Funding Liquidity and Its Risk Premiums*

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Abstract

This paper presents a new approach to measure funding liquidity. The key idea is that, as borrowing constraints become more binding, speculators withdraw first from small stocks and then from large stocks since large stocks require lower margins. Given the speculators' role in liquidity provision, the asset liquidity of large and small stocks would covary differently with shocks to speculators' capital depending on their participation in the markets. Based on the intuition, funding liquidity is measured as the difference of rolling correlations of stock market returns with large and small stocks' asset liquidity. The estimated funding liquidity appears highly correlated with aggregate hedge fund leverage ratios and bond liquidity premiums. The funding liquidity is able to predict aggregate stock market returns with strong significance in both in-sample and out-of-sample tests. It is also robust to various equity premium predictors, subsample periods, and long-horizon forecast bias.

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1 Introduction

Money is created not only by a central bank. It can also be created by the private sector in the form of credit. This paper suggests a new way to estimate how much credit is available in the stock market and calls it as funding liquidity.

Liquidity can be categorized into two types: asset liquidity and funding liquidity. Asset liquidity is the ease with which an asset is traded. Funding liquidity is the capacity for a trader to raise funds. These two types of liquidity reinforce each other (see Kyle and Xiong (2001), Gromb and Vayanos (2002), and Brunnermeier and Pedersen (2009)).

Their feedback relationship is often called the 'liquidity spiral.' A small capital loss can prevent risk-neutral speculators from providing enough asset liquidity to markets, thus raising margin requirements and further limiting their liquidity-providing activity.[1] As a result, risk-averse investors would end up paying high premiums for asset liquidity. Thus, the liquidity spiral can be attributed to the combined effects of margin requirements and speculators' capital, which are denoted by funding liquidity. Funding liquidity is considered low when speculators have little capital relative to margin requirements.

The first question is how to estimate funding liquidity empirically. I suggest a novel approach by combining two pieces of intuition. First, speculators prefer trading large stocks to small ones during a liquidity crisis.[2] Second, negative stock market returns are followed by decreasing asset liquidity since market returns cause exogenous capital shocks to speculators.[3] Having put them together, one can expect that, during a crisis, large stocks' liquidity becomes more correlated with market returns than small stocks' liquidity because of speculators' withdrawal from small stocks. In good times, however, large and small stocks' liquidity would be equally correlated with market returns. Building on the intuition, I estimate two rolling correlations (one is between large stocks' liquidity and market returns and

[1]For details of the liquidity spiral, one can refer to Allen and Gale (1994), Brunnermeier and Pedersen (2009), Fostel and Geanakoplos (2008), Geanakoplos (2009), Geanakoplos (2010) among many others.

[2]Ben-David, Franzoni, and Moussawi (2011) analyze the trading patterns of hedge funds during the global financial crisis and find that they sold more high- than low-volatility stocks and shifted their portfolio towards larger stocks during the crisis. Anand, Irvine, Puckett, and Venkataraman (2011, p.1) also document that "liquidity deteriorates more sharply and recovery patterns are slower for smaller, more volatile, and higher (ex-ante) liquidity beta stocks" and "institutions avoid illiquid stocks and defensively tilt trading activity towards liquid stocks."

[3]Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010) show that the NYSE specialists with deep pockets (e.g., affiliation with other corporates) are less affected by the negative market returns. Hameed, Kang, and Viswanathan (2010) find that the negative market returns are still a strong predictor of decreasing asset liquidity even after controlling for the changes in volatility.

the other is between small stocks' liquidity and market returns) and use their difference as a proxy of funding liquidity.

This paper derives a model to describe speculators' trading patterns. It assumes two risky assets, large (less volatile) and small (more volatile) stocks, and three agents: a customer, a speculator, and a financier. The customer is risk averse, holds the total fixed supplies of the risky assets, and immediately trades them to hedge their risks. The speculator is risk neutral and makes profits by taking the other side of the customer's liquidity-motivated trades. The financier funds the speculator's trades but also restricts them by demanding margin requirements.

In the equilibrium, the liquidity of large and small stocks varies depending on the speculator's participation. As borrowing constraints become more binding, the speculator withdraws first from high volatility (small) stocks and then from low volatility (large) stocks. This movement is due to the fact that high volatility stocks require higher margins to be traded. As a result, the liquidity of each group of stocks covaries differently with shocks to speculators' capital. When the speculator is unconstrained, he fully takes part in both markets. So, shocks to the speculator's capital generate similar variation in the asset liquidity of the two assets. However, if the speculator is constrained, he participates more in the market for large stocks than in the market for small stocks. In this case, shocks to the speculator's capital are more negatively correlated with the asset liquidity of large stocks than small stocks. So the distance in this correlation between small and large stocks is negatively related to the speculator's capital, that is, funding liquidity.

In its empirical implementation, shocks to the speculator's capital are proxied by stock market returns (see Hameed, Kang, and Viswanathan (2010) and Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010)). The sensitivities of asset liquidity to the capital shocks are measured by the rolling correlations of stock market returns with large and small stocks' asset liquidity, which is estimated as in Amihud (2002). The difference of the two rolling correlations is used to estimate funding liquidity.

The estimated time series of funding liquidity is shown to reach a peak in the beginning of recession but falls sharply to a low as recession comes to an end. High funding liquidity predicts low real GDP growth rates for the next two years. The estimated funding liquidity also appears positively correlated with aggregate hedge fund leverage ratios and the total number of M&A activities, and negatively correlated with bond liquidity premiums, Moody's Baa-Aaa corporate bond spreads, and the relative prevalence of liquidity mergers.[4]

[4]Liquidity mergers are defined by Almeida, Campello, and Hackbarth (2011) as liquid firms' acquiring

The financial media often relates asset price booms to excess liquidity in the financial system. Conversely, it is also repeatedly told that risky assets become more discounted during a liquidity crisis.[5] If this is true, high liquidity would forecast low market excess returns. However, there has not been any strong evidence to date to support the forecastability.[6]

This paper shows that the funding liquidity significantly forecasts aggregate stock market returns. A decrease in funding liquidity by one standard deviation predicts an increase in monthly excess returns by 0.56%. Its forecastability is significant both in in-sample and out-of-sample tests, and robust to other equity premium predictors such as log valuations ratio, variance premiums as the difference between squared VIX and realized stock return variance, riskfree interest rates, Goyal and Santa-Clara's (2003) average stock return variance, Campbell and Vuolteenaho's (2004) small-stock value spreads, Moody's Baa-Aaa corporate bond spreads, Boudoukh, Michaely, Richardson, and Roberts's (2007) total net payout yields, Lettau and Ludvigson's (2001) consumption-wealth ratio, and Pollet and Wilson's (2010) average correlation among individual stock returns. The forecastability is also robust to the long-horizon forecast bias and the small-sample bias of predictive regressions,[7] and appears significant across all subperiods of the Bretten Woods System (1946–1970), the pre-Volcker period (1971–1985), and the post-Volcker period (1986–2010). Market-timing strategies based on funding liquidity could generate 82.5% higher Sharpe ratio than a simple buy-and-hold strategy of stock market index funds.

The up-to-date evidence about liquidity's risk premium is found from the cross-section of stock portfolio returns. For example, Pástor and Stambaugh (2003), Acharya and Pedersen (2005), and Jensen and Moorman (2010) form stock portfolios based on stocks' liquidity or their sensitivity to market liquidity, and find significant evidence that less liquid (or, more sensitive to market liquidity) stocks provide higher returns. Amihud and Mendelson (1986) show that expected stock returns are increasing with bid-ask spreads. Sadka

financially distressed firms which would be otherwise inefficiently terminated.

[5] Diamond and Rajan (2006) show that the need to raise cash can lead to fire sales of risky assets so that liquidity problems can escalate into solvency issues. Johnson (2009) shows a negative monotonic relationship between liquidity and expected excess returns. Vayanos and Wang (2009) survey how market imperfections affect liquidity and find that low liquidity is related to high expected returns in most cases.

[6] All liquidity measures currently available in the literature fail to predict future stock market returns, or marginally succeed at best. For example, Jones (2002) compiles the bid-ask spreads of all 30 Dow Jones Industrial Average (DJIA) stocks since 1896 and tests the hypothesis, but fails to find any forecastability from the spreads during the post-war period. Amihud (2002) estimates illiquidity indirectly as the average of absolute stock returns normalized by trading volumes, but this illiquidity measure is unable to predict future stock returns by itself either.

[7] For details about the small-sample bias of predictive regressions, refer to Mankiw and Shapiro (1985), Nelson and Kim (1993), Stambaugh (1999), and Lewellen (2004).

(2006) decomposes asset liquidity into fixed and variable components and shows that the variable component can explain 40%–80% of momentum and post-earnings-announcement-drift portfolio returns. For this literature is to estimate asset liquidity's premiums, however, it is not able to explain high stock market returns that follow a liquidity crisis.

There are barely a few measures for funding liquidity, and most of the few measures are either not directly related to the stock market or have time spans that are too short to sufficiently test asset pricing implications. For example, Fontaine and Garcia (2012) estimate liquidity premiums using the yield difference between on-the-run and off-the-run Treasury bonds. In a similar vein, Hu, Pan, and Wang (2011) use the price deviations of US Treasury bonds to proxy the limit of arbitrage due to speculators' insufficient capital. Ang, Gorovyy, and van Inwegen (2011) aggregate the leverage ratios of all hedge funds from 2005 to 2010, and Adrian and Shin (2010) and Jordà, Schularick, and Taylor (2011) use leverage ratios in the banking industry. However, none of these studies examine whether the estimated funding liquidity is able to forecast future stock market excess returns.

The paper is organized as follows. Section 2 presents a model with two dates and three market participants: a customer, a speculator and a financier. It explains why large stocks are preferred to small stocks when the speculator is financially constrained. Section 3 explains the estimation strategy and describes the time series of the estimated funding liquidity. Section 4 discusses statistical tests that demonstrate funding liquidity's forecastability. Section 5 concludes.

2 Model

My model is a simplified version of Brunnermeier and Pedersen (2009). The economy has two risky assets (large and small stocks), and an equilibrium is made among three agents: a customer, a speculator, and a financier. The customer is risk-averse and trades his initial holdings of risky assets to hedge risk. The speculator is risk-neutral and makes profits by taking the other side of the customer's trades. The financier determines the speculator's borrowing constraints, which is a main friction in the economy. The model implies that, when the borrowing constraints are binding, the speculator prefers trading large stocks to small ones since large stocks require lower margins. As a result, an exogenous shock to the speculator's capital becomes increasingly more correlated with large stocks' liquidity relative to small stocks' as the shadow cost of the constraints rises.

2.1 The Economy

The economy has two risky assets, and the assets are in the fixed supply of one share for each. Risk-free interest rate is normalized to zero. There are two dates: $t = 0, 1$. At time $t = 1$, each securities j pays off $v^{(j)}$. The terminal payoffs $v^{(j)}$ are random variables which would be realized at $t = 1$, but their distributions are known ex ante at $t = 0$.

$$v \sim \mathcal{N}(\, \bar{v},\, \Omega \,) \qquad \text{where} \qquad \Omega \equiv \begin{bmatrix} \left\{\sigma^{(a)}\right\}^2 & \rho\,\sigma^{(a)}\,\sigma^{(b)} \\ \rho\,\sigma^{(a)}\,\sigma^{(b)} & \left\{\sigma^{(a)}\right\}^2 \end{bmatrix} \tag{1}$$

The economy has three market participants: a customer, a speculator, and a financier. They can be considered a representative agent of each class. Their objectives are treated separately by following subsections.

2.2 Customer

A customer holds the total fixed supplies of risky assets, one share for each, at $t = 0$. The customer immediately trades y shares to maximize his exponential utility (CARA) function over final wealth. His objective function subject to wealth constraint can be written as

$$\max_{y} \; E_0 \left[-\exp\left(-\gamma \, W_1^{(c)} \right) \right] \tag{2}$$

$$\text{s.t.} \quad W_1^{(c)} = p_0^\top \mathbf{1} + (v - p_0)^\top (y + \mathbf{1}) \tag{3}$$

where γ denotes the coefficient of absolute risk aversion, $W_1^{(c)}$ denotes the customer's wealth at $t = 1$, p_0 denotes the market price of securities at $t = 0$, and $\mathbf{1}$ denotes a vector of ones, $\mathbf{1} \equiv [1,\, 1]^\top$. p_0 will be endogenously determined by the equilibrium among market participants.

By solving the optimization problem in equation (2), a customer's optimal trade is derived as

$$y^* = \frac{1}{\gamma}\, \Omega^{-1} \left(\bar{v} - p_0 \right) - \mathbf{1} \tag{4}$$

which is the sum of speculation and hedge components. According to the first term of (4), the customer would buy more shares when the assets are underpriced, and the extent of this speculative trade is inversely proportional to his risk aversion and the diffusions of terminal asset payoffs. The second term of (4) suggests that the customer would hedge away all of his initial holdings of risky assets.

2.3 Speculator

A speculator is the second type of market participants. He is risk neutral, and trades x shares of securities to maximize his profits.

$$\max_x E_0 \left[(v - p_0)^\top x \right] = \max_x (\bar{v} - p_0)^\top x \tag{5}$$

The speculator's trades are constrained by margin requirements.

$$\left| x^{(a)} \right| m^{(a)} + \left| x^{(b)} \right| m^{(b)} \leq W_0^{(s)} \tag{6}$$

where $m^{(j)}$ denotes the margin requirement for trading securities j. The same amounts of margins are required for both long and short positions. The margins are determined by a financier using the Value-at-Risk (VaR) method, which will be explained in the next subsection. $W_0^{(s)}$ denotes the speculator's initial wealth.

2.4 Financier

A financier is the last market participant. He does not trade securities directly, but lend funds to a speculator so that the speculator can leverage up his trades. For the sake of simplicity, the financier is assumed to demand zero returns. However, he imposes margin requirements to limit his potential loss from the uncertainties of asset payoffs. A financier uses the VaR (Value-at-Risk) method to determine the margins as

$$\pi = \begin{cases} \mathrm{P}\left(v^{(j)} - p_0^{(j)} < -m_j \right) & \text{for a long position} \\ \mathrm{P}\left(v^{(j)} - p_0^{(j)} > m_j \right) & \text{for a short position} \end{cases} \tag{7}$$

where π denotes the probability by which a loss may incur. The same margins are required for both long and short positions.

Now assume that the financier is not aware of the ex ante expectation ($\bar{v}$) of terminal payoffs. Instead, he wrongly believes that the market prices of securities at $t = 0$ are equal to the expected terminal payoffs. In his belief,

$$v \sim \widehat{\mathcal{N}}(\, p_0, \, \Omega \,) \tag{8}$$

Thus, by combining equation (7) and (8), the financier determines the margin for securities j as

$$m^{(j)} = \Phi^{-1}(1-\pi) \cdot \sigma^{(j)} \tag{9}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of a standard normal random variable. Equation (9) implies that trading riskier assets requires higher margins.

The model makes two assumptions. First, the financier uses p_0 instead of $\bar{v}$. Second, margins are determined on an asset-basis rather than a portfolio. These assumptions are actually optimal for the financier when information acquisition is costly. The first one saves the efforts of collecting information about the securities meanwhile the second one saves the costs of analyzing the speculator's portfolio.

Even though the model divides a speculator and a financier's roles, they do not have to be separate corporate entities. They can be considered not only as a hedge fund and a brokerage firm but also as a trading desk and a risk management back-office within an investment bank.

2.5 Equilibrium

Risky assets are in fixed supplies. Thus, in equilibrium, a customer's trade demands should be matched with a speculator's trades.

$$x + y = 0 \tag{10}$$

The speculator's optimal trades can be derived by using the Lagrangian optimization method,

$$x^* = \frac{1}{2}\left\{\mathbf{1} - \frac{\lambda}{\gamma}\,\Omega^{-1}\,\tilde{m}\right\} \tag{11}$$

where λ denotes the shadow cost of margin constraints. λ is derived as

$$\lambda = \gamma\,\frac{\tilde{m}^\top \mathbf{1} - 2\,W_0}{\tilde{m}^\top \Omega^{-1} \tilde{m}} \qquad \text{and} \qquad \tilde{m} \equiv \begin{bmatrix} \operatorname{sign}\left(x^{(a)}\right)\; m^{(a)} \\ \operatorname{sign}\left(x^{(b)}\right)\; m^{(b)} \end{bmatrix} \tag{12}$$

if the speculator is constrained, and zero otherwise.

Note that this equilibrium is based on an implicit assumption that speculators collude to maximize profits or one speculator monopolizes the given securities. In the absence of this assumption, speculators would compete with each other and their profits would dissipate. In this alternative scenario, speculators' optimal trades (x) would be determined by the condition at which marginal trading profits (levered returns) equal the shadow costs of borrowing constraints. Appendix A explains the alternative scenario. As shown by comparing Figure 1 and Figure A1, the two scenarios lead to identical implications.

2.6 Model's Implication: Flight to Quality

The model is simulated with the following parameters.

$$\bar{v} = \begin{bmatrix} 5 & 1 \end{bmatrix}^\top, \quad \gamma = 3, \quad \pi = 0.01$$
$$\sigma^{(a)} = 0.5, \quad \sigma^{(b)} = 0.15, \quad \rho = 0.4$$

These parameters imply that Asset a and b correspond to large and small stocks. Asset a's ex ante expected payoff per share is five times bigger than Asset b's, but the diffusion of Asset b's terminal payoff is relatively 50% larger than that of Asset a's payoff $\left(\sigma^{(a)}/\bar{v}^{(a)} = 0.1,\, \sigma^{(b)}/\bar{v}^{(b)} = 0.15\right)$. ρ denotes the terminal payoffs' correlation. Speculator's initial wealth, $W_0^{(s)}$, varies from zero to one.

Note that there are two different sources of risk premiums. One is the correlation to a customer's consumption, which is a primary source of risk premium for large stocks.[8] The other is the volatility of each asset's terminal payoff, which is a principal component of risk premium to small stocks. The parameters above are engineered so that the discount rates of large and small stocks become comparable.

