Funding Risk, Market Liquidity, Market Volatility in the Cross-Section of Stocks

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Abstract

Intermediary asset pricing models predict that exposures to intermediaries funding conditions pose a risk to investors. We show that market liquidity is poorer and volatility is higher across stocks when funding conditions get worse. The dispersions of illiquidity and volatility across stocks are also wider. Consistent with this risk, we find a significant risk premium associated with intermediaries funding conditions when we sort stocks on illiquidity and volatility. Stocks that deteriorate more in illiquidity and volatility with worse funding conditions also experience negative contemporaneous returns, have larger betas with respect to intermediaries funding conditions, and earn higher average returns.

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Introduction

Financial intermediaries, including broker-dealers, provide liquidity and accommodate imbalances between buyers and sellers of securities. Intermediaries may face constraints when they need to raise funds either through debt (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009) or equity (He and Krishnamurthy, 2013; Kondor and Vayanos, 2019). Compared to the case of a frictionless asset pricing model, funding conditions will influence the behavior of intermediaries and enhance the role played by asset characteristics. In a model with intermediaries, Brunnermeier and Pedersen (2009) establish several theoretical predictions linking funding liquidity with the illiquidity, volatility and expected returns in the cross-section of stocks. In this paper, we complement and reinforce the current literature on asset pricing with financial intermediaries by building a set of tests of the following predictions:

(i) *Commonality.* Illiquidity across assets co-moves with funding conditions (i.e., a level effect).

(ii) *Flight to quality.* Illiquidity co-moves more strongly with funding conditions for assets with higher volatility (i.e., a dispersion effect).

(iii) *Asymmetry.* Illiquidity co-moves more strongly with funding conditions when initial funding conditions are worse.

(iv) *Returns and Funding Liquidity Risk Premium.* Predictions i), ii) and iii) also apply to returns. Moreover, securities with higher returns covariance with funding conditions have a higher risk premium.

We find that the predictions (i)-(iv) hold in the data and conclude that the intermediaries' funding conditions is an empirically important mechanism linking illiquidity, volatility and asset prices. The evidence provides additional support to models in which intermediaries are central to the evolution of asset prices and delivers an important message to investors.

Our contribution is to establish simultaneously the relationships between illiquidity, volatility, asset prices, and funding conditions. We test the theoretical predictions using the portfolios of stocks sorted on the level of market liquidity and market volatility. As recently put forward by Giglio, Xiu, and Zhang (2021), the strength or weakness of a factor is also a property of the set of assets used in a test. A liquidity factor may be weak in a cross-section of portfolios sorted by, say, value or profitability, but may be strong in a cross-section of assets sorted by characteristics such as liquidity or volatility, which are linked by theory to exposure to funding conditions. We proxy for funding conditions by using the measure of Fontaine and Garcia (2012), which captures price differences across Treasury securities that are widely traded and have nearly identical cash flows. Intuitively, a larger dispersion of prices for nearly identical securities indicates a scarcity of intermediation capital and identify periods with poor funding conditions. Section I(C) motivates this measure of funding shocks in detail.

Our results show that funding conditions are closely linked to the market liquidity across stocks. We find that the illiquidity of every portfolio increases when intermediaries' funding conditions deteriorate (*Prediction (i)*), which helps explain the well-known commonality of liquidity (Chordia, Roll, and Subrahmanyam, 2000). Next, we find that the dispersion of illiquidity across portfolios also increases when funding conditions are poor. Despite the commonality of market liquidity, stocks that are initially illiquid and volatile are more sensitive to funding conditions through flight to liquidity (*Prediction (ii)*). Intuitively, intermediaries provide less liquidity in securities that strain the most their funding constraints, such as high-volatility securities. We also find that the effects of changes in funding conditions on the level and dispersion of stocks' liquidity are stronger when the initial level of funding conditions is worse (*Prediction (iii)*). Intuitively, intermediaries respond more to changes in funding conditions when they are closer to their constraints.

These results suggest that variations in the intermediaries' funding conditions are associated with undiversifiable risk for investors. Consistent with this prediction, we find robust evidence that exposures to intermediaries' funding conditions generate a risk premium (*Prediction (iv)*). Portfolios of stocks that are more illiquid and volatile exhibit higher average returns that align well with their returns sensitivity to changes in funding conditions. This slope yields an estimate of the price of risk that is significant and, as expected, negative, meaning that stocks that have negative returns when funding conditions worsen have higher returns on average. These results from the equity market add to the existing evidence that intermediaries' funding conditions carry a risk premium.

The results also hold for traditional portfolios sorted on size, book-to-market or market betas. A version of CAPM augmented with funding risk explains close to 50 percent of the dispersion in average returns across these traditional portfolios, suggesting that sorting on size, value or betas also induces some dispersion in exposures to intermediaries' funding conditions.[1] Unsurprisingly, Fama and French factors offer a better fit in these traditional portfolios. We argue that exposures to funding conditions carry a robust price of risk in the cross-section of asset returns, not that this is the only dimension of risk that investors bear. We also present similar results for portfolios of stocks sorted on the covariance of returns with aggregate illiquidity and volatility, as in Acharya and Pedersen (2005).

The estimated price of risk is robust across a wide range of specifications combining exposures to funding conditions with either the market returns, Fama-French risk factors, market illiquidity shocks (Amihud, 2002), Pastor and Stambaugh (2003) liquidity risk factor, betting-against-beta factor (Frazzini and Pedersen, 2014), and shocks to the spread between Treasury bill and LIBOR rates (TED spread). Our results provide the same message when we use quarterly returns, in which case we pay special attention to broker-dealer (BD) leverage and primary dealers (PD) capital ratio (Adrian, Etula, and Muir 2014 or He, Kelly, and Manela 2017, respectively).

[1] A large literature have shown that the CAPM performs poorly for these test assets and some of this literature suggests links with liquidity in each case. See e.g., Pastor and Stambaugh (2003); Acharya and Pedersen (2005); Frazzini and Pedersen (2014); Akbas, Boehmer, Genc, and Petkova (2010).

Funding conditions and these balance-sheet proxies for the leverage of intermediaries have close theoretical underpinnings and similar asset pricing implications. Indeed, we find that shocks to either PD capital ratio or BD leverage in asset pricing tests lower the estimated prices of risk associated with funding shocks—a tell tale of their correlations. Consistent with He, Kelly, and Manela (2017), we find a positive sign for the price of capital ratio shocks, which indicates that an unexpected decline of capital ratio is bad news from the point of view of investors. This sign is consistent with intermediary asset pricing models where the constraint on equity financing plays a greater role than the constraint on debt financing. We also find theoretically-consistent opposite signs between the prices of PD and BD risks in asset pricing tests based on portfolios of stocks sorted on illiquidity. This contrasts with some of the existing mixed evidence based on standard portfolio sorts.

Related Literature

Our results are distinct from the existing literature that connects liquidity, volatility and asset returns to funding conditions. Existing results show strong illiquidity commonality across securities (Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Chordia, Sarkar, and Subrahmanyam, 2005); or that illiquidity increases with the volatilities of securities so that market makers are compensated either for their inventory risk or for their losses to better-informed investors; or that illiquidity and volatility may perpetuate each other in a self-fulfilling equilibrium (Benston and Hagerman, 1974; Stoll, 1978; Glosten and Milstom, 1985; Grossman and Miller, 1988; Pagano, 1989); or that illiquidity creates a higher risk premium (Amihud and Mendelson, 1986; Amihud, 2002; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005); or how shocks in funding liquidity induced by policy changes impact market liquidity in the corporate bond markets through repo positions (Fontaine and Garcia, 2012; Macchiavelli and Zhou, 2022).

We link these strands of literature by establishing the relation between illiquidity, volatility, asset prices, and funding conditions. A few papers look at the role of intermediaries' balance sheets but largely ignore the link with illiquidity and volatility. The paper by Hameed, Kang, and Vishnawathan (2010) stands out and shows that stocks' illiquidity increases and is more pervasive following market declines, which they interpret as shocks to intermediaries' wealth. Adrian, Etula, and Muir (2014) investigate the role of BD leverage while He, Kelly, and Manela (2017) investigate the role of PD capital ratio but they ignore the implications for illiquidity or find no links.

The rest of the paper is organized as follows. Section I describes our empirical strategy, including the construction of the test portfolios. Section II documents that funding conditions are closely linked with the illiquidity, volatility and returns of equities, and contains our main asset pricing results. In Section III, we take a closer look at the risk premium associated with funding conditions. We investigate if it is present in standard size and value portfolios, and if it is robust to portfolios constructed on exposures to funding risk, to the inclusion of competing or complementary measures of market or funding liquidity. The conclusion discusses remaining challenges and offers avenues for future research. An appendix provides details about data sources, preliminary filters that we applied to the raw data, and alternative risk factors used in our tests.

I Empirical Strategy

This section discusses the theoretical foundations for the tests of the cross-sectional implications (i)-(iv) listed in the introduction. It also details the construction of portfolios and the measure of funding conditions that we will use in the tests.

