Intermediary Leverage Shocks and Funding Conditions

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Abstract

The aggregate leverage of broker-dealers responds to demand and supply disturbances that have opposite effects on financial markets. Leverage supply shocks that relax broker-dealers' funding constraints raise leverage, improve liquidity, raise returns and carry a positive price of risk. Leverage demand shocks that tighten the constraints also raise leverage but worsen liquidity, lower returns and carry a negative price of risk. Because of these opposite effects, disentangling demand- and supply-like shocks yields consistent evidence across many markets of a central role for intermediation frictions and dealers' aggregate leverage in asset pricing and goes a long way in resolving existing puzzles around the price of leverage risk.

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Introduction

Large financial intermediaries provide broker-dealer services to major investors and asset managers, act as market-makers or providers of liquidity across several markets and are central in the issuance of new securities. Because their activities span complex investment strategies across essentially all financial markets, in stark contrast with the possibilities that households have, the marginal value of intermediaries' wealth may determine the compensation for risk. In their seminal contribution, Adrian, Etula, and Muir (2014), henceforth AEM, show that a measure of leverage from the aggregated balance sheet of broker-dealers is a good proxy for the intermediaries' marginal value of wealth and that the covariance of asset returns with leverage can explain expected returns across equity portfolios and Treasury bonds, thus bringing a new perspective to the field of empirical asset pricing. Assets and strategies that perform poorly when intermediaries' marginal value of wealth is high offer larger returns to investors.[1]

However, some questions remain that limit our understanding of intermediation frictions or may raise doubts about the centrality of intermediaries for asset pricing. First, while AEM asset pricing results are consistent with well-established models of intermediation friction in which leverage varies in tandem with conditions that broker-dealers face in funding markets (Brunnermeier and Pedersen, 2009), AEM also noted that leverage appears largely uncorrelated with proxies for market liquidity. This challenges a core theoretical prediction from these models that funding market conditions and market liquidity are intertwined. Second, broadening the study of intermediation frictions to several asset classes, He, Kelly, and Manela (2017) add to the challenges and found that estimates of the price of leverage risk can switch signs in some markets or across different portfolio sorts.

One reason why empirical work may yield muted or mixed estimates could be that the leverage decision by broker-dealers mixes demand-sided and supply-sided considerations. Specifically, leverage may increase because funding conditions improve, in which case the marginal value of intermediaries' wealth declines. We label these shifts as leverage supply shocks. However, leverage can also increase following a shift in the demand for intermediation by investors wanting to sell assets, in which case funding conditions tighten and the marginal value of wealth rises. We label these shifts as leverage demand shocks. Both these demand

[1]See the detailed survey by Gromb and Vayanos (2010) as well as Geanakoplos (2010); He and Krishnamurthy (2013); Brunnermeier and Sannikov (2014); Kondor and Vayanos (2019).

and supply shocks lead to a higher intermediaries' leverage but with opposite effects on the marginal value of wealth and, potentially, on the cross-section of asset returns and liquidity.

To analyze how this mix may determine the existing evidence, we introduce a simple model where distinct demand and supply shocks drive the leverage of intermediaries and their marginal value of wealth. We show that these shocks, if identified, can be used in two-stage asset pricing regressions to estimate the exposures of asset returns or liquidity to changes in the marginal value of intermediaries' wealth and to recover the price of risk associated with these exposures.

To identify the leverage demand and supply shocks, we follow an approach similar to the methodology that Goldberg (2020) and Goldberg and Nozawa (2021) use to analyze shocks to dealers' inventories in the bond market. We combine a proxy for funding conditions with AEM's measure of broker-dealers' aggregate leverage in a vector-autoregressive (VAR) system of equations and apply sign restrictions on the covariance matrix to recover the leverage demand and supply shocks.[2] The sign restrictions will imply that the supply shocks lift leverage and improve funding conditions, while demand shocks raise leverage but degrade funding conditions. Results from this VAR system suggest that demand and supply shocks explain similar shares in the variance of aggregate leverage, consistent with what Goldberg (2020) and Goldberg and Nozawa (2021) find for dealers' inventories of bonds. To complement and support this VAR decomposition, we provide in an appendix ample reduced-form and structural evidence showing that both demand and supply shocks matter for the intermediaries' leverage.

Empirically, our first contribution is to show that shocks to aggregate broker-dealers' leverage, once separated into demand- and supply-like shocks, carry consistent prices of risk and perform well across a broad range of financial markets. In our main set of asset pricing tests, we build equity and corporate bond portfolios by sorting securities on their betas with market illiquidity, market volatility and funding conditions. This is motivated by the theoretical relations put forward by Brunnermeier and Pedersen (2009), that the marginal value of intermediaries' wealth links returns with illiquidity, volatility and funding conditions. To broaden the cross-section of assets, we include the returns from a panel of Treasury bonds (as in AEM) as well as the returns from unlevered option portfolios from Constantinides, Jackwerth, and Savov (2013). The results show that the estimated betas for the demand and

[2]The funding conditions proxy is the first principal component from three existing measures of funding conditions, which mitigates the effect of any noise that is introduced by each measure. Section III.A provides the details.

supply shocks have negative and positive signs, as expected. We also find that the prices of risk that they command in second-stage Fama-McBeth regressions have the expected signs and we cannot reject the hypothesis that the magnitudes are the same, another implication of the model. These patterns are pervasive across asset classes. We conclude that exposures of asset returns to aggregate leverage variations, measured by either demand or supply betas, are priced consistently across markets: assets with similar leverage risk offer much the same average returns. Hence, this separation considerably strengthens the evidence about the importance of intermediaries' aggregate leverage in asset pricing, paving the way for more work to understand the distinct mechanisms underlying demand- and supply-sided shocks to broker-dealers leverage.

Our second empirical contribution is to show that disentangling demand and supply shocks provides a rationalization of the puzzling sign changes noted by He, Kelly, and Manela (2017). Like in their results, we find that the sign of the price of raw leverage risk alternates between asset classes. With the help of our model, we show that the cross-sectional dispersion of demand and supply betas can drive the sign of the estimates for the AEM's leverage factor, because this factor's beta mixes the demand and supply betas that have opposite signs. Consistent with the model's implication, we find that the price of leverage risk is negative for equities and options, where the leverage demand betas have a wider dispersion, but positive for bonds, where the supply betas are more dispersed.

Because of the alternating signs, we find that asset pricing results using raw leverage can quickly deteriorate when combining assets from different markets. Testing a pricing model that uses raw leverage and the market returns to price our set of option, bond and equity test assets considered jointly, we find a poor measure of fit (R^2 is 25 percent) and an attenuated as well as insignificant price of risk. A pricing model that disentangles leverage demand and supply shocks produces a much better fit even if we leave the market returns aside (R^2 is 90 percent). Therefore, the separation of raw leverage shocks into supply- and demand-sided shocks can explain why some existing results were muted or mixed.

We obtain similar asset pricing findings and infer the same conclusions using traditional Fama and French size, value, profitability and investment-sorted equity portfolios. We also use the larger set of asset classes considered in He, Kelly, and Manela (2017), where sovereign bonds, credit derivatives, commodities, and exchange rates are added to the Fama-French 25 portfolios, government and corporate bonds and equity derivatives. We also draw the same inference if we use AEM's test assets. In this case, aggregate leverage explains 88 percent of the cross-section of portfolio returns and the price-of-risk estimate is positive and significant. This sign is consistent with our other results, since we observe a small dispersion in leverage demand shocks betas across these assets but a marked dispersion in supply shocks betas. Overall, the evidence paves the way for more work to understand why the relative exposures to demand- and supply-sided leverage shocks vary across markets.

Finally, we embed in our model and verify the theoretical predictions by Brunnermeier and Pedersen (2009) that intermediaries' marginal value of wealth drives common market liquidity variations. Empirically, we find that leverage supply shocks have a significant positive impact on market liquidity while leverage demand shocks have a significant negative impact. In both cases, the impact is highest for the least liquid portfolios and decreases monotonically for the more liquid portfolios. The patterns are almost symmetrical and explain the puzzle noted by AEM that raw leverage appears unrelated to market liquidity.

Literature

Since at least the great financial crisis, an empirical literature has proposed to price assets in several markets with a stochastic discount factor (SDF) that includes different proxies for the financial intermediaries' marginal value of wealth. As discussed above, Adrian, Etula, and Muir (2014) proxy the intermediaries' marginal value of wealth by using the leverage of securities broker-dealers. He, Kelly, and Manela (2017) instead use shocks to the capital ratio of primary dealers' holding company and broaden the evidence to include corporate and sovereign bonds, derivatives, commodities, and currencies. Using a proxy for the risk-bearing capacity of intermediaries, Haddad and Muir (2021) find more pronounced return predictability for asset classes in which households are less active and quantify the aggregate risk premia variations that can be ascribed to intermediaries. We identify leverage demand and supply shocks that are consistently priced across asset markets and essential to understand the role of intermediaries' leverage across these markets.

Our paper also belongs to a strand of literature studying demand- or supply-sided channels in the determination of asset prices. For instance, Liu, Whited, and Zhang (2009) document linkages between stock prices and firms' demand for capital. Gârleanu, Pedersen, and Pothesman (2009) document large demand effects on option prices. More recently, Koijen and Yogo (2019) argue that stock returns are mostly explained by shocks to the supply of capital that are unrelated to observed characteristics. In an equilibrium framework, Bétermier, Calvet, and Jo (2020) map the cross-section of returns to the supply and demand for capital at the firm level. While we also combine prices with the quantity decisions (here the leverage decision), we identify shocks to the demand and supply for intermediation, which we then map to outcomes in the financial markets.

Froot and O'Connell (1999) provide an early analysis of prices and quantities in the catastrophe reinsurance market. Gabaix, Krishnamurthy, and Vigneron (2007) examine intermediation in the mortgage-backed securities. Gârleanu, Pedersen, and Pothesman (2009) show that demand pressure effects on dealers' inventory help explain well-known option-pricing puzzles. As noted above, Goldberg (2020) uses sign restrictions to estimate demand and supply shocks to dealers' inventory in the Treasury market. He finds that the supply shocks in this market are informative about liquidity in other markets and predicts reduced debt issuance and investment by nonfinancial firms and reduced aggregate economic activity.[3] Goldberg and Nozawa (2021) use a similar approach for dealers' inventory in the US corporate bond market. As in both of these papers, we find that leverage supply shocks play a larger role in bond returns. Our contribution is to show that the relative roles of demand- and supply-side exposures to aggregate broker-dealers' leverage can change across several asset markets and that this strengthens and deepens the evidence of intermediaries' leverage in asset pricing.

To identify the shocks, we combine leverage with existing price proxies of funding conditions introduced in a large literature that highlights the information content of apparent arbitrage opportunities. This apparent mispricing between securities with similar risk is taken to reflect tighter limits to the arbitrage activities of financial intermediaries. Longstaff (2004) studies the spreads of bonds guaranteed by the US Treasury. Krishnamurthy (2010) provides evidence on mortgage-backed securities. Fontaine and Garcia (2012) connect the spread of seasoned Treasuries with risk premia across several fixed-income securities. Frazzini and Pedersen (2014) connect a higher T-bill-Eurodollar (TED) spread with low contemporaneous returns of betting-against-beta strategies. Mitchell and Pulvino (2012) and Hu, Pan, and Wang (2013) provide similar evidence in the hedge fund industry and for exchange rates. Du, Tepper, and Verdelhan (2018) focus on persistent deviations from the covered interest rate parity condition (CIP) in the foreign exchange market.

Our results are also related to existing work showing strong illiquidity commonality across securities (Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Chordia, Sarkar, and Subrahmanyam, 2005), or that illiquidity increases with the volatilities of securities to compensate market-makers, either for their inventory risk or for their losses to

[3] Sign restrictions are also used more broadly in macro-finance. See e.g., Arias, Caldara, and Rubio-Ramirez (2019) and Cieslak and Pang (2021).

better-informed investors (Benston and Hagerman, 1974; Stoll, 1978; Glosten and Milstom, 1985; Grossman and Miller, 1988; Pagano, 1989). We show that both leverage supply and demand shocks connect intermediaries' balance sheets with market illiquidity but with opposite signs. Other results show that the risk premium increases with the level of illiquidity in a cross-section of equities (Amihud and Mendelson, 1986; Amihud, 2002; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005). As predicted in models with intermediaries, we find that leverage supply shocks bear a positive price of risk and leverage demand shocks bear a negative price of risk when assets are sorted on their level of illiquidity risk.

The rest of the paper is organized as follows. In Section I, we develop a simple econometric model where the intermediaries' leverage and marginal value of wealth are driven by supply- and demand-like disturbances, and draw its implications for asset pricing. Section II explains how to extract the leverage supply and demand shocks through identification with sign restrictions in a vector autoregressive system of empirical measures of leverage and funding conditions. Section III studies how the risks of leverage demand and supply shocks influence the risk premia in securities markets. Several asset classes are considered to show the differentiated effects of supply and demand shocks on the pricing of leverage risk in each class. In Section IV, we review the approach of AEM under the light of our econometric model. The Conclusion summarizes the main results and stresses the need for further research on the mechanisms underlying the channels of leverage supply and demand shocks across different asset markets. An appendix describes data sources, explains the construction of the portfolios that we use in our tests, and gives additional estimation results. We also provide reduced-form as well as structural evidence that the leverage constraints of intermediaries do not always bind and that, therefore, both supply- and demand-like shocks can influence leverage.

I An Econometric Model of Leverage Shocks

We develop a simple econometric model where the intermediaries' leverage and marginal value of wealth are driven by supply- and demand-like disturbances. In Section I.A, we show that these shocks, if identified, can be used to estimate the price-of-risk parameter in the intermediaries' pricing kernel. In Section I.B, we analyze how the mix of these shocks pins down what estimates are recovered when raw aggregate leverage is used on its own in asset pricing models. Section I.C discusses the implications for the link between leverage and market liquidity.

A Leverage demand and supply shocks

The intermediaries' marginal value of wealth ϕ is given by:

$$\phi = \gamma + \big(e_d - e_s\big), \tag{1}$$

where we ignore the time subscript for clarity, γ is a positive preference parameter, and the shocks e_d and e_s are independent with zero means and unit standard deviations. The intermediaries' aggregate leverage LEV (in log) is given by:

$$LEV = \mu^L + b \times \big(e_d + e_s\big), \tag{2}$$

where b is a positive parameter and the mean leverage $\mathbb{E}[LEV] = \mu^L$ is a free parameter that is kept constant for ease of exposition in this section, but we will let it vary over time in the empirical section.

Empirically, the leverage decision pins down the quantity of intermediation supplied by broker-dealers.[4] The first shock e_d has the interpretation of a demand shock: following a higher demand for intermediation by investors, leverage increases together with the marginal value of wealth, because the funding constraints tighten. The second shock e_s has the interpretation of a supply shock: following improved conditions for the supply of intermediation, leverage increases and the marginal value of intermediaries' wealth declines, because the constraints loosen. The restriction that both shocks have the same loading b on leverage is imposed for simplicity but does not influence our results.

Assuming for simplicity that there is no other source of risk in the economy, the returns for financial assets indexed by i will be given by:

$$R_i = \mu_i + \beta_i^{e_d} e_d + \beta_i^{e_s} e_s, \tag{3}$$

where $\beta_i^{e_d}$ and $\beta_i^{e_s}$ are the true betas defined as:

$$\beta_i^{e_d} = \frac{\mathrm{Cov}(e_d, R_i)}{\mathrm{Var}(e_d)} \qquad \text{and} \qquad \beta_i^{e_s} = \frac{\mathrm{Cov}(e_s, R_i)}{\mathrm{Var}(e_s)}. \tag{4}$$

[4] Adrian and Shin (2010a,b) show that intermediaries in the US manage the size of their balance sheet primarily by actively varying leverage, mainly through repos and reverse repos, with equity being the exogenous variable. Hence, leverage and total assets tend to move in lockstep at quarterly or shorter frequencies.

To pin down the expected returns $E[R_i] = \mu_i$, we assume that the intermediaries' marginal value of wealth drives the pricing kernel:

$$\mathrm{E}\big[R_i\big] = -\frac{\mathrm{Cov}\big[\phi, R_i\big]}{\mathrm{E}\big[\phi\big]}, \tag{5}$$

which is a defining relation posited in the intermediary asset pricing literature. Equations (1)-(2) and (5) imply that the expected return μ_i in equation (3) is as follows:

$$\mu_i = -\big(\beta_i^{e_d} - \beta_i^{e_s}\big) \times \lambda, \tag{6}$$

where $\lambda = \gamma^{-1}$. If asset i is risky with respect to its exposures to leverage demand and supply shocks, so that $\mu_i > 0$, then it must be that $\beta_i^{e_d} < 0$ and $\beta_i^{e_s} > 0$, respectively. For such an asset, leverage demand shocks are associated with lower contemporaneous returns but supply shocks with higher contemporaneous returns.

In a regression of average returns $\mathrm{E}[R_i]$ on the betas $\beta_i^{e_d}$ and $\beta_i^{e_s}$, the population value for the price of risk is given by:

$$\lambda^{e_d} = -\lambda \qquad \lambda^{e_s} = \lambda. \tag{7}$$

This symmetry in the prices of risk means that separating leverage shocks into supply and demand components does not result into uncovering new risk factors. As in Brunnermeier and Pedersen (2009) and AEM, there is a close connection between the intermediaries' marginal value of wealth and their leverage but, in this framework, the sign of the relationship may depend on the nature of the underlying shocks. Ultimately, this parsimonious model yields sharp predictions about the role of leverage supply and demand shocks in asset markets. We specify below three implications of the model that we will test in Section III.

Implication 1 If the intermediaries' leverage, marginal value of wealth and asset returns are driven by demand and supply shocks e_d and e_s as in Equations (1)-(5), then:

i. The return betas of assets that are risky with respect to leverage supply and demand shocks have the following opposite signs,

$$\beta_i^{e_d} < 0 \qquad \beta_i^{e_s} > 0.$$

ii. The prices of risk associated with the betas of leverage demand and supply shocks are negative and positive, respectively:

$$\lambda^{e_d} < 0 \qquad \lambda^{e_s} > 0.$$

iii. The prices of risk associated with demand and supply shocks are symmetric:

$$\lambda^{e_d} = -\lambda^{e_s}.$$

B Leverage and asset pricing

This econometric model also helps understand some of the mixed evidence produced when using raw aggregate leverage in asset pricing tests. Consider the case where the leverage innovations $\left(e_d + e_s\right)$ are used in an asset pricing test based on the standard two-stage regressions. With no loss in generality, suppose that the cross-sections of the demand and supply betas have standard deviations ω_1 and ω_2 as well as correlation $\mathrm{corr}(\beta_i^{e_d}, \beta_i^{e_s}) = \rho$. Then, using equations (1)-(5), the true time-series betas in the first-stage regressions of returns are given by:

$$\beta_i^L = \frac{1}{2}b^{-1} \times \left(\beta_i^{e_d} + \beta_i^{e_s}\right), \tag{8}$$

which is positive in markets where the returns' responses to leverage supply shocks are stronger, $|\beta_i^{e_d}| < |\beta_i^{e_s}|$, and negative if the opposite is true. In addition, the true value λ^L in a second-stage cross-sectional regression of average returns on the betas is given by:

$$\lambda^L = -c\lambda 2b \times (\omega_1^2 - \omega_2^2), \tag{9}$$

where $c > 0$ is a positive constant.[5] Equation (9) shows that the sign of λ^L depends on the relative magnitudes of the demand and supply beta variances, ω_1^2 and ω_2^2 respectively. Therefore, we add two more implications of the model that we will test in Section III.

