Funding Risk, Market Liquidity, Market Volatility and the Cross-Section of Asset Returns

Jean-Sébastien Fontaine
Bank of Canada
René Garcia
Université de Montréal
Sermin Gungor
Bank of Canada

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Abstract

We find strong evidence of a funding risk premium in the cross-section of asset returns. Our estimate for the price of funding risk is robust across Treasury bonds, corporate bonds, equities, and hedge funds. Funding shocks pose a risk to investors because they exacerbate the illiquidity and volatility of securities, increase the dispersions of asset illiquidity and volatility, and decrease contemporaneous returns. Our price-of-risk estimates are also robust to using mimicking portfolio returns, alternative portfolio sorts, traditional test assets, monthly returns or quarterly returns. Funding shocks are not subsumed by common proxies for market-wide illiquidity or dealers' balance sheet risk.

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Correspondence: `jsfontaine@bankofcanada.ca`.

Introduction

When capital is abundant in financial markets, providers of liquidity accommodate imbalances between demand and supply for an asset. When capital is scarce, funding liquidity affects the behavior of liquidity providers. The asset's own characteristics become less important, and its price can be driven away from fundamentals. Several economic mechanisms have been proposed to explain the relations between funding liquidity, asset characteristics, and expected returns. Intermediaries may face constraints or margins when using debt to raise funds (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009) or they may face constraints when using equity to raise funds (He and Krishnamurthy, 2013; Kondor and Vayanos, 2016). Both mechanisms have similar testable predictions:

(i) *Funding risk premium.* Securities with higher covariance with funding shocks have a higher risk premium.

(ii) *Commonality.* Illiquidity and returns co-move with funding shocks (i.e., a level effect).

(iii) *Flight to quality.* Illiquidity and returns co-move more strongly with funding shocks when the volatility of an asset is higher (i.e., a slope effect).

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

The goal of this paper is to test these theoretical predictions. Its core message is relevant for investors active in Treasury, corporate bond and equity markets, where we document the effect of funding shocks. Our empirical strategy has three main elements. The first element is a new measure of funding shocks based on Fontaine and Garcia (2012). This measure is particularly informative about funding conditions because it relies on price differences across widely traded Treasury securities with nearly identical cash flows. Intuitively, a larger dispersion of bond prices indicates the scarcity of capital and and an increase in funding risk, providing a more accurate proxy than general-purpose measures such as the VIX index or the TED spread often used to capture funding conditions. Section I.B discusses this measure of funding shocks in detail.

The second element of our strategy is to construct portfolios of assets that are more likely to be affected by funding shocks, consistent with theory. Following Prediction (i), we sort assets directly based on their exposures to funding shocks. In theoretical models, this covariance is endogenous and reflects how intermediaries interact with asset markets. Following Predictions (ii)-(iii), we sort assets based on their own illiquidity and volatility. In both Brunnermeier and Pedersen (2009) and Kondor and Vayanos (2016), the levels and dispersions of illiquidity and volatility vary in response to funding shocks. We also sort assets based on the covariance of returns with aggregate market illiquidity. This approach is especially useful when detailed data are not available to estimate security-specific illiquidity. Kondor and Vayanos (2016) argue for using this covariance as a better proxy for exposures to funding risk.

We find robust evidence for a *funding risk premium*: average returns are aligned with funding risk betas. Asset pricing tests show that exposures to funding shocks explain a large share of the cross-sectional dispersion across portfolios of stocks sorted on exposures to funding, illiquidity, and volatility shocks. The price-of-risk estimate is negative. Since greater price dispersion on the Treasury market indicates greater funding risk, a positive funding shock is bad news for investors.

The third element of our strategy is to confirm *how* funding shocks pose a risk to investors via their effects on illiquidity, volatility and returns. Predictions (i)-(iv) are joint. By checking for these predictions simultaneously we assert that the mechanism linking the risk premium and funding shocks works mainly through a deterioration of illiquidity and volatility, mitigating other potential explanations. We find that funding shocks increase the illiquidity and volatility of every portfolio (*commonality*). In addition, the dispersion of illiquidity increases across illiquidity-sorted portfolios and across volatility-sorted portfolios, supporting the interplay between illiquidity and volatility (*flight to quality*). Intuitively, intermediaries provide less liquidity in securities that use more capital, such as high-volatility securities, but illiquidity also raises volatility. We also find that the effects of ex-post funding shocks are stronger when the ex-ante level of funding risk is worse (*asymmetry*).

Funding shocks are not specific to one market. In theoretical models, funding shocks introduce commonality in the risk premiums across markets where intermediaries are active. To test this, we construct portfolios of Treasury bonds, corporate bonds, equities or hedge funds sorted on the covariance of returns with aggregate illiquidity and volatility. This keeps the sorting strategies fixed across asset classes and also circumvents the lack of detailed liquidity data in some asset classes.

The estimates for the price of funding risk are negative and robust across asset classes. The sign, magnitude and dispersion of funding risk betas can be different. The patterns of betas accord with intuition. Funding-risk betas are negative and highly dispersed in corporate bond portfolios, leading to larger funding-risk premiums. This is what one may have expected: inventory risk is large for corporate bonds. In fact, the dispersion of bond returns can be explained using exposures to funding shocks. For equities, we find that the most liquid stocks have funding-risk betas close to zero. Inventory risk is less relevant for these stocks. Hence, the returns spread across stocks is due to the negative funding-risk betas of less liquid stocks. The returns spread between portfolios of stocks with high and low (negative) exposures to funding shocks is close to three percent annually for small and middle-size stocks, but less than one percent for large stocks. For hedge funds, funding-risk betas are relatively smaller and less dispersed, suggesting that active management mitigates exposure to funding shocks. In contrast, Treasury bonds have positive betas and offer a hedge against funding shocks, which lowers their expected returns.

In our asset pricing tests, stocks are double-sorted on size. The size factor is included to control for the relation between market capitalization and liquidity. Estimates are also robust when using portfolios of stocks sorted on size, book-to-market or market beta as test assets. A version of CAPM augmented with funding risk produces significant prices of risk and a good fit, with $\bar{R}^2$s close to 50 percent, suggesting that sorting on size, value or betas also induces dispersion in the direction of funding risk.[1] Surely, other risk factors generate significant dispersion across these portfolios. Our claim is that funding shocks help understand the cross-section of asset returns in the dimension of illiquidity.

The estimated price of risk is also robust across a wide range of specifications combining funding risk with either market returns, the Fama-French risk factors, the market illiquidity shocks (Amihud, 2002), the Pastor and Stambaugh (2003) liquidity risk factor, the betting-against-beta factor (Frazzini and Pedersen, 2014) or shocks to the spread between Treasury bill and LIBOR rates. Asset pricing tests deliver the same message when using a mimicking portfolio.

Our results provide the same message when we use quarterly returns, in which case we pay special attention to broker-dealer (BD) leverage and primary dealers (PD) capital ratio (Adrian, Etula, and Muir 2014 or He, Kelly, and Manela 2015, respectively). Funding shocks and intermediaries' balance sheets have close theoretical underpinnings and with similar asset pricing implications for portfolios sorted on illiquidity. The capital ratio is the reciprocal of leverage and their shocks should have opposite prices of risk in principle. We find large, positive and significant price-of-risk estimates for PD capital ratio shocks in the bond market, but smaller estimates in the equity market. We find an insignificant price of risk for BD leverage shocks in the bond market but a significant and negative price of risk in the stock market. Finally,

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

we find that shocks to either PD capital ratio or BD leverage interact with funding shocks but are subsumed by the latter in asset pricing tests. Estimates for the price of funding shocks are very stable across several markets and provide strong evidence for the role of funding shocks.

The different estimates obtained for PD capital ratio and BD leverage in bond and equity markets may be due to the relative importance of different intermediaries in these markets. Our results stand out because we find theoretically consistent signs between the prices of PD and BD risks when sorting on illiquidity. This contrasts with the existing mixed evidence based on standard portfolio sorts. Our results also stand out because positive sign for the price of capital ratio shocks and a negative sign for the price of leverage shocks suggest a greater role for equity-funding frictions than for debt-funding frictions in these markets (see He et al. 2015).

Related Literature

Our results have three distinct features complementing the existing literature. First, we establish that a funding-risk premium is pervasive across several markets. Second, we show that funding shocks connect illiquidity, volatility and returns. Finally, we show that these connections are stronger when intermediaries face higher funding risk.

Existing results show strong illiquidity commonality across securities (Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Chordia, Sarkar, and Subrahmanyam, 2005); or that illiquidity increases with a the volatilities of securities to compensate market-makers, either for their inventory risk or for their losses to better-informed investors, or that illiquidity and volatility may perpetuate each other in a self-fulfilling equilibrium (Benston and Hagerman, 1974; Stoll, 1978; Glosten and Milstom, 1985; Grossman and Miller, 1988; Pagano, 1989). These results do not explore the relation with asset risk premiums. Other results show that the risk premium increases in the cross-section with illiquidity level and illiquidity risk. These results typically consider a single market or do not explore the relation with funding risk (Amihud and Mendelson, 1986; Amihud, 2002; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005).

A few papers look at the role of intermediaries' balance sheets. Hameed, Kang, and Vishnawathan (2010) show that stocks' illiquidity increases and is more pervasive following market declines, which they interpret as shocks to intermediaries' wealth. Adrian, Etula, and Muir (2014) investigate the role of BD leverage in cross-sectional returns. He, Kelly, and Manela (2015) investigate the role of PD capital ratio. These authors use standard sorting strategies and their estimates for the price of risk have signs that are inconsistent with each other. They ignore implications for illiquidity and volatility of stocks. We find the correct signs by sorting on illiquidity.

Funding shocks are also relevant to asset managers. Goyenko (2014) find that mutual funds exposed to illiquidity have higher returns. Franzoni et al. (2012) link private equity returns with overall market and funding liquidity measured by changes in credit standards. Aiken, Clifford, Ellis, and Huang (2015) find that fund performance increases when funding risk decreases, because it is easier to exploit risky mispricing. They also find that lockup funds achieve a better performance than non-lockup funds. Sadka (2010) finds that funds with high loadings on liquidity risk subsequently outperform funds with low loadings, but performance becomes negative during liquidity crises. Franzoni and Plazzi (2015) find that among institutional liquidity providers, hedge funds are more exposed to financial constraints. Agarwal, Aragon, and Shi (2016) examine the funding liquidity risk of funds of hedge funds by measuring the mismatch between the liquidity of a fund portfolio and the liquidity that the fund offers to its investors. Hu, Pan, and Wang (2013) show that the "noise" around the U.S. Treasury curve helps explain hedge-fund returns; we isolate funding shocks specifically and relate them to the cross-section of return for several asset classes.

The rest of the paper is organized as follows. Section I describes our empirical strategy, including the construction of portfolios. Section II contains our main asset pricing results. Section III documents that funding shocks affects illiquidity, volatility and returns. Robustness tests are included in Section IV. Section V concludes with remaining challenges and discusses avenues for future research. An appendix provides details about data sources, preliminary filters we applied to the raw data, and alternative risk factors used in our tests.

I Empirical Strategy

This section discusses the theoretical foundations of our empirical strategy, introduces our measure of funding shocks and details the construction of portfolios.

A Theoretical Underpinnings

Our empirical strategy builds on existing theoretical contributions. In Brunnermeier and Pedersen (2009), securities have in equilibrium properties (i)-(iv) listed in the introduction.[2] Investors arrive sequentially to the market and intermediaries provide liquidity, smoothing price fluctuations. Following funding shocks, when intermediaries risk hitting their funding constraints over the life of a trade, they reduce their positions. The market illiquidity and market volatility of every security increases. The dispersions of stock liquidity and volatility also increase. Volatile stocks become more illiquid because they add relatively more to the risk that an intermediary will hit its funding constraints. Illiquid stocks become more volatile because the price impact of trades increases. These effects of funding shocks exhibit asymmetry since they become more important when intermediaries operate closer to margin con-

[2] For instance, see their Proposition 6 and their Section 5. Vayanos (2004) proposes an equilibrium model where shocks to fund managers connect an asset's illiquidity and returns to its volatility. In Gromb and Vayanos (2002, 2010), intermediaries' wealth shocks exacerbate illiquidity and volatility. Brunnermeier and Pedersen (2009) and Kondor and Vayanos (2016) emphasize the case with multiple assets.

straints. Hence, exposures to funding risk make securities riskier and raise the risk premium in proportion to the covariance of returns with funding shocks.