A Theoretical Underpinnings

Our empirical strategy builds on existing theoretical contributions. In Brunnermeier and Pedersen (2009), investors arrive sequentially to the market and intermediaries provide liquidity, smoothing price fluctuations.[2] In the following, we focus on the cross-sectional implications that arise in equilibrium when intermediaries vary the provision of liquidity with changes in funding conditions.[3]

From Proposition 6 of Brunnermeier and Pedersen (2009), when funding conditions deteriorate, intermediaries reduce their positions and induce movements in market illiquidity of any stock i, as measured by the absolute deviation of the price from fundamental value $|\Lambda_i|$:

(i) *Commonality.* Illiquidity $|\Lambda_i|$ co-moves with funding conditions ϕ:

$$\mathrm{cov}(|\Lambda_i|, \phi) > 0.$$

However, the effect is not the same across all stocks and, as a result, the cross-sectional dispersion of illiquidity increases. Stocks that are more volatile become more illiquid, since they add relatively more to the intermediaries' risk. For stocks i and j such that volatilities $\sigma_i > \sigma_j$, the responses of market liquidity to funding conditions exhibit a flight-to-quality pattern:

(ii) *Flight to quality.* Illiquidity co-moves more strongly with funding conditions for assets with higher volatility:

$$\mathrm{cov}(|\Lambda_i|, \phi) > \mathrm{cov}(|\Lambda_j|, \phi).$$

[2] Brunnermeier and Pedersen (2009) also emphasize that, under certain conditions, margins can be destabilizing and market liquidity and funding liquidity are mutually reinforcing, leading to liquidity spirals.

[3] In earlier work, Vayanos (2004) proposes an equilibrium model where shocks to fund managers' wealth connect an asset's illiquidity and returns to its volatility. In Gromb and Vayanos (2002, 2010), intermediaries' wealth shocks exacerbate illiquidity and volatility. Brunnermeier and Pedersen (2009) and Kondor and Vayanos (2019) emphasize the case with multiple assets. In Kondor and Vayanos (2019), intermediaries face a constraint on equity capital but securities also have properties (i)-(iv).

As predicted in Brunnermeier and Pedersen (2009), the relationship between illiquidity and funding conditions is far from linear: “a marginal change in capital has a small effect when speculators are far from their constraints, but a large effect when speculators are close to their constraints”.

(iii) *Asymmetry.* Illiquidity co-moves more strongly with funding conditions when these conditions were initially worse.

Finally, these cross-sectional differences mean that certain securities are riskier for investors. Funding conditions also drive variations in stock returns and raise the risk premium in proportion to the covariance of returns with funding conditions.

(iv) *Funding Liquidity risk premium.* Securities with higher covariance with funding conditions have a higher risk premium:

$$\mathrm{E}[R_i] = -\frac{\mathrm{cov}(R_i, \phi)}{\mathrm{E}[\phi]},$$

where R_i is the net return. The liquidity risk is intuitive. A security carries a risk premium if the covariance is negative, that is, if the security has a low payoff when funding conditions are poor (i.e., ϕ is high).

B Equity Portfolios sorted on illiquidity and volatility

To implement tests of the predictions (i)-(iv) listed above we need to measure illiquidity and volatility in a cross-section of assets. For this purpose, we construct portfolios of equities sorted on the level of illiquidity and volatility, respectively. Appendix A.2 details the construction of these portfolios.

We measure the illiquidity of a stock using the Amihud (2002) price-impact ratio. For a given stock i and day d, the Amihud illiquidity ratio $Illiq_{id}$ is given by:

$$Illiq_{id} = \frac{|R_{id}|}{dvol_{id}} \times 10^6, \tag{1}$$

where R_{id} is the daily stock return and $DVOL_{id}$ is the dollar value of the trading volume. The Amihud ratio is widely used to measure illiquidity. It captures the price impact of a given transaction conditioning on the volume traded.[4] We measure the volatility of a stock using the standard deviation of daily returns over each month.

At the end of each year, we form 10 equal-weighted portfolios of stocks ranked by illiquidity and 10 portfolios of stocks ranked by volatility, using stocks observed in December. To be included in a portfolio, a stock must have at least 120 days of observations in the following year.

We track these portfolios' returns, volatility and illiquidity throughout the following year. Our monthly volatility measure for a portfolio is the average volatility of its component stocks. Our monthly illiquidity measure for a portfolio is given by the median illiquidity of its components scaled by the growth in total market trading volume, to control for the increase in market size and volume.

C Funding Conditions

To capture the funding conditions that intermediaries face, Vayanos (2004) suggests using the prices of two assets with similar cash flows, citing the well-known case of the just-issued (on-the-run) and the previously issued (off-the-run) 30-year Treasury bonds.[5] These bonds carry the same credit risk and promise essentially identical cash flows, but one of the bonds is more liquid and more expensive.[6] The idea behind this proxy for funding conditions is that arbitraging between two nearby bonds increases leverage because this requires repo transactions that cannot be netted against each other, as in Brunnermeier and Pedersen (2009). Repos are also the marginal source of funds for brokers-dealers (Adrian and Shin, 2010), implying that the re-

[4]Goyenko, Holden, and Trzcinka (2009) compare liquidity measures and conclude that the Amihud (2002) illiquidity ratio is an accurate proxy for price impact.

[5]Similarly, Longstaff (2004) uses Treasury and RefCorp bonds. Recently, Du et al. (2019) use a similar idea based on deviations from the covered interest rate no-arbitrage relationship in the currency markets.

[6](Cornell and Shapiro, 1989). Duffie (1996) and Vayanos and Weill (2006) show that Treasury securities that can be funded more easily and more cheaply via the repo market also have higher price. Empirically, this link has been confirmed by Jordan and Jordan (1997); Krishnamurthy (2002); Buraschi and Menini (2002); and Bartolini, Hilton, Sundaresan, and Tonetti (2011). See also the review in Fontaine and Garcia (2015).

sponse of broker-dealers' leverage to funding conditions also influences the arbitrage activities and the wedge between bonds.

Fontaine and Garcia (2012) extend this idea and extract a measure of funding liquidity risk (FL) in a balanced panel of U.S. Treasury security pairs. By construction, the two bonds within each pair have nearly identical maturities, and similar cash flows, but potentially have very different ages.[7] The estimation strategy for FL relies on arbitrage opportunities within each pair to identify funding conditions. Hence, the extent of outstanding arbitrage opportunities observed in the data—which is what the FL measure captures—can proxy for the funding conditions that the dealers face. This measure is similar in spirit to the noise measure of Hu, Pan, and Wang (2013) who use the dispersion of bond yields from a smooth yield curve. Fontaine and Garcia (2012) capture the dispersion within a dynamic no-arbitrage model.

Figure 1 shows the times-series of the FL funding conditions measure in our sample. Essentially every peak can be visually identified with significant financial marlet events. Fontaine and Garcia (2012) also demonstrate that FL can be interpreted as a measure of funding conditions, by relating FL to future bond returns (worse funding conditions predicts lower future returns for U.S. Treasury bonds but higher future returns for LIBOR rates, swap rates and corporate yields), by showing that FL is a determinant of growth in the shadow banking sector, and by linking FL to broader measures of funding conditions, such as non-borrowed reserves of commercial banks at the Federal Reserve and the rate of growth of M2 (which include growth in the repo market). The funding factor FL is available from January 1986 until December

[7] This strategy is consistent with the evidence that older bonds are less liquid, including the on-the-run effect. The market for old notes appears segmented from the markets for bills (Garbade, 1984; Kamara, 1994; Duffee, 1996) and, similarly, the market for old bonds appears segmented from the market for more recently issued bonds.

2015, therefore including the financial crisis.[8] In most of the tests, we will use the change in funding conditions $\Delta FL_t = FL_t - FL_{t-1}$.

II Funding Risk in the Equity Markets

In this section we will test the theoretical predictions (i)-(iv) listed in the introduction. Testing these joint predictions provides substantial support for theories emphasizing the role of intermediaries and funding constraints in financial markets.

A Summary Statistics

Table 1 reports summary statistics for the illiquidity-sorted portfolios (Panel a) and the volatility-sorted portfolios (Panel b). Portfolios that are more illiquid also have higher volatility, consistent with the theoretical links between illiquidity and volatility. Unsurprisingly, sorting on illiquidity also creates a spread in average returns (Amihud, 2002). The returns spread between the most illiquid and the least illiquid portfolios is close to 6 percent annually. As is well-known, market risk cannot explain the returns spread: the average pre-formation β with respect to market returns is lower across the illiquid portfolios. Portfolios that are less liquid also have smaller market capitalization.

The summary statistics in Panel (b) show that the more volatile portfolios are less liquid, again consistent with the theoretical link between illiquidity and volatility. Sorting by volatility also creates a returns spread. The difference between the least volatile and most volatile portfolios is around 3 percent annually. The average pre-formation market beta increases with the volatility of the average stocks. Market

[8]The funding factor FL is updated regularly and is available at www.jean-sebastienfontaine.com. The sample starts in 1986, since before this date interest income had a favorable tax treatment relative to capital gains and investors favored high-coupon bonds and distorts the FL measures. The resulting tax premium was entangled with the liquidity premium, since recently issued bonds were more liquid but also had relatively high coupons offered a tax premium (interest rates were trending up). Green and Ødegaard (1997) confirm that the tax premium mostly disappeared when the asymmetric treatment of interest income and capital gains was eliminated following the 1986 tax reform.

risk can explain some of the returns spread between volatility portfolios. The more volatile portfolios also have smaller market capitalization.