Implication 2 If the intermediaries' leverage, marginal value of wealth and asset returns are driven by demand and supply shocks e_d and e_s as in Equations (1)-(5), then:

[5] The constant c is given by $c = (\omega_1^2 + \omega_2^2 - 2\rho\omega_1\omega_2)^{-1}$. Appendix A.1 derive similar results in the more general case where the leverage shocks have distinct loadings on LEV in Equation 2 .

i. Equation (8): the sign of the leverage betas β_i^L is given by the relative magnitudes of the demand and supply betas,

$$\text{sign}(\beta_i^L) = \text{sign}(\beta_i^{e_d} + \beta_i^{e_s}).$$

ii. Equation (9): the sign of the price of leverage risk λ^L is given by the relative magnitudes of the demand and supply beta variances:

$$\text{sign}(\lambda^L) = -\text{sign}(\omega_1^2 - \omega_2^2).$$

C Leverage and illiquidity

Finally, we can also use this econometric model to understand the relationship between leverage and measures of market liquidity. We build on a central implication in the equilibrium model of Brunnermeier and Pedersen (2009), linking the market liquidity of an asset with the funding conditions that intermediaries face. Specifically, we assume that the illiquidity Λ^i of asset i is proportional to the intermediaries' marginal value of wealth ϕ, as follows:

$$\Lambda_i = \delta_i(\phi - 1), \tag{10}$$

where δ_i is a positive parameter that can be interpreted as the margin requirement for asset i.[6] In Brunnermeier and Pedersen (2009), the liquidity Λ_i in Equation (10) corresponds to the notion of price impact.

Given Equations (1) and (10), it is easy to see that the regression coefficients in a regression of the illiquidity, say using some price impact measure, on the demand and supply shocks have opposite signs and are symmetric, as follows:

$$\frac{\text{Cov}(e_d, \Lambda_i)}{\text{Var}(e_d)} = \delta^i \qquad \text{and} \qquad \frac{\text{Cov}(e_s, \Lambda_i)}{\text{Var}(e_s)} = -\delta^i. \tag{11}$$

However, because the shocks have the same loadings on leverage in Equation (2), a regression of the illiquidity on the raw leverage will produce a coefficient equal to zero:

$$\frac{\text{Cov}(LEV, \Lambda_i)}{\text{Var}(LEV)} = 0. \tag{12}$$

[6] Another line of research tests for the role of margin changes in financial markets. Jylhä (2018) uses infrequent changes to Federal Reserve's Regulation T requirements for initial margins between 1934 and 1974 to study changes in the slope of the security market line.

Therefore, we get two final implications of the model that we will test in Section III.

Implication 3 If the intermediaries' leverage, marginal value of wealth and asset illiquidity are driven by demand and supply shocks e_d and e_s as in Equations (1)-(2) and Equation (10), then:

i. Equation (11): the coefficients in a regression of illiquidity on demand and supply shocks have opposite signs and are symmetric:

ii. Equation (12): the coefficient in a regression of illiquidity on leverage innovations is zero.

II Data, Identification and Test Assets

We take the model described in the previous section to the data and test the listed asset pricing implications. To recover leverage supply and demand shocks separately, an instrument is needed that can indicate when leverage increases because of supply effects (with looser funding conditions) or demand effects (with tighter funding conditions). We describe how we construct this instrument in section II.A, how we identify and extract these shocks through sign restrictions in a vector autoregressive system in Section II.B, and how we construct test assets in Section II.C.

A Measures of Leverage and Funding Conditions

We follow AEM and compute the broker-dealers' aggregate leverage LEV using quarterly data from the Federal Reserve Flow of Funds (Table L.129) as the ratio of broker-dealers' total financial assets, which sums the value of long and short positions in securities for every broker-dealer, to their book equity, which is the difference between total financial assets and liabilities.

We construct a measure of funding conditions that builds on a strand of literature going back to the pioneering work of Gromb and Vayanos (2002) and Longstaff (2004). We extract the first principal component from three well-established measures derived from the US Treasury markets. The idea behind each measure is to use the wedge between the valuations of two assets with identical cash-flows as a proxy for the intermediaries' marginal value of wealth.[7] First, we include the well-known and often-used TED spread: the spread between

[7] In a model that shares several features with Brunnermeier and Pedersen (2009) but where some securities i and j have identical cash flows but different margins m_i and m_j, Gârleanu and Pedersen (2011) show that

the EuroDollar LIBOR rate and the T-bill rate. Frazzini and Pedersen (2014) use it in regressions to test for a link in the U.S. between funding conditions and the betting-against-beta factor.[8] Second, we rely on a well-accepted measure provided by Hu, Pan, and Wang (2013), which aggregates deviations of individual bond yields from a smooth parametric curve to conduct asset pricing tests across hedge funds and currency carry trades. Goldberg and Nozawa (2021) implement a similar measure in the market for corporate bonds. Third, we include the measure from Fontaine and Garcia (2012), who extract a proxy from a panel of U.S. Treasury securities using a dynamic term structure model. They test the predictive content of this proxy for risk premia across several securities markets. We label these three proxies TED, HPW and FG, respectively.

There are many reasons why the Treasury market may be the place par excellence to measure broad funding conditions, as opposed to market-specific conditions. First, investors' flight to quality is directed towards the Treasury market during crises. Second, broker-dealers play a central role in this market. Third, these bonds are the dominant collateral instruments for broker-dealers to manage short-term funding needs (Adrian and Shin, 2010b).

Overall, these proxies exhibit important commonalities despite the differences in their construction. Panels (a)-(c) of Figure 1 plot the monthly time series of these proxies in our sample, between January 1986 and December 2015, showing that they share the same peaks and troughs. The TED proxy features peaks following the crash of 1987, at the beginning of 2000 and, of course, during the financial crisis of 2008. There are two other smaller peaks during the European sovereign debt crisis. The FG proxy shares the same peaks, although the ranking of peaks can differ. For instance, the 1994 events and the European debt crisis exhibit higher peaks based on this proxy. The HPW proxy also shares many of the same peaks, but they are not always easy to see next to the very high peak of the 2008 crisis. The TED proxy has a correlation of 0.30 and 0.58 with FG and HPW, respectively, while the correlation between FG and HPW is 0.51.[9]

We label our proxy for funding conditions $FUND$. To construct this proxy, we extract the first principal component from the monthly TED, HPW and FG data, and we set its sign such

the wedge between the expected returns μ_i and μ_j depends on the shadow price of the funding constraint: $|\mu_i - \mu_j| = \phi(m_i + m_j)$.

[8] Gârleanu and Pedersen (2011) use the spread between the rates on LIBOR and GC repo loans instead of the TED spread, but the latter is more commonly used.

[9] The correlations are not driven by the 2008 financial crisis. After the crisis, the TED proxy has a correlation of 0.40 and 0.49 with FG and HPW, respectively, and the correlation between FG and HPW is 0.85.

that a higher value of $FUND$ identifies times with tighter funding conditions, as indicated by wide price differences between nearly identical securities. We also construct quarterly data for $FUND$ by extracting the last observation of every quarter to match the frequency of observations for LEV. We expect that the principal component can extract a more precise signal of the funding conditions than any of the three measures taken individually. Using the average instead of the first principal component across proxies does not qualitatively change the results.

B Identifying Leverage Shocks using Sign Restrictions

For simplicity of exposition, we ignored the time dimension in the model presented in Section I. In the empirical application, we specify a parsimonious reduced-form vector autoregressive (VAR) model to account for predictable variations in leverage and funding conditions in the time series dimension. We can then use this VAR to decompose the unpredictable leverage innovation into the demand and supply shocks.

The VAR model is given by:

$$y_{t+1} = a + \Phi y_t + u_{t+1}, \tag{13}$$

where $y_t = [LEV\ FUND]^\top$ is a 2×1 vector, Φ is a 2×2 coefficient matrix and u_{t+1} is the 2×1 vector of the reduced-form forecast errors with covariance matrix Σ_u. The reduced-form errors $u_t = [u_{L,t}\ u_{F,t}]^\top$ are driven by uncorrelated structural shocks $e_t = [e_t^D\ e_t^S]^\top$, where the superscripts D and S designate the demand and the supply shocks. The link between u_t and the structural shocks e_t is given by $u_t = B^{-1} e_t$ and restrictions are needed on the B^{-1} impact multiplier matrix to identify the structural shocks from the reduced-form estimates. From Equation (2), the demand and supply shocks both increase leverage forecast errors. However, leverage demand shocks tighten funding conditions while leverage supply shocks loosen funding conditions. Hence, we assume the following signs for the parameters in the B^{-1} matrix :

$$\begin{bmatrix} u_{L,t} \\ u_{F,t} \end{bmatrix} = \begin{bmatrix} + & + \\ - & + \end{bmatrix} \begin{bmatrix} e_t^S \\ e_t^D \end{bmatrix}.$$

Goldberg and Nozawa (2021) also use sign restrictions to identify liquidity supply and demand shocks in the corporate bond market. The use of sign restrictions to identify structural

VAR models were introduced in economics by Faust (1998), Canova and Nicolo (2002), and Uhlig (2005). The methodology is described in detail in Kilian and Lütkepohl (2017).[10]

(i) Impulse responses and variance decompositions. We show that supply and demand shocks both play significant roles in the dynamics of leverage. To see this, we report the impulse response functions in Panels (a)-(b) of Figure 2. The signs of the initial responses are given by construction—negative for $FUND$ and positive for LEV in the case of supply shocks—but the magnitude and persistence are estimated from the data. A one-standard-deviation supply shock raises leverage by 0.4 standard deviation and the impact dissipates after about two years. The impact of demand shocks is slightly larger but less persistent. A one-standard-deviation demand shock increases leverage by 0.55 standard deviation and the effect disappears after about one year. Similarly, Goldberg (2020) as well as Goldberg and Nozawa (2021) find that the initial impacts of demand and supply shocks to dealers' bond market inventories are similar, but that the supply shocks are more persistent.

We report the variance decompositions in Panels (c)-(d) of Figure 2. The point estimates imply that leverage demand shocks play a slightly bigger role than supply shocks in explaining the variability of LEV, which could be due to the very large demand shock in 2008. However, the confidence intervals do not exclude the case where each shock explains a similar share of leverage variance.

(ii) Historical decomposition. The decomposition of historical leverage forecast errors shows that both demand and supply shocks played important roles around periods of stress in financial markets. We report this decomposition in Figure 3. Negative supply shocks occurred with positive demand shocks around the 1987 stock market crash, around the year 2000 millenium market collapse, in 2004-2005 and during a period that covers the Greece debt bailout, the European sovereign debt crisis and the taper tantrum. Both supply and demand shocks contributed to worsen funding conditions. Positive demand shocks are also apparent during periods with small or positive supply shocks: around the 1994 bond market downturn, in the 1998 following the LTCM collapse and the Russian crisis, and during the period of the financial crisis (2007-2008), which exhibits a huge spike in the third quarter of 2008. The large Fed interventions kept funding conditions afloat during that period, which

[10] Briefly, the first step is to compute P the unique Cholesky decomposition of Σ_u from the data ($\Sigma_u = P'P$, with P' lower triangular). Then, we sample decompositions such that $\Sigma_u = P'S'SP$ where S' is drawn from the set of orthonormal matrices $S'S = I$. If the decomposition given by the matrix $\mathcal{P} = P'S'$ satisfies the sign restrictions, then we recover the structural shocks, the impulse response functions and the variance decompositions. We report median values for these objects across simulations for S.

may explain the estimated positive supply shocks that we observe for this period. Positive leverage supply shocks played an important role in the mid-1990s and a larger role after the turn of the millennium (2001-2003). They occurred together with positive demand shocks in the former period and negative demand shocks in the latter. This resulted in higher leverage (coming mainly from supply) and was associated with improved funding conditions in both periods (see also Figure 1).

(iii) Distribution of the structural shocks. Figure 4 reports the distribution of the leverage demand and supply shocks when the lagged $FUND$ value is in the lower third of its own distribution and, separately, when the lagged $FUND$ value is in the higher third of its distribution. The top two panels report the distributions of the leverage supply shocks, while the bottom two panels report the distributions of the leverage demand shocks. The histograms cover a range of ± 3 standard deviations (this range excludes from the figure one large demand shock in 2008) We also provide summary statistics advocated by Colacito, Ghysels, Meng, and Siwasarit (2016) that are robust to the small sample size: the median measure of central location, the Bowley measure of dispersion and the inter-quantile range measure of skewness. While the histograms exclude one observation, these summary statistics include all observations.

The distributions of leverage supply shocks are different between times with low and high $FUND$ values. When funding conditions are good, both the demand and the supply shocks have negative medians. The supply shocks have a range of 0.83 and a skewness of 0.09 while the demand shocks have a range of 0.62 and a skewness of -0.07. However, when funding conditions are tight, the dispersion of the supply shocks increases substantially. Its range increases from 0.83 to 1.83, while the range of the demand shocks increases from 0.62 to 0.86. We find similar results if we use the lower and higher terciles of LEV to create sub-samples. The fact that the supply shocks have a much wider dispersion when funding conditions are tight is consistent with theoretical predictions that supply plays a larger role when the leverage constraint is more likely to bind.[11]

C Test Assets

We construct test assets using data on stocks, corporate bonds, Treasury bonds and index options. For stocks and corporate bonds, for which a wide cross-section is available, we form

[11] Modeling the variance dynamics explicitly may increase efficiency but it would increase the risk of specification errors. We see Equation (13) as a robust quasi maximum likelihood approach to disentangle the leverage supply and demand shocks.

portfolios of securities sorted on betas with respect to three types of risk. Specifically, the betas are given by:

$$\beta_i^{\Delta Illiq} = \frac{cov(\Delta Illiq_m, R_i)}{var(\Delta Illiq_m)} \quad \beta_i^{\Delta\sigma} = \frac{cov(\Delta\sigma_m, R_i)}{var(\Delta\sigma_m)} \quad \beta_i^{\Delta FUND} = \frac{cov(\Delta FUND, R_i)}{var(\Delta FUND)},$$

where Δ is the first-difference operator, $Illiq_m$ is the stock market illiquidity, σ_m is the stock market volatility, and $FUND$ is the funding proxy constructed in section II.A. This strategy produces three sets of ten equity portfolios denoted LIQ1-LIQ10, VOL1-VOL10 and FUN1-FND10, where the index 1 and 10 indicates portfolios with securities that have the highest and lowest β, respectively. Similarly, this strategy creates three sets of ten corporate bond portfolios denoted CBL1-CBL10, CBV1-CBV10 and CBF1-CBF10. Appendix A.3 discusses the construction of these equity and corporate bond portfolios.

This choice of portfolios is motivated by the theoretical relations put forward by Brunnermeier and Pedersen (2009) between the marginal value of the intermediaries' wealth, on the one hand, and the aggregate illiquidity, volatility and funding liquidity on the other hand.[12] Table 1 provides summary statistics for each set of portfolios, where we report the average return, liquidity, volatility and market capitalization. Sorting on the betas produces a U-shaped pattern in the average returns, illiquidity and volatility for the three sets of portfolios, especially for the sorts on illiquidity and funding betas. By contrast, these sorts produce an inverted U-shaped pattern across the market capitalization, again especially for the sorts on illiquidity and funding betas. The patterns in the betas are also very similar across the three sorts. This is consistent with the prediction, in the model of Brunnermeier and Pedersen (2009), that these characteristics are closely related in equilibrium. Overall, the portfolios offer a substantial dispersion in average returns and provide an excellent testing ground for leverage demand and supply shocks. For robustness, we will also check that our main message is unchanged when using the standard Fama and French portfolios as well as other test assets used by Adrian, Etula, and Muir (2014) or He, Kelly, and Manela (2017).

Since the cross-sections of Treasury bonds and options are not rich enough to construct beta-sorted portfolios, we include the returns of individual securities. For options, we use portfolios of unlevered S&P index call and put options with different strike prices and maturities, labeled CLL1-CLL27 and PUT1-PUT27. The series are available from Constantinides

[12] Acharya and Pedersen (2005) follow a similar approach and use theoretical considerations to build three sets of β-sorted portfolios representing different forms of liquidity risk.

et al. (2013), who show how challenging it can be to price options returns, especially for puts, but that a proxy for illiquidity goes a long way toward reducing pricing errors.

For Treasury bonds, we compute constant-maturity returns for bonds with maturities of 2, 3, 4, 5, 7 and 10 years, available from the Center for Research on Securities Prices (CRSP). Hence, we do not rely on fitted zero-coupon curves. For each month and each maturity category, we select the observed prices of the most recently-issued bond and one other bond that is nearest to each of these maturity points but that has been issued some time ago. This creates a panel of 12 bonds labeled BND1-BND12. These bonds have different interest rates risk, along the maturity spectrum, and different liquidity, along the age dimension, which is especially relevant in our tests. The following month, we track these bonds to compute returns and we then select new bonds to repeat the same procedure.

III Leverage Shocks in Securities Markets

The model presented in Section I.A predicts that leverage supply shocks will tend to produce positive returns across risky assets and that leverage demand shocks will tend to produce negative returns. It also implies that the separation of leverage risk into its supply and demand components produces price-of-risk estimates that are symmetric with a positive price of risk for supply shocks and a negative price of risk for demand shocks. We will test these predictions across several asset classes.

A Leverage Shocks in Asset Pricing Tests—All Asset Classes

Table 2 reports the price-of-risk estimates from two-stage asset pricing regressions based on the stock, option and bond portfolios, jointly. We consider models based on the raw leverage factor from AEM and models based on the leverage demand shocks or leverage supply shocks, either separately or together.[13] In every case, we include the market returns as one of the pricing factors and among the test assets.[14] We also report the t-test statistics based on the Fama-Macbeth and Shanken (1996) standard errors, as well as a 95 percent confidence interval for the adjusted $\bar{R}^2$ measure of fit, which follows the methodology in Lewellen, Nagel, and Shanken (2010).

[13]We thank Tyler Muir for making AEM's leverage factor available on his web site. Results are very similar if we use the leverage innovations from the VAR(1) model estimated in Section II.

[14]AEM recommends using this combination of the leverage and market factors. Lewellen, Nagel, and Shanken (2010) also generally recommend including the market returns among the test assets.

The first column in Table 2 reports the results from a model that uses the leverage factor ΔLEV. The price of leverage risk is positive but not significant, and the $\bar{R}^2$ measure of fit is 24 percent. However, the estimate of the constant is close to zero and statistically insignificant, the estimated price of market risk is reasonable and the confidence interval for the $\bar{R}^2$, while quite wide, also includes some large values (it ranges from 6 to 84 percent). Overall, the evidence is consistent with the message in AEM but statistically weaker because we used different test assets. Section IV revisits AEM's results and reconcile these with our key messages.