In Kondor and Vayanos (2016), securities also have properties (i)-(iv), but intermediaries' funding constraint is modeled as a constraint on equity capital. Illiquidity, volatility and returns are also affected by funding shocks. In their model, the response of an asset's illiquidity to funding shocks is determined solely by its own volatility. In contrast, the response of returns is proportional to its sensitivity to aggregate liquidity. This is because (a) changes in aggregate illiquidity are driven by arbitrageurs' wealth, and (b) arbitrageurs increase their positions following higher asset returns. Since the intermediaries are the marginal investors, one implication is that sorting securities based on the covariance between returns and illiquidity should generate a spread in expected returns that is largely captured by their betas with respect to funding shocks. The covariance of returns and aggregate liquidity reveals the exposure to funding shocks. This contrasts with the model in Acharya and Pedersen (2005) where transactions costs and the covariances with returns are exogenous.

B Measuring Funding Shocks

The first step in our strategy is to use a new measure of funding risk (developed in Fontaine and Garcia 2012) which departs from the usual measures such as the VIX index or the TED spread. The measure gains its informational efficiency from the use of widely-traded Treasury securities. To capture how liquidity affects asset prices, Vayanos (2004) suggests using the prices of two assets with similar cash flows but different liquidity, citing the well-known case of the just-issued (on-the-run) and the previously issued (off-the-run) 30-year Treasury bonds. Similarly, Longstaff (2004) uses Treasury and RefCorp bonds. In each case, two bonds carry the same credit risk and promise very similar cash flows, but one of the bonds is more liquid and more expensive.

Fontaine and Garcia (2012) extend this idea and extract a measure of funding liquidity risk (FL) in a panel of U.S. Treasury security pairs across a range of maturities. The estimation strategy for FL relies on apparent arbitrage opportunities in a panel of U.S. Treasury bonds to identify funding conditions. Arbitraging between nearby bonds requires two repo transactions, but repo market frictions limit arbitrage activities. Dealers also use the repo market to make marginal leverage adjustments to provide market liquidity (Adrian and Shin, 2010). It is this dual role of the repo market—allowing for arbitrage activities and for dealers' funding activities—that connects estimates of FL to funding risk.[3]

The combination of a rich panel of Treasury bonds with a dynamic term structure model teases out the noise and provides a better measurement of latent funding conditions. Indeed, Fontaine and Garcia (2012) demonstrate that FL can be interpreted as a measure of funding risk, by relating FL to future bond returns, by showing that FL is a determinant of growth in the shadow banking sector, and by linking FL to broader measures of funding conditions, such as non-borrowed reserves of commercial banks at the Federal Reserve and the rate of growth of M2 (which include growth in the repo market). The funding factor FL is available from January 1986 until December 2015, therefore including the financial crisis.[4] For simplicity, funding shocks

[3]The market for old notes appears segmented from the markets for bills (Garbade, 1984; Kamara, 1994; Duffee, 1996) and, similarly, the market for old bonds appears segmented from the market for more recently issued bonds (Cornell and Shapiro, 1989). Duffie (1996) and Vayanos and Weill (2006) show that the price of Treasury securities can be funded more easily and more cheaply via the repo market. Empirically, this link has been confirmed by Jordan and Jordan (1997); Krishnamurthy (2002); Buraschi and Menini (2002); and Bartolini, Hilton, Sundaresan, and Tonetti (2011). See also the review in Fontaine and Garcia (2015).

[4]The funding factor FL is updated regularly and is available at `www.jean-sebastienfontaine.com`. Our sample ended in 2012 in previous versions of this paper. Our sample starts in 1986, since before this date interest income had a favorable tax treatment relative to capital gains and investors favored high-coupon bonds. The resulting tax premium was entangled with the liquidity premium, since recently issued bonds were more liquid but also had relatively high coupons offered a tax premium (interest rates were trending up). Green and Ødegaard (1997) confirm that the tax premium mostly disappeared when the asymmetric treatment of interest income and capital gains was eliminated following the 1986 tax reform.

are computed as the first difference $\Delta FL_t \equiv FL_t - FL_{t-1}$. We checked that ΔFL_t exhibits no autocorrelation.

C Portfolio Formation

The second element in our strategy is to build portfolios by sorting on illiquidity and volatility, where theory predicts funding shocks affect returns. We strive to keep the portfolio formation strategy as similar as possible across asset classes. In all cases, we form portfolios at the end of each year and compute monthly holding period returns over the following year. We use the risk-free rate from the Kenneth French data site to compute monthly excess returns.

C.1 Sorting by Risk Exposures

Our first and central set of findings relies on portfolios of assets sorted on their betas with respect to aggregate illiquidity and volatility. Specifically, we use the following funding, illiquidity and volatility βs to form the portfolios,

$$\beta_i^{Illiq} = \frac{cov(Illiq_m, r_i)}{var(Illiq_m)} \qquad \beta_i^{\sigma} = \frac{cov(\sigma_m, r_i)}{var(\sigma_m)} \qquad \beta_i^{\Delta FL} = \frac{cov(\Delta FL, r_i)}{var(\Delta FL)}. \tag{1}$$

Market volatility is the standard deviation of market returns using a 1-year rolling window. For market illiquidity, we aggregate stock-level illiquidity. For a given stock i and day d, the Amihud illiquidity ratio $ILLIQ_{id}$ is given by:

$$ILLIQ_{id} = \frac{|R_{id}|}{DVOL_{id}} \times 10^6, \tag{2}$$

where R_{id} is the daily stock return and $DVOL_{id}$ is the dollar value of the trading volume. The Amihud ratio is widely-used to measure illiquidity. It captures the price impact of a given transaction conditioning on the volume traded.[5] The market illiquidity $Illiq_m$ is the equal-weighted average of all stocks' Amihud ratio in a given month.

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

We follow Frazzini and Pedersen (2014) to estimate β_i^{Illiq} and β_i^{σ}. We use five years of daily data to estimate the correlations and one year of data to estimate the variances, for which we use 3-day overlapping returns to mitigate the effect of asynchronous trading. We estimate $\beta_i^{\Delta FL}$ with OLS regressions using a rolling three-year sample of monthly returns.[6]

C.2 Double-Sorts Based on Size and Risk Exposures

When sorting stocks based on risk exposures, we use the following double-sort strategy. We first sort all stocks into three size categories, we then construct three sets of 30 double-sorted portfolios: 3×10 portfolios of stocks sorted by size and $\beta^{\Delta FL}$; by size and β^{illiq}; and by size and β^{σ}. Together, these 90 portfolios present a stringent test for any factor model. Sorting by size in a first step alleviates concerns that funding risk may be essentially substituting for the Fama-French size factor in the cross-section of stock returns. This would be the case if exposures to funding shocks is correlated with size but does not change within size categories.

II The Price of Funding Risk

This section reports our main results documenting the price of funding risk in the cross-section of asset returns. Fontaine and Garcia (2012) show that higher funding risk predicts lower future returns for U.S. Treasury bonds but higher future returns for LIBOR rates, swap rates and corporate yields. We extend and complement these results, showing that funding risk is associated with a lower risk premium for Treasury bonds, but a higher risk premium in the cross-section of corporate bonds, equities and hedge funds.

A Average Returns and Funding Risk: A First Look

A visual inspection of portfolios' funding betas and average returns is instructive before we turn to formal asset pricing tests. Indeed, the slope going through the pairs

[6]We find similar results when using OLS in rolling three-year samples to estimate β_i^{Illiq} and β_i^{σ}.

of returns and betas corresponds to the price of risk. This is shown in Figure 1 using three panels, one for each asset class. All panels feature risk-adjusted returns where the adjustment is done according to a market portfolio.

Panel (a) reports the risk-adjusted returns of ninety double-sorted portfolios of equities. The slope between risk-adjusted returns and $\beta_{(i)}^{\Delta FL}$ is definitely negative. One can draw a line from the origin through the center mass, to obtain a visual estimate of the price of funding risk $\lambda^{\Delta FL}$. Its slope appears to be roughly -4 (10 on the y-axis divided by -2.5 on the x-axis). The line with the best fit may cross the y-axis above the origin (around 5), which would lower our visual estimates to about -2. We will find that our formal estimates in the following section always fall within this back-of-the-envelope range. Note that this range is not driven by one particular set of portfolios.

Panel (b) reports the risk-adjusted returns and funding shock betas for Treasury bonds at six constant maturities and thirty portfolios of corporate bonds (See Figure 1 for details on these portfolios). Across all bonds, there is a clear negative linear relationship. Visually plausible estimates fall within the same range that we found for equities. The negative price of risk is consistent with results in Fontaine and Garcia (2012) showing that funding shocks are bad news in fixed-income markets. Treasuries align negatively in the bottom right corner of the graph with betas close to zero and mostly positive. Treasuries offer a hedge against funding shocks, which lower their risk premium.[7]

Panel (c) plots the average risk-adjusted returns and the funding betas of 90 double-sorted portfolios of hedge funds. These ninety portfolios parallel the approach we adopted for equities but using net asset value to measure size. The betas are

[7] Three portfolios of corporate bonds are gathered in the higher-left part of the graph with negative betas around -3 and average returns of 10 to 12 percent. The scale of this figure leads to the impression that most of the other corporate bond portfolios are concentrated in the center of the graph. In fact, there is quite a lot of variation in both the betas and the average returns, and the slope among these more central portfolios is still negative (we will confirm this in the asset pricing tests in the next section).

negative and well spread out between 0 and -2 while returns are comprised between 2 and 10 percent. Once again, visually plausible estimates for the price of funding risk range between -2 and -4. We notice that the dispersion of hedge funds returns left unexplained appears to be larger, which will translate into less precise estimates. It suggests that other sources of risk may play an important role for hedge funds returns. However, our main message regarding their exposure to funding shocks remains unaffected.

B Estimation and Tests

We follow the usual two-step procedure to estimate the price of funding risk. The first stage is a contemporaneous time-series regression of returns on risk factors in the entire sample. The second stage is a cross-sectional regression of each month's returns on betas estimated in the first stage. The estimate of the prices of funding risk is given by the time-series average of the monthly estimates from the second stage. We report annualized prices of risk throughout. A typical table will present second-stage cross-sectional results for the following factors: the market portfolio (CAPM), three Fama-French factors (FF3), the funding risk ΔFL by itself and its equivalent with the mimicking portfolio ΔFL^m, the CAPM and FF3 augmented by either ΔFL or ΔFL^m. Inference is based on the usual two-step Fama-MacBeth standard errors as well as on Shanken standard errors, which correct for the errors-in-variables problem in first-stage estimates.

We follow several of the recommendations in Lewellen et al. (2010). First, we include traded risk factors as additional test assets to discipline estimates of the prices of risk (when applicable). Second, we use a wide range of test assets across several markets to mitigate concerns that our results follow from a factor structure inherent in the test assets. Finally, we provide bootstrap confidence intervals for all R^2 statistics. The bootstrap procedure is given in Lewellen et al. (2010). We report the R^2 and the adjusted $\bar{R}^2$, which measure the fit across all test assets. These

R^2s are not directly comparable across specifications when traded risk factors are included as additional test assets. Hence, we also report corrected analogues, R_c^2 and $\bar{R}_c^2$, constructed to measure the fit for the test assets of interest exclusively.

B.1 Equities

Table 1 report results from asset pricing tests for three sets of 30 portfolios double-sorted on both size and the sensitivity of stock returns to either changes in funding conditions, market-wide illiquidity or market-wide volatility (see Section I.C for details). The combination of market returns with size and value explains a very small part of the cross-sectional variation. The prices of size risk and value risk are insignificant. In contrast, the price of risk associated with exposures to funding risk is negative and significant in all cases. The results also show that around 40 percent of the variations of returns across these 90 portfolios can be explained by funding risk (whether measured by ΔFL or ΔFL^m). The point estimates are -2.2 for ΔFL and -1.4 for ΔFL^m.[8] The estimated intercept is high and significant for the CAPM and FF3, but it is reduced by half and becomes insignificant with the sole funding-risk factor. The results confirm our crude visual estimates based on Figure 2(a).

