Funding Liquidity Risk and the Cross-Section of Stock Returns

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Abstract

Intermediaries should transmit funding shocks to the cross-section of returns. Stocks that experience low returns when funding becomes scarce should exhibit higher illiquidity, higher volatility and ultimately a higher risk premium. This paper documents this mechanism empirically. We show that the illiquidity and volatility of individual portfolios are positively associated with the value of funding liquidity, a measure of funding scarcity, while the portfolio returns are negatively correlated. In addition, the cross-section dispersion of illiquidity, volatility, and returns widens when funding conditions deteriorate. We find that this risk is priced. The funding liquidity risk premium explains the cross-section of returns across liquidity-, volatility-, and size-sorted portfolios. Overall, our results provide strong support for the prediction that funding liquidity plays a significant role in the determination of equity liquidity, volatility, and risk premium.

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Introduction

Funding liquidity, market liquidity and volatility are closely connected. The value of funding liquidity, or the shadow cost of capital for financial intermediaries, changes over time, signalling varying degrees of uncertainty and illiquidity.[1] For instance, Vayanos (2004) proposes an equilibrium model where shocks to fund managers connect an asset volatility, its illiquidity and its risk premium. In Brunnermeier and Pedersen (2009), tighter funding conditions give constrained market-makers an incentive to avoid capital-intensive positions in high-margin securities: funding shocks raise the dispersion of equities illiquidity, volatility and returns.[2]

This paper's objective is to test and document the role of funding liquidity in the cross-section of stocks. We follow theory and look for the effect of funding shocks using portfolios of stocks sorted by their volatility and illiquidity. In our benchmark case, we use respectively the realized volatility and the Amihud measure (Amihud, 2002) to rank individual stocks. In every case, we use the measure of funding liquidity from Fontaine and Garcia (2012) (FG) to construct funding shocks. FG's measure of the value of funding liquidity (FL) is based on apparent deviations from arbitrage in a panel of U.S. Treasury bonds. These deviations persist because of frictions in the funding market (the repo market).

Our findings provide strong support for intermediary-based asset models with funding risk. We find that funding liquidity shocks increase the illiquidity and volatility of every portfolio. In addition, the dispersion of liquidity increases across illiquidity-sorted portfolios and, similarly, the dispersion of volatility increases across volatility-sorted portfolios. More importantly, and consistent with the model of Brunnermeier and Pedersen (2009), the evidence supports the cross-effect between illiq-

[1]These are often proxied using index option implied volatilities and price impact measures.

[2]Our results are also connected with the intermediary-based equilibrium model in He and Krishnamurthy (2008) but they focus on wealth shock directly, instead of funding shocks, and they do not consider the effect on liquidity and volatility

uidity and volatility. Following funding shocks, illiquidity increases more for volatile stocks and, similarly, volatility increases more for illiquid stocks.

The connection between funding shocks, illiquidity and volatility poses a risk to investors. Indeed, we find that funding risk is priced. The pattern of risk premia across portfolios matches almost exactly the pattern of funding risk betas. More formally, we run asset pricing tests using cross-sectional regressions. The results show that the exposure to funding shocks explain a large percentage of the cross-sectional dispersion, with pricing errors that are not significantly different from zero. The price of risk estimate is close to -4% annually. The funding risk beta ranges from -1.5 to almost zero from the illiquid to the liquid portfolios, translating into a risk premium of 6%.

The price of risk estimates are robust across a wide range of specifications, including the addition of the market factor or the Fama-French risk factors. We also consider the role of aggregate market liquidity, measured with either the market Amihud ratio or the Pastor and Stambaugh (2003) (PS) measure, or the inclusion of alternative funding liquidity proxies; the Betting-against-Beta (BAB) factor from Frazzini and Pedersen (2011) and the spread between Treasury bill and LIBOR rates (TED spread). We also consider consider sorting stocks using liquidity risk and volatility risk (instead of levels), as measured by the response of returns to changes in the aggregate market liquidity or volatility. In every case, the estimate remains significant and close to -4%.

Our choice of test assets was motivated by theory. Nonetheless, one may ask whether the usual portfolios sorted on size and book-to-market exhibit exposure to funding risk. We also consider Beta-sorted and Momentum-sorted portfolios, which have been linked to liquidity conditions in the literature. Repeating the asset pricing tests with these additional portfolios yields negative point estimates, again around -4%. Other liquidity measures do not typically add to the explanatory power with one striking exception. The combination of our funding risk factor with the PS market liquidity factor fits expected returns extremely well, with an R^2 of 65%. The value effect appears to be most weakly related to funding liquidity. Excluding portfolios based on book-to-market sorts increases the R^2s to 80%. The interaction between funding liquidity and market liquidity is not due to the correlation between funding liquidity and market liquidity shocks; this correlation is very low in our sample. Instead, we show that combination of PS and ΔFL separate out the most volatile and most illiquid portfolios when the market as whole is illiquid (or volatile), and therefore correctly increasing their expected returns.

These robustness checks also set the stage for a comparison with the results in Adrian, Etula, and Muir (2013) (AEM) who chose size, book-to-market and momentum portfolios as test assets. AEM use securities broker-dealer (BD) leverage to proxy for the marginal utility of wealth in different states of the economy. They find that shocks to BD leverage explain alone the dispersion of returns across portfolios sorted on size, book-to-market, and momentum. They point out that BD leverage shocks may be a good proxy for funding shocks, but they note that this interpretation is challenged by the lack of correlation between leverage shocks and the PS market liquidity factor. Clearly, we need to investigate the apparent contradiction between their conclusion and the above evidence: our measure of funding shocks is well-connected with the illiquidity and volatility portfolios, supporting the theoretical pro-cyclical leverage or margin channel.

We switch to the quarterly returns horizon, as in AEM. Consistent with their conclusion, we find that BD leverage shocks explains less than 10% of the cross-section of average returns across illiquidity and volatility portfolios. We also find that the price of BD leverage shocks has the wrong sign and the estimate is insignificant. In contrast, funding shocks are priced, as above for monthly returns. Turning to 10x10 double-sorted size and book-to-market portfolios, we confirm that small and value portfolios have larger exposures to funding shocks, with a significant price of risk. This risk is different from the BD leverage risk, which is also significant for these portfolios in our sample. A closer look at the size or book-to-market portfolios taken separately shows how the two factors differ. The leverage factor explains by itself 85% of the dispersion of book-to-market returns but only 1% of the size returns. This is consistent with both the high correlation between the leverage factor and asset growth reported by AEM. However, we obtain the opposite results for funding risk. Exposures to funding risk explains 72% of the size portfolios but only 9% of the book-to-market portfolios. This is consistent with the high commonality of securities between the size and the illiquidity portfolios. The price of risk of funding liquidity innovations is estimated at a robust value close to -2%, which is less than what we obtained for the shorter monthly investment horizon.

In Figure 1, we plot the quarterly series of the funding liquidity factor, its innovations and the leverage factor of AEM. The funding liquidity innovations series and the leverage factor series move in opposite directions at the beginning of the sample (in particular in the 1987 market crash and the 1994 Mexican peso crisis). However, leverage has tended to move together with funding conditions in the latter part of the sample (in particular at the beginning of the last financial crisis and also in the LTCM 1998 crisis), perhaps because previous commitment or concerns of financial intermediaries about their reputations delayed their response to funding conditions in terms of leverage. Therefore, it suggests that the funding liquidity measure and the leverage factor may complement each other in capturing the state of funding conditions.

The value of funding liquidity

Fontaine and Garcia (2012) extract a latent liquidity premium common to all bonds using a panel of pairs of U.S. Treasury securities. Each pair has similar cash flows but different ages and they use a dynamic term structure model to capture remaining differences in coupon or maturity. Therefore, the funding liquidity factor FL is derived from price differentials that can be attributed to differences in age. This strategy is consistent with the existence of an on-the-run premium in the short-run but also with the evidence that older bonds are even less liquid and offer higher yields. 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 in the foreseeable future. Empirically, this link has been confirmed by Jordan and Jordan (1997); Krishnamurthy (2002); Buraschi and Menini (2002) and by Bartolini, Hilton, Sundaresan, and Tonetti (2010), who show that securities that do not offer "special" repo rate can still offer substantial funding benefits relative to other bonds. In turn, Adrian and Shin (2009) show that repo markets are the key markets where investment banks, hedge funds and other speculators obtain the marginal funds for their activities.

Hence, FL measures how much more are investors willing to pay for assets that can be funded more easily and cheaply in the repo market: the value of funding liquidity. FG also links FL with broader funding conditions, using evidence at three successive levels of aggregation. First, they relate FL to the expected benefits of holding a more liquid security, where benefits are measured using repo spreads. Second, they trace the linkages of FL to the shadow banking sector, a large non-bank intermediation component that relies heavily on short-term funding to finance long-lived illiquid assets. Third, they study the relationship between FL and broader measures of funding conditions, such as variations of non-borrowed reserves of commercial banks at the Federal Reserve or changes in the rate of growth of M2 (controlling for a broad range of financial and economic variables). In each case, an increase in the value of funding liquidity is bad news for an investor demanding liquidity.

Indeed, FG show that FL is an aggregate risk factor driving a substantial share of risk premia across fixed-income markets. An increase in FL, which represent tighter funding conditions, lowers the risk premium on U.S. Treasury bonds substantially but raise the risk premium implicit in LIBOR rates, swap rates and corporate bond yields. The pattern is consistent with accounts of flight-to-quality but the relationship is pervasive even in normal times. This paper extends the evidence, showing that shocks to FL are risky for stock investors and carry a negative price of risk in the cross-section of equities.

Related Literature

FG measure funding liquidity from a panel of Treasury bonds. To capture how liquidity affects asset prices, Vayanos (2004) suggests to use the prices of two assets with similar cash flows and characteristics but different liquidity. He cites the well-known case of the difference between a just-issued (on-the-run) thirty-year Treasury bond and a thirty-year bond issued three months ago (off-the-run). Similarly, Longstaff (2004) uses Treasury and RefCorp bonds. In each case, the two bonds carry the same credit risk, yield very similar cash flows but the more recent issue is more liquid and more expensive.

Our findings reinforce the recent supporting evidence for the theory of Brunnermeier and Pedersen (2009) relating funding liquidity to market liquidity in other asset markets. Franzoni, Nowak, and Phalippou (2012) link between private equity returns with overall market and funding liquidity measured by changes in credit standards. The sensitivity of stocks' illiquidity and volatility to funding shocks measured in the bond market is consistent with the evidence that illiquidity and volatility shocks are both correlated across bond and stock markets (Chordia, Sarkar, and Subrahmanyam, 2005; Goyenko and Ukhov, 2009). It is also consistent with the evidence that, like funding liquidity, stock market illiquidity forecasts bond excess returns (Bouwman, Sojli, and Tham, 2012). A substantial literature has explored the link between asset returns and aggregate market liquidity risk.[3] Our results suggest that much of the market liquidity risk can be traced back to the funding risk of financial intermediaries.

The rest of the paper is organized as follows. In Section I we describe how we construct illiquidity and volatility portfolios, and we also detail the different risk factors and test assets used subsequently. The empirical results on the pricing of illiquidity and volatility portfolios are reported and discussed in Section II. Section III conducts similar empirical exercise using quarterly returns to compare with the leverage factor. A discussion of our empirical findings with respect to the implications of asset pricing models with funding frictions is included in Section IV. Section V concludes and discusses remaining challenges and other promising avenues.

I Data and Portfolio Formation

The measure of funding liquidity value in Fontaine and Garcia (2012) is available monthly, starting in 1986[4], and until March 2012, therefore including the recent financial crisis. We match this series with daily data for individual stocks over this 26-year period from the Center for Research Securities Prices (CRSP). To be included in the sample, a stock must meet the following criteria:

1. Ordinary common stock (CRSP share codes 10 and 11).[5]

[3] See in particular Amihud (2002), Pastor and Stambaugh (2003), Chordia, Sarkar, and Subrahmanyam (2005), Acharya and Pedersen (2005), Beber, Brandt, and Kavajecz (2008), and Li, Wang, and adn Y. He (2009) for bond markets, Longstaff, Mithal, and Neis (2005), Bongaerts, de Jong, and Driessen (2011) and Longstaff, Pan, Pedersen, and Singleton (2011) for credit derivative markets, and Boyson and Stulz (2010) and Sadka (2010) for hedge funds.

[4] 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.

[5] The sample excludes ADRs, SBIs, REITs, certificates, units, closed-end-funds, companies incorporated outside the U.S., and Americus Trust components.

2. Traded in NYSE or AMEX.[6]

3. A stock price between \$5 and \$1000.

4. At least 150 days of observations over the previous year.

5. At least 10 days of data in each month of the previous year.

A Portfolio formation

We form portfolios by sorting stocks by their illiquidity and their volatility. To measure a stock volatility, we adopt the concept of realized volatility. For each stock, the monthly measure of volatility is the standard deviation of daily returns in that month. The quarterly volatility is the average of the monthly volatility. The realized volatility of a portfolio is the average volatility of all stocks in the portfolio. To measure stock illiquidity, we use the Amihud (2002) illiquidity ratio. The Amihud is the most widely used, and provides a good measure of price impact.[7] For an individual stock, the illiquidity ratio ($ILLIQ_{id}$) is given by:

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

where R_{id} is the return on a stock i on day d and $DVOL_{id}$ is the dollar value of trading volume on the same day. For each security, the monthly measure for month t is based on the average of the daily illiquidity ratios in that month. To arrive to our monthly measure, we multiply the monthly average by the growth in the market capitalization of stock i between the beginning of the sample and until the end of the previous month, $CAP_{i,t-1}/CAP_{i,1}$ (i.e., $t = 1$ is December 1985). The quarterly measure is the average of the monthly measures. The illiquidity measure of a portfolio is an

[6] Nasdaq stock are excluded since their trading volume is significantly higher compared to NYSE and AMEX stocks, due to interdealer trades, distorting several illiquidity measure.

[7] Goyenko, Holden, and Trzcinka (2009) compare the various liquidity measures used in empirical studies and suggest other measures better able to capture both spreads and price impact. They conclude that the Amihud (2002) illiquidity ratio ia a good proxy for price impact.

equally-weighted average of the portfolio illiquidity measure. The illiquidity measure for the aggregate market is the equally-weighted average of the individual illiquidity ratios, which is then adjusted for the change in market capitalization since the start of the sample.

At the end of each year, we form 10 portfolios by sorting stocks by their illiquidity or their volatility. We keep the portfolio fixed throughout the year, and compute returns at the end of each month. We then re-balance the portfolios at the end of the year, and repeat the process in the following year.

B Alternative portfolio formation

Measures of illiquidity and volatility may be too noisy at the level of individual stocks. To circumvent this issue, and to provide a robustness check of our results, we will also consider the following alternative portfolio formation strategy based on stock returns sensitivities to market-wide illiquidity and volatility. At the end of each year, we estimate the following illiquidity and volatility betas,

$$\begin{aligned}\beta_i^{Illiq_m, r_i} &= \frac{cov(Illiq_m, r_i)}{var(Illiq_m)} \\ \beta_i^{\sigma_m, r_i} &= \frac{cov(\sigma_m, r_i)}{var(\sigma_m)},\end{aligned} \tag{2}$$

based on daily returns and using five years of data. We then sort using these two sensitivity estimates and construct two sets of 10 portfolios sorted by their liquidity risk and their volatility risk, respectively.[8] Again, we keep the portfolio composition fixed and compute monthly returns at the end of each month until the end of the year. We then re-balance the portfolios and repeat the process.

[8]To estimate the illiquidity and volatility betas, we only keep stocks with five years of data.

C Alternative illiquidity measures

A prime objective of this paper is to evaluate the role of exposures to a funding shock ΔFL_t. But we will evaluate how several alternative illiquidity risk factors fare in asset pricing tests. We consider two measures of market illiquidity: the Amihud market-wide price impact measure (Amihud, 2002) as well as Pastor-Stambaugh market-wide measure of price reversals sensitivity (Pastor and Stambaugh, 2003). Our construction of the market-wide Amihud measure is described above and we obtain the traded Pastor-Stambaugh liquidity risk factor from Lubos Pastor's website.[9]

We also consider two other proxies for funding conditions. We use the difference between the three-month T-bill and the LIBOR rate (TED spread) which is also used by Gârleanu and Pedersen (2009). The TED spread is computed using daily T-bill and LIBOR data from the Federal Reserve of St-Louis FRED database. This proxy is likely to be a noisy measure of funding conditions as perceived by market participants. It is also prone to manipulation. Our second proxy is the Betting-Against-Beta (BAB) factor proposed by Frazzini and Pedersen (2011). The BAB factor is the returns on a portfolio that is long low-beta securities and short high-beta securities. The idea is that leverage-constrained investors overweight high-beta stocks as a substitute for leverage. Then, the BAB portfolio is a strategy for those investors who can establish levered (long-short) positions to exploit any resulting mispricing. Theory predicts that BAB portfolio returns are increasing in the ex-ante tightness of constraints and in the spread in betas between high- and low-beta securities. We follow Frazzini and Pedersen (2011) closely to construct the BAB factor. First, we rank all securities based on their previous month-end beta. See Appendix A for details.