The second and third columns of Table 2 reports the results based on the leverage supply and leverage demand shocks, separately. Disentangling these two types of leverage shocks delivers significantly better results. The estimated constants are not significant, the price-of-risk estimates are significant, the $\bar{R}^2$ rises to 61 and 70 percent for the leverage supply and demand shocks respectively, and the corresponding confidence intervals are tighter ([36, 84] and [48, 86]). In the fourth column, we combine the supply and demand shocks in the same pricing model (always with market returns for comparability with the other columns). The constant is small and insignificant, the price-or-risk estimates are 2.60 and -4.67, respectively, and they remain statistically significant. The $\bar{R}^2$ is now 89 percent and its confidence interval is much tighter from 78 to 95 percent.

Based on the estimation results in Table 2, we can check two of the implications for the prices of risk listed in Section I.A. The first one is that the price-of-risk estimates of leverage supply and demand shocks have opposite signs. We find that this holds when these are estimated separately (Columns 2-3) or jointly (Column 4). In unreported results, we also checked that this holds when excluding the market returns from the asset pricing model. The second implication is that these two prices of risk are symmetric. On a separate line labeled H_0 in Table 2, we report the t-statistic of a test for the null hypothesis that the prices of risk for leverage demand and supply shocks have the same magnitude in absolute value but opposite signs. The statistic is based on Shanken standard errors. The low value of 0.89 means that we cannot reject the model implications for the signs and the symmetry of the prices of risk.

The results in Table 2 bring forward two new important take-outs for leverage risk. First, we find that leverage supply and demand shocks have significant and symmetric prices of risk. This result will be obtained in all our other tests across asset classes, confirming that intermediaries' leverage is an important source of risk and that it is compensated in financial markets. Second, disclosing this empirical support rests on separating leverage innovations into supply and demand shocks that have opposite correlations with funding conditions and opposite effects in financial markets.

Figure 5 illustrates how important it is to disentangle the two sources of leverage risk. The figure contrasts the pricing errors that are obtained in two asset pricing models, one that uses raw leverage shocks with the market returns, and the other model that uses the disentangled supply and demand leverage shocks. Panel (a) and Panel (b) of Figure 5 show the realized and fitted mean returns for each model, together with the 45-degree line that would arise if the fit were perfect. The improvement in fit appears clearly in the model with leverage supply and demand shocks. We do not include the market returns in the second model to maintain a level-playing field: both models have the same number of estimated parameters.

(i) Other Stock Portfolios. Existing empirical work on intermediaries' asset pricing has used traditional stock portfolios sorted on size and value. Since we use stock portfolios sorted on exposures to illiquidity, volatility and funding liquidity risks, it is instructive to see if the main messages from Table 2 and Figure 5 remain unchanged when we use traditional portfolios. For this purpose, we substitute the Fama-French portfolios sorted on size, value, profitability and investment (Fama and French, 2015), keeping the same bond and option portfolios unchanged, and repeat the estimation.

We find that the message is essentially unchanged and, for parsimony, we do not report the results. We checked that the estimated prices of risk for leverage supply and demand shocks have the expected signs and that the hypothesis $\lambda^{SS} = -\lambda^{DS}$ is not rejected when we substitute the Fama-French portfolios. We also checked that disentangling the leverage supply and demand shocks offers substantial improvements relative to using a two-factor model with ΔLEV and the market factor. Figure 5 in the previous section shows why the results are broadly unchanged with this choice of equity portfolios: the dispersion of returns across asset classes (e.g., bonds, options, equities) swamps the dispersion across the equity portfolios. For completeness, Figure A.1 in the appendix repeats the analysis in Figure 5 but substituting the Fama-French portfolios for stocks.

B Leverage Shocks in Asset Pricing—Individual Asset Classes

We now analyze the results separately for each of the three asset classes—equities, bonds and options—to verify the implications spelled out in Section I.A. To recall, apart from the implication that the prices of risk of the supply and demand shocks have the same magnitude and opposite signs that we confirmed for all assets taken together, the model also predicts that the returns betas of leverage demand and supply shocks are negative and positive, respectively.

(i) Equities. The first three columns of Table 3 report the estimation results for the equity portfolios. In Column (1), the price of risk for the raw leverage factor is negative and significant at the 10 percent level based on the Shanken t-statistic. This sign contrasts with the positive estimate in Table 2. The next section examines the sources of the sign change. Nonetheless, the $\bar{R}^2$ is 90 percent and the confidence interval is tight. In Columns (2) and (3), we verify that the price-of-risk estimates for leverage supply and demand shocks have the expected signs, that is negative for demand shocks and positive for supply shocks, and are of similar magnitude. For parsimony, we do not report results that combined both types of shocks but the H_0 row reports a t-statistic of 0.78, which means that we cannot reject the null hypothesis that the prices of risk of the supply and demand shocks have the same magnitude and opposite signs. Taken separately, only the demand price of risk is individually significant at the 1% level with the Shanken t-statistic. Despite the insignificant price-of-risk estimate, the $\bar{R}^2$ from using supply shocks remains high. Taken together, the demand and supply shocks are jointly significant.

We now check whether the returns betas of leverage demand and supply shocks have the expected signs. Panel (a) of Figure 6 shows a scatter plot, for the 30 equity portfolios, of the leverage demand-shock betas on the y-axis and the leverage supply-shock betas on the x-axis. The supply-shock betas are positive and the demand-shock betas are negative. In addition, the sample correlation between the estimated betas is -0.63, which agrees with economic intuition: the portfolios that are risky based on their supply-shock betas also tend to be risky based on their demand-shock betas. This marked correlation explains why using only supply or demand shocks produces a similar fit.[15]

(ii) Bonds. The results for corporate and Treasury bonds are reported in Columns (4) to (6) of Table 3. The price of risk for the raw leverage shock has a positive sign, which is the opposite of what we found for stocks. The next section will examine the difference

[15]For instance, if only e_d is included, then the R^2 in the model of Section 1 is given by: $R^{e_d} = 1 - \omega_2^2(1-\rho^2)/\iota^\top \Omega \iota$. This can explain why the R^2 remains elevated when only one of the two shocks is included, since the correlation ρ across demand and supply betas is negative in the data. In addition, the price-of-risk estimates are also larger when estimated separately because of the correlation between betas. The true price-of-risk estimate for this case in the model Section I is given by $\lambda^{e_d} = \lambda \times \left(1 - \rho \frac{\omega_2}{\omega_1}\right)$.

between these signs. The constant is positive and significant, and the $\bar{R}^2$ confidence interval is wide, from 36 to 85 percent.

The demand and supply shocks yield estimates that are significant and with the expected signs. Overall, the results are marginally more accurate based on the supply shocks. The constant is much smaller and insignificant, the price of market risk is more reasonable, the $\bar{R}^2$ is higher, and the $\bar{R}^2$ confidence interval is tighter, between 66 and 92 percent. Yet, as for stocks, we cannot reject the hypothesis that the prices of risk for both types of shocks combined in the same model have symmetric prices of risk (t-statistic: 0.26).

The scatter plot of bond betas in Panel (b) of Figure 6 shows that the leverage supply and demand betas have the expected signs. Like for the equity portfolios, the demand and supply betas are closely and negatively correlated. The riskier corporate bond portfolios tend to have the largest leverage supply betas and the most negative leverage demand betas. At the opposite of the spectrum, the Treasury bonds have much smaller leverage supply and demand betas.

(iii) Options. Columns (7)-(11) of Table 3 reports the results for the option portfolios. Column (7) shows that the price-of-risk estimate for raw leverage shocks is negative and very large. The constant is quite large, so options appear to present a challenge to a pricing model based on leverage risk, despite the fact that the $\bar{R}^2$ is above 90 percent. Already in Panel (a) of Figure 5, when the estimates are disciplined against over-fitting by the presence of multiple asset classes, we can see that some of the put and call portfolios have the largest pricing errors.

In Column (8), we also find very poor results using leverage supply shocks. The $\bar{R}^2$ is lower, the confidence interval is wide, the constant is large and imprecise, and the equity premium estimate is close to 18 percent. We have to conclude that the effects of leverage supply shocks are estimated extremely imprecisely and that the estimates in Column (8) cannot be trusted. In contrast, Column (9) shows that using leverage demand shocks produces a significant negative price of risk, a small constant and a more reasonable equity premium. The $\bar{R}^2$ is close to 94 percent, but this is probably somewhat inflated by treating option returns in isolation.

The results across Columns (8)-(9) can be traced back to the patterns across leverage demand and supply betas, which we report in Panel (c) of Figure 6. Like in the results for equities and bonds, the betas have opposite signs. The leverage demand betas are negative except for three portfolios of call options and exhibit a wide dispersion. This result is consistent with results from Gârleanu, Pedersen, and Pothesman (2009) who show that demand pressure effects on dealers' inventory contribute to explain well-known option-pricing puzzles as well as the overall expensiveness and skew patterns of index options.

The leverage supply betas are positive but the estimates have a narrow dispersion, especially across the put options for which the correlation with demand betas is small, and have the wrong sign. Overall, the low dispersion tells us that there is almost no information about the pricing of leverage supply shocks in the cross-section of put options. The low information content is reflected in the fact that the results are driven by noise or residuals in a few portfolios that are hard to price (e.g., see the pricing errors for the $PUT1$ and $PUT2$ portfolios in Figure 5b), a price-of-risk estimate that has the wrong sign and an erratic constant in the leverage supply-shock regression, as well as in the rejection of the null hypothesis $\lambda^{SS} = -\lambda^{DS}$.

We also investigate in Columns (10) and (11) whether leverage demand shocks earn a similar compensation in call and put options, taken separately. The price of risk for calls is very close to the one obtained for bonds or for equities. However, the price of risk for puts is much larger in magnitude and significant. The differences in the pricing of risks associated with leverage demand shocks may reflect the fact that funding constraints can be different for calls and puts. For instance, a higher margin is usually required by the Chicago Mercantile Exchange for selling naked puts.

(iv) Summary. We see that leverage demand and supply shocks produce consistent results across markets (except for put options, which seem to be uninformative about supply shocks on their own). Their prices of risk have opposite signs, similar magnitudes, and either or both of the leverage demand and supply shocks always play an important role. One key message from the results is that risky assets have a positive beta with respect to leverage supply shocks and a negative beta with respect to leverage demand shocks. This high degree of correlation is reassuring since it tells us that identifying different types of leverage shocks does not amount to uncovering new risk factors. Instead, the challenge in assessing the role of broker-dealer leverage risk is to determine whether a unit increase in leverage reveals a lower marginal value of intermediaries' wealth and better funding conditions, or whether it is the contrary.

C The Sign of Leverage Risk

The consistent positive and negative signs for the prices of risk associated with supply and demand shocks across assets are to be contrasted with the changing sign for the price of raw leverage risk. The price of risk estimate was negative for equities and options, but positive for bonds. This is not inconsistent with the predictions that intermediaries' leverage plays a key role in asset pricing. Instead, we conclude that the different signs for the betas and the price of raw leverage risk across asset markets can be explained by the underlying patterns in leverage demand and supply betas, consistent with the model in Section I.

(i) The leverage betas. Equation (8) implies that the magnitude and sign of the returns betas for the raw leverage factor are determined by the magnitudes of the leverage supply and demand betas. We repeat this equation here for convenience:

$$\beta_i^L = \frac{1}{2} b^{-1} \times \left(\beta_i^{e_d} + \beta_i^{e_s}\right).$$

To check this implication, we plot in Figure 7 the leverage betas $\hat{\beta}^L$ together with the sum of demand and supply shocks betas $\hat{\beta}^{DS} + \hat{\beta}^{SS}$, which were all obtained from the first-stage regressions. Despite the succinct simplicity of the model in Section I, we find a good fit and a positive relationship between the estimated leverage betas and the sum of the leverage supply and demand betas. The dotted line shows the fit from a linear regression: the slope coefficient of the regression is 0.47 and the R^2 is 62 percent.

The main takeaway in Figure 7 is that the leverage beta $\hat{\beta}^L$ changes signs with the patterns in leverage demand and supply betas (recall that $\hat{\beta}^{DS}$ and $\hat{\beta}^{SS}$ have opposite signs). We find that the estimates are negative for the put options as well as most call options, due largely to the large size of the demand betas. By contrast, we find positive estimates for most bond portfolios (and all portfolios of bonds sorted based on VOL or $FUND$ betas), due largely to the size of the supply betas. For the equity portfolios, the leverage betas $\hat{\beta}^L$ tend to be positive, but the values tend to be lower than the predictions based on demand and supply betas. In addition, the extreme portfolios $VOL1$ and $FND10$ appear to be outliers that do not fit the pattern of demand and supply betas across the other test assets.[16]

[16] Equation (8) relies on the restriction in Equations (1)-(2) that demand and supply shocks load on LEV with the same parameter. In Appendix A.1, we relax this restriction and allow for different loading parameters. In this case, the model prediction for the leverage betas has the form $\beta^L = a + b_1 \beta^{DS} + b_2 \beta^{SS}$. We report the fitted dash line in Figure 7 and the results are very similar.

(ii) The leverage price of risk. Equation (9) in Section I.B led to the additional prediction that the sign of the leverage price of risk is determined by the dispersions of the leverage supply and demand betas. We repeat this equation here for convenience:

$$\lambda^L = -c\lambda 2b \times (\omega_1^2 - \omega_2^2).$$

To check this, we report in Table 4, for all equity, bond and option portfolios separately, the sample averages μ_1 and μ_2 of the leverage demand and supply betas, their dispersions ω_1^2 and ω_2^2 as well as the wedge $-\Delta = -(\omega_1^2 - \omega_2^2)$, which has the same sign as λ^L in Equation (9). In the panel below, under the banner $Cov(\beta_i^L, E[R_i])$, Row A reports the baseline model-implied sign. In Row B, we report the implied sign in a model where Equation (2) let demand and supply shocks have different loadings (see Appendix A.1 for the derivation). The last row, labeled OLS, reports the sign of $\hat{\lambda}^L$ from the second-stage regression based on a single-factor model (to be consistent with the framework of Section I.B).

Consider the equity portfolios first. For the portfolios sorted on volatility risk VOL and those sorted on liquidity risk LIQ, we find that the dispersion of leverage demand betas is wider, 0.78 and 0.21, respectively, than the dispersion of supply betas, 0.59 and 0.08, respectively. Therefore, like the OLS estimates, the true sign of the prices of risk in the model are negative.[17]

For the portfolios of stocks sorted on funding risk FND, the results are not as clear. The two dispersions are small and close to each other (0.09 and 0.11, respectively) so that the difference is very small but positive. The restricted model predicts a positive price of leverage risk, but the more general unrestricted set-up predicts a negative value. This discrepancy is driven by one portfolio $FND10$ for which the demand beta appears too high and out of line relative to the average returns and supply beta (see Figure 6a). When we combine all the equity portfolios, we find a model-implied negative price of risk, consistent with the regression results in Table 3.

Across the bond portfolios, the leverage supply betas have a wider dispersion in three cases out of four but in all cases the sign of the prices of risk predicted by the model matches the sign of the OLS estimates. When we combine all the bond portfolios, we find that the supply betas also produce the wider dispersion and the model-implied price of risk is positive, like the regression results in Table 3. For portfolios of corporate and US Treasury bonds,

[17] Note that, consistent with the wider dispersion of leverage demand betas, we also find that the price for risk for leverage demand shocks is estimated more precisely in Table 3.

we find in three cases out of four that supply betas exhibit a larger price dispersion and hence determine the sign of leverage risk. This is consistent with results from Goldberg and Nozawa (2021) showing that liquidity supply shocks identified in bond dealers' inventories have significant explanatory power for cross-sectional and time-series variation in expected returns.

Finally, across the portfolios of put and call options, the leverage demand betas have a wider dispersion in all cases and the sign predicted by the model matches the estimated OLS one in every case. The demand betas also have a wider dispersion when we combine calls and puts and the model-implied sign matches the sign of regression results in Table 3. Consistent with the findings in Section III.B, the dispersion of supply betas is close to zero and we again conclude that the option market appears largely uninformative about the price of leverage supply shocks.

(iii) The sign of leverage risks across asset markets. He, Kelly, and Manela (2017), HKM thereafter, add credit derivatives, commodities and exchange rates to the Fama-French 25 portfolios, government bonds, corporate and sovereign bonds, and equity derivatives. They report that the estimated price of risk for the leverage factor changes across asset classes.

We check that the leverage demand and supply shocks are consistently priced across these test assets. To improve statistical power and the precision of the estimates, given that some of the samples are small, we impose the joint null hypotheses that the constant is zero and that the prices of risk have the same magnitude $\lambda^{SS} = -\lambda^{DS}$. This restriction is motivated theoretically by the prediction in Equation (7) and empirically in our earlier results. In addition, Kroencke and Thimme (2021) show in simulations with realistic sample sizes and asset returns distributions that the zero-intercept restriction can substantially improve the statistical power of the test.

We proceed with the same two-stage regression approach. To implement the restriction on the prices of risk, we use the sum of the leverage demand and supply betas in the second-stage regression. There is then only one parameter left to be estimated in each asset class, in addition to the price of market risk. With the restriction on the price of risk in place, we use the GMM framework to derive standard errors that account for estimation errors in the betas in the first stage.[18]

[18]See, e.g., Section 12 in Cochrane (2009).

The estimates are reported in Table 5. We can observe that the price of leverage supply and demand shocks exhibits the expected signs, is significant and has a similar magnitude across equities, US bonds, sovereign bonds, options and CDS. However, the estimates are small and insignificant in commodities and foreign exchange. Figure 8 reports the pricing errors associated with the raw leverage and market returns in Panel (a) and those associated with the leverage supply and demand shocks in Panel (b). We report actual returns along the y-axis, so that we can read the pricing errors based on the horizontal distance from the 45-degree line. Consistent with our other results, the pricing errors are substantially reduced across the board when we disentangle the leverage factor into supply and demand shocks. The results illustrate the importance of separating the leverage factors into demand and supply shocks when pricing HKM portfolios together.

In fact, the results look very much alike HKM core results that a pricing model based on shocks to intermediaries' equity capital ratio offers a good fit of returns across these test assets, except for commodities as well as a few equity derivatives portfolios.[19] As in the original Figure 2 of HKM, we can see a few option portfolios and all the commodities portfolios lying the furthest away from the 45° line. Therefore, the supply and demand leverage shocks share with the capital ratio similar challenges in pricing commodities.[20]

Additional results reported in Table A.1 of the appendix show that the patterns in betas can explain the patterns in the signs of the estimates of the price of leverage risk across HKM test assets, mirroring the analysis in Section III.C. The model-implied signs match the OLS signs for all asset classes except for commodities and exchange rates. Moreover, Figure A.2 in the appendix shows that the prices of risk across our baseline and the HKM test assets closely conform to the quantitative prediction in Equation (9) that estimates for the price of leverage risk vary across asset classes with changes in the relative dispersions of the supply and demand betas.

[19]This could appear surprising since the equity capital ratio is the reciprocal of the leverage ratio. HKM suggested that the difference could be due to (i) the fact that their equity ratio uses data on large holding companies while AEM's leverage ratio use data on the subsidiary broker-dealers and (ii) that they use market value of equity while AEM use book value.

[20]One natural question is whether the equity capital ratio could be used to extract demand and supply shocks. When we proceed with the decomposition of the capital ratio with sign restrictions as in Section II.B, we find that supply shocks explain most of the variance. Similarly, if we project HKM forecast errors on the broker-dealers' leverage supply and demand shocks and the contemporaneous market returns, we find that the supply shocks explain 12% of the variance but the demand shocks practically nothing. Consistent with the main conclusion of Gospodinov and Robotti (2021), we find that the market returns explains 40% of the variation.