Augmenting the funding-risk factor model with either the market returns or the three Fama-French factors does not change the magnitude and significance of the price of funding risk and does not increase explanatory power. In particular, this confirms that the small correlation between size and liquidity is not driving our results. In fact, we find that the level and the dispersion of $\beta^{\Delta FL}$ are small for large firms and increase substantially when moving toward small firms. This pattern is consistent with intermediaries balance sheets and inventory risk playing a smaller role for large firms with large trading volume and a diverse population of traders active in these stocks.

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

Table 2 reports the pricing errors associated with the 90 portfolios and several sub-groups. We compute the estimated intercept, the mean absolute pricing errors (MAPE), the χ^2 statistics, and the p-value associated with a test of zero pricing errors. In panels (a), (b) and (c), we report the test statistics related to the groups of 30 portfolios doubled-sorted on size and funding-risk betas, illiquidity betas and volatility betas, respectively. Panel (d) contains the same information for the 90 portfolios. One important finding is that the addition of the funding-risk beta in the second-stage regression reduces quite a lot the estimated intercept, showing that it explains a good portion of the average returns. For all sets of 30 portfolios, the p-values of the χ^2 statistic indicate that the hypothesis that all pricing errors are zero cannot be rejected when the funding-risk betas are added to the CAPM or the Fama-French factors–either for ΔFL or ΔFL^m. In Panel (b) for illiquidity-beta portfolios, the hypothesis is rejected with CAPM or Fama-French factors alone. For the two other sets, adding the funding betas always improve the p-values except for the CAPM in the volatility-beta 30 portfolios. For the 90 portfolios taken together, the bar is high for all models but the inclusion of funding risk lowers the pricing errors substantially.

B.2 Fixed-Income Securities

We now investigate whether funding shocks are priced consistently across equity and bond markets. This complements the results in Fontaine and Garcia (2012) showing that funding shocks are an important predictor of future bond returns in the time-series. For corporate bonds, we use 10 equal-weighted portfolios of bonds sorted on funding betas β^{FL}, 10 equal-weighted portfolios of bonds sorted on illiquidity betas β^{Illiq}, and 10 equal-weighted portfolios of bonds sorted on volatility betas β^{σ}. Following Fama and French (1993), we compare asset pricing results based on $Mrkt$,

$\Delta TERM$ and ΔDEF; either on their own or augmented with ΔFL or ΔFL^m.[9] Estimation and test results are reported in Table 3.

The CAPM appears to price corporate and Treasury bonds reasonably well with an $\bar{R}_c^2$ of 51 percent. However, this is achieved using a price of risk that is too large relative to the historical market-wide equity premium (15 percent compared to 8 percent). Including $\Delta TERM$ and ΔDEF increases the $\bar{R}_c^2$ to 66 percent, the constant is not statistically different from zero and the default factor has a significant price of risk.

Using funding shocks to price fixed-income securities yields a price of funding shocks around -4.5 percent, the constant is essentially zero, and the $\bar{R}_c^2$ reaches 91 percent. Funding shocks are perceived as bad news in the corporate bond markets as well. The estimate for the price of funding shocks is only slightly lower when combined with $Mrkt$, ΔDEF, and $\Delta TERM$; and the $\bar{R}_c^2$ stays the same. The price of stock market risk remains significant and is now very close to the historical average. In contrast, the price of risk and statistical significance for exposures to the default factor are halved. The results are essentially the same using the mimicking portfolio ΔFL^m, but—as for equities—with a lower estimate for the price of risk: -3.5.

When accounting for exposures to funding shocks, the intercepts in Table 3 are economically small and not statistically different from zero. Table 4 reports additional results from tests that the pricing errors are jointly zero. We show results when estimating and testing the models separately for each portfolio sort to make clear that the results are not driven by a subset of the test assets. Table 4 provides the same test statistics as for equities for each set of portfolios. In all cases where we account for exposures to funding risk, the pricing errors do not appear statistically different from zero.

[9] See Appendix A.6 for details about $\Delta TERM$, and ΔDEF and additional factors.

Overall, there is strong evidence that funding shocks are consistently priced across fixed-income securities. Essentially all of the dispersion in returns across our bond portfolios can be explained based on exposures to funding shocks. The price of risk is negative, stable and significant across several specifications. The point estimate varies within its confidence interval as we vary the test assets. For instance, using only Treasury bonds produces a lower estimate. Similarly, excluding the most illiquid corporate bonds also produces a lower estimate. But these variations, between -2 and -5 percent, can be attributed to sampling uncertainty. Section D also shows that other illiquidity or funding risk proxies do not perform as well.

B.3 Hedge Funds Funding Risk

Hedge funds face two types of funding shocks. On the asset side of their balance sheet, hedge funds are exposed to funding shocks to intermediaries that raise the illiquidity and volatility of their holdings. On the liability side of their balance sheet, hedge funds are exposed to shocks that cause withdrawal of funds by their investors or that raise the cost of using leverage. Hedge funds may experience lower returns following either types of funding shocks. Systematic funding shocks on the liability side may lead to lower returns because hedge funds are forced to sale assets at a discount price. Systematic funding shocks on the asset side may cause lower returns because the risk premiums of illiquid assets rise. Of course, these two types of shocks may be correlated.

Limited reporting on holdings and sources of funds[10] makes it very difficult to infer hedge-fund exposures to funding shocks from the composition of their assets and liabilities (see Agarwal, Aragon, and Shi 2016). The following double-sort strategy is used to generate dispersion of returns and measures the exposures to funding shocks. In a first step, hedge funds are sorted on their betas β^{nav} with respect to changes in the net asset values of all hedge funds. A larger beta indicates that a fund experiences

[10] Only long positions of large hedge funds (over \$100 millions of assets) are available on a quarterly basis for equity-oriented funds through their 13F mandatory reporting.

losses when other funds as a whole experience losses, either because of systematic outflows or losses on their holdings. In a second step, hedge funds are sorted on their funding risk, illiquidity risk and volatility risk (parallel to the sorting strategy for stocks detailed in Section C.1).

We follow the same estimation and inference procedures as in the previous sections, but with small changes to improve the precision of the estimates. Hedge funds tend to smooth reported returns over time (Getmansky et al., 2004), adding noise to reported returns. To circumvent this effect, we also include one lag of returns in the first-stage time-series regression. We also hold the prices of risk of traded risk factors fixed at their average returns in sample. This appears to be especially important when controlling for Fung and Hsieh (2001) Trend Following factors, which are commonly used to capture strategies involving derivatives or nonlinear exposures to fundamental factors.[11]

Results are reported in Table 5 for the 90 portfolios. The price of risk is estimated at around -2.5 and -3 and statistically significant when controlling for the trend following factors. The estimated constant are statistically significant, suggesting that we are not capturing the array of complex strategies used by hedge funds.[12] Also, we do not account for other tools used by hedge funds to manage liquidity. For instance they can actively manager the level of liquid holdings or impose restrictions to opt out in the form of lockups or notice periods that control the liquidity of the funds. We do not account for these important elements that could improve the fit considerably, since we focus on the price of funding shocks. The confidence intervals for R^2s are centered around 50 percent. The intervals are wide. This may again indicate that

[11]Note that R^2s may not necessarily increase when we add risk factors with fixed prices of risk. We verified that controlling for Fung and Hsieh (2001) Trend Following factors does not affect the point estimates but strengthens the results by improving precision. Precision increases because TF factors are relevant in the first-stage regression, reducing noise. Precision also improves when we fix the prices of risk to sample average, because TF factors are largely irrelevant in the second stage regression.

[12]For this reason we do not present pricing error tests as in previous sections.

these simple models do not capture the complexity of hedge funds strategies. Wide bootstrap intervals could also reflect a large noise component in the times series of hedge funds returns. Yet, our main message holds: hedge funds exhibit significant exposures to funding shocks and the price-of-risk estimates are close to estimates in securities markets.

Sorting by funding-risk betas $\beta^{\Delta FL}$ can help detect which funds are exposed to funding shocks. To illustrate this point, we estimate the price of risk separately across different investment styles. In each style category, we sort funds into six portfolios based on their funding-risk beta $\beta^{\Delta FL}$. Figure 2 reports estimates of the price of risk for each hedge fund style. The estimates exhibit a fairly large spread: around -4 for 'Global Macro' and 'Multi-Strategy' funds, around -2.5 for 'Fund of Funds' and 'Managed Futures', and around 0 and -1.5 for 'Fixed Income Arbitrage', 'Convertible Arbitrage', 'Long/Short Equity Hedge' and 'Event Driven' funds. The estimates suggest that the performance of funds with directional strategies is affected by exposures to funding risk while funds with explicit long-short strategy successfully control their exposures to funding risk. Unsurprisingly, 'Funds of Funds' stand in the middle, mixing the high and low exposures across fund styles. The differences across investment styles appear too large to be attributed to sampling variability. Instead, the differences between estimates may be due to non-linearities and complexities of hedge funds active management that we ignore in our simple benchmark linear model.

III Illiquidity, Flight to Quality and Asymmetry

The previous section documents that funding shocks carry a price of risk that is pervasive across markets, providing substantial support for the first theoretical prediction stated in the introduction. In this section we will test additional theoretical predictions about the response of illiquidity to funding shocks. The theoretical predictions (i)-(iv) in the introduction are joint predictions. Investors prefer certain portfolios because they are relatively more liquid and less volatile when funding conditions worsen. This translates into a cross-sectional dispersion of funding-risk betas and a significant dispersion of expected returns. This joint test provides substantial support for theories emphasizing the role of funding constraints in financial markets.

A Equity Portfolios sorted on illiquidity and volatility

Until now we were looking at portfolios sorted on illiquidity and volatility risk, that is sorted according to the betas with respect to market illiquidity and market volatility. In this section we use portfolios sorted on the levels of illiquidity and volatility of stocks and look for the effects of funding shocks on the level and dispersion of illiquidity across these portfolios.

At the end of each year, we form 10 equal-weighted portfolios of stocks ranked by illiquidity and 10 portfolios of stocks ranked by volatility. We track these portfolios' returns, volatility and illiquidity throughout the following year. We measure the illiquidity of a stock using the Amihud (2002) ratio in Equation (2). We compute each stock's average illiquidity ratio over the previous six months.[13] Our monthly illiquidity measure for a portfolio p is given by the median illiquidity of its components i:

$$ILLIQ_{pt} = \text{median}\left[\frac{1}{D_t}\sum_{d=1}^{D_t} ILLIQ_{id}\right]\left(\frac{dvol_{t-1}}{dvol_1}\right), \tag{3}$$

where D_t is the number of trading days in a given month, $dvol_{t-1}$ is the total dollar volume in this month. We use $\frac{dvol_{t-1}}{dvol_1}$ to control for the growth of market capitalization and trading activity.

We measure the volatility of a stock using the concept of realized volatility. We form portfolios using stocks observed in December that we sort based on the average of monthly standard deviations across the previous six months. We average over six months to mitigate the amplification of noise due to using squared returns. We also

[13] The average may be over less than six months, since some stocks may be absent from our sample in some of these months.

exclude extreme observations—one percent at each tail—to eliminate outliers. The results are robust to varying the number of months included in the computation. Our volatility measure for a portfolio is the average volatility of its component stocks.

B Summary Statistics

Table 6 reports summary statistics for the illiquidity-sorted portfolios (Panel a) and for the volatility-sorted portfolios (Panel b). Stocks in the illiquid portfolios have smaller market capitalization, higher volatility and higher returns. Sorting by illiquidity also creates a spread in average returns (Amihud, 2002). The returns spread between the most illiquid and the most liquid portfolios is close to 6 percent annually, but the average pre-formation β increases with liquidity, which implies that market risk cannot explain the returns spread. Stocks in the more volatile portfolios are less liquid, have smaller market capitalization, and exhibit higher returns. Sorting by volatility also creates a returns spread. The difference between our least volatile and most volatile portfolios is around 3 percent annually. The average pre-formation beta increases with the volatility of the average stocks. Market risk can explain some of the returns spread between volatility portfolios, but not for illiquidity- and volatility-sorted portfolios jointly.