[9] The traded factor is available from WDRS or from Lubos Pastor's website. It is the value-weighted return on the 10-1 portfolio from a sort on historical betas. This procedure is simpler than sorting on predicted betas (as in the original study), and through 2012 it is similarly successful at creating a spread in post-ranking betas. The traded factor has a positive and significant alpha through 2012, consistent with liquidity risk being priced.

D Leverage Factor

AEM argue that the leverage of security broker-dealers (BD) is a good empirical proxy for the marginal value of wealth of financial intermediaries (including the effect of balance-sheet constraints). We evaluate whether the leverage factor can price the cross-section of illiquidity- and volatility-sorted portflios. These results are reported in a separate section below since their measure is only available at the quarterly frequency. The BD leverage factor is constructed using quarterly aggregate data on the financial assets and financial liabilities of security broker-dealers as captured in Table L.129 of the Federal Reserve Flow of Funds. Following AEM, we compute the BD leverage as:

$$Leverage_t^{BD} = \frac{TotalFinancialAssets_t^{BD}}{TotalFinancialAssets_t^{BD} - TotalLiabilities_t^{BD}}, \tag{3}$$

and the BD leverage factor is then computed as the seasonally adjusted log changes in the level of broker dealer leverage

$$LevFact_t = [\Delta ln(Leverage_t^{BD})]^{SA}, \tag{4}$$

where, following AEM, the seasonal adjustment is estimated in real time using quarterly dummies.

II Pricing Illiquidity and Volatility Portfolios

In this section, we will investigate the empirical links between funding liquidity, market liquidity, volatility and the cross-section of returns. First, we will test if the funding liquidity risk is priced in the cross-section of liquidity-sorted and volatility-sorted portfolios. Second, we will check that periods with tight (loose) funding conditions are also periods with a higher (lower) level and dispersion of portfolios' illiquidity and volatility. We will also check that monthly funding shocks are connected with the level and dispersion of illiquidity and volatility shocks across portfolios. Finally, we consider several robustness checks: alternative measures of each stock's illiquidity and volatility risk, alternative measures of funding risk, a broader set of test assets, including size, value, momentum and beta-sorted portfolios. Our results strongly support the theoretical prediction that funding shocks affect the equilibrium rate of returns via its effect on market conditions.

A Summary Statistics

Sorting by illiquidity and by volatility creates a dispersion of returns that is unexplained by their market betas, or by the 3-factor Fama-French (FF3) model. Panel (a) of Table 1 reports summary statistics across illiquidity-sorted portfolios. Stocks in the illiquid portfolios have smaller market capitalization, higher volatility and higher returns. The returns difference between the most illiquid and the most liquid portfolios is 1.43%-0.88%=0.55%, monthly. The difference in average portfolio returns is not captured by their market betas, consistent with Amihud and Mendelson (1986).Market betas *decrease* with the porfolios' illiquidity, generating CAPM alphas that increase with illiquidity. Using the Fama-French risk factors does not change the patterns of alphas. Even though they are more volatile, the illiquid portfolios offer a larger Sharpe ratio than liquid portfolios.

Panel (b) of Table 1 reports summary statistics across volatility-sorted portfolios. The more volatile portfolios include stocks that are less liquid, that have smaller market capitalization, and higher returns. The least volatile and most volatile portfolios yielded average monthly returns of 0.02% and 1.56%, respectively. Portfolios that are more volatile have higher market betas, but CAPM alphas remain positive and significant for all portfolios. In contrast, Ang, Hodrick, Xing, and Zhang (2006) documents that portfolios of stocks with higher total or idiosyncratic volatility have lower average returns. Subsequently, Fu (2009) finds that the negative relationship can be largely explained by the return reversal of a subset of small stocks with high idiosyncratic volatilities. Huang, Liu, Rhee, and Zhang (2010) also find a positive relationship when controlling for reversals. To circumvent the effect of returns reversals, we form portfolios at the end of each year and keep their composition fixed over the remaining calendar year. This strategy is also consistent with how we form illiquidity portfolios.

B Pricing Illiquidity and Volatility Portfolios

To investigate whether the funding liquidity risk is priced in the cross-section of illiquidity and volatility portfolios we follow the usual two-step Fama-Macbeth procedure. The first-stage regression is re-estimated over time using a 5-year rolling window. Inference is based on the usual 2-stage standard errors as well as the Shanken standard errors, which correct for the use of estimated coefficients in the second stage. Following Lewellen, Nagel, and Shanken (2010), we include traded factors among the test assets, whenever applicable. We report the R^2 and the adjusted $\bar{R}^2$, which measure the fit across all test assets, as well as the corrected analog, R_c^2 and $\bar{R}_c^2$, which measure the fit across the 10 illiquidity and 10 volatility portfolios only.

The left hand side of Table 2 first displays the estimated price of risk, along with the R^2s for three asset pricing models: the CAPM, the FF3, and a model using only funding liquidity innovations ΔFL as a risk factor. Table 2 also reports results for versions of the CAPM and the FF3 that are augmented with ΔFL. What is immediately apparent from the results is that estimates for the price of funding risk are remarkably similar across specifications, around -4. We will find similar estimates in almost every specification and robustness check below. The negative sign means that stocks that are more sensitive to funding shocks – stocks with lower returns in months with funding shocks – have higher expected returns. Across specification, the estimates are significant at the 5% or the 10% level based on the Shanken adjusted t-statistic. Economically, funding risk on its own explains close to 50% of the dispersion of expected returns across illiquidity and volatility portfolios. In contrast, the CAPM explains only 22% and the FF3 explains 60% of the dispersion for the same portfolios.

Note that the intercept is not statistically different from zero. In addition, Table 3 reports results from formal χ^2-test that the pricing errors are jointly significant. Panel (a) and (b) reports results when estimating and testing the models separately in the cross-section of illiquidity- and volatility-sorted portfolios. Funding risk on its own generates p-values beyond 0.5. In contrast, the CAPM and the FF3 yields p-values of 0.03 and 0.08 for the illiquidity-sorted portfolios, respectively, and 0.02 for the volatility-sorted portfolios. The null that the portfolio pricing errors are not jointly different from zero is rejected for these alternative models.

C Illiquidity, Volatility and Funding Conditions

Brunnermeier and Pedersen (2009)' model predicts that the sensitivity of market liquidity is larger for securities that are risky and illiquid on average.[10] We check that the level and the dispersion of illiquidity and volatility co-moves with funding shocks. This verifies that investors prefer certain portfolios because they are more liquid and least volatile when funding conditions worsens. These results provide the economic mechanism behind the significant price of funding risk. Worsening funding conditions is associated with a higher level of market-wide illiquidity, with a wider dispersion of illiquidity and volatility across stocks. This is in turn associated with a cross-sectional dispersion of funding risk betas, generating a significant dispersion of expected returns across stocks. The same logic follows across volatility portfolios.

We check these predictions empirically. Table 4 reports the conditional averages of portfolio illiquidity and volatility when funding liquidity cost is low or high (Panel (a)

[10]See their Section 6.

and Panel (b), respectively). The differential in these quantities between states with low and high funding liquidity cost is reported in Panel (c). We find that the illiquidity and the volatility increase when funding conditions become tighter, showing that funding states affect the characteristics of the portfolios. This holds for every portfolio but one. We find that the dispersion also changes: the least liquid portfolios see their illiquidity worsen the most and the most volatile portfolios see their volatility worsen the most.

Importantly, the response of the volatility across illiquidity portfolios is a telling sign of funding shocks. The response of liquidity across volatility is also telling. Brunnermeier and Pedersen (2009) provide an intuitive mechanism (see e.g., their Proposition 6). The results support this cross-effect. The most volatile stocks become more illiquid than the least volatile stocks in bad times. Similarly, the most illiquid stocks become more volatile in bad times.

These results show how market conditions change when we change the funding conditions at a relatively large scale. We also assess the effect of funding shocks on market conditions via a regression of illiquidity changes $\Delta Illiq_{i,t}$ on the funding shock ΔFL_t and on the market-wide illiquidity changes $\Delta Illiq_t^{mkt}$. Similarly, we regress volatility changes $\Delta\sigma_{i,t}$ on the funding factor ΔFL_t and the market-wide volatility $\Delta\sigma_t^{mkt}$. The regressions are given by:

$$\begin{aligned} \Delta Illiq_{i,t} &= \gamma_{0,i} + \gamma_{1,i}\Delta FL_t + \gamma_{2,i}\Delta Illiq_t^{mkt} + \xi_{i,t} \\ \Delta\sigma_{i,t} &= \gamma_{0,i} + \gamma_{1,i}\Delta FL_t + \gamma_{2,i}\Delta\sigma_t^{mkt} + \xi_{i,t}, \end{aligned} \tag{5}$$

and the results, reported in Table 5, are consistent. Funding shocks are associated with an increased dispersion of illiquidity and volatility across portfolios. Again, we find evidence of the 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 in the dispersion of *illiquidity*-sorted portfolios.

D Alternative portfolio sorts

The illiquidity and volatility of a stock are unobservable characteristics that must be estimated. We check that alternative sorts, based on the stock returns sensitivities to changes in market-wide illiquidity or the sensitivities to changes in market-wide volatility, produce similar results. The connection between funding risk, illiquidity and volatility may work via change in the illiquidity and volatility level, as above, or via the illiquidity and volatility risk.

Table 6 reports summary statistics for portfolios sorted on their returns sensitivities to market-wide illiquidity (Panel a) and for portfolios sorted on their returns sensitivities to market volatility (Panel b). In each case, portfolio 1 has the highest beta: its returns have the highest (positive) correlation with a deterioration in market illiquidity or market volatility. Conversely, portfolio 10 has the lowest (negative) correlation with market declines. Except for one extreme portfolio 1, this ordering translates into a monotonic increase of expected returns, consistent with an increase in liquidity or volatility risk. Interestingly, this sorting strategy does not produce a strong dispersion in the portfolios' illiquidity or volatility. Therefore, asset pricing tests based on these portfolios are not redundant, and assess the validity of additional mechanisms linking funding market with volatility and liquidity risk. Similarly, the average size and market capitalization in each sorted portfolio does not exhibit a strong cross-sectional pattern. Hence, the CAPM and the FF3 α's are typically significant, especially for the riskiest portfolios.

Parallel to Table 2 above, Table 7 reports the estimated price of risk, along with the R^2, where the test assets are the portfolios sorted by illiquidity risk and volatility risk. As above, it is immediately apparent that all point estimates of the price of funding risk are grouped around -4. In fact, the estimates are very close numerically between each set of results and remain significant in all cases but one. In addition, the funding risk factor provides a close fit of the expected returns in this alternative set of test assets.

Figure 2 illustrates the success of funding risk in fitting the dispersion of expected returns for these portfolios. Panel (a) displays the average returns across $\beta_i^{Illiq_m,r_i}$-sorted portfolios, adjusted for market betas, against the correspond funding liquidity betas $\beta_{\Delta FL}$, obtained from a contemporaneous regression of monthly returns on the funding risk factor ΔFL and the market returns $r_{mrk,t}$. Panel (b) shows the average returns across $\beta_i^{\sigma_m,r_i}$-sorted portfolios, adjusted for market betas, against the correspond funding liquidity betas $\beta_{\Delta FL}$. As noted above, the average returns in one of the extreme liquidity-sorted portfolios flattens the results but, the otherwise, the slope of the risk-returns relationship is very similar across panels.

E Alernative Illiquidity Measure

This section asks whether other measures of market liquidity or funding liquidity conditions can price the cross-section of illiquidity- and volatility-sorted portfolios. Specifically, we consider the average Amihud ratio aggregated across all stocks and the PS factor based on the sensitivity of price reversals. We also consider the TED spread and the BAB factor. Table 8 reports asset pricing results based on two-stage Fama-MacBeth regressions where, as above, we use the portfolios sorted on the level of illiquidity and the level of volatility as test assets.

Panel (a) reports results when each of the alternative proxy is used on its own as trading factor while Panel (b) reports results when each proxy is combined with our measure of funding shock ΔFL. We also report results obtained when using only ΔFL_t for comparison. Looking across the panels, and across models, the price of risk estimate for ΔFL is remarkably stable, typically between -3.5 and -5.0, which is close to the estimates reported in Table 2. In every case, the α is not statistically different from zero.

Looking at the price of risk estimates for the alternative liquidity measures reveals mixed results. The estimates are insignificant in both specification except for PS, which is significant only when used on its own. The TED spread and the BAB factor change sign when used on its own or combined with ΔFL. Consistent with the lack of statistical significance, the R^2s show no increase when combining each alternative liquidity measure with ΔFL, except for PS are combined. This combination yields a R^2 of 94%. We devote the next section to this striking interaction.

F Funding Liquidity and Market Liquidity

The most interesting results from Table 8 follow from the combination of ΔFL with PS liquidity risk factor. The price of funding risk is estimated at -3.33 (statistically significant at the 5% level). The market liquidity factor emerges with a price of risk estimate of -0.35 (statistically significant at the 10% level). Together, these factors explain 94% of the cross-sectional dispersion in expected returns; which is more than the sum of the R^2s obtained using each risk factor individually.

The improvement in fit is due to the cross-sectional correlation between the funding liquidity beta and the market liquidity beta (0.32 across the illiquidity portfolios and 0.59 across the volatility portfolios) but *not* to the time-series correlation between the funding and liquidity risk factors. The correlation between ΔFL and PS is essentially zero. This implies that estimating the betas separately or combining them in the same first-pass regression does not change the results.

Economically, the correlation between betas implies that stocks that tend to be exposed to funding risk also tend to be exposed to market liquidity risk. The lack of correlation in the shocks' time-series suggests that the exposures to different risk arise in different parts of the sample. One possibility, following one of Brunnermeier and Pedersen (2009)'s prediction, is that the effect of funding constraints can be non-linear. Its effects are more likely to be perceptible in a volatile market where intermediaries are "closer" to be constrained. On the other hand, the sensitivity of each stock's returns to a *given* change of market-wide liquidity may well be similar whether volatility is high or low. Of course, the market liquidity shock may be larger when volatility is high.

To check this, we divide the sample into three sub-samples using the market-wide average Amihud measure to rank each month. Then, for the most illiquid and least illiquid subsamples we repeat the time-series regression of portfolio returns on ΔFL and PS. Panel (a)-(b) of Table 9 reports results for the illiquidity- and volatility-sorted portfolios, respectively.[11] 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 sensitivity of illiquid and volatile portfolios to PS liquidity shocks is large in both subsamples. The effect is statistically weaker than the response to ΔFL but the cross-section pattern is clear: illiquid stocks and volatile stocks have lower returns when PS worsens.

Table 9 also reports results for the full-sample. Since the low estimates in the high-liquidity subsample are close to zero, the full-sample β^{FL} estimates are close to a rescaled version of the estimates in the low-liquidity subsample. The estimates of β^{PS} remain individually insignificant but the cross-section pattern is similar to the subsample patterns: the most illiquid and volatile portfolios stand out for the exposure to PS and ΔFL.

The asset pricing tests and the sub-sample analysis suggest that the interaction between sensitivity to funding and market liquidity shocks plays an important role. We perform the following exercise to see more clearly this interaction at play. We first perform a univariate regression of the portolios' average returns on the (full-sample)

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

estimates of β^{FL}. This corresponds to the second-stage regression in the third column of Table 2. Figure 3 reports a scatter plot of the residual from this regression against the PS sensitivity coefficients, β^{PS}. This shows where the exposures to PS liquidity risk has the potential to improve the explanatory power of ΔFL.

The results show that the residuals can be separated between two groups. The most volatile portfolio and the three most illiquid portfolios stand out with positive residuals: their average returns appear too high. Most of the other portfolios have average returns that appear too low. In effect, the results reveals a trade-off between relatively large under-pricing of a few extreme portfolios and small over-pricing of most other portfolios. In addition, Figure 3 shows that the asset pricing residuals line up almost perfectly with the market liquidity betas. The most illiquid and most volatile portfolios appears extreme also have large negative market liquidity risk exposures while all other portfolios have zero or positive liquidity exposures. Hence, the combination of β^{PS} with β^{FL} identifies the riskiest portfolios correctly and yield an accurate fit of the cross-section of returns ($R^2 = 94\%$, see Table 9b).