[INSERT Figure 1 HERE]

Figure 1 shows how trades and discount rates respond to the speculator's initial wealth $\left(W_0^{(s)}\right)$. Panel (a) shows the speculator's optimal trades, and Panel (b) shows the discount rates which are defined as $\left(\bar{v}^{(j)} - p_0^{(j)}\right)/\bar{v}^{(j)}$. Vertical lines divide the plots into three areas depending on the margin constraints. The speculator is free of the constraints in area (a) but becomes constrained as he moves into area (b) and (c). As the speculator's initial wealth decreases, his trades decline and the risky assets become more discounted.

Area (a) shows that a speculator trades fixed amounts, $x = \frac{1}{2}$, when he is unconstrained. He withdraws first from small stocks in area (b), and then from large stocks in area (c). His

[8] In a similar vein, Cochrane, Longstaff, and Santa-Clara (2008) derive an equilibrium model with two i.i.d. Lucas trees. One of their model's implications is that a large tree is supposed to be discounted more than a small tree due to the difference of correlations to a representative agent's consumption.

preference for large stocks is due to the fact that holding large stocks requires lower margins than small stocks. Therefore, even when large and small stocks have similar holding returns, large stocks become more attractive to the speculator in terms of levered returns.

2.7 Simulated Correlation of Asset Liquidity with Market Returns

The previous section shows that the speculator prefers trading large stocks to small ones when he is contained by margin requirements. This section intends to show how the behavior affects asset liquidity, which is measured by the price impacts of trades. An exogenous trade shock (ϵ) is now added to the market clearing condition as follows

$$x + y + \epsilon = 0 \tag{13}$$

The price impacts of trades, or asset illiquidity, are defined as the difference of market price given a trade shock ($\hat{\epsilon}$) normalized by the ex-ante expected payoff ($\bar{v}$).

$$\text{Price Impacts of Trades} \equiv \left| \frac{p_0|_{\epsilon=\hat{\epsilon}} - p_0|_{\epsilon=0}}{\bar{v}} \right| \tag{14}$$

Note that the price impacts are the function of trade shock and the speculator's capital. In Figure 1, for example, small stocks' price impacts become the highest in area (b) in which the speculator is bound by margin requirements but still participates in both markets. He rapidly rebalances small stocks in his portfolio in the area, and this rebalancing activity amplifies small stocks' price impacts. Because of the same reason, large stocks' price impacts would peak in area (c).

In addition to the trade shock, this section assumes another exogenous shock to the speculator's capital. Meanwhile the trade shock directly affects asset prices, the capital shock affects the speculator's financial constraints and thereby his liquidity provision. For example, a capital shock would affect both assets' liquidity in area (b) but only the large stocks' liquidity in area (c).

The sensitivities of the two assets' liquidity to the capital shock are defined as

$$\begin{aligned}
\rho_{\text{small}} &= \text{corr}\left(\text{Small Stocks' Price Impacts of Trades, } W_0^{(s)} + \eta\right) \\
\rho_{\text{large}} &= \text{corr}\left(\text{Large Stocks' Price Impacts of Trades, } W_0^{(s)} + \eta\right)
\end{aligned} \tag{15}$$

where η denotes the exogenous capital shock. The trade shock is fixed at $\hat{\epsilon} = \left[-0.2,\ -0.2\right]^{\top}$. The price impacts are simulated by randomly drawing capital shocks from $\eta \sim \mathcal{N}\left(0,\ 0.3^2\right)$. The simulation is repeated for 10 million times for each value of $W_0^{(s)}$.

[INSERT Figure 2 HERE]

Figure 2 shows the correlations of the simulated capital shocks and their price impacts of trades. Panel (a) shows each asset's correlation, and Panel (b) shows their difference. The horizontal axes denote $W_0^{(s)}$, the speculator's initial wealth prior to the capital shock.

In Panel (a), both correlations show U-shapes because they converge to zero as the speculator becomes very rich. Remind that, if he is very rich, he will trade only the constant amounts of stocks, $\frac{1}{2}\left(\mathbf{1} - \epsilon\right)$. In this case, the asset liquidity would be increasingly insensitive to the capital shock. On the left end, in comparison, ρ_{small} goes positive since small stocks' price impacts become the highest in the middle area. Meanwhile, ρ_{large} is always negative since the large stocks' price impacts become stronger as the speculator becomes poorer.

Note that the gap between the two correlations widens almost monotonically as the speculator becomes poorer. The near-monotonic relationship between the difference of correlations and the speculator's initial wealth offers the key intuition of my measuring funding liquidity in the next section.

3 Estimating Funding Liquidity

3.1 How to Measure Funding Liquidity?

The model explains why large stocks are preferred to small stocks when borrowing constraints are binding. Building on this, the last section shows that the difference of two correlations $(\rho_{\text{large}} - \rho_{\text{small}})$ increases near-monotonically with the speculator's wealth. This section exploits the implication to construct an empirical proxy of the speculator's wealth, i.e., funding liquidity.

$$\rho_{\text{small}} \equiv \text{corr}\left(\text{Small Stocks' Illiquidity, Stock Market Returns}\right) \tag{16}$$

$$\rho_{\text{large}} \equiv \text{corr}\left(\text{Large Stocks' Illiquidity, Stock Market Returns}\right) \tag{17}$$

where large and small stocks' illiquidity is estimated by the Amihud (2002)'s measure of the price impacts of trades, which is the average of absolute stock returns divided by dollar trading volumes. Note that the capital shock is proxied by aggregate stock market returns, which is based on Hameed, Kang, and Viswanathan (2010) and Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010)'s finding that market returns create exogenous shocks to liquidity providers' capital. The correlations are estimated over the rolling window of previous 30 months.

Funding liquidity is measured as the difference of the two correlations.

$$fliq \equiv \rho_{\text{large}} - \rho_{\text{small}} \tag{18}$$

I use CRSP daily stock returns from Jan 1946 to Dec 2010. Observations are dropped if (i) trading activities are recorded for less than 10 days for a month, (ii) stock price is less than \$1 or higher than \$1,000, (iii) stocks are not ordinary shares (share code of 10 or 11), (iv) stocks are not traded by either NYSE, AMEX or NASDAQ, or (v) trading status is not active.

Stocks are divided into size quintile portfolios based on total market capitalizations. I estimate the Amihud measure for each stock and take their equal-weighted averages for each portfolio every month. Some stocks are dropped if their illiquidity lie in the outside of 0.5 and 99.5 percentiles of each portfolio. Rolling correlations are estimated between each portfolio's asset liquidity and aggregate stock market returns. Funding liquidity is estimated as the difference between the largest and the smallest stock portfolios' correlations.

[INSERT Figure 3 HERE]

Figure 3's Panel (a) shows the two rolling correlations' time series, one for the smallest and the other for the largest quintile stocks. Large stocks' correlations are negative in most cases, but those of small stocks fluctuate around both positive and negative territories. This pattern is consistent with Figure 2's implication that ρ_{small} can be both positive and negative meanwhile ρ_{large} is always negative.

Figure 3's Panel (b) plots $fliq$'s time series. The shaded areas denote NBER recessions. The figure shows that $fliq$ tends to rise sharply in the beginning of recession but plunge dramatically as recession nears to an end. It is consistent with a conventional wisdom that recession is in part triggered by excessive liquidity in the financial market (Jordà, Schularick, and Taylor, 2011). As recession deepens subsequently, however, financiers tend to tighten margin requirements to protect themselves from increasing risks.[9] $fliq$'s local minimums also coincide with financial crises such as the Tequila crisis in 1994, the Asian currency crisis and the Russian moratorium in 1997–1998, and the global financial crisis in 2010. Appendix C shows that high funding liquidity forecasts low real GDP growth over the next two years.

3.2 Comparison with Other Benchmarks of Funding Liquidity

$fliq$ is shown to be related to business cycles and financial crises. However, it still remains not convincing enough whether $fliq$ is really related to funding liquidity in the stock market. This section will focus on the comparison of $fliq$ with other funding liquidity benchmarks.

[INSERT Figure 4 HERE]

Figure 4's Panel (a) compares $fliq$ to aggregate hedge fund leverage ratio, which is provided by Ang, Gorovyy, and van Inwegen (2011) for the sample period from December 2004 to September 2009. Funding liquidity is defined as speculators' capacity to raise funds, thus it should have been positively related to hedge fund leverage ratio. The figure shows that both funding liquidity and hedge fund leverage ratio declined during the global financial crisis, but $fliq$ is lagging behind by almost one year. Except for the delay, however, their time series are closely overlapped.

$fliq$'s delay can be attributed to two reasons. First, $fliq$ is estimated over the past 30-month rolling window, which creates a mechanical delay by construction. This problem can be solved by using high-frequency data to estimate $fliq$ over the rolling window of 30 days instead of 30 months, but it couldn't be tested yet due to the lack of access to high-frequency data. Second, an alternative explanation is that hedge fund managers left the market early in the anticipation of a looming crisis. For example, Ang, Gorovyy, and van Inwegen (2011, p.120) argue that "hedge funds voluntarily reduced leverage much earlier than banks." The aggregate hedge fund leverage ratio gradually decreased after reaching a peak at 2.6 in June 2007, which is well before the worst periods of the financial crisis. In comparison, the leverage of investment banks soared to 40.7 in February 2009, in which the TARP money was injected into the financial sector.

[9] For example, as recently as on November 9th, 2011, LCH Clearnet raised the margin calls of dealing in Italian bonds amid the European debt crisis.

In Panel (b), $fliq$ is compared to bond liquidity premium, which is estimated by Fontaine and Garcia (2012) using the difference of bond yields between on-the-run and off-the-run Treasury bonds.[10] The premiums are likely to be higher when the liquidity is scarcer or there are stronger demands for liquidity in the bond market. If liquidity is contagious between the stock and bond markets, $fliq$ would be negatively correlated to the bond liquidity premium. To make the comparison easy, the liquidity premiums are denoted on the right axis in a reversed scale. The figure confirms the high correlation between them. In particular, it is notable that both time series show a sharp increase in 2001 and a rapid drop in 2008. One difference is that the bond liquidity premiums reached the peak at 3.08 in November 2008 and recovered to its normal level at 1.11 in June 2009 meanwhile $fliq$ has gradually decreased from -0.01 in November 2008 to -0.44 until September 2009 and has remained at the bottom until 2010.

[INSERT Figure 5 HERE]

Figure 5 compares $fliq$ with Moody's Baa-Aaa credit spreads, which are provided by the FRED database.[11] The credit spreads are denoted on the right axis as log values in a reversed scale since the spreads are likely to be high when liquidity is scarce.

The figure is divided into three subperiods based on two systemic events in the bond market. The first event is the abolition the the Bretten Woods System in 1971, under which the US government had been imposed to convert dollars into gold at the fixed exchange rate of $35 an ounce. Since its abolition, investors had lost confidence in greenback, a fiat money that is backed by no material means. High inflation due to the weakening confidence in the fiat-money currency system along with the two oil shocks in the 1970s had crippled the US economy until Paul Volcker crushed the inflation and restored investor confidence in the early 1980s, which is considered the second systemic event by the figure.

The figure shows high correlation between $fliq$ and the credit spreads. For example, high funding liquidity is accompanied with low credit spreads in 1965–1966, 1973–1974, 1977–1979, late 1983 and 1990. However, Panel (c) also shows notable diversions in 1994 and 1997–1998, during which $fliq$ dropped rapidly but the credit spreads make little changes. Considering the Tequila crisis in 1994, the Asian currency crisis in 1997, and the Russian moratorium and the subsequent demise of the Long-Term Capital Management in 1998, $fliq$ seems to capture crisis periods better than the credit spreads. Moreover, Moody's

[10] I am grateful to Jean-Sebastien Fontaine and Rene Garcia for sharing the data.

[11] `http://research.stlouisfed.org/fred2/categories/119`

Baa-Aaa spreads also fail to capture the excessive liquidity during the IT bubble in the early 2000s although it is well captured by $fliq$.

[INSERT Figure 6 HERE]

Figure 6 compares $fliq$ to the total number of mergers and acquisitions in Panel (a) and the ratio of liquidity mergers in Panel (b). Liquidity mergers are defined by Almeida, Campello, and Hackbarth (2011) as liquid firms' acquiring financially distressed firms which would be otherwise inefficiently terminated. Liquidity mergers can create values even in the absence of operational synergies since they prevent inefficient termination of distressed firms by reallocating liquidity. The M&A data are available from the paper's Table 1 at an yearly basis from 1980 to 2006. Note that the data are collected based on announcement dates, and the number of days between announcement and completion ranges from zero to 1,000 days. Both panels are supplemented by linear trend lines.

The figure's implications are consistent with the conventional wisdom. Panel (a) shows that M&As are made more frequently when funding liquidity is high. Panel (b) shows that liquidity mergers become more prevalent when funding liquidity is low. Note that, under the circumstances of low funding liquidity, distressed firms are more likely to be prematurely liquidated, and therefore liquidity mergers will be able to create higher profits. Both relationships are statistically significant. The OLS t-statistics of the slopes in Panel (a) and (b) are respectively 2.316 (p-value: 0.029) and -1.864 (p-value: 0.074). Thus, the figure shows that funding liquidity affects not only the frequency of mergers but also their characteristic compositions.

One caution is that the figure is based on the average funding liquidity in the next year. Thus, there is one-year time lag in the relations between $fliq$ and M&A activities. Though not reported here, $fliq$'s contemporary values also have the same signs, but their slopes are not statistically significant. Two reasons can be accounted for the time lag. First, $fliq$'s estimation is delayed due to a mechanical reason. Second, CEOs would have made M&A decisions in the anticipation of future funding liquidity. These possibilities are essentially equal to those which explain why $fliq$ is lagging behind aggregate hedge fund leverage ratios in Figure 4.

In a nutshell, this section estimates funding liquidity and describes its time series. Funding liquidity is shown to be exceptionally high in the beginning of recession but sharply drop and reach to a bottom as recession comes to an end. $fliq$ is positively correlated with aggregate hedge fund leverage ratios and the total number of M&As, and negatively with bond liquidity premiums, Moody's Baa-Aaa spreads, and the relative prevalence of liquidity mergers. Appendix D compares $fliq$ with market sentiments.

4 Forecast of Future Stock Market Returns

Section 2 provides a theoretical background about the measurement of funding liquidity. The key idea is to use the difference of market-return sensitivities of liquidity between small and large stocks. As implied by Figure 2, the higher the difference, a speculator would have been less constrained by margin requirements. Based on the intuition, Section 3 estimates the funding liquidity as the difference of two rolling correlations, $fliq \equiv \rho_{\text{large}} - \rho_{\text{small}}$, and describes its time series.

Now, Section 4 focuses on testing whether the estimated funding liquidity indeed has the predictability of future stock market returns. In sum, the estimates of funding liquidity show significant predictability by both in-sample and out-of-sample tests. The predictability is robust to the small-sample predictive regression bias (Stambaugh, 1999; Nelson and Kim, 1993) as well as to the long-horizon predictability bias (Boudoukh, Richardson, and Whitelaw, 2007). The results are also robust to controlling for various equity premium predictors such as valuation ratio, variance premium as the difference between squared VIX and realized stock return variance, Goyal and Santa-Clara (2003)'s average stock return variance, Boudoukh, Michaely, Richardson, and Roberts (2007)'s total net payout yields, Lettau and Ludvigson (2001)'s consumption-wealth ratio, and Pollet and Wilson (2010)'s average correlation among individual stock returns. Moreover, the predictability appears significant during each of the Bretten Woods System period (1946–1970), the pre-Volcker period (1971–1985), and the post-Volcker period (1986–2010). Thus, the funding liquidity's predictability overcomes Goyal and Welch (2008, p.1456)'s critique that "any earlier apparent statistical significance (of equity premium predictors) was often based exclusively on years up to and especially on the years of the Oil Shock of 1973–1975."

4.1 In-Sample Tests

[INSERT Table 1 HERE]

Table 1 regresses future stock market excess returns on the rolling correlations. The dependent variable is cumulative stock market excess returns over the next h months. The independent variable, ρ_{small} (ρ_{large}) denotes the rolling correlations between stock market excess returns and small (large)-stock illiquidity over the preceding 30 months. Panel A uses the two rolling correlations as predictors separately, and Panel B uses their difference, $fliq \equiv \rho_{\text{large}} - \rho_{\text{small}}$, which is the measurement of funding liquidity in this paper. Newey-West t-statistics with 12 lags are reported to control for the autocorrelation and heteroskedasticity of dependent variables. This table adds the log of cyclically-adjusted P/E ratio (CAPE)[12] as a control variable.

The table shows that the rolling correlations predict future stock returns with strong significance for all horizons. Interestingly, the correlations show opposite signs but their magnitudes are close to each other. Moreover, as shown by the first column of Table 1 as well as later results in Table 2, Table 6, and Table A6, the small stocks' rolling correlation is more significant than the large stocks'. These two patterns are consistent with the model's implication in Figure 2, which shows that small stocks' correlation is higher on the left meanwhile large stocks' correlation is relatively flat but slightly higher on the right. Since the figure's horizontal axis corresponds funding liquidity and low funding liquidity predicts high future returns, ρ_{small} comes to show positive predictability whereas ρ_{large} does negative and less significant one.

The table also shows that R^2 increases over predictability horizons. However, the increases in R^2 are likely to be spurious because the dependent variable becomes mechanically autocorrelated as it is measured for overlapping periods. This type of spuriousness is called the long-horizon predictability bias. For instance, Boudoukh, Richardson, and Whitelaw (2007, p.1577) test the bias and find that "R^2's are roughly proportional to the horizon under the null hypothesis (of no predictability)." Thus, my recommendation is to take into account only the one-month ahead prediction which is shown in the first column of this table. Also, all following tables will report only the one-month ahead predictions.

Table 1 shows that the two rolling correlations have significant predictability. According to the model, however, the predictability is expected to be summarized by the difference between them. The implication is supported by Table 1 with two facts. First, the two rolling correlations' coefficients in Panel A have opposite signs but almost equal in magnitudes. Second, R^2's in Panel B are virtually equal to those in Panel A.