Ang, Hodrick, Xing, and Zhang (2006) document that portfolios with higher volatility have lower average returns (total or idiosyncratic volatility). We differ from Ang, Hodrick, Xing, and Zhang (2006) in three respects. We use *equal-weighted* returns to form portfolios, we form portfolios *annually* and we use a *longer* sample period: 1986–2015 instead of 1986–2000.[14] We also exclude the one percent most volatile stocks.

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

C Illiquidity, Volatility and Funding Shocks

We verify the *commonality* and the *flight-to-quality* predictions in the response of illiquidity and volatility portfolios to funding shocks ΔFL. Table 7 reports the averages of portfolio illiquidity and volatility in subsamples when funding conditions are good or bad, as measured by the lowest and highest terciles of FL_{t-1} (Panels a and b, respectively). The differences between the subsamples are reported in Panel (c). First, all but one differences have a positive sign: the illiquidity and the volatility of every portfolio are worse when funding risk is high.[15] These differences are economically large when compared with the summary statistics for these portfolios in Table 6. All of these differences but one are also statistically significant. Hence, the effect of funding conditions on the illiquidity and volatility represents an undiversifiable risk for investors. We also find several pieces of evidence of *flight to quality*. Funding shocks widen the portfolio dispersion: the illiquid portfolios see their illiquidity worsen the most. Volatility and illiquidity interact as expected: the volatile stocks become more illiquid in bad times.

D The Asymmetric Response of Illiquidity to Funding Shocks

The previous section documents how the illiquidity and volatility levels change with the level of funding risk in average over a large sample. In addition, Brunnermeier and Pedersen (2009) predict that this relationship is far from linear: "a marginal change in capital has a small effect when speculators are far from their constraints, but a large effect when speculators are close to their constraints." We directly check the *asymmetry* in the relation between funding shocks and illiquidity and volatility changes for portfolio i via the following regressions:

$$\Delta Illiq_{i,t} = \gamma_{0,i} + \gamma_{1,i}\Delta FL_t + \gamma_{2,i}\Delta FL_t \mathbb{1}_{FL_{t-1}} + \xi_{i,t} \tag{4}$$

[15] It is reassuring that the only portfolio for which the average stock illiquidity improves following a funding shock is the portfolio of the least volatile stocks.

where $\mathbb{1}_{FL_{t-1}}$ is equal to 1 when the lag level FL_{t-1} lies in the top one-third of the sample, indicating that funding risk is high. In other words, the response to funding shocks ΔFL_t varies through time and it is given by

$$\left(\gamma_{1,i} + \gamma_{2,i}\mathbb{1}_{FL_{t-1}}\right). \tag{5}$$

We expect estimates of $\gamma_{2,i}$ to be economically significant, since it measures the additional sensitivity when funding risk is high. In addition, we expect the estimates of $\gamma_{1,i}$ to be small, since it measures the sensitivity when funding risk is lower. The results are reported in Table 8. The last column reports the difference between the estimates for the extreme portfolios.

First, all the coefficient estimates $\gamma_{2,i}$ are positive (except one tiny negative but insignificant estimate for the least volatile portfolio). Funding shocks are positively correlated with illiquidity and volatility shocks in poor funding conditions. In contrast, coefficient estimates of $\gamma_{1,i}$ reveal that the response is statistically insignificant when funding conditions are good. Second, portfolios that are more volatile or more illiquid experience greater deterioration of illiquidity following a funding shock. The estimates exhibit a clear pattern across portfolios. Hence, the level *and* the dispersion of illiquidity increase following a funding shock especially in poor funding conditions. Finally, we find evidence of *asymmetry*, since funding shocks are associated with increases in the level and dispersion of illiquidity across volatility-sorted portfolios.

E The Asymmetric Response of Returns to Funding Shocks

This asymmetric relationship with funding risk extends to returns: the sensitivity of a portfolio's returns to funding shocks varies as the level of funding risk varies. To check this, we divide the sample into three subsamples using the market-wide Amihud measure. Then, we estimate regressions of portfolio returns on ΔFL and PS in the high liquidity and low liquidity subsamples. We include PS to control for market liquidity conditions and contrast it with the effect of ΔFL_t. Panels (a) and (b) of Table 9 report results for the illiquidity- and volatility-sorted portfolios, respectively. As expected, the funding-risk betas β^{FL} are negative and significant in an illiquid market, for every portfolio. The cross-sectional pattern is clear: illiquid stocks and volatile stocks have lower returns when funding conditions worsen. The estimates of β^{PS} are generally smaller and remain insignificant across sub-samples.

F Asset Pricing Tests for Illiquidity-Sorted Portfolios

In terms of asset pricing tests, these portfolios behave very much the same as the previous illiquidity and volatility risk-based portfolios. In Table 10, we can see that the price of funding risk is negative and significant and that the funding liquidity betas explain about 40 percent of the cross-section of returns for both ΔFL and ΔFL^m.[16] The combination of the funding betas and the market betas makes the constant small and not statistically different from zero, while increasing considerably the statistical significance of the funding betas. The magnitudes of the price of risk are a bit larger than for the risk-based portfolios but cannot be distinguished statistically. Table 2 in the online appendix reports additional tests where the null hypothesis that pricing errors are jointly zero is not rejected.

IV Robustness

We consider several robustness checks. First, we verify whether funding shocks are priced in a broader set of test assets—including size, value, and beta-sorted portfolios. We will also test the robustness of our estimates with respect to other illiquidity or funding-risk factors. Some of these are available only at the quarterly frequency, giving us the opportunity to verify our findings at a different frequency than the

[16] We provide in the online appendix the corresponding tests for pricing errors for both the illiquidity and the volatility portfolios. Test results show clearly that the hypotheses that the errors are all zero cannot be rejected when the funding betas are added to the market or Fama-French betas.

monthly one adopted until now. Appendix A.6 details sources and construction of other factors.

A Alternative Test Assets

In this section, we consider common test assets, sorting stocks by size, book-to-market, or market beta. As discussed in the introduction, it is natural to ask whether and how much of these long-standing and well-documented risk premiums can be explained by their exposures to funding shocks.

Table 11 reports the results. Unsurprisingly, the CAPM cannot price these anomalies: the $\bar{R}_c^2$ is close to zero. The corresponding $\bar{R}_c^2$ is 42 percent for the FF model. Importantly, the price-of-risk estimates for ΔFL are negative, significant and close to other estimates reported above; and the estimated constants are small and statistically insignificant (estimates for ΔFL^m are also similar). When combined with the market returns in two-factor models, funding risk explains 53 percent of the cross-sectional variations in returns (42 percent on its own).

It is remarkable that the constant is tiny (0.1 percent p.a) and that the market price of risk is close to its sample average when pricing 10 beta-sorted portfolios (see Table 3 in the online appendix for tests conducted with the ten market beta portfolios). Frazzini and Pedersen (2014) argue that returns from the BAB portfolio can be rationalized by variations in funding conditions. Hence, this result provides strong additional support for Frazzini and Pedersen (2014) in that adjusting for the effect of the funding risk restores the slope of the capital market line.

The results show that funding risk plays a role in the cross-section of stock returns beyond the illiquidity- and volatility-sorted portfolios. Adding this evidence about portfolios conventionally used to conduct asset pricing tests, our results strongly support the theoretical prediction that exposures to funding shocks affect the equilibrium rate of returns across asset markets. Of course, the size, value, and betting-against-beta premium may not be completely, not even mostly, due to funding risk.

B Alternative Illiquidity and Funding Risk Factors

This section asks whether funding shocks are priced once we include other proxies for market liquidity or funding liquidity. Specifically, we consider the change in the market-wide Amihud measure ΔAm, the Pastor-Stambaugh PS factor, the change in the TED spread ΔTED , and the betting-against-beta BAB factor.[17]

Table 4 of the online appendix reports the correlation between ΔFL and the alternative liquidity factors. The highest correlations are with the ΔTED (0.35 and 0.15 for ΔFL and ΔFL^m), with BAB (-0.18 and 0.20) and with MTK (-0.15 and -0.21). Unsurprisingly, BAB and ΔTED are also often interpreted as funding risk proxies. Other correlations are close to zero, including with ΔAm and PS. However, the asymmetric relationship between returns, market liquidity and funding shocks suggests that low time-series correlation between funding and market liquidity shocks can be consistent with higher correlations between their βs. In other words, these factors may still yield similar risk-rankings of portfolios. Indeed, for illiquidity-sorted portfolios, the correlations between $\beta^{\Delta FL}$ and other betas (in univariate regressions) are 0.63 for PS and 0.17 for ΔAm. For volatility-sorted portfolios, the correlations are 0.83 and 0.79 for ΔPS and ΔAm, respectively (unreported).

Asset pricing results are reported in Table 12, which parallels Table 10 above, but where alternative liquidity factors replace CAPM and FF3. Panel (a) reports results when using each proxy on its own to price decile portfolios of stocks sorted on β^{illiq} and β^{σ}. We do not include portfolios sorted on $\beta^{\Delta FL}$ to avoid putting alternative proxies at a disadvantage. All the estimated constant are large and significant, except for ΔTED. This funding liquidity indicator fares well by itself, explaining 40% of the cross-section. The price-of-risk estimate for BAB is significant but the fit is

[17] We also considered the liquidity factors of Sadka (2006) as well as the measure of hedge funds illiquidity in Kruttli, Patton, and Ramadorai (2014). We find that the explanatory power of the funding risk is not subsumed in these cases either. These factors are available in shorter samples and we do not report the results for parsimony.

extremely poor: the statistical significance is entirely due to the BAB factor pricing itself. Other estimated prices of risk are insignificant (ΔAm and PS).

Panel (b) reports results when augmenting each alternative factor with ΔFL. The price of funding risk is not subsumed by other liquidity factors and the estimate for ΔTED is smaller and not statistically significant. The estimated intercept is close to zero. The estimated price of risk for ΔFL remains significant and robustly estimated around -3.5, as before. The R_c^2s are close to 50%.

C Quarterly Returns

We repeat several asset pricing tests using quarterly returns. Again, we verify that the price of funding risk is robustly estimated when controlling for alternative liquidity factors. In addition to liquidity factors used with monthly returns, we also consider the robustness to including shocks to the leverage of security broker-dealers (BD) or shocks to the equity capital ratio of primary dealers (PD). BD leverage shocks (ΔLev) were introduced in Adrian, Etula, and Muir (2014) and PD capital ratio shocks (ΔCap) were introduced in He, Kelly, and Manela (2015). Both are available quarterly and should proxy for shocks to the marginal value of financial intermediaries' wealth.[18]

Table 13 presents the results when each risk factor is used on its own or combined with funding shocks in two-factor models. The price of funding risk is robustly estimated at around -1.5 annually across specifications for quarterly returns. There is no reason to expect prices of risk to be identical across investment horizons. None of the alternative risk factors subsumes funding risk or adds to its explanatory power, but several are significant with good explanatory power on their own. Most interestingly, the price of funding risk and its statistical significance are slightly lower when funding shocks are combined with either ΔLev or ΔCap. This indicates that there

[18] Data availability for these factors restrict the sample to end in 2012Q1. See He et al. (2015) for a discussion about the differences in the construction of these proxies. Results are robust when controlling for market, size and value, but we do not report results for parsimony.

exists some degree of interaction between funding shocks and the balance sheet of intermediaries, which is consistent with theory.

D Intermediary Asset Pricing and Funding Shocks

Theory predicts that funding shocks work their way to asset returns via the balance sheet of intermediaries. It also predicts that this mechanism should be most visible when sorting assets by illiquidity and volatility. Their prices of risk should be of opposite sign in principle, since the capital ratio is the reciprocal of leverage. Indeed, when sorting stocks in these dimensions, we find that leverage shocks carry a negative price of risk and capital ratio shocks carry a positive price of risk. This contrasts with the existing mixed evidence for asset pricing tests based on size and value portfolios.

