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, increase returns and carry a positive price of risk. Leverage demand shocks also raise leverage but worsen liquidity, reduce returns and carry a negative price of risk. Disentangling demand- and supply-like shocks resolves existing puzzles around the price of leverage risk and yields consistent evidence across many markets of a central role for intermediation frictions and dealers' aggregate leverage in asset pricing.

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Large financial intermediaries provide broker-dealer services to major investors and asset managers, act as 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 limited 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, 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, other results have raised doubts about the centrality of intermediaries for asset pricing. First, while AEM asset pricing results are consistent with well-established models of intermediation frictions (Brunnermeier and Pedersen, 2009), AEM also noted that leverage appears largely uncorrelated with proxies for market liquidity, challenging a core theoretical prediction from these models. Second, in broadening the study of intermediation frictions to several asset classes, He, Kelly, and Manela (2017) find that estimates of the price of leverage risk can switch signs between asset classes.

One reason why the empirical work yields muted or inconsistent estimates may be that the leverage decision mixes demand-sided and supply-sided considerations. In a framework like in Brunnermeier and Pedersen (2009), intermediaries face cus-

[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).

tomers who demand immediacy as well as financiers that provide them with funds. On the side of supply, leverage may increase because funding conditions improve, in which case the marginal value of intermediaries' wealth declines. 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. Both types of shift 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. Both types of shock can be relevant if the leverage constraint is not binding, as in Du, Hébert, and Huber (2022).[2]

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. Second, we show that disentangling demand and supply shocks rationalize how the price of raw leverage risk changes sign across asset classes. Third, this separation also helps explain the weak correlation between raw leverage and market liquidity. Overall, disentangling the shocks considerably strengthens the evidence of a central role for intermediaries in asset pricing and paves the way for more work to understand mechanisms underpinning demand- and supply-sided frictions.

To analyze leverage shocks, we introduce an econometric model where two shocks capture the demand- and supply-sided variations in intermediaries leverage. We interpret the supply shocks as shifts in the supply of funds by financiers and the demand shocks as shifts in the demand for immediacy by clients. Both shocks lift leverage but they shift the marginal value of wealth in opposite directions. This

[2] In Section IV, we discuss reduced-form and structural evidence that intermediaries' funding constraints are not always binding.

interpretation amalgamates within leverage demand shocks the potential shifts in the intermediaries' demand for funds or supply of immediacy.

To identify the shocks, we combine a measure of leverage with an instrument that is correlated with the supply and demand shocks. We first restrict the signs of the impacts that each type of shocks has on leverage and the instrument within a vector autoregressive system (VAR). This identifies a set of potential structural parameters that has one degree of freedom. To achieve point identification, we add the assumption that the prices of risk for the leverage demand and supply shocks are symmetric. This yields the structural parameters with closed-form expressions in terms of moments from the VAR and the cross-section of asset returns.[3]

We stress that the symmetry assumption is mainly a useful starting point to establish the importance of disentangling demand and supply shocks. With symmetric prices of risk, the demand and supply shocks contribute equally to the variance of the stochastic discount factor, and the covariance risk of asset returns is the same whether it arises from supply- or demand-sided variations. Therefore, the cross-section of asset returns will be determined by the patterns of demand and supply betas. With asymmetric prices of risk, our core message remains the same and the fit of asset returns is identical, but the interpretation of some of the results changes. Asymmetry mechanically gives a greater role to one of the two shocks and shifts the relative dispersions of the betas. Overall, our sample is largely uninformative about the degree of asymmetry but excludes cases where either demand or supply shocks clearly dominate.