Ang, Hodrick, Xing, and Zhang (2006) document that portfolios with higher volatility (total or idiosyncratic volatility) have lower average returns, which is the opposite of what we find. This difference could be due to the following reasons: (i) we use *equal-weighted* returns to form portfolios, (ii) we form portfolios *annually*, (iii) we use a *longer* sample period (1986–2015 instead of 1986–2000).[9]

B Illiquidity when Funding Conditions are Good or Bad

Table 2 compares periods when funding conditions are good or bad and offers tests for the *commonality* and *flight to quality* predictions. We first report the averages of portfolio illiquidity and volatility in subsamples when the lag value of funding conditions FL_{t-1} lies in its lowest and highest terciles, in Panels (a) and (b) respectively. The results show that the post-formation illiquidity increases monotonously from the least illiquid portfolio to the most illiquid portfolio. Similarly, the portfolios sorted on volatility exhibit the expected post-formation pattern of volatility. Hence, the portfolios preserve the desired patterns of illiquidity and volatility both when funding conditions are good or bad.

The differences between the subsamples are reported in Panel (c). Consistent with the *commonality* prediction, all but one of the differences have a positive sign: the illiquidity and the volatility of every portfolio are worse when funding conditions were poor in the previous month. All of these differences but one are also statistically significant. These differences are economically large when compared with the summary statistics for these portfolios in Table 1. It is reassuring that the only portfolio for

[9]Huang, Liu, Rhee, and Zhang (2010) argue that monthly returns reversals generate a negative relationship when forming portfolios monthly. They also argue that returns reversals explain the difference between the strong positive relationship found in value-weighted returns and the weak relationship found in equal-weighted returns. Fu (2009) finds a positive relation between expected returns and the conditional idiosyncratic volatilities estimated with an exponential GARCH. However, Guo, Haimanot, and Ferguson (2014) find that the relationship is negligible when the exponential GARCH estimates are corrected for a look-ahead bias.

which the average stock illiquidity improves following a funding shock is the portfolio of the least volatile stocks.

The results also supports the *flight to quality* prediction. There is a monotonous increasing pattern across portfolios. The more illiquid and more volatile portfolios show a larger increase in illiquidity when funding conditions are poor. Volatility and illiquidity also interact as expected: the volatile stocks become more illiquid in bad times. Hence, the evidence so far supports two of the cross-sectional predictions in Brunnermeier and Pedersen (2009).

C Illiquidity when Funding Conditions Change

The previous section documents how the average illiquidity and volatility levels are different when the level of funding conditions is good or bad. We offer similar tests using the following regressions of monthly changes:

$$\Delta Illiq_{i,t} = \gamma_{0,i} + \gamma_{1,i}\Delta FL_t + \gamma_{2,i}\Delta FL_t \times \mathbb{1}_{FL_{t-1}} + \xi_{i,t} \tag{2}$$

where $\mathbb{1}_{FL_{t-1}}$ is equal to 1 when the lag level FL_{t-1} lies in the top one-third of the sample, indicating difficult funding conditions. In other words, the response of illiquidity $\Delta Illiq_{i,t}$ to funding shocks ΔFL_t varies across portfolios and over time and it is given by:

$$\left(\gamma_{1,i} + \gamma_{2,i} \times \mathbb{1}_{FL_{t-1}}\right).$$

We can use the estimates to obtain tests of the *commonality*, *flight-to-quality* and *asymmetry* predictions. First, the *commonality* prediction implies that the sum of the coefficients $\gamma_{1,i} + \gamma_{2,i}$ should be positive across all portfolios. Second, the *fligh-to-quality* predictions implies that the sum of the coefficients should increase with the illiquidity and the volatility of the portfolios. Finally, the *asymmetry* prediction implies that the coefficient $\gamma_{2,i}$ is positive and economically significant, since it measures the additional sensitivity when funding conditions are poor.

The results reported in Table 3 are consistent with and support the theoretical predictions. The sum of the coefficients $\gamma_{1,i} + \gamma_{2,i}$ is always positive, consistent with a strong commonality in the response of illiquidity to changes in intermediaries' funding conditions.

The coefficients also show a declining monotonous pattern as we move toward the more liquid and least volatile portfolios. The last column reports the difference between the estimates for portfolios 1 and 10, showing that the difference between the $\gamma_{2,i}$ coefficients is large and significant but the difference across the $\gamma_{1,i}$ coefficients is smaller and not statistically significant so that the difference across the sums $\gamma_{1,i} + \gamma_{2,i}$ is positive and statistically significant. Therefore, the level *and* the dispersion of illiquidity increase following a funding shock, especially in poor funding conditions.

Finally, the coefficients $\gamma_{2,i}$ are positive and statistically significant across every illiquidity-sorted portfolios and positive in all volatility portfolios except for the least volatile. The coefficient for this last portfolio echoes a similar result in Table 2 where the least volatile portfolio exhibited a small improvement in liquidity under poor funding conditions. The coefficients $\gamma_{2,i}$ are also statistically significant across volatility-sorted portfolios from 1 to 6. In contrast, coefficient estimates of $\gamma_{1,i}$ are all insignificant, suggesting that the response of illiquidity to funding conditions is inherently asymmetric. The contrasted patterns observed in the level and dispersion of the γ_2 and γ_1 coefficients, as well as the statistical significance results, provide a strong support for the asymmetry prediction.

D Portfolio Returns when Funding Conditions Change

Are the returns of the illiquidity and volatility portfolios also affected by changes in funding conditions? To answer this question, we analyze the βs of portfolio returns with respect to funding conditions. We estimate the following regression:

$$r_{i,t} = \alpha_i + \beta_i^{\Delta FL} \Delta FL_t + \epsilon_{i,t} \tag{3}$$

where $r_{i,t}$ is the monthly portfolio returns in excess of the risk-free rate.[10] Like in our previous tests for the response of illiquidity, we estimate this regression in subsamples with good and bad liquidity conditions. In this case, we use the market-wide Amihud illiquidity measure and we identify the first and last terciles of the sample. The results are similar if we use funding conditions to split the sample (which is not surprising given the close link between funding conditions and market liquidity).

Panels (a) and (b) of Table 4 report results for the illiquidity- and volatility-sorted portfolios, respectively. As expected, the funding betas $\beta^{\Delta FL}$ are negative and significant for all illiquidity-sorted and volatility-sorted portfolio in both subsamples. This is consistent with the prediction of commonality in the response of returns to funding conditions. We also find that the magnitude of the portfolios' funding betas $\beta^{\Delta FL}$ is larger when liquidity is low, consistent with the asymmetry prediction. The cross-sectional monotonicity in the dispersion of the betas is weaker than in the case of illiquidity observed in Table 3. Next, we will examine the role of funding conditions using well-known asset pricing models.

E Asset Pricing Tests

The evidence so far is consistent with some of the core predictions in intermediary asset pricing models. From an economic point of view, it suggests that funding conditions are associated with non-diversifiable risks for investors in this cross-section of stocks. In this section, we check that these risks are associated with a *funding liquidity risk premium*, consistent with Prediction (iv). In our baseline results, we focus on the same portfolios for which we documented exposures of volatility and illiquidity to funding conditions. As recently put forward by Giglio, Xiu, and Zhang (2021), the choice of the set of assets used in a test matters to judge the strength or weakness of a risk factor.

[10] We use the risk-free rate from the Kenneth French data site to compute monthly excess returns. Appendix A.1 provides additional details.

We follow the usual two-step procedure. The first stage is a contemporaneous time-series regression of excess returns on risk factors in the entire sample. The second stage is a cross-sectional regression of each month's returns on the betas estimated in the first stage. The estimate of the prices of risk is given by the time-series average of the monthly estimates from the second stage. We report annualized prices of risk throughout. Inference is based on the usual two-step Fama-MacBeth standard errors as well as on Shanken standard errors, which correct for the errors-in-variables problem in first-stage estimates.

To discipline the results and mitigate concerns that our results follow from a factor structure inherent in the test assets, we follow several of the recommendations in Lewellen, Nagel, and Shanken (2010). First, when applicable, we include any of risk factors that are also traded assets as additional test assets so that they are perfectly priced, which is a way to discipline the estimates. Second, we provide bootstrap confidence intervals for all R^2 statistics. The bootstrap procedure is described in Lewellen et al. (2010). The procedure provides a range of plausible values that can be supported based on the data.