To test the implication more in detail, Table 2 uses different combinations of ρ_{large}, ρ_{small}, and $fliq$ as predictors. The dependent variable is stock market excess returns in the

[12]CAPE valuation ratios are downloaded from Robert Shiller's website.
`http://www.econ.yale.edu/~shiller/data.htm`

next month so that the results are not affected by long-horizon forecast bias. Column (1) and (2) of Table 2 are identical with the first column of Table 1.

[INSERT Table 2 HERE]

Table 2 shows, based on the R^2's in column (1) and (2), that $fliq$'s forecastability is as powerful as the levels of the two rolling correlations combined. Moreover, as shown by column (3) and (4), the difference dominates the levels of rolling correlations in the regression. Column (5) and (6) also show that ρ_{large} and ρ_{small}'s significance becomes far weaker when a predictive regression is done on either one of them. Therefore, the table implies that the two rolling correlations' predictability largely comes from their difference.

$fliq$'s sample standard deviation is 0.183. Thus, according to column (2) of the table, one-standard-deviation-high $fliq$ predicts the next monthly stock market return to be lower by 0.536%. In comparison, the sample average of monthly stock market excess returns is 0.470%. Even though the R^2 from the predictive regression is only 1.9%, the magnitude of the prediction is quite substantial.

[INSERT Table 3 HERE]

One may argue that $fliq$'s forecastability is probably attributed to some omitted factors. Volatility-related equity premium predictors are particularly suspicious since volatility is highly correlated to liquidity. To address this concern, Table 3 presents a horse-race test of $fliq$'s forecastability along with other various equity premium predictors. In sum, the table shows that $fliq$'s forecastability survives all of the horse-race tests with strong significance.

First, column (2) of the table controls for variance premium, which is measured as the squared VIX index at the end of each month less the sample variance of daily stock market returns in a given month. The latter is annualized by multiplying 252 to match their scales. Variance premium is considered the best proxy of investors' risk aversion and known to be one of the strongest equity premium predictors.[13] The decrease in the number of observations is due to the availability of VIX data since the index was not available prior to 1990. The column shows that $fliq$'s forecastability is significant even after controlling for the variance premium.

[13] Todorov (2009), Bollerslev and Todorov (2011), and Drechsler and Yaron (2011) provide a model to explain the variance premium.

Second, column (3) controls for market return and average stock variances. The two variance factors' forecastability is based on Goyal and Santa-Clara (2003),[14] who find that the variance of idiosyncratic risks is related to equity premiums in the stock market. They argue that risks of non-tradable assets such as wages or family businesses are closely related to the variance of idiosyncratic risks in the stock market, which is the reason why the risks are priced by the market. Interestingly, market return variance is shown to have a negative coefficient. Again, the column confirms the significance of $fliq$'s forecastability.

Table 3's column (4) makes $fliq$ compete with short-term risk-free interest rates, which is considered one of the strongest equity premium predictors. For example, Ang and Bekaert (2007, p.652) conclude that "the most robust predictive variable for future excess returns is the short rate." Henkel, Martin, and Nardari (2011, p.560) investigate the riskfree rates' forecastability in relation to business cycle, and find that it is "non-existent during business cycle expansions but sizable during contractions." Once agin, even after controlling for the short rate, $fliq$ is still found to have a strong predictive power.

Column (5) controls for the small-stock value spread, which is defined as the difference in the log book-to-market ratios of small value and small growth stocks. Brennan, Wang, and Xia (2001), Campbell and Vuolteenaho (2004), and Campbell, Polk, and Vuolteenaho (2009) show that the spread is a significant predictor of equity premiums. Its data are downloaded from Campbell and Vuolteenaho (2004)'s publication web page on the American Economic Review,[15] spanning from December 1928 to December 2001. The table shows that the value spread's forecastability is not significant during the post-war sample. However, $fliq$'s forecastability is once again vindicated to be significant.

Moody's Baa-Aaa corporate bond spreads[16] are controlled for in column (6). Chen, Roll, and Ross (1986) and Keim and Stambaugh (1986) show that the credit spreads are informative of equity premiums. The credit spreads are also often used as a proxy of funding liquidity in the bond market. In the table, however, the credit spreads fail to show any significant predictability meanwhile $fliq$ still remains significant.

Boudoukh, Michaely, Richardson, and Roberts (2007)'s total net payout yields are used as a control variable in column (7). They argue that share repurchases and seasonal equity offerings are as important as dividend payments, but the net equity issuance is not accounted for by conventional equity premium predictors such as dividend yields or valuation ratios. The authors show that total net payout yields, measured as dividend yields less net equity

[14] I am grateful to Amit Goyal for sharing the average stock variance data.

[15] http://www.aeaweb.org/articles.php?doi=10.1257/0002828043052240

[16] http://research.stlouisfed.org/fred2/categories/119

issuances, outperform dividend yields as an equity premium predictor. The net payout yields turn out to be not significant in column (7), however, since its forecastability is largely owed to pre-war samples. In comparison, $fliq$'s forecastability is still significant.

Column (8) and (10) control for Lettau and Ludvigson (2001)'s consumption-wealth ratio, which is one of the most popular predictors of equity premiums. They measure consumption, asset holdings and labor income from quarterly data, and show that the deviation from their cointegration has important predictive information of future stock returns. The deviation is designated as the consumption-wealth ratio. The ratio is available on a quarterly bsis, so the dependent variable is replaced by quarter excess returns in the last three columns. It is why $fliq$'s coefficients are almost three times bigger than those in previous columns. Again, $fliq$'s forecastability turns out to be robust to the consumption-wealth ratio.

Lastly, column (9) and (10) control for Pollet and Wilson (2010)'s average correlation among individual stock returns[17]. Pollet and Wilson (2010) separate the variances of stock market returns into two components–average variances and correlations of individual stock returns–and show that the correlation component has significant forecastability of future stock market excess returns. Thanks to its forecasting power, R^2 shows a notable increase from 9.0% in column (8) to 13.2% in column (10). Once again, $fliq$'s forecastability is yet subsumed.

Polk, Thompson, and Vuolteenaho (2006) show that the difference of cross-sectional CAPM betas between value and growth stocks is able to predict future stock market returns. The cross-sectional beta premium also appears negatively correlated with the S&P500's valuation multiples, implying that it is related to the market price of risk in the stock market. However, the beta premium's forecastability is mostly found from the pre-1965 subsample only, so are the market valuation multiples. In contrast, as will be shown by Section 4.4 and Table 6, $fliq$'s forecastability is significant during the post-war sample but becomes insignificant prior to 1945. Thus, I pass over the replication of estimating the beta premium as a control variable.

[17] I am grateful to Joshua Pollet for sharing the average correlation data.

4.2 Out-of-Sample Tests

In-sample tests are not strong enough to convince predictability because their results are likely to be spurious for various reasons.[18] In contrast, out-of-sample tests, which have been a new norm of predictability tests since the seminal work by Meese and Rogoff (1983), are immune to the biases. Moreover, out-of-sample tests require higher standard of predictability than in-sample tests because the parameter of a predictor itself is estimated with noise. "Excluding some variables that truly belong in the model could adversely affect forecast accuracy. Yet including the variables could raise the forecast error variance if the associated parameters are estimated sufficiently imprecisely," explain Clark and McCracken (2011, p.1).

To show $fliq$'s forecastability in the out-of-sample test, three models–one restricted and two unrestricted–are specified as follows

$$\text{Model 1 (restricted)}: \text{exret}_{t+1} = \mu + \epsilon_{t+1} \tag{19}$$

$$\text{Model 2A (unrestricted)}: \text{exret}_{t+1} = \mu + \beta_1\,\rho_{\text{small}} + \beta_2\,\rho_{\text{large}} + \epsilon_{t+1} \tag{20}$$

$$\text{Model 2B (unrestricted)}: \text{exret}_{t+1} = \mu + \beta\,(\rho_{\text{small}} - \rho_{\text{large}}) + \epsilon_{t+1} \tag{21}$$

The restricted model does not have any predictor meanwhile the unrestricted models have the rolling correlations and their difference as predictors. The null hypothesis is the equal forecastability, which implies that the unrestricted models cannot improve forecastability over the restricted model. Table 4 compares the three models' out-of-sample forecastability. Its Panel A compares Model 1's forecastability with Model 2A's, and Panel B compares Model 1's with Model 2B's.

[INSERT Table 4 HERE]

The critical values of the out-of-sample test statistics are different depending on the ratio of the number of initial in-sample observations (R) to the number of out-of-sample forecast observations (P). Clark and McCracken (2001) provide the critical values for $\pi \equiv P/R = 0.1$, 0.2, 0.4, 1.0, 2.0, 3.0 and 5.0. I divide my samples according to each value of π and compute the statistical significances of the out-of-sample tests. Each row of Table 4 corresponds to one of the provided π's.

[18]For example, if some values are regressed on any random walk variable, its t-statistics tend to be statistically significant even though they don't have any relationship. However, out-of-sample tests are not subject to this problem.

Out-of-sample forecast errors are estimated as:

$$\hat{\epsilon}_{t+1} = \text{exret}_{t+1} - \hat{\beta}_{(t-1)}^{\top} x_t \tag{22}$$

where $\hat{\beta}_{(t-1)}$ denotes the regression coefficients estimated from the first $t-1$ observations, and x_t is a column vector of predictors at time t. RMSE1 and RMSE2 denote the root mean squared errors from the restricted and unrestricted models.

$$\text{RMSE} = \sqrt{\frac{1}{R}\sum_{t=P+1}^{P+R} (\hat{\epsilon}_{t+1})^2} \tag{23}$$

R^2 is computed as

$$R^2 = 1 - \left(\frac{RMSE2}{RMSE1}\right)^2 \tag{24}$$

R^2 is supposed to be positive if the unrestricted models improve forecastability over the restricted model. The table reports three test statistics (ENC-T, ENC-REG and ENC-NEW), each of which is based on Diebold and Mariano (2002), Ericsson (1992) and Clark and McCracken (2001) respectively.[19]

Table 4 shows that RMSE2 is smaller than RMSE1 in all cases. R^2's vary from 0.8% to 3.0%, which are consistent with the R^2 of 1.9% from the in-sample tests of Table 1 and 2. Furthermore, all test statistics reject the null hypothesis of equal forecastability. Only 3 out of 42 statistics are significant at 10% level, and the rest are significant at 5% level. Therefore, the out-of-sample test confirms that $fliq$ has significant forecastability of future stock market excess returns.

4.3 Profit & Loss of Trading Strategies Based on Funding Liquidity

This subsection derives simple market-timing trading strategies based on $fliq$'s forecastability and computes their tallies of profit and loss. This approach kills two birds with one stone. First, it augments out-of-sample forecastability. Second, it tests if the estimated funding liquidity is practically deployable.

The strategies are designed as follows. Suppose, at the end of each month t, an investor

[19] "ENC" means that the unrestricted model encompasses the restricted one. I follow the notations of Clark and McCracken (2001).

estimates the percentile of the current $fliq$ based on its past histories.

$$\begin{aligned} x_t &= p\left(fliq \leq fliq_t \,|\, fliq_1, \cdots, fliq_{t-1}\right) \\ &= \frac{1}{t-1}\sum_{s=1}^{t-1} \mathcal{I}\left\{fliq_s \leq fliq_t\right\} \end{aligned} \tag{25}$$

where $fliq$ denotes the funding liquidity, which is estimated as the difference of two rolling correlations. His investment portfolio consists of risk-free assets and stock market index funds. He adjusts the weight of stocks based on the percentile (x_t) as

$$\theta_t = \bar{\theta} - x_t\left(\bar{\theta} - \underline{\theta}\right) \in \left[\underline{\theta}, \bar{\theta}\right] \tag{26}$$

The investor would put $\bar{\theta}$ of his wealth in stocks and $1-\bar{\theta}$ in bonds if the current $fliq$ is the lowest compared to its past history ($fliq_1, \cdots, fliq_{t-1}$), or $\underline{\theta}$ in stocks and $1-\underline{\theta}$ in bonds if the current $fliq$ is the highest. In general, his portfolio return in the next month would be given as

$$R_{p,t+1} = \theta_t\left(R_{m,t+1} - R_{f,t}\right) + R_{f,t} \tag{27}$$

[INSERT Table 5 HERE]

Table 5 compares profitabilities of the trading strategy depending on the ranges of portfolio weights, $\left[\underline{\theta}, \bar{\theta}\right]$. The first two columns are benchmarks. The first one always holds stock market index funds only ($\theta = 1$), and the second one holds only risk-free assets ($\theta = 0$). Strategy 1 is placed in between of these two benchmarks ($\theta \in [0, 1]$). Strategy 2 sometimes borrows from risk-free assets and leverages up stock holdings ($\theta \in [0, 2]$). Strategy 3 is even more aggressive than Strategy 2, switching between long and short positions of stock markets ($\theta \in [-1, 2]$).

All three strategies of Table 5 achieve almost twice as high Sharpe ratios as the benchmark stock-only portfolio ($0.177/0.097 \approx 1.82$). Strategy 1 shows similar average returns with the benchmark, but it could halve the standard deviation of its excess returns. In comparison, Strategy 2 and 3 double average returns while keeping their standard deviations in tandem with the benchmark's.

Portfolio adjustment costs are not considered since both risk-free assets and stock market index funds have high liquidity. For a robustness check, I varied the starting date of portfolio formation and found similar results.

4.4 Predictability in Subsamples

One concern in the literature of equity premium predictors is that forecastability of many predictors is limited to specific periods. Goyal and Welch (2008, p.1456) comprehensively survey dozens of different predictors and find that "for many models, any earlier apparent statistical significance was often based exclusively on years up to and especially on the years of the Oil Shock of 1973–1975." In particular, most models are found to perform poorly in recent years. The concern naturally raises a question about how $fliq$'s forecastability changes over subsample periods.

[INSERT Table 6 HERE]

Table 6 compares $fliq$'s forecastability in subsamples. The first column covers entire sample periods available from CRSP (1928–2010). The second and third columns separate samples based on the second world war. The last three columns divide the post-war periods into three subsamples based on the Bretten Woods System and the Volcker regime.

The table shows that $fliq$ has significant forecastability during the post-war periods. Its forecastability is not weakened even after the Volcker regime. Thus, $fliq$ overcomes Goyal and Welch (2008)'s critique that many predictors' forecastability is limited to the Oil Shock periods of 1973–1975. However, $fliq$ shows weaker predictability during the Bretten Woods System periods, and even fails to show any significance prior to the second world war. In contrast, the log valuation ratio shows significant forecastability prior to 1970, but fails to do so thereafter.

There are several possible explanations about why $fliq$'s forecastability weakens during the early sample periods. The first candidate is the qualitative difference of the financial system before and after the World War 2. For example, Schularick and Taylor (2009) show that the money and credit aggregates had been tightly tied until 1939 but the credit aggregates "started to decouple from the broad money and grew rapidly, via a combination of increased leverage and augmented funding via the non-monetary liabilities of banks" since 1945. Given that funding liquidity is the important determinant of the non-monetary liabilities, the lack of forecastability from the pre-war sample is consistent with the paper's findings. Second, trading volume data in the early samples may not be as accurate as recent data, thus the estimated Amihud illiquidity measure might have been corrupted by higher noises.

4.5 $fliq$ Estimated Over Various Rolling Window Horizons

In previous tests, $fliq$ has been estimated over the preceding 30 months. Now, one may ask whether $fliq$'s estimation horizon affects the results. Given that the effects of capital constraints on asset liquidity are often considered weekly or daily frequency phenomena, the 30-month rolling window horizon seems to be excessively long. For example, Hameed, Kang, and Viswanathan (2010) show that negative stock market returns raise stock bid-ask spreads and these changes in liquidity last for about two weeks. Moreover, Figure 4 and Figure 6 also indicate that $fliq$ is lagging behind the aggregate hedge fund leverage ratios and the M&A activities by about one year. Provided the facts, one can feel urge to estimate funding liquidity over shorter horizons with high-frequency data. Due to the lack of access to high-frequency data, however, this possibility could not have been tested yet.

[INSERT Figure 7 HERE]

Figure 7 compares two versions of $fliq$. The red solid line is estimated over the past 30-month window, and the blue dashed line is estimated over the past 12 months. The figure shows that $fliq$'s estimates are likely to be blighted by noises when estimated from a small number of observations. Although not reported, $fliq$'s forecastability also vanishes when it is estimated over the 12-month window.

4.6 Funding Liquidity Estimated from Volatility Quintile Portfolios

The model's bottom line is that low funding liquify makes speculators withdraw first from small and more volatile stocks due to their high margin requirements. Thus, portfolio formation not only based on size but also on volatility is expected to yield similar results. To test the implication, this section estimates each stock's volatility as a standard deviation of daily stock returns every month, forms quintile portfolios based on the volatility, computes equal-weighted averages of Amihud measure for each portfolio, and estimates their rolling correlations to stock market excess returns over the preceding 30 months. Volatility-based funding liquidity is defined as $fliq^v \equiv \rho_{\text{least volatile}} - \rho_{\text{most volatile}}$. Table 7 tests $fliq^v$'s predictability for the forecast horizons of 1 to 12 months, which are specified on the table's first row.

[INSERT Table 7 HERE]

As expected, $fliq^v$ shows significant forecastability. The signs of two rolling correlations are also consistent with previous results. However, the volatility-based $fliq^v$'s statistical significance is not as strong as the size-based $fliq$'s. For example, the Newey-West t statistics drops from -3.926 for $fliq$ (Table 2) to -1.839 for $fliq^v$ (Table 7). $fliq^v$'s weakened significance is largely due to the fact that $\rho_{\text{least volatile}}$ loses most of its predictability relative to ρ_{large}. Panel A shows that $\rho_{\text{least volatile}}$'s predictability ($t$ statistics: -0.979 for 1 month to -2.408 for 12 months) is far weaker than ρ_{large}'s in Table 1 (t statistics: -2.874 for 1 month to -5.049 for 12 months).

$fliq^v$ underperforms the original $fliq$ since the industry charges margin requirements not based on volatility but by stock size. Large stocks' margins are usually 50% meanwhile small stocks are not accepted as collaterals on many occasions.