G Alternative test assets

We consider other common test assets, sorting stocks on size, book-to-market, momentum or market beta. This exercise may appear remote from theory. Nonetheless, it is natural to ask whether and how much of these long-standing and well-documented risk premiums can be explained by the portfolios' exposure to funding shocks. First, we consider 10 size-sorted and 10 book-to-market sorted portfolios. The size premium have often been related to the relative illiquidity of small firms, while borrowing constraints have been related to the value premium. Both channels can be linked with the funding markets. Second, we consider the 10 portfolios where stocks have been sorted by their market betas. Frazzini and Pedersen (2011) recently show that the returns from a long-short investment in low-beta and high-beta portfolios (the BAB factor) can be rationalized by variations in funding conditions. Finally, we also consider the momentum-sorted portfolios. In each case we compare results using funding shocks, ΔFL, TED spread, BAB returns, PS factor returns, and aggregate market Amihud ratio.

Table 10 report the estimated prices of risk and the R^2s. Panel (a) reports results using each risk factor individually and Panel (b) reports results combining each alternative factor with ΔFL. On its own, funding risk explain close to 30% of the cross-sectional dispersion. The price of risk estimate is -3.24, once again close to previous estimates, and the average pricing error is economically and statistically small. As in Section F, the alternative risk factor are not significant except for PS, with a price of risk estimated at -0.37 but a very large average pricing error.

More interestingly, the combination of PS and ΔFL produces a better fit of this challenging set of test assets, with an R^2 of 65%. The price of risk estimates are robust and the constant is insignificant. Looking at the pricing errors for each set of portfolios, the portfolios of stocks sorted on book-to-market have the largest residuals. Indeed, repeating the estimation but excluding these portfolios yields an $R2$ of 81%, smaller pricing errors on average and robust estimates of the prices of risk. Overall the results suggests that a large faction of the cross-section dispersion of returns can be linked to the combined exposures to funding risk and market liquidity risk. The value-sorted portfolios stand out as only weakly related to this effect, a result that will also be confirmed in Section III.

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 simply 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 but using 5×5 double-sorted portfolios. We first sort all stocks based on their Amihud illiquidity ratio. Second, within each quintile, we sort all stocks based on their lagged realized volatility and form five portfolios. Then, we check wether funding risk can explain the dispersion of average returns across the resulting 25 portfolios.

Table 11 reports the results. Across specifications, the estimates for the price of funding risk are close to the estimates obtained previously. The statistical significance and the fit appear to decrease somewhat but this mostly reflects the reduced cross-sectional variation of average returns: the spread between returns of quintile portfolios is smaller than the spread between returns from decile portfolios. Next, Table 12 reports results using alternate liquidity measures to price the double-sorted illiquidity and volatility portfolios (analog to the results reported in Table 8). The results are also broadly similar but the coefficients, their significance and the fit of alternate proxies are reduced. Nonetheless, the estimates and significance of the price of funding risk are remarkably stable.

III Quarterly Broker-Dealer Leverage

Adrian, Etula, and Muir (2013) (AEM) shifts the literature attention from measuring the stochastic discount factor (SDF) of the average household to measuring a financial intermediary SDF. AEM argue that the leverage of security BD is a good empirical proxy for the marginal value of wealth of financial intermediaries and it can thereby be used as a representation of the intermediary SDF. They find that exposures to the broker-dealer leverage factor can alone explain the average excess returns from equity portfolios sorted by size, book-to-market, and momentum.

However, AEM report that shocks to the PS liquidity factor are uncorrelated to PS liquidity factor innovation, concluding that their results pose a challenge to the mechanics of "margins spiral" (Brunnermeier and Pedersen, 2009). In contrast, Section II shows that funding shocks identified from the bond market are tightly connected with the dispersion of illiquidity, volatility and of expected returns in the cross-section of stocks. This section assesses and compares asset pricing results based on leverage shocks and funding shocks in the cross-section of illiquidity- and volatility-sorted portfolios, as above, and in the cross-section of size and book-to-market portfolios, as in AEM.

In Figure 1 we plot the quarterly series of leverage factor, as well as our funding liquidity factor and its innovations. While the funding liquidity innovations series and the leverage factor series move in opposite directions in the beginning of the sample (in particular in the 1987 market crash and the 1994 Mexican peso crisis), they have tended to move together in the latter part of the sample (in particular at the beginning of the last financial crisis and also in the LTCM 1998 crisis). Therefore, it suggests that the new measure may at least complement the leverage factor measure.

A Asset Pricing Tests – Quarterly results

We start by presenting asset pricing results based on quarterly illiquidity and volatility portfolio returns. First we run a set of time-series regressions:

$$r_{it} = \alpha_i + \beta_i^{\Delta FL} \Delta FL_t + \beta_i^{MKT} MKT_t + \varepsilon_{it} \tag{6}$$

in which we add the funding liquidity innovations to the market returns as a risk factor. Table 13 displays the estimates and the R^2 from these first-stage regressions. Panel 14a reports results across illiquidity portfolios, and Panel 14b reports results across volatility portfolios. For each set of portfolios, we observe negative exposures to funding changes, and a declining pattern in absolute magnitude from the most volatile to the least volatile and from the most illiquid to the least illiquid. The funding-liquidity beta of the most illiquid portfolio is equal to -3.05, compared to a beta of -0.28 for the most liquid portfolio. For volatility, the funding beta goes from a value of -2.64 for the most volatile to a value of -1.32 for the least volatile. The coefficients of regression range from 60% for the least volatile portfolio to more than 90% for the most liquid portfolio.

This pattern of funding risk betas matches almost exactly the pattern of CAPM alphas. Figure 4 shows the alignment of the funding risk loadings with the market risk-adjusted average returns for each set of portfolios. Clearly, the pattern of CAPM alphas matches almost exactly the pattern of $\beta_i^{\Delta FL}$, and the price of risk (the slope) is close to -2 in each case. This is confirmed by the results of the Fama-MacBeth cross-sectional regressions in Table 14. This table parallels Table 2 but for quarterly returns, and reports the estimated prices of risk for various asset pricing models using liquidity-sorted and volatility-sorted portfolios as test assets. On the left-hand side of the table, we report the estimated coefficients of the CAPM, the three-factor Fama-French model (FF3), the BD leverage factor, and our funding-liquidity innovations factor (ΔFL). On the right-hand side we report the estimated prices of risk for the first three asset pricing models (CAPM, FF3, Lev^{BD}) augmented by ΔFL. We find that the funding-liquidity explains 69% of the cross-sectional variation in returns, and 85% when augmented with FF3 factors (where ΔFL is the most significant regressor). The price of risk is again estimated at a value of -2. The Lev^{BD} explains only 8% of the cross-sectional variation in average returns, and with the wrong sign. Combining the leverage factor with funding shocks does not add to the fit but the price of risk for ΔFL becomes insignificant, reflecting some degree of interaction.

The illiquidity and volatility of the portfolios also exhibit significant sensitivities to funding shocks. In Table 15, we report the estimated sensitivities of changes in illiquidity or volatility of each portfolio to changes in funding conditions (ΔFL). We run the following regressions:

$$\Delta ILLIQ_{it} = \gamma_{0,i} + \gamma_i \Delta FL_t + \xi_{it} \tag{7}$$

$$\Delta VOL_{it} = \gamma_{0,i} + \gamma_i \Delta FL_t + \xi_{it}. \tag{8}$$

Panel(a) summarizes the results of the liquidity regressions. Only the most illiquid and the most volatile show a market sensitivity to changes in funding conditions. This tends to support the reinforcement of shocks to funding liquidity through market liquidity and volatility spiraling effects. In Brunnermeier and Pedersen (2009) a margin spiral occurs if margins are increasing in illiquidity. A funding shock will then lower market liquidity, leading to higher margins. Moreover, when funding conditions affect negatively the capital of financial intermediaries, they tend to provide liquidity in low-volatility securities (with lower margins) that require less capital, increasing the liquidity differential between high-volatility and low-volatility stocks[12]. No such differentiated effects are apparent in the volatility regressions. The coefficients are more or less uniform across liquidity portfolios. However, the high-volatility securities tend to react more than low-volatility securities.

B Size and Value Portfolios

We have seen that the leverage factor proposed by AEM does not explain the cross-section of returns of liquidity and volatility portfolios. However, AEM make a strong case for the capacity of their factor to explain the cross-section of size and value portfolios. In their sample (1968Q1-2009Q4) the leverage factor alone explains more than 70% of the cross-section of the 25 size and book-to-market portfolios, while the three-factor Fama-French model explains about 68%. Given that they interpret the leverage factor as a measure of funding conditions through the balance sheet positions

[12]The coefficient of the least volatile portfolio seems at odds with respect to the other low-volatility portfolios.

of brokers-dealers, we need to see how our measure of funding liquidity innovations behaves with respect to these portfolios and whether it complements the leverage factor in explaining the cross-section of size and value portfolios.

As before, we proceed in two stages. First, we run time-series regressions of portfolio returns on the liquidity factor (ΔFL or Lev^{BD}) and the market to compute the betas. The results for ΔFL are reported in Table 17. All portfolios except the largest low-value portfolios have a negative exposure to the liquidity factor, as it was the case for the liquidity and volatility portfolios. There seems to be a reasonable variation among the portfolio betas for ΔFL. In Figure 5 we plot in panel(a) these betas against the market-risk adjusted returns. The slope is negative as it should be and the portfolio betas seem to spread above and below the line. In Panel (b) we plot the equivalent betas for the leverage factor against also the risk-adjusted returns. The slope is positive and the betas seem to be a bit more concentrated around the center.

Second, to see if the funding liquidity innovations or the leverage factor are priced risks we run cross-sectional regressions. As for the liquidity and volatility portfolios we estimate and test the CAPM, the three-factor Fama-French model (FF3), the univariate Lev^{BD}, and our funding-liquidity innovations factor (ΔFL), as well the first three asset pricing models (CAPM, FF3, Lev^{BD}) augmented by ΔFL. We report the estimated prices of risk, alphas and R^2 in Table 18. In Panel (a), we conduct the tests with the double-sorted ten-by-ten size and book-to-market portfolios. The estimated prices of risk of Lev^{BD} and ΔFL are significant and have the right sign. The price of funding risk is close to -2% as before. The single-liquidity-factor models Lev^{BD} and ΔFL explain 47% and 36% of the cross-section of returns respectively. When considered together they keep their sign and explain 52% of the variation in average returns. When taken together, the leverage factor remains statistically significant but the estimated value of the price of risk for ΔFL is halved and it is not statistically significant any longer. We can conclude that the two liquidity factors share some common element and that size and book-to-market portfolios favor the leverage factor.

To better understand the difference between the two factors, we examine in Panel (b) and (c) the pricing of the 10 single-sorted size portfolios and 10 book-to-market portfolios. For the size portfolios, the leverage factor does not any explanatory power and the price of risk has the wrong sign, as opposed to the funding liquidity innovations that explains almost 70% of the cross-section of returns. The price of risk is estimated at -2.46 with a t-statistic of -2.66. In comparison the FF3 model has an adjusted R^2 of 78%. When the FF3 model augmented with the ΔFL factor it raises to almost 90%. The price of risk is still strongly significant. For the book-to-market portfolios, the single-leverage factor model explains close to 85% of the cross-section of returns, way above an adjusted R^2 of around 50% for the FF3 model. In the single-ΔFL factor, the price of risk is estimated at -1.61 and is borderline significant at a 5% level, but it explains a small percentage of the cross-section. When added to the FF3 model the funding liquidity factor becomes very significant but its price of risk doubles.

To complement these results, we form sets of 30 portfolios by adding to the 10 liquidity portfolios and 10 volatility portfolios either the 10 size portfolios or the 10 book-to-market portfolios separately. Results of the cross-sectional regressions for these two sets are reported in Table 19. Panel (a) contains the estimated prices of risk for the 30 portfolios including size. The ΔFL factor explains by itself 67% of the variation in returns, close to the 74% of the FF3 model. The price of risk estimated value is close to -2 and is statistically significant, even after controlling for the three Fama-French factors. For the 30 portfolios including book-to-market, the leverage factor explains by itself 25% of the cross-sectional variation in returns, compared to 7% for the ΔFL factor. However the latter is still close to significant in the augmented

FF3 model.

To summarize, the cross-section of returns of the size portfolios is very well explained by the ΔFL factor but not at all by the leverage factor, while the leverage factor is the best factor explaining the cross-section of returns of the book-to-market portfolios, with a marginal role for the liquidity innovations. This distinction was not apparent in Adrian, Etula, and Muir (2013). How to interpret these results? Several papers in the literature have stressed that illiquid securities tend to have a small capitalization (see for example Acharya and Pedersen (2005)). In our sample, we verified that the illiquidity and size portfolios share many of the same securities. Therefore our findings regarding the size portfolios are not surprising for the leverage factor since they did not explain the cross-section of returns of the liquidity portfolios either. For the value portfolios, the strong explanatory power of the leverage factor may be due to its high correlation with asset growth[13].

IV Discussion

In the recent empirical literature on cross-sectional asset pricing[14], a number of papers have considered liquidity risk in one form or another as a potential risk factor and have linked their results to the theoretical literature on limits of arbitrage and funding frictions. The measures of liquidity and the test assets vary among papers. We have amply compared our empirical findings to the results in Adrian, Etula, and Muir (2013) who use the balance sheet of financial intermediaries to measure the tightness of funding conditions. They interpret their results as supporting evidence of the view that leverage represents funding constraints based on the correlation of their leverage factor with funding constraint proxies such as volatility, the Baa-Aaa

[13]Adrian, Etula, and Muir (2013) report a correlation of 0.73 between their leverage factor and asset growth.

[14]See the survey by Goyal (2012).

spread, asset growth, and a betting-against-beta factor[15]. Using the same aggregate liquidity measure as in Acharya and Pedersen (2005) based on the Amihud (2002) individual illiquidity measure, Akbas et al. (2010) propose an explanation of the value premium based on time-varying liquidity risk. They show that small value stocks have higher liquidity exposures than small growth stocks in worst times, and that small growth stocks have higher liquidity exposures than small value stocks in best times. They conclude that these results are consistent with a flight-to-quality explanation for the counter-cyclical nature of the value premium. We need to refine our analysis by conditioning on the level of funding liquidity to verify if the same is true with exposures to funding liquidity. Engle et al. (2012) use the order book for the U.S. Treasury securities market to study the joint dynamics of liquidity and volatility during flight-to-safety episodes. They show that market depth declines sharply and price volatility increases during the crisis and on flight-to-safety days. They use market depth that is the quantity of securities available for purchase and sale to measure liquidity.

A substantial literature has explored the link between asset returns and aggregate market liquidity risk.[16] For stock returns, Pastor and Stambaugh (2003) show that aggregate liquidity risk is a priced factor. Their measure is based on daily price reversals and relies on the principle that order flow accentuates return reversals when liquidity is lower. Acharya and Pedersen (2005) derive a simple model for liquidity risk, which is a CAPM for returns net of illiquidity costs where illiquidity is measured by the Amihud (2002) measure as in this paper. They show that the model has a good fit for portfolios sorted on liquidity, liquidity variation, and size, but that it

[15]Frazzini and Pedersen (2011) build a factor that goes long leveraged low beta securities and short high beta securities and show that it should co-move with funding constraints.

[16]See in particular Amihud (2002), Pastor and Stambaugh (2003), Chordia, Sarkar, and Subrahmanyam (2005), Acharya and Pedersen (2005), Beber, Brandt, and Kavajecz (2008), and Li, Wang, and adn Y. He (2009) for bond markets, Longstaff, Mithal, and Neis (2005), Bongaerts, de Jong, and Driessen (2011) and Longstaff, Pan, Pedersen, and Singleton (2011) for credit derivative markets, and Boyson and Stulz (2010) and Sadka (2010) for hedge funds.

cannot explain the cross-sectional returns associated with the book-to-market effect. These results are consistent with our findings but are based on aggregate market liquidity risk. The Sadka (2006) measure is a market aggregate of the price impacts at the individual stock level. He shows that the cross-section of returns on portfolios sorted on momentum and post-earnings-announcement drift are well explained by the market-wide variations of the variable part of this price impact. Further evidence has been put forward for other asset markets[17].

Acharya and Pedersen (2005) are the closest to our paper in terms of empirical strategy since they form portfolios by sorting securities on liquidity, liquidity variations and size. They also find that illiquid securities have high liquidity risk, a result consistent with flight to liquidity in periods of illiquid markets, and that results are very similar for liquidity and size portfolios. They find in particular that a security with high average illiquidity tends to have high commonality in liquidity with market liquidity, high return sensitivity to market liquidity, and high liquidity sensitivity to market returns. It remains to be investigated whether this commonality is due to the presence of funding liquidity that affects all three elements of market liquidity. Conditioning on funding liquidity level or innovations may help in distinguishing statistically the relative impacts of each element on returns.

To better understand the relation between momentum returns and funding liquidity risk, we turn to the existing literature that aims at finding a risk-based explanation to momentum returns. Let us start with liquidity risk. The most recent paper on the topic by Asness et al. (2013) concludes that momentum loads either negatively or zero on liquidity risk[18]. So momentum strategies do well when liquidity cost is high.