Empirically, we use for leverage the AEM's measure of broker-dealers' aggre-

[3]Commonly-used methods use an outside criterion to choose among the structural parameters that satisfies the sign restrictions.

gate leverage and, as an instrument, a proxy for the funding conditions of intermediaries.[4] We also use a broad cross-section of test assets covering the bond, option and equity markets. First, we include the returns from a panel of Treasury bonds, as in AEM. Second, we also include option portfolios from Constantinides, Jackwerth, and Savov (2013), which are unlevered and appropriate for linear asset pricing tests. Third, we include portfolios of corporate bond securities sorted on their sensitivity to market illiquidity, market volatility and funding conditions, separately. Finally, we include portfolios of equities built on the same sorts. These sorts are motivated by the predictions in Brunnermeier and Pedersen (2009) linking securities' returns with illiquidity, volatility and funding conditions.

Our pricing model that disentangles leverage demand and supply shocks receives a strong empirical support. The estimated betas for the demand and supply shocks have negative and positive signs, as expected, and we show that the betas with respect to raw leverage can switch signs because they mix demand and supply exposures. We find relatively large leverage supply betas for bonds, which explains the negative betas that we obtain for raw leverage, and we find relatively large leverage demand betas in the option market, explaining the positive betas for raw leverage.

We find a significant price-of-risk estimate and a close fit across our equities, bonds and options portfolios, when excluding a constant. The model shows that the price of raw leverage risk can change sign across asset classes because the demand and supply betas have different dispersions. The price of raw leverage risk

[4] Our proxy is the first principal component from three existing measures of funding conditions. Section I motivates and explains the construction of this proxy. Section II discuss conditions for the validity of this proxy in the context of our econometric model. Section III verifies these conditions in our results.

is negative for options, where the demand betas have a wider dispersion, while it tends to be positive for bonds where the supply betas are more dispersed. By contrast, the symmetric price of risk for the leverage demand and supply shocks remains significant, with the same sign, and a similar magnitude when estimated separately for bonds, equities or options, and consequently for all test assets considered together. 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 risks offer much the same average returns.

Our conclusions are largely unchanged when we use traditional Fama and French size, value, profitability and investment-sorted equity portfolios. We also draw the same inference if we use AEM's original test assets, where, similar to their results, we find a positive and significant price of raw leverage risk. This sign is consistent with our model prediction because supply shocks betas have a relatively large dispersion across AEM's test assets. We find a robust sign for the price of demand and supply shocks across the larger set of asset classes introduced by He, Kelly, and Manela (2017) that includes sovereign bonds, credit derivatives, commodities, and exchange rates, the Fama-French 25 portfolios, government and corporate bonds and equity derivatives.

Disentangling leverage demand and supply shocks can also help understand the variations in market liquidity. We verify the theoretical predictions by Brunnermeier and Pedersen (2009) that intermediaries' marginal value of wealth is a significant driver of common market liquidity variations. We find that leverage supply shocks have a significant positive correlation with market liquidity. The impact appears highest for the least liquid and more volatile portfolios and decreases monotonically for more liquid and less volatile portfolios. By contrast, leverage demand shocks yield insignificant results, consistent with the evidence in Macchiavelli and Zhou (2022). Mixing the two sets of results explains the positive but weak and insignificant relationship between raw leverage and market liquidity. We offer a few conjectures for future research to explore the weaker correlations with the demand shocks.

Literature

Since at least the great financial crisis, an empirical literature has proposed a stochastic discount factor that includes the financial intermediaries' marginal value of wealth. As discussed above, Adrian, Etula, and Muir (2014) include the leverage of securities broker-dealers as a proxy. He, Kelly, and Manela (2017) use instead the capital ratio of primary dealers' holding companies and analyze a broader set of asset classes. We distinguish between the roles of leverage demand and supply shocks to strengthen and deepen the evidence of a central role for intermediaries' leverage in asset pricing.