For a robustness, I also measure individual stock return volatility every year rather than a month and rebalance quintile portfolios at an annual basis. Though not reported here, the results are almost the same but slightly less significant than those in the table.

5 Conclusion

There are plenty of anecdotes in which risky assets become hugely discounted during a liquidity crisis. As early as in the Asian currency crisis, many public and private firms were sold to foreign enterprises at fire-sale prices. As recently as this draft is being written, Greece is repeating the fire-sale privatizations to raise cash in hurry.

Thus, the conventional wisdom implies that liquidity crisis would be followed by high returns from risky assets. However, very few papers have been able to provide clear evidence that liquidity is able to predict stock market returns. The answer to the puzzle lies in the distinction of the two different types of liquidity: asset liquidity and funding liquidity. The up-to-date evidence of liquidity's risk premiums has been found from the cross-sectional abnormal returns of stock portfolios, which is the risk premiums of asset liquidity. In contrast, a general consensus has yet been made with regard to the funding liquidity.

This paper suggests a new way to estimate funding liquidity based on the theoretical framework of Brunnermeier and Pedersen (2009). When a speculator loses capital and becomes financially constrained, he would withdraw first from small stocks and then from large stocks since large stocks demand lower margin requirements than small stocks. Therefore, an exogenous shock to the speculator's capital would affect both assets' liquidity when he is rich enough to participate in trading both assets. However, the shock would affect only the large stocks' liquidity if he was so poor that he completely withdrew from small stocks. The sensitivities of asset liquidity to the capital shock vary depending on the speculator's own capital relative to margin requirements, which is the definition of funding liquidity.

Based on the intuition, funding liquidity is estimated by the rolling correlations of stock market returns with small and large stocks' liquidity. The estimated funding liquidity appears positively correlated with aggregate hedge fund leverage ratios and the total number of M&A activities, and negatively correlated with bond liquidity premiums and Moody's Baa-Aaa corporate bond spreads. Also, the funding liquidity is shown to forecast aggregate stock market returns with strong significance both in in-sample and out-of-sample tests.

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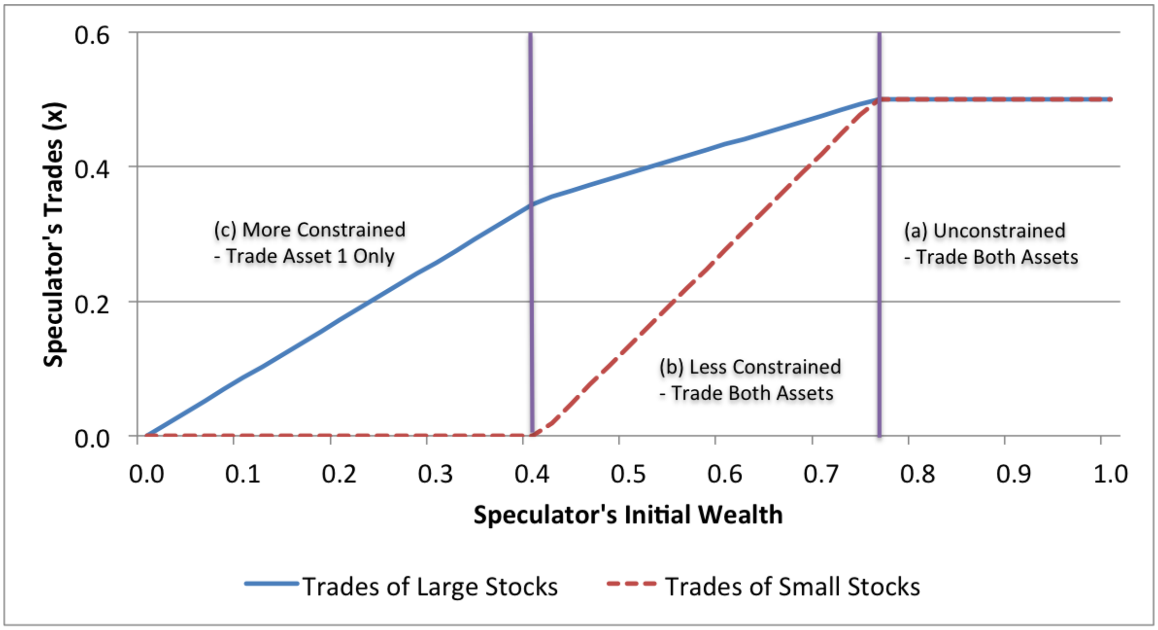
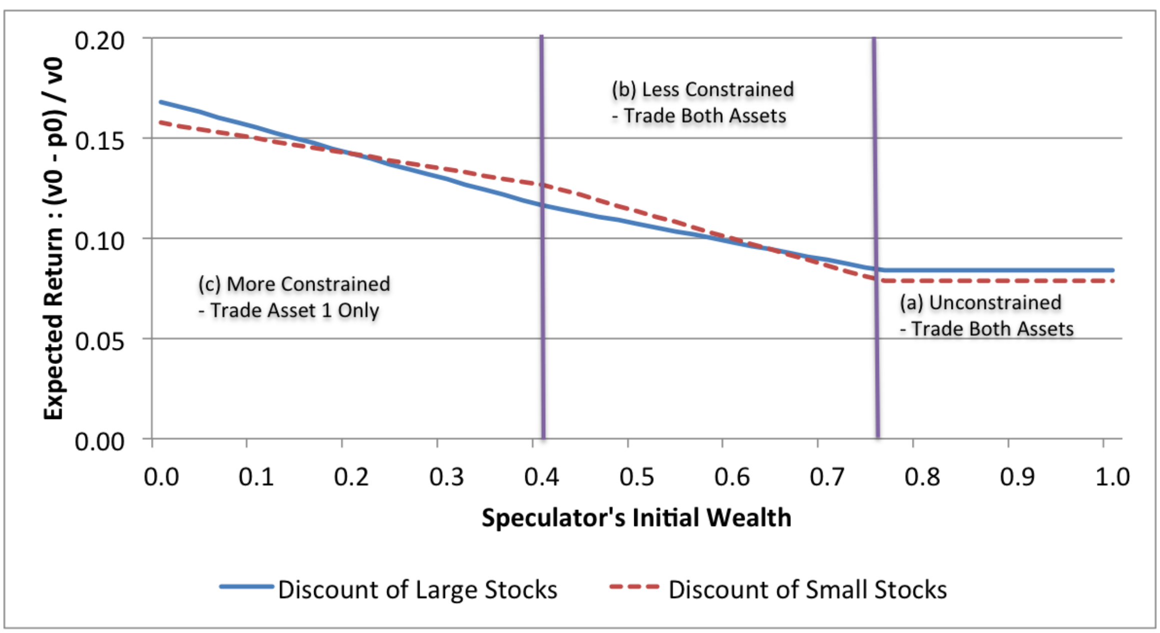
Figure 1: Market Reaction to a Speculator's Initial Wealth

This figure shows model-implied market reaction to a speculator's initial wealth, which is denoted by the horizontal axis. Panel (a) shows a speculator's optimal trades and Panel (b) shows the stocks' expected returns (discount rates). Vertical lines divide the figure into three areas depending on funding liquidity.



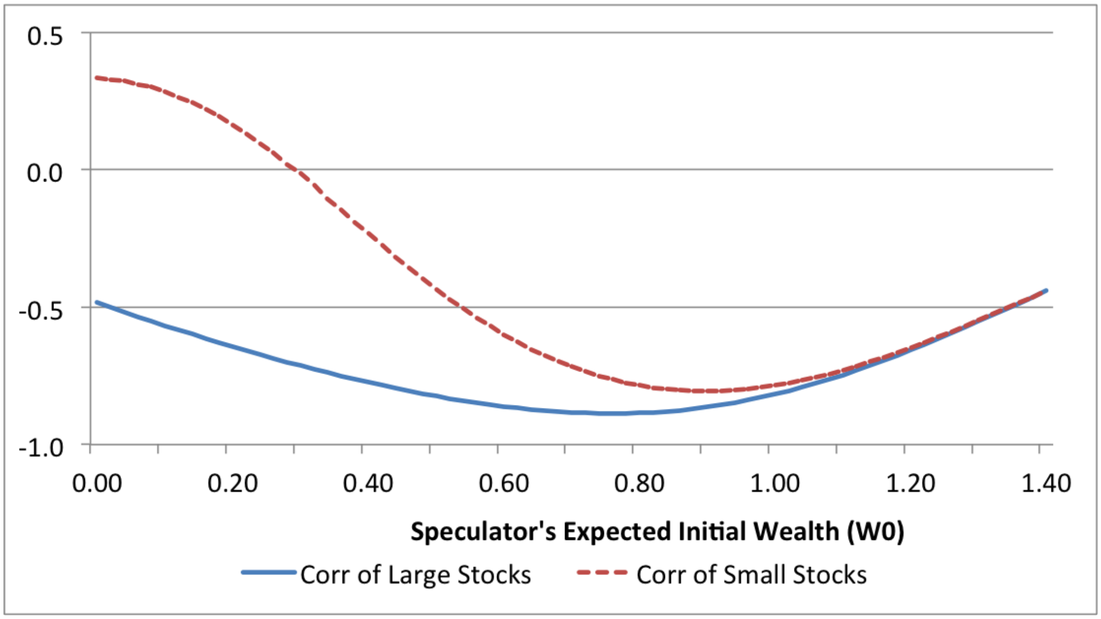
(a) Speculator's Optimal Asset Trades (x)



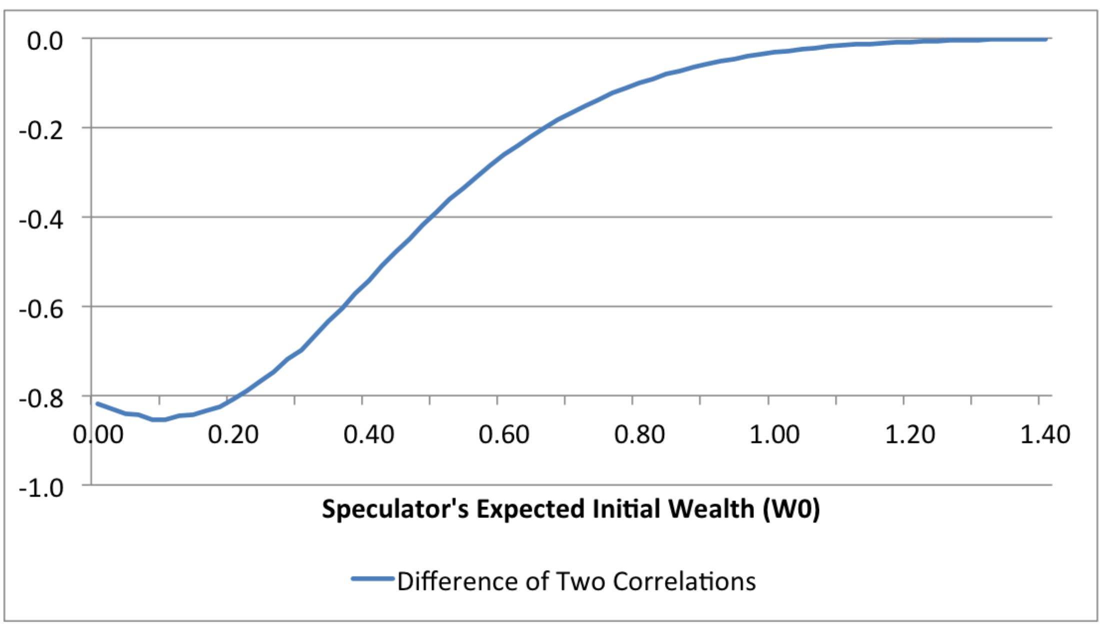
(b) Expected Returns ($(\bar{v} - p_0)/\bar{v}$)

Figure 2: Simulated Correlation of Asset Liquidity and Market Returns

This figure shows the simulated correlations between asset illiquidity, which is defined as the price impact of a trade, and an exogenous shock to a speculator's capital. His initial wealth is now given as $W_0^{(s)} + \eta$ where $\eta \sim \mathcal{N}\left(0, 0.3^2\right)$ denotes the capital shock. The horizontal axis denotes $W_0^{(s)}$. Panel (a) shows the correlations and Panel (b) shows their difference.



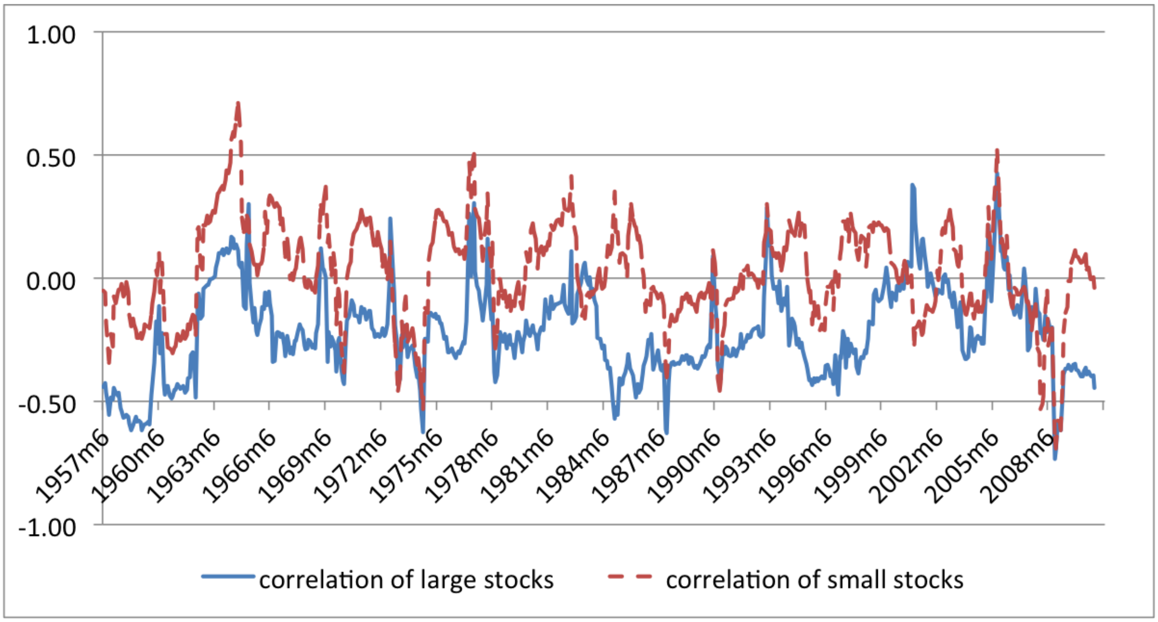
(a) Simulated Correlations (ρ_{small} and ρ_{large})



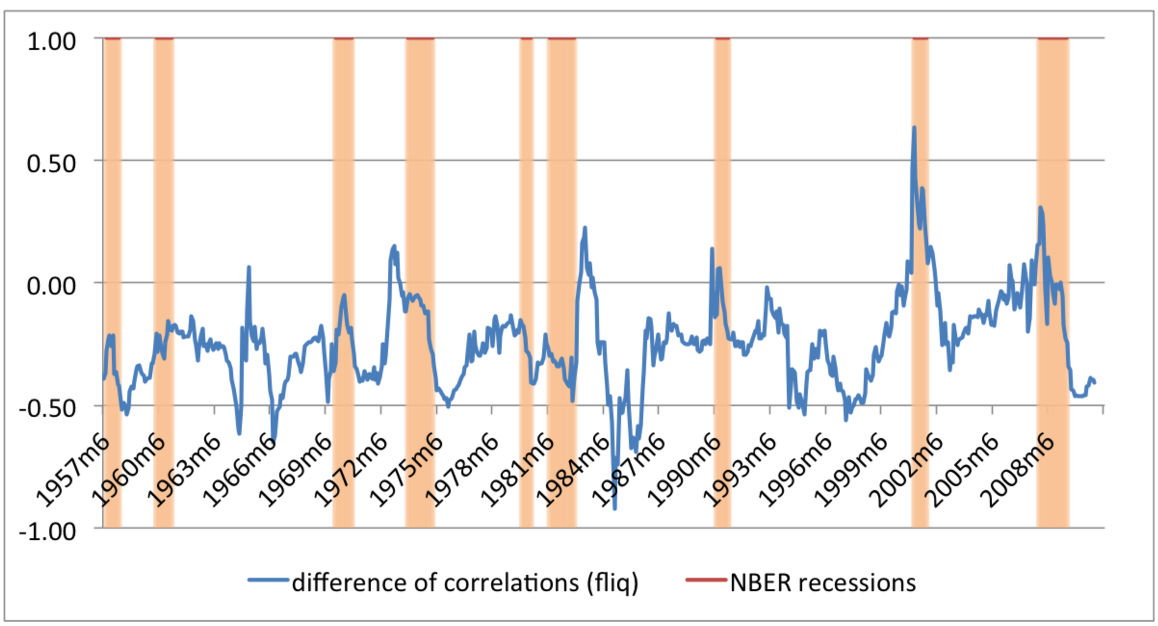
(b) Difference of Simulated Correlations ($\rho_{\text{large}} - \rho_{\text{small}}$)

Figure 3: Time Series of Rolling Correlations and Their Difference

Panel (a) shows the time series of rolling correlations between stock market excess returns and each size portfolio's asset illiquidity over the preceding 30 months. Panel (b) shows the difference of the two rolling correlations. This paper's argument is that funding liquidity can be estimated by the difference of the two rolling correlations. The shaded areas denote NBER recessions.