The prediction is that exposures to intermediaries' funding conditions can reveal a risk premium, not that these exposures fully explain stock prices. To measure the contribution of funding conditions in fitting average returns, we report the R^2 and the adjusted $\bar{R}^2$. These R^2s measure the goodness of fit across all test assets, but they are not directly comparable across specifications if the number of test assets changes when the traded risk factors are included as additional test assets. Hence, we also report the corrected analogue $\bar{R}^2_c$, constructed to measure the fit for the test assets of interest exclusively.

In Table 5, we report price-of-risk estimates for the following asset pricing models: the market portfolio (CAPM), three Fama-French factors (FF3), the funding risk ΔFL, as well as the CAPM and FF3 augmented by ΔFL. We also report results where we replace ΔFL with a mimicking portfolio equivalent ΔFL^m (see Appendix A.2 for the construction of this mimicking portfolio). The price of risk associated with changes to intermediaries' funding conditions is negative and estimated around -4 percent (annualized) across all specifications. The betas of the sole factor ΔFL or ΔFL^m explain about 40 percent of the cross-section of returns (which is quite a lot more than the CAPM or FF3) but the price-of-risk estimates are not statistically significant. The results are similar when using ΔFL^m but the price-of-risk estimates are smaller, which is likely due to an attenuation bias introduced by measurement errors in the construction of the mimicking portfolio.[11]

The lack of statistical significance in the simplest single-factor model arises because we are omitting the market returns. When we combine the funding betas and the market betas—augmenting the CAPM with ΔFL—we find that the constant is small and not statistically different from zero, and that the price of risk associated with changes to intermediaries' funding conditions is -3.96 and statistically significant. Including market returns captures a substantial share of the systematic risk and increases the precision of the estimates.

Overall, there is strong evidence that exposures to changes in intermediaries' funding conditions generate an economically and statistically significant risk premium in equity markets. This is consistent with existing evidence based on standard portfolio sorts (e.g., Hu, Pan, and Wang 2013). Here, we show that stocks with a higher risk premium are also the stocks that carry a higher illiquidity and volatility risk.

III A Closer Look at the Risk Premium

In this section, we explore the dispersion in returns due exposures to intermediaries' funding conditions across different portfolios sorts. For one, it is natural to ask whether part of the long-standing and well-documented risk premiums, such as

[11]The lower price of risk for ΔFL^m is also consistent with funding shocks being measured with errors: non-traded factors contain noise that is uncorrelated with returns, inflating beta estimate. See also the discussion in Adrian et al. 2014.

the size or value premiums, also embed some dispersion in the betas with respect to funding conditions. Another line of investigation is to test the robustness of the price-of-risk estimates obtained in the last section. Finally, we introduce competing or complementary measures of market or funding liquidity to see their relative pricing powers. To sum up the results, we find evidence that funding conditions carry a robust negative price of risk in most portfolios.

A Standard Portfolio Sorts

We first consider traditional sets of ten portfolios sorted either on the size, book-to-market, or market beta of a stock. In these portfolios, firms with smaller market capitalizations, higher book-to-market valuations or lower market betas have relatively higher average returns than predicted by the CAPM. We ask whether the exposures to intermediaries' funding conditions generate robust price-of-risk estimates based on these portfolios as well.

Panel (a) of Table 6 reports asset pricing results using these portfolios. As expected, the CAPM does not price these anomalies very well ($\bar{R}_c^2$ is around 18%) but the corresponding $\bar{R}_c^2$ improves substantially (to 42 percent) when funding conditions are added to the market. Results are similar when we replace ΔFL by the mimicking portfolio ΔFL^m except for the magnitude of the price of risk, which is roughly halved as in Table 5. Notice that the constant is substantially reduced and becomes insignificant when the CAPM is augmented with ΔFL. Hence, this result provides additional support for the point made by Frazzini and Pedersen (2014) that adjusting for the effect of funding conditions restores the slope of the capital market line. Of course, the dispersion of excess returns across the size-, value-, and betting-against-beta-sorted portfolios is not completely, not even mostly for some of the portfolios, due to exposures to intermediaries' funding conditions.

B Sorting by Risk Exposures

In our baseline results of Table 5, we used portfolios sorted on the level of illiquidity or volatility of a stock. An alternative strategy is to sort portfolios based on the returns beta of a stock with respect to aggregate market illiquidity and volatility. Specifically, we use the following illiquidity and volatility βs to form the portfolios (see details of the portfolio construction in Section A.1.2 of the Appendix):

$$\hat{\beta}_i^{\Delta Illiq} = \hat{\rho}_{\Delta Illiq,i} \frac{\hat{\sigma}_i}{\hat{\sigma}_{\Delta Illiq}} \qquad \hat{\beta}_i^{\Delta \sigma} = \hat{\rho}_{\Delta \sigma,i} \frac{\hat{\sigma}_i}{\hat{\sigma}_{\Delta \sigma}} \tag{4}$$

Portfolios sorted on the returns' exposures to market illiquidity and volatility have been studied in, e.g., Acharya and Pedersen (2005) and Ang et al. (2006). The existing evidence shows that investors care about the covariance of a stock's returns with market-wide illiquidity or volatility, and both these sources of risk carry a significant (negative) price of risk. Since, the evidence in Section II shows that variations in intermediaries' funding conditions are associated with commonality in volatility, illiquidity and returns, it is natural to ask if sorting stocks on betas given in Equation 4 also generates exposures to funding conditions and a negative price of risk.[12]

To estimate $\beta_i^{\Delta Illiq}$ and $\beta_i^{\Delta \sigma}$, we follow Frazzini and Pedersen (2014). First, we use five years of data to estimate the correlations $\rho_{\Delta Illiq,i}$ and $\rho_{\Delta \sigma,i}$. Second, we use one year of data to estimate the variances. In both cases, we use 3-day overlapping excess returns to mitigate the effect of asynchronous trading.[13] We form portfolios at the end of each year and we compute monthly holding period returns over the following year.

Panel (b) of Table 6 reports results from asset pricing tests for 10 portfolios sorted on the sensitivity of stock returns to either changes in market-wide illiquidity or

[12]Kondor and Vayanos (2019) also argue for using this covariance as a better proxy for exposures to funding risk than sorting on the level of illiquidity.

[13]We find similar results when using OLS in rolling three-year samples to estimate $\beta_i^{\Delta illi}$ and $\beta_{id}^{\Delta \sigma}$.

market-wide volatility. The CAPM offers a very poor performance with a negative $\bar{R}_c^2$ and a high significant alpha. In contrast, around 40 percent of the variations of returns across these portfolios can be explained by exposures to funding conditions (whether measured by ΔFL or ΔFL^m) and, in addition, the estimated intercepts are reduced considerably and are insignificant. The price-of-risk estimates in the single-factor models are negative and significant in all cases. The point estimate is -3.45 for ΔFL and -1.5 for ΔFL^m, similar to the baseline results in Table 7.

Augmenting the CAPM with funding conditions increases slightly the magnitude of both prices of risk for ΔFL and ΔFL^m, but their t-stats are now 80 percent higher in absolute value. As in Table 5, including market returns improve the precision of the estimates. Relative to the simpler CAPM, the explanatory power measured by $\bar{R}_c^2$ is heightened to 50 percent while the market price of risk is more reasonable in magnitude. Our overall conclusion is that funding conditions are an important determinant of the risk premium of illiquidity and volatility beta-sorted portfolios, since it carries a robust price of risk, and it captures some significant dispersion of the excess returns. In the next section we assess the robustness of ΔFL as a pricing factor when alternative measures of market liquidity or funding liquidity are introduced.

C Alternative Illiquidity and Funding Risk Factors

Several measures have been proposed in the literature to proxy for market liquidity or funding conditions. Specifically, we consider the betting-against-beta BAB factor, the change in the market-wide illiquidity Amihud measure ΔAm, the Pastor-Stambaugh PS factor, and the change in the TED spread ΔTED.[14] The most correlated variables with ΔFL are ΔTED and the BAB factor with correlation coefficients of 0.35 and -0.18, respectively. This is not surprising since BAB and ΔTED are also often interpreted as proxies for funding conditions.

[14]We also considered the liquidity factors of Sadka (2006) as well as the measure of hedge funds illiquidity in Kruttli, Patton, and Ramadorai (2015). We find that the explanatory power of the funding risk is not subsumed in these cases either. These factors are available in shorter samples and we do not report the results for parsimony.

The asset pricing results are reported in Table 7. Results for asset pricing models using each proxy on its own are reported in the first four columns. The price of risk has the correct sign in every case and is statistically significant for BAB, PS and ΔTED. The fit is better for ΔTED with a $\bar{R}_c^2$ of 38%. However, the constant is quite large and significant for BAB and PS, and the corresponding $\bar{R}_c^2$ are negative or close to zero. The reason for this contrast between a poor fit but a significant price-of-risk estimate is that, in both cases, the risk factor is included among the test assets. The results show that this traded risk factor can price itself very accurately (its price of risk is statistically significant), but that it does not price the other test assets (the R_c^2s are low).