[17] See in particular Chordia, Sarkar, and Subrahmanyam (2005), Acharya and Pedersen (2005), Beber, Brandt, and Kavajecz (2008), and Li, Wang, and adn Y. He (2009) for bond markets, Longstaff, Mithal, and Neis (2005), Bongaerts, de Jong, and Driessen (2011) and Longstaff, Pan, Pedersen, and Singleton (2011) for credit derivative markets, and Boyson and Stulz (2010) and Sadka (2010) for hedge funds.

[18] They also find that value loads positively on liquidity risk, which means that value strategies do worse when liquidity is poor.

They pool several asset classes and different markets and use a number of measures for funding liquidity risk such as the U.S. Treasury-Eurodollar (TED) spread, a global average of TED spreads, and LIBOR-term repo spreads, along with market liquidity measures mentioned earlier to compute an illiquidity index. They also find that the importance of liquidity risk rises sharply after the liquidity crisis, suggesting that the effects are time-varying and are conditional on the relative tightness of funding conditions. Previously, Sadka (2006) had used a market aggregate of the price impacts at the individual stock level and showed that the cross-sections of returns on portfolios sorted on momentum and post-earnings-announcement drift are well explained by the market-wide variations of the variable part of this price impact. Pastor and Stambaugh (2003) show that their liquidity risk factor accounts for half of the profits to a momentum strategy over the period 1966 to 1999. Another strand of literature shows that momentum profits are stronger in small stocks[19]. Avramov et al. (2007) show that momentum profitability is large and significant among low-grade firms but nonexistent among high-grade firms. Recently, Mahajan et al. (2012) show that momentum profits are linked to innovations in aggregate default risk. They show that momentum returns are conditional on high economy-wide default shocks, which is also consistent with our results. They measure aggregate default risk as innovations in the yield spread between Moody's CCC corporate bond index and the 10-year U.S. Treasury bond. This yield spread is well explained by our measure of funding liquidity. This literature tour tends to establish from various angles a link between illiquidity or funding liquidity risk and momentum returns. Our empirical findings tend to support the fact that funding shocks explain momentum-sorted portfolios.

We have considered funding liquidity shocks and not the level of funding liquidity as a source of risk. In first-stage regressions of portfolio returns on the level and the innovations of funding liquidity factor for different portfolio sorts, estimates for

[19]See in particular Hong et al. (2000) and Fama and French (2011).

the funding liquidity factor level are almost always insignificant. In contrast, the coefficients on funding liquidity changes are always very significant. However, the level of funding liquidity value is an important conditioning variable to capture episodes of funding tensions on the market. We used it in Section II to study the sensitivity of liquidity and volatility portfolios to the state of funding conditions. We should pursue this investigation for value and momentum portfolios.

Finally, Chen and Petkova (2012) decompose aggregate market variance (which is linked to the aggregate liquidity measure of Pastor and Stambaugh (2003)) into an average correlation component and an average variance component. They show that only the latter commands a negative price of risk in the cross section of portfolios sorted by idiosyncratic volatility (IV), therefore providing a risk-based explanation behind the IV puzzle. We need to investigate if the spread in loadings of IV-sorted portfolios to our funding liquidity factor is large enough to explain the difference in average returns between high and low IV stocks.

V Conclusion

In this paper, we focus on measuring the effect of funding constraints in the cross-section of equity liquidity, volatility and risk premium. Several theoretical models emphasizes the role of funding market frictions in linking together a stock's volatility, liquidity and valuations. Fontaine and Garcia (2012) proposed a measure of funding liquidity value based on apparent arbitrage opportunities in the Treasury market which can be attributed to funding market frictions. Building on this measure, we show that funding shocks increase the dispersion of illiquidity across liquidity-sorted portfolios, increase the dispersion of volatility across volatility-sorted portfolios and, consistent with theory, we provide evidence of the cross-effect – that funding shocks increase the dispersion of illiquidity across volatility-sorted portfolios.

Our results provide strong supportive evidence for limits-to-arbitrage theories based on frictions in the intermediation mechanism. We also provide a partial answer to what Adrian, Etula, and Muir (2013) identified as a challenge to their results. Namely, that the leverage of broker-dealer appears to be unrelated to the cross-sectional liquidity or to a liquidity risk factor. We argue that our measure of funding liquidity value complement their proxy based on leverage, especially in the recent history where leverage tended to increase in the early phase of a financial crisis. Finally, the approach in this paper is based on unconditional cross-section tests and a fuller analysis would require assessing the effect of funding liquidity on returns, conditionally.

A Appendix

A Betting-against-Beta Returns

We construct the BAB factor as follow. First, we assign the ranked securities to one of the two porftfolios: low-beta and high-beta. Let z be the $N \times 1$ vector beta ranks $z_i = rank(\beta_{it})$ at portfolio formation, and let $\bar{z} = 1_n' z/N$ be the average rank, where N is the number of securities and 1_n is an $N \times 1$ vector of ones. The portfolio weights of the low-beta and high-beta portfolios are given by

$$\begin{aligned} \omega_H &= (1/k)sign(z-\bar{z})(z-\bar{z})^+ \\ \omega_L &= (1/k)sign(z-\bar{z})(z-\bar{z})^- \end{aligned} \tag{9}$$

where k is a normalizing constant $k = 1_N'|z_i - \bar{z}|/2$, x^+ and x^- indicate the positive and negative elements of a vector x and $sign(x)$ indicates the sign of the elements of x. Multiplying the weights by the $sign(x)$ keeps the weights positive. In other words, the low (high) beta portfolio is comprised of all stocks with a beta below (above) its asset class median. Note that by construction we have $1'_N\omega_H = 1$ and $1'_N\omega_L = 1$. The BAB factor is based on the self-financing zero-beta portfolio that is long the low beta portfolio and that short sells the high beta portfolio. However, both portfolios are rescaled to have a beta of one at portfolio formation.

$$r_{t+1}^{BAB} = \frac{1}{\beta_t^L}(r_{t+1}^L - r^f) - \frac{1}{\beta_t^H}(r_{t+1}^H - r^f) \tag{10}$$

where $r_{t+1}^L = r'_{t+1}\omega_L$ and $r_{t+1}^H = r'_{t+1}\omega_H$. Finally, we rebalance the portfolios every calendar month.

References

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

Adrian, T., E. Etula, and T. Muir (2013). Financial intermediaries and the cross-section of asset returns. Forthcoming in *Journal of Finance*.

Adrian, T. and H. Shin (2009). The shadow banking system: Implications for financial regulation. working paper 382, Federal Reserve Bank of New York.

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*, 31–56.

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

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

Asness, C., T. Moskowitz, and L. H. Pedersen (2013). Value and momentum everywhere. Forthcoming in *Journal of Finance*.

Avramov, D., T. Chordia, G. Jostova, and A. Philipov (2007). Momentum and credit rating. *The Journal of Finance 62*, 2503–2520.

Bartolini, L., S. Hilton, S. Sundaresan, and C. Tonetti (2010). Collateral values by asset class : Evidence from primary security dealers. *Review of Financial Studies. forthcoming*.

Beber, A., M. W. Brandt, and K. A. Kavajecz (2008). Flight to quality or flight to liquidity? evidence from the euro-area bond market. *Review of Financial Studies 22*, 925–957.

Bongaerts, D., F. de Jong, and J. Driessen (2011). Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market. *The Journal of Finance 66*, 203–240.

Bouwman, K. E., E. Sojli, and W. Tham (2012). Stock market illiquidity, funding liquidity, and bond risk premia. Working paper, Erasmus University.

Boyson, N. C. W. S. and R. M. Stulz (2010). Hedge fund contagion and liquidity. *The Journal of Finance 65*, 1789–1816.

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

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

Chen, Z. and R. Petkova (2012). Does idiosyncratic volatility proxy for risk exposure. *Review of Financial Studies 25(9)*, 2745–2787.

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

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

Engle, R., M. Fleming, E. Ghysels, and G. Nguyen (2012). Liquidity, volatility, and flights to safety in the u.s. treasury market: Evidence from a new class of dynamic order book models. Working Paper, New York University.

Fama, E. and K. R. French (2011). Size, value and momentum in international stock returns. Booth School of Business, University of Chicago.

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

Franzoni, F., E. Nowak, and L. Phalippou (2012). Private equity performance and liquidity risk. *The Journal of Finance 67*, 2341–2373.

Frazzini, A. and L. Pedersen (2011). Betting against beta. Working Paper, New York University.

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

Gârleanu, N. and L. Pedersen (2009). Margin-based asset pricing and deviations from the law of one price. Working Paper.

Goyal, A. (2012). Empirical cross-sectional asset pricing. *Financial Markets and Portfolio Management 26*, 3–38.

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

Goyenko, R. Y. and A. D. Ukhov (2009, 2). Stock and bond market liquidity: A long-run empirical analysis. *JFQA 44*, 189–212.

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

He, Z. and A. Krishnamurthy (2008). Intermediary asset prices. *American Economic Review 103*, 732–770.

Hong, H., T. Lim, and J. Stein (2000). Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance 55*, 265–295.

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. *The Journal of Finance 52*, 2051–2072.

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

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

Li, H., J. Wang, and C. W. adn Y. He (2009). Are liquidity and information risks priced in the treasury bond market? *The Journal of Finance 64*, 467–503.

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

Longstaff, F., S. Mithal, and E. Neis (2005). Corporate yield spreads: Default risk or liquidity? new evidence from the credit-default swap market. *The Journal of Finance 60*, 2213–2253.

Longstaff, F., J. Pan, L. H. Pedersen, and K. J. Singleton (2011). How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics 3*, 75–103.

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

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

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

Sadka, R. (2010). Liquidity risk and the cross-section of expected hedge-fund returns. *Journal of Financial Economics 98*, 54–71.

Vayanos, D. (2004). Flight to quality, flight to liquidity, and the pricing of risk. NBER W10327.

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

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

Average monthly returns, Amihud illiquidity ratio, realized volatility, ex-ante β estimates across illiquidity and volatility-sorted portfolios. The monthly market capitalization for each portfolio is in trillion dollars. The values in parentheses are t-statistics. Monthly data, January 1987 - March 2012.

Panel (a) Liquidity-Sorted Portfolios

	Illiqu.	2	3	4	5	6	7	8	9	Liquid
Illiqu.	3.32	0.51	0.18	0.08	0.03	0.02	0.01	0.00	0.00	0.00
Vol.	2.30	2.35	2.28	2.22	2.14	2.07	2.05	2.01	1.91	1.83
Cap.	0.29	0.71	1.28	1.94	2.90	4.31	6.28	11.04	21.49	93.31
$E(R)$	1.43	1.52	1.36	1.30	1.22	1.13	1.07	1.10	0.96	0.88
β	0.71	0.83	0.87	0.89	0.91	0.93	0.95	0.97	0.97	1.00
CAPM α	0.73	0.71	0.53	0.45	0.38	0.30	0.21	0.26	0.16	0.09
	(4.51)	(3.68)	(3.00)	(2.60)	(2.37)	(2.04)	(1.54)	(2.02)	(1.54)	(1.23)
FF3 α	0.52	0.46	0.29	0.22	0.17	0.10	0.04	0.09	0.04	0.04
	(4.87)	(3.93)	(2.72)	(1.91)	(1.45)	(0.94)	(0.35)	(0.92)	(0.47)	(0.70)
Sharpe R.	0.26	0.22	0.19	0.18	0.17	0.16	0.14	0.15	0.14	0.13

Panel (b) Volatility-Sorted Portfolios

	Most	2	3	4	5	6	7	8	9	Least
Illiq.	0.85	0.49	0.46	0.35	0.30	0.33	0.27	0.24	0.25	0.38
Vol.	3.04	2.69	2.47	2.30	2.16	2.01	1.89	1.73	1.58	1.33
Cap.	4.46	6.15	8.20	10.45	13.08	18.06	17.30	20.10	22.73	23.01
$E(R)$	1.56	1.41	1.26	1.28	1.19	1.12	1.11	1.06	0.97	1.02
β	1.08	1.02	0.99	0.97	0.95	0.92	0.89	0.85	0.80	0.71
CAPM α	0.55	0.48	0.36	0.39	0.34	0.32	0.32	0.32	0.28	0.43
	(2.50)	(2.64)	(2.35)	(2.56)	(2.31)	(2.39)	(2.42)	(2.79)	(2.41)	(3.85)
FF α	0.34	0.26	0.16	0.18	0.13	0.13	0.13	0.17	0.13	0.31
	(2.06)	(2.04)	(1.49)	(1.66)	(1.23)	(1.33)	(1.37)	(1.90)	(1.45)	(3.27)
Sharpe R.	0.18	0.18	0.17	0.17	0.17	0.17	0.17	0.18	0.17	0.23

Table 2: **Pricing Volatility and Liquidity Portfolios**

Cross-sectional asset pricing tests across volatility and illiquidity-sorted portfolios based on two-stage Fama-MacBeth regressions. The parameter estimates are annualized (multiplied by 12). The confidence intervals for R-squares are based on 5000 bootstrap replicates. For the specifications that include traded assets as factors, those factors are also included as test assets. Monthly data, January 1987 - March 2012.

	CAPM	FF3	ΔFL	Augmented by ΔFL	
α	4.22	-0.94	-2.39	-3.41	-2.45
t-FM	(1.60)	(-0.96)	(-0.66)	(-0.93)	(-2.99)
t-Sh.	(1.59)	(-0.93)	(-0.47)	(-0.62)	(-2.37)
ΔFL			-4.22	-4.72	-3.23
t-FM			(-2.43)	(-3.43)	(-3.25)
t-Sh.			(-1.73)	(-2.32)	(-2.60)
MKT	6.48	7.49		11.20	8.69
t-FM	(1.46)	(2.24)		(2.20)	(2.61)
t-Sh.	(1.46)	(2.23)		(1.66)	(2.54)
SMB		4.38			5.59
t-FM		(1.76)			(2.28)
t-Sh.		(1.75)			(2.20)
HML		4.94			5.42
t-FM		(2.13)			(2.33)
t-Sh.		(2.12)			(2.25)
$\bar{R}_c^2$	21.68%	60.12%	46.65%	42.75%	70.95%
R_c^2	25.80%	66.42%	49.46%	48.78%	77.07%
R^2	20.46%	84.14%	49.46%	54.58%	89.59%
C.I.	[0.12, 59.20]	[66.25, 90.79]	[17.84, 70.81]	[20.83, 72.97]	[79.73, 93.37]
$\bar{R}^2$	16.27%	81.63%	46.65%	49.53%	87.28%
C.I.	[-5.08, 57.88]	[60.26, 88.83]	[14.93, 69.49]	[9.69, 69.84]	[74.18, 91.87]

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

We report the individual pricing errors ($E(R^e) - \gamma_0 - \beta\gamma_1$) in percent per year for CAPM, FF3, ΔFL. Below, we report the intercept (γ_0) from the cross-sectional regressions, MAPE (the mean pricing error $\frac{1}{N}\sum\eta$), and the χ^2_{N-K} statistic of joint significance of pricing errors, and its p-value.

Panel (a) Liquidity Portfolios

	$E(R^e)$	CAPM	FF3	ΔFL
Least Liquid	13.38	1.36	3.50	1.65
2	14.47	4.08	1.27	2.14
3	12.59	2.53	-0.32	1.95
4	11.83	2.19	-1.04	1.67
5	10.92	1.13	-0.85	0.36
6	9.76	-0.24	-1.02	-1.20
7	9.03	-0.58	-1.31	-2.65
8	9.49	-0.25	-0.45	-2.59
9	7.71	-2.91	-0.05	-1.29
Most Liquid	6.83	-3.86	1.10	-0.04
Intercept		18.20	-2.69	-4.91
MAPE		2.05	0.97	1.55
χ^2_{N-K}		20.00	16.93	7.45
p-value		0.03	0.08	0.59

Panel (b) Volatility Portfolios

	$E(R^e)$	CAPM	FF3	ΔFL
Least Liquid	14.93	1.83	1.16	3.30
2	13.16	1.19	0.38	0.67
3	11.35	-0.02	-0.57	-0.07
4	11.61	0.34	-0.35	-0.64
5	10.52	-0.17	-0.74	-0.45
6	9.67	-0.23	-0.50	-0.97
7	9.59	-0.27	-0.40	-1.93
8	8.99	-0.05	0.35	-0.40
9	7.81	-0.32	0.15	-0.56
Most Liquid	8.47	1.91	2.81	1.04
Intercept		2.35	-0.47	-1.04
MAPE		0.96	0.75	1.00
$\chi^2_{N-K}7$		20.59	21.27	8.02
p-value		0.02	0.02	0.53

Table 4: **Conditional Average Liquidity and Volatility**

Average illiquidity and volatility of liquidity-sorted and volatility-sorted portfolios conditional on lagged value of funding liquidity FL. 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. Portfolio 1 is the least liquid or most volatile, and portfolio 10 is the most liquid or least volatile. The illiquidity ratio is multiplied by 100. Monthly data, January 1987 - March 2012.