A broader strand of literature also studies demand or supply channels in the determination of asset prices but beyond the roles of intermediaries. For instance, Liu, Whited, and Zhang (2009) emphasises the role of firms' demand for capital for stock prices. Koijen and Yogo (2019) argue that stock returns are mostly explained by shocks to the supply of capital. 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, we focus on the demand and supply for intermediation.[5]

Our results are closely related to Goldberg (2020) and Goldberg and Nozawa (2021) who estimate inventory demand and supply shocks in the Treasury market and the US corporate bond market, respectively. Like them, we find that leverage supply shocks play a larger role in the bond markets. Hanson, Malkhozov, and Venter (2022) document that both demand and supply shocks play a role in the determination of swap spreads. One key methodological contribution, relative to existing work seeking demand and supply shocks, is to rely on the asset pricing implications to achieve point identification of the shocks.[6]

These existing results combine information about intermediaries' balance sheets with measures of apparent mispricing, and rely on sign restrictions to identify shocks. These apparent arbitrage opportunities between securities with identical or similar risk can proxy for 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 spreads between seasoned Treasuries with risk premia across several fixed-income securities. Hu, Pan, and Wang (2013) provide a similar connection to the hedge fund industry and the exchange rates. Du, Tepper, and Verdelhan (2018) study the persistent deviations from the covered interest rate parity condition (CIP). In a closely related paper Du, Hébert, and Huber (2022) show that these measures of apparent mispricing complement

[5] Froot and O'Connell (1999) provide an early analysis of prices and quantities in the intermediation of catastrophe reinsurance and Gabaix, Krishnamurthy, and Vigneron (2007) examine intermediation in the mortgage-backed securities.

[6] Our approach could have wider practical implications since sign restrictions are used more broadly in macro-finance, for example in Cieslak and Pang (2021).

information about intermediaries' wealth or leverage in asset pricing tests when intertemporal considerations enter the intermediaries' portfolio decisions (see also Kondor and Vayanos 2019). We build on this insight to identify leverage demand and supply shocks and find that the relative roles of demand- and supply-side effects can change across asset markets. This is in line with Haddad and Muir (2021), who ascribe a greater share of the aggregate risk premia variations to intermediaries in asset classes where households are less active, and in line with Siriwardane, Sunderam, and Wallen (2022), who show that intermediation frictions differ across markets because of segmentation in funding markets.

Our results are also related to existing work showing strong illiquidity commonality across securities (Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001), or that illiquidity increases with the volatilities of securities to compensate market makers, either for their inventory risk or for their losses to better-informed investors (Benston and Hagerman, 1974; Stoll, 1978; Glosten and Milstom, 1985; Grossman and Miller, 1988; Pagano, 1989). We show that leverage supply 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; Pástor 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.

In Section I, we draw implications from an econometric model where the intermediaries' leverage and marginal value of wealth are driven by supply- and demand-like disturbances. Section II explains how we estimate the leverage supply and demand shocks using measures of funding conditions and leverage. Section III analyzes how leverage demand and supply shocks influence the risk premia across several asset classes. In Section IV, we review AEM's seminal results under the light of our econometric model. The conclusion stresses the need for further research on the mechanisms underlying the channels of leverage supply and demand shocks. The appendix contains proofs, description of data and supplemental results.

I. An Econometric Model of Leverage Shocks

We develop an econometric asset pricing model in which the intermediaries' leverage and marginal value of wealth are influenced by supply- and demand-like disturbances that are priced in financial markets. We show that the patterns of demand and supply returns betas determine the price-of-risk estimate for raw aggregate leverage in asset pricing tests.

A. Leverage demand and supply shocks

Brunnermeier and Pedersen (2009) analyze a market for multiple securities in an equilibrium model where specialized traders or speculators provide intermediation between customers and financiers. The customers are investors that arrive sequentially to the markets and demand immediacy, in the spirit of Grossman and Miller (1988). The intermediaries smooth price fluctuations thus providing market liquidity. The intermediaries also face financiers that provide funding against margins but where long positions cannot be netted against short positions. In this class of models, like AEM noted, leverage variations play a central role for asset pricing in equilibrium.[7]

In our econometric model, the intermediaries' aggregate leverage LEV (in log) is given by:

$$LEV = \mu_l + b_d e^d + b_s e^s, \tag{1}$$

where b_d and b_s are positive parameters. We ignore the time subscript for clarity in this section but we introduce it in the empirical analysis. The shocks e^d and e^s are independent with zero means and unit standard deviations. The superscripts d and s indicate that there are two types of shocks. We label these shocks demand and supply shocks, respectively, but these labels are devoid of economic content based on Equation (1) alone.