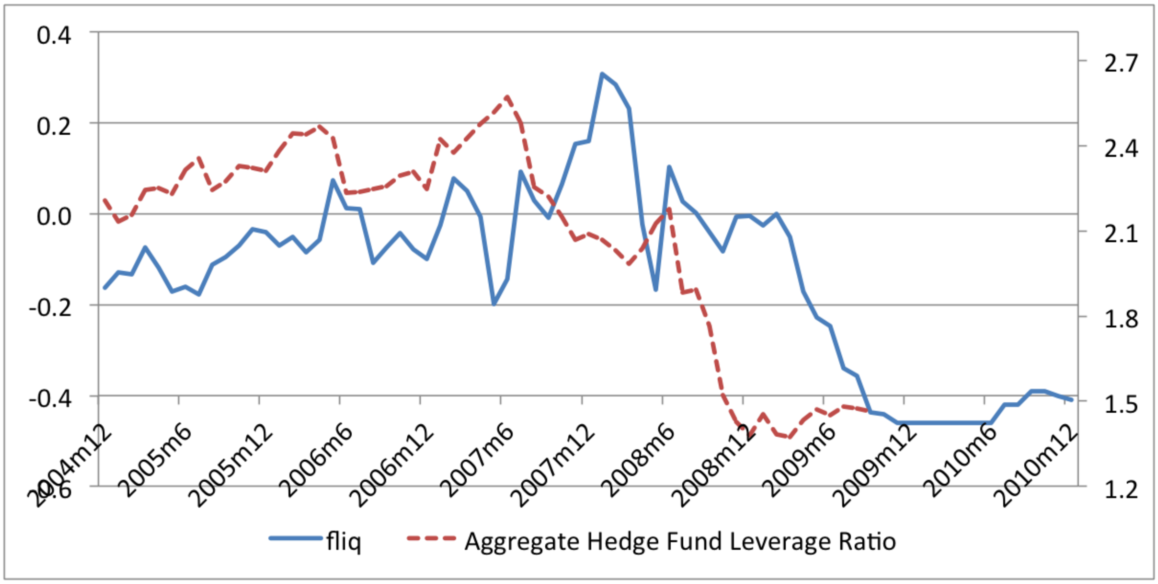
(a) Rolling Correlations (ρ_{small} and ρ_{large})



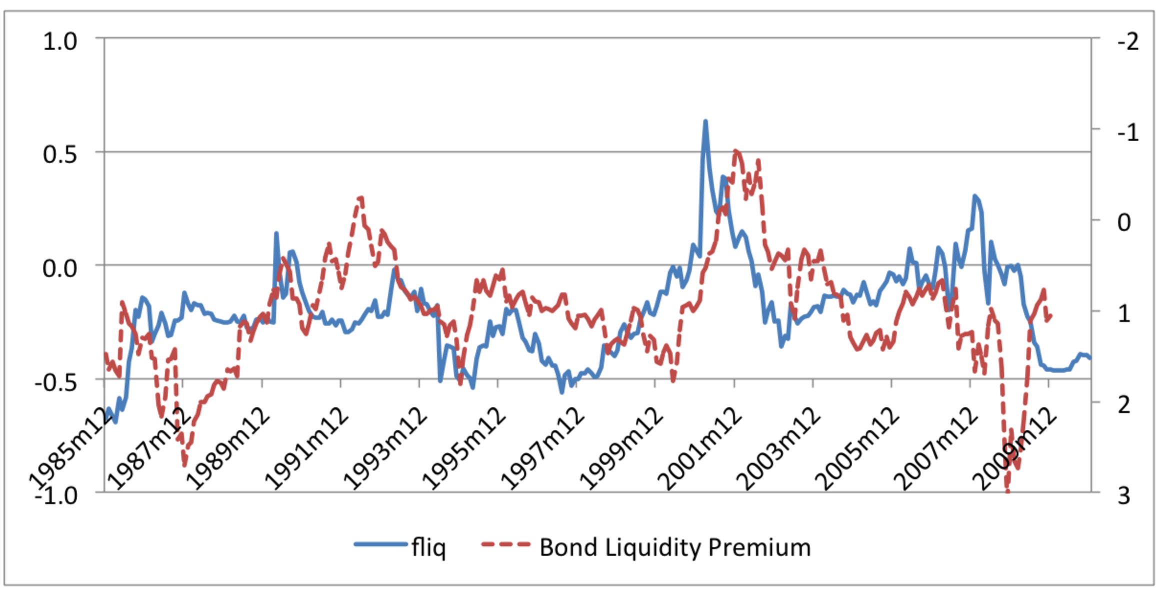
(b) Difference of Rolling Correlations ($\rho_{\text{small}} - \rho_{\text{large}}$)

Figure 4: Comparing $fliq$ to Other Measures of Liquidity

Panel (a) compares $fliq$ to the aggregate hedge fund leverage ratio, which is provided by Ang, Gorovyy, and van Inwegen (2011). Panel (b) compares $fliq$ to the bond liquidity premiums, which are estimated by Fontaine and Garcia (2012) using the difference of bond yields between on-the-run and off-the-run Treasury bonds. The bond liquidity premiums are denoted in a reversed scale on the right axis since they become higher when liquidity is scarcer in the market.



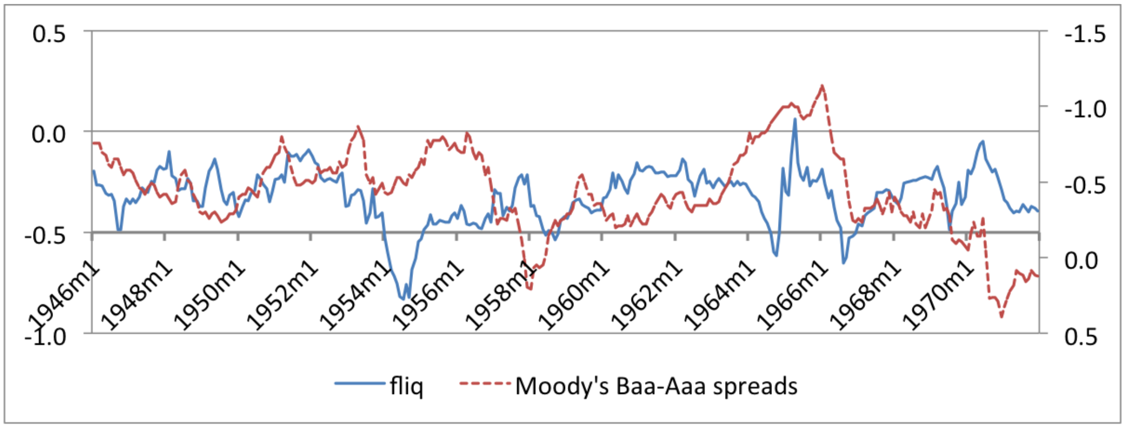
(a) Aggregate Hedge Fund Leverage Ratio (Ang, Gorovyy, and van Inwegen, 2011)



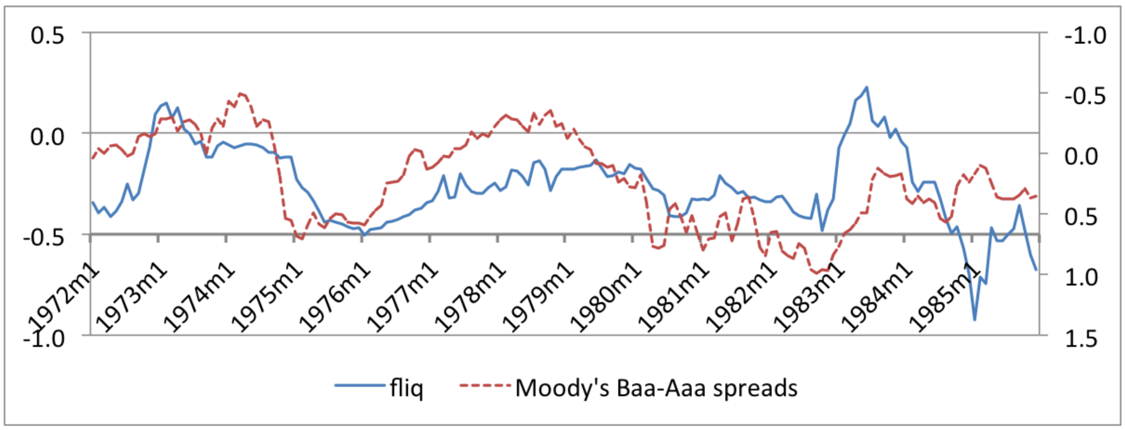
(b) Bond Risk Premium (Fontaine and Garcia, 2012)

Figure 5: Comparing $fliq$ to Moody's Baa-Aaa Credit Spreads

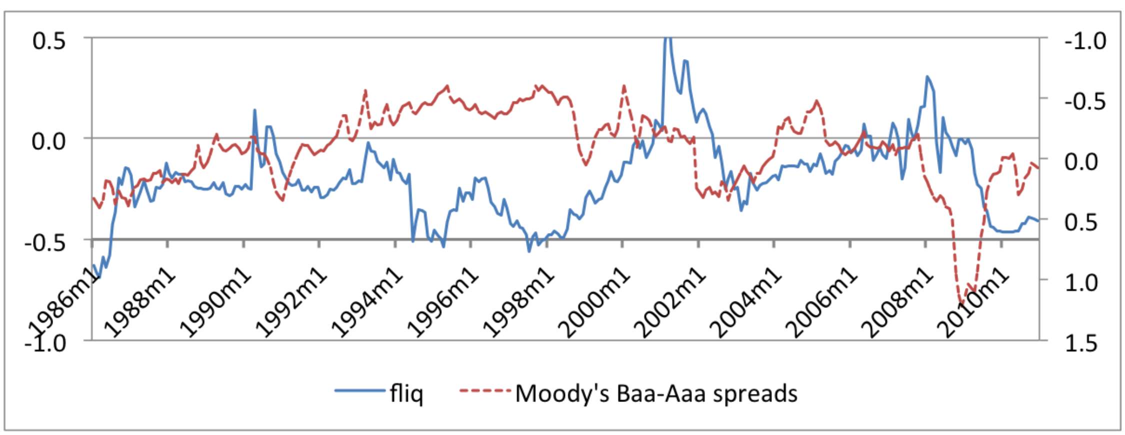
This figure compares $fliq$ to Moody's Baa-Aaa credit spreads for three subperiods, each of which corresponds to each subfigure. The credit spreads are denoted on the right axis as log values in a reversed scale.



(a) Bretton Woods System (1946 ∼ 1971)



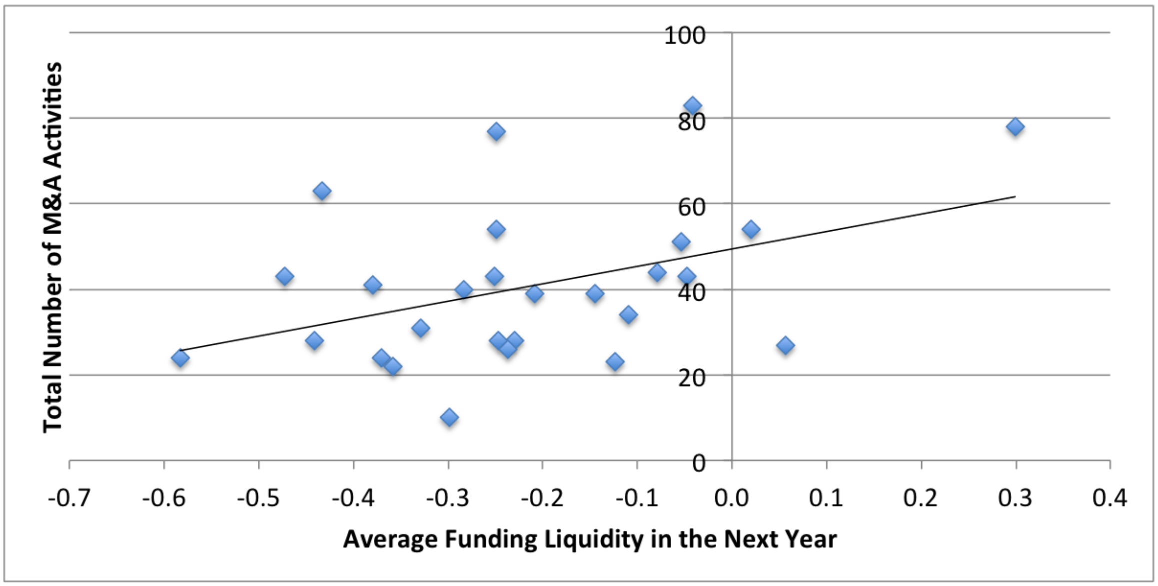
(b) Pre-Volcker Periods (1972 ∼ 1985)



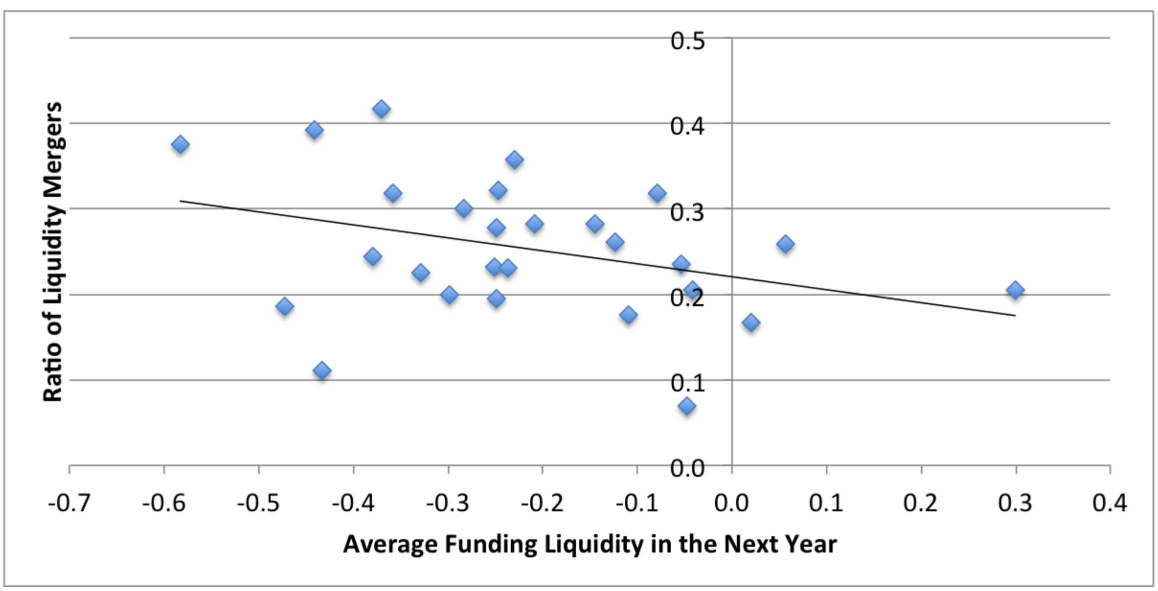
(c) Post-Volcker Periods (1986 ∼ 2010)

Figure 6: $fliq$ and the Frequency of M&A Activities

This figure compares $fliq$ to the total number of mergers and acquisitions in Panel (a) and the ratio of liquidity mergers in Panel (b). Liquidity mergers are defined by Almeida, Campello, and Hackbarth (2011) as liquid firms' acquiring financially distressed firms which would be otherwise inefficiently terminated. The M&A data are available from the paper's Table 1 at an yearly basis from 1980 to 2006. Both panels are supplemented by linear trend lines. The OLS t-statistics of the slopes in Panel (a) and (b) are respectively 2.316 (p-value: 0.029) and -1.864 (p-value: 0.074).



(a) Total Number of M&A Activities



(b) Ratio of Liquidity Mergers

Figure 7: $fliq$ Estimated Over Various Horizons

This figure compares funding liquidity estimated over different rolling window horizons. The blue dashed line is estimated over the past 12 months meanwhile the red solid line is over 30 months. For reference, $fliq$ has been estimated over the past 30 months so far.

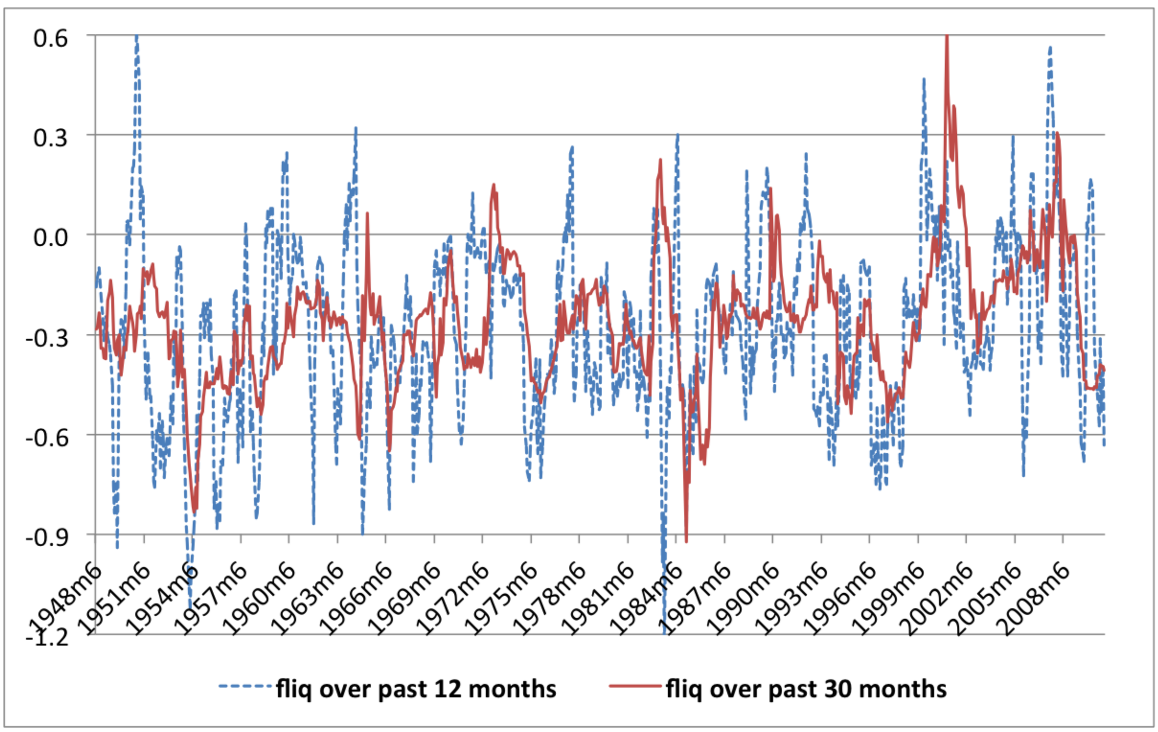


Table 1: Rolling Correlations Predict Future Stock Market Returns

The dependent variable is cumulative stock market excess returns for the next h months. The excess returns are collected from Kenneth French's website, and the cumulative horizon is denoted on the first row. The independent variable, ρ_{small} (ρ_{large}) denotes the rolling correlations between stock market excess returns and small (large)-stock illiquidity over the preceding 30 months. $CAPE$ denotes cyclically-adjusted price/earnings ratios, which are downloaded from Robert Shiller's website. Numbers in parentheses are Newey-West t statistics with 12 lags. ***, **, and * denote significances at 1%, 5%, and 10% levels respectively.

