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by

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Abstract

Following theory, we check that funding risk connects illiquidity, volatility and returns in the cross-section of stocks. We show that the illiquidity and volatility of stocks increase with funding shocks, while contemporaneous returns decrease with funding shocks. The dispersions of illiquidity, volatility and returns widen following funding shocks. Funding risk is priced, generating a returns spread of 4.25 percent (annually) between the most and least illiquid portfolios, and of 5.30 percent between the most and least volatile portfolios. Estimates are robust using mimicking portfolio returns, alternative portfolio sorts, traditional test assets, other risk factors, monthly returns or quarterly returns.

JEL classification: E43, H12
Bank classification: Asset pricing; Financial markets

Résumé

En se fondant sur la théorie, les auteurs vérifient si le risque de financement relie l'illiquidité et la volatilité aux rendements dans un échantillon d'actions. Ils montrent que l'illiquidité et la volatilité des actions augmentent lorsque surviennent des chocs de financement, alors que les rendements contemporains diminuent. La dispersion des niveaux de l'illiquidité, de la volatilité et des rendements s'accroît à la suite des chocs de financement. Le risque de financement induit des écarts (annuels) de rendement de 4,25 % entre les portefeuilles les plus illiquides et les moins illiquides, et de 5,30 % entre les portefeuilles les plus volatils et les moins volatils. Ces résultats sont robustes à l'utilisation des rendements de portefeuilles sensibles à certains facteurs, de divers types de portefeuilles, d'actifs de test conventionnels, d'autres facteurs de risques, et de rendements mensuels ou trimestriels.

Classification JEL : E43, H12
Classification de la Banque : Évaluation des actifs; Marchés financiers

Non-Technical Summary

Financial markets assign intermediaries—market-makers, hedge funds and other liquidity providers—a key role in the reallocation of capital across financial assets. Nonetheless, their wealth is limited. Hence, the intermediaries' ability to provide liquidity varies over time with willingness and their ability to access funding markets, which we identify as funding shocks, imparting additional variations to stock prices. We find evidence that the level and the dispersion of illiquidity and volatility across stocks increase following funding shocks (i.e., *commonality)*. We show that volatile stocks become more illiquid following negative funding shocks—when borrowing constraints tighten—because these stocks add relatively more to the borrowing constraint of intermediaries (i.e., f*light to quality*). Total volatility also increases, since the price impact of trades increases. Finally, illiquidity and volatility are exacerbated when intermediaries operate close to their borrowing constraints (i.e., *asymmetry),* increasing the illiquidity and volatility differentials in the cross-section of stocks. Hence, exposures to funding risk make stocks riskier for investors. Consistent with theoretical predictions, we find a robust and economically significant *funding risk premium*. Variations in stock prices and volatility attributed to changes in fundamental economic conditions often reflect the limited ability of intermediaries.

Introduction

Funding risk, market illiquidity and market volatility are closely interrelated. For instance, Vayanos (2004) proposes an equilibrium model where shocks to fund managers connect an asset's illiquidity and returns to its volatility. In Gromb and Vayanos (2002, 2010), intermediaries' wealth shocks exacerbate illiquidity and volatility. With multiple assets, these shocks raise the dispersion of illiquidity, volatility and expected returns (Brunnermeier and Pedersen, 2009). This paper tests and validates the following theoretical predictions:

(i) *commonality.* Illiquidity and returns co-move with intermediaries' funding shocks (i.e., a level effect).

(ii) *flight to quality.* Illiquidity and returns exhibit higher co-movement with funding shocks for securities with higher volatility (i.e., a slope effect).

(iii) *asymmetry.* Illiquidity and returns co-move more strongly with funding shocks when the level of funding risk is higher.

(iv) *funding risk premium.* Securities with higher covariance with intermediaries' funding shocks have a higher risk premium.

Brunnermeier and Pedersen (2009) study an equilibrium where stock returns have properties (i)-(iv).[1] Funding shocks increase the market illiquidity and market volatility of every stock. Volatile stocks become more illiquid because they add relatively more to the risk that an intermediary meets its constraint. Total volatility also increases, since the price impact of trades increases. These effects of funding shocks are more important when intermediaries operate closer to their borrowing constraints, increasing the liquidity and volatility differentials in the cross-section. Hence, exposures to funding risk make stocks riskier and raise the risk premium in proportion to the covariance with funding shocks.

We follow theory and look for the effect of funding shocks on portfolios of stocks sorted by their volatility and illiquidity. We find that funding risk increases the illiquidity and volatility of every portfolio (*commonality*). In addition, the dispersion of

[1] For instance, see their Proposition 6 and their Section 5, "*Liquidity Risk*."

illiquidity increases across illiquidity-sorted portfolios and, similarly, the dispersion of volatility increases across volatility-sorted portfolios. The evidence also supports the interplay between illiquidity and volatility (*flight to quality*). Illiquidity increases more for volatile stocks following funding shocks. Consistent with one of the distinct predictions of Brunnermeier and Pedersen (2009), we find that the relationships with funding shocks are stronger when funding risk was worse in the previous month (*asymmetry*).

The relationships between funding shocks, illiquidity and volatility create a risk for investors. We find that funding risk is priced: the pattern of average returns across portfolios is close to the pattern of funding risk betas (*funding risk premium*). Asset pricing tests show that exposures to funding shocks explain a large share of the cross-sectional dispersion of returns across illiquidity- and volatility-sorted portfolios. Pricing errors are not significantly different from zero. The price-of-risk estimate is close to -4 percent annually and translates into a spread in returns of 4.25 to 5.30 percent between the extreme portfolios.

Asset pricing tests deliver the same message when using a mimicking portfolio that combines returns from Treasury bonds, illiquidity-sorted portfolios and volatility-sorted portfolios.[2] Estimates are robust when sorting stocks using liquidity risk and volatility risk (instead of levels). Estimates are also robust across a wide range of specifications that combine funding risk with other risk factors, including the market returns, the Fama-French risk factors, the market illiquidity ratio (Amihud, 2002), the Pastor and Stambaugh (2003) measure (PS), the betting-against-beta (BAB) factor (Frazzini and Pedersen, 2014) and the spread between Treasury bill and LIBOR

[2] The average returns of these portfolios may not be attainable for most investors due, for instance, to high trading costs or to the risk premium associated with illiquidity and shorting fees of the underlying assets (Amihud, 2002; Drechsler and Drechsler, 2014). Intermediation frictions play an important role in either of these cases and, to the extent that these span variations in ΔFL, reflect conditions in the funding markets. In addition, this choice of spanning assets is close in spirit to theoretical predictions. The results are robust when including traditional portfolios among the spanning assets.

rates (TED spread). Estimates of the price of risk decrease slightly but remain significant when funding risk is combined with other liquidity proxies (these proxies typically become insignificant). This is not due to the correlation between shocks in the time series—these correlations are very low—but to the correlation between the risk exposures. The β estimates are correlated even if the shocks are uncorrelated. This apparent contradiction is due to the asymmetric nature of funding risk: the correlation of portfolio returns with funding shocks is higher when funding risk is high.

Our choice of test assets was motivated by theory. We find that estimates of the price of risk remain robust when using portfolios sorted by size, book-to-market, market beta and momentum. Each of these test assets has been linked to liquidity conditions in the literature (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Frazzini and Pedersen, 2014; Akbas, Boehmer, Genc, and Petkova, 2010). We also find that the combination of funding risk with the market returns—a version of the capital asset pricing model (CAPM) augmented with funding risk—produces very significant prices of risk and a good fit. The CAPM yields an adjusted $\bar{R}^2$ close to zero but yields $\bar{R}^2$s of 35 and 74 percent when combined with funding shocks or with the mimicking portfolio returns, respectively. As a benchmark, the Fama-French three-factor model yields an $\bar{R}^2$ of 73 percent. Other liquidity measures do not perform as well in this challenging test.

In the final section of the paper, we switch to quarterly returns and compare our funding shocks ΔFL and the broker-dealer (BD) leverage factor in Adrian, Etula, and Muir (2014), AEM hereafter.[3] AEM find that BD leverage shocks explain alone a large part of the dispersion of returns across portfolios sorted by size, book-to-market and momentum. They point out that BD leverage shocks may proxy for funding shocks, but that the lack of correlations between leverage and illiquidity challenges

[3]We repeat in quarterly returns several of the exercises discussed above at the monthly frequency. The message is essentially unchanged and we place these additional results in the appendix.

this interpretation. Consistent with their observation, we find that BD leverage shocks explain very little of the cross-section of average returns across illiquidity and volatility portfolios. But AEM show that leverage risk successfully prices the cross-section of size and book-to-market portfolios. We find that the leverage factor explains by itself 87 percent of the dispersion of returns in the cross-section of portfolios sorted by book-to-market, but only 1 percent in the cross-section sorted by size. On the other hand, exposures to funding risk explain 67 percent of the dispersion of returns across size portfolios but only 22 percent across the book-to-market portfolios. Hence, exposures to leverage and funding shocks appear to be different risks. The ability of funding shocks to price illiquidity- and size-sorted portfolios follows, since these portfolios have a large majority of stocks in common. We see two potential explanations for the ability of the BD leverage factor to price the book-to-market portfolios. One is the correlation of leverage shocks with asset growth (as reported by AEM), and the other is the ability of the BD leverage factor to capture the leverage constraint of stockholders, as measured by betting-against-beta returns (also discussed in AEM).

Our results establish a link between the vast literature on the cross-section of stock returns and the theoretical literature on intermediation frictions. We complement empirical results, showing that funding shocks connect illiquidity, volatility and returns together. One distinct feature of our results is due to the asymmetric nature of funding risk: the interrelationships with funding shocks are stronger when intermediaries face higher funding risk. Existing results show that illiquidity exhibits a strong commonality across securities (Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Chordia, Sarkar, and Subrahmanyam, 2005); that illiquidity increases with a securities' volatility to compensate market-makers for their inventory risk or for their losses to better-informed investors (Benston and Hagerman, 1974; Stoll, 1978; Glosten and Milstom, 1985; Grossman and Miller, 1988), or because illiquidity and volatility perpetuate each other in a self-fulfilling equilibrium

(Pagano, 1989). Hameed, Kang, and Vishnawathan (2010) show that the level and correlation of stocks' illiquidity increase with market declines, which they interpret as a proxy for shocks to intermediaries' wealth. In addition, existing results show that the risk premium increases in the cross-section with equities' illiquidity and illiquidity risk (Amihud and Mendelson, 1986; Amihud, 2002; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005), and that mutual funds exposed to illiquidity have better performance (Goyenko, 2014).

The rest of the paper is organized as follows. In Section I we describe our empirical strategy, detailing the construction of the risk factors and the portfolios. The empirical results on the pricing of illiquidity and volatility portfolios are reported and discussed in Section II. Section III conducts a similar empirical exercise using quarterly returns to compare with the leverage factor. Section IV concludes and discusses some remaining challenges and avenues for future research.

I Empirical Strategy

A Measuring the Value Funding Liquidity

To capture how liquidity affects asset prices, Vayanos (2004) suggests using the prices of two assets with similar cash flows but different liquidity, citing the well-known case of the just-issued (on-the-run) and the previously issued (off-the-run) 30-year Treasury bonds. Similarly, Longstaff (2004) uses Treasury and RefCorp bonds. In each case, two bonds carry the same credit risk and promise very similar cash flows, but one of the bonds is more liquid and more expensive.

Fontaine and Garcia (2012) extract a measure of funding liquidity risk (FL) from a panel of U.S. Treasury security pairs across a range of maturities. By construction, the elements of each pair have nearly identical maturities, and similar cash flows, but potentially have very different ages. This strategy is consistent with the evidence that older bonds are less liquid, including the on-the-run effect.[4] Fontaine and Garcia (2012) control for cash flow differences by estimating the funding factor jointly within a dynamic no-arbitrage model. The combination of a rich panel of Treasury bonds with a dynamic term structure model teases out the noise and provides a better measurement of the latent funding risk factor. Estimates of FL are based on apparent deviations from arbitrage in a panel of U.S. Treasury bonds. This instance of limits to arbitrage arises because of frictions in the repo market: arbitraging between nearby bonds requires two transactions on the repo market. In turn, dealers use the repo market to make marginal leverage adjustments (Adrian and Shin, 2010). It is this dual role of the repo market—allowing for arbitrage activities and for dealers' funding activities—that connects estimates of FL to funding risk.[5]

Indeed, Fontaine and Garcia (2012) demonstrate that FL can be interpreted as a measure of the funding liquidity risk by relating FL to future repo spreads, 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). Finally, Fontaine and Garcia (2012) show that higher funding risk predicts a lower risk premium for U.S. Treasury bonds but a higher risk premium for LIBOR rates, swap rates and corporate yields.

[4]The market for old notes is segmented from the markets for bills (Garbade, 1984; Kamara, 1994; Duffee, 1996) and, similarly, the market for old bonds is segmented from the market for more recently issued bonds (Cornell and Shapiro, 1989). See also Fontaine and Garcia (2015).

[5]Duffie (1996) and Vayanos and Weill (2006) discuss how the price of two identical Treasury securities should reflect the value of holding a security that can be funded more easily and more cheaply via the repo market. Empirically, this link has been confirmed by Jordan and Jordan (1997); Krishnamurthy (2002); Buraschi and Menini (2002); and Bartolini, Hilton, Sundaresan, and Tonetti (2011).

B Data and Portfolio Formation

The funding factor FL is available monthly starting in 1986 and we end our sample in March 2012, therefore including the recent financial crisis.[6] For simplicity, funding shocks are computed as the first difference $\Delta FL_t \equiv FL_t - FL_{t-1}$. We checked that ΔFL_t exhibits no autocorrelation.

We form portfolios ranked by market liquidity and market volatility to test the theoretical implications listed in the Introduction. We start from daily returns and trading volume data for individual stocks in the Center for Research on Securities Prices (CRSP) data set for the 26-year period from January 1986 to March 2012. We consider ordinary common stocks traded on the NYSE or AMEX.[7] Each month, we use the following filter. To be included in our sample, a stock must have

(i) a stock price of between \$5 and \$1,000,

(ii) at least 150 observations over the previous year, and

(iii) at least 10 observations in the current month.

At the end of each year we form 10 equal-weighted portfolios of stocks ranked by their year-end illiquidity and 10 portfolios of stocks ranked by their year-end volatility. We track these portfolios' returns, volatility and illiquidity throughout the following year and rebalance at the end of each year. We consider alternative portfolios sorted by illiquidity risk and volatility risk below. We also consider other test assets commonly used in the asset pricing literature.

[6] The funding factor FL is updated regularly and is available at `www.jean-sebastienfontaine.com`. Before 1986, interest income had a favorable tax treatment compared to capital gains and investors favored high-coupon bonds. In that period, interest rates rose steadily, and recently issued bonds had relatively high coupons and were priced at a premium both for their liquidity and for their tax benefits. The resulting tax premium cannot be disentangled from the liquidity premium using bond ages. 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.

[7] CRSP share codes 10 and 11, excluding American Depositary Receipts, SBIs, real estate investment trusts, certificates, units, closed-end-funds, companies incorporated outside the United States, and American Trust components. Nasdaq stock are excluded, since their trading volume is significantly higher compared to NYSE and AMEX stocks, due to interdealer trades, distorting several illiquidity measures.

We measure the volatility of a stock using the concept of realized volatility. Specifically, we use the standard deviation of a stock's daily returns to measure monthly volatility. We are interested in the volatility of a representative stock in the portfolios. Hence, our volatility measure for a portfolio is the average volatility of its component stocks. We measure the illiquidity of a stock using the Amihud (2002) ratio, which is the most widely used illiquidity proxy.[8] This ratio measures the price impact of a given transaction conditioning on the traded volume. For a given day d and stock i, the illiquidity ratio $ILLIQ_{id}$ is given by

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

where R_{id} is the stock return and $DVOL_{id}$ is the dollar value of the trading volume. The illiquidity ratio at the end of month t with D_t trading days for a portfolio p with N stocks is defined as

$$ILLIQ_{pt} = \text{median}\left[\frac{1}{D_t}\sum_{d=1}^{D_t} ILLIQ_{id}\right]\left(\frac{dvol_{t-1}}{dvol_1}\right), \tag{2}$$

where $dvol_{t-1}$ is the total dollar volume in the previous month. Hence, the illiquidity of a portfolio is the median illiquidity of its components and we use $\frac{dvol_{t-1}}{dvol_1}$ to control for the growth of market capitalization and trading activity.