The last four columns of Table 7 feature asset pricing models that augment each alternative factor with ΔFL. The key observation is that the estimates for the price of risk associated with ΔFL remains negative, in a range between -3 and -4, similarly to results in Table 5. Note that, in all cases, the estimated intercept becomes very small and statistically insignificant. The overall fit obtained for the $\bar{R}_c^2$ is now around 40%, the value obtained for ΔFL as a sole risk factor in Panel (b) of Table 6. The coefficients of the alternative factors keep the same sign and magnitude. In terms of statistical significance, the t-stats of ΔBAB and PS remain very close to their former values with the sole alternative factor, but ΔTED becomes insignificant. We can again conclude that the price of funding risk is not subsumed by other liquidity factors.

D Intermediary Balance Sheets

Theory predicts that funding conditions work their way to asset returns via the balance sheet of intermediaries. Therefore, we also consider asset pricing tests that include shocks to the leverage of security broker-dealers (Lev) from Adrian, Etula, and Muir (2014) or the equity capital ratio of primary dealers (Cap) from He, Kelly, and Manela (2017). Both should proxy for shocks to the marginal value of financial intermediaries' wealth and we expect a significant interaction with funding conditions in asset pricing tests.

Because these two balance sheet proxies are available quarterly, we repeat the previous asset pricing tests with quarterly returns. Panel (a) of Table 8 presents the results when each risk factor is used on its own. We include the balance sheet proxies as well as the alternative liquidity factors from the previous section one at a time. The price of risk for ΔFL is now estimated at around -1.5 annually and is significant. There is no reason to expect prices of risk to be identical across investment horizons. The prices of risk for leverage or capital ratio shocks carry opposite signs. This is consistent with the fact that the theoretical capital ratio is the reciprocal of leverage, but the construction of the two factors is different so that the reciprocal relationship is not exact.[15] The better fits in terms of $\bar{R}_c^2$ are obtained for ΔFL (82.5%), Lev (71%) and ΔTED (69%). Overall, the quarterly results confirm what we found at the monthly frequency.

In Panel (b) of Table 8, we report results when ΔFL is added to each risk factor. The price of funding risk appears with the right sign in every case. None of the alternative risk factors subsumes funding conditions or adds to its explanatory power, and only the BAB factor remains significant. However, the statistical significance of ΔFL is reduced when funding shocks are combined with either Lev or Cap. As expected, the evidence shows that there exists some degree of interaction between funding conditions and the balance sheet of intermediaries.

Hence, sorting on illiquidity or volatility brings further evidence to the debate on the relative importance of equity constraints and debt constraints for intermediaries. For equity-constrained intermediaries (Kondor and Vayanos, 2019; He and Krishnamurthy, 2013), a decrease of the capital ratio reflects bad states of the world due

[15] See He et al. (2017) for a discussion about the differences in the construction of these proxies. Results are robust when controlling for market, size and value, but we do not report results for parsimony.

to a reduction of risk-bearing capacity. For debt-constrained intermediaries (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009), an increase in leverage reflects good states of the world where additional loans are readily available to them. Our estimates indicate that an unexpected decline of the capital ratio (or an unexpected increase of leverage) is considered bad news from the point of view of investors, suggesting a greater role for a constraint on equity financing for intermediaries.

IV Conclusion

In this paper, we focus on measuring the influence of intermediaries' funding condition in the cross-section of stocks. Consistent with existing theoretical predictions, we find that when funding conditions worsen for financial intermediaries, the level and dispersion of illiquidity increase significantly across stocks. Also consistent with theories based on constrained intermediaries, these relationships are stronger when funding conditions were initially worse. These results confirm that funding conditions capture important risks that equity investors bear. Using several different sorting strategies, we find in every case some dispersion in the returns betas with respect to intermediaries' funding conditions and that these exposures carry uniformly a robust price of risk.

Several important questions remain for future research. First, our results are unconditional in nature. Turning to dynamic implications, it remains to be seen whether the intermediaries' funding conditions represent a significant state variable for investors. Similarly, we have not considered how investors should adjust benchmark asset allocation models to reflect funding risk. Finally, several ongoing technological and regulatory changes suggest that the role of intermediaries' funding conditions may be affected in the future.

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A Appendix

This section provides more information about the data sources and portfolio construction. The analysis use data over the sample period from January 1986 to December 2015.

A.1 Portfolio Sorts

We start by downloading daily returns and trading volume of individual securities from the CRSP equity data set. We consider ordinary common stocks (share codes 10 and 11) traded on the NYSE or AMEX with prices between \$5 and \$1,000. Nasdaq stocks are excluded to avoid distorting the illiquidity measure (Amihud, 2002). Then, for every month we only keep stocks with at least 10 observations. Excluding stocks with a small price or too many missing observations reduces the noise when computing stock-level illiquidity or volatility proxies. These exclusions make our results conservative, since we expect a greater impact of funding shocks on relatively less liquid securities. We construct portfolios a the monthly and quarterly frequency. For monthly portfolios, we sort individual stocks based on information in the last month of every year. For quarterly portfolios, we sort individual stocks based on information in the last quarter of every year.

A.1.1 Portfolios sorted by illiquidity and volatility

We construct two sets of decile portfolios sorted on the level of illiquidity and volatility, respectively. For a given stock i and day d, we measure its illiquidity by the Amihud ratio $illiq_{id}$. At the end of each year, we form 10 equal-weighted portfolios of stocks sorted on the average of their Amihud ratio in the last month (quarter) of the year. In the case of volatility, we sort stocks on their volatility, which is computed as the standard deviation of returns over the last month (quarter) of the year. We then track the returns, volatility and illiquidity of these portfolios for one year and we form new portfolios using the same procedure at the end of the next year. The volatility of a portfolio p is the average of its component stocks. The illiquidity of a portfolio is the median illiquidity of its components,

$$illiq_{pt} = \text{median}\left[\frac{1}{d_t}\sum_{n=1}^{d_t} ILLIQ_{in}\right]\left(\frac{dvol_{t-1}}{dvol_1}\right), \tag{A.1}$$

where d_t is the number of trading days in a month (quarter) we use $\frac{dvol_{t-1}}{dvol_1}$ to control for the growth trend in market capitalization and trading activity.

A.1.2 β-sorted portfolios

We compute a market beta for every day d and for each stock i as in Frazzini and Pedersen (2014). The market beta is given by:

$$\tilde{\beta}_{id}^{mkt} = \hat{\rho}_{mi}\frac{\hat{\sigma}_i}{\hat{\sigma}_m},$$

where $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the volatility of stock i and market portfolio m returns, respectively, and where $\hat{\rho}_{mi}$ is the correlation between the stock and market returns. To estimate the volatilities, we use the standard deviation of daily log returns over a rolling window of 250 trading days. To estimate the correlation $\hat{\rho}_{mi}$, we use overlapping 3-day log excess returns and a rolling window of 1,250 trading days. To reduce noise, we require at least 120 trading days with non-missing data to estimate the volatilities and at least 750 trading days of non-missing data to estimate the correlations. Finally, to reduce the effect of outliers, we shrink the estimate of the beta towards the cross-sectional mean: $\hat{\beta}_{id}^{mkt} = \tilde{\beta}_{id}^{mkt} \times 0.6 + 0.4 \times 1$.

Using the same approach, the market illiquidity beta is

$$\hat{\beta}_{id}^{\Delta illiq} = \hat{\rho}_{\Delta Illiq,i}\frac{\hat{\sigma}_i}{\hat{\sigma}_{\Delta Illiq}}.$$

The volatility for stock i is the same as in Section (i) above and the volatility $\hat{\sigma}_{\Delta Illiq}$ is the standard deviation of the market illiquidity changes computed over a 250-day rolling window. The market illiquidity on day d is the mean illiquidity for all stocks:

$$ILLIQ_{m,d} = \frac{1}{N}\sum_{i=1}^{N}\frac{|r_{id}|}{dvol_{id}} * 10^6,$$

where r_{id} represents the daily stock returns and $dvol_{id}$ is the trading volume in dollars. This ratio measures the price impact of a \$1M transaction. The Amihud ratio is widely used to measure illiquidity. Goyenko, Holden, and Trzcinka (2009) conclude that this is an accurate proxy for the price impact. $\Delta ILLIQ$ is simply the daily change: $\Delta ILLIQ_{m,d} = ILLIQ_{m,d} - ILLIQ_{m,d-1}$. The correlation $\hat{\rho}_{\Delta Illiq,i}$ is computed using overlapping 3-day log excess returns over a rolling window with 1,250 trading days. Similarly, the market volatility beta

$$\hat{\beta}_{id}^{\Delta\sigma} = \hat{\rho}_{\Delta\sigma,i} \frac{\hat{\sigma}_i}{\hat{\sigma}_{\Delta\sigma}}.$$

where the volatility for stock i is the same as in Section (i) above and the volatility $\hat{\sigma}_{\Delta\sigma}$ is the standard deviation of market volatility changes $\Delta\hat{\sigma}_{m,d} = \hat{\sigma}_{m,d} - \hat{\sigma}_{m,d-1}$ over a rolling window with 250 trading days. The correlation $\hat{\rho}_{\Delta\sigma,i}$ between the stock log excess return and the market-volatility changes is computed using overlapping 3-day log excess returns and over a rolling window with 1,250 trading days. As before, we require at least 120 trading days of non-missing data to estimate volatilities and at least 750 trading days of non-missing data for the correlations.

