/$FPC_{double}$ and 14 funding liquidity proxies with 5% statistical significance indicated with $*$. Panel B reports the results of time series regressions where $FLS_{orth}$/$FPC_{single}$/$FPC_{double}$ are regressed on common risk factors, including the BAB factor, the Fama-French three factors, the Carhart momentum factor, the market liquidity factor proxied by a long-short portfolio based on stocks' Amihud measures, and the short-term reversal (STR) factor. Newey-West five-lag adjusted $t$-statistics are in parentheses. The sample period in Panel A depends on the specific proxy (Appendix A.1). The sample period for Panel B is January 1965 to October 2012.

Panel A: Correlations with 14 funding liquidity proxies

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

Panel B: Time series regressions

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

Table 7: Hedge Fund Decile Portfolios: Performance and Characteristics

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

Panel A: Hedge fund decile portfolio performance

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

Panel B: Hedge fund decile portfolio characteristics

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

Table 7 (cont.): Hedge Fund Decile Portfolios: Performance and Characteristics

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

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

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

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

Table 8: Hedge Fund Decile Portfolios' Performance during Normal and Stressful Periods

This table presents hedge fund decile portfolio performance during normal and stressful periods. Stressful periods are defined as the NBER recession months (March 2001-November 2001 and December 2007-April 2009, 26 months in total), and normal periods are the rest (134 months). At the end of each month, we sort hedge funds into ten decile portfolios according to their sensitivities to the extracted funding liquidity shock. Funding liquidity sensitivities are computed using a 24-month rolling-window regression of monthly excess returns on the funding liquidity shock and the market factor with a minimum observation requirement of 18 months. Panels A and B report monthly portfolio excess returns, the Fung-Hsieh seven-factor adjusted alphas, portfolio volatilities, and Sharpe ratios for normal periods and NBER recessions, respectively. Newey-West four-lag adjusted $t$-statistics are reported in parentheses. The sample period is from January 1996 to April 2009.

Panel A: Normal periods

| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | LMH |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Exret | 1.16 | 0.86 | 0.69 | 0.57 | 0.58 | 0.58 | 0.59 | 0.66 | 0.63 | 0.51 | 0.65 |
| | (4.33) | (4.42) | (4.70) | (5.07) | (4.76) | (4.98) | (4.56) | (4.27) | (3.32) | (1.58) | (2.50) |
| Alpha | 0.70 | 0.52 | 0.43 | 0.37 | 0.35 | 0.36 | 0.35 | 0.37 | 0.24 | -0.11 | 0.81 |
| | (3.32) | (2.92) | (3.31) | (4.17) | (3.49) | (3.62) | (3.44) | (3.10) | (1.98) | (-0.48) | (2.40) |
| Vol | 10.76 | 7.82 | 5.87 | 4.52 | 4.87 | 4.64 | 5.21 | 6.20 | 7.55 | 12.89 | 10.50 |
| SR | 1.30 | 1.32 | 1.41 | 1.52 | 1.42 | 1.49 | 1.37 | 1.28 | 0.99 | 0.47 | 0.75 |

Panel B: Stressful periods

| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | LMH |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Exret | -0.21 | -0.27 | -0.64 | -0.61 | -0.70 | -0.75 | -0.77 | -1.02 | -1.28 | -2.31 | 2.10 |
| | (-0.33) | (-0.81) | (-1.6) | (-1.45) | (-1.76) | (-1.69) | (-1.60) | (-1.69) | (-1.70) | (-1.95) | (2.24) |
| Alpha | 0.12 | 0.20 | -0.02 | 0.07 | -0.06 | 0.01 | 0.07 | -0.07 | 0.01 | -0.44 | 0.56 |
| | (0.35) | (1.58) | (-0.16) | (0.53) | (-0.49) | (0.04) | (0.4) | (-0.36) | (0.03) | (-0.75) | (1.03) |
| Vol | 11.32 | 5.87 | 7.07 | 7.41 | 7.06 | 7.78 | 8.56 | 10.64 | 13.30 | 20.90 | 16.61 |
| SR | -0.22 | -0.55 | -1.09 | -0.98 | -1.19 | -1.15 | -1.08 | -1.15 | -1.16 | -1.33 | 1.52 |

Table 9: Hedge Fund Decile Portfolios: Robustness Tests

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

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

Table 9 (cont.): Hedge Fund Decile Portfolios: Robustness Tests

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

Table 10: Time Series Forecasts of Macro Variables with the Funding Liquidity Shock

This table shows the results of forecasting four macro variables with the funding liquidity shock (FLS). Dependent variables are the cumulative growth rates of each variable calculated over one, two, four, and eight quarters. All growth measures are seasonally adjusted and defined as $\log(\frac{Y_{t+i}}{Y_t})$, where $i$ = 1, 2, 4, and 8. ΔGDP is the growth of the real GDP per capita; ΔINV is the growth of the real private fixed investment; ΔUE is the growth of the unemployment rate for full-time workers; ΔCON is the growth of the real consumption per capita on nondurable goods and services. Lagged ΔY refers to one-quarter lag of the dependent variable. MKT is the market excess return. Vol is the realized volatility of the market portfolio calculated using daily returns. Credit spread is the BAA-AAA corporate bond spread. Term spread is the yield spread between 10-year Treasury bonds and 3-month Treasury bills. For presentation convenience, all coefficients are multiplied by 100. Newey-West three-lag adjusted t-statistics are reported in parentheses.