C Alternative Portfolio Formation

We also use double-sorted portfolios using volatility and illiquidity. We start from the same 10 illiquidity-sorted portfolios constructed above. Each decile portfolio is then divided into five by sorting the stocks by their volatility in the previous month (as above). This procedure yields $10 \times 5 = 50$ portfolios while guaranteeing a sufficient

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

number of stocks in each portfolio.

Measures of illiquidity and volatility may be too noisy. To circumvent this issue, and to check the robustness of our results, we repeat our analysis using alternative portfolios where stocks are sorted by their returns sensitivities to market-wide illiquidity and volatility. Specifically, we use the following illiquidity and volatility βs to form the new portfolios,

$$\begin{aligned} \beta_i^{Illiq} &= \frac{cov(Illiq_m, r_i)}{var(Illiq_m)} \\ \beta_i^{\sigma} &= \frac{cov(\sigma_m, r_i)}{var(\sigma_m)}. \end{aligned} \tag{3}$$

The market illiquidity $Illiq_m$ is the equal-weighted average of all stocks' Amihud ratio. The market volatility is the standard deviation of market returns using a 1-year rolling window. At the end of each year, we estimate β_i^{Illiq} and β_i^{σ} for each stock using five years of daily returns for estimation (we exclude stocks with less than five years of data). We then construct two sets of portfolios where stocks are sorted by their liquidity risk and their volatility risk, respectively. Again, we keep the portfolio composition fixed for one year and compute returns at the end of each month. We also consider other commonly used assets in the robustness section, including portfolios sorted by size, book-to-market and momentum (available from Kenneth French's web library), as well as beta-sorted portfolios (following Frazzini and Pedersen 2014).

D Alternative Illiquidity Measures

We also produce asset pricing results using alternative liquidity measures as risk factors. 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 (2) but including all stocks in the computation. 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 (also used by Gârleanu and Pedersen 2011) and the betting-against-beta (BAB) factor proposed by Frazzini and Pedersen (2014).[9]

Following AEM, we also compute the book leverage of broker-dealers, $Leverage_t^{BD}$, using quarterly financial assets and liabilities of all security broker-dealers as captured in Table L.129 of the Federal Reserve Flow of Funds data:

$$Leverage_t^{BD} = \frac{TotalFinancialAssets_t^{BD}}{TotalFinancialAssets_t^{BD} - TotalLiabilities_t^{BD}}. \tag{4}$$

The leverage factor used for pricing assets is given by the seasonally-adjusted log-change in broker-dealer leverage

$$LevFact_t = [\Delta ln(Leverage_t^{BD})]^{SA}, \tag{5}$$

where we use quarterly seasonal dummies estimated in real time.

E Mimicking Portfolio

The funding liquidity factor measures deviations with respect to arbitrage-free bond prices. These deviations persist because frictions in the repo markets make the required arbitrage strategies either too costly, too risky or simply infeasible (see Section IA). Similarly, trading some of the volatile or illiquid stocks may imply significant transaction or shorting costs.[10] Nonetheless, we can use a projection of the funding factor ΔFL on the space of excess returns to construct a portfolio that mimics ΔFL as closely as possible. As spanning assets, we use the returns on bonds used in

[9] We use the tradable version Paster-Stambaugh factor available from Lubos Pastor's website. We compute the TED spread using data from the Federal Reserve Bank of St. Louis FRED database. The BAB portfolio returns are available from Lasse Pedersen's website.

[10] Drechsler and Drechsler (2014) show that several well-known anomalies occur only across stocks with high shorting fees and high shorting risk.

Fontaine and Garcia (2012) for estimation of the funding risk factor, as well as returns on illiquidity- and volatility-sorted portfolios. We obtain portfolio loadings from the following returns regression:

$$\Delta FL_t = a + B' XR_t + \epsilon_t, \tag{6}$$

where XR_t stacks the spanning asset excess returns. The mimicking portfolio returns ΔFL^m are then given by

$$\Delta FL_t^m \equiv \hat{B}' XR_t. \tag{7}$$

II Pricing Illiquidity and Volatility Portfolios

We next report the main results linking funding liquidity with market illiquidity, market volatility and the cross-section of stock returns. First, we ask whether funding liquidity risk is priced in the cross-section of liquidity-sorted and volatility-sorted portfolios. Second, we verify that the mechanism linking the risk premium and funding shocks works through a deterioration of illiquidity and volatility. Third, we confirm that funding shocks are priced in a broader set of test assets—including size, value, momentum and beta-sorted portfolios. Finally, we consider several robustness checks: using mimicking portfolio returns, using other illiquidity and volatility risk metrics to form portfolios, comparing with alternative liquidity factors in the literature. Our results strongly support the theoretical prediction that funding shocks affect the equilibrium rate of return in the stock market.

A Summary Statistics

Table 1 reports summary statistics across the illiquidity-sorted (Panel a) and volatility-sorted portfolios (Panel b). Stocks in the illiquid portfolios have smaller market capitalization, higher volatility and higher returns. Sorting by illiquidity also creates a spread in average returns (Amihud, 2002). The returns spread between the most illiquid and the most liquid portfolios is 6.8 percent annually. The ex-ante β of the typical stock increases with liquidity. Consistent with previous results, adjusting returns for market risk still produces average returns (CAPM α) that increase with illiquidity. The α's based on Fama-French factors and the Sharpe ratios also share this pattern.

Looking at Panel (b), the more volatile portfolios include stocks that are less liquid, have smaller market capitalization, and exhibit higher returns. Sorting by volatility also creates a returns spread. The difference between the least volatile and the most volatile portfolios is 7.0 percent annually. Ang, Hodrick, Xing, and Zhang (2006) document that portfolios with higher total or idiosyncratic volatility have lower average returns, but the more recent evidence is mixed (Fu, 2009; Huang, Liu, Rhee, and Zhang, 2010; Guo, Haimanot, and Ferguson, 2014). We find a positive relationship, but our results differ from Ang, Hodrick, Xing, and Zhang (2006) in three important respects. We use *equal-weighted* returns from portfolios formed *annually* in a *longer* sample period: 1986–2012 instead of 1986–2000.[11]

B Asset Pricing Tests

We first check for the presence of a *funding risk premium*. We test whether funding shocks are priced in the cross-section of illiquidity and volatility portfolios. We follow the usual two-step procedure. We estimate the first-stage regression of contemporaneous returns on risk factors using the full sample and we estimate the second-stage regression every month using the cross-section of returns and betas estimated in the first stage. Estimates of the prices of risk are given by the time-series averages of the

[11] 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. We also find a positive relationship when forming portfolios monthly. 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.

monthly estimates. Inference is based on the usual two-step Fama-MacBeth standard errors as well as Shanken standard errors, which correct for the errors-in-variables due to using estimates from the first stage. We report the R^2 and the adjusted $\bar{R}^2$, which measure the fit across all test assets. These R^2s are not directly comparable across specifications, because we include traded risk factors as additional test assets when applicable (following Lewellen, Nagel, and Shanken 2010). Hence, we also report corrected analogs, R_c^2 and $\bar{R}_c^2$, constructed to measure the fit for the 10 illiquidity and 10 volatility portfolios, exclusively. All price-of-risk estimates are annualized.

Table 2 shows the results. The left-hand side of the table reports results for the CAPM, the Fama-French three-factor model (FF3), the funding shocks ΔFL as a risk factor and the mimicking portfolio returns ΔFL^m. The right-hand side of Table 2 reports results for versions of the CAPM and the FF3 that are augmented with either ΔFL and ΔFL^m. First, estimates for the price of funding risk are remarkably similar across specifications, around -4 when using ΔFL and around -1 when using ΔFL^m. Across specifications, the estimates are significant based on the Shanken adjusted t-statistic. The robustness of the estimates is striking and pervasive throughout the rest of the paper.

The negative sign is consistent with the fact that funding shocks correspond to bad states of the world for investors. Stocks that are more sensitive to funding shocks—stocks with lower returns in months with funding shocks—have higher expected returns. Figure 1 reports the average returns and the ΔFL beta for the illiquidity-sorted portfolios (Panel a) and the volatility-sorted portfolios (Panel b). The figure illustrates the empirical success of funding risk: average returns increase smoothly as the estimated βs become more negative. The negative betas confirm that higher funding risk is bad news for investors. The betas range between -2.3 and -3.3 for the illiquidity-sorted portfolios and between -2.2 and -3.5 for the volatility-sorted portfolios, implying a returns spread of 4.25 and 5.30 percent annually, respectively.

The risk premium associated with the mimicking returns ΔFL^m is very close. The price-of-risk estimates for ΔFL^m is consistently lower in Table 2, but the beta estimates are correspondingly larger in magnitude and they exhibit a wider dispersion. As discussed in AEM, the price of risk of the non-traded factor is typically higher since it contains a component that is uncorrelated with returns.

Funding risk on its own explains approximately 40 percent of the returns dispersion across illiquidity and volatility portfolios (see the reported R_c^2s). The CAPM explains only 23 percent, and the FF3 explains two-thirds, of the dispersion. Combining funding shocks with the FF3 model does not increase the cross-sectional fit, but the price of funding risk remains significant. This suggests that some of the explanatory power from the Fama-French factors can be attributed to funding risk.

The intercepts in Table 2 are not statistically different from zero when using either ΔFL or ΔFL^m. Table 3 reports each portofolio's pricing error as well as results from χ^2 tests that pricing errors are jointly zero. Panels (a) and (b) report results when estimating and testing the models separately in the cross-section of illiquidity- and volatility-sorted portfolios, respectively. This provides a distinct diagnostic for each set of portfolios. We find that our funding risk factor ΔFL yields p-values of 0.32 and 0.24 across illiquidity and volatility portfolios, respectively. Therefore, we cannot reject the null hypothesis that all pricing errors are jointly zero. In contrast, the CAPM and the FF3 yields p-values below 5 percent, implying that the null of zero pricing errors is rejected for some portfolios. Results are similar when using prices of risk estimated using illiquidity and volatility portfolios altogether.

C Alternative Portfolio Sorts

Using alternative proxies to sort stocks in illiquidity and volatility portfolios produces similar results. We use the sensitivity of stock returns to changes in market-wide illiquidity or market-wide volatility as a measure of illiquidity or volatility *risk*. To preserve space, descriptive statistics for these portfolios are reported in Table A.1 of the appendix. To summarize, portfolio 1 has the highest risk in each case: its returns are negatively correlated with increases in market illiquidity or market volatility. Conversely, portfolio 10 has the lowest risk, since this correlation is positive. This ordering translates into a decreasing pattern of expected returns across portfolios sorted by illiquidity risk, except for the least risky portfolio, and a decreasing pattern across portfolios sorted by volatility risk. This sorting strategy does not produce a strong dispersion in the portfolios' illiquidity and volatility levels (or capitalization level). Therefore, asset pricing tests based on these portfolios provide additional information.

Table 4 parallels Table 2 above and reports asset pricing results for portfolios sorted by illiquidity risk and volatility risk. It is immediately apparent that estimates remain close to -4 for ΔFL (close to -1 for ΔFL^m) and remain significant in all cases but one. In addition, using funding factors alone provides a close fit of the expected returns, with an R_c^2 close to 60 percent.

D Alternative Illiquidity and Funding Risk Factors

This section asks whether funding shocks are priced once we include other proxies for market liquidity or funding liquidity. Specifically, we consider the change in the market-wide Amihud measure ΔAm, the PS factor, the change in the TED spread ΔTED , and the BAB factor.[12] Table 5 parallels Table 2 above and reports asset pricing results using portfolios sorted by the level of illiquidity and the level of volatility as test assets.

Panel (a) reports results when using each proxy on its own. Looking at the price-of-risk estimates reveals mixed results. The estimates are insignificant and have the

[12] We also considered the liquidity factors of Sadka (2006) as well as the measure of hedge funds illiquidity in Kruttli, Patton, and Ramadorai (2014). 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.

wrong sign for the BAB factor and the PS factors. The estimates are marginally significant for the ΔAm factor and significant for the ΔTED factor. Shocks to Am or to TED explain close to one-third of the cross-sectional returns dispersion across illiquidity and volatility portfolios.

Panel (b) reports results when augmenting each alternative factor with ΔFL. Estimates for the BAB and PS factors have the right sign when combined with ΔFL, but they remain insignificant. Estimates for ΔAm and ΔTED are nearly halved when combined with ΔFL. On the other hand, the estimated price of risk for ΔFL remains significant and robustly estimated around -3. Some interaction is expected between these different market or funding liquidity proxies. Indeed, the estimates for the price of funding risk are lower in Panel (b) relative to results in Table 2 using ΔFL on its own. The interaction is *not* due to the correlation with the alternative illiquidity proxies: these correlations are low. Instead, the interaction is due to the correlation between factors' β across portfolios. Nonetheless, the price of funding liquidity remains robustly estimated: its information is not subsumed by other liquidity factors.

E Illiquidity, Volatility and Funding Conditions

We check the *commonality* in the level and the dispersion of the response of illiquidity and volatility to changes in funding risk ΔFL. The results provide the economic mechanism behind the significant price of funding risk documented above. Investors prefer certain portfolios because they are relatively more liquid and less volatile when funding conditions worsen. This translates into a cross-sectional dispersion of funding risk betas and a significant dispersion of expected returns. The results are consistent with theoretical predictions in Brunnermeier and Pedersen (2009).[13]

Table 6 reports the averages of portfolio illiquidity and volatility in subsamples

[13] From their Section 6: "the model predicts that the sensitivity of margins and market liquidity to speculator capital is larger for securities that are risky and illiquid on average."

when funding conditions are good or bad, as measured by the lowest and highest terciles of FL_{t-1} (Panels a and b, respectively). The differences between the subsamples are reported in Panel (c). First, note that every difference has a positive sign: the illiquidity and the volatility of every portfolio is worse when funding risk is high. Hence, it represents an undiversifiable risk for investors. We also find that the dispersion widens: the illiquid portfolios see their illiquidity worsen the most, and the most volatile portfolios see their volatility increase the most. Finally, we also find evidence of *flight to quality* since volatility and illiquidity interact as expected. The illiquid stocks become more volatile in bad times and, similarly, the volatile stocks become more illiquid in bad times. This is telling evidence of the effect of funding shocks as predicted in Brunnermeier and Pedersen (2009).

F The Effects of Funding Shocks Are Asymmetric

The previous results document how the illiquidity and volatility levels change with the level of funding risk over long horizons. Brunnermeier and Pedersen (2009) predict that this relationship 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." We directly check the *asymmetry* in relationships of funding shocks with illiquidity and volatility changes via the following regressions:

$$\begin{aligned} \Delta Illiq_{i,t} &= \gamma_{0,i} + \gamma_{1,i}\Delta FL_t + \gamma_{2,i}\Delta FL_t \mathbb{1}_{FL_{t-1}} + \xi_{i,t} \\ \Delta\sigma_{i,t} &= \gamma_{0,i} + \gamma_{1,i}\Delta FL_t + \gamma_{2,i}\Delta FL_t \mathbb{1}_{FL_{t-1}} + \xi_{i,t}, \end{aligned} \tag{8}$$

where $\mathbb{1}_{FL_{t-1}}$ is equal to 1 when FL_{t-1} lies in the top one-third of the sample, indicating that funding risk is high. We expect estimates of γ_2 to be economically significant, since it measures the additional sensitivity when funding risk is high. In addition, we expect the estimates of γ_1 to be small, since it measures the sensitivity when funding risk is lower. In other words, the response to funding shocks ΔFL_t varies through time and it is given by

$$\left(\gamma_{1,i} + \gamma_{2,i}\mathbb{1}_{FL_{t-1}}\right). \tag{9}$$

The results are reported in Table 7. The last column reports the difference between the estimates for the extreme portfolios. First, all the coefficient estimates are positive except one: funding shocks are positively correlated with illiquidity and volatility shocks. The estimates are statistically significant beyond the conventional levels. Second, the estimates exhibit a clear pattern across portfolios: portfolios that are more volatile or more illiquid experience greater deterioration following a funding shock. Hence, the level *and* the dispersion of illiquidity and volatility increase following a funding shock. Finally, we find evidence of cross-portfolio effects. Funding shocks are associated with an increase in the dispersion of illiquidity across volatility-sorted portfolios and with an increase in the dispersion of volatility across illiquidity-sorted portfolios.