D Leverage Shocks and Stock Market Liquidity

Another puzzling fact that has been put forward in AEM is that changes in leverage are largely uncorrelated with changes in stock market liquidity. This is a puzzle because the theoretical prediction, e.g., in Brunnermeier and Pedersen (2009), that liquidity and leverage move in tandem. However, the model in Section I implies that one reason for this result could be that aggregate leverage combines demand and supply shocks and that these shocks have opposite and symmetric effects on liquidity. We test these predictions in this section.

One way to check this prediction is to estimate the coefficients of leverage demand and supply shocks in regressions of market liquidity, where we expect to find coefficients with opposite signs and similar magnitudes. To run this test, we construct 10 portfolios of stocks sorted on liquidity, measured using the Amihud ratio. We also construct 10 portfolios of stocks sorted on volatility, measured using the standard deviation of daily returns over the last quarter. See Appendix A.4 for further details about the construction of these portfolios. The first set of portfolios exploits the predictions that intermediaries' marginal value of wealth drives the commonality in liquidity. The second set exploits the prediction that the sensitivity of market liquidity is larger for securities that are more illiquid and volatile on average (Brunnermeier and Pedersen, 2009, pp.20-21). Expanding the number of portfolios also adds power to the test. Table 6 provides summary statistics starting from the least liquid or the most volatile portfolios (Column 1) to the most liquid or the least volatile portfolios (Column 10). As expected, illiquid portfolios exhibit higher volatility and higher returns but smaller capitalization. The pattern is almost monotone across portfolios. Similarly, the more volatile portfolios exhibit lower liquidity, higher returns and smaller market capitalization.

We first ask whether the portfolios' illiquidity responds to changes in the raw leverage ΔLEV. Panel (a) of Table 7 reports the results from regressions of the changes in portfolios' Amihud illiquidity ratio on ΔLEV. Row I reports results for liquidity sorts and Row II for volatility sorts. The estimates of the ΔLEV coefficient are never statistically significant, which is consistent with the results reported by AEM. Note the every regression includes the market returns as a control variable. We do not report the estimated coefficients for market returns but we checked that they are large, negative and significant coefficient in all cases.

Panel (b) of Table 7 shows the results from regressions on the leverage supply shocks. The coefficients are significant in every regression and have the right sign: supply shocks improve market liquidity across the portfolios. In addition, the estimates exhibit a clear monotone pattern: the estimates are larger for the least liquid and most volatile portfolios.

Panel (c) reports the results from regressions on the leverage demand shocks. The estimates have the expected sign in all cases but one where the result is not statistically significant. We find that demand shocks lead to poorer market liquidity. The estimates also exhibit the predicted monotone pattern across portfolios: the effect is larger for the least liquid and most volatile portfolios. However, the estimates seem to be less precise across the volatility-sorted portfolios.

Looking across Panels (b)-(c), the coefficients for the demand and supply shocks are very similar but with opposite signs. This is a similar pattern to what we found for returns betas in the asset-pricing tests, but here the magnitudes are much closer. This explains the lack of significance of the coefficients for raw leverage in Panel (a). Using the raw leverage innovations produces insignificant coefficient estimates because it mixes the opposing effects of leverage demand and supply shocks. Therefore, the decomposition of leverage into supply and demand shocks sheds a light on the puzzle raised in AEM. It also confirms that both leverage demand and supply shocks play significant roles to explain stock market liquidity, consistent with established theories of intermediation frictions in financial markets.

IV AEM's Leverage Results in Perspective

In this section, we review the approach of AEM under the light of the model developed in Section I.A. In many existing theoretical models, including the leading example of Brunnermeier and Pedersen (2009), the leverage and marginal value of wealth of intermediaries move monotonously with each other because the funding constraints are always binding.[21] Based on this prediction, AEM pin down the pricing kernel with $\phi \approx a - b \times LEV$, use balance sheet data about leverage to measure its variations and provide important evidence supporting intermediary asset pricing.

Formally, this identification strategy is consistent with the statistical model in Section I.A if the demand shocks e_d drop out from the specification for leverage in Equation (2). This is the case when the funding constraints are binding. Then, as in AEM, the projection of ϕ on LEV only reveals the supply shocks, Equation (8) associates the time-series betas for

[21] In Brunnermeier and Pedersen (2009), specialized traders ensure intermediation between investors who demand immediacy and financiers who provide funds. The specialized traders must collateralize margin constraints imposed by financiers separately for each asset, ruling out cross-margining between the positions (netting). Because the intermediaries are risk-neutral, the funding constraints are always binding. Intermediary asset pricing also relies on the assumption that intermediaries are active traders in all asset markets and that there is a degree of homogeneity in the pricing kernels of individual financial intermediaries (He and Krishnamurthy, 2018).

leverage with the positive betas of supply shocks, and Equation (9) predicts that the cross-sectional regression recovers a positive price of risk λ. We check this in Table A.2 of the Appendix. In Column (1), we obtain in our sample that the original model based on the raw leverage factor produces a significant positive estimate for the price of risk across FF25 size and book-to-market portfolios, 10 momentum portfolios and 6 Treasury bonds, as in AEM. The results produce a high $\bar{R}^2$ of 84 percent with a fairly narrow confidence interval (61 to 96 percent), which is close to the value of 77 percent reported by AEM.[22]

However, we find pervasive evidence that both leverage supply and demand shocks are priced across financial markets. Therefore, based on Implication 2 in Section I.B, the fact that AEM finds a positive price of leverage risk must be due to the pattern in the leverage demand and supply betas for these test assets. As expected, Columns (2) and (3) in Panel (a) of Table A.2 show that leverage supply shocks have a positive and significant price-of-risk estimate but that leverage demand shocks have an estimate that is essentially zero in AEM test assets, essentially because the leverage demand betas exhibit a small dispersion (unreported).

Overall, the evidence is consistent with intermediation models in which the leverage constraints typically do not bind. In Appendix B, we provide additional empirical evidence with reduced-form and structural approaches that intermediaries funding constraints are not always binding. One simple observation supporting this conclusion is that across the sample, ΔLEV_t and $\Delta FUND_t$ move in opposite directions in 42 percent, which is what we expect if the constraints are binding, but move in the same direction in 58 percent of all observations, including in the Fall of 2008 when we observe the largest demand shock in our sample. Similarly, but based on a system of constrained simultaneous equations, Figure B.3 reports the period-by-period probability that the funding constraints are binding. Consistent with the prediction that only supply shocks influence leverage when the constraints are binding, the estimated probabilities are lowest during the same periods for which the VAR produces large demand shocks. Overall, the evidence motivates a framework combining demand- and supply-like disturbances to leverage to analyze the role of intermediaries across financial

[22] AEM finds that the leverage factor provides a competitive fit relative to a model that includes the Fama-French three factors, the momentum factor and the first principal component of the yield curve. See Adrian, Etula, and Muir 2014, Figure 1 and Table III. For completeness, Panel (b) of Table A.2 reports the results in models based on the three Fama-French factors, the momentum factor, and the first principal component of the yield curve. The $\bar{R}^2$ of the five-factor model is 93 percent, only slightly higher than what AEM found, and its confidence interval ranges from 72 to 97 percent. The price-of-risk magnitudes for the momentum and book-to-market factors are close to the values obtained by AEM but significantly different from zero, which was not the case in their findings.

markets. The evidence also reassures us that the VAR estimates can distinguish between demand- and supply-sided influence on leverage.

From a theoretical perspective, the constraints are not binding and leverage demand shocks will also be important whenever intermediaries weigh inter-temporal considerations (Brunnermeier and Pedersen, 2009 study the two-period case). Liu, Longstaff, and Mandell (2006) examine the portfolio problem of traders facing arbitrage opportunities that vary over time. With preference over terminal wealth, it is often optimal to invest less than the maximum allowed by the margin constraint, especially when opportunities are very persistent or volatile. In equilibrium, Du, Hébert, and Huber (2019) also find that the constraints do not bind when intermediaries with Epstein-Zin preferences anticipate higher profits in the future. More work is needed to understand the leverage decisions of intermediaries and why the relative importance of exposures to leverage demand and supply shocks can vary across financial markets.

V Conclusion

We offer an econometric model where the intermediaries' leverage and marginal value of wealth are driven by supply and demand shocks. We use sign restrictions to separately identify these two types of shocks in the observed variations of dealers' leverage. The leverage supply shocks relax the funding constraint and lead to an increase in the supply of intermediation capital and a higher leverage. Another type of shock raises the demand for intermediation capital, which also leads to higher leverage but tightens the funding constraint. The evidence confirms that leverage supply shocks improve liquidity and carry a positive price of risk but leverage demand shocks worsen liquidity and carry a negative price of risk. Our findings reinforce the importance of financial intermediaries' balance sheets to understand the pricing of assets. More work is needed to distinguish and quantify the mechanisms underlying the channels of leverage supply and leverage demand shocks across different asset markets.

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Table 1: **Summary Statistics—Equity Portfolios**

Summary statistics for three groups of 10 portfolios of stocks sorted on illiquidity, volatility and funding risk, respectively. We report statistics for the $\tilde{\beta}^{\Delta \text{Illiq}}$, $\tilde{\beta}^{\Delta \sigma}$ and $\tilde{\beta}^{\Delta \text{FUND}}$, measured ex-ante, as well as the mean annualized returns, illiquidity, volatility and market capitalization of each portfolio. The Amihud illiquidity measure is the median across stocks in a portfolio ($\times$ 100). A portfolio volatility is the average of the annualized standard deviation of daily returns over a quarter for each stock. Mkt Cap is the sum of the market quarter-end capitalization (in $ billions) across stocks in each portfolio.

Panel (a) $\beta^{\Delta \text{Illiq}}$ Decile Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\overline{R}_i$	16.06	15.01	13.83	12.84	13.97	14.03	14.97	14.21	14.88	16.06
Illiqu.	2.92	1.79	1.43	1.30	1.26	1.54	1.63	1.91	2.05	3.94
Volatil.	42.08	36.44	34.32	32.89	31.40	30.93	30.61	29.60	30.55	33.84
Mkt Cap	4.06	5.38	6.58	6.95	8.25	7.82	8.24	8.30	7.66	6.07
$\tilde{\beta}^{\Delta \text{Illiq}}$	-2.78	-1.93	-1.54	-1.28	-1.08	-0.85	-0.63	-0.40	-0.10	0.54
$\tilde{\beta}^{\Delta \text{Vol}}$	-13.68	-10.92	-9.85	-9.29	-8.71	-8.38	-8.23	-7.57	-7.51	-9.35
$\tilde{\beta}^{\Delta \text{FUND}}$	-5.94	-5.15	-4.18	-3.88	-4.03	-3.03	-2.93	-2.83	-2.78	-2.99

Panel (b) $\beta^{\Delta \sigma}$ Decile Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\overline{R}_i$	19.97	16.29	15.68	15.38	13.62	13.89	12.63	13.33	12.71	12.56
Illiqu.	7.41	3.17	2.39	1.90	1.64	1.34	1.29	1.04	1.11	1.53
Volatil.	42.43	36.54	34.64	32.62	32.18	30.87	30.49	29.62	29.75	33.64
Mkt Cap	1.82	3.67	4.86	6.84	6.07	7.93	8.13	10.57	9.75	9.60
$\tilde{\beta}^{\Delta \text{Illiq}}$	-1.25	-1.07	-1.06	-1.04	-0.96	-0.96	-0.91	-0.92	-0.92	-0.97
$\tilde{\beta}^{\Delta \text{Vol}}$	-36.23	-22.79	-16.97	-13.03	-9.73	-6.76	-3.78	-0.28	3.57	11.94
$\tilde{\beta}^{\Delta \text{FUND}}$	-4.73	-4.41	-3.81	-3.82	-3.57	-3.52	-3.13	-3.32	-3.22	-4.18

Panel (c) $\beta^{\Delta \text{FUND}}$ Decile Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\overline{R}_i$	19.11	16.34	15.35	13.81	13.46	13.26	14.18	13.79	13.77	15.64
Illiqu.	3.95	2.15	1.88	1.63	1.81	2.02	1.78	2.11	2.82	4.01
Volatil.	42.52	37.00	34.57	32.81	31.89	30.84	30.83	31.58	32.45	37.33
Mkt Cap	4.59	7.39	8.33	8.73	8.02	8.52	7.67	7.24	5.86	3.93
$\tilde{\beta}^{\Delta \text{Illiq}}$	-1.22	-1.08	-1.03	-0.93	-0.89	-0.87	-0.83	-0.88	-0.85	-0.98
$\tilde{\beta}^{\Delta \text{Vol}}$	-17.27	-13.62	-11.82	-11.16	-10.47	-8.65	-8.90	-8.79	-8.78	-10.22
$\tilde{\beta}^{\Delta \text{FUND}}$	-15.96	-10.00	-7.61	-5.79	-4.43	-3.00	-1.62	-0.25	1.59	6.29

Table 2: **Asset-pricing Tests—All Test Assets**

Cross-sectional tests based on two-stage Fama-MacBeth regressions for portfolios of equities, corporate and Treasury bonds, and options. ΔLEV is the leverage factor of AEM, and SS and DS are the supply and demand leverage shocks. The market returns MKT are included as a risk factor and a test asset. We use the one-month T-bill rate to compute excess returns. Fama-MacBeth (t-FM) and Shanken-corrected (t-Sh) t-statistics are reported in parentheses. Bootstrap $\bar{R}^2$ confidence intervals are in square brackets. The row labeled H_0 reports the Shanken-corrected t-statistic in curly brackets { } for a test of the null hypothesis that the prices of risk of SS and DS have the same absolute value: $\lambda^{DS} = -\lambda^{SS}$. The intercepts and prices of risk are annualized.

	(1)	(2)	(3)	(4)
int	0.55	-1.03	0.59	-0.94
t-FM	(0.70)	(-1.20)	(0.71)	(-1.10)
t-Sh	(0.63)	(-0.83)	(0.40)	(-0.66)
ΔLEV	1.61			
t-FM	(1.35)			
t-Sh	(1.24)			
SS		4.12		2.60
t-FM		(3.97)		(2.61)
t-Sh		(2.89)		(1.67)
DS			-6.12	-4.67
t-FM			(-5.55)	(-4.67)
t-Sh			(-3.34)	(-3.01)
MKT	7.80	7.33	4.98	5.77
t-FM	(1.95)	(1.86)	(1.26)	(1.46)
t-Sh	(1.92)	(1.75)	(1.13)	(1.33)
H_0	—	—	—	{0.89}
R^2	25.04	61.55	70.50	89.67
$\bar{R}^2$	23.83	60.93	70.08	89.41
	[6, 84]	[36, 84]	[48, 86]	[78, 95]

Table 3: **Asset-pricing Tests—Individual Asset Classes**

Cross-sectional tests based on two-stage Fama-MacBeth regressions for portfolios of equities, bonds and options, separately. ΔLEV is the leverage factor of AEM, and SS and DS are supply and demand leverage shocks. The market returns MKT are included as a risk factor and a test asset. Fama-MacBeth (t-FM) and Shanken-corrected (t-Sh) t-statistics are reported in parentheses. Bootstrap $\bar{R}^2$ confidence intervals are in square brackets. The row labeled H_0 reports the Shanken-corrected t-statistic in curly brackets { } for a test of the null hypothesis that the prices of risk of SS and DS have the same absolute value: $\lambda^{DS} = -\lambda^{SS}$. The intercepts and prices of risk are annualized.

	Equities			Bonds			De-Levered Options			Call	Put
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
int	4.84	1.05	2.62	1.41	-0.11	0.53	-6.44	-19.91	1.91	-2.36	-1.03
t-FM	(2.79)	(0.58)	(1.68)	(2.85)	(-0.28)	(0.95)	(-3.57)	(-5.38)	(1.71)	(-2.03)	(-0.96)
t-Sh	(2.17)	(0.51)	(1.46)	(1.98)	(-0.18)	(0.53)	(-1.29)	(-1.32)	(0.85)	(-1.58)	(-0.38)
ΔLEV	-3.11			3.64			-10.22				
t-FM	(-2.19)			(3.75)			(-5.47)				
t-Sh	(-1.73)			(2.72)			(-2.01)				
SS		2.02			4.31			-15.23			
t-FM		(1.87)			(4.09)			(-6.68)			
t-Sh		(1.66)			(2.79)			(-1.66)			
DS			-2.26			-5.95			-7.01	-3.27	-9.25
t-FM			(-2.37)			(-3.46)			(-5.55)	(-2.51)	(-6.89)
t-Sh			(-2.10)			(-1.95)			(-2.87)	(-2.00)	(-2.86)
MKT	8.11	8.64	8.61	14.56	9.59	11.60	6.38	17.83	3.99	6.19	5.94
t-FM	(2.41)	(2.56)	(2.52)	(3.64)	(2.80)	(3.32)	(1.78)	(4.00)	(1.15)	(1.79)	(1.72)
t-Sh	(2.36)	(2.53)	(2.48)	(3.13)	(2.65)	(2.94)	(1.47)	(1.48)	(1.11)	(1.79)	(1.72)
H_0	—	{0.78}		—	{0.26}		—	{3.33}		—	—
R^2	90.49	85.25	90.48	59.46	83.33	74.77	93.79	73.55	93.97	92.21	95.05
$\bar{R}^2$	89.81	84.20	89.80	57.43	82.50	73.51	93.55	72.53	93.73	91.58	94.65
	[72, 99]	[52, 97]	[67, 98]	[36, 85]	[64, 94]	[49, 91]	[88, 98]	[46,86]	[88,97]	[81, 99]	[89, 98]

Table 4: **Price of Leverage Risk and Dispersion in Betas**

The estimate $\hat{\mu}_1$ and $\hat{\mu}_2$ are the sample averages of the leverage demand and supply shocks betas, $\hat{\beta}^{DS}$ and $\hat{\beta}^{SS}$ respectively. The estimates $\hat{\omega}_1^2$ and $\hat{\omega}_2^2$ are the sample dispersions of the demand and supply shocks betas, and the row $-\Delta$ reports the wedge $-(\hat{\omega}_1^2 - \hat{\omega}_2^2)$. The last rows compare the sign of $\text{cov}(\beta_i^L, E[R_i])$ in the data with the signs implied by the model in Section I.A. A: the predicted sign for the leverage price of risk based on Equation (9). B: the predicted sign where we relax the symmetry restriction in Equation (2). OLS: the sign in a regression of average returns on leverage betas $\hat{\beta}_i^L$, for each asset class separately, without the market returns MKT.