Panel A: Forecasts for one-quarter growth

| | $\Delta GDP^{1qtr}$ | | $\Delta INV^{1qtr}$ | | $\Delta UE^{1qtr}$ | | $\Delta CON^{1qtr}$ | |
|---|---|---|---|---|---|---|---|---|
| Constant | 0.19 | 0.35 | 0.08 | 0.48 | 0.22 | -0.61 | 0.09 | 0.13 |
| | (4.42) | (4.18) | (0.92) | (2.26) | (1.24) | (-1.08) | (3.75) | (2.66) |
| FLS | 0.33 | 0.16 | 1.41 | 0.73 | -2.09 | -0.22 | 0.05 | -0.04 |
| | (1.78) | (0.75) | (2.99) | (1.64) | (-1.82) | (-0.18) | (0.58) | (-0.58) |
| Lagged ΔY | 31.99 | 24.81 | 55.19 | 46.38 | 58.60 | 48.16 | 54.92 | 46.82 |
| | (3.80) | (2.31) | (7.70) | (5.07) | (9.61) | (4.36) | (7.48) | (4.51) |
| MKT | | 0.27 | | 2.00 | | -2.14 | | 0.53 |
| | | (0.98) | | (3.16) | | (-1.24) | | (2.93) |
| Vol | | -0.06 | | 0.73 | | 3.65 | | 0.41 |
| | | (-0.17) | | (0.92) | | (1.22) | | (1.76) |
| Credit spread | | -15.28 | | -65.72 | | 51.38 | | -13.16 |
| | | (-2.68) | | (-3.00) | | (0.86) | | (-3.31) |
| Term spread | | -0.08 | | 6.73 | | -21.37 | | 0.12 |
| | | (-0.04) | | (1.43) | | (-2.13) | | (0.12) |
| adj. $R^2$ | 0.13 | 0.24 | 0.37 | 0.55 | 0.38 | 0.40 | 0.30 | 0.41 |
| obs | 191 | 107 | 191 | 107 | 178 | 107 | 191 | 107 |

Panel B: Forecasts for two-quarter growth

| | $\Delta GDP^{2qtr}$ | | $\Delta INV^{2qtr}$ | | $\Delta UE^{2qtr}$ | | $\Delta CON^{2qtr}$ | |
|---|---|---|---|---|---|---|---|---|
| Constant | 0.40 | 0.49 | 0.21 | 0.41 | 0.52 | -0.13 | 0.20 | 0.22 |
| | (5.24) | (3.63) | (1.12) | (1.12) | (1.3) | (-0.16) | (4.06) | (2.29) |
| FLS | 0.73 | 0.42 | 2.87 | 1.78 | -5.05 | -1.66 | 0.14 | 0.04 |
| | (2.36) | (1.34) | (2.89) | (1.77) | (-2.28) | (-0.66) | (0.92) | (0.28) |
| Lagged ΔY | 55.09 | 57.90 | 93.92 | 95.15 | 100.96 | 101.24 | 95.02 | 90.33 |
| | (4.09) | (4.72) | (6.54) | (6.55) | (8.46) | (6.08) | (6.08) | (4.18) |
| MKT | | 0.72 | | 3.91 | | -4.11 | | 0.83 |
| | | (1.62) | | (3.33) | | (-1.45) | | (3.06) |
| Vol | | 0.35 | | 2.34 | | 3.96 | | 0.74 |
| | | (0.58) | | (1.30) | | (0.75) | | (1.82) |
| Credit spread | | -20.74 | | -98.69 | | 79.83 | | -20.85 |
| | | (-1.92) | | (-2.53) | | (0.82) | | (-2.67) |
| Term spread | | 0.14 | | 16.72 | | -57.32 | | 0.57 |
| | | (0.04) | | (1.55) | | (-2.71) | | (0.28) |
| adj. $R^2$ | 0.16 | 0.30 | 0.36 | 0.57 | 0.37 | 0.49 | 0.30 | 0.43 |
| obs | 191 | 107 | 191 | 107 | 178 | 107 | 191 | 107 |

Table 10 (cont.): Time Series Forecasts of Macro Variables with the Funding Liquidity Shock

Panel C: Forecasts for four-quarter growth

| | $\Delta GDP^{4qtr}$ | | $\Delta INV^{4qtr}$ | | $\Delta UE^{4qtr}$ | | $\Delta CON^{4qtr}$ | |
|---|---|---|---|---|---|---|---|---|
| Constant | 0.92 | 0.82 | 0.61 | -0.52 | 1.36 | 3.37 | 0.46 | 0.25 |
| | (6.48) | (2.85) | (1.52) | (-0.56) | (1.46) | (1.74) | (4.65) | (1.1) |
| FLS | 1.16 | 0.68 | 5.42 | 3.66 | -11.99 | -4.07 | 0.41 | 0.26 |
| | (2.17) | (1.46) | (3.27) | (2.27) | (-3.18) | (-1.03) | (1.45) | (1.05) |
| Lagged $\Delta$Y | 74.43 | 81.77 | 130.19 | 171.51 | 129.04 | 168.26 | 153.75 | 175.27 |
| | (3.23) | (3.19) | (4.76) | (5.49) | (5.18) | (5.96) | (5.74) | (3.97) |
| MKT | | 1.60 | | 8.06 | | -13.25 | | 1.58 |
| | | (2.03) | | (3.84) | | (-2.26) | | (2.89) |
| Vol | | 1.15 | | 7.06 | | 5.79 | | 1.54 |
| | | (0.85) | | (1.72) | | (0.55) | | (1.82) |
| Credit spread | | -30.67 | | -150.18 | | -21.83 | | -29.66 |
| | | (-1.33) | | (-1.88) | | (-0.11) | | (-2.00) |
| Term spread | | 4.61 | | 61.54 | | -185.93 | | 4.62 |
| | | (0.65) | | (2.93) | | (-3.80) | | (1.03) |
| adj. $R^2$ | 0.12 | 0.19 | 0.27 | 0.53 | 0.24 | 0.44 | 0.26 | 0.41 |
| obs | 189 | 105 | 189 | 105 | 176 | 105 | 189 | 105 |