We sort stocks at the end of each year and we form 10 equally-weighted decile portfolios based on the beta estimates. The portfolio allocations are kept unchanged for the following year. However, to be included in a portfolio, a stock must have at least 120 daily returns observations in the following year. The portfolio returns, volatility, and other variables are computed as averages across stocks in each portfolio. However, a portfolio's illiquidity is the median of the stocks' illiquidities scaled by the growth of the market trading volume.

A.2 Asset-pricing factors

A.2.1 Mimicking portfolio

ΔFL^m is a projection of the funding factor ΔFL on the space of excess returns to construct a mimicking portfolio. As spanning assets, we use the returns on Traesury bonds used in Fontaine and Garcia (2012) for estimation of the funding risk factor, as well as returns on portfolios of equities sorted by illiquidity, volatility, liquidity beta, volatility beta, size, value and momentum. We obtain portfolio loadings from the following returns regression:

$$\Delta FL = a + B^{\top} XR_t + \epsilon_t,$$

where XR_t stacks the spanning asset excess returns. The mimicking portfolio returns $\Delta \mathrm{FL}^m$ are then given by:

$$\Delta FL^m \equiv \hat{B}^{\top} XR_t.$$

A.2.2 Alternative liquidity factors

We compare our results with several alternative liquidity or funding conditions proxies that have been proposed as risk factors in the literature. We consider two measures of market illiquidity: the Amihud (Am) market-wide price-impact measure (Amihud, 2002) and the Pastor-Stambaugh (PS) market-wide price-reversal measure (Pastor and Stambaugh, 2003). The market-wide Amihud is given by Equation (1) but including all stocks in the computation. We use the tradable Pastor-Stambaugh factor available from Lubos Pastor's website. We also consider other proxies of funding conditions: the TED spread, given by the difference between the three-month T-bill and the LIBOR rate from FRED and the betting-against-beta BAB factor proposed by Frazzini and Pedersen (2014). The BAB portfolio returns are available from AQR Capital's website. Finally, we also consider the leverage factor Lev from Adrian et al. (2014), which proxies for shocks to the leverage of broker-dealers in the US, and the capital ratio factor Cap from He et al. (2017), which proxies for shocks to the capital ratio of primary dealers in the US. The leverage factor Lev is available from Tyler Muir's website. The capital ratio factor Cap is available from Bryan Kelly's website. The market MKT, size SMB, and book-to-market HML factors are from Ken French's data library.

Table 1: **Summary Statistics – Illiquidity and Volatility Portfolios**

Summary statistics for decile portfolios of equities sorted on the level of illiquidity (Panel a) or volatility (Panel b). Illiquidity, volatility, market capitalization and returns are the time-series averages of monthly values of a portfolio, $\times 100$ in the case of illiquidity; in billions of dollars for market cap, in annualized percentages for returns and volatility. The ex-ante CAPM β for each portfolio is the time-series average of monthly values. Monthly data, Jan 1986–Dec 2015.

Panel (a) Illiquidity-sorted portfolios

	Most	2	3	4	5	6	7	8	9	Least
Illiqu.	418.29	71.82	25.52	11.76	5.86	2.87	1.52	0.77	0.36	0.12
Vol.	28.25	29.40	28.66	27.98	26.73	25.87	24.93	24.19	22.89	21.41
Cap.	0.12	0.27	0.46	0.72	1.04	1.52	2.26	3.76	7.72	34.18
E(R)	17.25	16.72	14.90	14.46	12.92	13.36	12.21	12.82	12.16	11.34
β	0.83	0.93	0.96	0.99	0.99	1.00	1.02	1.03	1.02	1.02

Panel (b) Volatility-sorted portfolios

	Most	2	3	4	5	6	7	8	9	Least
Illiqu.	14.48	9.83	7.94	5.48	3.73	2.74	2.11	1.87	2.02	4.47
Vol.	40.53	34.74	31.57	29.10	26.87	24.83	22.85	20.94	18.62	15.35
Cap.	1.23	1.80	2.44	3.05	3.66	5.06	6.21	7.68	9.24	11.28
E(R)	15.88	16.16	14.55	15.30	15.15	13.83	13.40	14.26	13.46	12.67
β	1.34	1.20	1.13	1.08	1.05	1.01	0.97	0.92	0.85	0.73

Table 2: **Portfolio Illiquidity and Volatility across Funding Conditions**

Time-series average of illiquidity (× 100) and volatility (annualized, in percentage) in sub-samples for decile portfolios of equities sorted on the level of illiquidity or volatility. Panel (a) report the statistics in the sub-sample when previous month's funding conditions are in the bottom tercile of the empirical distribution (low FL_{t-1}). Panel (b) report the statistics in when funding conditions are in the top tercile (high FL_{t-1}). Panel (c) reports differences between each average, with t-statistics for a test of equality between the two sub-samples reported in parentheses. Monthly data, Jan 1986–Dec 2015.

Panel (a) Low FL_{t-1}

	Illiquidity Portfolios		Volatility Portfolios	
	Illiqu.	Vol.	Illiq.	Vol.
1	324.96	26.76	10.17	39.84
2	54.51	28.32	6.79	33.43
3	19.16	27.35	5.51	30.10
4	8.22	26.92	3.86	27.58
5	4.03	25.41	2.68	25.11
6	1.98	24.05	2.29	22.96
7	1.12	23.43	1.39	21.11
8	0.58	22.72	1.34	19.50
9	0.28	21.60	1.58	17.56
10	0.10	19.94	8.26	14.67

Panel (b) High FL_{t-1}

	Illiquidity Portfolios		Volatility Portfolios	
	Illiqu.	Vol.	Illiqu.	Vol.
1	446.30	30.45	17.56	42.57
2	83.22	31.88	11.41	37.16
3	30.35	31.27	9.71	34.17
4	14.41	30.16	6.96	31.95
5	7.05	28.92	4.20	29.54
6	3.53	28.38	3.09	27.52
7	1.82	27.28	2.61	25.67
8	0.90	26.45	2.29	23.20
9	0.42	25.01	2.44	20.38
10	0.13	23.52	3.15	16.46

Panel (c) High FL_{t-1} – LowFL_{t-1}

	Illiquidity Portfolios		Volatility Portfolios	
	Illiqu.	Vol.	Illiqu.	Vol.
Most	121.33	3.70	7.39	2.73
	(2.41)	(4.06)	(4.61)	(1.49)
2	28.71	3.56	4.61	3.73
	(3.61)	(2.36)	(5.65)	(2.21)
3	11.19	3.92	4.20	4.07
	(4.13)	(2.76)	(5.16)	(2.47)
4	6.19	3.25	3.10	4.37
	(4.83)	(2.29)	(6.08)	(2.74)
5	3.02	3.51	1.52	4.42
	(4.89)	(2.43)	(4.70)	(2.94)
6	1.55	4.33	0.80	4.56
	(5.50)	(3.12)	(3.07)	(3.19)
7	0.70	3.84	1.22	4.56
	(4.98)	(2.63)	(5.52)	(3.31)
8	0.32	3.73	0.94	3.70
	(4.63)	(2.55)	(4.13)	(3.09)
9	0.14	3.42	0.85	2.82
	(4.47)	(2.31)	(2.58)	(2.61)
Least	0.04	3.57	-5.11	1.79
	(4.54)	(2.42)	(-3.02)	(2.13)

Table 3: **Illiquidity and Funding Shocks**

Regressions of monthly changes in the illiquidity $\Delta ILLIQ_{i,t}$ of each portfolio on changes in funding conditions:

$$\Delta ILLIQ_{i,t} = \gamma_{0,i} + \gamma_{1,i}\Delta FL_t + \gamma_{2,i}\Delta FL_t \times \mathbb{1}_{\mathrm{FL}_{t-1}} + \xi_{i,t},$$

where $\mathbb{1}_{\mathrm{FL}_{t-1}}$ is the indicator function equal to 1 when FL_{t-1} lies in the highest sample tercile (i.e., poor funding conditions). Coefficient estimates are multiplied by 100. Monthly data, Jan 1986–Dec 2015.