This asymmetric relationship with funding risk extends to returns: the sensitivity of a portfolio's returns to funding shocks varies as the level of funding risk varies. To check this, we divide the sample into three subsamples using the market-wide Amihud measure. Then, we estimate regressions of portfolio returns on ΔFL and PS in the three subsamples separately. We include PS to illustrate the interaction with ΔFL_t. Panels (a) and (b) of Table 8 report results for the illiquidity- and volatility-sorted portfolios, respectively.[14] As expected, the funding risk betas β^{FL} are negative and significant in an illiquid market, for every portfolio. On the other hand, β^{FL} estimates are much smaller and insignificant in a liquid market. This contrasts with estimates of β^{PS}: the returns sensitivities of illiquid and volatile portfolios to PS liquidity shocks are similar across subsamples. The effect is also statistically weaker than the response

[14]Repeating this exercise but splitting the sample based on market-wide volatility yields very similar results.

to ΔFL. But the cross-sectional pattern is clear: illiquid stocks and volatile stocks have lower returns when PS worsens.

Table 8 also reports results for the full sample. The estimates for β^{FL} mix the patterns from different subsamples: they remain significant and they exhibit the pattern shown in Figure 1. The estimates of β^{PS} remain individually insignificant but the cross-sectional pattern is similar to the subsample patterns: the most illiquid and volatile portfolios stand out for the exposure to PS and ΔFL.

Importantly, the asymmetric relationship between returns and funding shocks also explains how the lack of correlation in the shocks' time-series can be consistent with correlation between the βs. As we noted above, funding risk has low correlations with other illiquidity proxies in the full sample. The highest correlations are with the ΔTED (0.30 and 0.24 for ΔFL_t and ΔFL_t^m) and with market returns (-0.19 and -0.31 for ΔFL_t and ΔFL_t^m). Other correlations are close to zero.[15] Nonetheless, the correlations between βs are higher, indicating that different risk factors produce a similar ranking of portfolios. As expected, the correlations with β^{FL} are high. The correlations between univariate βs among the illiquidity-sorted portfolios range from 0.54 and 0.74 with ΔAm and ΔTED, respectively, to 0.39 and -0.27 with the PS and BAB factors, respectively. Similarly, the correlations among volatility-sorted portfolios range from 0.89 and 0.79 with ΔAm and ΔTED, respectively, to 0.51 and -0.70 with PS and BAB, respectively. This explains the interaction between the price-of-risk estimates in Section IIE. To preserve space, we report the complete correlation matrix in the appendix (see Panels b and c of Table A.2).

[15] To preserve space, the complete correlation matrix is reported in Table A.2 of the appendix. All correlations are low but for one exception: the correlation between the BAB factor and the HML factor is 0.5.

G Alternative Test Assets

We consider other common test assets, sorting stocks by size, book-to-market, momentum or market beta. It is natural to ask whether and how much of these long-standing and well-documented risk premiums can be explained by their exposures to funding shocks. The size premium has been linked to the illiquidity of small firms and the value premium has been associated with financial distress of value firms. Frazzini and Pedersen (2014) argue that returns from the BAB portfolio can be rationalized by variations in funding conditions. Returns from the momentum factors have been linked to liquidity risk (Pastor and Stambaugh, 2003; Sadka, 2006) and to innovations in aggregate default risk (Mahajan, Petkevich, and Petkova, 2012).

Table 9 reports the results. Unsurprisingly, the CAPM cannot price these anomalies: the $\bar{R}_c^2$ is close to zero. The corresponding $\bar{R}_c^2$ is 67 percent for the FF3. Importantly, the price-of-risk estimates for ΔFL and ΔFL^m are close to the values obtained before. In all cases, the constant is small and statistically insignificant. When combined with the market returns in two-factor models, funding risk explains close to 31 percent of the cross-sectional dispersion, and the mimicking portfolio ΔFL^m explains 62 percent of the dispersion. Looking at individual test assets (unreported), the fit and parameter estimates are robust, except for the value portfolios, which have larger pricing errors.

To sum up, we find that funding shocks are priced in a broad range of test assets and their price of risk is robustly estimated. These results provide a stringent robustness check, but they also show that funding risk plays a broader role in the cross-section of stock returns beyond the illiquidity- and volatility-sorted portfolios. Of course, the size, value, momentum and betting-against-beta premium are not wholly, and not even mostly, due to funding risk. In particular, value-sorted portfolios stand out as only weakly related to funding risk, a result that will be confirmed in Section III for quarterly returns.

H Illiquidity and Volatility Double-Sort

The volatility and liquidity risks are correlated across stocks. Hence, funding risk may offer a good fit of expected returns across illiquidity-sorted (or volatility-sorted) portfolios, because those portfolios also generate volatility risk (or illiquidity risk). As a simple check for this, we repeat the asset pricing tests of Table 2 using double-sorted portfolios.[16] We start from the same 10 illiquidity-sorted portfolios above. Within each decile, we then form five groups of stocks sorted by their lagged monthly realized volatility. This produces $10 \times 5 = 50$ portfolios with 5 portfolios in each illiquidity category. We check that sorting by volatility within each illiquidity decile does not produce a spread between the average illiquidity of the portfolios. Therefore, the ability to price these additional portfolios is not due to a correlated sort by illiquidity. Our choice of 10 and 5 illiquidity and volatility grid points remains close to the sorting strategy used above (10 illiquidity portfolios), but ensures a large enough number of stocks in each portfolio to reduce the effect of idiosyncratic noise.[17]

Figure 2 shows the average returns against the funding risk beta for each portfolio: the relationship is clearly negative. Table 10 reports the results. Across specifications, the estimates for the price of funding risk are slightly lower than the estimates obtained previously, around -3 instead of -4, while the price-of-risk estimates based on the mimicking portfolios are higher, around -1.5 instead of -1. The statistical significance and the fit decrease somewhat when using ΔFL on its own but not when combined with the market returns, and not when using ΔFL^m (on its own or combined with the market returns). With 50 portfolios, this poses a more stringent test than the 20 portfolios used in Table 2, and the results provide additional evidence that funding risk is priced in the cross-section of returns. Table A.3 of the appendix re-

[16] We also checked that the price-of-risk estimates are similar when using only 10 illiquidity-sorted or only 10 volatility-sorted portfolios.

[17] We checked that using 10×10 double-sorted portfolios or using individual stocks as test assets only increases the sampling uncertainty around estimates of the first-stage β without increasing the dispersion of average returns.

ports additional results using alternative liquidity measures to price the double-sorted illiquidity and volatility portfolios. This table parallels Table 5: the price of funding risk remains significant and robust when combined with other liquidity proxies.

III Funding Risk and Broker-Dealer Leverage

AEM argue that the leverage of security broker-dealers (BD) is a good empirical proxy for the marginal value of the financial intermediaries' wealth. They find that exposures to a BD leverage factor can alone explain much of the dispersion of returns. However, AEM report that shocks to the broker-dealer leverage are uncorrelated with liquidity, concluding that their results pose a challenge to the mechanics of the "margin spiral" in Brunnermeier and Pedersen (2009)—see their Section 5. In contrast, Section II shows that funding shocks identified by ΔFL_t are correlated with the dispersion of illiquidity, volatility and returns. Given that AEM interpret the leverage factor as a measure of funding conditions, this section assesses and compares asset pricing results based on leverage shocks and funding shocks.

A Illiquidity and Volatility Portfolios

We start by presenting asset pricing results based on quarterly returns for the illiquidity and volatility portfolios. We estimate the first-stage regressions in the full sample. For brevity, we report results for a regression that combines funding shocks and market returns (augmented CAPM) in Table A.4 of the appendix:

$$r_{it} = \alpha_i + \beta_i^{\Delta FL} \Delta FL_t + \beta_i^{MKT} MKT_t + \varepsilon_{it}. \tag{10}$$

Panel (a) reports results across illiquidity portfolios, while Panel (b) reports results across volatility portfolios. Each portfolio is negatively exposed to funding shocks. In addition, there is a clear declining pattern (in absolute value) from the most illiquid to the least illiquid (between -2.9 and -0.5), and from the most volatile to the least volatile (between -2.4 and -1.2). The coefficients of regression range between 65 and 93 percent across portfolios.

As above, the pattern of $\beta^{\Delta FL}$ matches almost exactly the pattern of average returns. This is confirmed by the results of the Fama-MacBeth cross-sectional regressions reported in Table 11. This table parallels Table 2, but for quarterly returns and where we also include the leverage factor $LevFact_t$ to price assets. We find that funding risk on its own explains 63 percent of the variation across illiquidity and volatility portfolios with a price of risk close to -2. In contrast, the leverage factor has little explanatory power, its price-of-risk estimate has the wrong sign and it is insignificant. The results are similar whether we include the market returns or the FF3 factors, whether we use the mimicking portfolio returns ΔFL_t^m, and whether we combine funding shocks with the leverage factors. In particular, estimates of the price of funding risk are robust across all specifications.[18]

B Size and Value Portfolios

AEM make a strong case that leverage explains the cross-section of size and value portfolios. In their sample (1968Q1-2009Q4), the leverage factor alone explains more than 70 percent of the returns dispersion, while the three-factor Fama-French model explains 68 percent. In this section, we produce and compare results based on the leverage factor and funding risk using the size and value portfolios.

As before, we proceed in two stages. Table A.6 of the appendix reports first-stage betas for ΔFL and market returns. All portfolios except two portfolios of large-value firms have a negative exposure to the funding shocks, we note a reasonable variation among the portfolio betas for ΔFL, and the slope is negative.

[18] In the appendix, we also confirm that the illiquidity and volatility of the portfolios change with funding shocks at a quarterly frequency. In particular, Table A.5 repeats the analysis from Table 6 but using quarterly returns. The level and dispersion of portfolios' illiquidity and volatility increase following funding risk changes.

Second, we run asset pricing tests using 10×10 double-sorted size and value portfolios in quarterly data, where we compare ΔFL_t, ΔFL_t^m, and $LevFact_t$ on their own or when augmented with market returns, or with the Fama-French factors. We report the results in Table A.7 of the appendix, since the results related to ΔFL are consistent with those obtained in Section IIG above and the results for $LevFact$ are consistent with those obtained in AEM. To summarize, the estimated prices of risk are significant and have the right sign. In particular, the price of funding risk is close to -2, as in Table 11, while the price of risk associated with $LevFact_t$ ranges between 30 and 40, a value only slightly lower than that reported in AEM. Interestingly, combining $LevFact$ and ΔFL reduces the point estimates and the precision.

To better understand the interaction between the two sources of risk, we repeat the asset pricing test using 10 size portfolios or 10 value portfolios, separately. We report the results in Tables 12 and 13, respectively. We find that funding risk and leverage play distinct roles when pricing size and value portfolios. For the size portfolios, funding shocks alone explain 63 percent of the cross-section of returns. The estimates of the price of funding risk are close to -3 and remain significant across all specifications. In contrast, the leverage factor does not have any explanatory power in size portfolios.

Funding risk and leverage exchange their roles when pricing the book-to-market portfolios. The leverage factor on its own explains close to 85 percent of the cross-section of returns, outperforming the FF3 model. The price-of-risk estimate is large and positive. In contrast, funding risk on its own provides a poor fit of value portfolios' average returns. The price-of-risk estimates remain negative, often close to -3 (-14 for ΔFL^m) but often marginally significant, especially when the leverage factor is also included in the specification. There was no reason to expect that funding conditions would drive the value premium.

To complement these results, we repeat asset pricing tests using 10 illiquidity portfolios, 10 volatility portfolios and 10 size portfolios. This formally tests whether the relationship between average returns and funding risk is the same across these portfolios. We report results in Table A.8. Adding the size portfolios leaves the price-of-risk estimates broadly unchanged. If anything, the estimates are larger and the precision increases. Consistent with the results above, the estimate for the leverage factor has the wrong sign and it is insignificant.

To summarize, the cross-section of returns of the size portfolios is very well explained by funding risk but not at all by the leverage factor, while the leverage factor explains the cross-section of returns of the book-to-market portfolios, with a marginal role for the liquidity innovations. How should we interpret these results? Several papers in the literature have stressed that illiquid securities tend to have a small capitalization (Acharya and Pedersen, 2005). In our sample, we verified that the illiquidity and size portfolios have a large majority of stocks in common. Therefore, our findings regarding funding risk in the size portfolios are not surprising in the light of the results above regarding illiquidity-sorted portfolios. For the value portfolios, the strong explanatory power of the leverage factor may be due to its high correlation with asset growth.[19]

In Figure 3, we plot the leverage factor $LevFact_t$ and the funding shocks ΔFL_t. While funding liquidity shock and leverage shock series move in opposite directions in the beginning of the sample (see the 1987 market crash and the 1994 Mexican peso crisis), they have tended to move together in the latter part of the sample (see the last financial crisis and the LTCM 1998 crisis). Somewhat unexpectedly, broker-dealer leverage sometimes increases in the face of tightening funding conditions—at least initially.

[19] AEM report a correlation of 0.73 between the leverage factor and asset growth.

IV Conclusion

In this paper, we focus on measuring the effect of funding constraints in the cross-section of stocks. We show that funding shocks increase the dispersion of illiquidity across liquidity-sorted portfolios and increase the dispersion of volatility across volatility-sorted portfolios. Consistent with theory, we provide evidence of the cross-effect: funding shocks increase the dispersion of illiquidity across volatility-sorted portfolios. The fact that relationships are stronger when funding risk is high, or when market-wide illiquidity is high, is a distinct feature of our results that distinguishes funding risk from other sources of risk. Our results provide strong supportive evidence for limits-to-arbitrage theories based on frictions in the intermediation mechanism.

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 level of funding risk is a significant state variable for investors. Second, we have documented that funding shocks are risky to investors and that they are associated with a robust risk premium. However, we have not considered how investors should adjust benchmark asset allocation models to reflect funding risk. Finally, several ongoing technology and regulatory changes suggest that funding shocks may play a lesser role in the future, but this remains to be confirmed.

References

Acharya, V. V. and L. Pedersen (2005). Asset pricing with liquidity risk. *Journal of Financial Economics 77*(2), 375–410.

Adrian, T., E. Etula, and T. Muir (2014). Financial intermediaries and the cross-section of asset returns. *Journal of Finance 69*(6), 2557–2596.

Adrian, T. and H. Shin (2010). Liquidity and leverage. *Journal of Financial Intermediation 19*(3), 418–437.

Akbas, F., E. Boehmer, E. Genc, and R. Petkova (2010). The time-varying liquidity risk of value and growth stocks. Working Paper, Texas A&M University.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Amihud, Y. and H. Mendelson (1986). Asset pricing and the bid-ask spreads. *Journal of Financial Economics 17*(2), 223–249.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006). The cross-section of volatility and expected returns. *Journal of Finance 61*(1), 259–299.

Bartolini, L., S. Hilton, S. Sundaresan, and C. Tonetti (2011). Collateral values by asset class: Evidence from primary security dealers. *Review of Financial Studies 24*(1), 248–278.

Benston, G. J. and R. L. Hagerman (1974). Determinants of bid-asked spreads in the over-the-counter market. *Journal of Financial Economics 1*(4), 353–364.

Brunnermeier, M. K. and L. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Buraschi, A. and D. Menini (2002). Liquidity risk and specialness. *Journal of Financial Economics 64*(2), 243–284.

Chordia, T., R. Roll, and A. Subrahmanyam (2000). Commonality in liquidity. *Journal of Financial Economics 56*(1), 3–28.

Chordia, T., A. Sarkar, and A. Subrahmanyam (2005). An empirical analysis of stock and bond market liquidity. *Review of Financial Studies 18*(1), 85–129.

Cornell, B. and A. C. Shapiro (1989). The mispricing of US treasury bonds: A case study. *Review of Financial Studies 2*(3), 297–310.

Drechsler, I. and Q. Drechsler (2014). The shorting premium and asset pricing anomalies. Working paper 20282, NBER.

Duffee, G. R. (1996). Idiosyncratic variation of treasury bill yields. *Journal of Finance 51*(2), 527–551.

Duffie, D. (1996). Special repo rates. *Journal of Finance 51*(5), 493–526.

Fontaine, J.-S. and R. Garcia (2012). Bond liquidity premia. *Review of Financial Studies 25*(4), 1207–1254.

Fontaine, J.-S. and R. Garcia (2015). *Recent advances in old fixed income topics: learning, liquidity, and lower bound*. in Handbook of Fixed Income. Elsevier.

Frazzini, A. and L. Pedersen (2014). Betting against beta. *Journal of Financial Economics 111*(1), 1–25.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics 91*(1), 24–37.