Panel D: Forecasts for eight-quarter growth

| | $\Delta GDP^{8qtr}$ | | $\Delta INV^{8qtr}$ | | $\Delta UE^{8qtr}$ | | $\Delta CON^{8qtr}$ | |
|---|---|---|---|---|---|---|---|---|
| Constant | 2.20 | 1.54 | 1.89 | -2.68 | 3.03 | 12.22 | 1.18 | 0.28 |
| | (9.39) | (2.59) | (2.47) | (-1.19) | (1.61) | (2.78) | (6.08) | (0.51) |
| FLS | 1.68 | 0.69 | 8.66 | 4.68 | -21.04 | -5.97 | 0.58 | 0.32 |
| | (2.04) | (1.03) | (3.21) | (1.94) | (-3.48) | (-1.08) | (1.18) | (0.74) |
| Lagged $\Delta$Y | 39.90 | 90.96 | 95.61 | 227.75 | 84.30 | 210.51 | 178.75 | 262.46 |
| | (1.10) | (2.06) | (2.09) | (3.35) | (2.35) | (5.11) | (3.64) | (2.87) |
| MKT | | 1.81 | | 11.58 | | -19.07 | | 2.32 |
| | | (1.56) | | (3.08) | | (-1.75) | | (2.27) |
| Vol | | 1.80 | | 12.13 | | 7.95 | | 3.05 |
| | | (0.75) | | (1.41) | | (0.4) | | (1.69) |
| Credit spread | | -59.48 | | -199.56 | | -189.98 | | -41.02 |
| | | (-1.40) | | (-1.57) | | (-0.51) | | (-1.23) |
| Term spread | | 32.17 | | 211.69 | | -553.51 | | 19.99 |
| | | (1.88) | | (4.21) | | (-4.61) | | (1.63) |
| adj. $R^2$ | 0.04 | 0.16 | 0.10 | 0.44 | 0.10 | 0.42 | 0.13 | 0.26 |
| obs | 185 | 101 | 185 | 101 | 172 | 101 | 185 | 101 |

## Table 11: Determinants of the Funding Liquidity Shock

This table presents time series regression results of the funding liquidity shock (FLS) regressed on systemic risk measures. Panel A reports the results when the independent variables are the contemporaneous risk measures. Panel B reports the results when the independent variables are the lagged risk measures. Panel C reports the results when the independent variables include both the contemporaneous and the lagged risk measures. Backward elimination is used for variable selection over the 17 systemic risk measures. CoVaR is the conditional (on an institution being in distress) value-at-risk of the financial system. MES and MES-BE measure the expected return of a firm conditional on the system is in its lower tail, where the latter employs dynamic volatility models to estimate MES. Size con is the Herfindahl index of the market equity calculated using the 100 largest financial firms. Vol is the average return volatility across the 20 largest financial institutions computed using daily returns. TED is the spread between the three-month LIBOR and three-month T-bill rates. Turbulence captures the excess return volatility of the largest 20 financial institutions. DCI is the dynamic causality index that captures the interconnectness of the largest 20 financial institutions. Default spread is the yield difference between the BAA and AAA corporate bonds. Book lev is the aggregate book leverage of the largest 20 financial institutions. Mkt lev is the aggregate market leverage of the largest 20 financial institutions. Intl spill measures the interdependence of asset returns and volatilities in 19 global equity markets. Term spread is the yield difference between the ten-year and three-month Treasury bonds. Newey-West five-lag adjusted $t$-statistics are in parentheses. The sample period is December 1984 to December 2011.

Panel A: Contemporaneous systematic risk measures

| Constant | $CoVaR_t$ | $\Delta CoVaR_t$ | $MES\text{-}BE_t$ | Size $con_t$ | $Vol_t$ | $TED_t$ | $Turbulence_t$ | adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|
| 0.05 | 8.73 | -13.11 | 2.44 | -0.04 | -2.54 | 0.00 | 0.00 | 0.16 |
| (1.06) | (3.96) | (-3.58) | (2.51) | (-2.76) | (-2.85) | (-3.13) | (-1.73) | |

Panel B: Lagged systematic risk measures

| Constant | $\Delta CoVaR_{t-1}$ | $MES_{t-1}$ | $DCI_{t-1}$ | Default $spread_{t-1}$ | Size $con_{t-1}$ | $TED_{t-1}$ | $Turbulence_{t-1}$ | adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|
| 0.09 | -7.61 | 3.68 | -0.28 | 0.03 | -0.03 | 0.00 | 0.00 | 0.11 |
| (3.05) | (-2.47) | (3.18) | (-2.72) | (2.08) | (-2.20) | (-3.12) | (-2.74) | |