Hence, sorting on illiquidity or volatility brings further evidence to the debate on the relative importance of equity constraints and debt constraints for intermediaries. For equity-constrained intermediaries (Kondor and Vayanos, 2016; He and Krishnamurthy, 2013), a decrease of the capital ratio reflects bad states of the world due to a reduction of risk-bearing capacity. For debt-constrained intermediaries (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009), an increase in leverage reflects good states of the world where additional loans are readily available to them. Our estimates indicate that an unexpected decline of capital ratio (or an unexpected increase of leverage) is considered bad news from the point of view of investors, suggesting a greater role for constraint on equity financing for intermediaries.

To provide further evidence, Table 14 repeats the analysis for corporate and Treasury bonds (similar to Table 3 but with quarterly returns). The price of funding shocks is robustly estimated again, close but higher than in the stock market. Funding shocks explain most of the dispersion of returns for bonds sorted on illiquidity and volatility risk. Our measure of funding shocks continues to produce robust and significant estimates and subsumes PD capital ratio shocks (last column of Table 14). Similar results hold in monthly returns (unreported).

Beyond providing further robustness, these results show that the price of risk to PD capital ratio is much higher when measured in fixed-income markets. Variation to the balance sheet of primary dealers can also explain most of the dispersion of returns for these assets. Together, Tables 13 and 14 suggest that the balance sheet information from different types of intermediaries may be more or less relevant to explain the dispersion of returns in one market or another. It seems plausible that information from either the large set of broker-dealers or the small set of primary dealers is relevant to explain the cross-section of stock returns. It seems also plausible that information about broker-dealers is less relevant to explain bond returns but that balance-sheet information from primary dealers is highly relevant. This appears consistent with the view that primary dealers play a more prominent role in providing funding to bond investors than to equity investors.

V Conclusion

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

Several important questions remain for future research. First, our results are unconditional in nature. Turning to dynamic implications, it remains to be seen whether the level of funding risk is a significant state variable for investors. Second, we have documented that funding shocks are risky to investors and that they are associated with a robust risk premium. However, we have not considered how investors should adjust benchmark asset allocation models to reflect funding risk. Finally, several ongoing technological and regulatory changes suggest that funding shocks may play a lesser role in the future, but this remains to be confirmed.

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A Data Appendix

A.1 Treasury bond returns

We extract Treasury bond prices from the Center for Research on Securities Prices (CRSP) fixed-income data and construct constant-maturity bond returns. We consider bonds with maturity of 2, 3, 4, 5, 7 and 10 years. Each month, we select one bond that is nearest to each of these maturity points and we compute returns over the following month. For consistency with other results, we use the one-month T-bill rate from the Fama-French data set to compute excess returns (see below). We use observable bond prices and do not rely on fitted zero-coupon curves. We always exclude the most recently issued "on-the-run" bonds to avoid the predictable returns as these bonds roll and become "off-the-run".

A.2 Corporate bond returns

We use monthly corporate bond returns for individual securities between 1986 and 2015 available by merging several data sets: the Lehman Brothers fixed income database, Mergent FISD/NAIC, TRACE, Bloomberg and Datastream. We closely follow Bai et al. (2015) to merge these data sources and exclude bonds with special features.

A.3 Stocks returns

We extract daily stock returns and trading volume data for individual securities from the CRSP equity data set. We consider ordinary common stocks traded on the NYSE or AMEX with stock price between \$5 and \$1,000.[19] Nasdaq stocks are excluded, since their trading volume is significantly higher compared to NYSE and AMEX stocks, distorting several illiquidity measures (Amihud, 2002). We extract a monthly sample including individual stocks with at least 10 observations in a given month. The monthly returns for these securities is available from the CRSP monthly data set. Excluding stocks with too many missing observations reduces the noise when computing stock-level illiquidity or volatility proxies. This exclusion makes our results conservative, since we expect a greater impact of funding shocks for relatively illiquid securities.

A.4 Hedge funds returns

We extract hedge funds returns, net asset values and characteristics from TASS "live" and "graveyard" data sets between January 1994 and December 2015. We include US dollar funds reporting net values (instead of gross) and with initial asset under management greater than 10 millions. The aggregate net asset value is computed as the sum of net asset values for all hedge funds in our sample and reporting results in a given month.

A.5 Mimicking Portfolio

The funding liquidity factor measures deviations with respect to arbitrage-free bond prices. These deviations persist because frictions in the repo markets make the required arbitrage strategies either too costly, too risky or simply infeasible. Similarly, trading some of the volatile or illiquid stocks may imply significant transaction or shorting costs. Drechsler and Drechsler (2014) show that several well-known anomalies occur only across stocks with high shorting fees and high shorting risk. Nonetheless, we can use a projection of the funding factor ΔFL on the space of excess returns to construct a mimicking portfolio ΔFL reflecting

[19] We include CRSP share codes 10 and 11, but we exclude American Depositary Receipts, SBIs, real estate investment trusts, certificates, units, closed-end-funds, companies incorporated outside the United States, and American Trust components.

conditions in the funding markets. As spanning assets, we use the returns on bonds used in Fontaine and Garcia (2012) for estimation of the funding risk factor, as well as returns on portfolios of equities sorted by illiquidity, volatility, liquidity beta, volatility beta, size, value and momentum. We obtain portfolio loadings from the following returns regression:

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

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

$$\Delta FL^m_t \equiv \hat{B}^\top XR_t. \tag{7}$$

A.6 Additional Risk Factors and Liquidity Proxies

In the case of equities, we use the benchmark Fama-French $Mrkt$, HML and SMB factors (available from Kenneth French's web library). We consider the stock market factor either on its own ($CAPM$) or combined with the size and value factors (FF). For hedge funds we use Fung and Hsieh (2001) five Trend-Following factors TF (available from David A. Hsieh's web data Library). For corporate bond returns, we follow Fama and French (1993) and combine the $Mrkt$, $TERM$ and DEF factors. We compute $TERM$ as the difference between the 10-year and 1-year constant maturity Treasury yields, available from FRED's web site at the Federal Reserve Bank of St-Louis, and we compute DEF as the difference between Moody's Aaa and Baa corporate bond indices, also available from FRED. We construct a proxy for the overall Treasury market return by averaging monthly returns across a wide range of maturities between 3 months and 10 years. Our Treasury market factor corresponds to the standard "level" factor widely used in the literature on term structure models. Standard results show that exposures to the level factor is priced (conditionally) in Treasury bond returns.

We compare our results with several alternative liquidity or funding proxies that have been proposed as risk factors in the literature. We consider two measures of market illiquidity: the Amihud (AM) market-wide price-impact measure (Amihud, 2002) and the Pastor-Stambaugh (PS) market-wide price-reversal measure (Pastor and Stambaugh, 2003). The market-wide Amihud is given by Equation (3) but including all stocks in the computation. We use the tradable Pastor-Stambaugh factor available from Lubos Pastor's website. We also consider other proxies of funding conditions: the TED spread, given by the difference between the three-month T-bill and the LIBOR rate from $FRED$ (also used by Gârleanu and Pedersen 2011) and the betting-against-beta (BAB) factor proposed by Frazzini and Pedersen (2014). The BAB portfolio returns are available from AQR Capital's website. Finally, we also consider the leverage factor (ΔLev) from Adrian et al. (2014), which proxies for shocks to the leverage of broker-dealers in the US, and the capital ratio factor (ΔCap) from He et al. (2015), which proxies for shocks to the capital ratio of primary dealers in the US. The leverage factor is available from Tyler Muir's website, but only until 2009. Both ΔLev and ΔCap are available from Bryan Kelly's website until 2012Q4.

Table 1: **Asset Pricing Tests – Equity Portfolios**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for double-sorted portfolios of equities, first sorted in three portfolios based on market capitalization, which are then sorted in ten portfolios using funding betas $\beta^{\Delta FL}$, illiquidity betas β^{illiq} or volatility betas β^{σ}, respectively, producing ninety portfolios ($3 \times 3 \times 10$). The intercept and prices of risk are annualized (multiplied by 12). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Monthly data, January 1986–December 2015.

					Augmented by ΔFL		Augmented by ΔFL^m	
	CAPM	FF3	ΔFL	ΔFL^m	CAPM	FF3	CAPM	FF3
int	10.68	11.29	5.14	5.16	4.95	6.38	4.91	6.64
t-FM	(3.58)	(4.01)	(1.78)	(1.77)	(1.71)	(2.61)	(1.69)	(2.74)
t-Sh	(3.55)	(3.95)	(1.54)	(1.57)	(1.46)	(2.21)	(1.48)	(2.38)
ΔFL			-2.18		-2.24	-2.28		
t-FM			(-2.44)		(-2.49)	(-2.58)		
t-Sh			(-2.11)		(-2.14)	(-2.20)		
ΔFL^m				-1.41			-1.47	-1.48
t-FM				(-2.40)			(-2.52)	(-2.64)
t-Sh				(-2.14)			(-2.23)	(-2.32)
MKT	6.07	6.70			5.83	6.18	6.00	6.37
t-FM	(2.09)	(2.31)			(2.00)	(2.13)	(2.06)	(2.20)
t-Sh	(2.09)	(2.31)			(1.99)	(2.12)	(2.05)	(2.19)
SMB		-2.98				-1.71		-1.17
t-FM		(-1.06)				(-0.65)		(-0.46)
t-Sh		(-1.06)				(-0.61)		(-0.44)
HML		0.59				-0.20		0.13
t-FM		(0.23)				(-0.08)		(0.05)
t-Sh		(0.23)				(-0.08)		(0.05)
R_c^2	-3.96%	4.06%	43.82%	44.55%	41.23%	47.57%	43.21%	50.11%
$\bar{R}_c^2$	-5.14%	0.72%	43.19%	43.92%	39.88%	45.10%	41.90%	47.76%
		[0.00, 0.07]	[0.16, 0.94]	[0.16, 0.84]	[0.14, 0.94]	[0.15, 0.74]	[0.14, 0.85]	[0.16, 0.76]
R^2	7.85%	11.92%	43.82%	44.15%	47.53%	50.97%	49.00%	53.77%
$\bar{R}^2$	6.82%	8.95%	43.19%	43.53%	46.33%	48.74%	47.85%	51.69%
	[0.09, 0.99]	[0.00, 0.34]	[0.16, 0.94]	[0.16, 0.84]	[0.20, 0.95]	[0.19, 0.78]	[0.20, 0.89]	[0.19, 0.80]

Table 2: **Pricing Error Tests – Equity Portfolios**

Estimated intercept (annualized), mean absolute pricing error (MAPE), χ^2_{N-K} statistic and the associated p-value for a test that pricing errors are jointly zero. Monthly data, January 1986–December 2015.

Panel (a) 30 Double-sorted size and $\beta^{\Delta FL}$ portfolios

					Augmented CAPM	
	CAPM	FF3	ΔFL	ΔFL^m	ΔFL	ΔFL^m
Intercept	10.98	17.12	4.13	4.03	4.20	4.06
MAPE	1.82	1.90	0.86	1.03	0.86	1.03
χ^2_{N-K}	32.64	37.87	23.34	27.99	24.28	28.86
p-value	0.29	0.08	0.76	0.52	0.67	0.42

Panel (b) 30 Double-sorted size and β^{illiq} portfolios

					Augmented CAPM	
	CAPM	FF3	ΔFL	ΔFL^m	ΔFL	ΔFL^m
Intercept	11.00	19.84	5.66	2.78	5.92	2.87
MAPE	1.74	1.77	1.59	1.46	1.57	1.44
χ^2_{N-K}	54.38	49.78	45.23	38.55	45.82	38.84
p-value	0.00	0.00	0.03	0.11	0.02	0.08

Panel (c) 30 Double-sorted size and β^{σ} portfolios

					Augmented CAPM	
	CAPM	FF3	ΔFL	ΔFL^m	ΔFL	ΔFL^m
Intercept	10.96	21.39	5.96	4.18	6.20	4.26
MAPE	1.52	1.55	1.36	1.50	1.35	1.48
χ^2_{N-K}	34.45	39.97	37.78	38.09	38.92	40.12
p-value	0.22	0.05	0.13	0.12	0.08	0.06

Panel (d) 90 Double-sorted portfolios

					Augmented CAPM	
	CAPM	FF3	ΔFL	ΔFL^m	ΔFL	ΔFL^m
Intercept	11.00	16.71	5.14	4.44	5.34	4.55
MAPE	1.69	1.61	1.29	1.31	1.27	1.29
χ^2_{N-K}	140.60	135.44	122.02	124.69	126.73	130.86
p-value	0.00	0.00	0.01	0.01	0.00	0.00

Table 3: **Asset Pricing Tests – Fixed-Income Portfolios**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for 10 portfolios of corporate bonds sorted by $\beta^{\Delta FL}$, β^{Illiq} and β^{σ} (thirty portfolios) as well as individual Treasury bonds with maturity 2, 3, 4, 5, 7 and 10 years. The estimated prices of risk are annualized (multiplied by 12). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Monthly data, January 1986–December 2015.