horizon	1 month	3 months	6 months	1 year
Panel A. Regression on Two Rolling Correlations				
ρ_{small}	3.268***	9.660***	18.021***	34.062***
	(3.720)	(3.857)	(3.961)	(3.942)
ρ_{large}	-2.431***	-9.029***	-18.865***	-36.970***
	(-2.874)	(-3.725)	(-4.323)	(-5.049)
$\log(CAPE)$	-0.469	-1.368	-2.924	-6.072*
	(-1.145)	(-1.199)	(-1.405)	(-1.804)
obs	779	777	774	768
R^2	0.020	0.059	0.109	0.206
Panel B. Regression on $fliq \equiv \rho_{\textbf{large}} - \rho_{\textbf{small}}$				
$\rho_{\text{large}} - \rho_{\text{small}}$	-2.931***	-9.407***	-18.358***	-35.210***
	(-3.926)	(-4.385)	(-4.778)	(-4.936)
$\log(CAPE)$	-0.419	-1.330	-2.976	-6.254*
	(-1.073)	(-1.205)	(-1.451)	(-1.869)
obs	779	777	774	768
R^2	0.019	0.058	0.109	0.205

Table 2: Difference of Rolling Correlations

The dependent variable is stock market excess returns in the next month. The independent variable, ρ_{small} (ρ_{large}) denotes the rolling correlations between stock market excess returns and small (large)-stock illiquidity over the preceding 30 months. $CAPE$ denotes cyclically-adjusted price/earnings ratios, which are downloaded from Robert Shiller's website. This table is intended to show that the difference alone is able to capture the two rolling correlations' forecastability. Numbers in parentheses are Newey-West t statistics with 12 lags. ***, **, and * denote significances at 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ρ_{small}	3.268***		0.837		2.062**	
	(3.720)		(0.892)		(2.419)	
ρ_{large}	-2.431***			0.837		-0.492
	(-2.874)			(0.892)		(-0.568)
$\rho_{\text{large}} - \rho_{\text{small}}$		-2.931***	-2.431***	-3.268***		
		(-3.926)	(-2.874)	(-3.720)		
$\log(CAPE)$	-0.469	-0.419	-0.469	-0.469	-0.695*	-0.634
	(-1.145)	(-1.073)	(-1.145)	(-1.145)	(-1.662)	(-1.447)
obs	779	779	779	779	779	779
R^2	0.020	0.019	0.020	0.020	0.013	0.004

Table 3: Horse-Race Forecast Tests

The dependent variable is stock market excess returns in the next month. The explanatory variable, ρ_{small} (ρ_{large}), denotes the rolling correlations between stock market excess returns and small (large)-stock illiquidity over the preceding 30 months. The rest of the independent variables are to control for other equity risk premium predictors. $CAPE$ denotes cyclically-adjusted price/earnings ratios. *Variance premium* is the difference between squared VIX index and realized variance of stock returns. *Market return variance* and *average stock variance* are provided by Goyal and Santa-Clara (2003), who argue that idiosyncratic risks are priced by the stock market. *Small-stock value spreads*, provided by Campbell and Vuolteenaho (2004), are the difference in the log book-to-market ratios of small value and small growth stocks. *Total net payout yields*, provided by Boudoukh, Michaely, Richardson, and Roberts (2007), are the sum of dividend yields, share repurchases, and equity issuances. *cay* denotes Lettau and Ludvigson (2001)'s consumption-wealth ratio, and *average correlation* denotes Pollet and Wilson (2010)'s average correlation among individual stock returns. The last two control variables are available at a quarterly basis, so quarterly market excess returns are used as a dependent variable in column (8) to (10). The sample horizon is from January 1946 to December 2010, but the number of observations varies depending on the availability of control variables. Numbers in parentheses are Newey-West t statistics with 12 lags in column (1)–(7) and 4 lags in (8)–(10). ***, **, and * denote significances at 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)
$\rho_{\text{large}} - \rho_{\text{small}}$	-2.931***	-2.782***	-3.077***	-2.598***	-2.638***
	(-3.926)	(-2.911)	(-2.997)	(-3.344)	(-3.172)
$\log(CAPE)$	-0.419	-1.611*	-0.741	-0.805*	-0.311
	(-1.073)	(-1.829)	(-1.457)	(-1.878)	(-0.652)
variance premium		28.826***			
		(4.915)			
market return variance			-0.014***		
			(-2.744)		
average stock variance			0.005***		
			(3.689)		
riskfree interest rate				-1.862**	
				(-2.561)	
small-stock value spreads					-1.088
					(-0.796)
obs	779	251	450	779	672
R^2	0.019	0.077	0.035	0.029	0.017

continued on the next page

Table 3: Horse-Race Forecast Tests (continued)

	(6)	(7)	(8)	(9)	(10)
$\rho_{\text{large}} - \rho_{\text{small}}$	-3.067***	-3.134***	-8.250***	-8.417***	-7.415***
	(-4.140)	(-3.701)	(-3.453)	(-2.875)	(-3.050)
$\log(CAPE)$	-0.255		-1.283	0.323	0.308
	(-0.584)		(-0.961)	(0.243)	(0.232)
Moody's Baa-Aaa spreads	0.345				
	(0.662)				
net payout yields		0.628			
		(0.874)			
consumption-wealth ratio (cay)			101.247***		95.377***
			(3.050)		(2.682)
average correlation				23.328***	22.507***
				(3.821)	(3.591)
obs	779	708	234	176	176
R^2	0.020	0.022	0.090	0.095	0.132

Table 4: Out-of-Sample Predictability

This table tests the out-of-sample predictabilities of the rolling correlations. The dependent variable is stock market excess returns in the next month. The restricted model uses only a constant term, assuming that stock market returns are not predictable. The unrestricted model uses the two rolling correlations in Panel A, and their difference in Panel B. The sample data span Jul 1955 to Dec 2010. The initial periods of in-sample observations are shown in the first column. RMSE1 and RMSE2 denote the root mean squared errors of the restricted and unrestricted models. R^2 is computed as $R^2 = 1 - \left(\frac{RMSE2}{RMSE1}\right)^2$. ENC-T, ENC-REG and ENC-NEW show the test statistics of equal forecastability based on Diebold and Mariano (2002), Ericsson (1992) and Clark and McCracken (2001) respectively. ** and * denote significances at 5% and 10% levels.

# in-sample	# predictions	RMSE1	RMSE2	R^2	ENC-T	ENC-REG	ENC-NEW
Panel A. Prediction with $\rho_{\mathbf{small}}$ and $\rho_{\mathbf{large}}$							
∼ Dec 2005	Jan 2006 ∼	5.431	5.348	0.030	1.30*	1.36*	1.60**
∼ Dec 2001	Jan 2002 ∼	4.807	4.729	0.032	1.71**	1.94**	2.87**
∼ Jul 1995	Aug 1995 ∼	4.873	4.812	0.025	1.81**	2.15**	4.51**
∼ Feb 1984	Mar 1984 ∼	4.625	4.595	0.013	1.87**	2.13**	5.68**
∼ Mar 1975	Apr 1975 ∼	4.579	4.559	0.008	1.93**	2.12**	6.40**
∼ Sep 1970	Oct 1970 ∼	4.664	4.634	0.013	2.27**	2.55**	8.06**
∼ Apr 1966	May 1967 ∼	4.649	4.622	0.011	2.27**	2.56**	8.17**
Panel B. Prediction with $\rho_{\mathbf{small}} - \rho_{\mathbf{large}}$							
∼ Dec 2005	Jan 2006 ∼	5.431	5.347	0.030	1.58**	1.40*	1.48**
∼ Dec 2001	Jan 2002 ∼	4.807	4.729	0.032	2.04**	1.97**	2.73**
∼ Jul 1995	Aug 1995 ∼	4.873	4.812	0.025	1.91**	2.17**	4.48**
∼ Feb 1984	Mar 1984 ∼	4.625	4.593	0.014	2.01**	2.18**	5.81**
∼ Mar 1975	Apr 1975 ∼	4.579	4.557	0.010	2.09**	2.19**	6.66**
∼ Sep 1970	Oct 1970 ∼	4.664	4.630	0.015	2.51**	2.71**	8.60**
∼ Apr 1966	May 1967 ∼	4.649	4.618	0.013	2.50**	2.71**	8.73**

Table 5: Profitability of Trading Strategies

This table compares profitability of trading strategies based on the funding liquidity's forecastability. They are simple market-timing strategies balancing between risk-free assets and stock market index funds. The weights on the stock market funds are given as

$$\theta_t = \bar{\theta} - x_t \left(\bar{\theta} - \underline{\theta} \right) \in \left[\underline{\theta}, \bar{\theta} \right]$$

where x_t denotes the percentile of today's funding liquidity based on its history.

$$x_t = p\left(fliq \leq fliq_t \,|\, fliq_1, \cdots, fliq_{t-1} \right) = \frac{1}{t-1} \sum_{s=1}^{t-1} \mathcal{I}\left\{ fliq_s \leq fliq_t \right\}$$

where $fliq$ denotes the funding liquidity, which is estimated as the difference of two rolling correlations. The lowest and highest stock weights, $\underline{\theta}$ and $\bar{\theta}$, are specified by the figure's legends. All strategies are assumed to start with a seed money of $100 at the end of December 1969 and come to an end in December 2010.

	Stocks Only $\theta = 1$	risk-free Only $\theta = 0$	Strategy 1 $\theta \in [0, 1]$	Strategy 2 $\theta \in [0, 2]$	Strategy 3 $\theta \in [-1, 2]$
		Panel A. Portfolio Holding Returns $(R_{p,t+1})$			
average	0.908	0.452	0.856	1.259	1.206
stdev	4.685	0.253	2.272	4.545	4.431
		Panel B. Portfolio Excess Returns $(R_{p,t+1} - R_{f,t})$			
average	0.456	0	0.404	0.807	0.754
stdev	4.696	0	2.279	4.559	4.437
Sharpe Ratio	0.097	.	0.177	0.177	0.170

Table 6: Predictability in Subsamples

The dependent variable is stock market excess returns in the next month. The independent variable, ρ_{small} (ρ_{large}) denotes the rolling correlations between stock market excess returns and small (large)-stock illiquidity over the preceding 30 months. Subsample periods are specified in the first row. $CAPE$ denotes cyclically-adjusted price/earnings ratios, which are downloaded from Robert Shiller's website. Numbers in parentheses are Newey-West t statistics with 12 lags. ***, **, and * denote significances at 1%, 5%, and 10% levels respectively.

sample periods	All 1928 $\sim$ 2010	Pre-WW2 1928 $\sim$ 1945	Post-WW2 1946 $\sim$ 2010	Bretten Woods 1946 $\sim$ 1970	Pre-Volcker 1971 $\sim$ 1985	Post-Volcker 1986 $\sim$ 2010
Panel A. Regression on Two Rolling Correlations						
ρ_{small}	2.691**	2.532	3.268***	2.562*	4.329***	4.598***
	(2.415)	(0.686)	(3.720)	(1.686)	(2.991)	(3.304)
ρ_{large}	-1.181	-3.011	-2.431***	-2.172	-1.980	-1.519
	(-1.024)	(-0.667)	(-2.874)	(-1.345)	(-1.038)	(-1.274)
$\log(CAPE)$	-1.366**	-6.283***	-0.469	-1.875**	-2.174	-1.701**
	(-2.441)	(-2.752)	(-1.145)	(-2.450)	(-1.587)	(-2.378)
obs	984	205	779	300	180	299
R^2	0.018	0.053	0.020	0.024	0.046	0.034
Panel B. Regression on $fliq \equiv \rho_{\text{large}} - \rho_{\text{small}}$						
$\rho_{\text{large}} - \rho_{\text{small}}$	-2.042*	-2.610	-2.931***	-2.423*	-3.639***	-3.193***
	(-1.918)	(-0.708)	(-3.926)	(-1.688)	(-2.841)	(-3.019)
$\log(CAPE)$	-1.348**	-6.184***	-0.419	-1.807**	-2.269	-0.943
	(-2.387)	(-2.944)	(-1.073)	(-2.501)	(-1.608)	(-1.392)
obs	984	205	779	300	180	299
R^2	0.016	0.053	0.019	0.023	0.041	0.026

Table 7: Rolling Correlations Estimated from Volatility Quintile Portfolios

In the table, stock portfolios are formed not based on firm size but on stock return volatility. Rolling correlations are estimated between stock market excess returns and each volatility-quintile portfolio's asset illiquidity over the preceding 30 months. Forecast horizons are denoted on the first row. $CAPE$ denotes cyclically-adjusted price/earnings ratios, which are downloaded from Robert Shiller's website. Numbers in parentheses are Newey-West t statistics with 12 lags. ***, **, and * denote significances at 1%, 5%, and 10% level respectively.

horizon	1 month	3 months	6 months	1 year
Panel A. Regression on Two Rolling Correlations				
$\rho_{\text{most volatile}}$	2.180**	6.471***	10.126**	17.804**
	(2.403)	(2.631)	(2.280)	(2.180)
$\rho_{\text{least volatile}}$	-0.607	-2.691*	-5.522**	-11.512**
	(-0.979)	(-1.690)	(-2.029)	(-2.408)
$\log(CAPE)$	-0.768*	-2.473*	-5.159**	-10.471**
	(-1.757)	(-1.952)	(-2.148)	(-2.548)
obs	779	777	774	768
R^2	0.013	0.039	0.062	0.117
Panel B. Regression on $fliq \equiv \rho_{\mathbf{large}} - \rho_{\mathbf{small}}$				
$\rho_{\text{least volatile}} - \rho_{\text{most volatile}}$	-1.076*	-3.818**	-6.895***	-13.385***
	(-1.839)	(-2.522)	(-2.674)	(-2.831)
$\log(CAPE)$	-0.760*	-2.455*	-5.136**	-10.441**
	(-1.744)	(-1.932)	(-2.128)	(-2.533)
obs	779	777	774	768
R^2	0.009	0.032	0.058	0.113

INTERNET APPENDIX

Appendix A Alternative Scenario: Multiple Speculators Compete with Each Other

If more than one speculator compete with each other, they are not able to maximize profits as suggested by the optimization problem in Section 2.3. Instead, a new equilibrium would be made at which their shadow cost of capital equals the maximum of each asset's expected levered return.

$$\phi = \max_j \left\{ 1 + \frac{\left| \bar{v}^j - p_0^j \right|}{m_j} \right\} \tag{A-1}$$

where ϕ denotes the shadow cost of capital. Moreover, the expected returns of all traded assets should equal the shadow cost of capital. If an asset's levered return is lower than ϕ, it implies that the asset is currently not traded due to the constraints of margin requirements. By combining the above condition with a customer's optimization solution in equation (4) and a speculator's budget constraints in equation (6), we can derive the following system of linear equations

$$x + \frac{1}{\gamma}\,\Omega^{-1}\,\tilde{m}\,\phi = \mathbf{1} + \frac{1}{\gamma}\,\Omega^{-1}\,\tilde{m} \tag{A-2}$$

$$\tilde{m}^\top x = W_0^{(s)} \tag{A-3}$$

if the speculators are constrained by margin requirements. Note that the above two equations can be generalized for any number of securities. $W_0^{(s)}$ now indicates the initial aggregate wealth of all speculators. In comparison, if the speculators were not constrained, the solutions would be given as

$$p_0 = \bar{v} \tag{A-4}$$

$$x = \mathbf{1} \tag{A-5}$$

[INSERT Figure A1 HERE]

Figure A1 shows the model implications under the alternative scenario, which are virtually identical with those of the original model. First, the figure is still divided into three sections depending on funding liquidity: no, less, and more constraints. Second, speculators withdraw first from small stocks and then from large stocks later. The only difference between the two models is the levels of trades and discount rates in equilibrium. When speculators are not constrained in the alternative model, they absorb all trading needs, thereby pushing discount rates down to zero.

Appendix B Amihud (2002) Measure of Asset Liquidity

Amihud (2002)'s illiquidity measure is defined as

$$illiq_t^{(i)} = \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{|\, r_{i,t,d} \,|}{vol_{i,t,d}} \tag{A-6}$$

where D_t is the number of business days in month t, $r_{i,t,d}$ is the holding return of stock i on day d of month t, and $vol_{i,t,d}$ is its trading volume in units of currency.

The Amihud measure has the following advantages. First, it can be readily estimated with daily stock returns. Second, the Amihud measure has a large popularity in the literature.[20] Third, Hasbrouck (2009, p.1459) compares several illiquidity measures and concludes that "the Amihud illiquidity measure is most strongly correlated with the TAQ (high frequency trade and quote data)-based price impact coefficient." Næ s, Skjeltorp, and Ø degaard (2011) also compare several versions of liquidity measures and conclude that the Amihud measure shows the highest comovements with business cycles and macroeconomic variables. Marshall, Nguyen, and Visaltanachoti (2012) examine liquidity proxies in commodities and conclude that the Amihud measure has the highest correlation with liquidity benchmarks.

Stocks are then divided into size quintiles based on total market capitalizations, and equal-weighted averages of illiquidity are computed for each quintile every month. Some stocks are dropped if their illiquidity lie in the outside of 0.5 and 99.5 percentiles of each portfolio.

[INSERT Table A1 HERE]

[20] For example, the Amihud measure is the one used by Acharya and Pedersen (2005) to test their liquidity-adjusted CAPM.

Table A1 shows their summary statistics. According to the table, the illiquidity of smallest stocks are about 300 times higher than that of largest stocks because the denominator in the definition of Amihud measure, equation (A-6), is denoted in units of currency.