We introduce the intermediaries' marginal value of wealth ϕ as follows:

$$\phi = \gamma + \alpha_d e^d - \alpha_s e^s, \tag{2}$$

where α_d, α_s and γ are positive preference parameters. The opposite signs with which e^d and e^s enter the marginal value of wealth provide the economic interpretation that these shocks capture demand- and supply-like disturbances, respectively. The demand-side shock e^d lifts leverage and the marginal value of wealth, for example, when investors' order imbalances increase. The supply-side shock e^s lifts leverage but in this case the marginal value of intermediaries' wealth declines, for

[7] The role of leverage emerges when raising new equity is costly or takes time. Adrian and Shin (2010a) 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 slow-moving variable. Hence, leverage and total assets tend to move in lockstep at quarterly or shorter frequencies. The leverage constraint is the focus of several other theoretical papers. See He and Krishnamurthy (2018) for an insightful review.

example, when funding conditions improve for intermediaries. The magnitudes of α_d and α_s determine the relative contributions of demand- and supply-sided disturbances, respectively, to the variability of the marginal value of wealth ϕ. In one of the robustness checks, we add to the pricing kernel a source of aggregate risk that is unrelated to leverage.

We introduce financial assets indexed by i with excess returns xR_i given by:

$$xR_i = \mu_i + \beta_{i,d} e^d + \beta_{i,s} e^s + e^i, \tag{3}$$

where the shock e^i is uncorrelated with other shocks and, based on the interpretation of the demand and supply shocks, we expect that $\beta_{i,d} < 0$ and $\beta_{i,s} > 0$ for risky assets. Finally, we assume that the intermediaries price financial assets and that their marginal value of wealth spans the pricing kernel:

$$\mathrm{E}\big[xR_i\big] = -\frac{\mathrm{Cov}\big[\phi, xR_i\big]}{\mathrm{E}\big[\phi\big]}, \tag{4}$$

which is a defining relation in the intermediary asset pricing literature. Equations (1)-(4) pin down the expected returns $E[xR_i] = \mu_i$ in Equation (3) as follows:

$$\mu_i = \beta_{i,d}\lambda_d + \beta_{i,s}\lambda_s = \beta_i^\top \lambda, \tag{5}$$

with $\lambda_d = -\alpha_d \gamma^{-1}$, $\lambda_s = \alpha_s \gamma^{-1}$, $\beta_i^\top = [\beta_{i,d} \;\; \beta_{i,s}]$, and $\lambda^\top = [\lambda_d \;\; \lambda_s]$. We list 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)-*

(4), *then:*

i. The return betas of assets that are risky with respect to leverage demand and supply shocks are negative and positive, respectively:

$$\beta_{i,d} < 0 \qquad \beta_{i,s} > 0.$$

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

$$\lambda_d < 0 \qquad \lambda_s > 0.$$

B. Leverage and asset pricing

This econometric model can help understand existing asset pricing results that use the leverage innovations $L = LEV - E[LEV] = \big(b_d e^d + b_s e^s\big)$ in two-stage asset pricing regressions. The first-stage regressions of returns on the innovations lead to estimates of the following leverage betas $\beta_{i,l}$ in population:

$$\beta_{i,l} \equiv \frac{\text{Cov}(L, xR_i)}{\text{Var}(L)} = \big(\sigma_l^2\big)^{-1}\big(b_d\beta_{i,d} + b_s\beta_{i,s}\big), \tag{6}$$

where $\sigma_l^2 \equiv \text{Var}(L) = b_d^2 + b_s^2$. Equation (6) shows that the leverage beta $\beta_{i,l}$ can take either sign because it mixes the demand and supply betas with positive weights b_d and b_s.