Panel C: Contemporaneous and lagged systematic risk measures

| Constant | $\Delta CoVaR_{t-1}$ | $MES_{t-1}$ | Book $lev_t$ | $DCI_{t-1}$ | Default $spread_t$ | Default $spread_{t-1}$ | Intl $spill_t$ | Intl $spill_{t-1}$ | Size $con_t$ | Size $con_{t-1}$ | Mkt $lev_t$ | $Vol_t$ | Term $spread_t$ | adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| -1.21 | -16.16 | 6.54 | 1.46 | -0.27 | -0.14 | 0.22 | -0.01 | 0.01 | -0.15 | 0.12 | -0.01 | -2.83 | 0.01 | 0.25 |
| (-3.65) | (-4.71) | (4.91) | (3.80) | (-2.18) | (-2.83) | (4.62) | (-3.05) | (3.15) | (-2.26) | (1.75) | (-2.59) | (-3.89) | (1.93) | |

# Appendices

## A Data Appendix

### A.1 Funding liquidity proxies

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

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

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

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

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

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

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

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

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

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

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

**Swap T-bill spread (Swap spread):** We calculate the spread between the 1-year interest rate swap (the shortest maturity swap available in the FRED database) and the 3-month T-bill. Data are obtained from the FRED data library. The sample period is 2000:M7-2013:M4.

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

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

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

## A.2 Hedge Fund Data

Table A.1: List of Hedge Fund Strategies

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

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

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

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

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

$$r_{i,t}^0 = (1 - \Sigma_{j=1}^l \alpha_{i,j}) r_{i,t}^m + \Sigma_{j=1}^l \alpha_{i,j} r_{i,t-j}^0,$$

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

$$\begin{aligned}
r_{i,t}^1 &= \frac{r_{i,t}^0 - c_i^1 r_{i,t-1}^0}{1 - c_i^1}, \quad where \;\; c_i^1 = \rho_{i,1}^0. \\
r_{i,t}^2 &= \frac{r_{i,t}^1 - c_i^2 r_{i,t-2}^1}{1 - c_i^2}, \quad where \;\; c_i^2 = \frac{1 + \rho_{i,4}^1 - \sqrt{(1 + \rho_{i,4}^1)^2 - 4{\rho_{i,2}^1}^2}}{2\rho_{i,2}^1}. \\
r_{i,t}^3 &= \frac{r_{i,t}^2 - c_i^3 r_{i,t-1}^2}{1 - c_i^3}, \quad where \;\; c_i^3 = \rho_{i,1}^2.
\end{aligned}$$

# B Mathematics Appendix

## B.1 Proof of Lemma 1

For type A investors who do not have funding constraints (or in other words, whose funding constraints are not binding at optimal), and type B investors who face funding constraints as in Equation 3, we have two Lagrange problems:

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

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

## B.2 Proof of Lemma 2

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

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

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

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

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

## B.3 Proof of Proposition 1

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

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

## B.4 Proof of Proposition 2

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

$$BAB^1 - BAB^2 = \frac{\beta_H - \beta_L}{\beta_H\beta_L}((a^1_{BAB,t} - a^2_{BAB,t})\psi_t - (b_1 - b_2)).$$

As $a_{BAB,t}$ is drawn from some distribution with a time-invariant dispersion, we have the difference between $a^1_{BAB,t}$ and $a^2_{BAB,t}$ across two groups of stocks as a constant. In addition, because $(b_1 - b_2)$ does not depend on time, we conclude that the source of time series variation in the $BAB^1 - BAB^2$ spread is the time-varying funding liquidity shock $\psi_t$.□