[INSERT Figure A2 HERE]

Figure A2 shows the time series of asset liquidity for small and large stocks. Their values are denoted on the left and right axes separately because of the difference of scales. Their trends show very different patterns. The illiquidity of large stocks seems to be non-stationary and gradually decreases over time. However, the illiquidity of small stocks seems to be relatively more stationary.

The different scales and stationarity of large and small stocks' liquidity raise a question about how to measure the market's asset liquidity. For example, Amihud (2002), Pástor and Stambaugh (2003), Acharya and Pedersen (2005), and Sadka (2006) estimate the market's liquidity as an equal-weighted average of individual stocks' liquidity. The problem is that the equal-weighted average is likely to be driven by small stocks' liquidity due to the huge difference of scales although large stocks are more representative of the stock market. If a value-weighted average is used instead, however, the estimated time series of the market's liquidity will become non-stationary and seemingly converge to zero. The answer to this question is beyond this paper's scope.

Appendix C Forecast of GDP Growth

[INSERT Table A3 HERE]

To investigate further the relationship of funding liquidity to macroeconomic activity, Table A3 regresses future real GDP growth rates on $fliq$. The table shows that high $fliq$ predicts low GDP growth for almost two years. According to its Panel A (Panel B), one-standard-deviation-high $fliq$ predicts the GDP growth to be lower by 0.182%, 0.232%, 0.212%, 0.216%, 0.181%, 0.160%, and 0.118% (0.172%, 0.219%, 0.202%, 0.207%, 0.174%, 0.156%, and 0.114%) in the next seven quarters respectively, summing to a decrease by 1.301% (1.244%). Moreover, the forecastability appears significant at 1% confidence level for each of the first six quarters.

Panel B of the table adds yield curve slope, which is measured as the difference of 5- and 1-year Fama-Bliss zero-coupon discount bond yields, as a control variable. Note that the yield curve slope has attracted the attention not only of financial economists but also of monetary policymakers since the slope is known to be the best predictor of recessions. For example, Stambaugh (1988) explains that "inverted term structures precede recessions and upward-sloping structures precede recoveries," Estrella and Mishkin (1998) find that "the slope of the yield curve emerges as the clear individual choice" as a predictor of US recessions. Ang, Piazzesi, and Wei (2006) also document that "every recession after the mid-1960s was predicted by a negative slope–an inverted yield curve–within 6 quarters of the impending recession. Moreover, there has been only one 'false positive' (an instance of an inverted yield curve that was not followed by recession) during this time period." The Federal Reserve Bank also acknowledges that "the slope of the yield curve is a reliable predictor of future real economic activity."[21]

Panel B shows that $fliq$ and the yield curve slope have equally significant forecastability. $fliq$'s statistical significance is hardly subsumed by the addition of the slope. Moreover, R^2's in Panel B are almost twice as high than those in Panel A. The penal implies that $fliq$ and the slope span independent dimensions of information about financial markets and macroeconomies. Moreover, up to the author's best knowledge, no macroeconomic predictor has ever been found to be as strong as the slope. $fliq$ is the first independent predictor with comparable predictability to the yield curve slope.

Appendix D Comparison of $fliq$ with Market Sentiments

[INSERT Figure A3 HERE]

Figure A3's Panel (a) is based on the institutional investors' stock market confidence index, which is measured by the survey of the Yale School of Management.[22] The figure shows that $fliq$ and the confidence index share high volatility in 1990s, a huge increase in 2001, and a brief local peak in 2006. However, the confidence index seems to be too flat in the late 2000s compared to $fliq$. Moreover, it is awkward that the index shows little changes even during the global financial crisis, which casts doubt upon the index's informative contents.

Panel (b) of Figure A3 compares $fliq$ to market sentiment index,[23] which is is created by Baker and Wurgler (2007) as the first principal component of the following six variables:

[21] http://www.ny.frb.org/research/capital_markets/ycfaq.html
[22] http://icf.som.yale.edu/stock-market-confidence-indices
[23] http://people.stern.nyu.edu/jwurgler/

closed-end fund discount, detrended log turnover, number of IPOs, first-day return on IPOs, dividend premium, and equity share in new issues. The figure shows that the sentiment index is more closely related to $fliq$ than the confidence index. They show particularly close comovement in 1990s and 2000s. However, their correlation is not strong enough to conclude that $fliq$ also proxies market sentiments, particularly because of their large diversions in the 1980s. The comovement is in part due to the fact that some of the index's compositions are actually based on funding liquidity.

Appendix E Asset Flows to the Hedge Fund Industry

[INSERT Figure A4 HERE]

One may ask whether the changes in $fliq$ may be correlated to asset flows to the hedge fund industry, which acts as typical speculators in the financial markets. Figure A4 compares the two of them. The vertical axis denotes the changes in funding liquidity, $fliq_t - fliq_{t-1}$, and the horizontal axis denotes the hedge fund asset flows, asset flows_t/total assets_{t-1}. The total assets and asset flows of the industry are provided by the HFR Global Hedge Fund Industry Report at an annual basis. The scatter plot shows a positive correlation, but it is not significantly different from zero. One may earn a better understanding by separating the increases in equities and liabilities of the industry, but unfortunately the author could not obtain such detailed information.

Appendix F Forecast of Portfolio Returns and Cross-sectional Stock Market Factors

In most previous predictability tests, the dependent variable has been value-weighted stock market excess returns. Thus, small stocks' returns have been under-represented, and one may wonder whether they are also predicted by $fliq$ with similar significance.

[INSERT Table A4 HERE]

Table A4's Panel A regresses Fama-French 25 portfolio returns of the next month on $fliq$. To save space, only five of them are reported. The table shows that, although $fliq$'s forecastability is significant across all portfolio returns, $fliq$ predicts large or growth stocks' returns better than small or value stocks. Large-and-growth portfolio returns in column (4) present the highest Newey-West t statistics ($t = 4.234$), followed by large-and-value stocks ($t = 2.730$) and small-and-growth stocks ($t = 2.685$).

Panel B of the table uses cross-sectional stock market factors as dependent variables, each of which denotes stock market excess returns (MktRf), size premium (SMB), value premium (HML), momentum factor (MOM), and liquidity factor (LIQ). The first four factors are downloaded from Kenneth French's website while the last liquidity factor is from Robert Stambaugh's.[24] The panel shows that no cross-sectional factors other than MktRf are significantly predicted by $fliq$. Note that the no-predictability of cross-sectional factors is actually consistent with the model's implication. For example, Figure 1 implies that size premium (i.e., the difference of expected holding returns between large and small stocks) is not monotonic with funding liquidity.

Appendix G Small-Sample Bias of Predictive Regressions

Another concern of a predictive regression is the small-sample bias (Mankiw and Shapiro, 1985; Nelson and Kim, 1993; Stambaugh, 1999; Lewellen, 2004). For example, suppose the following predictive regression where its predictor follows a stochastic AR(1) process.

$$y_t = \alpha + \beta\, x_{t-1} + u_t \tag{A-7}$$

$$x_t = \theta + \rho\, x_{t-1} + v_t \tag{A-8}$$

Some may consider the significance of the estimated β the evidence of predictability. However, the estimate of β can be easily biased if the two innovation shocks (u_t and v_t) are correlated and the predictor follows a persistent process (ρ close to one).

One example of the small-sample bias is the regression of stock market returns on lagged dividend yields. The estimated predictability of dividend yields is corrupted by the small-sample bias since high stock returns lower subsequent dividend yields and the dividend yields have strong persistence. Stambaugh (1999) estimates that the OLS estimate of β is biased by one third. Moreover, according to the paper, the null hypothesis of zero predictability of dividend yields is not rejected after the bias is corrected.

To test if the predictability of rolling correlations is also subject to the small-sample

[24] http://finance.wharton.upenn.edu/~stambaugh/

bias problem, I estimate the bias as suggested by Stambaugh (1999).

$$\hat{\beta} - \beta = \frac{w^\top A\, w}{w^\top B\, w} \tag{A-9}$$

where $\hat{\beta}$ denotes the OLS estimate of β, $w \equiv \begin{bmatrix} u \\ x - \bar{x}\,\iota_T \end{bmatrix}$, ι_T is a column vector of ones, $A \equiv \frac{1}{2}\begin{bmatrix} 0 & F \\ F & 0 \end{bmatrix}$, $B \equiv \begin{bmatrix} 0 & 0 \\ 0 & F \end{bmatrix}$, and $F \equiv I_T - \frac{1}{T}\iota_T \iota_T^\top$.

$fliq$ is used as a predictor, and its bias is estimated to be -2.578×10^{-15}. This bias is very tiny compared to the estimate of β in Table 2 ($\hat{\beta} = 3.066$). Note that the numerator of equation (A-9) depends on the covariance between a dependent variable and a predictor. Forecasts made by $fliq$ are little biased because $fliq$ has weak covariance with market returns. Thus, this test confirms that $fliq$ is robust to the small-sample bias.

Lewellen (2004) recently shows that the previous correction methods actually underestimate the dividend yields' forecastability. He suggests a new bias correction based on the near-unit-root persistence of dividend yields ($\rho \approx 1$) and finds that the dividend yields' forecastability is significant even during the post-war periods, a finding which contrasts with the previous literature. Stambaugh (1999)'s bias correction is found to be a far conservative standard. Thus, the recent literature also provides support to $fliq$'s robustness to small-sample bias.

Appendix H Forecast with Different Combinations of Rolling Correlations

$fliq$ has been defined as the difference of the largest and smallest stocks' rolling correlations. Given that the smallest stocks account for less then 1% of the stock market's total market capitalizations, however, the $fliq$'s definition can be considered unrepresentative of the market. One may suspect that $fliq$'s predictability might have been driven by smallest stocks' unique characteristics.

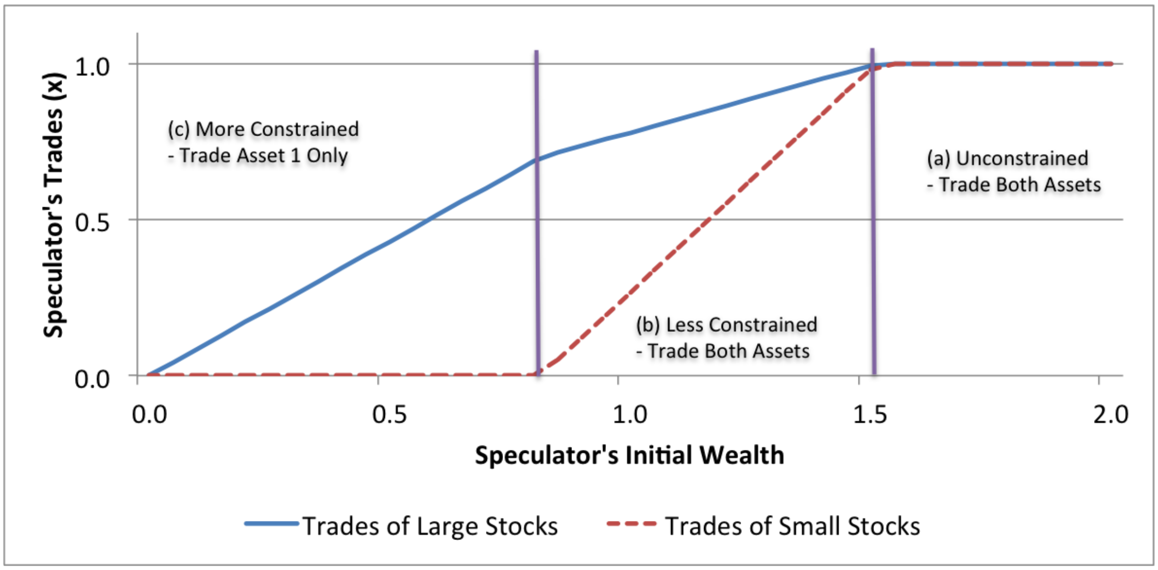
[INSERT Table A5 HERE]

Table A5 tests whether predictability can still be found from different combinations of rolling correlations. The table's predictor is $\rho_i - \rho_j$, where i and j denote stock size portfolio numbers. Portfolio 1 and 5 denote the smallest and largest stocks respectively. For example, $\rho_5 - \rho_1$ in column (1) is identical with the previous definition of $fliq$. $\rho_5 - \rho_4$ in column (4) denotes the difference of rolling correlations between the largest and the second-largest stocks.

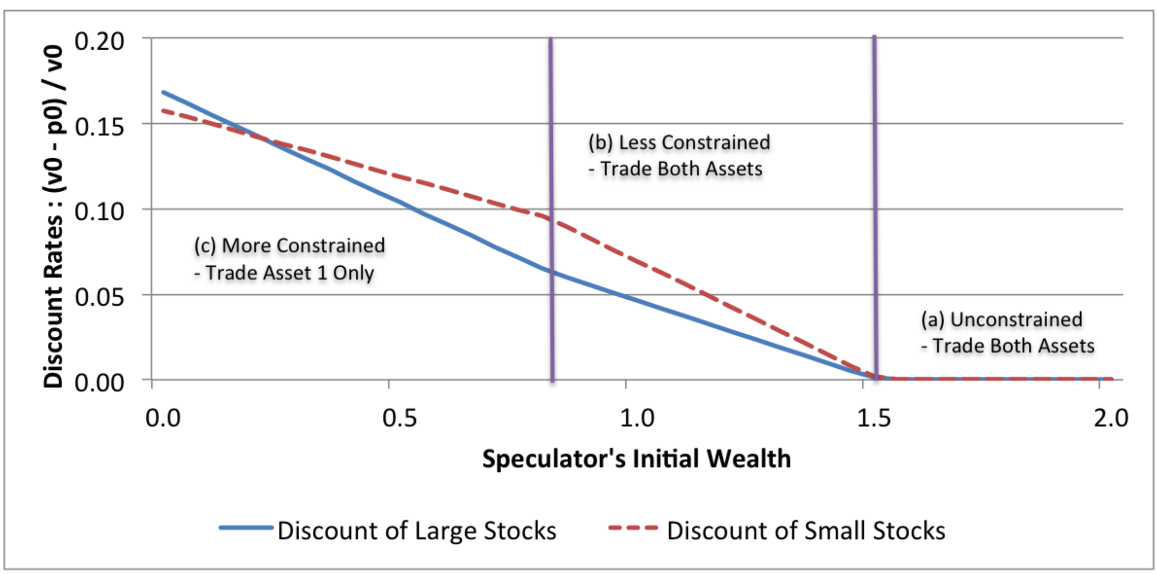
The table shows that the predictability is significant no matter which combination is used. Four of them are significant at 1% level, and the other two are at 5%. $fliq$'s original definition, $\rho_5 - \rho_1$, delivers the highest Newey-West t statistics, followed by $\rho_5 - \rho_3$ and $\rho_4 - \rho_1$. The table confirms that the predictability is not due to the smallest stocks' unique characteristics.

Figure A1: Alternative Scenario: Multiple Speculators Compete with Each Other

This figure shows model implications under the alternative scenario under which multiple speculators compete with each other. The solutions are derived in Appendix A. Panel (a) shows a speculator's optimal trades and Panel (b) shows the stocks' expected returns (discount rates). The horizontal axes denote speculators' initial wealth, $W_0^{(s)}$. Vertical lines divide the figure into three areas depending on funding liquidity.



(a) Speculator's Optimal Asset Trades (x)



(b) Expected Returns $((\bar{v} - p_0)/\bar{v})$

Figure A2: Time Series of Illiquidity for Small and Large Stocks

Asset illiquidity of each size portfolio is estimated as equal-weighted averages of Amihud (2002)'s illiquidity measure of member stocks. The solid line denotes the illiquidity of small stocks, scaled on the left axis. In comparison, large stocks' illiquidity is denoted by the dashed line and scaled on the right axis.