					Augmented by ΔFL		Augmented by ΔFL^m	
	CAPM	FF3	ΔFL	ΔFL^m	CAPM	FF3	CAPM	FF3
int	2.92	1.22	-0.38	-0.12	-0.38	-1.09	0.09	-0.48
t-FM	(4.33)	(1.95)	(-0.46)	(-0.17)	(-0.47)	(-5.01)	(0.13)	(-1.65)
t-Sh	(4.15)	(1.52)	(-0.29)	(-0.10)	(-0.32)	(-3.38)	(0.08)	(-0.94)
ΔFL			-4.53		-4.16	-4.00		
t-FM			(-4.24)		(-3.77)	(-3.49)		
t-Sh			(-2.72)		(-2.54)	(-2.37)		
ΔFL^m				-3.59			-3.80	-3.69
t-FM				(-4.48)			(-4.40)	(-4.08)
t-Sh				(-2.64)			(-2.49)	(-2.35)
MKT	15.34	11.47			8.01	7.89	9.16	9.14
t-FM	(4.18)	(3.60)			(2.72)	(2.68)	(3.01)	(3.00)
t-Sh	(4.11)	(3.43)			(2.70)	(2.66)	(2.78)	(2.80)
ΔTERM		0.06				0.01		0.06
t-FM		(1.13)				(0.18)		(1.11)
t-Sh		(0.89)				(0.12)		(0.64)
ΔDEF		-0.08				-0.04		-0.05
t-FM		(-4.56)				(-3.12)		(-3.35)
t-Sh		(-3.64)				(-2.29)		(-2.05)
R_c^2	52.83%	69.02%	91.70%	90.12%	91.88%	93.17%	88.99%	89.58%
$\bar{R}_c^2$	51.45%	66.11%	91.46%	89.83%	91.38%	92.29%	88.32%	88.24%
	[0.59, 0.96]	[0.40, 0.87]	[0.78, 0.97]	[0.80, 0.97]	[0.78, 0.97]	[0.80. 0.97]	[0.79, 0.97]	[0.80, 0.97]
R^2	48.70%	70.10%	91.70%	87.93%	92.69%	93.86%	87.64%	88.31%
$\bar{R}^2$	47.24%	67.54%	91.46%	87.59%	92.26%	93.14%	86.94%	86.98%
	[0.52, 0.95]	[0.44, 0.88]	[0.78, 0.97]	[0.76, 0.96]	[0.80, 0.97]	[0.83, 0.98]	[0.77, 0.96]	[0.78, 0.97]

Table 4: **Pricing Error Tests – Corporate Bond Portfolios**

Estimated intercept (annualized), mean absolute pricing error (MAPE), χ^2_{N-K} statistic and the associated p-value for a test that pricing errors are jointly zero. Monthly data, January 1986–December 2015.

Panel (a) 10 $\beta^{\Delta FL}$ portfolios

					Augmented CAPM	
	CAPM	FF	ΔFL	ΔFL^m	ΔFL	ΔFL^m
Intercept	5.22	2.35	1.31	1.78	1.33	1.90
MAPE	1.41	1.60	0.55	0.90	0.58	0.94
χ^2_{N-K}	17.94	32.13	10.99	9.87	12.17	8.77
p-value	0.04	0.00	0.28	0.36	0.14	0.36

Panel (b) 10 β^{illiq} portfolios

					Augmented CAPM	
	CAPM	FF	ΔFL	ΔFL^m	ΔFL	ΔFL^m
Intercept	5.31	1.93	0.90	1.41	0.94	1.57
MAPE	1.41	1.47	0.68	0.86	0.67	0.91
χ^2_{N-K}	28.92	59.88	16.72	10.54	17.83	9.54
p-value	0.00	0.00	0.05	0.31	0.02	0.30

Panel (c) 10 β^{σ} portfolios

					Augmented CAPM	
	CAPM	FF	ΔFL	ΔFL^m	ΔFL	ΔFL^m
Intercept	5.21	1.62	0.44	1.58	0.40	1.75
MAPE	1.61	1.53	0.81	1.05	0.73	1.13
χ^2_{N-K}	22.28	32.73	15.77	14.24	16.58	11.75
p-value	0.01	0.00	0.07	0.11	0.03	0.16

Table 5: **Asset Pricing Tests – Hedge Funds Portfolios**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for double-sorted portfolios of hedge funds, first sorted in three portfolios based on exposures to aggregated hedge funds net asset value β^{hf}, which are then sorted in ten portfolios using funding betas $\beta^{\Delta FL}$, illiquidity betas β^{illiq} or volatility betas β^{σ}, respectively, producing ninety portfolios ($3 \times 3 \times 10$). The estimated prices of risk are annualized (multiplied by 12). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. The price of risk is fixed to the sample average returns in the case of traded factors to increase precision. The R^2s and R_c^2s are the same in this case. Monthly data, January 1986–December 2015.

		Augmented with ΔFL			
	ΔFL	CAPM	FF	CAPM+TF	FF + TF
int.	2.02	2.07	2.13	2.06	2.51
t-FM	(2.83)	(3.64)	(3.31)	(3.34)	(3.63)
t-Sh	(2.39)	(3.35)	(2.89)	(2.51)	(2.79)
ΔFL	-2.74	-2.62	-2.45	-3.32	-3.13
t-FM	(-1.30)	(-1.34)	(-2.13)	(-3.35)	(-3.27)
t-Sh	(-1.10)	(-1.15)	(-1.81)	(-2.56)	(-2.56)
R^2	51.23%	51.95%	52.75%	43.73%	43.99%
$\bar{R}^2$	50.68%	51.40%	52.21%	43.09%	43.35%
	[0.15, 0.99]	[0.15, 0.99]	[0.16, 0.99]	[0.11, 0.99]	[0.14, 0.99]

Table 6: **Summary Statistics–Illiquidity and Volatility Portfolios**

Time-series average for sample statistics of decile portfolios of equities sorted with the level of illiquidity (Panel a) or volatility (Panel b). The Amihud illiquidity measure is the median across stocks in a portfolio ($\times 100$); the volatility, capitalization and average returns measures are the equal-weighted average across stocks in a portfolio, in \$ billions or annualized %. The ex-ante CAPM β is computed for each portfolio using 5-year and 1-year rolling windows to estimate the correlations and variances, respectively. Monthly data, January 1986–December 2015.

Panel (a) Illiquidity-sorted portfolios

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

Panel (b) Volatility-sorted portfolios

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

Table 7: **Portfolio Illiquidity and Volatility across Funding Conditions**

Average illiquidity (×100) and volatility (annualized %) of liquidity-sorted and volatility-sorted portfolios conditional on the level of lagged funding liquidity risk FL_{t-1}. Panel (a) reports averages when FL is in the bottom tercile of the empirical distribution (low FL_{t-1}). Panel (b) reports averages when FL is in the top tercile (high FL_{t-1}). Panel (c) reports differences between each average, with t-statistics reported in parenthesis. Monthly data, January 1986–December 2015.

Panel (a) Low FL_{t-1}

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

Panel (b) High FL_{t-1}

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

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

	Illiquidity Portfolios			Volatility Portfolios	
	Illiquidity	Volatility		Illiquidity	Volatility
Most	121.33	3.70	Most	7.39	2.73
	(2.41)	(4.06)		(4.61)	(1.49)
2	28.71	3.56	2	4.61	3.73
	(3.61)	(2.35)		(5.65)	(2.21)
3	11.19	3.92	3	4.20	4.07
	(4.13)	(2.75)		(5.16)	(2.47)
4	6.19	3.25	4	3.10	4.37
	(4.82)	(2.29)		(6.07)	(2.74)
5	3.02	3.51	5	1.52	4.42
	(4.89)	(2.42)		(4.70)	(2.94)
6	1.55	4.33	6	0.80	4.56
	(5.50)	(3.11)		(3.07)	(3.19)
7	0.70	3.84	7	1.22	4.56
	(4.98)	(2.62)		(5.52)	(3.31)
8	0.32	3.73	8	0.94	3.70
	(4.62)	(2.55)		(4.12)	(3.08)
9	0.14	3.42	9	0.85	2.82
	(4.46)	(2.31)		(2.57)	(2.61)
Least	0.04	3.57	Least	-5.11	1.79
	(4.54)	(2.41)		(-3.02)	(2.13)

Table 8: **Illiquidity and Funding Shocks**

Regressions of changes in the illiquidity of each portfolio on funding shocks $\Delta ILLIQ_{i,t} = \gamma_{0,i} + \gamma_{1,i}\Delta FL_t + \gamma_{2,i}\Delta FL_t \mathbb{1}_{FL_{t-1}} + \xi_{i,t}$, where $\mathbb{1}_{FL_{t-1}}$ is the indicator function equal to 1 when FL_{t-1} lies in the highest sample tercile (i.e., high funding risk). Parameter estimates are multiplied by 100. Monthly data, January 1986–December 2015.

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

Table 9: **Funding and Market Liquidity Risk in Liquid and Illiquid Samples**

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

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

Panels (a) and (b) report results for illiquidity- and volatility-sorted portfolios, respectively, and with t-statistics reported in parentheses. Monthly data, Jan 1986–Dec 2015.

Panel (a) Illiquidity Portfolios

		Most	2	3	4	5	6	7	8	9	Least
Lo Liq	$\beta^{\Delta FL}$	-5.01	-5.90	-5.43	-4.85	-4.44	-4.70	-4.67	-4.06	-4.11	-2.95
		(-4.10)	(-3.52)	(-3.13)	(-2.76)	(-2.54)	(-2.80)	(-2.82)	(-2.41)	(-2.68)	(-2.10)
	β^{PS}	0.05	-0.05	-0.03	-0.02	0.04	0.08	0.12	0.10	0.13	0.08
		(0.53)	(-0.42)	(-0.26)	(-0.11)	(0.29)	(0.62)	(0.93)	(0.75)	(1.12)	(0.77)
Hi Liq	$\beta^{\Delta FL}$	-2.10	-2.49	-2.47	-2.29	-2.55	-2.32	-2.39	-2.29	-2.11	-2.32
		(-2.03)	(-1.93)	(-2.00)	(-1.89)	(-2.25)	(-2.00)	(-2.07)	(-2.08)	(-2.04)	(-2.27)
	β^{PS}	-0.10	-0.06	-0.01	-0.13	-0.07	-0.05	-0.09	-0.11	-0.07	-0.13
		(-0.94)	(-0.46)	(-0.11)	(-1.03)	(-0.58)	(-0.42)	(-0.69)	(-0.90)	(-0.66)	(-1.16)

Panel (b) Volatility Portfolios

		Most	2	3	4	5	6	7	8	9	Least
Lo Liq	$\beta^{\Delta FL}$	-4.29	-5.25	-5.16	-5.70	-5.05	-5.11	-4.97	-4.20	-4.13	-3.19
		(-1.75)	(-2.50)	(-2.69)	(-3.17)	(-2.96)	(-3.18)	(-3.41)	(-3.17)	(-3.50)	(-3.45)
	β^{PS}	0.08	-0.06	-0.01	0.02	0.05	0.03	0.08	0.07	0.11	0.09
		(0.45)	(-0.38)	(-0.08)	(0.12)	(0.39)	(0.25)	(0.69)	(0.74)	(1.27)	(1.32)
Hi Liq	$\beta^{\Delta FL}$	-2.78	-3.25	-2.74	-2.56	-2.34	-2.39	-2.28	-2.35	-1.72	-1.27
		(-1.62)	(-2.33)	(-2.06)	(-2.06)	(-1.96)	(-2.21)	(-2.12)	(-2.52)	(-1.98)	(-1.66)
	β^{PS}	-0.06	-0.10	-0.06	-0.10	-0.05	-0.08	-0.12	-0.09	-0.09	-0.10
		(-0.33)	(-0.65)	(-0.40)	(-0.71)	(-0.37)	(-0.69)	(-1.03)	(-0.92)	(-0.94)	(-1.25)

Table 10: **Asset Pricing Tests – Illiquidity and Volatility Portfolios**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for ten illiquidity- and ten volatility-sorted portfolios. The estimated prices of risk are annualized (multiplied by 12). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Monthly data, January 1986–March 2015.