Garbade, K. (1984). Analyzing the structure of treasury yields: Duration, coupon and liquidity effects. In *Topics in Money and Securities Markets*.

Gârleanu, N. and L. Pedersen (2011). Margin-based asset pricing and deviations from the law of one price. *Review of Financial Studies 24*(6), 1980–2022.

Glosten, L. and P. Milstom (1985). Bid, ask and transaction prices in specialist market with heterogeneously informed traders. *Journal of Financial Economics 14*(1), 71–100.

Goyenko, R. (2014). Treasury illiquidity and funding liquidity risk. Working paper, McGill University.

Goyenko, R., C. Holden, and C. Trzcinka (2009). Do liquidity measures measure liquidity? *Journal of Financial Economics 92*(2), 153–181.

Green, R. and B. Ødegaard (1997). Are there tax effects in the relative pricing of the U.S. government bonds? *Journal of Finance 52*(2), 609–633.

Gromb, D. and D. Vayanos (2002). Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of Financial Economics 66*(2), 361–407.

Gromb, D. and D. Vayanos (2010). A model of financial market liquidity based on intermediary capital. *Journal of the European Economic Association 8*(2-3), 456–466.

Grossman, S. and M. Miller (1988). Liquidity and market structure. *Journal of Finance 43*(3), 617–633.

Guo, H., K. Haimanot, and M. Ferguson (2014). On the relation between EGARCH idiosyncratic volatility and expected stock returns. *Journal of Financial and Quantitatitve Analysis 49*(1), 271–296.

Hameed, A., W. Kang, and S. Vishnawathan (2010). Stock market declines and liquidity. *Journal of Finance 65*(1), 257–293.

Hasbrouck, J. and D. J. Seppi (2001). Common factors in prices, order flows, and liquidity. *Journal of Financial Economics 59*(3), 383–411.

Huang, W., Q. Liu, S. G. Rhee, and L. Zhang (2010). Return reversals, idiosyncratic risk, and expected returns. *Review of Financial Studies 23*(1), 147–168.

Jordan, B. and S. Jordan (1997). Special repo rates: An empirical analysis. *Journal of Finance 52*(5), 2051–2072.

Kamara, A. (1994). Liquidity, taxes, and short-term treasury yields. *Journal of Financial and Quantitative Analysis 29*(3), 403–417.

Krishnamurthy, A. (2002). The bond/old-bond spread. *Journal of Financial Economics 66*(2-3), 463–506.

Kruttli, M., A. J. Patton, and T. Ramadorai (2014). The impact of hedge funds on asset markets. Working paper, Duke University.

Lewellen, J., S. Nagel, and J. Shanken (2010). A skeptical appraisal of asset pricing tests. *Journal of Financial Economics 96*(2), 175–194.

Longstaff, F. (2004). The flight-to-liquidity premium in U.S. treasury bond prices. *Journal of Business 77*(3), 511–526.

Mahajan, A., A. Petkevich, and R. Petkova (2012). Momentum and aggregate default risk. Working Paper, University of Toledo.

Pagano, M. (1989). Endogenous market thinness and stock price volatility. *Review of Financial Studies 56*(2), 269–287.

Pastor, L. and R. Stambaugh (2003). Liquidity risk and expected stock returns. *Journal of Political Economy 111*(3), 642–685.

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics 80*(2), 309–349.

Stoll, H. R. (1978). The pricing of security dealers services: An empirical study of NASDAQ stocks. *Journal of Finance 33*(4), 1153–1172.

Vayanos, D. (2004). Flight to quality, flight to liquidity, and the pricing of risk. Working Paper 10327, NBER.

Vayanos, D. and P.-O. Weill (2006). A search-based theory of the on-the-run phenomenon. *Journal of Finance 63*(3), 1361–1398.

Table 1: **Summary Statistics – Illiquidity and Volatility Portfolios**
Time-series average of each portfolio's Amihud illiquidity ratio, realized volatility, capitalization, returns and market β. The Amihud illiquidity measure is the median ratio in a portfolio ($\times 100$). The volatility, capitalization and average returns measures are computed as the equal-weighted average within each portfolio, in \$ billions or annualized %. The ex-ante CAPM β is computed for each portfolio using 5-year and 1-year rolling windows to estimate the covariance and variance, respectively. The CAPM and FF3 α's, as well as the Sharpe ratio, are estimated using the full sample. Monthly data, January 1986 - March 2012.

Panel (a) Illiquidity-Sorted Portfolios

	Most	2	3	4	5	6	7	8	9	Least
	Average Security Statistics									
Illiqu.	289.11	45.48	6.68	7.80	3.70	1.86	1.04	0.54	0.27	0.09
Vol.	27.79	28.61	27.85	27.40	26.39	25.32	24.94	24.35	23.12	22.08
Cap.	0.12	0.27	0.47	0.71	1.05	1.55	2.27	3.92	7.71	34.27
E(R)	17.39	18.77	16.39	15.76	14.22	13.99	12.79	12.99	11.54	10.56
β	0.71	0.83	0.87	0.88	0.91	0.92	0.95	0.96	0.97	1.00
	Portfolio Statistics									
CAPM α	8.96	9.18	6.45	5.49	3.97	4.00	2.48	2.78	1.90	1.07
	(4.70)	(3.97)	(3.06)	(2.53)	(2.11)	(2.31)	(1.45)	(1.93)	(1.43)	(1.12)
FF3 α	6.57	6.13	3.70	2.51	1.61	1.72	0.32	0.88	0.39	0.33
	(5.14)	(4.38)	(2.98)	(1.82)	(1.19)	(1.32)	(0.24)	(0.79)	(0.36)	(0.50)
Sharpe R.	0.26	0.23	0.19	0.18	0.16	0.17	0.14	0.15	0.14	0.13

Panel (b) Volatility-Sorted Portfolios

	Most	2	3	4	5	6	7	8	9	Least
	Average Security Statistics									
Illiq	10.79	6.35	3.91	3.12	2.21	1.74	1.51	1.24	1.34	2.23
Vol.	37.03	32.88	30.34	28.17	26.29	24.56	23.04	21.11	19.19	16.13
Cap.	1.77	2.26	2.82	3.55	4.84	6.05	6.33	7.48	8.50	9.36
E(R)	19.04	16.96	15.24	15.65	14.45	13.54	13.04	12.89	11.61	11.96
β	1.08	1.02	1.00	0.97	0.95	0.92	0.89	0.86	0.81	0.71
	Portfolio Statistics									
CAPM α	7.01	5.70	4.37	4.98	4.24	3.80	3.49	3.92	3.34	4.91
	(2.62)	(2.65)	(2.31)	(2.69)	(2.41)	(2.38)	(2.24)	(2.85)	(2.43)	(3.67)
FF3 α	4.47	3.13	1.98	2.40	1.81	1.53	1.27	2.08	1.56	3.45
	(2.26)	(2.13)	(1.50)	(1.88)	(1.42)	(1.32)	(1.12)	(1.96)	(1.45)	(3.04)
Sharpe R.	0.18	0.18	0.16	0.17	0.17	0.17	0.16	0.18	0.17	0.22

Table 2: **Asset Pricing Tests – Illiquidity and Volatility Portfolios**

Cross-sectional asset pricing tests for illiquidity- and volatility-sorted portfolios based on two-stage Fama-MacBeth regressions. The estimated prices of risk are annualized (multiplied by 12). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Monthly data, January 1986 - March 2012.

	CAPM	FF3	ΔFL	ΔFL^m	Augmented by ΔFL		Augmented by ΔFL^m	
α	4.19	-1.08	-2.53	0.14	-3.70	-2.60	-0.15	-0.96
t-FM	(1.60)	(-1.11)	(-0.70)	(0.23)	(-1.01)	(-3.30)	(-0.19)	(-1.90)
t-Sh.	(1.59)	(-1.08)	(-0.49)	(0.20)	(-0.68)	(-2.66)	(-0.17)	(-1.77)
ΔFL			-4.25		-4.63	-3.06		
t-FM			(-2.41)		(-3.37)	(-2.93)		
t-Sh.			(-1.71)		(-2.30)	(-2.38)		
ΔFL^m				-1.22			-1.25	-0.95
t-FM				(-3.17)			(-4.12)	(-2.95)
t-Sh.				(-2.90)			(-3.79)	(-2.78)
MKT	6.55	7.46			11.54	8.59	8.28	7.27
t-FM	(1.48)	(2.23)			(2.25)	(2.58)	(2.29)	(2.21)
t-Sh.	(1.47)	(2.23)			(1.71)	(2.52)	(2.23)	(2.20)
SMB		4.66				5.87		5.04
t-FM		(1.88)				(2.41)		(2.08)
t-Sh.		(1.87)				(2.33)		(2.06)
HML		5.08				5.55		4.31
t-FM		(2.20)				(2.40)		(1.91)
t-Sh.		(2.19)				(2.32)		(1.90)
$\bar{R}_c^2$	19.1%	58.1%	38.2%	36.5%	34.1%	66.3%	33.0%	69.8%
R_c^2	23.4%	64.7%	41.5%	39.8%	41.0%	73.4%	40.0%	76.1%
R^2	19.0%	82.5%	41.5%	70.7%	47.5%	87.3%	71.0%	90.2%
C.I.	[0.1, 58.9]	[60.1, 89.2]	[12.2, 70.0]	[29.8, 93.1]	[11.5, 66.1]	[76.5, 90.8]	[34.9, 91.1]	[78.5, 93.2]
$\bar{R}^2$	14.7%	79.8%	38.2%	69.2%	41.7%	84.5%	67.9%	88.1%
C.I.	[-5.2, 55.6]	[52.7, 87.9]	[7.3, 65.0]	[25.6, 92.2]	[-1.7, 62.4]	[70.7, 88.8]	[27.2, 90.2]	[75.0, 93.2]

Table 3: **Pricing Error Tests: Illiquidity and Volatility Portfolios**

Annualized pricing errors in percent from the CAPM, FF3 model, and variants augmented with ΔFL and ΔFL^m, for asset pricing tests using illiquidity portfolio in Panel (a) and for tests using volatility portfolio in Panel (b). Below, we report the mean absolute pricing error (MAPE), the χ^2_{N-K} statistic for a joint test that pricing errors are jointly zero, and the associated p-value. Monthly data, January 1986 - March 2012.

Panel (a) Illiquidity Portfolios

	$E(R^e)$	CAPM	FF3	ΔFL	ΔFL^m
Most	13.63	0.95	3.92	2.04	2.33
2	15.00	4.30	2.00	3.24	3.59
3	12.63	2.52	-0.18	1.46	1.59
4	12.00	2.46	-1.46	0.59	0.81
5	10.45	0.86	-1.37	0.49	0.18
6	10.23	0.20	-0.63	-0.43	-0.48
7	9.03	-0.45	-1.58	-2.98	-2.54
8	9.22	-0.44	-0.57	-2.82	-2.37
9	7.77	-2.86	-0.16	-1.68	-2.18
Least	6.79	-4.09	1.04	0.10	-1.41
Intercept		20.60	-2.66	-5.85	0.27
MAPE		2.05	1.16	1.58	1.63
χ^2_{N-K}		19.53	22.00	10.38	14.08
p-value		0.03	0.02	0.32	0.17

Panel (b) Volatility Portfolios

	$E(R^e)$	CAPM	FF3	ΔFL	ΔFL^m
Most	15.27	2.01	1.24	3.91	3.97
2	13.19	0.99	0.22	1.01	1.16
3	11.48	-0.18	-0.66	-0.54	-0.41
4	11.89	0.51	-0.22	0.00	0.12
5	10.69	-0.05	-0.54	0.08	0.05
6	9.77	-0.30	-0.57	-1.61	-1.55
7	9.27	-0.53	-0.71	-2.35	-2.26
8	9.12	0.13	0.46	-0.43	-0.58
9	7.85	-0.18	0.21	-0.74	-1.01
Least	8.19	1.86	2.63	0.68	0.29
Intercept		1.75	-0.78	-0.85	0.51
MAPE		1.00	0.73	1.13	1.05
χ^2_{N-K}		21.17	20.58	11.48	15.80
p-value		0.02	0.02	0.24	0.11

Table 4: **Pricing Liquidity and Volatility – Alternative Portfolio Sorts**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for portfolios sorted by market illiquidity risk and market volatility risk. The estimated prices of risk are annualized (multiplied by 12). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Monthly data, January 1986 - March 2012.

	CAPM	FF3	ΔFL	Δ FL^m	Augmented by ΔFL		Augmented by ΔFL^m	
α	-1.19	-2.85	-1.33	0.26	-3.28	-2.87	-0.25	-2.10
t-FM	(-0.31)	(-2.40)	(-0.33)	(0.57)	(-0.82)	(-2.40)	(-0.40)	(-2.93)
t-Sh.	(-0.31)	(-2.31)	(-0.25)	(0.52)	(-0.60)	(-2.09)	(-0.37)	(-2.48)
ΔFL			-3.80		-3.93	-2.25		
t-FM			(-2.54)		(-2.43)	(-1.11)		
t-Sh.			(-1.90)		(-1.79)	(-0.98)		
ΔFL^m				-1.18			-1.03	1.04
t-FM				(-3.23)			(-2.30)	(1.75)
t-Sh.				(-2.97)			(-2.15)	(1.49)
MKT	11.93	9.04			11.44	9.20	8.69	9.16
t-FM	(2.34)	(2.71)			(2.27)	(2.74)	(2.57)	(2.79)
t-Sh.	(2.31)	(2.70)			(1.84)	(2.69)	(2.55)	(2.75)
SMB		4.23				4.40		3.61
t-FM		(1.66)				(1.70)		(1.49)
t-Sh.		(1.65)				(1.65)		(1.46)
HML		5.70				5.66		5.58
t-FM		(2.31)				(2.31)		(2.40)
t-Sh.		(2.29)				(2.23)		(2.33)
$\bar{R}_c^2$	48.5%	52.7%	58.5%	35.0%	57.2%	56.3%	36.3%	56.2%
R_c^2	51.2%	60.2%	60.7%	38.4%	61.7%	65.5%	43.0%	65.4%
R^2	34.1%	88.1%	60.7%	79.5%	65.3%	89.7%	79.5%	92.7%
C.I.	[0.4, 73.9]	[62.7, 96.1]	[17.5, 85.6]	[17.9, 95.4]	[21.1, 83.1]	[65.4, 96.8]	[28.6, 94.6]	[64.9, 97.0]
$\bar{R}^2$	30.6%	86.2%	58.5%	78.4%	61.4%	87.5%	77.4%	91.2%
C.I.	[-4.9, 72.1]	[57.3, 95.7]	[11.2, 85.7]	[16.6, 95.9]	[14.5, 82.4]	[54.2, 96.0]	[24.5, 94.5]	[60.7, 96.4]

Table 5: **Pricing Liquidity and Volatility Portfolios – Alternative Liquidity Factors**

Cross-sectional asset pricing tests based on two-stage regressions. BAB is the betting-against-beta factor, ΔAm is the market illiquidity ratio, PS is the traded liquidity risk factor, TED is 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 confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Monthly data, January 1986 - March 2012.

	Panel (a) Alternative Factors				Panel (b) Augmented with ΔFL			
α	10.47	3.13	10.86	0.18	0.64	-1.95	3.03	-0.55
t-FM	(3.43)	(1.22)	(3.17)	(0.26)	(0.22)	(-0.61)	(1.09)	(-0.74)
t-Sh.	(3.42)	(1.15)	(3.14)	(0.19)	(0.17)	(-0.48)	(0.94)	(-0.59)
ΔFL					-3.32	-3.24	-2.48	-3.05
t-FM					(-2.70)	(-3.14)	(-1.62)	(-2.65)
t-Sh.					(-2.14)	(-2.51)	(-1.40)	(-2.12)
BAB	-3.14				6.70			
t-FM	(-0.74)				(1.75)			
t-Sh.	(-0.74)				(1.52)			
ΔAm		-0.23				-0.12		
t-FM		(-1.82)				(-1.00)		
t-Sh.		(-1.72)				(-0.81)		
PS			-6.81				1.04	
t-FM			(-1.52)				(0.28)	
t-Sh.			(-1.51)				(0.26)	
ΔTED				-0.21				-0.10
t-FM				(-3.14)				(-2.69)
t-Sh.				(-2.32)				(-2.20)
$\bar{R}_c^2$	11.3%	30.0%	15.1%	28.2%	27.1%	36.6%	23.4%	34.8%
R_c^2	16.0%	33.7%	19.6%	32.0%	34.7%	43.3%	31.5%	41.6%
R^2	13.3%	33.7%	32.7%	65.7%	31.8%	43.3%	42.5%	70.6%
C.I.	[0.2, 51.7]	[0.2, 71.8]	[18.7, 42.6]	[6.0, 91.3]	[6.4, 55.0]	[6.9, 68.2]	[31.3, 52.1]	[26.0, 91.6]
$\bar{R}^2$	8.7%	30.0%	29.2%	63.9%	24.2%	36.6%	36.1%	67.1%
C.I.	[-5.1, 49.6]	[-5.2, 70.6]	[16.4, 39.8]	[0.4, 91.2]	[-5.1, 49.3]	[-7.5, 63.1]	[22.6, 48.8]	[17.9, 89.6]

Table 6: **Portfolio Illiquidity and Volatility across Funding Conditions**
Average illiquidity ($\times 100$) and volatility (annualized %) of liquidity-sorted and volatility-sorted portfolios conditional on the level of lagged funding liquidity risk FL_{t-1}. Panel (a) reports averages when ΔFL is in the bottom tercile of the empirical distribution (low FL_{t-1}). Panel (b) reports averages when ΔFL is in the top tercile (high FL_{t-1}). Panel (c) reports differences between each average. Monthly data, January 1986 - March 2012.