	Stocks				Bonds					Delevered Options		
	VOL	LIQ	FND	All	VOL	LIQ	FND	BND	All	PUT	CLL	All
$\hat{\mu}_1$	-1.99	-1.98	-2.04	-2.00	-0.63	-1.10	-0.63	-0.02	-0.79	-2.47	-0.63	-1.55
$\hat{\mu}_2$	2.88	2.87	2.98	2.91	1.49	0.83	1.51	1.51	1.28	1.23	0.74	0.98
$\hat{\omega}_1^2$	0.78	0.21	0.09	0.34	0.11	0.30	0.35	0.00	0.33	0.34	0.35	1.19
$\hat{\omega}_2^2$	0.59	0.08	0.11	0.33	0.30	0.43	0.26	0.04	0.68	0.01	0.02	0.08
$-\Delta$	-0.20	-0.12	0.02	-0.01	0.19	0.12	-0.09	0.04	0.35	-0.33	-0.32	-1.12
							$\text{cov}(\beta_i^L, E[R_i])$					
A	−	−	+	−	+	+	−	+	+	−	−	−
B	−	−	−	−	+	−	−	+	+	−	−	−
OLS	−	−	−	−	+	+	−	+	+	−	−	−

Table 5: **Asset-pricing Tests—HKM test assets**

Cross-sectional tests based on two-stage Fama-MacBeth regressions for the test assets in HKM with two restrictions in the second-stage regression: the constant is fixed to zero and the prices of risk of leverage supply and demand shocks have the same magnitudes but opposite signs, $\lambda^{SS} = -\lambda^{DS}$. ΔLEV is the leverage factor of AEM, SS is the leverage supply shocks. The market returns MKT are included as a risk factor and a test asset. Fama-MacBeth (t-FM) and Shanken-corrected (t-Sh) t-statistics are reported in parentheses. The Shanken correction with parametric restrictions is derived using GMM. Bootstrap $\bar{R}^2$ confidence intervals are in square brackets. The prices of risk are annualized.

	FF25	US Bonds	Sov. Bonds	Options	CDS	Commodities	FX
SS	1.87	3.80	3.22	5.70	1.64	0.21	-0.81
t-FM	(2.02)	(4.74)	(2.86)	(4.95)	(2.05)	(0.24)	(-0.60)
t-Sh	(1.97)	(4.82)	(2.58)	(4.73)	(2.02)	(0.24)	(-0.54)
MKT	6.05	4.93	6.74	10.12	4.77	3.23	6.97
t-FM	(1.74)	(1.40)	(1.48)	(2.74)	(0.88)	(0.65)	(1.94)
t-Sh.	(1.73)	(1.42)	(1.25)	(2.66)	(0.87)	(0.91)	(1.91)
R^2	89.07	87.16	95.43	94.63	63.70	3.02	32.32
$\bar{R}^2$	88.16	85.81	93.60	93.99	59.87	-5.80	20.01
	[64, 98]	[66, 96]	[76, 99]	[86, 98]	[14, 95]	[-6, 41]	[0, 91]

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

Summary statistics for portfolios of stocks sorted on illiquidity and volatility (see Appendix A.4 for the construction of the portfolios). $\overline{R}_i$ and Volatil. are the average returns and volatility across stocks in each portfolio, respectively. Illiq. is the median across stocks. Mkt Cap is the sum of the market quarter-end capitalization across stocks in each portfolio (in $ billions) .

Panel (a) Illiquidity Sort

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\overline{R}_i$	23.06	20.36	18.09	16.43	15.68	14.23	13.21	12.71	12.15	11.83
Illiqu.	321.87	55.23	20.55	9.41	4.58	2.30	1.26	0.64	0.31	0.10
Volatil.	39.02	40.67	39.54	38.00	36.26	35.24	33.82	33.50	31.11	29.20
Mkt Cap	0.16	0.34	0.57	0.87	1.25	1.81	2.66	4.33	8.87	39.87

Panel (b) Volatility Sort

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\overline{R}_i$	22.61	18.58	16.97	16.15	13.60	14.26	13.29	13.73	13.47	14.88
Illiqu.	11.35	6.82	5.56	3.99	2.97	2.25	2.09	1.66	1.75	4.32
Volatil.	54.33	46.66	41.75	38.60	35.99	33.20	30.84	28.19	25.51	21.52
Mkt Cap	1.67	2.30	3.26	3.99	5.00	5.62	6.99	9.73	10.38	12.51

Table 7: **Leverage Shocks in Illiquidity Regressions**

Panel (a): Estimates of the coefficients on ΔLEV. Panel (b): Estimates of the coefficients on leverage supply shocks SS. Panel (c): Estimates of the coefficients on leverage demand shocks DS. Row I: regressions for portfolios sorted on illiquidity. Row II: regressions for portfolios sorted on volatility. Columns 1-10 rank portfolios from high illiquidity (or volatility) to low illiquidity (or volatility). Newey-West t-statistics with three lags are reported in parenthesis.

Panel (a) $\Delta illiq_{i,t} = a + b_i \Delta LEV_t + c_i MKT_t + e_t$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
I	0.03	-0.02	-0.03	-0.01	-0.02	-0.03	-0.08	-0.11	-0.16	-0.09
	(0.41)	(0.48)	(0.49)	(0.20)	(0.61)	(0.55)	(1.09)	(1.35)	(1.54)	(1.00)
II	-0.04	0.01	-0.06	-0.02	-0.07	-0.04	-0.06	-0.00	-0.03	0.00
	(0.78)	(0.13)	(1.37)	(0.50)	(1.32)	(1.28)	(0.93)	(0.07)	(0.80)	(0.21)

Panel (b) $\Delta illiq_{i,t} = a + b_i SS_t + c_i MKT_t + e_t$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
I	-36.69	-9.06	-2.86	-1.36	-0.80	-0.38	-0.21	-0.11	-0.05	-0.01
	(2.36)	(3.62)	(2.72)	(2.97)	(3.27)	(3.14)	(3.30)	(3.31)	(3.02)	(3.37)
II	-2.53	-0.91	-0.84	-0.63	-0.54	-0.23	-0.19	-0.15	-0.11	0.20
	(2.50)	(2.27)	(2.30)	(3.39)	(3.45)	(2.93)	(2.49)	(1.48)	(1.79)	(0.98)

Panel (c) $\Delta illiq_{i,t} = a + b_i DS_t + c_i MKT_t + e_t$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
I	40.10	6.06	1.84	0.93	0.50	0.24	0.11	0.05	0.02	0.01
	(3.51)	(2.50)	(2.05)	(2.08)	(2.26)	(2.36)	(2.14)	(2.04)	(1.39)	(2.22)
II	1.06	0.62	0.28	0.38	0.29	0.15	0.11	0.11	0.07	-0.14
	(1.44)	(1.92)	(1.05)	(2.29)	(2.15)	(1.99)	(1.68)	(1.49)	(1.43)	(0.31)

Figure 1: Funding Conditions Proxies

Panel (a): TED spread measure. Panel (b): FL funding conditions measure from Fontaine and Garcia (2012). Panel (c): HPW noise measure from Hu, Pan, and Wang (2013). Monthly data, 1986-2015.

(a) TED

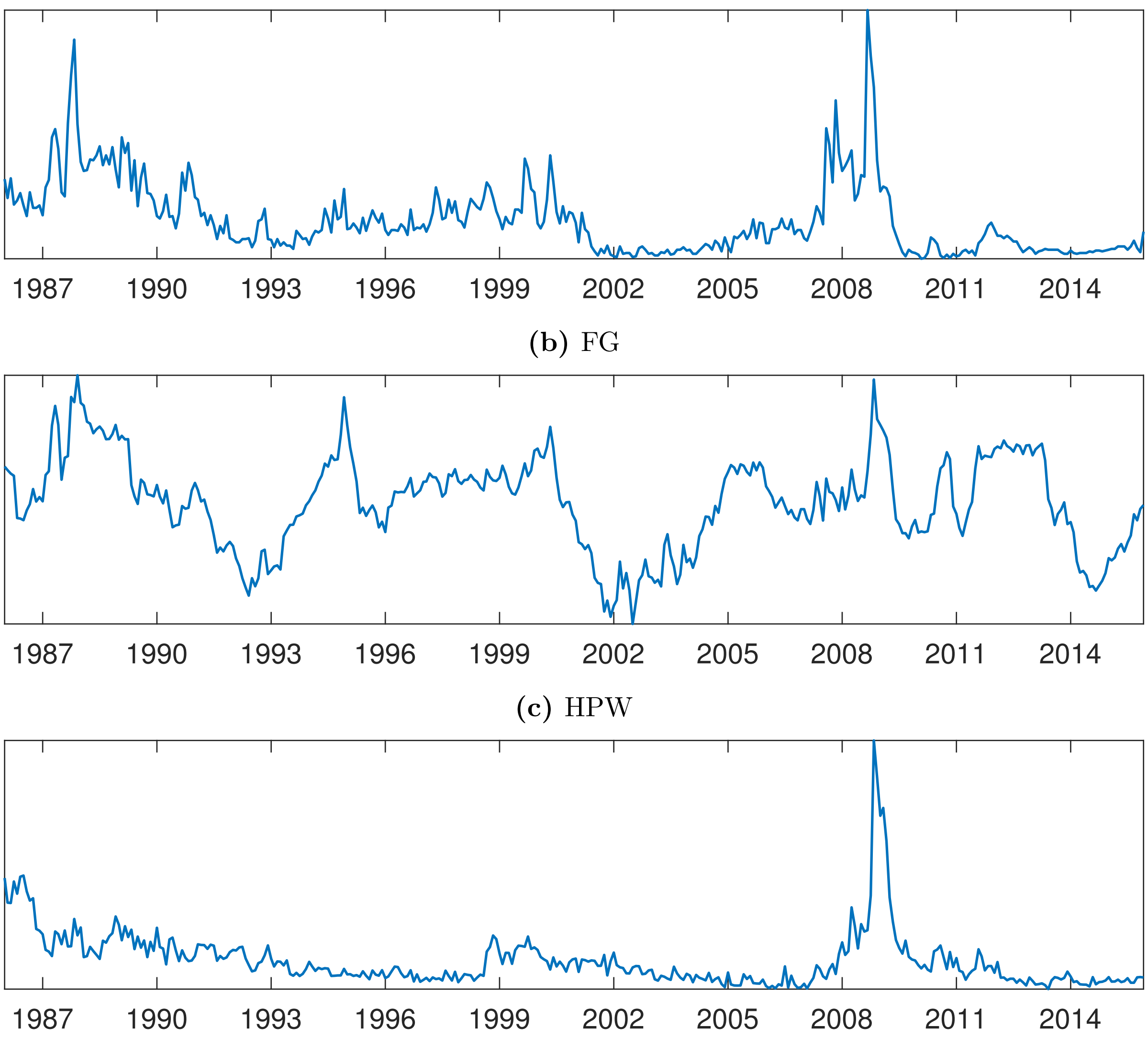
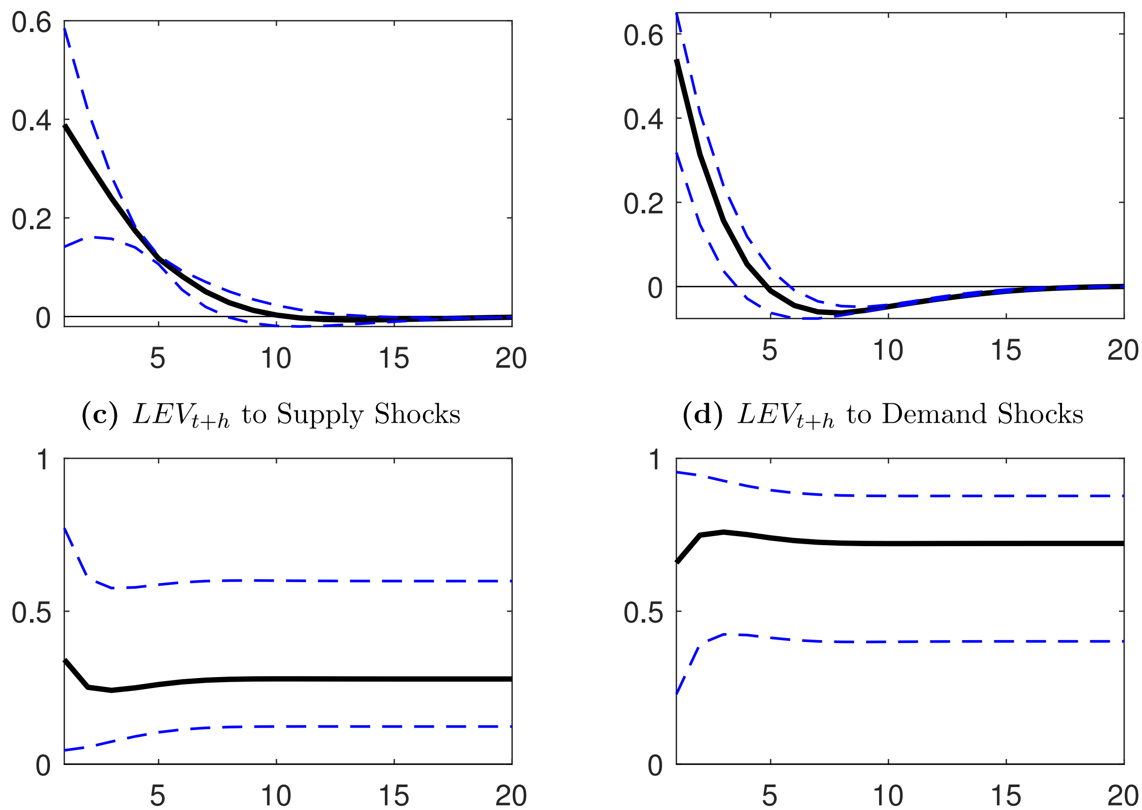


Figure 2: Impulse Response Functions and Variance Decompositions

Impulse response functions (Panels a and b) and variance decompositions (Panels c and d) for LEV_{t+h} and horizons $h = 1 \ldots 20$ quarters with respect to leverage supply and demand shocks identified with sign restrictions in a bivariate VAR(1) with 95 percent confidence intervals (dashed blue lines).



(a) LEV_{t+h} to Supply Shocks

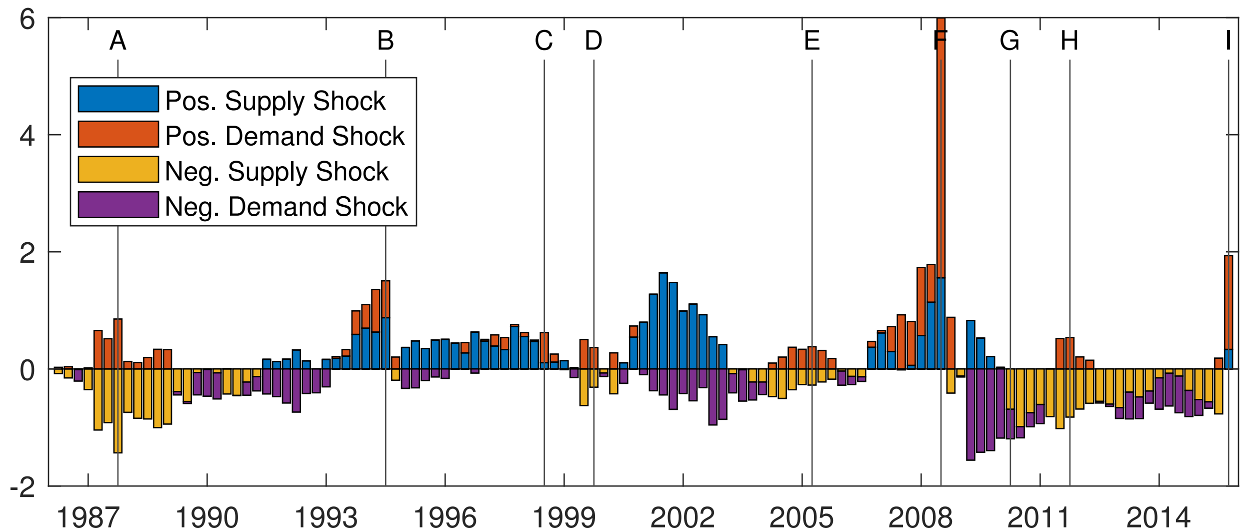
(b) LEV_{t+h} to Demand Shocks

(c) LEV_{t+h} to Supply Shocks

(d) LEV_{t+h} to Demand Shocks

Figure 3: Historical Decomposition

Decomposition of leverage forecast errors in terms of leverage demand and leverage supply shocks identified with sign restrictions in a bivariate VAR(1) for LEV_t and $FUND_t$ in levels. Quarterly data, 1986Q2-2015Q4.

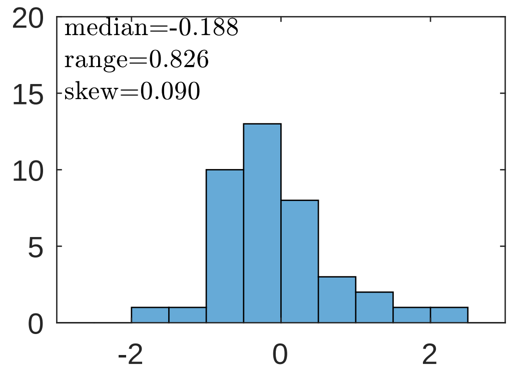


Note: (A) 1987 stock market crash, (B) 1994 bond market massacre, (C) LTCM bailout, (D) Turn of the millenium, (E) Ford & GM downgrades, (F) 2008 financial crisis, (G) First Greece bailout, (H) Second Greece bailout, (I) Oil & China sell-off.

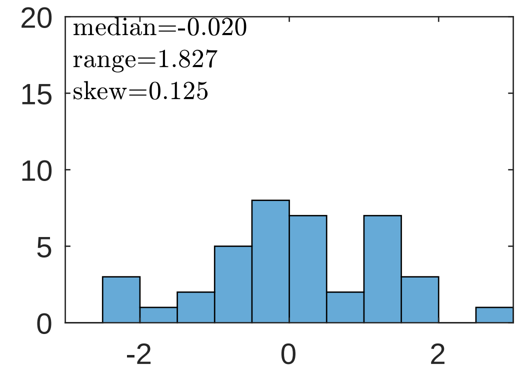
Figure 4: Conditional Distribution of Leverage Supply and Demand Shocks

Distributions of leverage supply and leverage demand shocks from a bivariate VAR(1) for LEV_t and $FUND_t$ in levels identified with sign restrictions. Panels (a)-(b) report the distributions of leverage supply shocks when $FUND_t$ is below its own lowest tercile or above its own tercile, respectively. Panels (c)-(d) repeat this exercise but report the distributions of leverage demand shocks. We also report the median measure of central location, the Bowley measure of dispersion and the inter-quantile range measure of skewness. Units on the x-axis are standard deviations.