# C Additional Figures and Tables

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

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

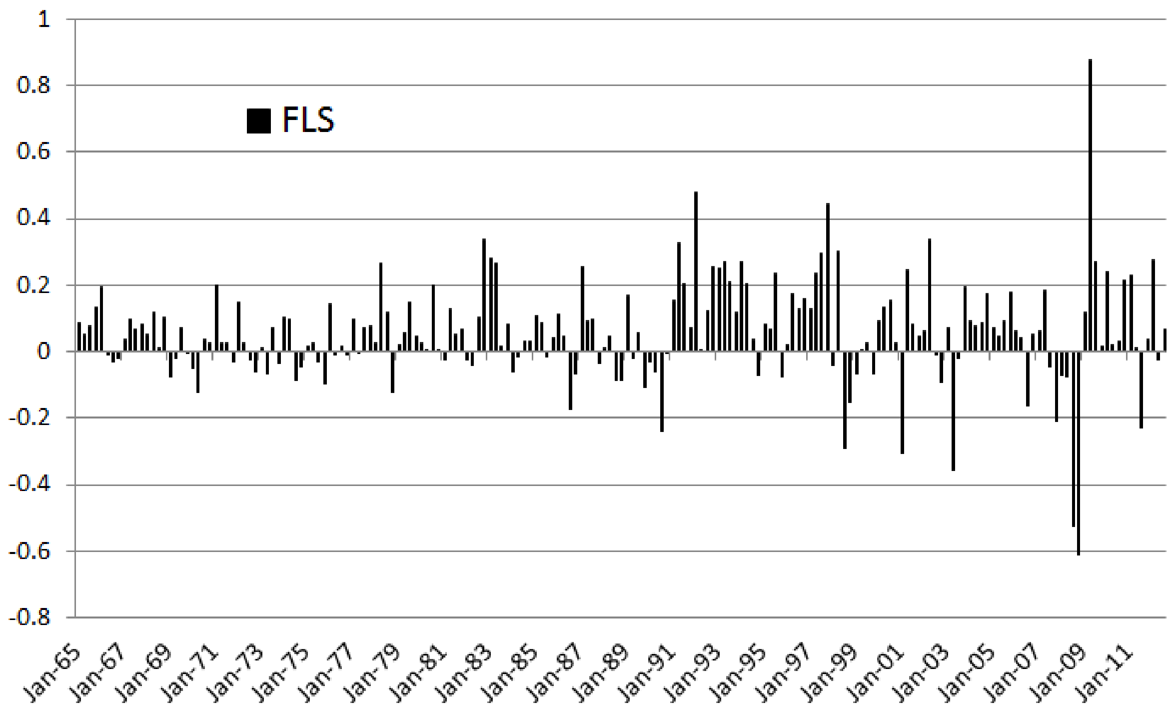
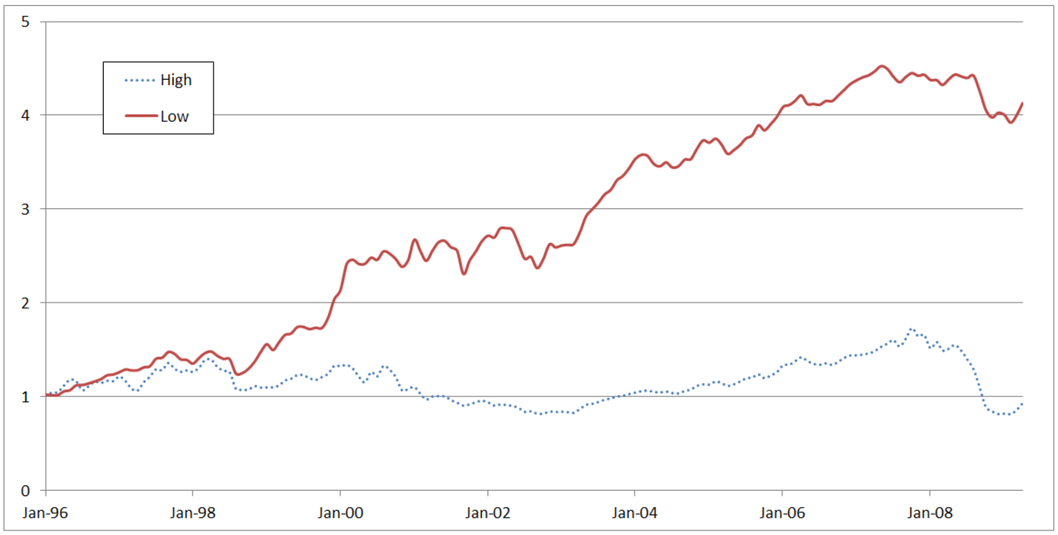


Figure C.2: Hedge Fund Portfolios' Performance

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

Panel A: Decile portfolios' cumulative returns




Panel B: Decile portfolios' maximum drawdowns

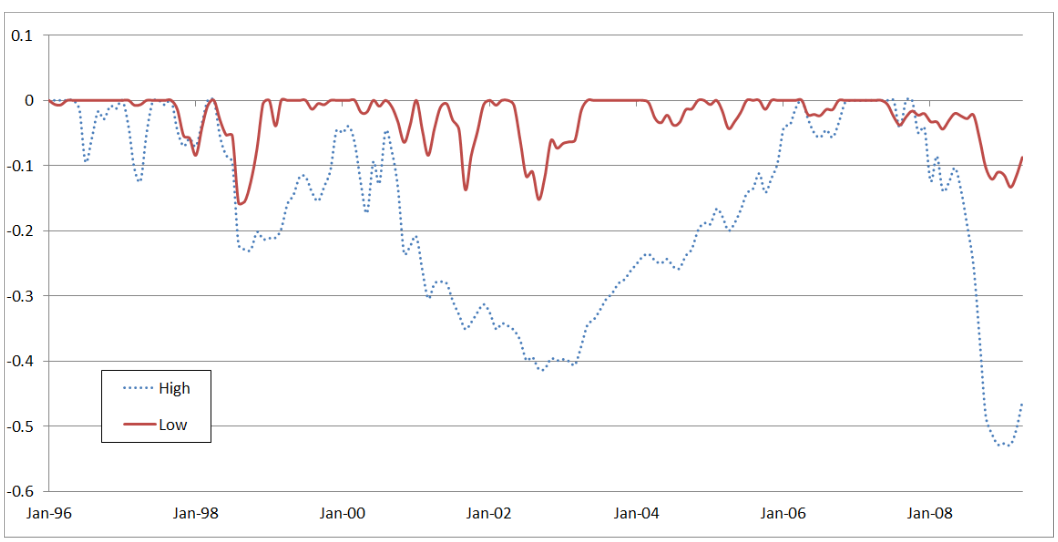
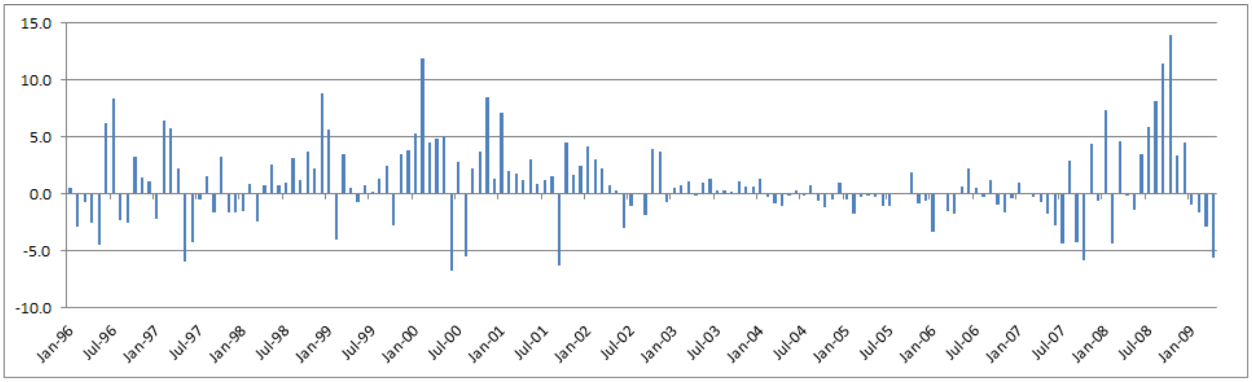