Panel (a) Low FL_{t-1}

	Illiquidity Portfolios			Volatility Portfolios	
	Illiquidity	Volatility		Illiquidity	Volatility
Most	226.91	25.56	Most	8.43	35.94
2	43.04	27.31	2	5.27	31.27
3	15.03	26.42	3	3.16	28.64
4	6.85	26.44	4	2.85	26.60
5	3.08	24.85	5	2.08	24.72
6	1.59	23.65	6	1.51	22.82
7	0.91	23.65	7	1.25	21.48
8	0.48	23.11	8	0.97	19.88
9	0.24	21.77	9	1.34	17.83
Least	0.08	20.77	Least	2.39	15.16

Panel (b) High FL_{t-1}

	Illiquidity Portfolios			Volatility Portfolios	
	Illiquidity	Volatility		Illiquidity	Volatility
Most	381.85	31.39	Most	15.44	40.12
2	52.61	31.83	2	8.48	36.21
3	20.29	31.07	3	4.96	33.92
4	9.42	30.29	4	3.73	31.24
5	4.59	29.15	5	2.42	29.48
6	2.32	28.39	6	2.13	27.82
7	1.27	27.69	7	1.97	26.10
8	0.68	27.18	8	1.56	23.74
9	0.33	25.71	9	1.51	21.49
Least	0.11	24.42	Least	2.23	17.97

Panel (c) High FL_{t-1} - Low FL_{t-1}

	Illiquidity Portfolios			Volatility Portfolios	
	Illiquidity	Volatility		Illiquidity	Volatility
Most	154.94	5.83	Most	7.01	4.18
2	9.57	4.52	2	3.22	4.94
3	5.25	4.65	3	1.80	5.28
4	2.57	3.84	4	0.88	4.64
5	1.51	4.30	5	0.34	4.76
6	0.73	4.74	6	0.62	5.00
7	0.36	4.04	7	0.72	4.62
8	0.19	4.07	8	0.59	3.86
9	0.09	3.95	9	0.17	3.66
Least	0.02	3.65	Least	-0.16	2.80

Table 7: **Illiquidity, Volatility and Funding Shocks**

Panel (a) reports coefficient estimates in regressions of portfolio illiquidity changes on funding shocks $\Delta ILLIQ_{i,t} = \gamma_{0,i} + \gamma_{1,i}\Delta FL_t + \gamma_{2,i}\Delta FL_t \mathbb{1}_{FL_{t-1}} + \xi_{i,t}$. Panel (b) reports coefficient estimates in regressions of portfolio volatility changes on funding shocks $\Delta VOL_{i,t} = \gamma_{0,i} + \gamma_{1,i}\Delta FL_t + \gamma_{2,i}\Delta FL_t \mathbb{1}_{FL_{t-1}} + \xi_{i,t}$, where $\mathbb{1}_{FL_{t-1}}$ is the indicator function equal to 1 when FL_{t-1} lies in the highest sample tercile. Parameter estimates are multiplied by 100. Monthly data, January 1986 - March 2012.

Panel (a) Illiquidity Regressions

	Most	2	3	4	5	6	7	8	9	Least	1-10
	Illiquidity Portfolios										
γ_1	4.30	1.10	0.52	0.29	0.14	0.05	0.01	0.01	0.00	(0.00)	4.30
	(0.10)	(0.30)	(0.41)	(0.47)	(0.47)	(0.34)	(0.17)	(0.33)	(0.07)	(-0.34)	(0.10)
γ_2	214.19	1.32	2.05	0.95	0.58	0.58	0.35	0.18	0.11	0.04	214.15
	(3.61)	(0.25)	(1.11)	(1.06)	(1.36)	(2.97)	(3.08)	(2.94)	(3.55)	(3.97)	(3.61)
R^2	8.28%	0.17%	1.34%	1.35%	1.94%	6.45%	6.39%	6.30%	7.95%	8.50%	8.28%
$\bar{R}^2$	7.66%	-0.50%	0.67%	0.69%	1.28%	5.82%	5.77%	5.67%	7.33%	7.89%	7.66%
	Volatility Portfolios										
γ_1	0.60	0.10	0.17	0.04	0.01	0.01	0.09	0.04	0.04	-0.05	0.64
	(0.48)	(0.15)	(0.46)	(0.16)	(0.04)	(0.04)	(0.81)	(0.45)	(0.27)	(-0.17)	(0.53)
γ_2	3.86	2.44	1.12	0.80	0.89	0.50	0.37	0.29	0.21	0.11	3.75
	(2.18)	(2.64)	(2.10)	(2.09)	(3.62)	(2.61)	(2.32)	(2.11)	(1.13)	(0.27)	(2.17)
R^2	4.12%	4.78%	3.84%	3.14%	8.14%	4.41%	5.47%	3.84%	1.17%	0.03%	4.20%
$\bar{R}^2$	3.47%	4.14%	3.20%	2.49%	7.52%	3.77%	4.84%	3.20%	0.51%	-0.65%	3.56%

Panel (b) Volatility Regressions

	Most	2	3	4	5	6	7	8	9	Least	1-10
	Illiquidity Portfolios										
γ_1	13.16	24.78	13.17	9.36	9.49	12.38	9.77	10.94	7.83	4.82	8.34
	(1.44)	(2.18)	(1.16)	(0.85)	(0.84)	(1.04)	(0.80)	(0.88)	(0.63)	(0.38)	(1.09)
γ_2	52.46	54.28	67.72	77.66	67.20	75.36	75.70	75.91	77.28	75.65	-23.19
	(4.01)	(3.34)	(4.17)	(4.91)	(4.15)	(4.42)	(4.35)	(4.27)	(4.34)	(4.13)	(-2.11)
R^2	14.90%	14.85%	14.52%	16.96%	13.17%	15.28%	13.99%	13.93%	13.33%	11.41%	1.58%
$\bar{R}^2$	14.33%	14.28%	13.95%	16.40%	12.59%	14.71%	13.41%	13.36%	12.75%	10.81%	0.92%
	Volatility Portfolios										
γ_1	19.75	17.63	16.61	14.87	11.76	11.86	8.10	5.13	6.47	4.35	15.40
	(1.39)	(1.35)	(1.37)	(1.21)	(0.97)	(1.03)	(0.70)	(0.48)	(0.67)	(0.50)	(1.67)
γ_2	76.58	74.20	69.44	68.84	82.30	66.89	75.47	71.12	68.53	56.50	20.08
	(3.78)	(3.99)	(4.00)	(3.92)	(4.74)	(4.06)	(4.55)	(4.62)	(4.93)	(4.51)	(1.52)
R^2	13.61%	14.41%	14.56%	13.50%	16.56%	13.50%	14.57%	14.12%	16.37%	13.65%	5.45%
$\bar{R}^2$	13.03%	13.84%	13.99%	12.92%	16.00%	12.92%	13.99%	13.55%	15.81%	13.07%	4.82%

Table 8: **Funding and Market Liquidity Risk in Liquid and Illiquid Samples**

Risk exposures to PS and ΔFL funding shocks when the market liquidity is high (Hi Liq) or low (Lo Liq) as measured by the aggregate Amihud measure in the current month. The sample is divided into three equal-sized subsamples. For each subsample, we estimate the regression of returns on $\beta^{\Delta FL}$ and β^{PS}:

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

Panels (a) and (b) report results for illiquidity- and volatility-sorted portfolios, respectively, and with t-statistics reported in parentheses. Monthly data, Jan 1986 - Dec 2012.

Panel (a) Illiquidity Portfolios

		Most	2	3	4	5	6	7	8	9	Least
Lo Liq	$\beta^{\Delta FL}$	-7.50	-8.12	-8.78	-8.65	-8.36	-8.09	-8.15	-8.31	-7.02	-5.58
		(-6.26)	(-5.09)	(-5.57)	(-5.02)	(-5.09)	(-5.28)	(-4.99)	(-5.45)	(-4.94)	(-4.28)
	β^{PS}	-0.10	-0.27	-0.21	-0.25	-0.15	-0.08	-0.05	-0.07	0.00	-0.03
		(-1.03)	(-2.03)	(-1.57)	(-1.73)	(-1.08)	(-0.59)	(-0.35)	(-0.57)	(0.01)	(-0.26)
Hi Liq	$\beta^{\Delta FL}$	-0.82	-0.49	-0.03	-0.23	-0.09	-0.18	-0.91	-0.34	0.19	-0.10
		(-0.67)	(-0.35)	(-0.02)	(-0.17)	(-0.06)	(-0.14)	(-0.71)	(-0.27)	(0.17)	(-0.09)
	β^{PS}	-0.22	-0.22	-0.13	-0.15	-0.04	-0.09	-0.05	-0.05	-0.04	-0.02
		(-2.09)	(-1.80)	(-1.03)	(-1.25)	(-0.35)	(-0.84)	(-0.45)	(-0.50)	(-0.38)	(-0.18)
All	$\beta^{\Delta FL}$	-3.27	-3.30	-3.19	-3.24	-2.97	-3.10	-3.35	-3.36	-2.87	-2.35
		(-3.59)	(-3.43)	(-3.78)	(-3.95)	(-4.15)	(-3.88)	(-3.37)	(-3.88)	(-3.88)	(-3.88)
	β^{PS}	-0.02	-0.09	-0.02	-0.04	0.04	0.05	0.06	0.05	0.08	0.05
		(-0.55)	(0.52)	(0.64)	(0.80)	(0.73)	(1.21)	(0.75)	(-1.14)	(-1.14)	(-1.14)

Panel (b) Volatility Portfolios

		Most	2	3	4	5	6	7	8	9	Least
Lo Liq	$\beta^{\Delta FL}$	-9.43	-9.27	-8.79	-8.84	-8.22	-7.87	-8.18	-6.93	-6.48	-4.97
		(-4.12)	(-4.97)	(-5.19)	(-5.13)	(-5.25)	(-5.44)	(-5.82)	(-5.61)	(-5.69)	(-5.61)
	β^{PS}	-0.30	-0.22	-0.15	-0.15	-0.18	-0.08	-0.08	-0.08	0.01	0.01
		(-1.52)	(-1.39)	(-1.07)	(-1.03)	(-1.39)	(-0.62)	(-0.64)	(-0.75)	(0.07)	(0.12)
Hi Liq	$\beta^{\Delta FL}$	-0.07	-0.08	-0.68	-0.23	-0.05	-0.76	-0.44	-0.27	-0.01	-0.30
		(-0.04)	(-0.05)	(-0.44)	(-0.16)	(-0.04)	(-0.62)	(-0.38)	(-0.25)	(-0.01)	(-0.39)
	β^{PS}	-0.15	-0.17	-0.15	-0.14	-0.08	-0.08	-0.06	-0.09	-0.06	-0.01
		(-0.97)	(-1.27)	(-1.18)	(-1.21)	(-0.69)	(-0.71)	(-0.55)	(-0.93)	(-0.79)	(-0.17)
All	$\beta^{\Delta FL}$	-3.30	-3.52	-3.47	-3.44	-3.09	-3.30	-3.37	-2.81	-2.55	-2.26
		(-3.81)	(-3.65)	(-4.26)	(-4.50)	(-4.16)	(-4.22)	(-4.70)	(-3.53)	(-3.53)	(-3.53)
	β^{PS}	-0.04	-0.01	0.01	0.01	0.00	0.03	0.05	0.02	0.05	0.04
		(0.11)	(-0.04)	(0.49)	(0.67)	(0.40)	(0.91)	(0.98)	(-0.08)	(-0.08)	(-0.08)

Table 9: **Alternative Test Assets**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions of decile portfolios sorted by size, value, beta and momentum. The prices-of-risk estimates are annualized ($\times 12$). The confidence intervals for R^2s are based on 5,000 bootstrap replicates. For the specifications that include traded portfolios as factors, those factors are also included as test assets. Monthly data, January 1986 - March 2012.

	CAPM	FF3	ΔFL	ΔFL^m	Augmented by ΔFL		Augmented by ΔFL^m	
α	10.96	-1.75	0.12	-0.71	0.70	-2.81	-0.43	-1.63
t-FM	(3.64)	(-1.45)	(0.02)	(-0.75)	(0.15)	(-2.52)	(-0.41)	(-2.55)
t-Sh.	(3.64)	(-1.37)	(0.02)	(-0.67)	(0.10)	(-2.18)	(-0.30)	(-2.25)
ΔFL			-3.23		-4.78	-2.21		
t-FM			(-1.74)		(-3.08)	(-2.09)		
t-Sh.			(-1.39)		(-2.06)	(-1.82)		
ΔFL^m				-1.28			-2.20	-1.29
t-FM				(-3.08)			(-5.54)	(-3.11)
t-Sh.				(-2.79)			(-4.30)	(-2.78)
MKT	-0.62	6.33			6.25	7.35	5.90	6.22
t-FM	(-0.14)	(1.87)			(1.14)	(2.21)	(1.61)	(1.89)
t-Sh.	(-0.14)	(1.86)			(0.84)	(2.18)	(1.47)	(1.87)
SMB			3.99			3.71		3.35
t-FM			(1.47)			(1.38)		(1.25)
t-Sh.			(1.44)			(1.32)		(1.20)
HML			8.84			9.28		8.21
t-FM			(3.58)			(3.83)		(3.34)
t-Sh.			(3.53)			(3.71)		(3.24)
$\bar{R}^2_c$	-2.6%	66.7%	20.4%	32.5%	31.1%	69.6%	62.2%	74.8%
R^2_c	0.0%	69.3%	22.4%	34.3%	34.6%	72.7%	64.1%	77.4%
R^2	0.2%	75.0%	22.4%	55.0%	38.6%	78.3%	75.3%	84.1%
C.I.	[0.0, 2.2]	[45.1, 84.7]	[0.5, 54.9]	[25.2, 83.5]	[7.7, 61.4]	[59.2, 86.2]	[56.5, 85.2]	[66.6, 88.6]
$\bar{R}^2$	-2.4%	73.0%	20.4%	53.8%	35.4%	76.0%	74.0%	82.4%
C.I.	[-2.6, -0.4]	[33.6, 83.4]	[-2.1, 53.8]	[23.0, 83.1]	[3.7, 59.7]	[48.5, 84.2]	[54.5, 84.0]	[64.0, 88.0]

Table 10: **Double-Sorted Volatility and Liquidity Portfolios**

Cross-sectional asset pricing tests for 10×5 double-sorted illiquidity- and volatility-sorted portfolios based on two-stage Fama-MacBeth regressions. The estimated prices of risk are annualized (multiplied by 12). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Monthly data, January 1986 - March 2012.