					Augmented by ΔFL		Augmented by ΔFL^m	
	CAPM	FF3	ΔFL	ΔFL^m	CAPM	FF3	CAPM	FF3
int	5.59	4.46	2.35	3.24	1.29	2.14	1.70	2.40
t-FM	(4.55)	(4.52)	(0.73)	(1.14)	(1.25)	(2.64)	(1.67)	(2.97)
t-Sh	(4.53)	(4.48)	(0.55)	(1.00)	(0.87)	(1.77)	(1.40)	(2.48)
ΔFL			-3.38		-3.96	-4.28		
t-FM			(-1.88)		(-4.62)	(-4.60)		
t-Sh			(-1.42)		(-3.28)	(-3.13)		
ΔFL^m				-1.48			-1.75	-1.78
t-FM				(-1.89)			(-4.64)	(-4.57)
t-Sh				(-1.66)			(-3.98)	(-3.90)
MKT	5.23	4.35			7.18	6.80	6.95	6.44
t-FM	(1.70)	(1.49)			(2.35)	(2.38)	(2.28)	(2.25)
t-Sh	(1.70)	(1.49)			(2.20)	(2.36)	(2.21)	(2.24)
SMB		1.80				2.65		2.68
t-FM		(0.85)				(1.26)		(1.27)
t-Sh		(0.84)				(1.19)		(1.24)
HML		2.23				2.04		2.06
t-FM		(1.16)				(1.06)		(1.07)
t-Sh		(1.16)				(1.04)		(1.06)
R_c^2	-9.45%	17.83%	43.35%	43.36%	43.04%	61.70%	43.36%	59.54%
$\bar{R}_c^2$	-15.54%	2.42%	40.21%	40.21%	36.34%	51.49%	36.69%	48.75%
R^2	44.46%	54.14%	43.35%	39.08%	73.70%	80.03%	70.82%	70.67%
$\bar{R}^2$	41.54%	46.90%	40.21%	35.87%	70.78%	75.59%	67.74%	70.54%

Table 11: **Alternative Test Assets**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for decile portfolios of equities sorted by size, value, or β. The price-of-risk estimates are annualized ($\times 12$). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Monthly data, January 1986–December 2015.

					Augmented by ΔFL		Augmented by ΔFL^m	
	CAPM	FF3	ΔFL	ΔFL^m	CAPM	FF3	CAPM	FF3
int	8.43	4.55	1.20	2.25	1.86	1.97	2.44	2.19
t-FM	(5.70)	(4.05)	(0.30)	(0.59)	(1.35)	(1.73)	(1.79)	(2.03)
t-Sh	(5.70)	(3.98)	(0.22)	(0.51)	(0.91)	(1.29)	(1.47)	(1.72)
ΔFL			-3.45		-4.27	-3.46		
t-FM			(-2.53)		(-4.59)	(-3.35)		
t-Sh			(-1.90)		(-3.12)	(-2.52)		
ΔFL^m				-1.47			-1.91	-1.69
t-FM				(-2.32)			(-4.27)	(-3.66)
t-Sh				(-2.05)			(-3.54)	(-3.14)
MKT	1.25	2.91			5.58	5.91	5.11	5.88
t-FM	(0.40)	(0.96)			(1.74)	(1.99)	(1.58)	(1.99)
t-Sh	(0.40)	(0.96)			(1.54)	(1.92)	(1.50)	(1.96)
SMB		0.57				-0.51		-0.63
t-FM		(0.25)				(-0.23)		(-0.28)
t-Sh		(0.24)				(-0.22)		(-0.27)
HML		5.57				5.69		5.41
t-FM		(2.70)				(2.77)		(2.62)
t-Sh		(2.69)				(2.61)		(2.54)
R_c^2	-11.28%	50.28%	44.18%	40.12%	56.42%	72.75%	52.40%	72.02%
$\bar{R}_c^2$	-15.25%	44.54%	42.19%	37.98%	53.19%	68.39%	48.88%	67.54%
		[0.10, 0.69]	[0.12, 0.93]	[0.10, 0.80]	[0.16, 0.84]	[0.33, 0.84]	[0.12, 0.71]	[0.35, 0.85]
R^2	1.82%	49.56%	44.18%	38.44%	67.94%	73.21%	62.07%	71.98%
$\bar{R}^2$	-1.56%	44.34%	42.19%	36.31%	65.64%	69.39%	59.45%	68.11%
	[0.00, 0.38]	[0.09, 0.67]	[0.12, 0.93]	[0.08, 0.79]	[0.32, 0.91]	[0.34, 0.84]	[0.23, 0.80]	[0.35, 0.85]

Table 12: **Asset Pricing Tests – Alternative Liquidity Factors**

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

	Panel (a) Alternative Factors				Panel (b) Augmented with ΔFL			
int	10.75	4.76	10.27	2.85	0.38	1.01	1.93	1.42
t-FM	(3.56)	(1.55)	(3.37)	(1.01)	(0.13)	(0.29)	(0.61)	(0.46)
t-Sh	(3.51)	(1.50)	(3.35)	(0.85)	(0.09)	(0.22)	(0.46)	(0.36)
ΔFL					-4.08	-3.30	-3.47	-2.97
t-FM					(-3.46)	(-2.55)	(-2.64)	(-2.43)
t-Sh					(-2.40)	(-1.95)	(-1.98)	(-1.92)
BAB	7.54				8.68			
t-FM	(3.10)				(3.62)			
t-Sh	(3.09)				(3.59)			
ΔAm		-0.21				-0.07		
t-FM		(-1.41)				(-0.46)		
t-Sh		(-1.37)				(-0.36)		
PS			4.78				4.67	
t-FM			(1.99)				(1.95)	
t-Sh			(1.99)				(1.94)	
ΔTED				-1.82				-1.25
t-FM				(-2.31)				(-1.67)
t-Sh				(-1.96)				(-1.32)
R^2_c	-38.02%	15.35%	1.46%	41.65%	46.76%	48.72%	47.54%	50.95%
$\bar{R}^2_c$	-45.69%	10.65%	-4.01%	38.41%	40.50%	42.69%	41.37%	45.18%
		[0.00, 0.98]		[0.07, 0.85]	[0.05, 0.86]	[0.06, 0.85]	[0.06, 0.90]	[0.10, 0.82]
R^2	44.13%	15.35%	30.15%	35.75%	79.03%	48.72%	62.81%	48.18%
$\bar{R}^2$	41.19%	10.65%	26.47%	32.37%	76.70%	42.69%	58.67%	42.42%
	[0.53, 0.90]	[0.00, 0.98]	[0.26, 0.88]	[0.03, 0.79]	[0.52, 0.98]	[0.06, 0.85]	[0.23, 0.96]	[0.08, 0.81]

Table 13: **Asset Pricing Tests – Quarterly Returns in Equity Portfolios**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for quarterly returns of decile portfolios sorted by β^{illiq} and β^{σ}. The estimated prices of risk are annualized (multiplied by 4). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Quarterly data, 1986Q1 - 2012Q4.

Panel (a) Single-factor models

	Single Factor						
	ΔFL	BAB	ΔAm	PS	ΔTED	ΔLev	ΔCap
int.	2.47	8.58	2.61	10.08	4.32	15.01	0.21
t-FM	(0.68)	(2.39)	(0.98)	(2.78)	(1.41)	(3.14)	(0.07)
t-Sh.	(0.58)	(2.31)	(0.87)	(2.73)	(1.22)	(2.32)	(0.06)
ΔFL	-1.44						
t-FM	(-2.40)						
t-Sh.	(-2.09)						
BAB		8.31					
t-FM		(2.65)					
t-Sh.		(2.65)					
ΔAm			-0.76				
t-FM			(-2.11)				
t-Sh.			(-1.90)				
PS				5.51			
t-FM				(1.98)			
t-Sh.				(1.98)			
ΔTED					-1.97		
t-FM					(-2.36)		
t-Sh.					(-2.07)		
ΔLev.						-0.61	
t-FM						(-2.21)	
t-Sh.						(-1.65)	
ΔCap							0.17
t-FM							(2.15)
t-Sh.							(2.08)
R_c^2	83.99%	-1.53%	41.27%	7.04%	71.36%	61.78%	46.90%
$\bar{R}_c^2$	83.10%	-7.17%	38.01%	1.88%	69.76%	59.66%	43.95%
	[0.50, 0.99]		[0.06, 0.98]	[0.00, 0.99]	[0.28, 0.94]	[0.19, 0.98]	[0.09, 0.98]
R^2	83.99%	51.39%	41.27%	33.65%	66.17%	61.78%	46.90%
$\bar{R}^2$	83.10%	48.83%	38.01%	30.16%	64.39%	59.66%	43.95%
	[0.50, 0.99]	[0.73, 1.00]	[0.06, 0.98]	[0.24, 0.82]	[0.20, 0.93]	[0.19, 0.98]	[0.09, 0.98]

Table 13: **Asset Pricing Tests – Quarterly Returns in Equity Portfolios *(continued)***

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for quarterly returns of decile portfolios sorted by β^{illiq} and β^{σ}. The estimated prices of risk are annualized (multiplied by 4). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Quarterly data, 1986Q1 - 2012Q4.

Panel (b) Augmented by ΔFL

	Augmented by ΔFL					
	BAB	ΔAm	PS	ΔTED	Δ Lev	ΔCap
int.	1.77	2.13	2.74	2.54	4.73	1.39
t-FM	(0.51)	(0.77)	(0.77)	(0.67)	(1.58)	(0.46)
t-Sh.	(0.43)	(0.66)	(0.65)	(0.57)	(1.40)	(0.40)
ΔFL	-1.51	-1.41	-1.42	-1.48	-1.13	-1.35
t-FM	(-2.59)	(-2.18)	(-2.35)	(-2.10)	(-1.97)	(-2.01)
t-Sh.	(-2.22)	(-1.90)	(-2.04)	(-1.80)	(-1.78)	(-1.77)
BAB	8.19					
t-FM	(2.61)					
t-Sh.	(2.60)					
ΔAm		-0.32				
t-FM		(-0.88)				
t-Sh.		(-0.77)				
PS			4.81			
t-FM			(1.74)			
t-Sh.			(1.73)			
ΔTED				-0.83		
t-FM				(-1.02)		
t-Sh.				(-0.88)		
ΔLev.					-0.08	
t-FM					(-0.35)	
t-Sh.					(-0.32)	
ΔCap						0.12
t-FM						(1.62)
t-Sh.						(1.49)
R^2_c	80.63%	84.17%	80.89%	83.79%	85.18%	84.01%
$\bar{R}^2_c$	78.35%	82.30%	78.64%	81.88%	83.44%	82.12%
	[0.40, 0.98]	[0.46, 0.97]	[0.48, 0.98]	[0.47, 0.95]	[0.48, 0.98]	[0.48, 0.98]
R^2	90.61%	84.17%	86.19%	82.98%	85.18%	84.01%
$\bar{R}^2$	89.57%	82.30%	84.66%	81.09%	83.44%	82.12%
	[0.67, 0.99]	[0.46, 0.97]	[0.54, 0.99]	[0.44, 0.95]	[0.48, 0.98]	[0.48, 0.98]

Table 14: **Asset Pricing Tests–Quarterly Returns in Bond Portfolios**

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for decile portfolios of corporate bonds sorted by β^{Illiq} β^{σ} as well as for Treasury bonds with maturity 2,3,4,5,7 and 10 years. The estimated prices of risk are annualized (multiplied by 4). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Quarterly data, 1986Q1 - 2012Q4.