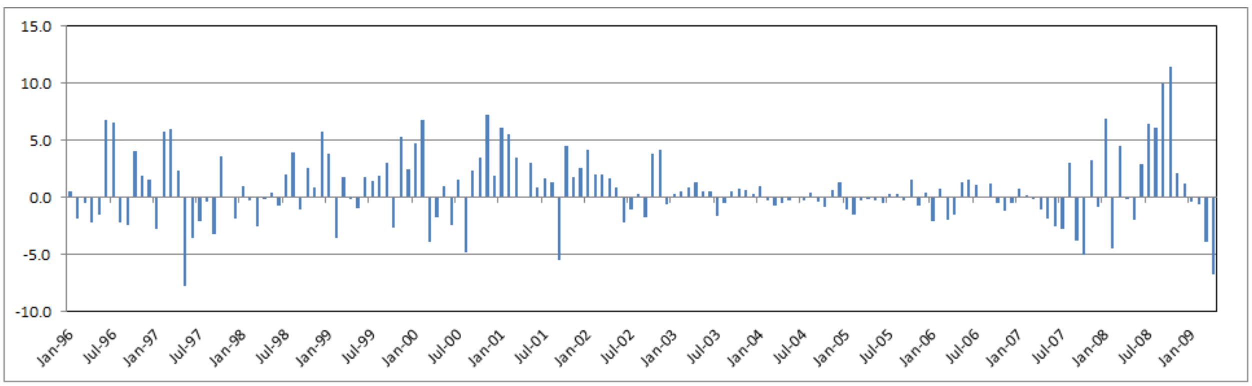
Figure C.3: Hedge Fund Portfolios' Spreads over Different Holding Horizons