Panel (a) Low FL_{t-1}

	Liquidity Portfolios			Volatility Portfolios		
	Returns	Illiquidity	Volatility	Returns	Illiquidity	Volatility
1	19.17	281.46	2.12	16.18	72.47	2.94
2	17.20	49.01	2.19	11.81	38.92	2.53
3	14.99	16.57	2.16	13.50	38.80	2.33
4	12.38	7.15	2.10	12.16	28.78	2.17
5	13.62	2.83	2.00	13.08	27.95	2.01
6	11.27	1.46	1.95	9.63	31.51	1.86
7	10.27	0.84	1.93	10.58	22.92	1.75
8	9.96	0.45	1.89	10.34	26.27	1.62
9	8.59	0.22	1.79	10.69	21.98	1.46
10	3.63	0.08	1.71	12.59	36.56	1.24

Panel (b) High FL_{t-1}

	Liquidity Portfolios			Volatility Portfolios		
	Returns	Illiquidity	Volatility	Returns	Illiquidity	Volatility
1	10.31	370.77	2.59	19.40	94.44	3.30
2	12.53	53.26	2.61	15.53	57.49	2.99
3	10.86	20.37	2.54	9.77	49.99	2.76
4	12.26	8.68	2.46	11.77	36.72	2.56
5	10.41	4.06	2.39	9.34	30.51	2.43
6	11.05	1.99	2.31	9.08	37.97	2.27
7	9.29	0.98	2.28	9.52	32.15	2.15
8	9.92	0.52	2.24	8.34	23.41	1.94
9	8.28	0.25	2.12	5.53	27.91	1.78
10	8.60	0.09	2.02	5.67	40.20	1.47

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

	Liquidity Portfolios		Volatility Portfolios	
	Illiquidity	Volatility	Illiquidity	Volatility
1	89.30	0.47	21.97	0.36
2	4.25	0.43	18.57	0.46
3	3.81	0.38	11.19	0.43
4	1.54	0.36	7.94	0.39
5	1.23	0.39	2.56	0.42
6	0.53	0.37	6.46	0.41
7	0.14	0.36	9.23	0.40
8	0.07	0.35	-2.87	0.32
9	0.04	0.33	5.94	0.32
10	0.01	0.31	3.65	0.23

Table 5: **Illiquidity, Volatility and Funding Shocks**

Panel (a) reports coefficient estimates in regressions of portfolio illiquidity changes on funding liquidity innovations, $\Delta ILLIQ_{i,t} = \gamma_{0,i} + \gamma_{1,i}\Delta FL_t + \gamma_{2,i}\Delta ILLIQ_t^{mkt} + \xi_{i,t}$. Panel (b) reports coefficient estimates in regressions of portfolio volatility changes on funding liquidity innovations, $\Delta VOL_{i,t} = \gamma_{0,i} + \gamma_{1,i}\Delta FL_t + \gamma_{2,i}\Delta VOL_t^{mkt} + \xi_{i,t}$. Portfolio 1 is the least liquid or the most volatile, and portfolio 10 is the most liquid or the least volatile portfolio. Estimates are multiplied by 100. Monthly data, January 1987 - March 2012.

Panel (a) Liquidity Regressions

	Most	2	3	4	5	6	7	8	9	Least
	Illiquidity Portfolios									
γ_1	12.12	0.13	-0.07	0.20	0.22	0.15	0.08	0.05	0.03	0.01
	(2.08)	(0.07)	(-0.10)	(0.60)	(1.66)	(2.55)	(2.57)	(2.73)	(3.21)	(2.30)
γ_2	776.56	93.14	30.40	12.74	5.47	2.23	1.13	0.55	0.26	0.09
	(26.67)	(9.72)	(8.20)	(7.78)	(8.24)	(7.54)	(7.08)	(6.03)	(6.19)	(4.80)
R^2	70.94%	24.18%	18.43%	17.22%	19.74%	18.33%	16.78%	13.56%	14.90%	9.24%
$\bar{R}^2$	70.75%	23.67%	17.88%	16.67%	19.20%	17.79%	16.22%	12.98%	14.33%	8.63%
	Volatility Portfolios									
γ_1	1.54	6.06	1.27	-1.45	2.17	-1.56	0.86	1.23	1.37	-1.51
	(0.35)	(2.23)	(0.42)	(-0.59)	(1.44)	(-0.72)	(0.51)	(0.80)	(0.86)	(-0.58)
γ_2	225.30	1d13.22	137.39	134.57	56.07	67.16	60.65	43.23	28.00	35.42
	(10.24)	(8.34)	(9.14)	(11.01)	(7.42)	(6.17)	(7.17)	(5.59)	(3.49)	(2.72)
R^2	26.23%	20.74%	22.14%	28.86%	16.58%	11.30%	14.98%	9.89%	4.33%	2.46%
$\bar{R}^2$	25.74%	20.21%	21.62%	28.38%	16.02%	10.71%	14.42%	9.29%	3.69%	1.80%

Panel (b) Volatility Regressions

	Most	2	3	4	5	6	7	8	9	Least
	Illiquidity Portfolios									
γ_1	7.23	7.07	2.48	-0.22	-0.47	0.52	-2.66	-3.64	-5.44	-8.22
	(2.20)	(2.00)	(1.01)	(-0.10)	(-0.25)	(0.29)	(-1.44)	(-1.78)	(-2.51)	(-3.36)
γ_2	69.73	95.06	96.99	95.66	100.19	103.87	108.66	109.27	108.97	111.39
	(31.26)	(39.63)	(57.92)	(65.68)	(77.54)	(83.88)	(86.68)	(78.83)	(73.90)	(66.88)
R^2	79.13%	85.72%	92.62%	94.10%	95.69%	96.31%	96.49%	95.78%	95.19%	94.14%
$\bar{R}^2$	78.99%	85.63%	92.57%	94.06%	95.66%	96.28%	96.47%	95.75%	95.16%	94.10%
	Volatility Portfolios									
γ_1	3.49	1.55	2.18	-0.60	0.67	-3.01	-1.13	-3.10	0.05	-1.51
	(0.86)	(0.52)	(0.98)	(-0.27)	(0.41)	(-1.78)	(-0.65)	(-1.57)	(0.03)	(-0.60)
γ_2	116.60	110.80	107.27	108.35	106.78	101.00	102.36	92.63	86.86	73.87
	(42.15)	(54.98)	(71.02)	(72.26)	(95.17)	(87.81)	(86.85)	(69.04)	(66.26)	(43.30)
R^2	86.94%	91.84%	94.95%	95.07%	97.11%	96.57%	96.52%	94.56%	94.20%	87.31%
$\bar{R}^2$	86.85%	91.78%	94.92%	95.03%	97.09%	96.55%	96.50%	94.53%	94.16%	87.22%

Table 6: **Summary Statistics – Alternative portfolios sorts**

Average monthly returns, Amihud illiquidity ratio, realized volatility, ex-ante β estimates across portfolios sorted on market liquidity risk and volatility risk betas. Portfolio 1 has the highest beta and portfolio has the lowest beta. The monthly market capitalization for each portfolio is in trillion dollars. The values in parentheses are t-statistics. Monthly data, January 1987 - March 2012.

Panel (a) β^{Illiq_m,r_i}-Sorted Decile Portfolios

	1	2	3	4	5	6	7	8	9	10
$E(R)$	14.20	13.09	13.48	12.32	13.86	13.34	13.36	13.70	15.07	16.83
Illiquidity	0.29	0.32	0.31	0.27	0.27	0.24	0.27	0.32	0.33	0.41
Volatility	2.17	1.92	1.92	1.94	1.97	1.97	1.99	2.05	2.15	2.43
β ex-ante	0.92	0.87	0.88	0.89	0.91	0.91	0.91	0.92	0.94	0.99
Mkt Cap	12.38	14.90	15.44	16.14	15.02	16.49	15.11	11.05	10.29	6.36
$\beta_i^{\sigma_m,r_i}$	0.09	0.08	0.06	0.05	0.05	0.04	0.04	0.03	0.02	-0.01
$\beta_i^{L_m,r_i}$	1.41	0.48	0.06	-0.30	-0.61	-0.92	-1.26	-1.67	-2.17	-3.51
CAPM α	0.33	0.31	0.37	0.26	0.36	0.31	0.30	0.34	0.42	0.48
	(2.43)	(2.34)	(2.92)	(2.07)	(2.71)	(2.31)	(2.34)	(2.35)	(2.81)	(2.69)
FF α	0.18	0.12	0.18	0.09	0.17	0.11	0.13	0.15	0.23	0.28
	(1.65)	(1.24)	(2.05)	(0.92)	(1.78)	(1.18)	(1.33)	(1.36)	(1.98)	(2.00)
Sharpe Ratio	0.17	0.17	0.18	0.16	0.18	0.17	0.16	0.17	0.18	0.18

Panel (b) β^{σ_m,r_i}-Sorted Portfolios

	1	2	3	4	5	6	7	8	9	10
$E(R)$	13.69	11.75	11.88	12.65	12.83	12.65	14.12	15.11	15.46	19.15
Illiquidity	0.37	0.25	0.27	0.25	0.23	0.24	0.24	0.32	0.34	0.52
Volatility	2.39	2.09	1.98	1.89	1.84	1.87	1.89	1.97	2.11	2.48
β ex-ante	0.97	0.93	0.90	0.89	0.88	0.89	0.89	0.90	0.93	0.97
Mkt Cap	7.12	10.52	13.01	13.01	15.05	15.43	17.02	16.60	15.47	9.95
$\beta_i^{\sigma_m,r_i}$	0.35	0.19	0.13	0.09	0.06	0.02	-0.01	-0.05	-0.10	-0.25
$\beta_i^{L_m,r_i}$	-0.44	-0.59	-0.70	-0.69	-0.71	-0.78	-0.90	-1.01	-1.13	-1.54
CAPM α	0.26	0.16	0.20	0.28	0.30	0.27	0.39	0.48	0.47	0.68
	(1.62)	(1.13)	(1.53)	(2.24)	(2.30)	(2.06)	(2.94)	(3.35)	(3.02)	(3.18)
FF α	0.08	-0.01	0.02	0.11	0.12	0.09	0.21	0.29	0.28	0.45
	(0.69)	(-0.12)	(0.25)	(1.16)	(1.22)	(0.89)	(2.08)	(2.61)	(2.24)	(2.53)
Sharpe Ratio	0.15	0.13	0.14	0.16	0.17	0.16	0.18	0.20	0.19	0.20

Table 7: **Pricing Liquidity and Volatility – Alternative Portfolio Sorts**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions two sets of decile portfolios sorted on market illiquidity risk and market volatility risk. The parameter estimates are annualized (multiplied by 12). The confidence intervals for R-squares are based on 5000 bootstrap replicates. For the specifications that include traded portfolios as factors, those factors are also included as test assets. Monthly data, January 1987 - March 2012.

	CAPM	FF3	ΔFL	Augmented by ΔFL	
α	-2.06	-3.12	-2.68	-3.81	-3.04
	(-0.49)	(-2.45)	(-0.67)	(-0.88)	(-2.44)
	(-0.48)	(-2.35)	(-0.48)	(-0.60)	(-1.94)
ΔFL			-4.21	-4.45	-3.22
			(-2.88)	(-2.94)	(-1.87)
			(-2.06)	(-2.05)	(-1.48)
MKT	12.76	9.10		11.51	9.25
	(2.34)	(2.72)		(2.16)	(2.75)
	(2.30)	(2.70)		(1.65)	(2.67)
SMB		4.41			4.54
		(1.70)			(1.74)
		(1.69)			(1.64)
HML		5.93			5.84
		(2.38)			(2.36)
		(2.36)			(2.22)
R^2	35.29%	87.91%	73.06%	75.46%	92.02%
C.I. R^2	[0.27, 76.90]	[51.98, 94.91]	[25.70, 93.51]	[33.39, 91.80]	[66.87, 97.27]
$\bar{R}^2$	31.88%	86.00%	71.56%	72.74%	90.25%
C.I. $\bar{R}^2$	[-5.04, 74.64]	[46.84, 93.88]	[16.86, 92.27]	[26.84, 91.24]	[61.24, 96.75]

Table 8: **Pricing Liquidity and Volatility Portfolios – Alternative Liquidity Factors**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions. BAB is the Betting-Against-Beta factor, Am is the Amihud (2002) market illiquidity ratio, PS is the liquidity-factor mimicking portfolio from Pastor and Stambaugh (2003), and TED spread is the difference between the three-month LIBOR rate and the three-month U.S. Treasuries rate. The parameter estimates are annualized (multiplied by 12). The 95% confidence intervals for R-squares are based on 5000 bootstrap replicates. Traded risk factors are included among test assets. Monthly data, January 1987 - March 2012.

Panel (a) Alternative Proxies

α	10.41	-0.45	10.87	-0.89
	(3.43)	(-0.11)	(3.31)	(-0.26)
	(3.42)	(-0.08)	(2.41)	(-0.19)
ΔFL				
BAB	-3.05			
	(-0.72)			
	(-0.72)			
Am		-1.18		
		(-1.73)		
		(-1.27)		
PS			-0.45	
			(-2.99)	
			(-2.19)	
TED				-4.96
				(-2.21)
				(-1.62)
R^2	13.85%	21.04%	31.52%	31.04%
	[0.10, 52.71]	[0.59, 43.26]	[0.08, 78.54]	[0.30, 60.83]
$\bar{R}^2$	9.32%	16.65%	27.92%	27.21%
	[-5.00, 50.88]	[-4.58, 40.26]	[-5.18, 78.14]	[-5.42, 58.66]

Panel (b) Augmented Models

α	-2.39	-0.13	-0.71	0.92	-2.72
	(-0.66)	(-0.04)	(-0.17)	(1.95)	(-0.69)
	(-0.47)	(-0.03)	(-0.11)	(1.33)	(-0.50)
ΔFL	-4.22	-3.59	-5.00	-3.33	-4.02
	(-2.43)	(-2.84)	(-3.36)	(-2.93)	(-2.57)
	(-1.73)	(-2.18)	(-2.15)	(-2.02)	(-1.87)
BAB		7.65			
		(1.95)			
		(1.66)			
Am			0.46		
			(1.05)		
			(0.67)		
PS				-0.35	
				(-2.55)	
				(-1.75)	
TED					-0.94
					(-0.75)
					(-0.55)
R^2	49.46%	39.25%	50.63%	94.14%	49.57%
	[17.84, 70.81]	[9.29, 63.16]	[17.16, 73.68]	[85.86, 98.34]	[13.26, 67.68]
$\bar{R}^2$	46.65%	32.50%	44.82%	93.49%	43.63%
	[14.93, 69.49]	[0.03, 57.83]	[8.43, 71.18]	[84.54, 98.18]	[6.55, 64.59]

Table 9: **Funding and Market Liquidity Risk in Liquid and Illiquid Samples**
Risk exposures to market liquidity and funding liquidity shocks when the aggregate market is liquid (Hi Liq) or illiquid (Lo Liq). The monthly observations are ranked using the market-wide average Amihud measure for the current month. The sample is divided in three equal-sized subsamples. For each sub-sample, we compute the regression coefficient of volatility- and illiquidity-sorted portfolio returns on ΔFL and PS, $\beta^{\Delta FL}$ and β^{PS}, respectively, with t-statistics reported in parenthesis. Panel (a)-(b) report results for illiquidity- and volatility- sorted portfolios, respectively. Monthly data, Jan 1987 - Dec 2012.