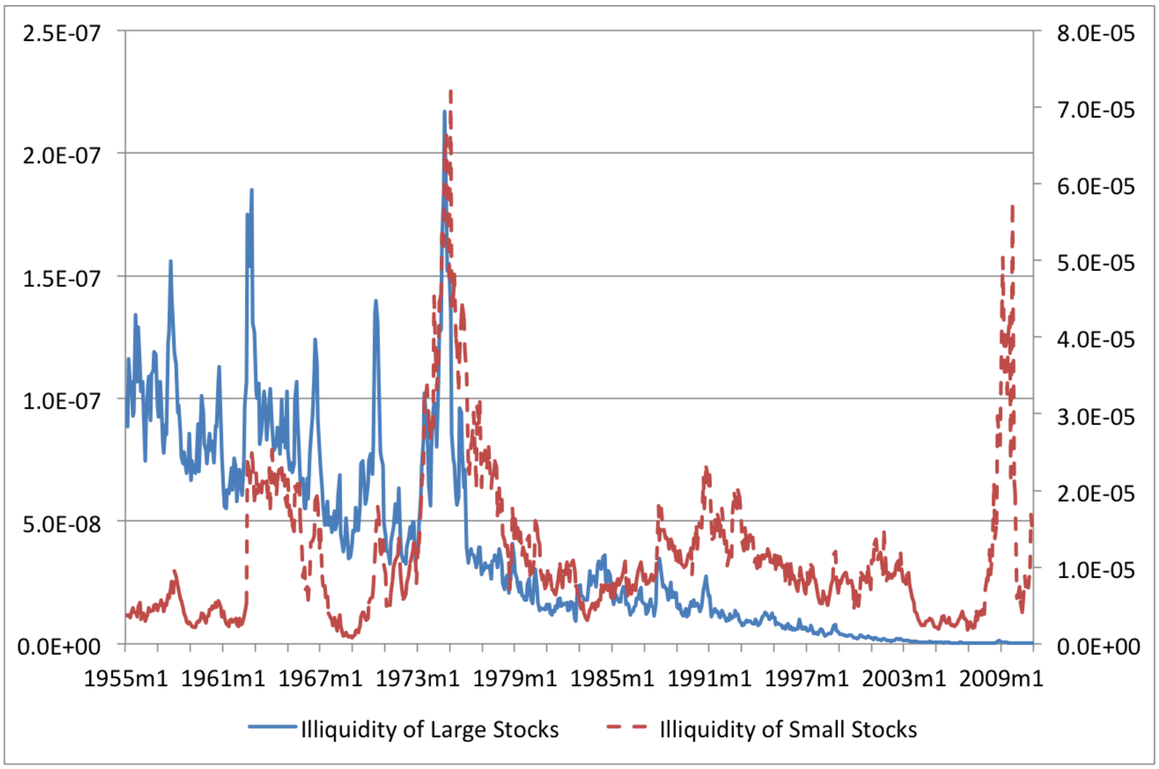
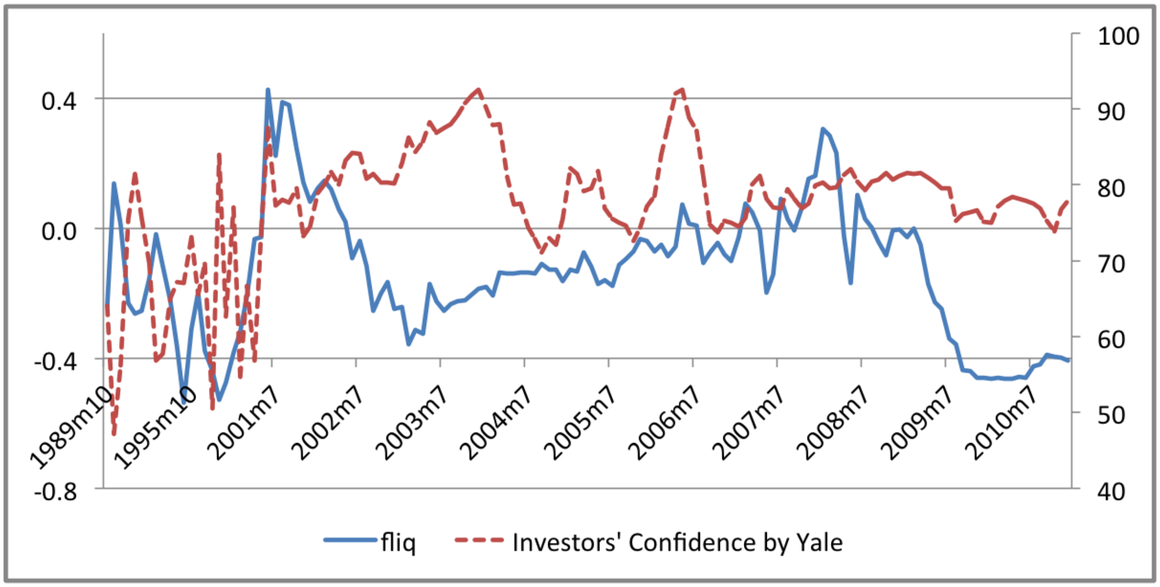
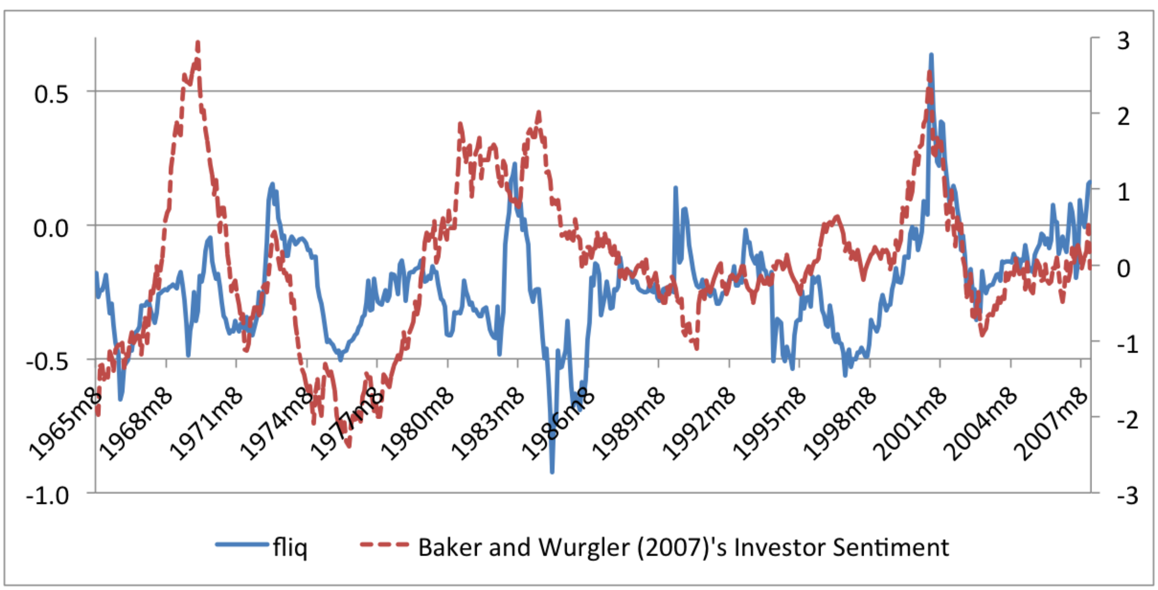


Figure A3: Comparing $fliq$ to Market Sentiments

Panel (a) compares $fliq$ to institutional investors' stock market confidence index, which is based on the survey by the Yale School of Management. Panel (b) compares $fliq$ to the investor sentiment index, which is estimated by Baker and Wurgler (2007) as the first principal component of sentiment-related variables.



(a) Stock Market Confidence Index by the Yale School of Management



(b) Investor Sentiment by Baker and Wurgler (2007)

Figure A4: Hedge Fund Asset Flows

The horizontal axis denotes equity-type hedge fund asset flows relative to total assets in the previous year, and the vertical axis denotes contemporary changes in $fliq$. The data of hedge fund total assets and asset flows are provided by the HFR Global Hedge Fund Industry Report, spanning from 1990 to 2008. $fliq$'s values are chosen at the end of each year. Labels next to each point show sample years.

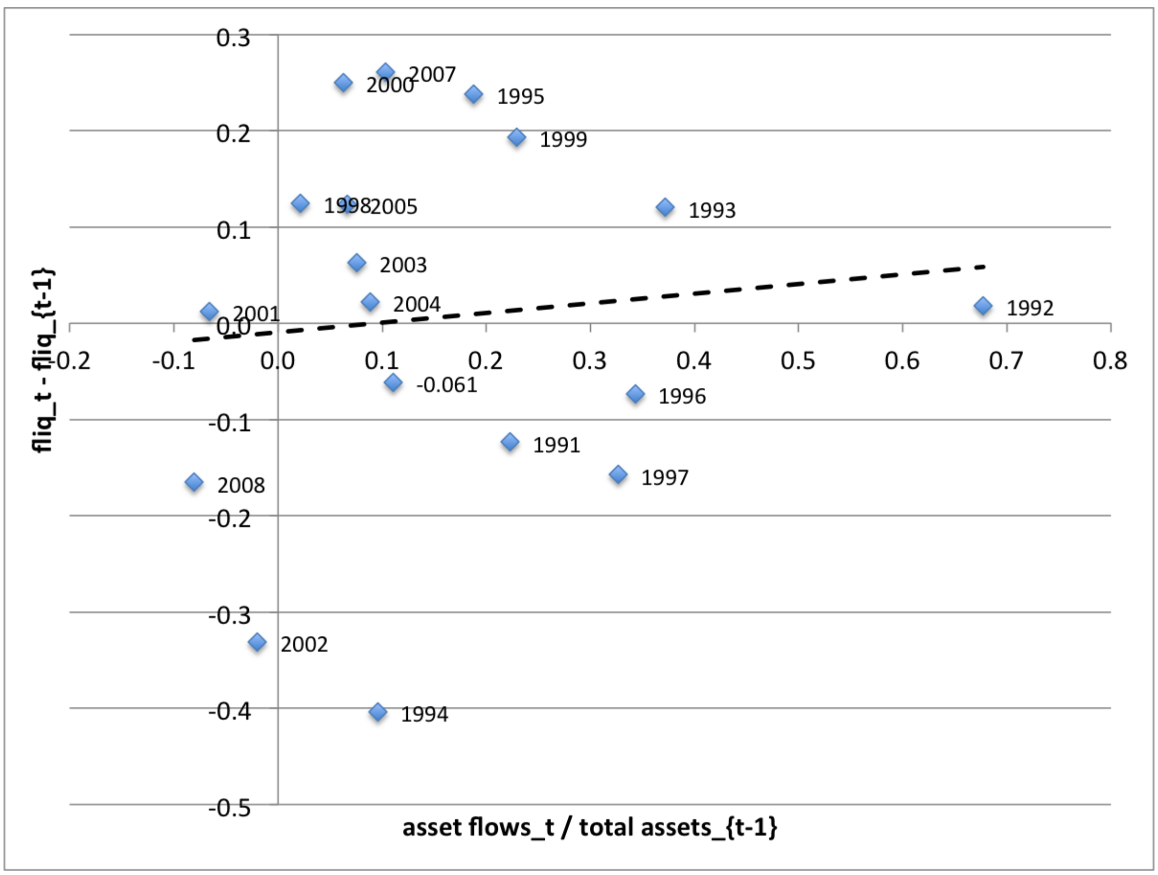


Table A1: Summary Statistics of Asset Illiquidity for Each Size Quintile

This table shows the summary statistics of each size-quintile stock portfolio's asset illiquidity, which is estimated as follows. First, asset illiquidity is estimated using the Amihud (2002)'s measure for each stock and each month.

$$illiq_t^{(i)} = \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{|\, r_{i,t,d} \,|}{vol_{i,t,d}}$$

where D_t denotes the total number of trading days in a given month t. Second, size quintile stock portfolios are formed every month. Third, equal-weighted averages of asset illiquidity are taken for each portfolio and month. Numbers in this table are multiplied by 10^5. The data span from January 1946 to December 2010.

Size	mean	stdev	.25 pctile	.75 pctile
Smallest	1.1400	0.9560	0.5360	1.3600
2	0.2100	0.1820	0.0942	0.2750
3	0.0702	0.0609	0.0294	0.0955
4	0.0269	0.0278	0.0088	0.0333
Largest	0.0069	0.0096	0.0008	0.0091

Table A2: Summary Statistics of Rolling Correlations

This table shows the summary statistics of rolling correlations between contemporary stock market excess returns and each size-quintile stock portfolio's asset illiquidity over the preceding 30 months. Size-quintile stock portfolios are formed every month, and their asset illiquidity is measured as the equal-weighted average of individual stocks' Amihud (2002) measures. The half-life is measured under the assumption that each variable follows an AR(1) process.

	mean	stdev	.25 pctile	.75 pctile	half-life (months)
ρ_{small}	0.026	0.195	-0.100	0.172	8.22
ρ_2	-0.072	0.191	-0.196	0.046	7.99
ρ_3	-0.108	0.185	-0.208	0.008	7.21
ρ_4	-0.176	0.181	-0.289	-0.063	7.24
ρ_{large}	-0.236	0.182	-0.364	-0.114	7.65
$\text{fliq} \equiv \rho_{\text{large}} - \rho_{\text{small}}$	-0.262	0.183	-0.376	-0.174	10.16

Table A3: Real GDP Growth Forecast by Funding Liquidity

The dependent variable is future real GDP growth rates in h quarters, $(\text{GDP}_{t+h} / \text{GDP}_{t+h-1} - 1) \times 100$ for $h = 1, \cdots, 7$. Forecast horizons (h) are specified in the first row. Panel A uses funding liquidity ($fliq$) as the only predictor, and Panel B adds yield curve slope, which is measured as the difference of 5- and 1-year Fama-Bliss zero-coupon discount bond yields, as a control variable. Since the regressions are made at a quarterly basis, explanatory variables are taken from the predictors' average values over the last quarter. Numbers in parentheses are OLS t statistics. ***, **, and * denote significances at 1%, 5%, and 10% level respectively.

Horizon (h)	1 qtr	2 qtr	3 qtr	4 qtr	5 qtr	6 qtr	7 qtr
Panel A. Regression on $fliq \equiv \rho_{\text{large}} - \rho_{\text{small}}$							
fliq	-0.996***	-1.270***	-1.160***	-1.183***	-0.992***	-0.876***	-0.645*
	(-2.975)	(-3.828)	(-3.518)	(-3.582)	(-2.967)	(-2.611)	(-1.933)
obs	234	233	232	231	230	229	228
R^2	0.037	0.060	0.051	0.053	0.037	0.029	0.016
Panel B. Regression on $fliq$ and Yield Curve Slope							
fliq	-0.940***	-1.197***	-1.104***	-1.134***	-0.954***	-0.854**	-0.625*
	(-2.845)	(-3.712)	(-3.419)	(-3.516)	(-2.913)	(-2.566)	(-1.882)
slope	0.221***	0.297***	0.262***	0.270***	0.259***	0.173**	0.151*
	(2.833)	(3.912)	(3.439)	(3.527)	(3.320)	(2.168)	(1.886)
obs	234	233	232	231	230	229	228
R^2	0.069	0.118	0.098	0.102	0.082	0.049	0.032

Table A4: Forecast of Portfolio Returns and Stock Market Factors

The dependent variable in Panel A is 5 out of the Fama-French 25 stock portfolio returns in the next month. The panel's first two rows specify the characteristics of each portfolio. The dependent variable in Panel B is cross-sectional stock market factors. The first four factors–market excess return, size premium, value premium, and momentum factor–are provided by Kenneth French's website. The last factor in column (5) denotes Pástor and Stambaugh (2003)'s liquidity factor, which is downloaded from Robert Stambaugh's website. Numbers in parentheses are Newey-West t statistics with 12 lags. ***, **, and * denote significances at 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)
Panel A. Forecast of Portfolio Returns					
size	small	small	mid-size	large	large
value	growth	value	mid-value	growth	value
$\rho_{\text{large}} - \rho_{\text{small}}$	-3.753***	-2.459*	-1.987**	-3.318***	-2.657***
	(-2.685)	(-1.957)	(-2.210)	(-4.234)	(-2.730)
$\log(CAPE)$	-0.609	-0.570	-0.724*	-0.394	-0.693*
	(-0.686)	(-1.062)	(-1.721)	(-0.945)	(-1.780)
obs	779	779	779	779	779
R^2	0.010	0.009	0.011	0.021	0.015
Panel B. Forecast of Stock Market Factors					
dep. var.	MktRf_{t+1}	SMB_{t+1}	HML_{t+1}	MOM_{t+1}	LIQ_{t+1}
$\rho_{\text{large}} - \rho_{\text{small}}$	-2.931***	0.107	1.009	-0.593	0.006
	(-3.926)	(0.174)	(1.632)	(-0.770)	(0.803)
$\log(CAPE)$	-0.419	-0.113	-0.090	0.369	0.002
	(-1.073)	(-0.341)	(-0.225)	(0.998)	(0.586)
obs	779	779	779	779	516
R^2	0.019	0.000	0.004	0.002	0.002

Table A5: Forecast with Different Combinations of Rolling Correlations

This table measures funding liquidity using different combinations of rolling correlations, $\rho_i - \rho_j$. i and j denote size quintile portfolio numbers. Portfolio 1 represents the smallest stocks and 5 does the largest ones. $i = 5$ and $j = 1$ in column (1) corresponds to the same measure that has been used so far, $fliq \equiv \rho_{\text{large}} - \rho_{\text{small}}$. The dependent variable is stock market excess returns in the next month. $CAPE$ denotes cyclically-adjusted price/earnings ratios, which are downloaded from Robert Shiller's website. Numbers in parentheses are Newey-West t statistics with 12 lags. ***, **, and * denote significances at 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
i	5	5	5	5	4	3
j	1	2	3	4	1	1
$\rho_i - \rho_j$	-2.931***	-2.390***	-4.540***	-4.883**	-2.645***	-2.418**
	(-3.926)	(-2.692)	(-2.802)	(-2.493)	(-2.744)	(-2.491)
$\log(CAPE)$	-0.419	-0.628	-0.645*	-0.857**	-0.349	-0.484
	(-1.073)	(-1.628)	(-1.749)	(-2.210)	(-0.825)	(-1.135)
obs	779	779	779	779	779	779
R^2	0.019	0.011	0.016	0.012	0.013	0.010

Table A6: $fliq$ Estimated Over Various Horizons

This table tests whether $fliq$'s forecastability is robust to various estimation horizons. The horizons vary from 12 to 42 months, which are shown on the first row. For reference, $fliq$ has been estimated over the preceding 30 months so far. The dependent variable is stock market excess returns in the next month. $CAPE$ denotes cyclically-adjusted price/earnings ratios, which are downloaded from Robert Shiller's website. Numbers in parentheses are Newey-West t statistics with 12 lags. ***, **, and * denote significances at 1%, 5%, and 10% levels respectively.

horizon	12 months	18 months	24 months	30 months	36 months	42 months
Panel A. Regression on Two Rolling Correlations						
ρ_{small}	1.301**	1.516**	2.653***	3.385***	3.483***	4.029***
	(2.389)	(1.991)	(3.158)	(3.811)	(3.246)	(3.575)
ρ_{large}	-0.083	0.083	-1.962**	-2.606***	-2.836***	-3.401***
	(-0.115)	(0.089)	(-2.344)	(-3.107)	(-3.141)	(-3.803)
$\log(CAPE)$	-0.656	-0.691	-0.500	-0.455	-0.527	-0.551
	(-1.515)	(-1.588)	(-1.184)	(-1.087)	(-1.299)	(-1.356)
obs	768	762	756	750	744	738
R^2	0.011	0.011	0.017	0.022	0.022	0.025
Panel B. Regression on $fliq \equiv \rho_{\text{large}} - \rho_{\text{small}}$						
$\rho_{\text{large}} - \rho_{\text{small}}$	-0.830	-0.948	-2.397***	-3.071***	-3.188***	-3.715***
	(-1.552)	(-1.314)	(-3.385)	(-4.124)	(-3.659)	(-4.261)
$\log(CAPE)$	-0.614	-0.618	-0.463	-0.415	-0.500	-0.530
	(-1.431)	(-1.469)	(-1.135)	(-1.033)	(-1.279)	(-1.338)
obs	768	762	756	750	744	738
R^2	0.007	0.007	0.016	0.021	0.021	0.025