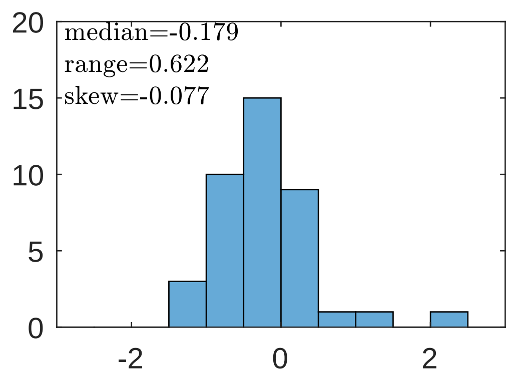
(a) Supply Shocks when $FUND$ is low



(b) Supply Shocks when $FUND$ is high



(c) Demand Shocks when $FUND$ is low



(d) Demand Shocks when $FUND$ is high

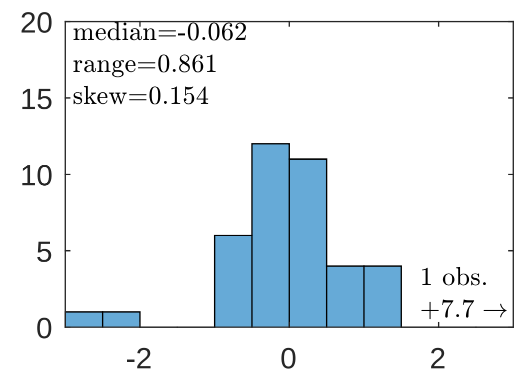
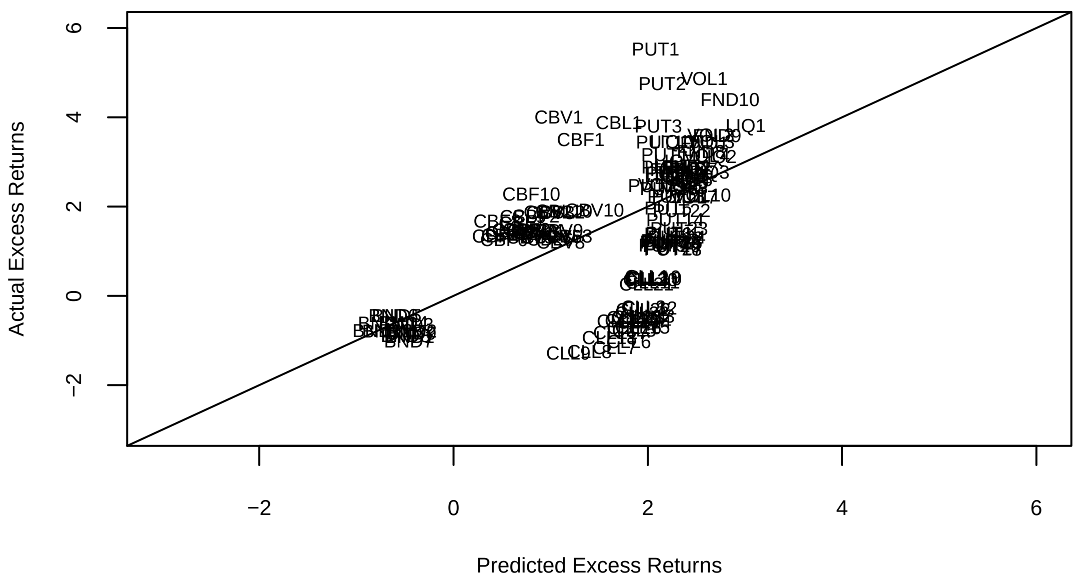


Figure 5: Leverage Demand and Supply Shocks in Asset Pricing

Realized and fitted mean excess returns to 3×10 portfolios of equities and 3×10 portfolios of corporate bonds sorted on $\beta^{\Delta illiq}$, $\beta^{\Delta\sigma}$ and $\beta^{\Delta \text{FUND}}$, labeled LIQ, VOL and FND, and CBL, CBV and CBF, respectively, and ordered from 1 to 10; 2×6 portfolios of recently issued and of old Treasury bonds with different maturities, labeled BND and ordered from 1 to 12; and 2×27 unlevered call and put options, labeled CLL and PUT, respectively. Panel (a): results using market returns and the leverage factor from AEM. Panel (b): results using leverage demand and leverage supply shocks identified with sign restrictions. Each model is estimated with no intercept $E(R^e) = \beta_i \lambda_i$ and we draw a 45-degree line.

(a) Raw Leverage and Market Returns



(b) Leverage Demand and Supply Shocks

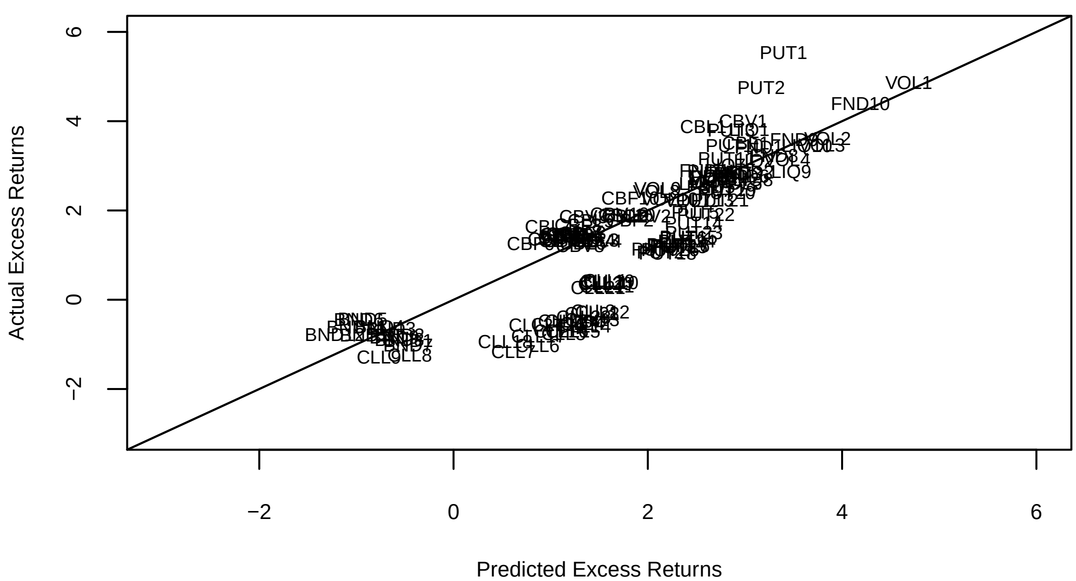
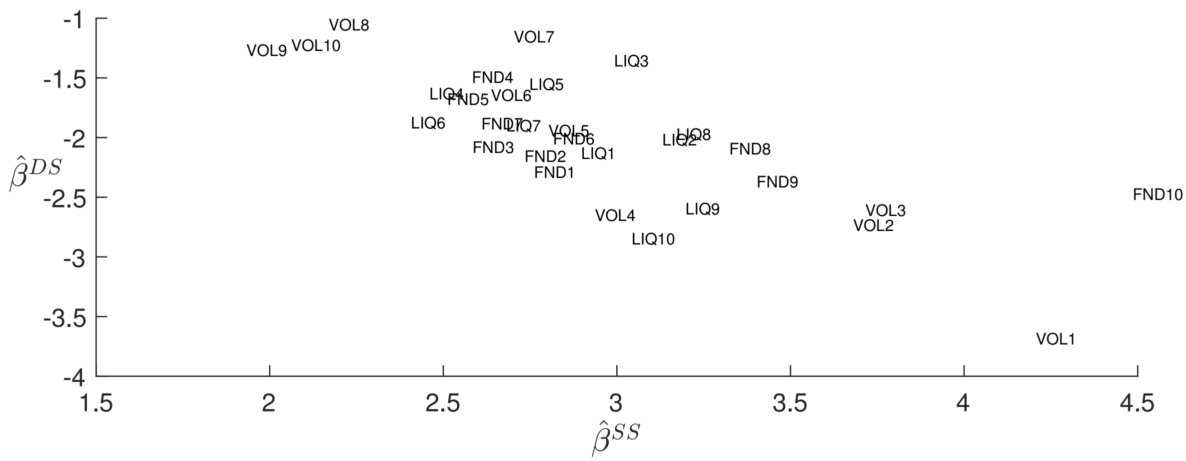


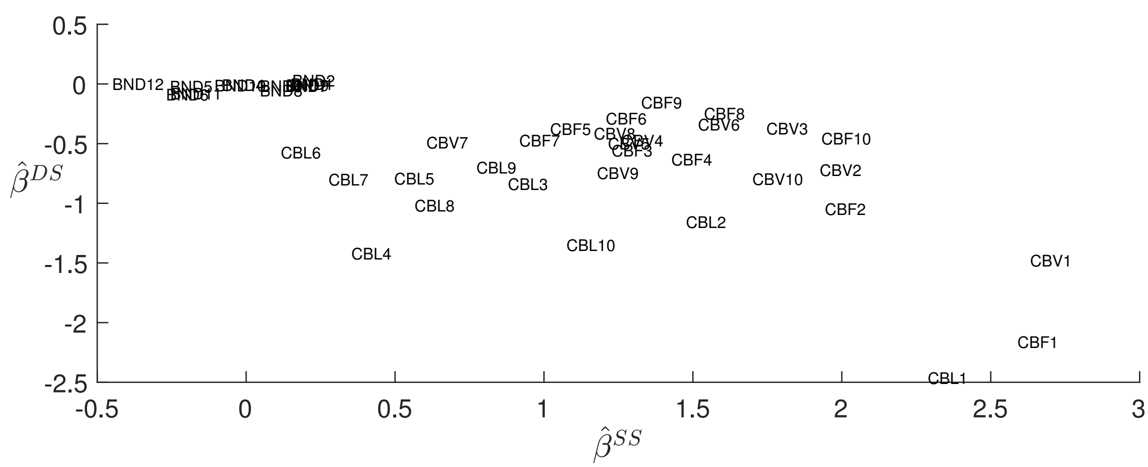
Figure 6: First-Stage β Estimates—Leverage Demand and Supply Shocks

First-stage β estimates of leverage supply and demand shocks in single-factor models. Panel (a): equity portfolios. Panel (b): Treasury bonds and corporate bond portfolios. Panel (c): unlevered options portfolios.

(a) Stocks



(b) Bonds



(c) Options

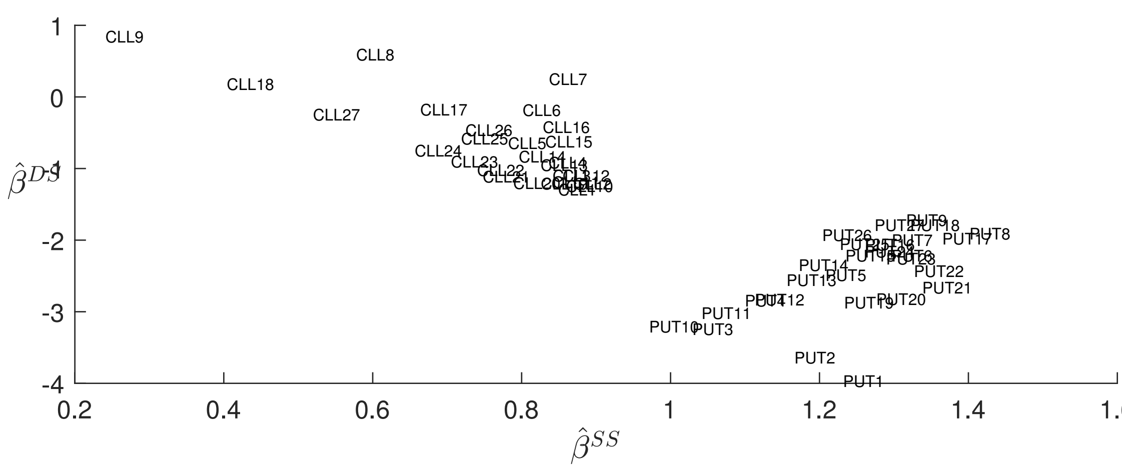


Figure 7: Leverage Betas and Leverage Shocks Betas

Scatter plot based on two ways to estimate β^L. Y-axis: $\hat{\beta}^L$ is the estimate in the first-stage time-series regressions of returns on the leverage factor from AEM. X-axis: $\tilde{\beta}$ is the estimate based on the sum of $\hat{\beta}^{DS}$ and $\hat{\beta}^{SS}$ obtained from first-stage regressions on leverage and demand shocks, respectively (see Equation 8). Case A (dotted line) reports the OLS fitted line of $\tilde{\beta}^L = (2b)^{-1}(\hat{\beta}^{DD} + \hat{\beta}^{SS})$. Case B (dashed line) reports the OLS fitted line of $\tilde{\beta}^L = b_1\hat{\beta}^{DD} + b_2\hat{\beta}^{SS}$.

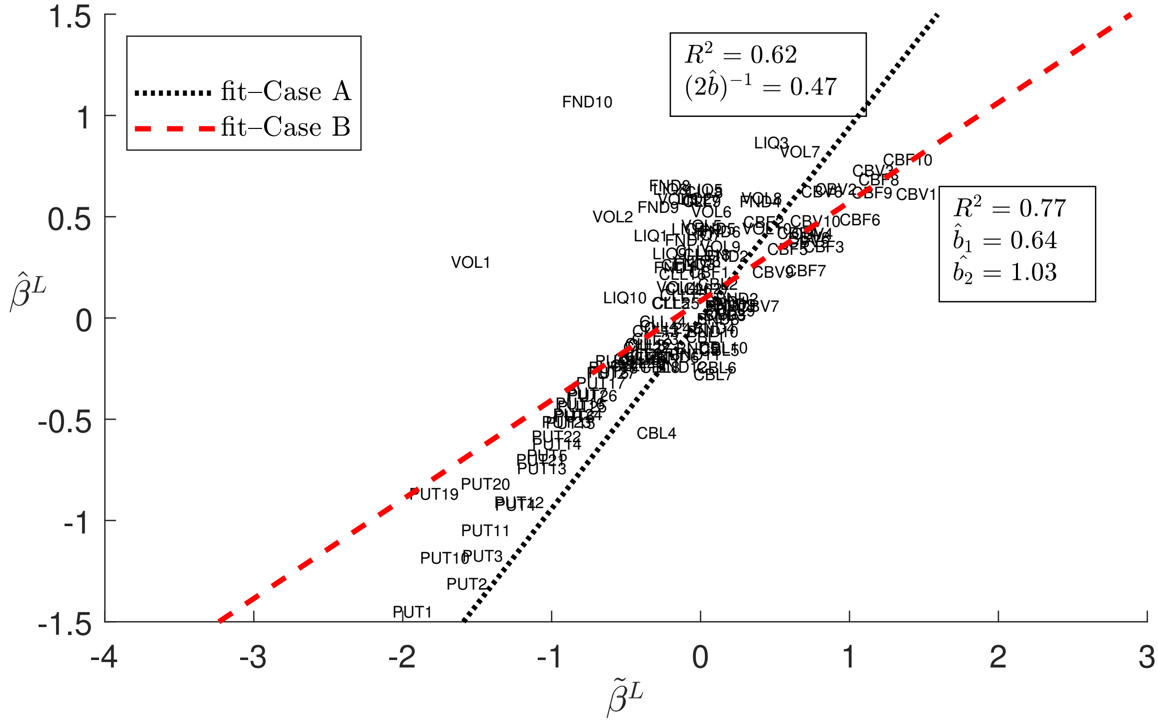
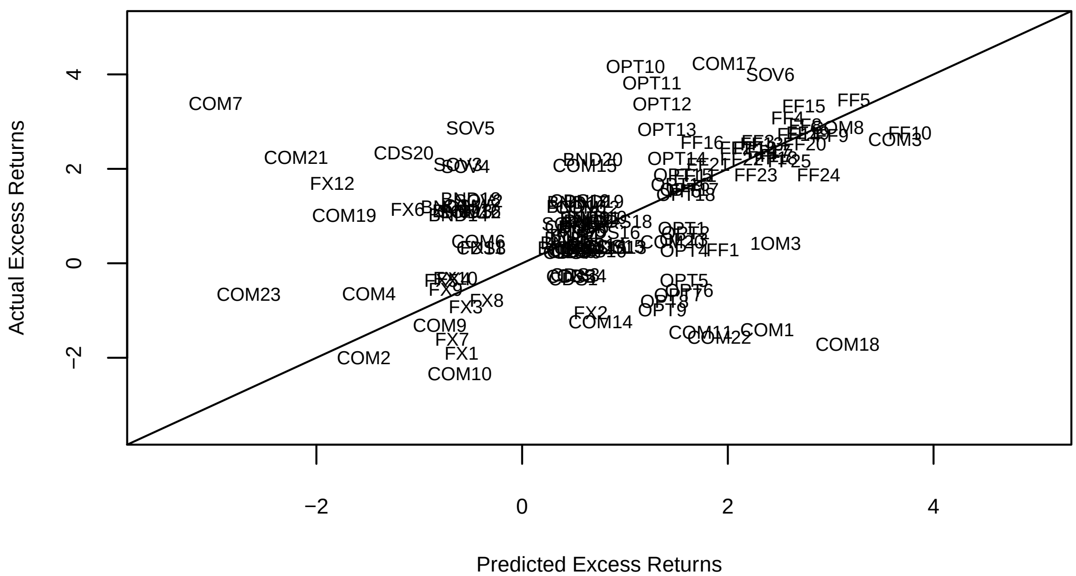


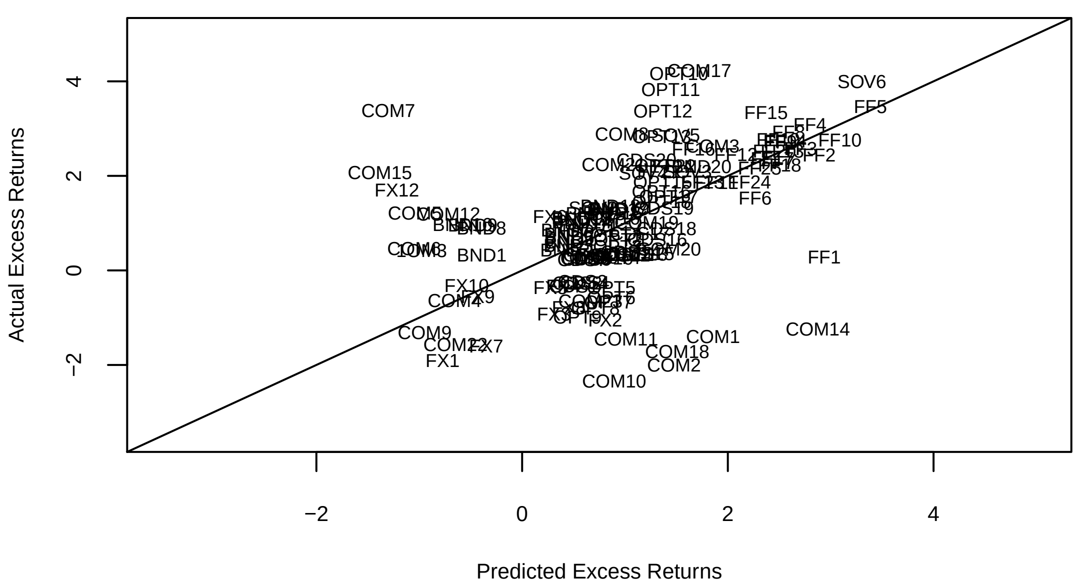
Figure 8: Leverage Demand and Supply Shocks in Asset Pricing: HKM Assets

Realized and fitted mean excess returns of HKM assets. Panel (a) shows results using market returns and the leverage factor from AEM. Panel (b) shows the results using leverage demand shocks and leverage supply shocks identified with sign restrictions. Each model is estimated with no intercept $E(R^e) = \beta_i \lambda_i$ and we draw a 45-degree line. Equities (FF), US bonds (BND), foreign sovereign bonds (SOV), options (OPT), CDS, commodities (COM), and foreign exchange (FX).