Panel (a) Liquidity Portfolios

		Illiquid	2	3	4	5	6	7	8	9	Liquid
Lo Liq	β^{FL}	-7.32	-7.81	-7.61	-6.93	-6.72	-7.7	-6.73	-7.07	-5.93	-5.05
		(-5.17)	(-4.31)	(-4.17)	(-3.70)	(-3.97)	(-4.46)	(-4.02)	(-4.33)	(-4.11)	(-3.58)
	β^{PS}	-3.59	-16.41	-18.48	-10.01	0.77	7.26	6.48	5.19	6.08	4.03
		(-0.31)	(-1.12)	(-1.25)	(-0.66)	(0.06)	(0.52)	(0.48)	(0.39)	(0.52)	(0.35)
Hi Liq	β^{FL}	-0.16	0.09	0.43	-0.03	-0.15	-0.46	-0.7	-0.19	-0.37	-0.72
		(-0.14)	(0.07)	(0.35)	(-0.02)	(-0.13)	(-0.41)	(-0.60)	(-0.18)	(-0.36)	(-0.74)
	β^{PS}	-31.26	-25.88	-21.63	-15.42	-10.82	-15.65	-9.60	-8.36	-8.94	-7.17
		(-3.05)	(-2.06)	(-1.85)	(-1.33)	(-0.95)	(-1.48)	(-0.87)	(-0.82)	(-0.94)	(-0.78)
All	β^{FL}	-3.18	-3.33	-3.17	-2.83	-3.02	-3.56	-3.1	-3.22	-2.76	-2.36
		(-4.46)	(-3.83)	(-3.62)	(-3.22)	(-3.71)	(-4.34)	(-3.78)	(-4.11)	(-3.89)	(-3.39)
	β^{PS}	-3.74	-7.25	-7.32	-0.37	5.35	5.40	6.42	8.13	5.68	3.66
		(-0.58)	(-0.93)	(-0.93)	(-0.05)	(0.73)	(0.73)	(0.87)	(1.15)	(0.89)	(0.58)

Panel (b) Volatility Portfolios

		Volatile	2	3	4	5	6	7	8	9	Stable
Lo Liq	β^{FL}	-8.27	-8.65	-7.64	-7.73	-7.43	-6.85	-6.91	-5.86	-5.59	-4.26
		(-3.40)	(-4.30)	(-4.16)	(-4.11)	(-4.24)	(-4.30)	(-4.44)	(-4.32)	(-4.53)	(-4.41)
	β^{PS}	-18.89	-8.17	-4.85	-5.63	-3.45	3.15	2.85	2.99	9.62	3.78
		(-0.96)	(-0.50)	(-0.33)	(-0.37)	(-0.24)	(0.24)	(0.23)	(0.27)	(0.96)	(0.48)
Hi Liq	β^{FL}	0.44	0.56	-0.02	0.02	-0.29	-0.91	-0.55	-0.38	-0.46	-0.58
		(-0.26)	(-0.40)	(-0.01)	(0.01)	(-0.24)	(-0.83)	(-0.54)	(-0.40)	(-0.58)	(-0.79)
	β^{PS}	-26.32	-21.09	-24.39	-16.19	-13.09	-13.34	-10.57	-12.99	-9.65	-6.46
		(-1.64)	(-1.61)	(-1.94)	(-1.36)	(-1.16)	(-1.29)	(-1.12)	(-1.45)	(-1.30)	(-0.94)
All	β^{FL}	-3.35	-3.49	-3.45	-3.27	-3.2	-3.32	-3.24	-2.6	-2.52	-2.19
		(-2.95)	(-3.54)	(-3.84)	(-3.65)	(-3.85)	(-4.31)	(-4.39)	(-3.90)	(-4.20)	(-4.50)
	β^{PS}	-5.41	-0.10	-0.02	1.12	0.99	4.71	4.28	2.65	5.38	2.95
		(-0.53)	(-0.01)	(-0.00)	(0.14)	(0.13)	(0.68)	(0.64)	(0.44)	(1.00)	(0.67)

Table 10: **Adding Test Assets**

Cross-sectional asset pricing tests with 75 illiquidity-, volatility-, size-, book-to-market-, beta- and momentum-sorted portfolios based on two-stage Fama-MacBeth regressions. BAB is the Betting-Against-Beta factor, Am is the Amihud (2002) market illiquidity ratio, PS is the liquidity-factor mimicking portfolio from Pastor and Stambaugh (2003), and TED spread is the difference between the three-month LIBOR rate and the three-month U.S. Treasuries rate. The parameter estimates are annualized (multiplied by 12). Traded risk factors are included among test assets when applicable. Monthly data, January 1987 - March 2012.

	Panel (a) Alternative Proxies					Panel (b) Augmented Models			
α	0.07	10.19	8.67	10.62	7.12	-2.11	0.76	2.27	3.84
	-0.02	-3.39	-2.37	-3.16	-3.35	(-0.65)	-0.17	-1.51	(2.23)
	-0.01	-3.39	-2.34	-2.49	-3.25	(-0.46)	-0.12	-1.14	(1.91)
ΔFL	-3.24					-4.17	-4.01	-2.66	-2.51
	(-1.91)					(-3.54)	(-2.44)	(-2.27)	(-1.71)
	(-1.52)					(-2.55)	(-1.74)	(-1.73)	(-1.47)
BAB		-0.49				11.21			
		(-0.12)				-2.99			
		(-0.12)				-2.46			
Am			-0.27				0.54		
			(-0.52)				-1.22		
			(-0.51)				-0.88		
PS				-0.37				-0.28	
				(-3.24)				(-2.88)	
				(-2.58)				(-2.22)	
TED					-1.31				0.33
					(-1.32)				(0.35)
					(-1.28)				(0.30)
R^2	28.46%	0.22%	1.45%	36.73%	12.30%	35.63%	32.20%	65.19%	22.78%
	[0.05, 53.92]	[0.02, 41.90]	[0.01, 34.79]	[0.25, 57.59]	[0.02, 41.32]	[2.07, 64.03]	[0.94, 58.91]	[7.39, 75.36]	[0.89, 54.81]

Table 11: **Double-Sorted Volatility and Liquidity Portfolios**

Cross-sectional asset pricing tests across double-sorted volatility and illiquidity portfolios based on two-stage Fama-MacBeth regressions. The parameter estimates are annualized (multiplied by 12). For the specifications that include traded assets as factors, those factors are also included as test assets. Monthly data, January 1987 - March 2012.

	CAPM	FF3	ΔFL	Augmented by ΔFL	
α	9.02	0.31	2.52	0.82	-2.21
t-FM	(3.51)	(0.25)	(0.79)	(0.30)	(-2.36)
t-Sh.	(3.51)	(0.24)	(0.68)	(0.20)	(-1.73)
ΔFL			-2.51	-4.94	-3.89
t-FM			(-1.52)	(-4.48)	(-4.38)
t-Sh.			(-1.32)	(-2.96)	(-3.26)
MKT	1.19	4.63		6.23	6.70
t-FM	(0.29)	(1.33)		(1.44)	(1.98)
t-Sh.	(0.29)	(1.32)		(1.13)	(1.88)
SMB		4.91			6.08
t-FM		(1.98)			(2.46)
t-Sh.		(1.97)			(2.32)
HML		6.90			7.82
t-FM		(2.71)			(3.05)
t-Sh.		(2.68)			(2.73)
R_c^2	1.08%	59.98%	21.33%	34.62%	73.06%
$\bar{R}_c^2$	-3.22%	54.26%	17.90%	28.68%	67.67%
R^2	1.11%	65.77%	21.33%	39.08%	78.99%
$\bar{R}^2$	-3.01%	61.49%	17.90%	33.79%	75.33%

Table 12: **Double-Sorted Liquidity and Volatility Portfolios – Alternative Liquidity Factors**

Cross-sectional asset pricing tests across double-sorted volatility and illiquidity portfolios based on two-stage Fama-MacBeth regressions. BAB is the Betting-Against-Beta factor, Am is the Amihud (2002) market illiquidity ratio, PS is the liquidity-factor mimicking portfolio from Pastor and Stambaugh (2003), and TED spread is the difference between the three-month LIBOR rate and the three-month U.S. Treasuries rate. The parameter estimates are annualized (multiplied by 12). The 95% confidence intervals for R-squares are based on 5000 bootstrap replicates. Traded risk factors are included among test assets. Monthly data, January 1987 - March 2012.

	Panel (a) Alternative Proxies				Panel (b) Augmented Models			
α	10.21	9.49	10.70	10.2	-0.99	5.44	1.85	4.94
	(3.36)	(2.69)	(3.31)	-2.89	(-0.37)	(1.37)	(1.44)	-1.22
	(3.36)	(2.68)	(2.55)	-2.89	(-0.27)	(0.81)	(0.98)	-0.82
ΔFL					-3.85	-4.75	-2.96	-3.97
					(-4.02)	(-3.69)	(-2.37)	3.08
					(-3.01)	(-2.20)	(-1.62)	2.08
BAB	-1.22				10.85			
	(-0.27)				(2.67)			
	(-0.27)				(2.20)			
Amihud		-0.09				1.04		
		(-0.16)				(2.53)		
		(-0.16)				(1.51)		
PS			-0.39				-0.39	
			(-3.18)				(-3.15)	
			(-2.47)				(-2.17)	
TED				-0.05				2.68
				0.02				-1.62
				0.02				-1.1
R_c^2	1.29%	0.23%	50.19%	0.01%	28.26%	36.86%	68.73%	35.42%
$\bar{R}_c^2$	-3.00%	-4.11%	48.03%	-4.34%	21.73%	31.12%	65.89%	29.55%
R^2	1.60%	0.23%	31.76%	0.01%	28.44%	36.86%	78.72%	35.42%
$\bar{R}^2$	-2.50%	-4.11%	28.92%	-4.34%	22.22%	31.12%	76.87%	29.55%

Table 13: **Time-Series Regressions – Quarterly Returns**

Time-series regression of portfolios returns on funding liquidity changes, ΔFL_t and market returns, MKT_t: $r_{it} = \alpha_i + \beta_i^{\Delta FL} \Delta FL_t + \beta_i^{MKT} MKT_t + \varepsilon_{it}$. Panel (a) displays results for liquidity-sorted decile portfolios, with t-statistics in parenthesis. Panel (b) displays results for volatility-sorted decile portfolios. Quarterly data, Q2/1986 - Q4/2011.

Panel (a) Liquidity-Sorted Decile Portfolios

	Illiquid	2	3	4	5	6	7	8	9	Liquid
$\beta^{\Delta FL}$	-3.05	-3.01	-2.28	-2.10	-2.22	-2.25	-2.04	-1.76	-1.39	-0.28
	(-3.47)	(-2.97)	(-2.26)	(-2.22)	(-2.57)	(-3.11)	(-2.98)	(-2.67)	(-2.54)	(-0.78)
β^{MKT}	0.71	0.85	0.90	0.94	0.92	0.88	0.95	0.94	0.83	0.86
	(11.4)	(11.9)	(12.6)	(13.9)	(14.9)	(17.1)	(19.5)	(20.1)	(21.4)	(33.9)
R^2	64.3%	65.1%	66.4%	70.4%	73.4%	78.6%	82.3%	82.8%	84.4%	92.7%

Panel (b) Volatility-Sorted Portfolios

	Most Vol.	2	3	4	5	6	7	8	9	Least Vol.
$\beta^{\Delta FL}$	-2.64	-2.75	-2.52	-2.23	-1.94	-2.07	-2.03	-1.39	-1.40	-1.32
	(-2.24)	(-2.91)	(-3.07)	(-2.72)	(-2.46)	(-2.78)	(-3.03)	(-2.24)	(-2.29)	(-2.05)
β^{MKT}	1.19	1.07	1.00	1.01	0.93	0.85	0.83	0.76	0.67	0.50
	(14.3)	(15.9)	(17.2)	(17.3)	(16.7)	(16.1)	(17.5)	(17.2)	(15.6)	(11.6)
R^2	71.3%	76.0%	78.7%	78.5%	77.1%	76.2%	79.1%	78.0%	74.7%	60.4%

Table 14: **Pricing Volatility and Liquidity Portfolios**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for liquidity-sorted decile portfolios and volatility-sorted decile portfolios. Quarterly data, Q2/1986 - Q4/2011.

	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	3.83	-0.95	12.90	1.12	2.96	-1.21	2.09
	(1.35)	(-1.06)	(2.75)	(0.39)	(1.01)	(-1.42)	(0.82)
ΔFL				-1.63	-2.32	-2.00	-1.56
				(-2.12)	(-2.90)	(-2.62)	(-2.12)
LevFct			-40.42				-8.19
			(-1.43)				(-0.38)
MKT	6.62	8.52			2.82	7.97	
	(1.36)	(2.33)			(0.63)	(2.18)	
SMB		4.98				4.98	
		(2.19)				(2.19)	
HML		4.59				4.46	
		(1.52)				(1.47)	
R^2	21.49%	81.01%	7.90%	69.23%	81.87%	84.67%	69.80%
$\bar{R}^2$	17.36%	78.01%	2.78%	67.52%	79.86%	81.26%	66.24%

Table 15: **Sensitivity of Volatility and Illiquidity to Funding Liquidity**

Slope coefficient estimates in regressions of changes in portfolios' illiquidity on funding liquidity innovations, $\Delta ILLIQ_{it} = \gamma_{0,i} + \gamma_i \Delta FL_t + \xi_{it}$ (Panel a) and of changes of portfolios volatility on funding liquidity innovations, $\Delta VOL_{it} = \gamma_{0,i} + \gamma_i \Delta FL_t + \xi_{it}$, (Panel b). Portfolio 1 is the least liquid or the most volatile, and portfolio 10 is the most liquid or the least volatile portfolio. Estimates are multiplied by 100. Quarterly data, Q2/1986 - Q4/2011.

Panel (a) Liquidity Regressions

	Worse	2	3	4	5	6	7	8	9	Best
Liq. port.	30.8	7.4	4.2	1.6	0.8	0.4	0.2	0.1	0.05	0.01
t-stat.	(2.31)	(2.16)	(3.28)	(2.59)	(3.37)	(3.48)	(3.42)	(3.36)	(3.63)	(3.39)
R^2	5.0%	4.4%	9.6%	6.2%	10.1%	10.7%	10.4%	10.1%	11.5%	10.2%
Vol. port.	8.2	11.6	4.7	4.2	-0.8	1.3	1.9	0.1	-0.1	9.1
t-stat.	(1.49)	(2.39)	(1.31)	(1.13)	(-0.54)	(0.39)	(0.70)	(0.04)	(-0.05)	(1.76)
R^2	2.2%	5.4%	1.7%	1.3%	0.3%	0.2%	0.5%	0.0%	0.0%	3.0%

Panel (b) Volatility Regressions

	Worse	2	3	4	5	6	7	8	9	Best
Liq. port.	0.49	0.58	0.62	0.52	0.55	0.62	0.57	0.60	0.61	0.64
t-stat.	(4.62)	(3.94)	(4.42)	(3.66)	(3.68)	(4.29)	(3.70)	(3.86)	(4.11)	(4.20)
R^2	17.4%	13.3%	16.2%	11.7%	11.8%	15.4%	12.0%	12.9%	14.3%	15.0%
Vol. port.	0.77	0.70	0.64	0.64	0.64	0.55	0.52	0.53	0.47	0.43
t-stat.	(4.59)	(4.69)	(4.05)	(4.06)	(4.10)	(3.71)	(3.29)	(4.03)	(3.50)	(3.76)
R^2	17.3%	17.9%	14.0%	14.0%	14.3%	12.0%	9.7%	13.8%	10.8%	12.3%

Table 16: **Conditional Average Liquidity and Volatility**

Average illiquidity and volalitity of liquidity-sorted and volatility-sorted decile portfolios conditional on the lagged value of funding liquidity being in the bottom 30% (low FL_{t-1}) or the top 30% (high FL_{t-1}). Portfolio 1 is the least liquid or most volatile, and portfolio 10 is the most liquid or least volatile. The illiquidity ratio and volatility are multiplied by 100. Quarterly data, Q2/1986 - Q4/2011.

Panel (a) Low FL_{t-1}

	Liquidity Portfolios			Volatility Portfolios		
	Returns	Illiqu.	Vol.	Returns	Illiqu.	Vol.
1	13.52	382.51	3.72	10.45	104.49	5.11
2	12.35	66.09	3.82	6.16	54.86	4.39
3	10.78	22.15	3.77	8.18	52.89	4.08
4	7.94	9.44	3.66	7.76	36.13	3.78
5	9.08	3.79	3.51	8.51	37.72	3.52
6	9.27	1.88	3.38	6.87	41.25	3.26
7	6.02	1.07	3.39	7.62	31.95	3.08
8	6.74	0.58	3.34	7.23	33.19	2.85
9	6.01	0.28	3.15	8.05	32.50	2.58
10	0.38	0.10	3.02	10.87	44.99	2.20

Panel (b) High FL_{t-1}

	Liquidity Portfolios			Volatility Portfolios		
	Returns	Illiqu.	Vol.	Returns	Illiqu.	Vol.
1	13.90	475.23	4.40	21.69	117.07	5.66
2	17.38	76.23	4.40	19.10	74.84	5.07
3	15.92	28.16	4.31	14.35	58.99	4.70
4	15.48	11.35	4.18	14.33	49.22	4.37
5	15.05	5.29	4.08	12.66	39.10	4.14
6	13.62	2.57	3.96	13.07	49.66	3.89
7	13.27	1.27	3.91	12.65	43.25	3.66
8	12.58	0.67	3.85	11.09	32.26	3.33
9	9.88	0.64	3.68	9.69	38.65	3.08
10	10.69	0.12	3.57	9.28	56.74	2.55

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

	Liquidity Portfolios			Volatility Portfolios		
	Returns	Illiqu.	Vol.	Returns	Illiqu.	Vol.
1	0.38	92.72	0.67	11.24	12.57	0.55
2	5.03	10.13	0.57	12.94	19.98	0.68
3	5.14	6.01	0.53	6.17	6.10	0.62
4	7.53	1.91	0.52	6.57	13.09	0.59
5	5.97	1.50	0.58	4.14	1.38	0.62
6	4.35	0.69	0.58	6.20	8.41	0.63
7	7.25	0.20	0.53	5.03	11.30	0.58
8	5.84	0.09	0.52	3.86	-0.93	0.47
9	3.87	0.06	0.53	1.64	6.14	0.51
10	10.32	0.02	0.55	-1.59	11.75	0.36

Table 17: **Time-series CAPM regressions augmented by ΔFL_t**

Time-series regression of size and book-to-market portfolios 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, Q2/1986 - Q4/2011.