The opposite influences of leverage demand and supply shocks also determine the estimate of the price of leverage risk. With no loss in generality, suppose that the cross-sections of the demand and supply betas have population standard deviations ω_d and ω_s as well as covariance $\omega_{ds} = \rho\omega_d\omega_s$. Then, the price of leverage risk λ_l in population in the cross-sectional regression of average returns on the leverage betas is given by:

$$\lambda_l = c\left(b_s\omega_s^2\lambda_s + b_d\omega_d^2\lambda_d + \omega_{ds}(b_s\lambda_d + b_d\lambda_s)\right), \tag{7}$$

where $c = \sigma_l^2(b^\top\Omega b)^{-1} > 0$ with $\Omega = \text{Var}(\beta_i)$. Equation (7) shows that the sign of λ_l depends on the dispersions and correlation of demand and supply betas. We add two more implications of the model that we will test in Section III.

IMPLICATION 2: *If the intermediaries' leverage and marginal value of wealth, as well as the asset returns are driven by demand and supply shocks e^d and e^s as in Equations (2)-(4), then:*

i. Equation (6): the leverage betas $\beta_{i,l}$ is a weighted average of the demand and supply betas.

ii. Equation (7): the price of leverage risk λ_l is determined by the dispersions and correlation of the demand and supply betas.

II. Identification, Data and Estimation

We will take the model described in the previous section to the data and test its asset pricing implications. In this section, we describe the identification strategy, the data that we use and the estimation method. In Section A, we introduce an instrument, exploit the asset pricing implications to identify the shocks e_d and e_s and offer closed-form expressions for the structural parameters in terms of moments of the data. In Section B, we extend this identification strategy to add another source of aggregate risk and discuss some of the model assumptions. Section C describes the estimation procedure based on linear regressions, Section D constructs an instrument based on measures of funding conditions that intermediaries face, and Section E describes the test assets used in estimation.

A. Identification

We assume that we observe an instrument Z that is correlated with the intermediary's leverage and value of wealth:

$$Z = \mu_Z + a_d e^d - a_s e^s, \tag{8}$$

where $a_d, a_s > 0$ and we construct the following system linking the observed innovations u to the structural shocks e:

$$u = \begin{bmatrix} u^z \\ u^l \end{bmatrix} = \begin{bmatrix} Z - \mu^z \\ LEV - \mu^l \end{bmatrix} = \begin{bmatrix} a_d & -a_s \\ b_d & b_s \end{bmatrix} \begin{bmatrix} e^d \\ e^s \end{bmatrix} = Ae. \tag{9}$$

The choice of signs for a_d and a_s is without loss of generality, as long as the econometrician knows how to choose the signs based on a priori economic reasoning (given the instrument). We discuss our choice of instrument in Section D.

The first set of identification restrictions is standard and comes from the variances of the innovations and that of the shocks:

$$\text{Var}(u) = AA^\top. \tag{10}$$

Empirically, the left-hand side of Equation (10) can be recovered as the variance of the innovations u. Since the variance matrix is symmetric, Equation (10) embeds three restrictions but four parameters (a_d, a_s, b_d, b_s). The problem of achieving point identification is to find and exploit an additional economic restriction to recover the parameters and, therefore, the shocks. A long-standing identification strategy in macroeconomics restricts one of these parameters to zero, which implies that one variable does not respond contemporaneously to one of the shocks, but restrictions on the timing of responses are harder to motivate in financial markets.

We propose a novel identification approach that exploits the asset pricing implications from the model. We include a detailed derivation in Appendix A. The idea is to first re-write Equation (3) for returns xR_i in terms of the innovations u, where the mapping to the betas $\tilde{\beta}_i$ from ordinary least squares regressions of returns on the innovation is given by: $\beta_i = A^\top \tilde{\beta}_i = A^{-1} E\left[xR_i u\right]$.[8] Substituting in Equation (5) yields:

$$\mathrm{E}[xR_i] = E\left[xR_i u\right]^\top C, \tag{11}$$

where the coefficient $C = [c_z \; c_l]^\top$ can be recovered from a cross-sectional regression of average returns $E\left[xR_i\right]$ on the covariances $E\left[xR_i u\right]$ between individual returns and the reduced-form innovations, as long as the covariances are not co-linear. This reduced-form vector C is related to the structural parameters as follows:

$$C = \left(A^{-1}\right)^\top \lambda. \tag{12}$$

In addition to mapping the observed reduced-form innovations to structural shocks, the matrix A maps the reduced-form covariances to the leverage shocks betas $\beta_i = A^{-1}E[R_i u]$ and the reduced-form prices of risk to the structural parameters $\lambda = A^\top C$. We introduce one economic assumption linking the prices of risk to

[8] This uses the facts that $u = Ae$, $E[u] = 0$ and $\mathrm{Var}(u) = AA^\top$.

identify the model. Such a restriction can be summarized with $\lambda_s = -\kappa\lambda_d$, where $\kappa > 0$ to be consistent with Equation (2).[9] This produces the following restriction on the parameters of A in terms of the data, as follows:

$$\frac{c_l}{c_z} = \frac{a_s - a_d\kappa}{b_s + b_d\kappa}, \tag{13}$$

and, for a given κ, we can combine Equations (10) and (13) to obtain closed-form expressions for the parameters of the A matrix. Exploiting the restriction in Equation (13) requires that the regression coefficient C is well-defined and that the instrument is priced in the cross-section of the test assets $|c_z| > 0$. One simple and useful choice is $\kappa = 1$, in which case the prices of risk are symmetric $\lambda_d = -\lambda_s$ and the cross-section of returns is determined by the patterns of betas across demand and supply. We group the identification assumptions with the closed-form solutions in the following:

ASSUMPTION 1: *If the shocks e^d and e^s are independent with zero means and unit standard deviations, the parameters a_s, a_d, b_s and b_d are positive and we assume that the prices of risk are symmetric $\lambda_d = -\lambda_s$ when $\kappa = 1$, then the structural parameters are identified and given by:*

$$\begin{aligned} a_d &= \frac{\sigma_z^2\varphi_a}{2a_s} \qquad & a_s &= \sigma_z\sqrt{\frac{1 \pm \sqrt{1-\varphi_a^2}}{2}} \\ b_d &= \frac{\sigma_l^2\varphi_b}{2b_s} \qquad & b_s &= \sigma_l\sqrt{\frac{1 \pm \sqrt{1-\varphi_b^2}}{2}}, \end{aligned} \tag{14}$$

[9]We are indebted to Bruno Feunou for insightful discussions around this approach to the identification problem. Note that the case with $\kappa = 0$ collapses to a model with only one type of leverage shocks, as in AEM.

where $\varphi_a, \varphi_b \leq 1$ depend on the moments $\text{Var}(u)$ *and C (see Appendix A).*

The ambiguous sign $\pm$ requires choosing the solution that satisfies Equation (9) but satisfying $a_d, b_d > 0$ may not be possible if $\varphi_a, \varphi_b \leq 0$ in the data which would mean that the sign-identified set is empty or does not include a solution with symmetric prices of risk.

B. Discussion

Our strategy builds on the earlier analysis of AEM in allowing for distinct leverage demand and supply shocks. Identification of these shocks relies on sign restrictions together with one restriction on the prices of risk, leading to the solution in Equation (14). We stress that these identification assumptions are a useful step in establishing that both types of shocks play important roles and to offer further support for intermediary asset pricing. We will explore in the empirical analysis how some other model implications vary around the symmetry case and check that our core message remains unchanged.

The symmetry restriction is needed because we cannot separately identify the contributions of each type of shocks to the variance of the stochastic discount factor ϕ from the structural betas using only the observed dispersion of returns $\overline{xR_i} = \beta_i^\top \lambda$. Assuming symmetry means that demand and supply shocks have equal contributions to the variance of the stochastic discount factor and, therefore, that the dispersion of returns follows from the dispersion in the betas. An increase in one of the prices of risk raises the importance of the corresponding type of shocks and shifts the relative dispersions of the betas, but it results in the same fit of the price of raw leverage risk λ_l and the same fit in both stages of the asset pricing regressions.