	Most	2	3	4	5	6	7	8	9	Least	$1-10$
	Illiquidity Portfolios										
γ_1	-53.46	-9.05	-2.85	-0.89	-0.49	-0.25	-0.16	-0.07	-0.04	-0.01	-53.45
	(-1.08)	(-1.32)	(-1.22)	(-0.77)	(-0.85)	(-0.92)	(-1.10)	(-0.97)	(-1.06)	(-1.34)	(-1.08)
γ_2	268.39	15.89	8.26	3.31	1.96	1.28	0.73	0.40	0.21	0.06	268.33
	(3.67)	(1.57)	(2.39)	(1.95)	(2.29)	(3.25)	(3.47)	(3.72)	(4.16)	(4.01)	(3.67)
R^2	4.61%	0.72%	1.66%	1.21%	1.71%	3.69%	4.03%	4.90%	6.09%	5.22%	4.61%
	Volatility Portfolios										
γ_1	-2.45	-1.11	-1.15	-0.66	-0.73	-0.44	0.00	-0.16	-0.06	0.26	-2.71
	(-1.46)	(-1.09)	(-1.46)	(-1.27)	(-2.06)	(-1.73)	(0.01)	(-0.81)	(-0.24)	(0.29)	(-1.51)
γ_2	9.57	4.24	3.94	2.28	2.21	1.34	0.45	0.48	0.35	-0.02	9.60
	(3.87)	(2.83)	(3.40)	(2.97)	(4.24)	(3.57)	(1.43)	(1.60)	(0.95)	(-0.02)	(3.61)
R^2	4.68%	2.54%	3.50%	2.68%	5.13%	3.69%	1.06%	0.76%	0.33%	0.04%	3.95%

Table 4: **Funding and Market Liquidity Risk in Liquid and Illiquid Samples**

Regressions of the monthly returns $r_{i,t}$ of a portfolio on changes in funding conditionsΔFL_t:

$$r_{i,t} = \alpha_i + \beta_i^{\Delta\mathrm{FL}} \Delta FL_t + \varepsilon_{i,t}.$$

Panel (a) reports OLS estimates of $\beta_i^{\Delta\mathrm{FL}}$ for the portfolios of equities sorted on the level of illiquidity. Coefficient are estimated separately in subsample when the market liquidity is high (Hi Liq) or low (Lo Liq), as measured by the aggregate Amihud measure in a given month. Panel (b) reports the estimates for portfolios of equities sorted on the level of volatility. The t-statistics reported in parentheses. Monthly data, Jan 1986–Dec 2015.

Panel (a) Illiquidity Portfolios

	Most	2	3	4	5	6	7	8	9	Least
Lo Liq	-5.07	-5.83	-5.39	-4.83	-4.49	-4.80	-4.81	-4.18	-4.27	-3.06
	(-4.19)	(-3.51)	(-3.13)	(-2.78)	(-2.59)	(-2.88)	(-2.93)	(-2.50)	(-2.80)	(-2.19)
Hi Liq	-2.07	-2.47	-2.47	-2.25	-2.53	-2.31	-2.37	-2.26	-2.09	-2.28
	(-2.01)	(-1.92)	(-2.01)	(-1.86)	(-2.24)	(-1.99)	(-2.06)	(-2.05)	(-2.02)	(-2.23)

Panel (b) Volatility Portfolios

	Most	2	3	4	5	6	7	8	9	Least
Lo Liq	-4.40	-5.18	-5.15	-5.72	-5.11	-5.15	-5.06	-4.30	-4.27	-3.31
	(-1.81)	(-2.49)	(-2.70)	(-3.21)	(-3.02)	(-3.24)	(-3.50)	(-3.26)	(-3.63)	(-3.58)
Hi Liq	-2.77	-3.22	-2.72	-2.53	-2.33	-2.37	-2.24	-2.32	-1.69	-1.24
	(-1.62)	(-2.32)	(-2.05)	(-2.05)	(-1.96)	(-2.20)	(-2.09)	(-2.49)	(-1.96)	(-1.62)

Table 5: **Asset Pricing Tests – Illiquidity and Volatility Portfolios**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for ten illiquidity- and ten volatility-sorted portfolios. The estimated prices of risk are annualized (multiplied by 12). Standard errors and Shanken-corrected standard errors are reported in parentheses. The 95% confidence intervals in square brackets for $\bar{R}^2$s are derived from 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. $\bar{R}_c^2$ is the adjusted-R^2 computed across the target test assets and excluding the traded factors that are included as test assets for estimation. Monthly data, January 1986–March 2015.

					Augmented by ΔFL		**Augmented by ΔFL^m**	
	CAPM	FF3	ΔFL	ΔFL^m	CAPM	FF3	CAPM	FF3
int	5.59	4.46	2.35	3.27	1.29	2.14	1.70	2.40
t-FM	(4.55)	(4.52)	(0.73)	(1.14)	(1.25)	(2.64)	(1.67)	(2.97)
t-Sh	(4.53)	(4.48)	(0.55)	(1.00)	(0.87)	(1.77)	(1.40)	(2.48)
ΔFL			-3.38		-3.96	-4.28		
t-FM			(-1.88)		(-4.62)	(-4.60)		
t-Sh			(-1.42)		(-3.28)	(-3.13)		
ΔFL^m				-1.48			-1.75	-1.78
t-FM				(-1.89)			(-4.64)	(-4.57)
t-Sh				(-1.66)			(-3.98)	(-3.90)
MKT	5.23	4.35			7.18	6.80	6.95	6.44
t-FM	(1.70)	(1.49)			(2.35)	(2.38)	(2.28)	(2.25)
t-Sh	(1.70)	(1.49)			(2.20)	(2.36)	(2.21)	(2.24)
SMB		1.80				2.65		2.68
t-FM		(0.85)				(1.26)		(1.27)
t-Sh		(0.84)				(1.19)		(1.24)
HML		2.23				2.04		2.06
t-FM		(1.16)				(1.06)		(1.07)
t-Sh		(1.16)				(1.04)		(1.06)
R^2	44.46%	54.14%	43.35%	39.08%	73.70%	80.03%	70.82%	75.67%
$\bar{R}^2$	41.54%	46.90%	40.21%	35.87%	70.78%	75.59%	67.74%	70.54%
	[0.11, 0.99]	[0.04, 0.84]	[0.06, 0.99]	[0.04, 0.80]	[0.32, 0.95]	[0.30, 0.89]	[0.34, 0.89]	[0.26, 0.89]
$\bar{R}_c^2$	-15.54%	2.42%	40.21%	40.21%	36.34%	51.49%	36.69%	48.75%

Table 6: **Alternative Test Assets**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for decile portfolios of equities sorted by size, value, or β^M. The price-of-risk estimates are annualized ($\times 12$). Standard errors and Shanken-corrected standard errors are reported in parentheses. The 95% confidence intervals in square brackets for $\bar{R}^2$s are derived from 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. $\bar{R}^2_c$ is the adjusted-R^2 computed across the target test assets and excluding the traded factors that are included as test assets for estimation. Monthly data, Jan 1986–Dec 2015.

Panel (a) Size, value and β^M portfolios

				Augmented CAPM	
	CAPM	ΔFL	ΔFL^m	ΔFL	ΔFL^m
int	2.65	1.94	2.76	1.02	1.22
t-FM	(2.19)	(0.62)	(0.92)	(0.81)	(0.99)
t-Sh	(2.17)	(0.46)	(0.81)	(0.63)	(0.89)
ΔFL		-3.44		-3.09	
t-FM		(-2.65)		(-2.42)	
t-Sh		(-1.99)		(-1.90)	
ΔFL^m			(-1.52)		-1.33
t-FM			(-2.63)		(-2.46)
t-Sh			(-2.32)		(-2.22)
MKT	7.74			7.72	7.71
t-FM	(2.67)			(2.66)	(2.67)
t-Sh	(2.67)			(2.62)	(2.64)
R^2	62.34%	46.77%	42.05%	74.81%	73.00%
$\bar{R}^2$	60.36%	43.81%	39.00%	72.01%	70.16%
	[0.36, 1.00]	[0.10, 0.92]	[0.06, 0.79]	[0.41, 0.96]	[0.44, 0.94]
$\bar{R}^2_c$	17.80%	43.81%	43.14%	41.79%	41.07%

Table 6: **Alternative Test Assets *(continued)***

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for decile portfolios sorted on $\beta^{\Delta \mathrm{Illiq}}$ or $\beta^{\Delta\sigma}$. The intercept and prices of risk are annualized (multiplied by 12). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^{2}s are based on 5,000 bootstrap replicates. The 95% confidence intervals in square brackets for $\bar{R}^2$s are derived from 5,000 bootstrap replicates. $\bar{R}^2_c$ is the adjusted-R^2 computed across the target test assets and excluding the traded factors that are included in the test assets for estimation. Monthly data, January 1986–December 2015.