(a) Raw Leverage and Market Returns



(b) Leverage Demand and Supply Shocks



A Online Appendix

A.1 Model-Implied Price of Leverage Risk

In the baseline model of Section II.A, the demand and supply shocks load on the leverage with the same loading parameter: $LEV = \mu + b(e_d + e_s)$. We also consider the unrestricted case:

$$LEV = \mu + b_1 e_d + b_2 e_s \tag{A.1}$$

Note that Equations 6 and 7 remain unchanged. However, the prediction for the leverage betas β_i^L and price of leverage risk λ^L are different. For the leverage betas, we have that:

$$\beta_i^L = \frac{1}{b_1^2 + b_2^2} \times \left(b_1 \beta_i^{e_d} + b_2 \beta_i^{e_s}\right), \tag{A.2}$$

and for the price of leverage risk, we have that:

$$\lambda^L = -\lambda\left(b_1^2 + b_2^2\right) \frac{b_1 \omega_1^2 - b_2 \omega_2^2 + (b_1 - b_2)\rho\omega_1\omega_2}{b_1^2\omega_1^2 + b_2^2\omega_2^2 - 2b_1 b_2 \rho\omega_1\omega_2}, \tag{A.3}$$

and these simplify to Equations (8)-(9) if $b_1 = b_2 = b$.

A.2 Test Assets

(i) Data. This section provides more information about the test assets underlying the core results in Section III.A of the paper. In every case, we construct time series of quarterly returns. The sample period changes across asset classes, with the longest series for equities ranging from 1986Q1 to 2015Q4, in which case the start date matches the start date from the $FUND$ time series.

In the case of Treasury bonds, we construct a sample of bonds with constant maturities. For each date and each maturity category 2, 3, 4, 5, 7 and 10 years, we select the observed prices of the most recently issued bond and one other bond that is nearest to each of these maturity points. The data span the 1989Q2-2014Q4 period.

For option data, we use unlevered option portfolios available from Alexis Savov's website and constructed from a panel of S&P 500 Index call and put option portfolios, daily adjusted to maintain targeted maturity, moneyness, and *unit market beta*. The data span the 1986Q2-2011Q4 period.

For corporate bonds, we construct a monthly sample merging several data sets: the Lehman Brothers fixed income database, Mergent FISD/NAIC, TRACE, Bloomberg, and Datastream. We closely follow Bai, Turan, and Wen (2016) to merge these data sources and exclude bonds with special features. The data span the 1989Q2-2014Q4 period.

For equities, we start from daily CRSP data for ordinary common stocks (share codes 10 and 11) traded on the NYSE or AMEX with prices between $5 and $1,000. Nasdaq stocks are excluded to avoid distorting the illiquidity measure (Amihud, 2002). Then, for every month we only keep stocks with at least 10 observations. Excluding stocks with 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 intermediaries' leverage shocks on relatively less liquid securities.

A.3 β-sorted Portfolios

(i) Corporate bonds. For corporate bonds, we estimate betas with respect to changes in $Illiq_m$, σ_m and $FUND$ with monthly data using a rolling window of 36 months. Every year, we form 3x10 portfolios by sorting on estimated betas and track the portfolios for one year.

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

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

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

Using the same approach, the market illiquidity beta is

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

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

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

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

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

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

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

A.4 Illiquidity and Volatility Sorts

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

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

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

A.5 Additional Results

Figure A.1 reports average returns and the fitted returns, discussed in Section III.A, where the Fama-French portfolios of equities sorted on size, value, profitability and investment are substituted for the equity portfolios that we used in our baseline results.

Figure A.2 reports the numerical values of the price of leverage risk predicted based on Equation (A.3) against the numerical value $\text{cov}(\beta_i^L, LEV)/\text{var}(LEV)$ from the OLS for each of portfolios or securities, separately. To obtain these results, we calibrate Equation (A.3) as follows. The parameters ω_1, ω_2 and ρ are calibrated to the distribution of the returns betas β_i^{DS} and β_i^{SS} estimated in first-stage returns regressions. The parameters b, b_1 and b_2 are obtained from regressions of the betas:

$$\beta_i^L = a_0\big(\beta_i^{DS} + \beta_i^{SS}\big) + \varepsilon_i \tag{A.4}$$

$$\beta_i^L = a_1\beta_i^{DS} + a_2\beta_i^{SS} + \varepsilon_i \tag{A.5}$$

where we have $b = (2a)^{-1}$ and $[b_1\ b_2]^\top = (a^\top a)^{-1} a$ with $a = [a_1\ a_2]^\top$. We calibrate the correlation parameter to $\rho = -0.8$ but the results are not qualitatively sensitive to this choice. Finally, we calibrate the price of risk to $\lambda = 2$. Varying this parameter steepens the slope in Equation (A.3) but this does change the sign of the model-implied value.

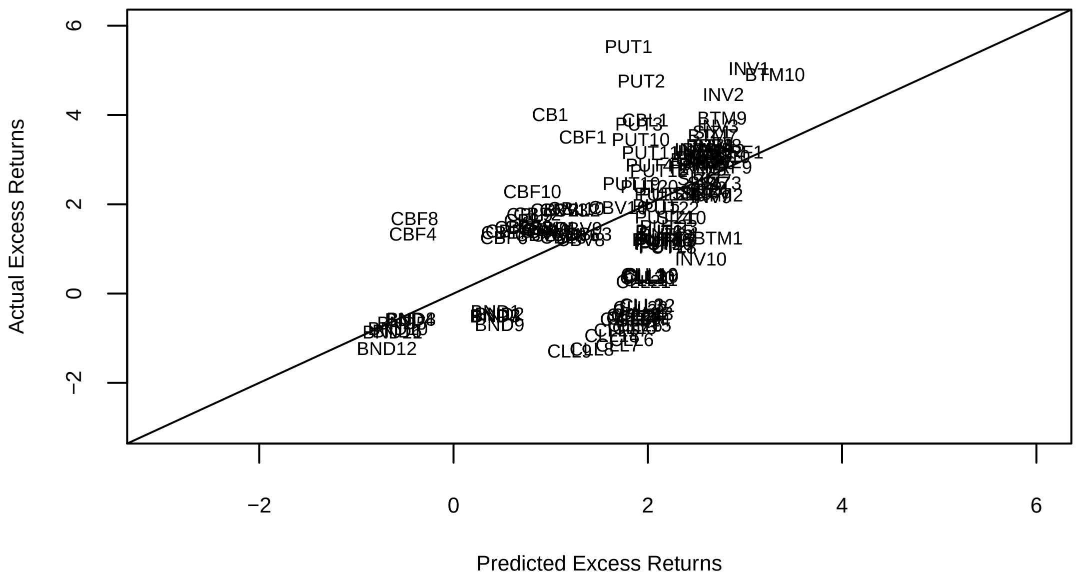
In Table A.1, we check that the sign of the price-of-risk estimates for the leverage factor across HKM test assets matches the model predictions based on the dispersions of the supply and demand betas, mirroring the analysis in section III.C.

Table A.2 reports the asset pricing results for AEM test assets, also discussed in Section III.A. Panel (a) reports results using the leverage factor or either of the leverage demand and supply shocks. Panel (b) reports results using the three Fama-French factors, the momentum factor, and the first principal component of the yield curve. The results can be compared with Table III in AEM.

Figure A.1: Leverage Demand and Supply Shocks in Asset Pricing—Alternative Equity Portfolios

Realized and fitted mean excess returns including all non-equity portfolios from Figure 5 and Fama-French 4×10 portfolios of equities sorted on size, book-to-market, profitability, and investment, labeled SIZ, BTM, PRF, and INV, respectively and ordered from 1 to 10. Panel (a) shows results using market returns and the leverage factor from AEM. Panel (b) shows the results using leverage demand shocks and leverage supply shocks identified with sign restrictions. Each model is estimated with no intercept $E(R^e) = \beta_i \lambda_i$ and we draw a 45-degree line.

(a) Raw Leverage and Market Returns



(b) Leverage Demand and Supply Shocks

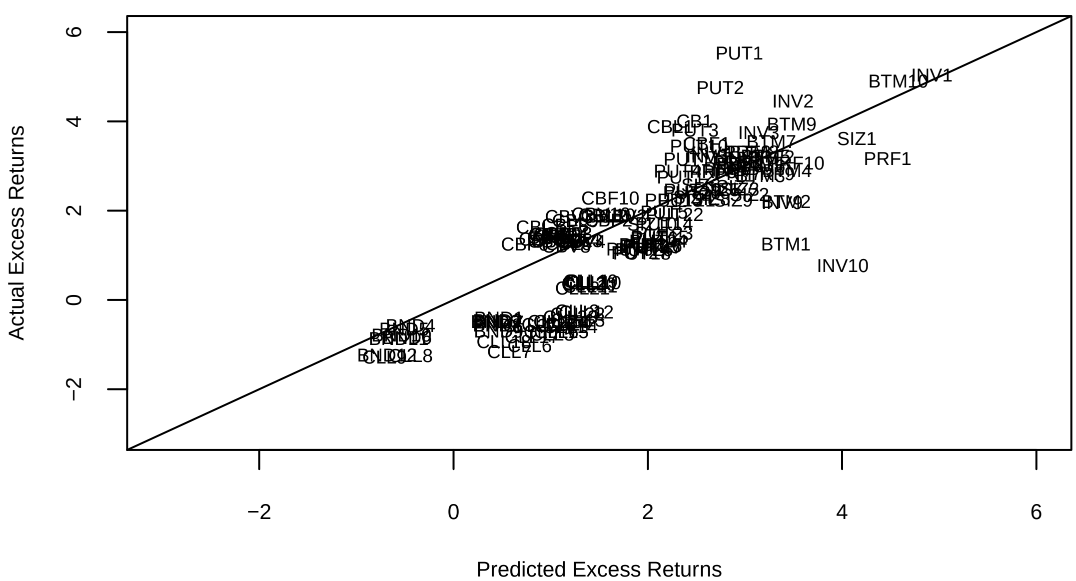
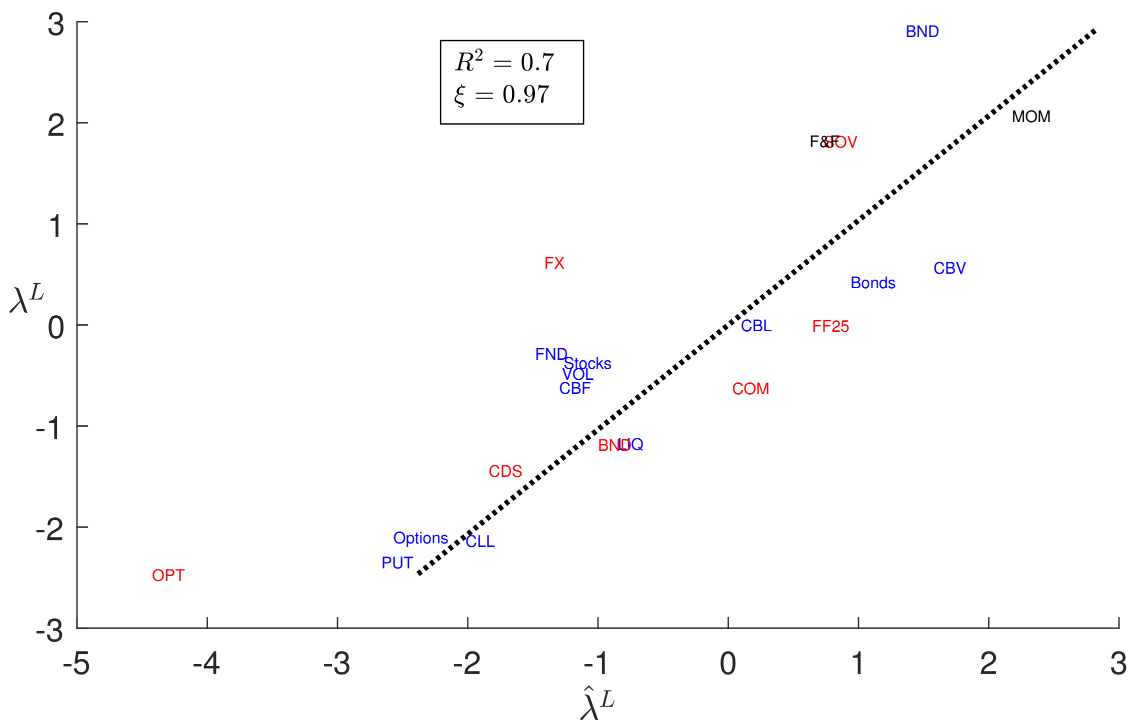


Figure A.2: Comparison of Leverage Price-of-Risk

Scatter plot based on two types of estimates for λ^L across test assets. X-axis: estimates from the second-stage time-series regressions $\hat{\lambda}^L$. Y-axis: estimate λ^L based on Equation (A.3) calibrated to the data as described in Section A.5. The dotted line report the OLS fit $\hat{\lambda}^L = \xi\lambda^L + \varepsilon$.



Note: The following are in blue. PUT, CLL are sets of unlevered put and call SP500 option portfolios; VOL, LIQ, FND are three 1x10 sets of equity portfolios sorted on volatility, illiquidity and funding risk, respectively; Stocks combine VOL, LIQ and FND; CBV, CBL, CBF are three 1x10 sets of corporate bond portfolios sorted on volatility, illiquidity and funding risk, respectively; BND is a set of Treasury bonds; Stocks groups VOL, LIQ and FND; Bonds group CBV, CBL, CBF and BND; Options group PUT and CLL. See Section A.2. The following HKM test assets are in red. FF25 are 5x5 portfolios sorted on size and book-to-market in HKM sample; BND are portfolios of corporate bonds sorted on spreads; SOV are portfolios of sovereign sorted on market risks; OPT are unlevered portfolios of options; CDS are portfolios of short CDS returns; COM are commodities portfolios and FX are exchange rate portfolios. See He, Kelly, and Manela (2017). The following AEM test assets are in black. F&F are the Fama-French portfolios in AEM sample, MOM are the momentum portfolios. See AEM and Table A.2.

Table A.1: **The Signs of Leverage Risk—HKM test assets**

The estimate $\hat{\mu}_1$ and $\hat{\mu}_2$ are the sample averages of the leverage demand and supply shocks betas $\hat{\beta}^{DS}$ and $\hat{\beta}^{SS}$, respectively. The estimates $\hat{\omega}_1^2$ and $\hat{\omega}_2^2$ are the sample dispersions of the demand and supply shocks betas, and the row $-\Delta$ reports $-(\hat{\omega}_1^2 - \hat{\omega}_2^2)$. The last rows compare the sign of $\text{cov}(\beta_i^L, E[R_i])$ in the data with the signs implied by the model in Section I.A. A: the predicted sign for the leverage price of risk based on Equation (9). B: the predicted sign where we relax the symmetry restriction in Equation (2). OLS: the sign in regression of average returns on leverage betas $\hat{\beta}_i^L$, for each asset class separately, without the market returns MKT.

	FF25	US Bonds	Sov. Bonds	Options	CDS	Commodities	FX
$\hat{\mu}_1$	-2.33	-0.45	-1.19	-1.40	-0.24	-1.43	-0.47
$\hat{\mu}_2$	0.43	0.23	1.16	0.83	0.50	0.31	-0.09
$\hat{\omega}_1^2$	0.31	0.28	0.26	0.98	0.06	2.60	0.10
$\hat{\omega}_2^2$	0.43	0.43	1.39	0.09	0.03	1.25	0.24
$-\Delta$	0.12	0.16	1.13	-0.89	-0.04	-1.36	0.14
				$\text{cov}(\beta_i^L, E[R_i])$			
A	+	−	+	−	−	−	+
B	+	−	+	−	−	−	+
OLS	+	−	+	−	−	+	−

Table A.2: **Asset-pricing Tests—Adrian, Etula, and Muir (2014)**

Cross-sectional tests based on two-stage Fama-MacBeth regressions for the 25 size and book-to-market-sorted portfolios, 10 momentum-sorted portfolios, and 6 new and 6 old Treasury bonds with maturities 2, 3, 4, 5, 7, and 10 years. ΔLEV is the leverage factor of AEM, and SS and DS are supply and demand leverage shocks. The market returns MKT are included as a risk factor and as a test asset. Fama-MacBeth (t-FM) and Shanken-corrected (t-Sh) t-statistics are reported in parentheses. PC1 is the change in the first component of the yields curve. Bootstrap $\bar{R}^2$ confidence intervals are in square brackets. The intercepts and prices of risk are annualized.

Panel (a) Leverage

	(1)	(2)	(3)
int	-0.58	-0.30	-0.04
t-FM	(-2.28)	(-0.81)	(-0.09)
t-Sh	(-1.61)	(-0.69)	(-0.09)
ΔLEV	3.79		
t-FM	(2.78)		
t-Sh	(2.01)		
SS		2.28	
t-FM		(2.18)	
t-Sh		(1.89)	
DS			-0.02
t-FM			(-0.01)
t-Sh			(-0.01)
MKT	10.55	7.06	9.25
t-FM	(2.94)	(2.00)	(2.63)
t-Sh	(2.71)	(1.95)	(2.62)
R^2	84.52	75.21	68.83
$\bar{R}^2$	83.83	74.11	67.44
	[61, 96]	[43, 97]	[33, 97]

Panel (b) Fama-French

	(4)	(5)	(6)	(7)
int	-0.04	-0.67	-1.02	-0.79
t-FM	(-0.10)	(-2.90)	(-5.61)	(-4.62)
t-Sh	(-0.09)	(-2.74)	(-4.89)	(-3.84)
SMB		1.57	2.84	2.53
t-FM		(0.67)	(1.24)	(1.11)
t-Sh		(0.65)	(1.18)	(1.04)
HML		4.14	4.80	4.90
t-FM		(1.63)	(1.89)	(1.93)
t-Sh		(1.63)	(1.86)	(1.89)
MOM			6.79	7.26
t-FM			(1.95)	(2.10)
t-Sh			(1.93)	(2.06)
PC1				3.37
t-FM				(3.13)
t-Sh				(2.92)
MKT	9.11	8.51	9.88	9.56
t-FM	(2.50)	(2.53)	(2.94)	(2.85)
t-Sh	(2.48)	(2.52)	(2.92)	(2.81)
R^2	68.78	78.13	90.58	91.15
$\bar{R}^2$	68.10	76.71	89.76	90.17
	[36, 98]	[47, 95]	[72, 97]	[72, 97]

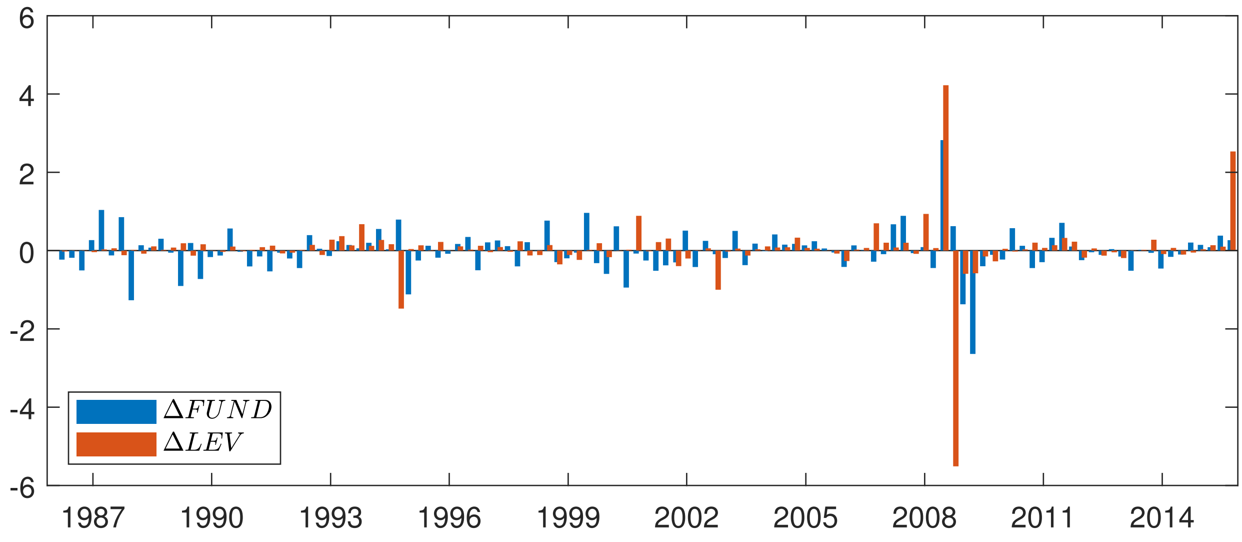
B Do the Funding Constraints always Bind?