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

Panel A: One-month holding horizon




Panel B: Six-month holding horizon




Panel C: Twelve-month holding horizon

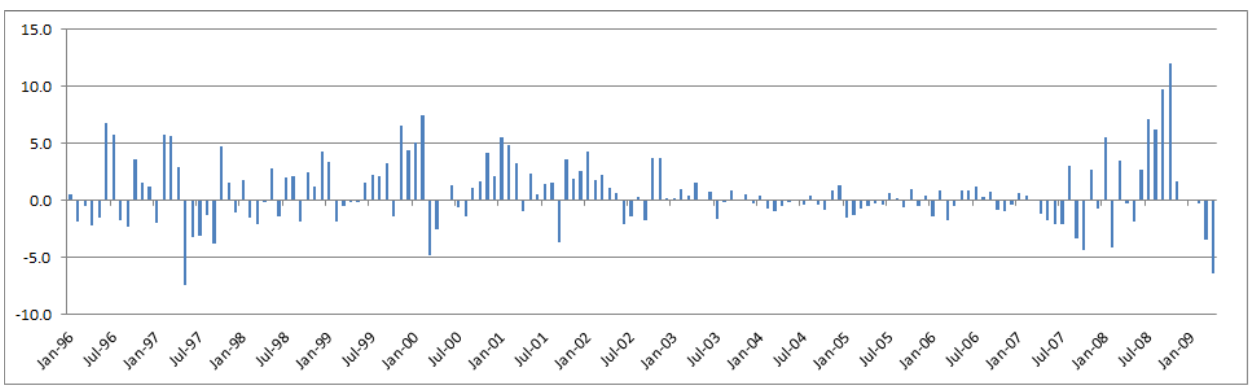


Figure C.4: Histograms of Hedge Fund Returns' First-Order Autocorrelations

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

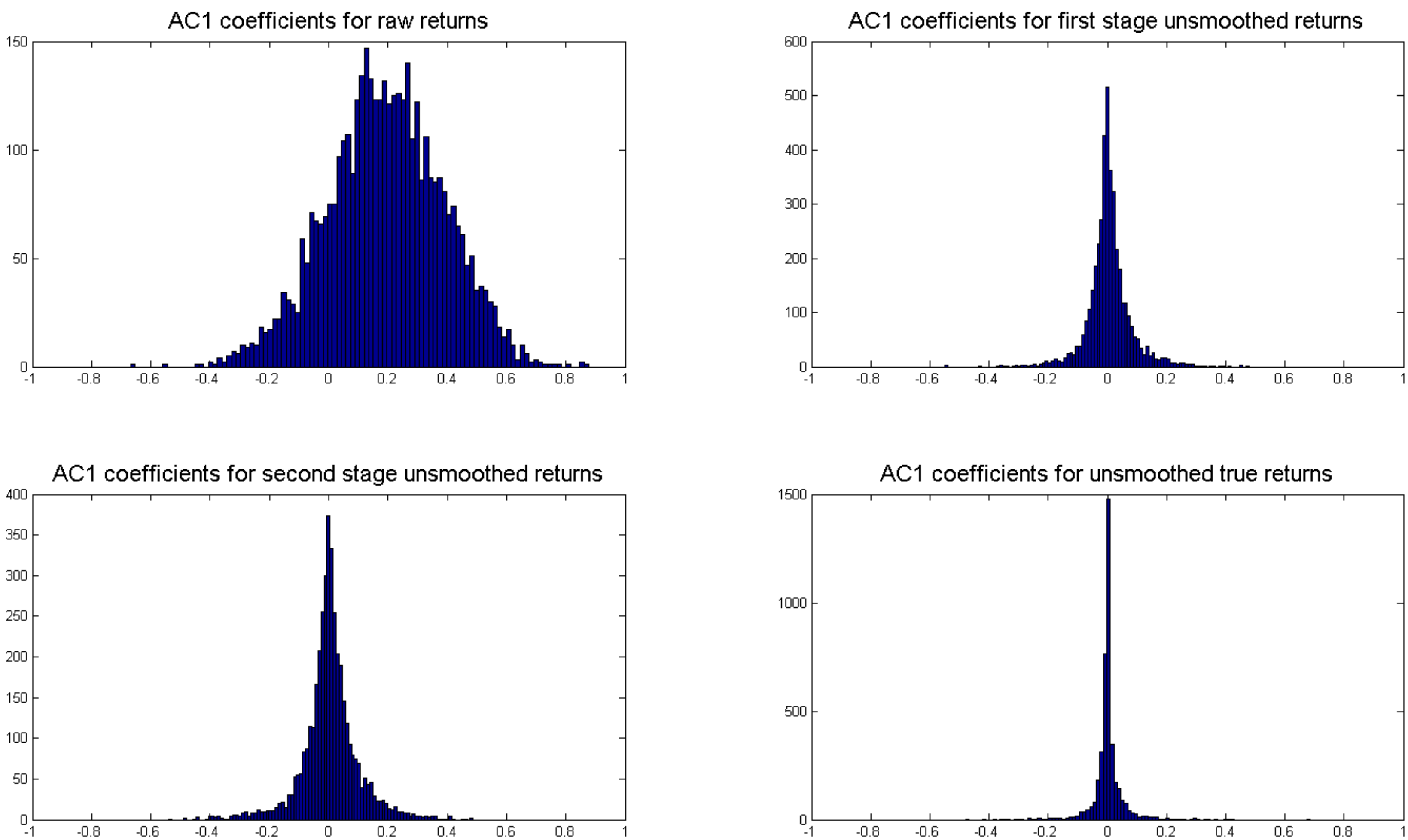


Figure C.5: Histograms of Hedge Fund Returns' Second-Order Autocorrelations

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

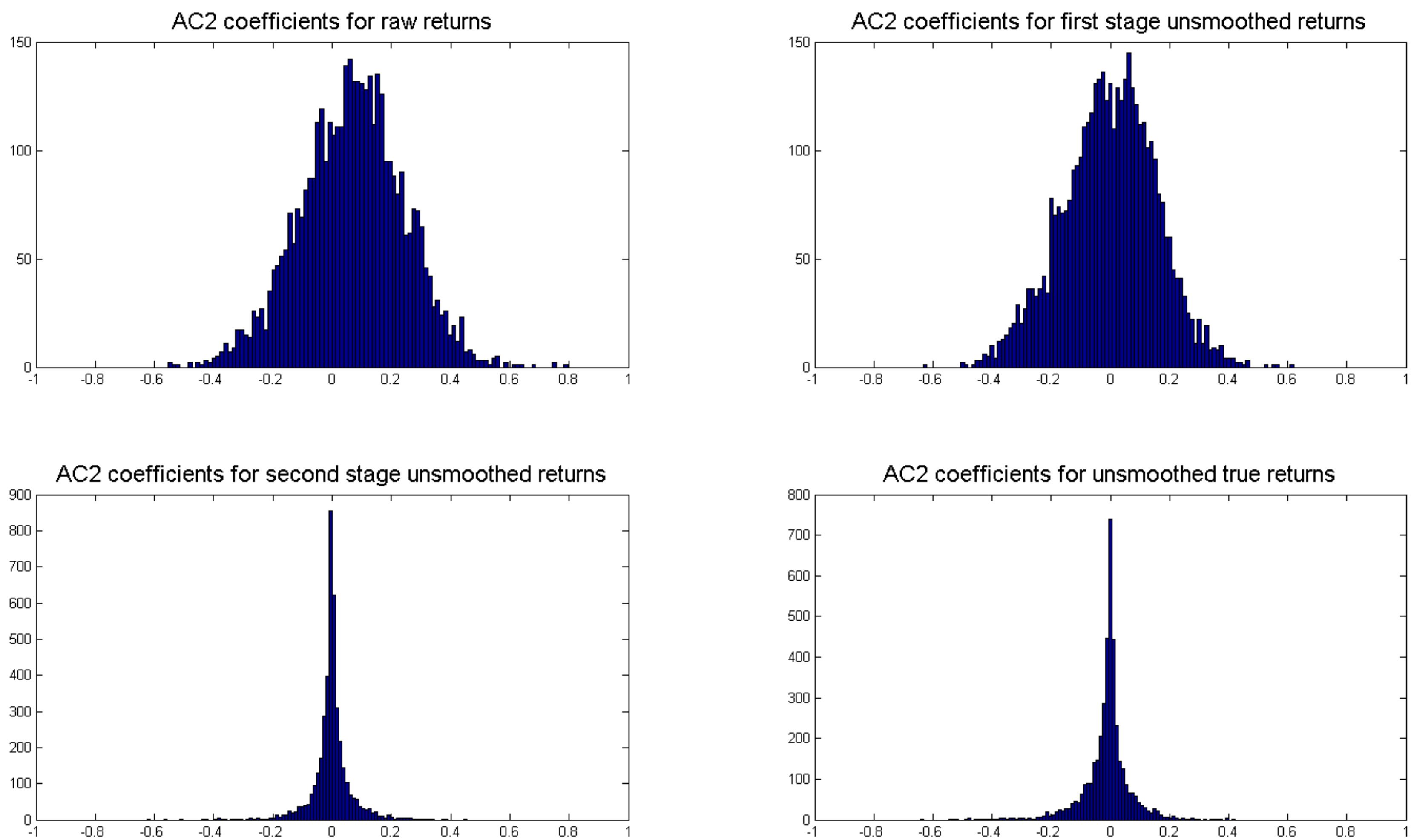


Table C.1: BAB Portfolio Characteristics

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

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

Table C.2: BAB Portfolio Returns, Orthogonalized Margin Proxies

This table presents BAB portfolio returns conditional on orthogonalized margin proxies. Each month, we orthogonalize each margin proxy by running a cross-sectional regression of margin proxies on market betas, and use the regression residuals to sort stocks into five groups: 1 indicates the low-margin group and 5 indicates the high-margin group. "Diff" indicates the return difference between two BAB portfolios constructed over high-margin and low-margin stocks. 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. Monthly returns and alphas are reported in percentage. The Newey-West five-lag adjusted $t$-statistics are in parentheses.

| | 1 (Low) | 2 | 3 | 4 | 5 (High) | Diff |
|---|---|---|---|---|---|---|
| Panel A: Size [1965M1-2012M10] | | | | | | |
| Exret | 0.35 | 0.37 | 0.65 | 0.76 | 1.49 | 1.14 |
| | (2.59) | (2.71) | (4.59) | (5.01) | (8.18) | (5.86) |
| Alpha | 0.16 | 0.11 | 0.30 | 0.40 | 0.99 | 0.83 |
| | (1.21) | (0.85) | (2.09) | (2.73) | (4.32) | (3.24) |
| Panel B: Idiosyncratic volatility [1965M1 - 2012M10] | | | | | | |
| Exret | 0.12 | 0.27 | 0.39 | 0.43 | 1.27 | 1.15 |
| | (0.75) | (1.68) | (2.55) | (2.75) | (6.78) | (6.48) |
| Alpha | -0.02 | 0.13 | 0.20 | 0.18 | 0.75 | 0.78 |
| | (-0.17) | (0.81) | (1.31) | (1.09) | (3.37) | (3.62) |
| Panel C: Amihud [1965M1 - 2012M10] | | | | | | |
| Exret | 0.26 | 0.41 | 0.41 | 0.43 | 1.56 | 1.30 |