Panel (b) $\beta^{\Delta \mathrm{Illiq}}$ and $\beta^{\Delta\sigma}$-sorted portfolios

				Augmented CAPM	
	CAPM	ΔFL	ΔFL^m	ΔFL	ΔFL^m
int	8.43	1.20	2.25	1.86	2.45
t-FM	(5.70)	(0.30)	(0.59)	(1.35)	(1.80)
t-Sh	(5.70)	(0.22)	(0.52)	(0.91)	(1.47)
ΔFL		-3.45		-4.27	
t-FM		(-2.53)		(-4.59)	
t-Sh		(-1.90)		(-3.12)	
ΔFL^m			-1.48		-1.91
t-FM			(-2.32)		(-4.27)
t-Sh			(-2.05)		(-3.54)
MKT	1.25			5.58	5.11
t-FM	(0.40)			(1.74)	(1.58)
t-Sh	(0.40)			(1.54)	(1.50)
R^2	1.82%	44.18%	38.44%	67.94%	62.07%
$\bar{R}^2$	-1.56%	42.19%	36.31%	65.64%	59.45%
	[-0.02, 0.38]	[0.11, 0.94]	[0.08, 0.80]	[0.31, 0.91]	[0.23, 0.81]
$\bar{R}^2_c$	-15.25%	42.19%	37.98%	53.19%	48.88%

Table 7: **Alternative Liquidity Factors**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for monthly returns of decile portfolios sorted by β^{illiq} and β^{σ}. BAB is the betting-against-beta factor, ΔAm is the change of market illiquidity, PS is the traded liquidity risk factor, ΔTED is the change of the spread between the three-month LIBOR and U.S. Treasury rates. The estimated prices of risk are annualized (multiplied by 12). Standard errors and Shanken-corrected standard errors are reported in parentheses. The 95% confidence intervals in square brackets for $\bar{R}^2$s are derived from 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. $\bar{R}^2_c$ is the adjusted-R^2 computed across the target test assets and excluding the traded factors that are included as test assets for estimation. Monthly data, Feb 1986–Dec 2015 (LIBOR starts in January 1986).

	Alternative Factors				Augmented with ΔFL			
int	10.75	4.76	10.27	2.85	0.38	1.01	1.93	1.42
t-FM	(3.56)	(1.55)	(3.37)	(1.01)	(0.13)	(0.29)	(0.61)	(0.46)
t-Sh	(3.51)	(1.50)	(3.35)	(0.85)	(0.09)	(0.22)	(0.46)	(0.36)
ΔFL					-4.08	-3.30	-3.47	-2.97
t-FM					(-3.46)	(-2.55)	(-2.64)	(-2.43)
t-Sh					(-2.40)	(-1.95)	(-1.98)	(-1.92)
BAB	7.54				8.68			
t-FM	(3.10)				(3.62)			
t-Sh	(3.09)				(3.59)			
ΔAm		-0.21				-0.07		
t-FM		(-1.41)				(-0.46)		
t-Sh		(-1.37)				(-0.36)		
PS			4.78				4.67	
t-FM			(1.99)				(1.95)	
t-Sh			(1.99)				(1.94)	
ΔTED				-1.82				-1.25
t-FM				(-2.31)				(-1.67)
t-Sh				(-1.96)				(-1.32)
R^2	44.13%	15.35%	30.15%	35.75%	79.03%	48.72%	62.81%	48.18%
$\bar{R}^2$	41.19%	10.65%	26.47%	32.37%	76.70%	42.69%	58.67%	42.42%
	[0.53, 0.90]	[0.00, 0.98]	[0.26, 0.88]	[0.03, 0.79]	[0.52, 0.98]	[0.06, 0.85]	[0.23, 0.96]	[0.08, 0.81]
$\bar{R}^2_c$	-45.69%	10.65%	-4.01%	38.41%	40.50%	42.69%	41.37%	45.18%

Table 8: **Asset Pricing Tests – Quarterly Returns**

Cross-sectional asset pricing tests based on two stage Fama-MacBeth regressions for quarterly returns of decile portfolios sorted on β^{illiq} and β^{σ}. The estimated prices of risk are annualized (multiplied by 4). Standard errors and Shanken-corrected standard errors are reported in parentheses. The 95% confidence intervals in square brackets for $\bar{R}^2$s are derived from 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. $\bar{R}^2_c$ is the adjusted-R^2 computed across the target test assets and excluding the traded factors that are included in the test assets for estimation. Quarterly data, 1986Q1–2015Q4.

Panel (a) Single-factor models

	ΔFL	BAB	ΔAm	PS	ΔTED	Lev	Cap
int	2.24	8.62	3.80	10.36	4.67	12.36	1.70
t-FM	(0.65)	(2.60)	(1.54)	(3.10)	(1.64)	(3.31)	(0.57)
t-Sh.	(0.54)	(2.49)	(1.40)	(3.04)	(1.41)	(2.43)	(0.55)
ΔFL	-1.56						
t-FM	(-2.57)						
t-Sh.	(-2.18)						
BAB		9.30					
t-FM		(3.26)					
t-Sh.		(3.26)					
ΔAm			-0.65				
t-FM			(-1.98)				
t-Sh.			(-1.82)				
PS				5.19			
t-FM				(2.03)			
t-Sh.				(2.03)			
ΔTED					-1.88		
t-FM					(-2.50)		
t-Sh.					(-2.18)		
Lev						-48.87	
t-FM						(-2.44)	
t-Sh.						(-1.82)	
Cap							14.71
t-FM							(2.03)
t-Sh.							(1.98)
R^2	83.37%	60.24%	32.07%	33.40%	65.61%	72.45%	36.69%
$\bar{R}^2$	82.45%	58.15%	28.29%	29.89%	63.80%	70.92%	33.18%
	[0.50, 0.98]	[0.30, 0.92]	[0.02, 0.98]	[0.22, 0.90]	[0.20, 0.90]	[0.32, 0.98]	[0.03, 0.98]
$\bar{R}^2_c$	82.45%	-1.72%	28.29%	4.95%	69.20%	70.92%	33.18%

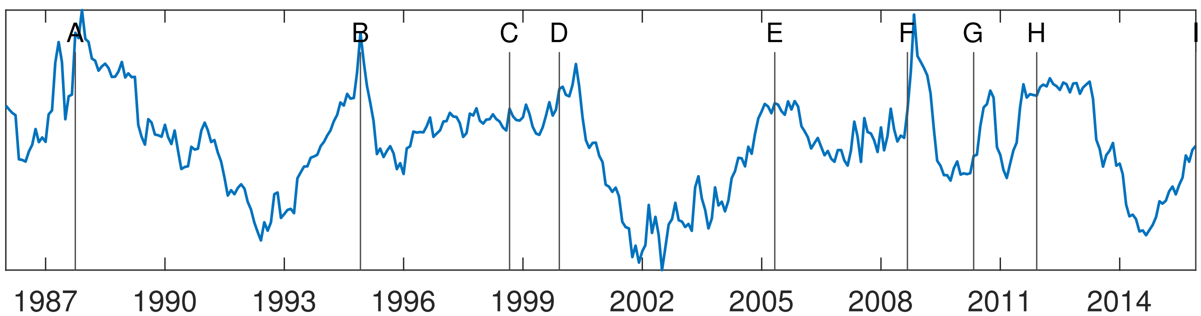
Table 8: **Asset Pricing Tests – Quarterly Returns *(continued)***

Cross-sectional asset pricing tests based on two stage Fama-MacBeth regressions for quarterly returns of decile portfolios sorted on β^{illiq} and β^{σ}. The estimated prices of risk are annualized (multiplied by 4). Standard errors and Shanken-corrected standard errors are reported in parentheses. The 95% confidence intervals for $\bar{R}^2$s based on 5,000 bootstrap replicates are in square brackets. Traded risk factors are included as test assets whenever applicable. $\bar{R}^2_c$ is the adjusted-R^2 computed across the target test assets and excluding the traded factors that are included as test assets for estimation. Quarterly data, 1986Q1 – 2015Q4.

Panel (b) Augmented by ΔFL

	BAB	ΔAm	PS	ΔTED	Lev	Cap
int	1.53	2.73	2.68	2.14	5.00	2.46
t-FM	(0.46)	(1.03)	(0.79)	(0.56)	(1.77)	(0.86)
t-Sh.	(0.37)	(0.85)	(0.66)	(0.45)	(1.56)	(0.71)
ΔFL	-1.61	-1.62	-1.51	-1.68	-1.05	-1.58
t-FM	(-2.70)	(-2.37)	(-2.48)	(-2.19)	(-1.95)	(-2.27)
t-Sh.	(-2.24)	(-1.98)	(-2.11)	(-1.79)	(-1.75)	(-1.90)
BAB	9.12					
t-FM	(3.20)					
t-Sh.	(3.19)					
ΔAm		-0.17				
t-FM		(-0.50)				
t-Sh.		(-0.42)				
PS			4.52			
t-FM			(1.78)			
t-Sh.			(1.77)			
ΔTED				-0.73		
t-FM				(-0.96)		
t-Sh.				(-0.79)		
Lev					-11.88	
t-FM					(-0.73)	
t-Sh.					(-0.65)	
Cap						10.17
t-FM						(1.45)
t-Sh.						(1.29)
R^2	91.92%	83.83%	86.69%	82.59%	85.60%	83.41%
$\bar{R}^2$	91.02%	81.92%	85.21%	80.65%	83.90%	81.46%
	[0.71, 0.99]	[0.48, 0.87]	[0.56, 0.98]	[0.46, 0.94]	[0.52, 0.98]	[0.46, 0.87]
$\bar{R}^2_c$	78.27%	81.92%	79.88%	81.30%	83.90%	81.46%

Figure 1: Funding Conditions FL_t



Note: (A) 1987 stock market crash, (B) 1994 bond market "massacre", (C) LTCM bailout, (D) Turn of the millenium, (E) Ford & GM downgrades, (F) 2008 financial crisis, (G) First Greece bailout, (H) Second Greece bailout, (I) Oil & China sell-off.