	CAPM	FF3	ΔFL	ΔFL^m	Augmented by ΔFL		Augmented by ΔFL^m	
α	7.32	1.73	1.36	-0.42	1.17	0.38	-0.44	-0.03
t-FM	(2.90)	(1.26)	(0.52)	(-0.26)	(0.41)	(0.35)	(-0.27)	(-0.04)
t-Sh.	(2.90)	(1.21)	(0.42)	(-0.23)	(0.32)	(0.31)	(-0.22)	(-0.03)
ΔFL			-3.01		-3.42	-2.00		
t-FM			(-2.20)		(-3.56)	(-2.75)		
t-Sh.			(-1.80)		(-2.81)	(-2.48)		
ΔFL^m				-1.29			-1.64	-1.26
t-FM				(-2.85)			(-4.69)	(-3.96)
t-Sh.				(-2.57)			(-4.04)	(-3.60)
MKT	3.43	3.86			7.39	5.31	7.61	5.68
t-FM	(0.81)	(1.09)			(1.63)	(1.54)	(1.93)	(1.68)
t-Sh.	(0.81)	(1.08)			(1.41)	(1.51)	(1.80)	(1.66)
SMB		4.92				5.73		5.80
t-FM		(1.95)				(2.30)		(2.31)
t-Sh.		(1.94)				(2.25)		(2.27)
HML		6.29				5.91		4.68
t-FM		(2.44)				(2.30)		(1.86)
t-Sh.		(2.41)				(2.22)		(1.80)
$\bar{R}_c^2$	4.5%	59.7%	22.7%	34.2%	21.4%	60.0%	36.8%	66.6%
R_c^2	6.5%	62.2%	24.3%	35.5%	24.6%	63.3%	39.3%	69.4%
R^2	6.1%	63.0%	24.3%	47.4%	26.2%	66.8%	51.5%	77.0%
C.I.	[0.1, 21.9]	[39.2, 70.7]	[7.5, 45.0]	[25.1, 69.8]	[8.3, 46.6]	[50.6, 72.3]	[27.4, 71.4]	[64.2, 83.0]
$\bar{R}^2$	4.2%	60.7%	22.7%	46.3%	23.1%	64.0%	49.5%	75.1%
C.I.	[-2.0, 20.3]	[37.1, 69.7]	[4.9, 43.9]	[23.7, 68.2]	[3.6, 42.9]	[46.6, 70.0]	[23.6, 69.6]	[59.9, 81.8]

Table 11: **Pricing Volatility and Liquidity Portfolios – Quarterly Returns**

Cross-sectional asset pricing tests for illiquidity- and volatility-sorted portfolios based on two-stage Fama-MacBeth regressions. The estimated prices of risk are annualized (multiplied by 4). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Quarterly data, 1986Q1 - 2012Q1.

	CAPM	FF3	ΔFL	ΔFL^m	LevFact	Augmented by ΔFL			Augmented by ΔFL^m		
α	3.61	-2.58	1.46	0.15	12.08	1.81	-1.37	1.57	0.45	-0.55	0.72
t-FM	(1.29)	(-0.99)	(0.16)	(0.17)	(2.79)	(0.61)	(-1.71)	(0.62)	(0.48)	(-1.19)	(1.22)
t-Sh.	(1.27)	(-0.94)	(0.14)	(0.14)	(2.67)	(0.44)	(-1.32)	(0.51)	(0.39)	(-1.01)	(0.99)
ΔFL			-1.75			-2.45	-2.06	-1.70			
t-FM			(-2.20)			(-3.03)	(-2.69)	(-2.22)			
t-Sh.			(-1.84)			(-2.20)	(-2.12)	(-1.84)			
ΔFL^m				-0.99					-1.22	-1.01	-1.00
t-FM				(-2.85)					(-3.50)	(-2.87)	(-2.84)
t-Sh.				(-2.52)					(-2.93)	(-2.52)	(-2.39)
LevFact					-21.50			-10.45			-19.50
t-FM					(-0.97)			(-0.52)			(-0.76)
t-Sh.					(-0.93)			(-0.44)			(-0.62)
MKT	7.14	8.53				4.12	8.01		5.97	7.33	
t-FM	(1.49)	(2.36)				(0.92)	(2.22)		(1.60)	(2.06)	
t-Sh.	(1.47)	(2.35)				(0.79)	(2.18)		(1.54)	(2.04)	
SMB		5.37					5.52			5.36	
t-FM		(2.36)					(2.43)			(2.38)	
t-Sh.		(2.34)					(2.34)			(2.34)	
HML		4.58					4.58			3.61	
t-FM		(1.52)					(1.53)			(1.22)	
t-Sh.		(1.52)					(1.50)			(1.21)	
$\bar{R}_c^2$	26.2%	51.9%	62.8%	61.6%	-3.4%	69.5%	57.3%	61.5%	62.2%	67.4%	64.8%
R_c^2	30.1%	59.5%	64.7%	63.6%	2.0%	72.7%	66.3%	65.5%	66.2%	74.3%	68.5%
R^2	23.2%	79.9%	64.7%	83.8%	2.0%	76.1%	84.4%	65.5%	85.7%	90.4%	86.0%
C.I.	[0.6, 62.9]	[63.6, 86.3]	[38.6, 81.7]	[56.3, 96.0]	[0.0, 21.4]	[48.1, 85.9]	[71.3, 88.8]	[36.6, 81.2]	[64.5, 95.9]	[78.2, 93.8]	[60.4, 97.3]
$\bar{R}^2$	19.2%	76.7%	62.8%	82.9%	-3.4%	73.4%	81.0%	61.5%	84.2%	88.4%	84.5%
C.I.	[-5.1, 58.2]	[57.2, 84.6]	[34.4, 81.0]	[54.6, 90.1]	[-5.6, 16.3]	[46.2, 84.4]	[62.0, 86.1]	[30.2, 79.0]	[61.5, 95.8]	[67.6, 92.5]	[54.5, 96.7]

Table 12: **Pricing Size Portfolios – Quarterly Returns**

Cross-sectional asset pricing tests for size-sorted portfolios based on two-stage Fama-MacBeth regressions. The estimated prices of risk are annualized (multiplied by 4). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Quarterly data, 1986Q1 - 2012Q1.

	CAPM	FF3	ΔFL	ΔFL^m	LevFact	Augmented by ΔFL			Augmented by ΔFL^m		
α	16.65	-8.32	-15.88	-0.19	9.17	5.71	-3.19	-4.17	1.30	-0.42	0.06
t-FM	(4.13)	(-3.00)	(-1.00)	(-0.28)	(3.12)	(0.99)	(-3.51)	(-0.78)	(4.71)	(-0.84)	(0.10)
t-Sh.	(4.05)	(-2.79)	(-0.67)	(-0.24)	(3.02)	(0.68)	(-2.21)	(-0.49)	(3.42)	(-0.60)	(0.07)
ΔFL			-2.76			-2.56	-3.07	-2.89			
t-FM			(-2.69)			(-2.61)	(-4.67)	(-2.92)			
t-Sh.			(-1.84)			(-1.81)	(-3.08)	(-1.87)			
ΔFL^m				-1.03					-1.51	-1.59	-1.12
t-FM				(-3.14)					(-3.60)	(-4.67)	(-3.61)
t-Sh.				(-2.77)					(-2.72)	(-3.54)	(-2.77)
LevFact					17.85			-25.93			-39.13
t-FM					(0.50)			(-0.84)			(-1.29)
t-Sh.					(0.48)			(-0.54)			(-0.93)
MKT	-6.95	9.85				-0.41	8.91		3.76	6.66	
t-FM	(-1.19)	(2.66)				(-0.06)	(2.41)		(1.04)	(1.84)	
t-Sh.	(-1.18)	(2.64)				(-0.04)	(2.22)		(1.02)	(1.78)	
SMB		6.87					6.50			4.86	
t-FM		(2.97)					(2.81)			(2.14)	
t-Sh.		(2.93)					(2.53)			(2.03)	
HML		5.11					5.29			3.12	
t-FM		(1.66)					(1.72)			(1.04)	
t-Sh.		(1.65)					(1.61)			(1.02)	
$\bar{R}_c^2$	-15.7%	15.5%	63.5%	54.7%	-11.2%	77.6%	57.2%	62.3%	78.2%	63.2%	58.5%
R_c^2	-2.8%	43.6%	67.6%	59.8%	1.1%	82.6%	76.2%	70.6%	83.0%	79.5%	67.7%
R^2	3.5%	79.6%	67.6%	85.6%	1.1%	83.7%	91.3%	70.6%	93.0%	92.9%	88.5%
C.I.	[0.0, 24.7]	[42.7, 96.5]	[25.6, 89.7]	[49.2, 98.0]	[0.0, 11.6]	[25.5, 95.0]	[71.4, 94.6]	[15.7, 86.7]	[71.9, 98.7]	[81.6, 94.6]	[53.3, 97.8]
$\bar{R}^2$	-7.3%	72.7%	63.5%	84.0%	-11.2%	79.6%	86.9%	62.3%	91.5%	89.7%	85.6%
C.I.	[-11.1, 17.7]	[16.8, 94.8]	[17.0, 87.7]	[44.4, 97.8]	[-12.5, 1.0]	[-3.3, 93.5]	[59.0, 92.4]	[-7.1, 82.7]	[65.1, 98.3]	[75.1, 92.6]	[41.2, 97.0]

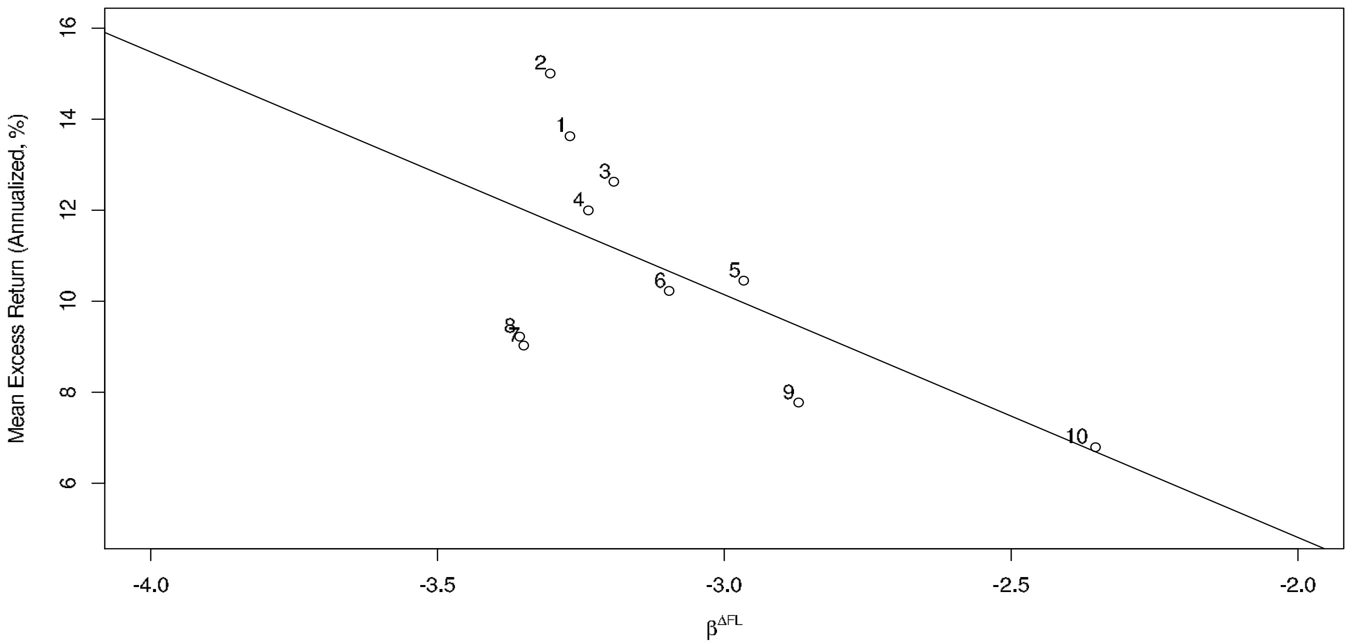
Table 13: **Pricing Book-to-Market Portfolios – Quarterly Returns**

Cross-sectional asset pricing tests for value-sorted portfolios based on two-stage Fama-MacBeth regressions. The estimated prices of risk are annualized (multiplied by 4). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Quarterly data, 1986Q1 - 2012Q1.

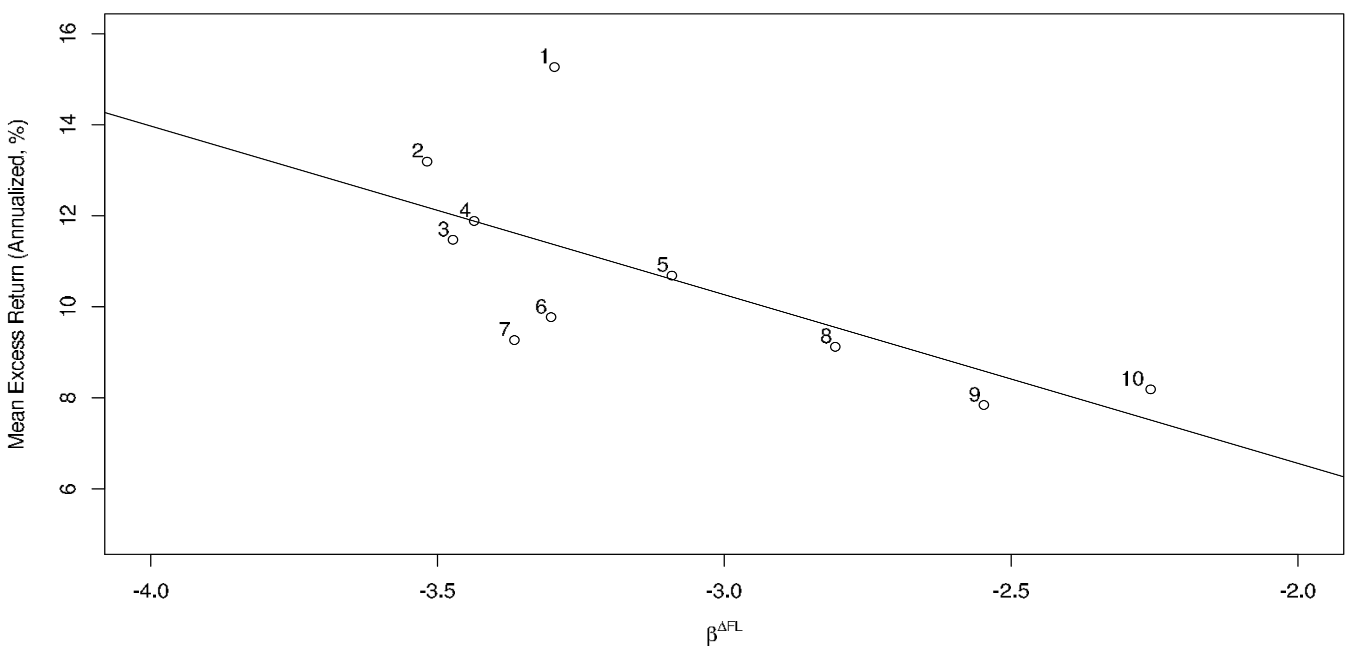
	CAPM	FF3	ΔFL	ΔFL^m	LevFact	Augmented by ΔFL			Augmented by ΔFL^m		
α	23.70	-12.43	-25.05	-0.90	4.01	14.72	1.13	-7.34	2.14	0.52	-0.08
t-FM	(4.25)	(-3.13)	(-1.31)	(-1.36)	(0.70)	(2.90)	(0.58)	(-1.18)	(3.20)	(0.54)	(-0.18)
t-Sh.	(4.04)	(-2.84)	(-0.93)	(-1.18)	(0.34)	(1.91)	(0.20)	(-0.57)	(2.05)	(0.24)	(-0.09)
ΔFL			-2.51			-2.45	-6.46	-1.81			
t-FM			(-2.54)			(-3.08)	(-4.57)	(-1.85)			
t-Sh.			(-1.82)			(-2.09)	(-1.58)	(-0.91)			
ΔFL^m				-0.95					-1.87	-3.16	-0.93
t-FM				(-2.64)					(-4.31)	(-4.49)	(-2.58)
t-Sh.				(-2.35)					(-2.89)	(-2.01)	(-1.42)
LevFact					124.87			119.56			116.76
t-FM					(3.37)			(3.21)			(3.00)
t-Sh.					(1.66)			(1.56)			(1.54)
MKT	-11.31	8.49				-9.77	3.42		1.18	4.96	
t-FM	(-1.80)	(2.35)				(-1.56)	(0.88)		(0.29)	(1.37)	
t-Sh.	(-1.74)	(2.33)				(-1.13)	(0.56)		(0.25)	(1.18)	
SMB		3.98					-0.65			1.66	
t-FM		(1.63)					(-0.23)			(0.68)	
t-Sh.		(1.59)					(-0.11)			(0.49)	
HML		10.98					4.03			4.56	
t-FM		(3.27)					(1.14)			(1.41)	
t-Sh.		(3.19)					(0.62)			(1.06)	
$\bar{R}^2_c$	29.4%	53.2%	12.4%	22.9%	85.5%	88.7%	57.6%	93.7%	91.5%	60.6%	89.0%
R^2_c	37.2%	68.8%	22.1%	31.5%	87.1%	91.2%	76.5%	95.1%	93.4%	78.1%	91.4%
R^2	22.0%	70.9%	22.1%	61.7%	87.1%	90.5%	81.1%	95.1%	92.3%	87.2%	95.2%
C.I.	[0.0, 87.7]	[35.7, 85.5]	[0.1, 76.6]	[6.3, 87.8]	[57.9, 97.2]	[77.2, 97.3]	[72.0, 82.2]	[74.9, 98.8]	[75.2, 97.9]	[83.3, 88.5]	[67.8, 97.4]
$\bar{R}^2$	13.4%	61.1%	12.4%	57.4%	85.5%	88.1%	71.7%	93.7%	90.6%	81.5%	94.0%
C.I.	[-11.1, 87.8]	[17.3, 80.7]	[-12.4, 75.2]	[-4.9, 85.2]	[52.7, 96.5]	[67.1, 96.8]	[50.4, 73.4]	[68.8, 98.4]	[68.0, 97.5]	[77.0, 83.7]	[54.8, 96.7]