	$\beta^{\Delta FL}$					β^{MKT}					R^2				
	Small	2	3	4	Big	Small	2	3	4	Big	Small	2	3	4	Big
Low	-1.89	-0.12	0.42	1.03	0.84	1.51	1.39	1.31	1.23	0.98	72.3%	82.2%	83.2%	84.9%	88.3%
	(-1.33)	(-0.13)	(0.49)	(1.37)	(1.62)	(15.01)	(20.44)	(21.36)	(22.96)	(26.65)					
2	-2.30	-1.31	-0.70	-1.60	-0.42	1.23	1.12	1.07	0.96	0.89	73.4%	78.8%	84.2%	82.6%	87.4%
	(-2.02)	(-1.49)	(-1.00)	(-2.36)	(-0.83)	(15.19)	(17.93)	(21.71)	(20.03)	(24.85)					
3	-2.44	-2.08	-1.95	-2.20	-1.06	1.01	0.98	0.87	0.95	0.82	72.3%	77.1%	74.4%	79.7%	79.7%
	(-2.49)	(-2.51)	(-2.45)	(-2.92)	(-1.68)	(14.55)	(16.63)	(15.43)	(17.87)	(18.35)					
4	-3.03	-2.04	-2.10	-2.07	-1.50	0.93	0.92	0.92	0.91	0.81	67.1%	69.6%	70.6%	77.8%	74.3%
	(-2.90)	(-2.15)	(-2.26)	(-2.73)	(-2.04)	(12.52)	(13.70)	(13.98)	(16.91)	(15.55)					
High	-3.34	-2.8	-1.89	-2.69	-2.21	1.08	1.05	0.89	0.96	0.83	66.7%	66.7%	63.2%	71.4%	65.4%
	(-2.74)	(-2.37)	(-1.79)	(-2.80)	(-2.31)	(12.48)	(12.65)	(11.89)	(14.04)	(12.28)					

Table 18: **Pricing Size and Book-to-Market Portfolios**

Cross-section asset pricing tests based on two-stage Fama-MacBeth regressions for size and value portfolios. Panel (a) displays results for the 10 × 10 double-sorted Fama-French portfolios. Panel (b) displays results for 10 size-sorted (excluding Nasdaq stocks) and Panel (c) displays results for 10 portfolios sorted by book-to-market. Quarterly data, Q2/1986 - Q4/2011.

Panel (a) 10 × 10 Size and Book-to-Market Double-Sorts

	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	27.82	19.89	1.93	-4.64	9.82	18.83	-2.42
	(2.65)	(4.51)	(0.40)	(-0.67)	(1.47)	(4.72)	(-0.37)
ΔFL				-1.87	-1.40	-1.05	-1.09
				(-2.09)	(-1.84)	(-1.35)	(-1.49)
LevFct			99.54				75.55
			(2.65)				(3.11)
MKT	-18.52	-16.88			-4.95	-13.75	
	(-1.89)	(-2.47)			(-0.70)	(-2.42)	
SMB		5.82				4.22	
		(1.94)				(1.58)	
HML		2.47				-2.60	
		(0.52)				(-0.67)	
R^2	16.11%	69.90%	46.70%	35.79%	41.32%	75.01%	52.16%
$\bar{R}^2$	15.27%	68.98%	46.16%	35.13%	40.13%	73.99%	51.18%

Panel (b) 10 Size Portfolios

	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	17.00	-3.12	11.22	-3.48	6.36	-3.29	-1.94
	(3.82)	(-3.33)	(3.65)	(-0.72)	(1.10)	(-3.55)	(-0.40)
ΔFL				-2.46	-2.28	-2.59	-2.43
				(-2.66)	(-2.48)	(-3.95)	(-2.62)
LevFct			-15.92				-20.95
			(-0.62)				(-0.83)
MKT	-7.77	10.08			-0.89	9.30	
	(-1.29)	(2.70)			(-0.13)	(2.49)	
SMB		6.63				6.24	
		(2.87)				(2.70)	
HML		5.25				5.30	
		(1.70)				(1.72)	
R^2	3.59%	83.38%	1.13%	71.90%	84.23%	91.58%	74.79%
$\bar{R}^2$	-7.13%	77.84%	-11.23%	68.38%	80.29%	87.37%	67.59%

Panel (c) 10 Book-to-Market Portfolios

	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	25.91	-3.44	2.15	-2.39	18.41	-0.14	-3.06
	(4.61)	(-2.54)	(0.38)	(-0.45)	(3.62)	(-0.07)	(-0.57)
ΔFL				-1.61	-2.09	-4.22	-1.01
				(-1.82)	(-2.74)	(-3.28)	(-1.13)
LevFct			111.95				110.32
			(3.42)				(3.34)
MKT	-14.52	8.02			-13.40	4.61	
	(-2.29)	(2.19)			(-2.12)	(1.91)	
SMB		2.82				0.01	
		(1.15)				(0.00)	
HML		10.32				6.24	
		(3.05)				(1.75)	
R^2	37.65%	61.57%	85.49%	9.02%	90.83%	68.22%	87.32%

Table 19: **Pricing Liquidity, Volatility, Size and Value**

Cross-section asset pricing tests based on two-stage Fama-MacBeth regressions for liquidity, volatility, size and value portfolios. Panel (a) displays results for 3x10 portfolios sorted by volatility, liquidity and size (excluding Nasdaq stocks) while Panel (b) displays results for 3x10 portfolios sorted by volatility, liquidity and book-to-market. Quarterly data, Q2/1986 - Q4/2011.

Panel (a) 30 Volatility, Liquidity, and Size Portfolios

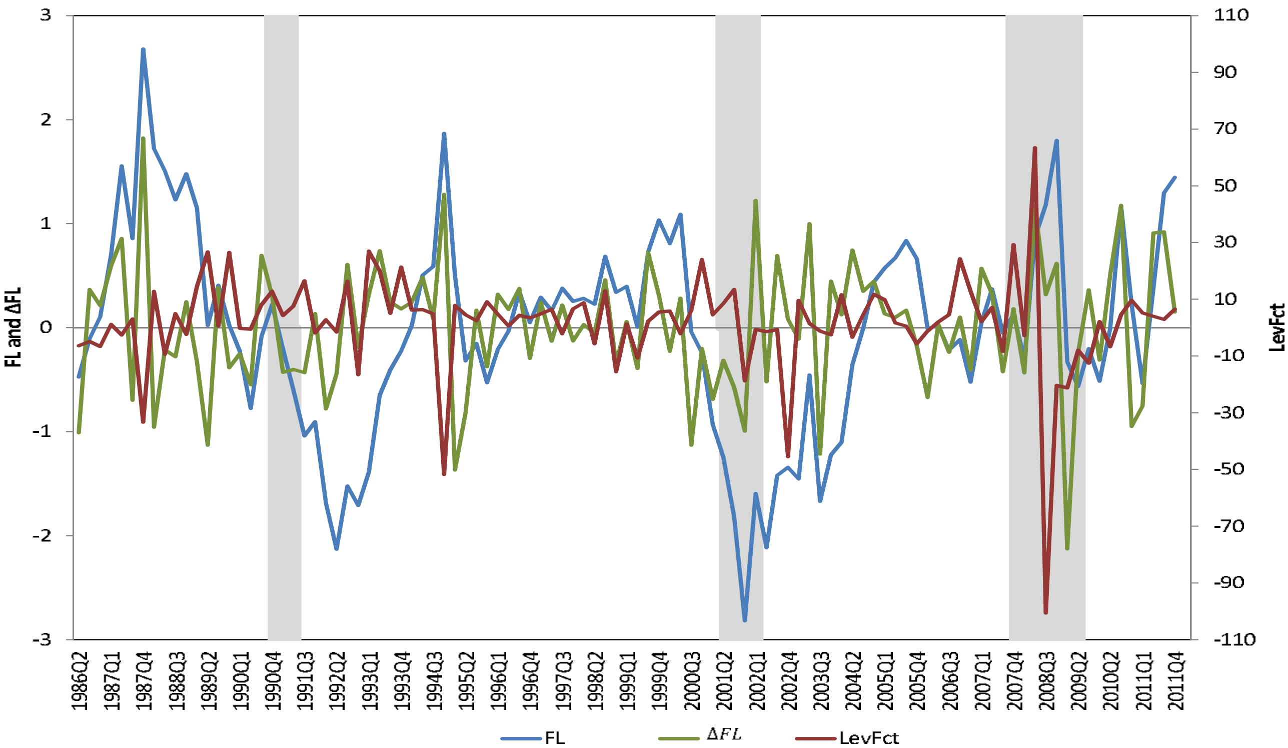
	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	4.38	-0.39	12.27	0.06	3.26	-1.08	1.13
	(1.58)	(-0.45)	(3.09)	(0.02)	(1.13)	(-1.39)	(0.37)
ΔFL				-1.82	-2.45	-2.19	-1.76
				(-2.37)	(-2.98)	(-3.50)	(-2.28)
LevFct			-31.20				-9.94
			(-1.54)				(-0.52)
MKT	6.10	7.87			2.20	7.54	
	(1.24)	(2.14)			(0.49)	(2.05)	
SMB		5.59				5.50	
		(2.47)				(2.43)	
HML		4.02				4.36	
		(1.32)				(1.44)	
R^2	12.51%	76.15%	4.55%	67.79%	81.56%	82.90%	68.59%
$\bar{R}^2$	9.50%	73.69%	1.15%	66.64%	80.25%	80.46%	66.26%

Panel (b) 30 Volatility, Liquidity, and Value Portfolios

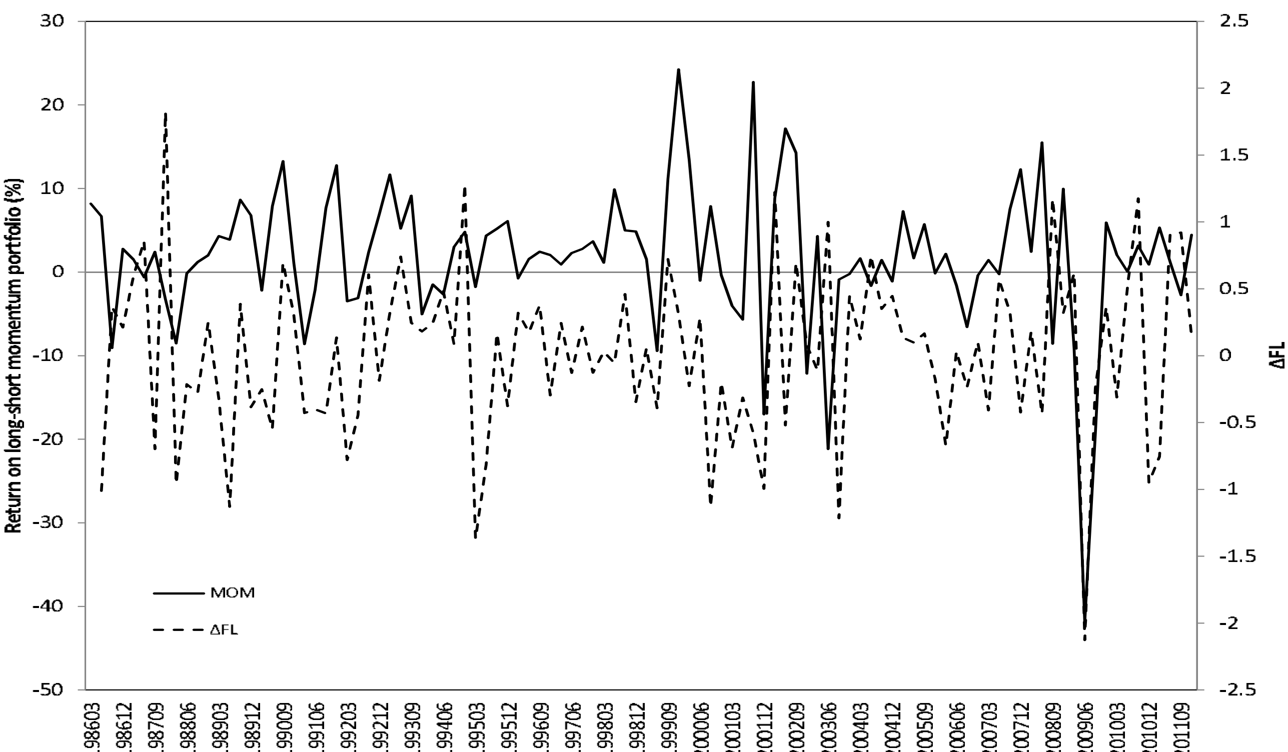
	CAPM	FF3	LevFct	ΔFL	Augmented by ΔFL		
α	11.71	-1.66	5.31	5.57	10.12	-1.50	-0.07
	(2.75)	(-1.59)	(1.07)	(1.45)	(2.34)	(-1.47)	(-0.02)
ΔFL				-0.70	-2.47	-1.41	-1.00
				(-0.84)	(-3.24)	(-1.82)	(-1.25)
LevFct			68.17				74.48
			(2.34)				(2.81)
MKT	-1.92	7.60			-6.12	7.05	
	(-0.34)	(2.11)			(-1.13)	(1.95)	
SMB		2.00				1.64	
		(0.80)				(0.67)	
HML		10.86				10.45	
		(3.35)				(3.23)	
R^2	1.75%	58.05%	28.02%	10.56%	64.63%	59.56%	42.34%
$\bar{R}^2$	-1.64%	53.71%	25.45%	7.36%	62.10%	53.78%	38.07%

Figure 1: The Value of Funding Liquidity

(a) ΔFL and Broker-Dealer Leverage



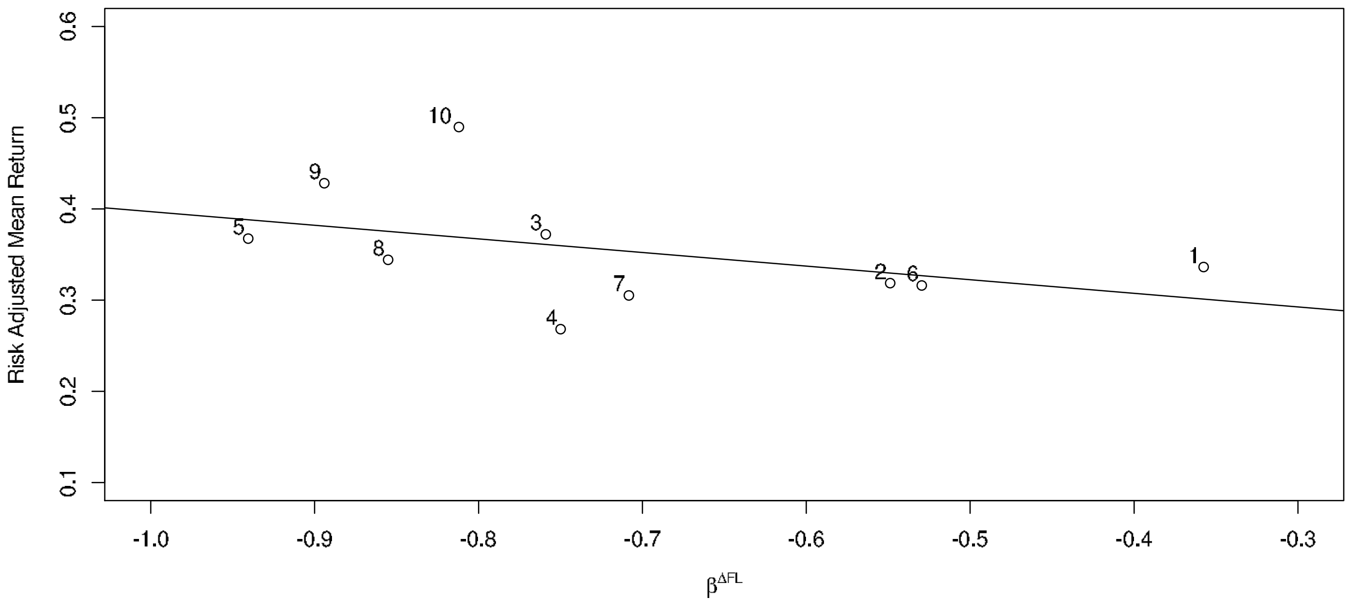
(b) ΔFL and Long-Short Momentum Portfolio Returns