| | (2.27) | (3.96) | (3.71) | (3.85) | (7.88) | (7.27) |
| Alpha | 0.17 | 0.31 | 0.19 | 0.22 | 1.14 | 0.97 |
| | (1.17) | (3.09) | (2.22) | (1.95) | (6.39) | (4.88) |
| Panel D: Institutional ownership [1980M4 - 2012M3] | | | | | | |
| Exret | 0.36 | 0.54 | 0.74 | 0.88 | 1.38 | 1.02 |
| | (2.05) | (2.91) | (3.61) | (4.03) | (5.48) | (4.66) |
| Alpha | 0.14 | 0.32 | 0.52 | 0.56 | 0.84 | 0.70 |
| | (0.80) | (1.72) | (2.79) | (2.72) | (2.77) | (2.35) |

Table C.3: Correlations Between the Extracted Funding Liquidity Shock and Existing Funding Liquidity Proxies

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

Correlations with 14 funding liquidity proxies

| | Asset growth | Bond liquidity | CDS | Credit spread | Financial leverage | HF leverage | IB exret | Broker leverage | LIBOR | Loan | Swap spread | TED spread | Term spread | VIX |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Monthly | | | | | | | | | | | | | | |
| Size | 13.9* | 11.5* | 42.1* | 20.2* | 19.7* | 47.6* | 25.0* | -3.3 | -10.5 | 18.4* | 19.1* | 15.3* | -1.5 | 23.7* |
| $\sigma_{ang}$ | 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* |
| $\sigma_{ang}$ | 28.4* | 28.4* | 39.2* | 37.6* | 43.9* | 50.7* | 34.2* | 19.3* | -12.2 | 36.1* | 13.4 | 22.5* | -15.2 | 32.7* |
| Amihud | 24.1* | 29.4* | 46.8* | 36.9* | 43.4* | 65.1* | 45.6* | 7.3 | -14.3 | 43.0* | 26.7 | 27.3* | -12.2 | 35.6* |
| Inst. | 18.9 | 15.7 | 36.8* | 38.2* | 34.4* | 50.9* | 24.6* | 9.4 | -6.0 | 42.2* | 17.4 | 22.2* | 1.6 | 26.8* |
| Analyst | 10.3 | 23.5* | 39.5* | 33.5* | 43.3* | 54.0* | 34.6* | 1.6 | -16.6 | 29.9* | 11.5 | 16.2 | -15.6 | 36.0* |

Table C.4: Descriptive Statistics of the CISDM Hedge Fund Data

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

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

Table C.5: Hedge Fund Decile Portfolio Alphas and the Fung-Hsieh Seven-factor Loadings

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

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

Table C.6: Mutual Fund Decile Portfolios

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

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