Figure 1: Average Returns and Funding Risk β

(a) Liquidity Portfolios

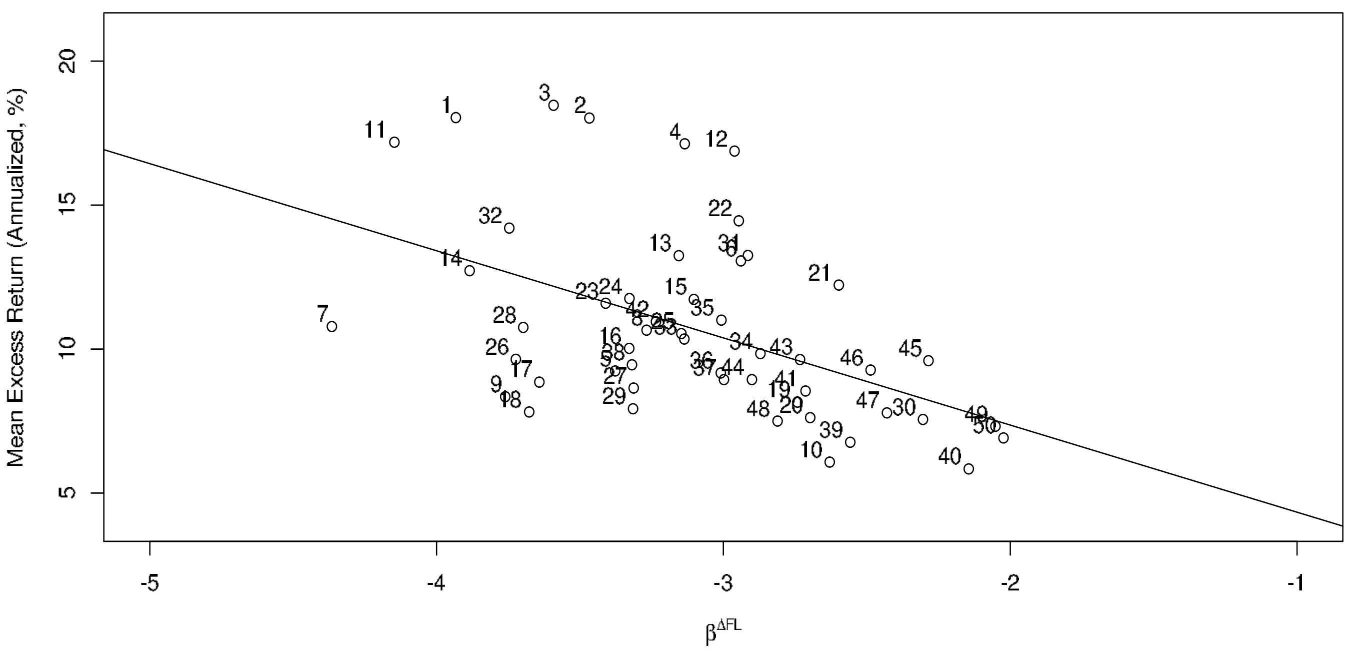


(b) Volatility Portfolios



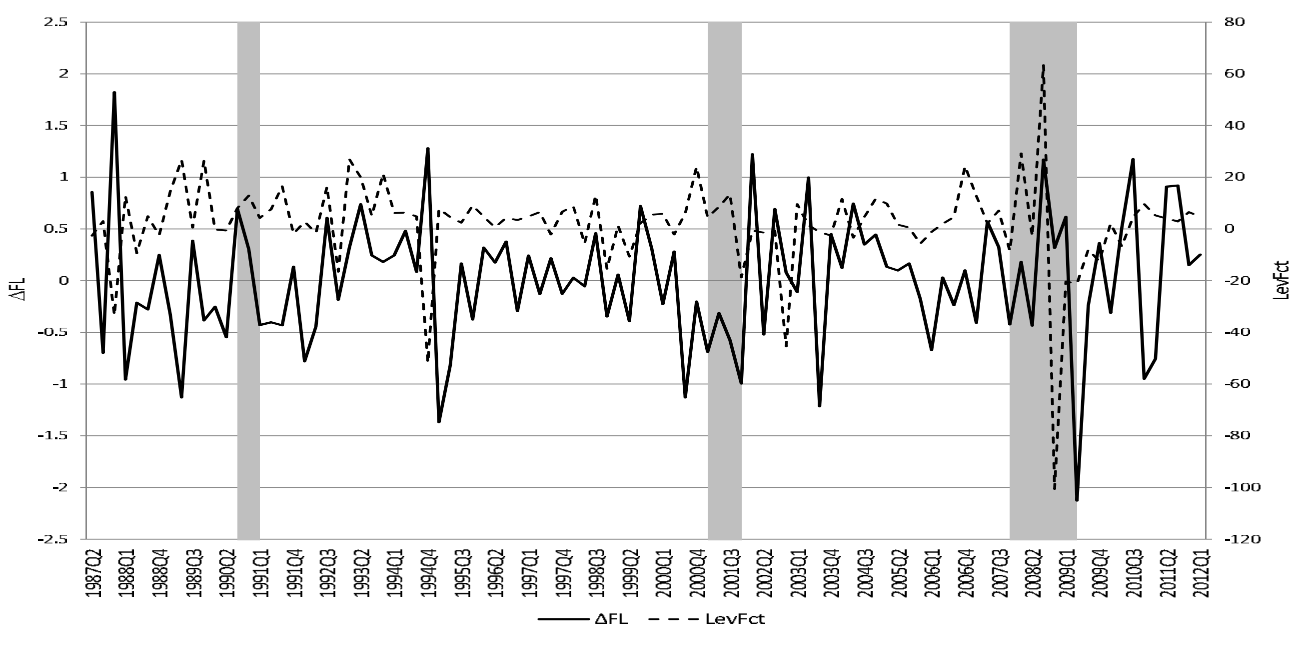
Average excess returns against funding liquidity factor betas $\beta^{\Delta FL}$ obtained from $r_{it} = a_i + \beta_i^{\Delta FL} \Delta FL_t + \varepsilon_{it}$. Panel (a) reports the results for the liquidity-sorted portfolios. Panel (b) reports the results for the volatility-sorted portfolios. Portfolios 1 and 10 are the most and least risky, respectively. Monthly data, January 1986 - March 2012.

Figure 2: Average Returns and Funding Risk β in Double-Sorted Portfolios



Average returns and funding liquidity beta, $\beta^{\Delta FL}$ for 10×5 double-sorted illiquidity and volatility portfolios from the regression $r_{it} = \alpha_i + \beta_i^{\Delta FL} \Delta FL_t + \varepsilon_{it}$. Portfolios 1 and 10 are the most and least risky, respectively. Monthly data, January 1986 - March 2012.

Figure 3: ΔFL and Broker-Dealer Leverage



Funding shocks ΔFL and the leverage factor $LevFact$. NBER recessions are shaded. Quarterly data from 1986Q1 - 2012Q1.

Table A.1: **Summary Statistics – Alternative Illiquidity and Volatility Portfolios**
Time-series average of each portfolio's Amihud illiquidity ratio, realized volatility, capitalization, returns and market β. The Amihud illiquidity measure is the median ratio in a portfolio ($\times 100$). The volatility, capitalization and average returns measures are computed as the equal-weighted average within each portfolio, in \$ billions or annualized %. The average stocks' β, $\beta^{i,illiq}$ and $\beta^{i,vol}$ are computed 5-year and 1-year rolling windows to estimate the covariance and variance, respectively. The ex-ante portfolio CAPM and FF3 α's, as well as the Sharpe ratios, are estimated using the full sample. Monthly data, January 1986 - March 2012.

Panel (a) $\beta^{i,illiq}$-Sorted Portfolios

	High	2	3	4	5	6	7	8	9	Low
	Average Security Statistics									
Illiqu.	3.33	2.34	2.05	1.38	1.21	1.35	1.28	1.21	1.33	1.89
Vol.	29.29	26.13	24.85	24.01	23.73	23.60	23.47	23.48	23.14	26.60
Cap.	3.15	4.78	5.21	6.92	7.87	7.35	7.28	8.01	6.99	6.10
E(R)	17.39	15.55	13.67	12.49	14.33	12.89	13.08	13.73	13.27	14.55
β	0.98	0.94	0.92	0.91	0.91	0.90	0.89	0.88	0.87	0.92
$\beta^{i,L}$	-3.48	-2.16	-1.62	-1.24	-0.89	-0.60	-0.28	0.06	0.49	1.42
β^{i,σ_m}	-0.03	0.01	0.02	0.04	0.05	0.05	0.06	0.06	0.07	0.09
	Portfolio Statistics									
CAPM α	6.31	5.49	3.93	2.81	4.66	3.37	3.92	4.55	3.93	4.24
	2.94	3.05	2.27	1.80	2.84	2.14	2.45	3.13	2.47	2.58
FF3 α	3.81	3.15	1.69	0.83	2.25	1.09	1.67	2.44	1.60	2.33
	2.27	2.33	1.27	0.67	1.94	0.97	1.42	2.34	1.42	1.84
Sharpe R.	0.19	0.19	0.17	0.15	0.18	0.16	0.17	0.19	0.17	0.17

Panel (b) $\beta^{i,vol}$-Sorted Portfolios

	High	2	3	4	5	6	7	8	9	Low
	Average Security Statistics									
Illiqu.	3.10	1.63	1.52	1.21	1.19	1.22	1.22	1.63	1.95	3.89
Vol.	30.04	25.78	23.78	22.85	22.50	22.27	22.66	24.09	25.43	29.18
Cap.	4.26	7.10	8.64	8.05	7.82	6.99	6.26	6.41	4.81	3.18
E(R)	18.16	15.80	15.31	14.48	12.87	12.96	12.94	11.62	12.12	14.66
β	0.97	0.93	0.90	0.89	0.89	0.88	0.89	0.91	0.93	0.96
$\beta^{i,L}$	-1.53	-1.13	-0.98	-0.88	-0.76	-0.67	-0.65	-0.65	-0.57	-0.49
β^{i,σ_m}	-0.30	-0.11	-0.05	-0.01	0.02	0.06	0.10	0.14	0.20	0.39
	Portfolio Statistics									
CAPM α	7.11	5.85	5.94	5.01	3.50	3.66	3.78	2.07	2.18	3.98
	2.88	3.11	3.51	3.20	2.18	2.34	2.51	1.29	1.24	2.07
FF3 α	4.34	3.56	3.75	2.86	1.25	1.47	1.72	-0.14	0.02	1.89
	2.15	2.35	2.82	2.42	1.05	1.27	1.52	-0.12	0.01	1.33
Sharpe R.	0.19	0.19	0.20	0.19	0.16	0.17	0.17	0.14	0.14	0.16

Table A.2: **Correlations – Funding and Market Illiquidity Risk**

Correlation between liquidity proxies: ΔFL is our measure of funding shocks, ΔFL^m is the corresponding mimicking portfolio returns, BAB is the betting-against-beta factor, ΔAm is the market Amihud measure, PS is the traded liquidity risk factor, TED is the spread between the three-month LIBOR and U.S. Treasury rates, MKT is the market returns, SMB is the size factor returns and the HML is the value factor returns.

Panel (a) Factor Correlations

	ΔFL	ΔFL^m	MKT	SMB	HML	BAB	ΔAm	PS	ΔTED
ΔFL	1.00								
ΔFL^m	0.60	1.00							
MKT	-0.19	-0.31	1.00						
SMB	-0.07	-0.08	0.25	1.00					
HML	-0.10	-0.15	-0.28	-0.33	1.00				
BAB	-0.15	-0.18	-0.26	-0.19	0.50	1.00			
ΔAm	0.08	0.16	-0.33	-0.22	0.11	0.00	1.00		
PS	0.00	0.06	0.01	-0.03	-0.07	0.06	-0.04	1.00	
ΔTED	0.30	0.24	-0.15	-0.10	0.02	-0.19	0.07	-0.13	1.00

Panel (b) β Correlations – Illiquidity Portfolios

	$\hat{\beta}^{\Delta FL}$	$\hat{\beta}^{BAB}$	$\hat{\beta}^{\Delta Am}$	$\hat{\beta}^{PS}$	$\hat{\beta}^{\Delta TED}$
$\hat{\beta}^{\Delta FL}$	1.00				
$\hat{\beta}^{BAB}$	-0.27	1.00			
$\hat{\beta}^{\Delta Am}$	0.54	0.42	1.00		
$\hat{\beta}^{PS}$	0.39	-0.12	0.13	1.00	
$\hat{\beta}^{\Delta TED}$	0.74	-0.51	0.44	0.13	1.00

Panel (c) β Correlations – Volatility Portfolios

	$\hat{\beta}^{\Delta FL}$	$\hat{\beta}^{BAB}$	$\hat{\beta}^{\Delta Am}$	$\hat{\beta}^{PS}$	$\hat{\beta}^{\Delta TED}$
$\hat{\beta}^{\Delta FL}$	1.00				
$\hat{\beta}^{BAB}$	0.70	1.00			
$\hat{\beta}^{\Delta Am}$	0.89	0.90	1.00		
$\hat{\beta}^{PS}$	0.51	0.90	0.81	1.00	
$\hat{\beta}^{\Delta TED}$	0.77	0.78	0.92	0.75	1.00

Table A.3: **Double-Sorted Illiquidity and Volatility Portfolios – Alternative Liquidity Factors**

Cross-sectional asset pricing tests in double-sorted illiquidity and volatility portolios based on two-stage regressions. BAB is the betting-against-beta factor, ΔAm is the market illiquidity ratio, PS is the traded liquidity risk factor, TED is the spread between the three-month LIBOR and U.S. Treasury rates. The estimated prices of risk are annualized (multiplied by 4). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Monthly data, January 1986 - March 2012.

	Panel (a) Alternative Proxies				Panel (b) Augmented Models			
α	10.42	5.22	10.97	3.72	1.96	1.29	5.99	0.72
t-FM	(3.43)	(2.23)	(3.22)	(2.27)	(0.77)	(0.48)	(2.77)	(0.45)
t-Sh.	(3.42)	(2.17)	(3.14)	(1.94)	(0.64)	(0.41)	(2.57)	(0.37)
ΔFL					-2.85	-2.42	-1.59	-2.96
t-FM					(-3.02)	(-3.22)	(-1.25)	(-2.90)
t-Sh.					(-2.54)	(-2.82)	(-1.16)	(-2.40)
BAB	-3.20				5.15			
t-FM	(-0.70)				(1.30)			
t-Sh.	(-0.70)				(1.17)			
ΔAm		-0.16				-0.09		
t-FM		(-1.41)				(-0.80)		
t-Sh.		(-1.37)				(-0.70)		
PS			-10.94				-6.51	
t-FM			(-2.48)				(-1.80)	
t-Sh.			(-2.44)				(-1.74)	
ΔTED				-0.14				-0.07
t-FM				(-2.34)				(-1.58)
t-Sh.				(-2.01)				(-1.31)
$\bar{R}^2_c$	4.3%	15.4%	25.4%	10.7%	20.6%	22.4%	32.3%	21.4%
R^2_c	6.2%	17.2%	26.9%	12.5%	23.9%	25.6%	35.0%	24.6%
R^2	5.6%	17.2%	24.8%	25.8%	23.1%	25.6%	31.4%	37.6%
C.I.	[0.0, 21.7]	[3.9, 36.0]	[14.5, 46.1]	[6.1, 56.6]	[7.1, 42.1]	[7.4, 42.5]	[19.8, 62.1]	[14.5, 64.5]
$\bar{R}^2$	3.7%	15.4%	23.3%	24.2%	19.9%	22.4%	28.6%	35.0%
C.I.	[-2.0, 19.5]	[1.7, 34.8]	[10.9, 45.7]	[4.2, 55.1]	[2.9, 38.1]	[3.7, 39.0]	[16.7, 61.8]	[10.8, 62.8]

Table A.4: **Time-Series Regressions – Quarterly Returns**

Time-series regression of portfolio returns on funding shocks and market returns, $r_{it} = \alpha_i + \beta_i^{\Delta FL} \Delta FL_t + \beta_i^{MKT} MKT_t + \varepsilon_{it}$. Panel (a) reports results for illiquidity-sorted decile portfolios, with t-statistics in parentheses. Panel (b) reports results for volatility-sorted decile portfolios. Quarterly data, 1986Q2 - 2012Q1.