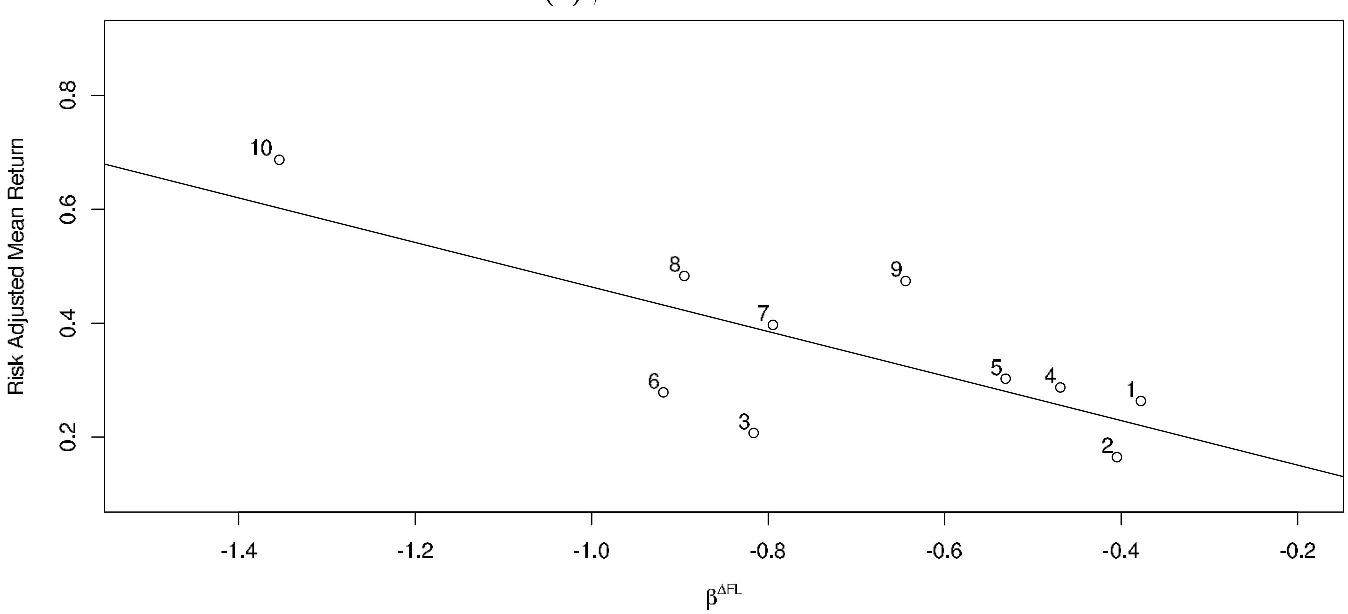
Panel (a) compares the value of funding liquidity from Fontaine and Garcia (2012), (FL), its changes, (ΔFL), and the leverage factor (Lev^{BD}) from Adrian et al. (2013). NBER recessions are shaded. Panel (b) compares changes in the value of funding liquidity, (ΔFL), with the returns on a long-short momentum portfolio. Quarterly data from Q2/1986 to Q4/2011.

Figure 2: Risk-Adjusted Returns and Funding Risk in β-sorted Illiquidity and Volatility Portfolios

(a) β^{L_{mkt},r_i} Portfolios

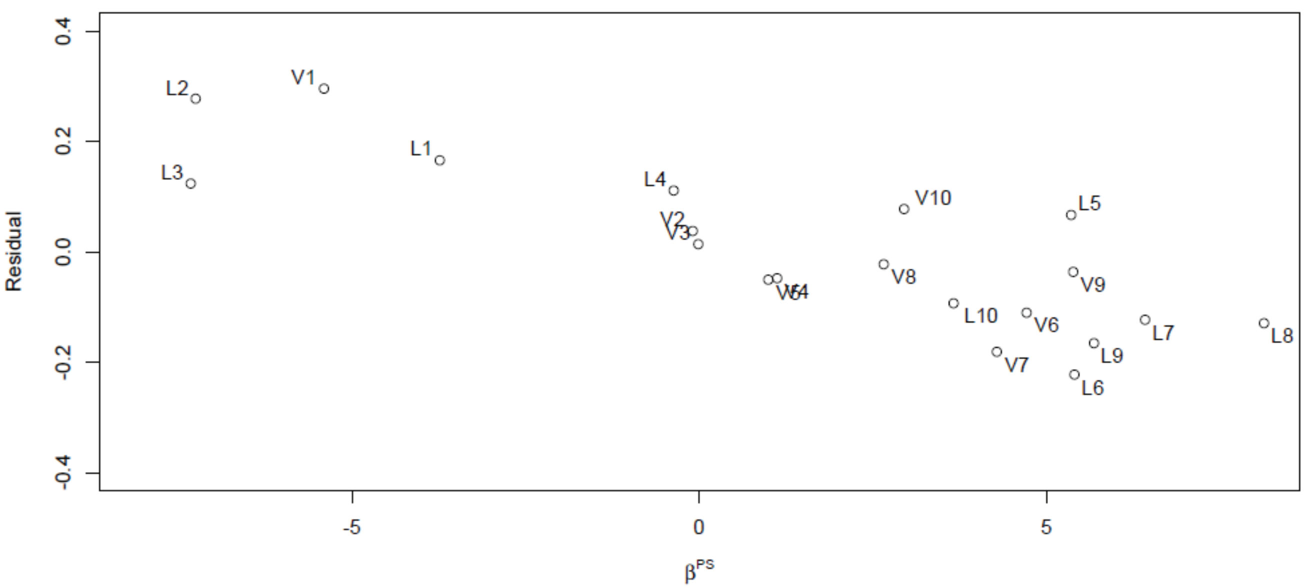


(b) β^{σ_{mkt},r_i} Portfolios



Average risk-adjusted returns against funding liquidity betas, $\beta^{\Delta FL}$, obtained from $r_{it} = a_i + \beta_i^{\Delta FL} \Delta FL_t + \beta_i^{MKT} MKT_t + \varepsilon_{it}$. The risk-adjusted return is then obtained as $r_{it}^{RA} = r_{it} - \beta_i^{MKT} MKT_t$. Panel (a) displays the results for the β^{L_{mkt},r_i}-sorted portfolios. Panel (b) displays the results for the β^{σ_{mkt},r_i}-sorted portfolios. Portfolio 1 has a high (positive) average beta and portfolio 10 has a low (negative) average beta.

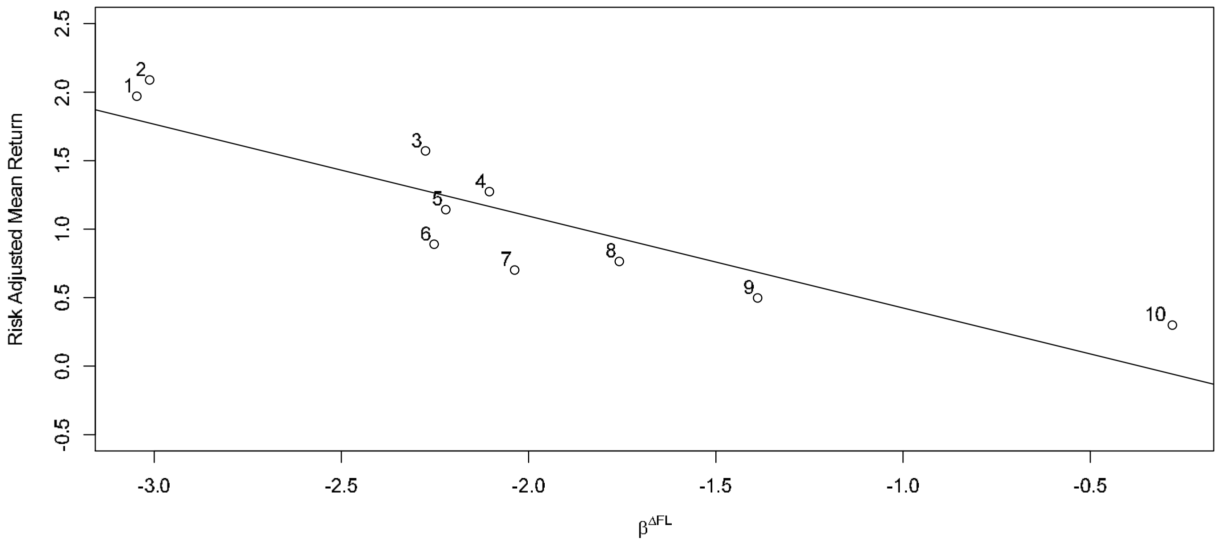
Figure 3: Interaction between Funding and Market Liquidity Risk



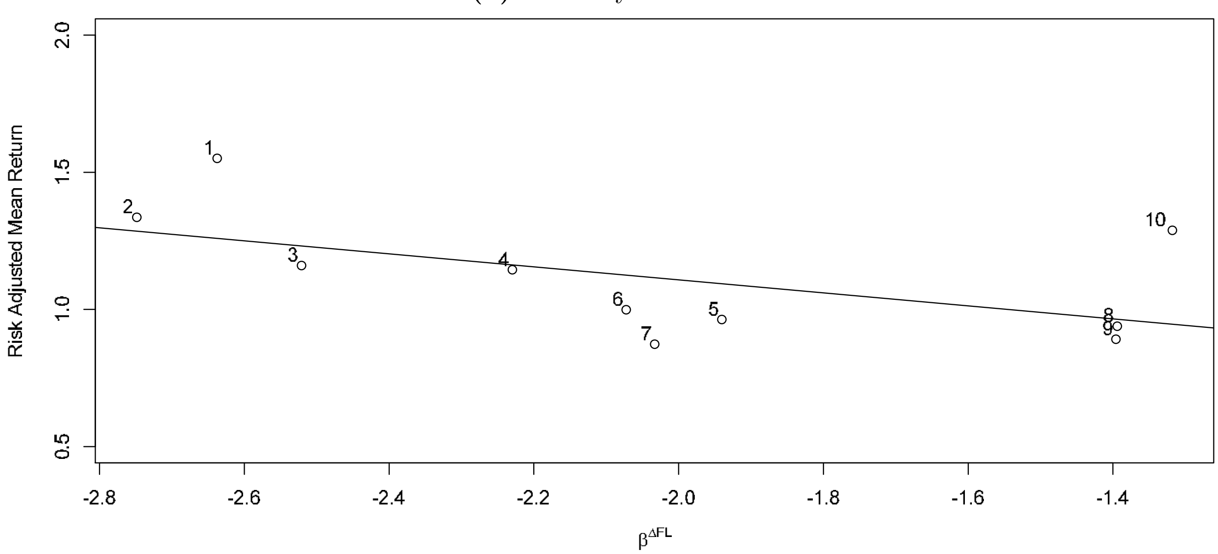
Portfolio pricing errors and β^{PS}. Residuals from the cross-section regressions of average returns for illiquidity-sorted (L1 to L10) and volatility-sorted portfolios (V1 to V10) on funding liquidity betas β^{FL} plotted against the PS betas, β^{PS}. $V1$ and $L1$ are the residuals for the most illiquid and most volatile portfolios. Monthly data, January 1987 - March 2012.

Figure 4: Risk-Adjusted Returns and Funding Risk in Liquidity and Volatility Portfolios

(a) Liquidity Portfolios



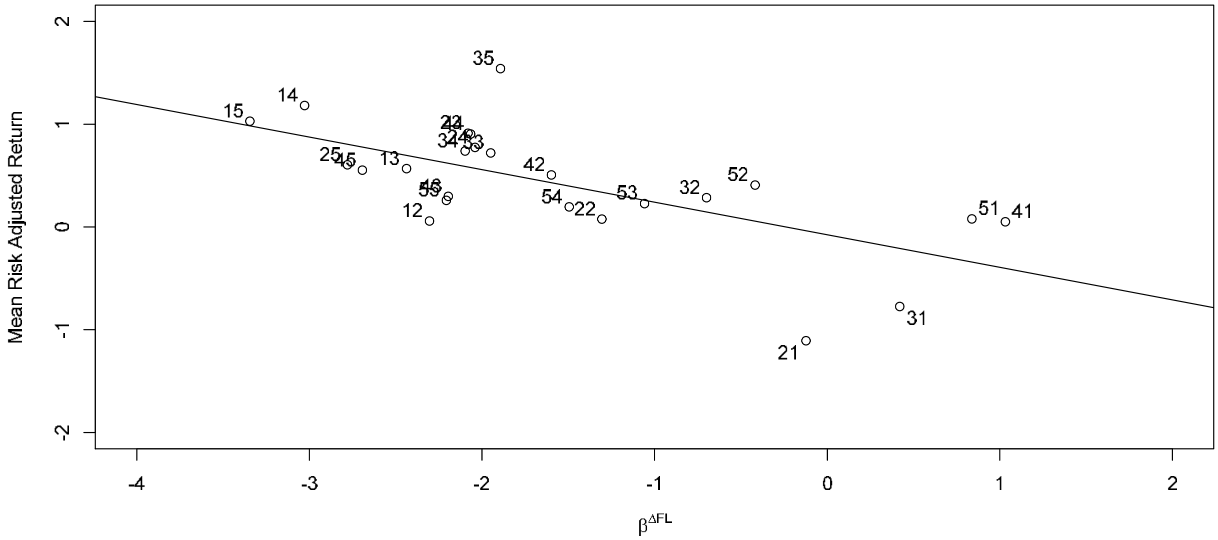
(b) Volatility Portfolios



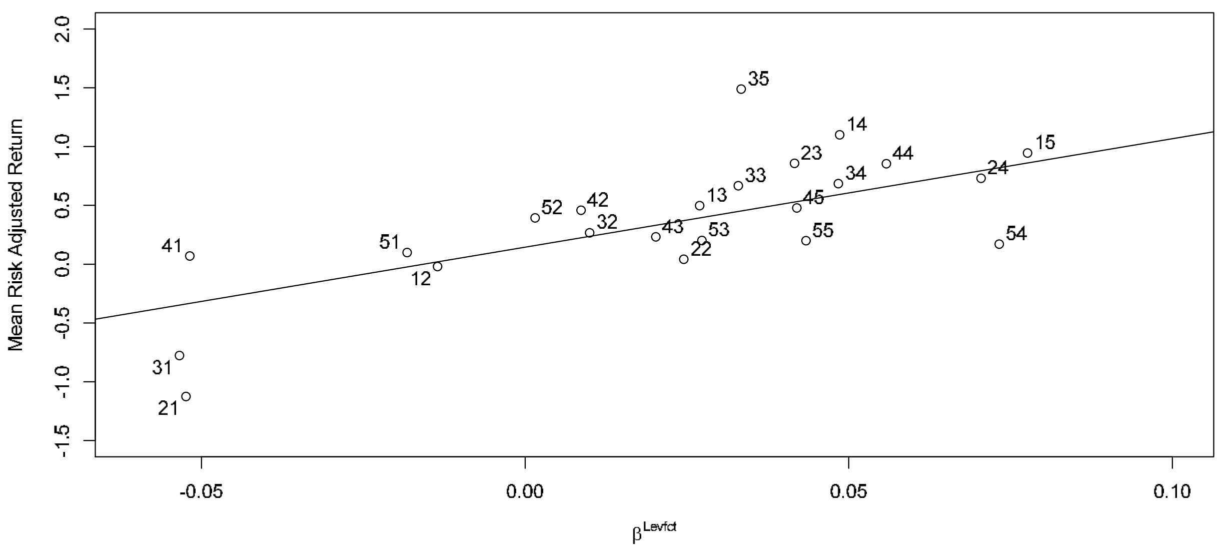
Average risk-adjusted returns and funding liquidity beta, $\beta^{\Delta FL}$, for liquidity-sorted (Panel a) and volatility-sorted (Panel b) decile portfolios. Funding liquidity betas are obtained from the regressions $r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta FL} \Delta FL_t + \varepsilon_{it}$ and risk-adjusted return are computed as $r_{it} - \beta_i^{MKT} MKT_t$. Portfolio 1 is the least liquid or most volatile and portfolio 10 is the most liquid or least volatile. Quarterly data, Q2/1986 - Q4/2011.

Figure 5: Risk-Adjusted Returns, Funding Risk and Leverage in 5×5 Size and Value Sorted Portfolios

(a) Funding Liquidity Risk



(b) Broker-Dealer Leverage



Panel (a) compares average risk-adjusted portfolio returns and funding liquidity beta, $\beta^{\Delta FL}$, for size and value portfolios from a 5×5 double-sort excluding the small growth portfolios. Panel (b) compares average risk-adjusted returns with leverage factor beta, β^{Lev}. Funding liquidity betas are obtained from the regression $r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta FL} \Delta FL_t + \varepsilon_{it}$ and leverage factor betas are obtained from the regressions $r_{it} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{Lev} LevFact_t + \varepsilon_{it}$. In each case, the risk-adjusted return are computed as $r_{it} - \beta_i^{MKT} MKT_t$. Portfolio 1 contains losers and portfolio 10 contains winner. Quarterly data, Q2/1986 - Q4/2011.