Panel (a) Single-factor models

	Single Factor						
	ΔFL	BAB	ΔAm	PS	ΔTED	ΔLev	ΔCap
int.	0.04	3.88	0.71	4.21	-0.82	4.32	0.08
t-FM	(0.06)	(3.77)	(1.01)	(4.07)	(-1.36)	(4.24)	(0.11)
t-Sh.	(0.04)	(3.57)	(0.64)	(3.88)	(-0.67)	(2.79)	(0.08)
ΔFL	-2.50						
t-FM	(-3.67)						
t-Sh.	(-2.53)						
BAB		11.02					
t-FM		(3.30)					
t-Sh.		(3.30)					
ΔAm			-1.87				
t-FM			(-3.32)				
t-Sh.			(-2.15)				
PS				9.11			
t-FM				(2.91)			
t-Sh.				(2.89)			
ΔTED					-4.78		
t-FM					(-4.19)		
t-Sh.					(-2.11)		
ΔLev						0.79	
t-FM						(2.57)	
t-Sh.						(1.72)	
ΔCap							0.57
t-FM							(3.55)
t-Sh.							(2.46)
R_c^2	91.20%	8.38%	79.00%	10.16%	80.97%	13.44%	84.64%
$\bar{R}_c^2$	90.83%	4.56%	78.13%	6.42%	80.18%	9.84%	83.99%
	[0.75, 0.97]	[0.01, 0.99]	[0.47, 0.94]	[0.01, 0.99]	[0.62, 0.94]	[0.00, 0.66]	[0.84, 0.95]
R^2	91.20%	19.71%	79.00%	14.41%	77.15%	13.44%	84.64%
$\bar{R}^2$	90.83%	16.50%	78.13%	10.99%	76.24%	9.84%	83.99%
	[0.75, 0.97]	[0.08, 0.99]	[0.47, 0.94]	[0.01, 0.99]	[0.54, 0.93]	[0.00, 0.66]	[0.60, 0.95]

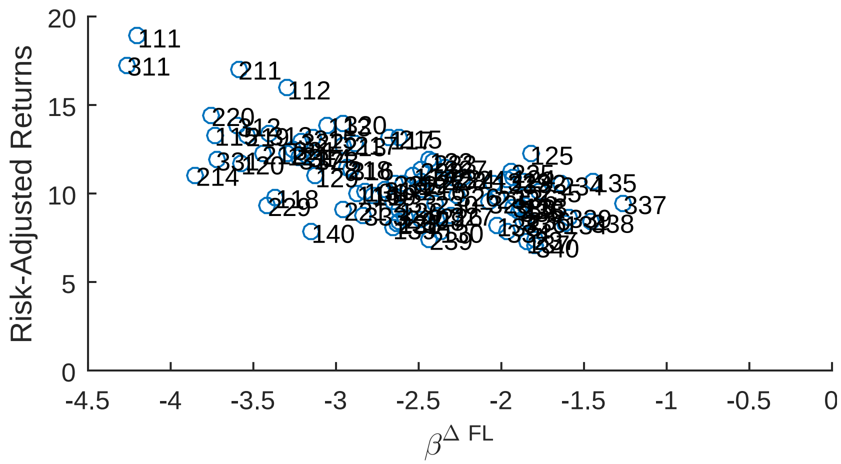
Table 14: **Asset Pricing Tests – Quarterly Returns in Bond Portfolios *continued***

Cross-sectional asset pricing tests based on two-stage Fama-MacBeth regressions for decile portfolios of corporate bonds sorted by β^{Illiq} β^{σ} as well as for Treasury bonds with maturity 2,3,4,5,7 and 10 years. The estimated prices of risk are annualized (multiplied by 4). Standard errors and Shanken-corrected standard errors are reported in parentheses. The confidence intervals for R^2s are based on 5,000 bootstrap replicates. Traded risk factors are included as test assets whenever applicable. Quarterly data, 1986Q1 - 2012Q4.

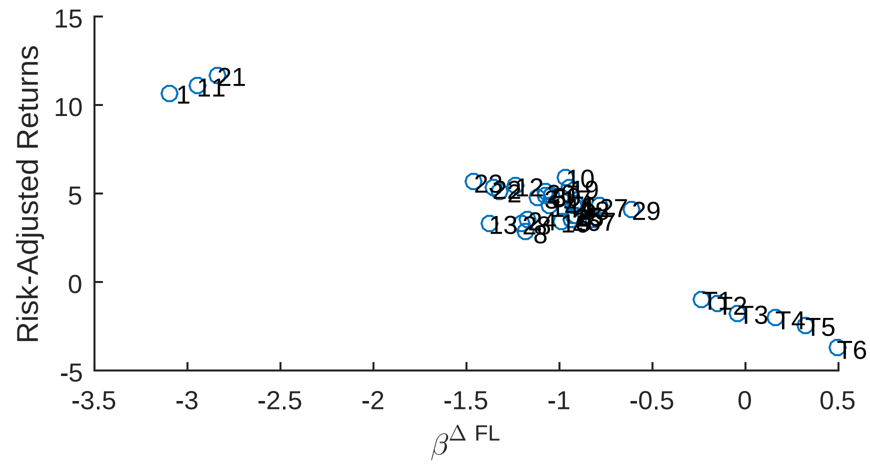
Panel (b) Augmented by ΔFL

	Augmented by ΔFL					
	BAB	ΔAm	PS	ΔTED	ΔLev	ΔCap
int.	-0.11	-0.04	0.03	-0.02	0.11	0.06
t-FM	(-0.17)	(-0.06)	(0.04)	(-0.05)	(0.16)	(0.08)
t-Sh.	(-0.11)	(-0.04)	(0.03)	(-0.03)	(0.11)	(0.05)
ΔFL	-2.49	-3.09	-2.47	-2.46	-2.50	-2.59
t-FM	(-3.66)	(-6.28)	(-3.63)	(-2.98)	(-3.67)	(-4.31)
t-Sh.	(-2.52)	(-3.84)	(-2.51)	(-2.05)	(-2.50)	(-2.94)
BAB	9.61					
t-FM	(2.89)					
t-Sh.	(2.87)					
ΔAm		0.09				
t-FM		(0.14)				
t-Sh.		(0.08)				
PS			6.28			
t-FM			(2.11)			
t-Sh.			(2.10)			
ΔTED				-1.28		
t-FM				(-1.36)		
t-Sh.				(-0.94)		
ΔLev					0.24	
t-FM					(1.23)	
t-Sh.					(0.84)	
ΔCap						0.15
t-FM						(1.13)
t-Sh.						(0.77)
R^2_c	91.97%	92.24%	91.36%	91.29%	91.63%	91.22%
$\bar{R}^2_c$	91.27%	91.57%	90.61%	90.53%	90.91%	90.46%
	[0.75, 0.97]	[0.77, 0.97]	[0.75, 0.97]	[0.75, 0.97]	[0.75, 0.97]	[0.74, 0.97]
R^2	92.98%	92.24%	91.91%	91.06%	91.63%	91.22%
$\bar{R}^2$	92.39%	91.57%	91.23%	90.31%	90.91%	90.46%
	[0.75, 0.98]	[0.77, 0.97]	[0.76, 0.97]	[0.73, 0.97]	[0.75, 0.97]	[0.74, 0.97]

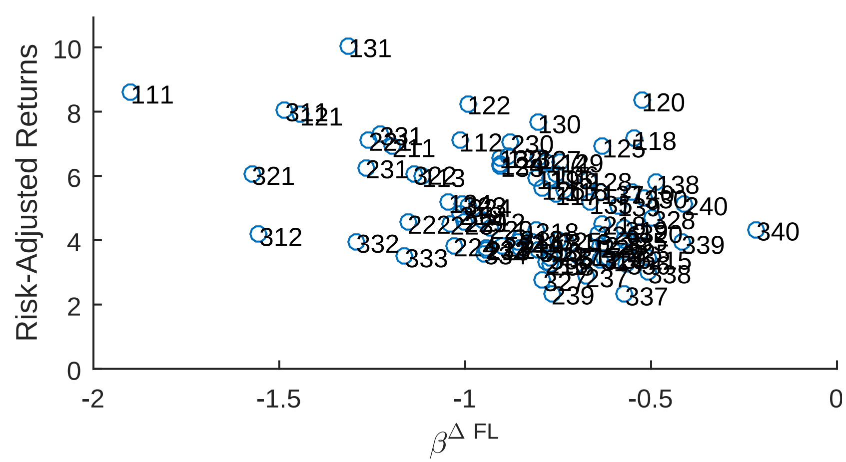
Figure 1: Average Returns and Funding Risk $\beta^{\Delta FL}$



((a)) Equity Portfolios



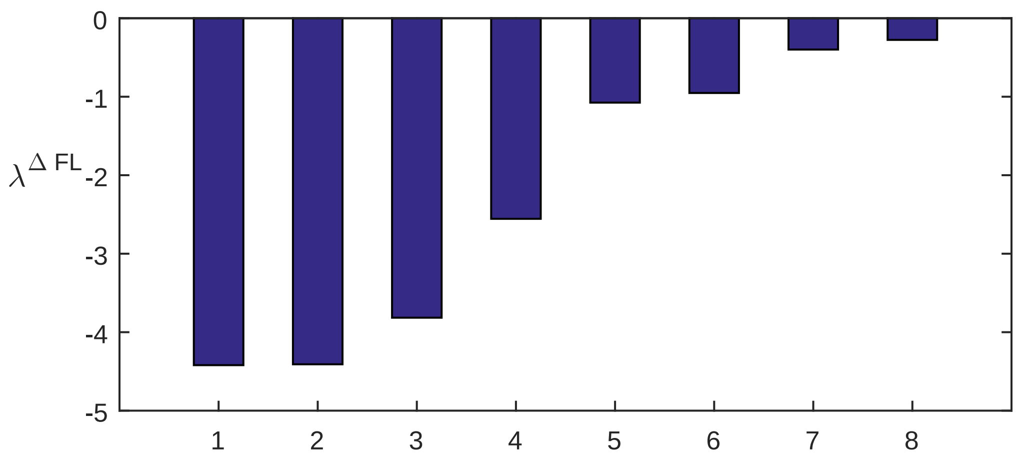
((b)) Bond Portfolios



((c)) Hedge Fund Portfolios

Average returns and funding and funding shock betas $\beta^{(n)}_{\Delta FL}$. Panel (a): ninety equity portfolios double-sorted with size and either $\beta^{\Delta FL}$, β^{illiq} or β^{σ}. Panel (b): thirty corporate bond sorted with $\beta^{\Delta FL}$, β^{illiq} and β^{σ} and six Treasury bonds. Panel (c): ninety portfolios of hedge funds double-sorted with β^{nav} and either $\beta^{\Delta FL}$, β^{illiq} and β^{σ}. Average returns are adjusted for market risk $\overline{XR}_{(i)} = \beta^{Mrkt}_{(i)}\lambda^{Mrkt} + \beta^{\Delta FL}_{(i)}\lambda^{\Delta FL}$ where $Mrkt$ is the equity markets, except for Treasury bonds where we use the average Treasury market returns (see Appendix A.1). We estimate $\beta^{Mrkt}_{(i)}$ and $\beta^{\Delta FL}_{(i)}$ with OLS and we fix λ^{Mrkt} to the sample mean to impose discipline. Monthly data, January 1986 - December 2015.

Figure 2: Funding Risk β across Hedge Fund Categories



Price of funding risk estimated across hedge funds with different investment styles. Labels from 1 to 8: 'Global Macro', 'Multi-Strategy', 'Fund of Funds', 'Managed Futures', 'Fixed Income Arbitrage', 'Convertible Arbitrage', 'Long/Short Equity Hedge' and 'Event Driven' funds. For each category, we sort funds based on $\beta^{\Delta FL}$ estimated based on a rolling univariate regression using 36 months of data. We report the price of risk estimated in a single-factor model. Monthly data, January 1994 - December 2015.