Panel (a) Illiquidity Portfolios

	Most	2	3	4	5	6	7	8	9	Least
$\beta^{\Delta FL}$	-2.95	-3.08	-1.99	-2.48	-2.27	-1.95	-2.29	-1.71	-1.39	-0.48
	(-3.54)	(-3.05)	(-2.03)	(-2.46)	(-2.52)	(-2.60)	(-3.18)	(-2.76)	(-2.38)	(-1.34)
β^{MKT}	0.70	0.84	0.94	0.95	0.95	0.89	0.95	0.94	0.86	0.85
	(11.70)	(11.52)	(13.28)	(13.13)	(14.60)	(16.41)	(18.29)	(21.14)	(20.62)	(33.12)
R^2	66.31%	64.80%	68.95%	69.09%	73.18%	77.30%	81.09%	84.69%	83.88%	92.71%

Panel (b) Volatility-Sorted Portfolios

	Most	2	3	4	5	6	7	8	9	Least
$\beta^{\Delta FL}$	-2.40	-2.47	-2.58	-2.18	-1.88	-2.23	-2.11	-1.75	-1.68	-1.22
	(-2.04)	(-2.55)	(-3.18)	(-2.71)	(-2.35)	(-3.05)	(-3.04)	(-2.69)	(-2.65)	(-1.89)
β^{MKT}	1.21	1.09	1.03	1.02	0.93	0.88	0.84	0.76	0.66	0.51
	(14.20)	(15.64)	(17.63)	(17.58)	(16.08)	(16.67)	(16.87)	(16.13)	(14.48)	(11.00)
R^2	71.60%	75.66%	80.02%	79.57%	76.42%	78.21%	78.58%	76.82%	73.03%	60.76%

Table A.5: **Conditional Average Liquidity and Volatility**

Average illiquidity ($\times 100$) and volatility (annualized %) of liquidity-sorted and volatility-sorted portfolios conditional on the level of lagged funding liquidity risk FL_{t-1}. Panel (a) reports averages when ΔFL is in the bottom tercile of the empirical distribution (low FL_{t-1}). Panel (b) reports averages when ΔFL is in the top tercile (high FL_{t-1}). Panel (c) reports differences between each average. Quarterly data, 1986Q1-2012Q1.

Panel (a) Low FL_{t-1}

	Illiquidity Portfolios			Volatility Portfolios	
	Illiquidity	Volatility		Illiquidity	Volatility
Most	247.75	9.00	Most	8.87	12.56
2	46.29	9.45	2	5.68	10.82
3	16.35	9.06	3	3.32	9.95
4	7.01	9.17	4	3.17	9.17
5	3.15	8.62	5	2.15	8.53
6	1.63	8.15	6	1.54	7.90
7	0.93	8.18	7	1.33	7.38
8	0.49	7.99	8	1.04	6.88
9	0.25	7.53	9	1.49	6.13
Least	0.09	7.14	Least	2.92	5.17

Panel (b) High FL_{t-1}

	Illiquidity Portfolios			Volatility Portfolios	
	Illiquidity	Volatility		Illiquidity	Volatility
Most	384.18	10.73	Most	17.63	13.81
2	57.28	10.98	2	9.50	12.55
3	22.03	10.80	3	5.61	11.77
4	10.03	10.55	4	4.19	10.83
5	4.87	10.18	5	2.60	10.25
6	2.42	9.89	6	2.22	9.67
7	1.31	9.71	7	2.02	9.12
8	0.69	9.55	8	1.63	8.35
9	0.34	9.04	9	1.64	7.64
Least	0.11	8.65	Least	2.39	6.33

Panel (c) High FL_{t-1} - Low FL_{t-1}

	Illiquidity Portfolios			Volatility Portfolios	
	Illiquidity	Volatility		Illiquidity	Volatility
Most	136.43	1.74	Most	8.76	1.24
2	10.99	1.53	2	3.81	1.74
3	5.68	1.74	3	2.29	1.82
4	3.01	1.38	4	1.02	1.66
5	1.72	1.56	5	0.45	1.72
6	0.79	1.74	6	0.68	1.77
7	0.38	1.52	7	0.69	1.74
8	0.19	1.56	8	0.59	1.47
9	0.09	1.51	9	0.16	1.50
Least	0.02	1.51	Least	-0.52	1.16

Table A.6: **Time-series CAPM Regressions – Quarterly Returns**

Time-series regression of size and book-to-market portfolio returns on the funding liquidity innovations, ΔFL_t and the market returns, MKT_t: $r_{it} = \alpha_i + \beta_i^{\Delta FL}\Delta FL_t + \beta_i^{MKT} MKT_t + \varepsilon_{it}$. Quarterly data, 1986Q1 - 2012Q1.

Panel (a) Augmented by ΔFL

	β^{FL}					β^{MKT}					R^2				
	Small	2	3	4	Big	Small	2	3	4	Big	Small	2	3	4	Big
Low	-3.00	-0.99	-0.42	0.48	0.32	1.52	1.47	1.42	1.32	1.12	58.55%	78.21%	80.06%	82.16%	92.32%
	(-1.51)	(-0.86)	(-0.40)	(0.53)	(0.68)	(10.63)	(17.54)	(18.72)	(20.33)	(32.81)					
2	-3.85	-2.23	-1.54	-1.93	-1.92	1.26	1.17	1.15	1.02	0.94	64.31%	77.40%	82.63%	82.02%	87.81%
	(-2.56)	(-2.27)	(-1.92)	(-2.63)	(-3.53)	(11.63)	(16.59)	(19.86)	(19.15)	(23.97)					
3	-3.34	-2.69	-2.41	-2.74	-1.89	1.07	1.03	0.97	1.02	0.89	65.26%	77.02%	77.20%	79.36%	78.95%
	(-2.66)	(-3.02)	(-2.92)	(-3.33)	(-2.64)	(11.85)	(16.07)	(16.21)	(17.18)	(17.26)					
4	-3.64	-2.57	-2.47	-2.48	-2.01	0.95	0.99	0.99	0.95	0.86	62.90%	71.13%	72.50%	78.05%	73.57%
	(-3.05)	(-2.57)	(-2.57)	(-3.10)	(-2.49)	(10.99)	(13.79)	(14.31)	(16.56)	(14.77)					
High	-4.46	-3.80	-2.92	-3.19	-2.52	1.08	1.16	0.99	1.08	0.84	56.06%	65.46%	62.96%	69.93%	64.95%
	(-2.81)	(-2.79)	(-2.40)	(-2.81)	(-2.57)	(9.44)	(11.84)	(11.33)	(13.26)	(11.80)					

Panel (b) Augmented by ΔFL^m

	β^{FL}					β^{MKT}					R^2				
	Small	2	3	4	Big	Small	2	3	4	Big	Small	2	3	4	Big
Low	-1.74	0.20	-0.32	1.40	0.54	1.55	1.49	1.42	1.33	1.12	57.71%	78.05%	80.04%	82.29%	92.33%
	(-0.56)	(0.11)	(-0.20)	(1.01)	(0.74)	(10.55)	(17.42)	(18.38)	(20.20)	(32.22)					
2	-4.12	-3.19	-3.14	-3.89	-3.33	1.28	1.17	1.13	0.99	0.92	63.05%	77.23%	83.11%	82.89%	88.20%
	(-1.73)	(-2.09)	(-2.56)	(-3.50)	(-4.02)	(11.32)	(16.12)	(19.40)	(18.79)	(23.50)					
3	-4.86	-4.32	-3.91	-4.06	-2.84	1.06	1.01	0.95	1.01	0.88	64.97%	77.19%	77.39%	79.16%	78.86%
	(-2.49)	(-3.15)	(-3.07)	(-3.17)	(-2.55)	(11.45)	(15.58)	(15.72)	(16.60)	(16.74)					
4	-5.64	-4.63	-5.06	-4.40	-3.66	0.93	0.97	0.96	0.93	0.84	62.89%	71.82%	73.89%	78.74%	74.21%
	(-3.05)	(-3.02)	(-3.48)	(-3.62)	(-2.96)	(10.58)	(13.37)	(13.93)	(16.13)	(14.34)					
High	-6.25	-6.05	-4.76	-5.16	-4.01	1.07	1.14	0.97	1.07	0.82	55.41%	65.61%	63.20%	70.15%	65.07%
	(-2.52)	(-2.88)	(-2.54)	(-2.94)	(-2.63)	(9.11)	(11.43)	(10.94)	(12.82)	(11.40)					

Table A.7: **Pricing Size and Book-to-Market Portfolios – Quarterly Returns**

Cross-sectional asset pricing tests for size- and value-sorted portfolios based on two-stage Fama-MacBeth regressions. The estimated prices of risk are annualized (multiplied by 4). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Quarterly data, 1986Q1 - 2012Q1.

	CAPM	FF3	ΔFL	ΔFL^m	LevFact	Augmented by ΔFL			Augmented by ΔFL^m		
α	13.90	30.82	4.86	-1.02	6.69	10.13	10.30	1.01	4.93	6.03	-0.77
t-FM	(2.32)	(4.45)	(0.38)	(-0.24)	(1.48)	(1.73)	(4.44)	(0.23)	(1.16)	(4.30)	(-0.18)
t-Sh.	(2.30)	(4.23)	(0.35)	(-0.21)	(1.26)	(1.54)	(3.99)	(0.19)	(1.01)	(3.65)	(-0.16)
ΔFL			-1.08			-1.13	-0.95	-0.99			
t-FM			(-1.99)			(-2.10)	(-1.73)	(-1.85)			
t-Sh.			(-1.86)			(-1.91)	(-1.59)	(-1.62)			
ΔFL^m				-0.87					-0.89	-0.93	-0.86
t-FM				(-2.62)					(-2.67)	(-2.60)	(-2.58)
t-Sh.				(-2.38)					(-2.39)	(-2.28)	(-2.28)
LevFact					42.12			35.77			28.24
t-FM					(2.26)			(2.00)			(1.61)
t-Sh.					(1.97)			(1.73)			(1.41)
MKT	-4.47	-5.18				-3.42	-4.72		0.95	-0.28	
t-FM	(-0.70)	(-1.20)				(-0.53)	(-1.11)		(0.18)	(-0.07)	
t-Sh.	(-0.69)	(-1.17)				(-0.49)	(-1.07)		(0.16)	(-0.07)	
SMB		3.76					3.14			3.06	
t-FM		(1.52)					(1.30)			(1.26)	
t-Sh.		(1.50)					(1.26)			(1.21)	
HML		3.77					1.89			1.99	
t-FM		(1.16)					(0.57)			(0.61)	
t-Sh.		(1.15)					(0.55)			(0.58)	
$\bar{R}^2_c$	2.2%	37.9%	20.0%	36.9%	17.0%	30.4%	43.3%	30.7%	45.0%	52.4%	40.3%
R^2_c	3.2%	39.7%	20.8%	37.5%	17.8%	31.9%	45.6%	32.1%	46.1%	54.3%	41.5%
R^2	3.1%	31.0%	20.8%	39.5%	17.8%	32.0%	38.8%	32.1%	47.2%	53.1%	43.4%
C.I.	[0.0, 17.2]	[9.9, 50.1]	[2.3, 54.2]	[13.2, 63.7]	[1.8, 35.4]	[5.5, 63.3]	[11.4, 60.1]	[12.7, 54.3]	[24.1, 70.4]	[24.3, 70.4]	[19.8, 63.8]
$\bar{R}^2$	2.1%	28.9%	20.0%	38.9%	17.0%	30.6%	36.3%	30.7%	46.1%	51.2%	42.3%
C.I.	[-1.0, 16.3]	[7.0, 49.2]	[16.6, 52.3]	[12.9, 63.8]	[0.7, 33.8]	[3.7, 62.8]	[8.5, 57.9]	[9.9, 53.2]	[22.7, 69.4]	[18.0, 68.7]	[17.8, 62.5]

Table A.8: **Pricing Illiquidity, Volatility and Size Portfolio – Quarterly Returns**

Cross-sectional asset pricing tests for illiquidity-, volatility- and size-sorted portfolios based on two-stage Fama-MacBeth regressions. The estimated prices of risk are annualized (multiplied by 4). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Quarterly data, 1986Q1 - 2012Q1.

	CAPM	FF3	ΔFL	ΔFL^m	LevFact	Augmented by ΔFL			Augmented by ΔFL^m		
α	4.51	-0.20	-2.21	-0.34	11.07	2.10	-1.22	0.19	0.60	-0.37	0.34
t-FM	(1.70)	(-0.08)	(-0.23)	(-0.29)	(3.09)	(0.71)	(-1.67)	(0.06)	(0.60)	(-0.87)	(0.37)
t-Sh.	(1.68)	(-0.07)	(-0.18)	(-0.24)	(3.07)	(0.48)	(-1.19)	(0.05)	(0.45)	(-0.70)	(0.29)
ΔFL			-1.96			-2.69	-2.44	-1.94			
t-FM			(-2.45)			(-3.17)	(-3.79)	(-2.42)			
t-Sh.			(-1.96)			(-2.19)	(-2.81)	(-1.93)			
ΔFL^m				-1.04					-1.40	-1.20	-1.05
t-FM				(-2.96)					(-3.68)	(-3.76)	(-2.97)
t-Sh.				(-2.59)					(-2.91)	(-3.18)	(-2.44)
LevFact					-7.86			-9.74			-22.87
t-FM					(-0.43)			(-0.53)			(-1.10)
t-Sh.					(-0.43)			(-0.43)			(-0.88)
MKT	6.25	7.65				3.25	7.41		5.02	6.72	
t-FM	(1.30)	(2.11)				(0.73)	(2.05)		(1.35)	(1.88)	
t-Sh.	(1.29)	(2.10)				(0.61)	(1.97)		(1.29)	(1.85)	
SMB		5.96					6.04			5.75	
t-FM		(2.63)					(2.66)			(2.55)	
t-Sh.		(2.61)					(2.53)			(2.48)	
HML		3.81					4.43			3.34	
t-FM		(1.26)					(1.46)			(1.12)	
t-Sh.		(1.26)					(1.42)			(1.11)	
$\bar{R}_c^2$	12.7%	55.5%	61.7%	61.1%	-3.3%	74.4%	66.9%	61.0%	68.4%	74.1%	64.7%
R_c^2	15.7%	60.1%	63.0%	62.5%	0.3%	76.2%	71.4%	63.7%	70.6%	77.7%	67.2%
R^2	12.6%	73.8%	63.0%	78.5%	0.3%	77.4%	82.7%	63.7%	83.8%	88.8%	81.5%
C.I.	[0.1, 42.8]	[51.7, 86.3]	[42.4, 78.4]	[55.9, 92.9]	[0.0, 2.8]	[59.3, 85.8]	[68.5, 87.6]	[40.8, 76.9]	[67.2, 94.2]	[76.9, 92.8]	[60.4, 94.0]
$\bar{R}^2$	9.6%	71.1%	61.7%	77.8%	-3.3%	75.8%	80.3%	61.0%	82.7%	87.3%	80.2%
C.I.	[-3.4, 41.3]	[37.1, 82.3]	[40.6, 77.8]	[53.4, 92.6]	[-3.6, -1.2]	[56.5, 84.7]	[65.8, 85.8]	[38.2, 75.8]	[65.0, 93.8]	[72.5, 92.0]	[57.5, 93.6]