We provide several lines of evidence that the constraints of intermediaries do not always bind and that both supply- and demand-like shocks can influence leverage. First, we simply inspect whether ΔLEV and $\Delta FUND$ tend to move in opposite directions (Section II.A in the text defines both variables). Second, we look at a reduced-form test for the hypothesis that the constraints are always binding. Third, we provide estimates for the probabilities that the constraint is binding at each point in time.

(i) Changes in leverage and funding conditions. Figure B.1 shows the first difference in the funding measure $\Delta FUND_t$ and in the leverage measure ΔLEV_t. These two variables should move in opposite directions when the funding constraints are binding. When inspecting the time series, we can identify significant dates where the leverage and funding conditions move in the same direction. For instance, in the second quarter of 2008 when the aggregate broker-dealers leverage increases during one of the most severe tightenings in funding conditions. Across the entire sample, ΔLEV_t and $\Delta FUND_t$ move in the same direction in 58 percent of all observations and they move in opposite directions in 42 percent of all observations. The correlation is positive but close to zero. Overall, this is suggestive that both supply and demand disturbances influence leverage.

Figure B.1: ΔLEV and $\Delta FUND$

Changes in leverage ΔLEV and changes in funding conditions $\Delta FUND$ normalized with mean zero and standard deviation of one.



(ii) A reduced-form look at the evidence. One way to test whether the constraints are always binding and that leverage and funding conditions always move in opposite direction is to estimate the following predictive regressions:

$$LEV_{t+h} = \beta_h + \beta_{f,h} FUND_t + \beta_{l,h} LEV_t + \beta_{\times,h} FUND_t \times LEV_t + \epsilon_{t+h}, \qquad \text{(B.6)}$$

where h is the quarterly forecast horizon and ϵ_{t+h} is a forecast error and then test whether $\beta_{f,h} < 0$ and $\beta_{\times,h} = 0$.

To see how the test works, consider periods when leverage is high and the constraint is binding. In this case, we expect that the partial effect of $FUND_t$ on future leverage should be negative. Contrast this case with periods when leverage is low and the constraint is not binding. Then, in this case, tighter funding conditions may lead to lower leverage after a supply shift or to higher leverage after a demand shift. If both types of shift are equally likely in the data, then the estimated partial effect of $FUND_t$ would be close to zero. The interaction term $FUND_t \times LEV_t$ plays an essential role in capturing how this partial effect may change with the level of leverage. Our test asks whether the corresponding coefficient $\beta_{\times,h} = 0$. If not, we expect the estimate to be negative: a higher level of the leverage shifts the partial effects toward negative values.

Panel (a) of Figure B.2 shows that the estimate of the interaction coefficients $\beta_{\times,h}$ is negative for every horizon up to 8 quarters ahead, as expected, and significant at horizons up to 6 quarters. We estimate the regressions using ordinary least squares and standardized variables. The $\bar{R}^2$s is 68 percent when $h = 1$ and it gradually declines to around 20 percent when $h = 8$. The coefficient of LEV_{t+h} on its own lag LEV_t is 0.7 for $h = 1$ and remains significant up to 8 quarters ahead. In every case, we checked that the estimates of $\beta_{f,h}$ and $\beta_{\times,h}$ that determine the partial effect are jointly significant.

Therefore, there is substantial statistical evidence that the partial effect changes with the level of leverage. Panel (b) of Figure B.2 reports the partial effect of funding conditions $FUND_t$ on leverage LEV_{t+4} as we vary the current leverage LEV_t from -2 standard deviations to $+4$ standard deviations around its sample average (this is the range of sample values). For high current values of leverage, when the constraints are likely to bind, the partial effect of funding conditions on future leverage is large, significant and negative, as expected. However, the partial effect becomes small or positive for low values of leverage, suggesting that leverage is then the result of a mix of demand and supply shifts.

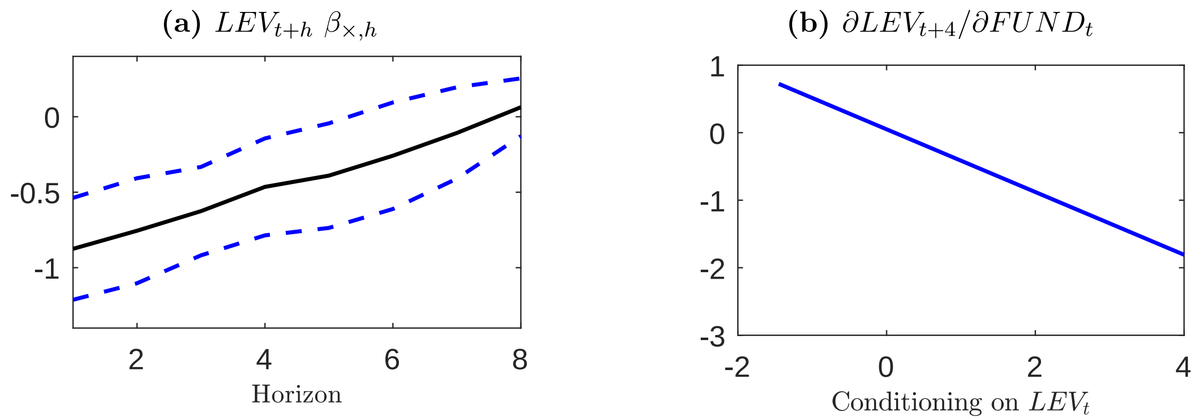
Estimating Equation (B.6) separately for each horizon implies that the inference is not efficient, relative to estimating a dynamic VAR model, but the estimator is more robust and is not encumbered by a specification of the time-series dynamics and complements the dynamic approach in Section A.

Conversely, the estimated VAR(1) system in Equation (13) does not include the nonlinear effects documented here. We checked in unreported results that, in a model that includes one lag of the interaction term $y_{t+1} = a + \Phi y_t + b z_t + u_{t+1}$, we recover essentially the same shocks. The R^2s of one set of shocks on the other are 96.1 and 99.3 percent for the supply and demand supply shocks, respectively. Intuitively, the reason is that the variations in the interaction term z_t lay very close to the line generated by a linear combination of the elements of y_t. The R^2 from this regression is 81 percent.

(iii) A Structural Look at the Evidence. As a third source of evidence, we provide estimates of the probability that the funding constraints are binding. To do this, we specify a constrained system of demand and supply functions where LEV will represent the quantity variable and $FUND$ the price variable, building on existing econometric models to address this challenge while preserving the simplicity of estimation by least squares. This demand

Figure B.2: Leverage and Funding Conditions

Results from predictive regressions of LEV_{t+h} on current values of LEV_t, $FUND_t$ and the interaction term $LEV_t \times FUND_t$ for $h = 1 \ldots 8$ quarters (Equation B.6 in the text). Panel (a) reports estimates of the interaction coefficient $\beta_{\times,h}$ with the 95 percent confidence interval based on Newey-West standard errors with $h+4$ lags (dashed blue lines). Panel (b) reports the partial effect $\frac{\partial LEV_{t+4}}{\partial FUND_t}$ across different conditioning values of LEV_t.



and supply system is symbolically represented with the following equations:

$$\begin{aligned} S_t &= \beta_0 Z_t + \beta_1 P_t + v_t \\ D_t &= \alpha_0 X_t + \alpha_1 P_t + u_t \\ Q_t &= \min(D_t, S_t), \end{aligned} \tag{B.7}$$

where Q_t is the quantity, P_t is the price, X_t and Z_t are exogenous variables and the residuals are $u_t \sim N(0, \sigma_u)$ and $v_t \sim N(0, \sigma_v^2)$. The shorthands Q and P for LEV and $FUND$, respectively, are useful to keep the exposition lighter. See Maddala and Nelson (1974) and Laffont and Garcia (1977) and references therein for a discussion of this class of models.

The last equation says that the observed quantity is given by S_t or D_t, whichever is lower. The presence of a constraint introduces a challenge: the relationship between the observed leverage and its determinants changes as the system moves between the constrained and unconstrained states. However, the system provides a way to infer the probability that we observe the supply or the demand schedule at each point in time. These endogenous probabilities are a function of funding conditions, the exogenous variables included in the demand and supply equations, and the model parameters. They are given by:

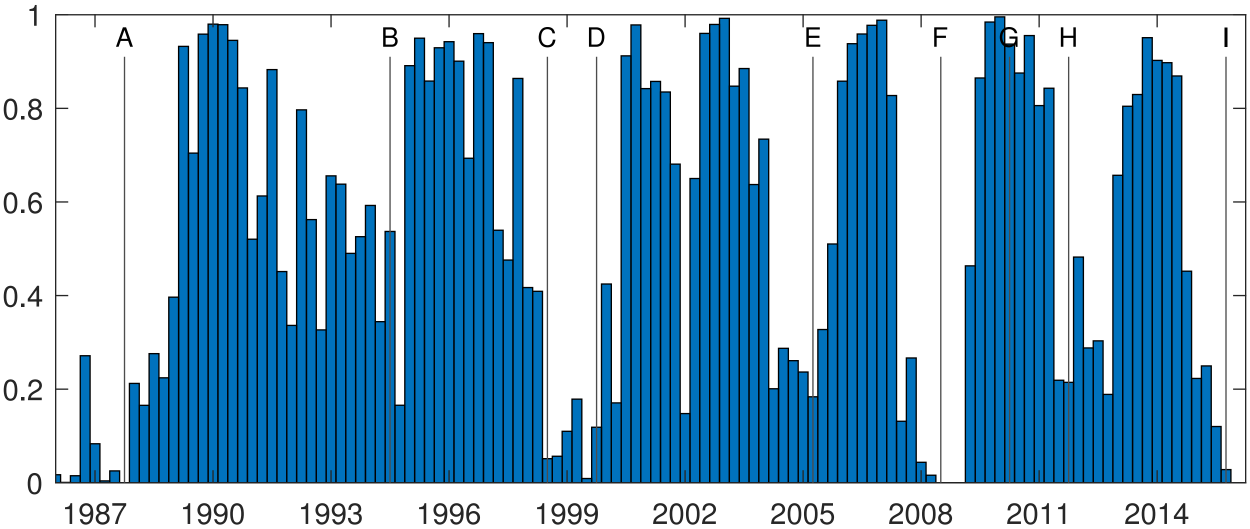
$$\pi_t = pr(S_t < D_t) = pr(\beta_0 Z_t + \beta_1 P_t + v_t < \alpha_0 X_t + \alpha_1 P_t + u_t). \tag{B.8}$$

Since $v_t - u_t$ is normally distributed with variance $\sigma^2 = \sigma_v^2 + \sigma_u^2$, the probability in Equation (B.8) is obtained by $\pi_t = \int_{-\infty}^{(\alpha_0 X_t - \beta_0 Z_t + (\alpha_1 - \beta_1) P_t)/\sigma} \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du$. The benefits of this specification, which is in the spirit of the Tobit model, are its simplicity and the relative ease with which we can estimate the parameters and the probabilities that the supply is constrained.

We provide in the following section the details of the specification of the demand and supply equations as well as the estimation results. We focus here on the estimated implied probabilities plotted in Figure B.3. We will comment on the periods leverage is more likely to be moving along the supply schedule or on the demand schedule (when the probability is closer to one and zero, respectively). There are obviously other periods when both types of shocks are playing a role..

Figure B.3: Probabilities of Constrained Intermediation Supply

The probability of constrained intermediation supply estimated in the demand and supply system defined in Equations (B.7)-(B.8).



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

Several episodes feature a very low or close to zero probability. The natural interpretation of a low probability is that the intermediaries' leverage that we observe is larger than the predicted value from the estimated supply equation. This would be the case, for instance, if intermediaries accommodate a shift in the demand: around the 1987 crash, the 93-94 period of sudden increase in interest rates, around 1998 with the LTCM collapse and the Russian crisis, and the European debt crisis of 2011-2012. The probability is also close to zero during the last quarter of 2008, which may be a reflection of the large-scale interventions by the Federal Reserve and the US Treasury, which are unaccounted for in the model. The constraint is definitely binding with a probability closer to one in the 1994-1998, 2001-2004 and 2009-2010 periods, which are associated with improved funding conditions. We check that the conclusions are robust to the specification of the demand and supply equations. In particular, we verify that the classification of periods as demand or supply driven is very similar if we explicitly use $\Delta FUND$ (the directional change in price) in the system of equations (B.7). See the directional methods in Maddala and Nelson (1974) and Laffont and Garcia (1977).

Reassuringly, even though the methodologies differ, the periods where the estimated probabilities are close zero are consistent with periods when we extract relatively large demand shocks based on the sign restrictions (See the historical decomposition in Figure 3). In our baseline results, we focus on the shocks recovered based on sign restrictions because this is more robust and agnostic regarding the structure of the supply and demand channels and let the data determine how big a role each type of shocks plays.

(iv) Supply and demand equations. To complete the demand and supply system in Section B(iii), we specify the variables included in the supply and demand equations, i.e., in Z_t and X_t. In the supply equation, we include the total assets of money market mutual funds (MMMF), the MMMF allocation to time deposits (MMA1) and the MMMF allocation to Treasury, agency and municipal bonds (MMA2). The size and allocation of MMMF assets influence the availability of funds and hence the supply conditions for the intermediaries. Broker-dealers can more easily adjust their leverage when MMMF are larger and when they have smaller allocations to the safest assets. Fontaine and Garcia (2012) use the same variables in a supply equation to explain the growth of shadow banking activity. These variables are based on the US Financial Accounts data available from the Federal Reserve Board web site.

The demand equation includes the aggregate mortgage level, the ratio of the aggregate shadow bank level over the aggregate mortgage level, and the consumption-to-wealth ratio (CAY) introduced by Lettau and Ludvigson (2001). The mortgage activity and the relative importance of the shadow banking sector are significant sources of demand for intermediation throughout the sample. The aggregate mortgage data is available from the US Financial Accounts data. To compute the shadow banking level, we follow Adrian, Moench, and Shin (2010) and aggregate the total assets of Agency and GSE-backed mortgages pools, Issuers of asset-backed securities, Finance companies and Funding corporations also available from the US Financial Accounts data. The variable CAY is defined as the ratio of aggregate consumption over the sum of asset wealth and human capital wealth and is entered as a proxy for household demand of leverage. It is available from Martin Lettau website. Haddad and Muir (2021) use the variable CAY to measure household risk aversion to predict stock returns along with the standardized average of the AEM and HKM intermediary factors to proxy for intermediary risk aversion. Both the supply and demand equations also include term structure factors (level, slope and curvature) to capture how the strength of economic activity influences the leverage of financial intermediaries.

(v) Estimation. Estimates of the parameters can be obtained using two-stage least-squares (TSLS). Estimation is also feasible using maximum likelihood, in which case we use the gradients provided by Maddala and Nelson (1974) and the TSLS estimates as initial parameter values. The mortgage variable in the demand equation is the instrument to estimate the supply equation while the MMMF allocation variables used in the supply equation are the instruments to estimate the demand equation. We note that using the analytical gradients to search for the highest likelihood produces only modest improvements to the likelihood obtained with TSLS. In addition, the estimated probabilities are very robust to these small changes in the likelihood. Finally, estimates from models incorporating the information in $\Delta FUND$ to identified constrained observations produced similar probabilities of observing the demand or the supply quantity of leverage.

For completeness, we report the OLS and TSLS results in Table B.1. The first-stage projection on the demand instruments leads to higher TSLS parameter estimates in the second stage, with the correct sign in every case. Therefore, we are reassured that our interpretation of this equation as the supply equation is valid. The predicted supply of leverage increases when $FUND$ increases and when the size of MMMF total assets increases but the predicted supply decreases when the MMMF allocation to safe assets increases.

Table B.1: **Leverage Demand and Supply Equations**

OLS and TSLS regressions of intermediaries' leverage LEV on funding conditions $FUND$. Panel (a): estimates for the supply equation including Level, Slope and Curvature factors from the term structure of interest rates, Money Market Mutual Funds total assets (MMG), Money Market Mutual Funds allocation to time deposits (MMA1) and Money Market Mutual Funds allocation to Treasury, Agency and Municipal bonds (MMA2). Panel (b): estimates for the demand equation, including Level, Slope and Curvature factors from the term structure of interest rates, the ratio of the aggregate shadow bank level over the aggregate mortgage level (Ratio), the aggregate mortgage level (Mrtg), and the CAY. Standard instrumental variables t-statistics in parentheses.

Panel (a) Supply equation

	int	FUND	Level	Slope	Curv.	MMG	MMA1	MMA2	R^2
OLS	116.10	5.28	-10.62	-3.21	1.57	0.45	-3.39	0.99	
	(9.70)	(4.30)	(-7.13)	(-3.30)	(1.75)	(0.87)	(-4.13)	(1.16)	47.66
2SLS	169.55	25.89	-19.84	-11.62	6.76	2.09	-4.26	-2.16	
	(6.14)	(3.23)	(-4.73)	(-3.30)	(2.80)	(2.06)	(-3.20)	(-1.20)	51.15

Panel (b) Demand equation

	int	FUND	Level	Slope	Curv.	Ratio	Mrtg	CAY	R^2
OLS	57.84	4.33	-6.47	-2.45	3.27	5.67	0.66	4.89	
	(3.88)	(3.55)	(-4.52)	(-2.74)	(3.74)	(3.60)	(1.99)	(3.05)	50.81
2SLS	2.26	-8.05	-0.17	2.06	1.84	4.59	1.68	9.48	
	(0.06)	(-1.17)	(-0.04)	(0.87)	(1.38)	(2.27)	(2.44)	(2.98)	46.20

The results for the demand equation indicate that the OLS estimates suffer from a strong bias since the coefficient of the $FUND$ variable is positive and significant. The second-stage estimate for $FUND$ is negative but insignificant, indicating that the demand for leverage may be price inelastic. The three quantity variables, the ratio of the shadow bank level over the mortgage level, the mortgage level itself, and the CAY, have the right sign and are significantly different from zero for both the OLS and 2SLS methods. Therefore, the results are also consistent with our interpretation of this equation as the demand equation. To be clear, estimates of this demand and supply system are only used as one piece of evidence that the intermediaries constraints are not always binding. Our main results do not rely on this system but instead build on agnostic sign restrictions.