The baseline model assumes that no shocks other than the leverage demand and supply shocks enter the pricing kernel. An important extension is to introduce a new aggregate shock e^m and the pricing kernel becomes:

$$\phi = \gamma + \alpha_m e^m + \alpha_d e^d + \alpha_s e^s, \tag{15}$$

where $\alpha_m > 0$ is a positive parameter. This shock enters the returns equation for every asset, including the market returns xR_m, so that this more general model can be summarized by:

$$\begin{bmatrix} Z - \mu_z \\ L - \mu_l \\ xR_m - \mu_m \end{bmatrix} = \begin{bmatrix} a_d & -a_s & 0 \\ b_d & b_s & 0 \\ -b_{m,d} & b_{m,s} & b_{m,m} \end{bmatrix} \begin{bmatrix} e^d \\ e^s \\ e^m \end{bmatrix}, \tag{16}$$

The two exclusion restrictions mean that this new aggregate shock captures risks uncorrelated to the leverage shocks. Together with the symmetry restriction on the price of risk, these exclusion restrictions yield point-identification and closed-form expressions for the parameters. Results based on this extended model are consistent with our baseline results (Appendix B).

Our contribution is to ask whether there is more than one type of shocks underpinning the role of intermediaries' leverage in asset markets. We do not claim that there are exactly two sources of leverage risk. Instead, the two shocks e_d and e_s that we recover will likely commingle a variety of demand or supply disturbances. Leverage demand shocks may originate from the portfolios decision of households or firms, across a range of markets, or from the actions of asset managers holding wealth on their behalf, such as mutual funds, pension plans or insurers. Leverage supply shocks could originate from decisions of the dealers or from the decisions of their lenders.

The assumption that the demand and supply shocks are uncorrelated is common to a large literature attempting to separate demand- and supply-like shocks. It is useful in that it delivers a projection on two types of leverage shocks, and establishes the importance of having more than one type of leverage shocks. However, we do not claim that some of the true shocks affecting the economy influence the demand for intermediation exclusively and that others influence its supply. In fact, the same shock or set of shocks is likely to drive at the same time the decisions of households, firms, lenders and dealers, and may influence leverage trough both demand and supply mechanisms.

While there are limits to the type of questions that we can confidently answer in the framework that we propose, these assumptions are appropriate to explore the importance of demand- and supply-sided disturbances, relative to a baseline where only one type of shock operates, as well as to provide empirical guidance on the relative importance of demand- and supply-sided mechanisms that are likely to explain the sources of leverage risk. Based on the guidance that emerges from our results, deeper models for the behaviors of dealers and investors will be needed to further our understanding of leverage risk.

C. Estimation

We specify a parsimonious vector autoregressive (VAR) model to account for the predictable variations in leverage and the instrument, so that we can recover the covariance matrix of the unpredictable innovations. We introduce the time subscript t and the VAR model for $y_t = [LEV_t \; Z_t]^\top$ is given by:

$$y_{t+1} = a + \Phi y_t + u_{t+1}, \tag{17}$$

where Φ is a 2×2 coefficient matrix. We estimate the VAR by ordinary least squares, recover the forecast errors $\hat{u}_{t+1}$ and their covariance matrix $\hat{\Sigma}_u$.

Next, we recover the coefficient $\hat{C}$ in Equation (12) from a cross-sectional ordinary least-square regression of the sample average returns $E_T[xR_i]$ on the sample covariances $E_T[xR_i u]$ between individual returns and the innovations without a constant. Results are robust if we include a constant. We recover the matrix $\hat{A}$ using Equation (14), the price of risk $\hat{\lambda}$ using Equation (12) and the leverage shocks using $\hat{e}_t = \hat{A}^{-1}\hat{u}_t$.

The standard errors in what follows are based on a bootstrap procedure that account for the sampling variations due to estimation of the VAR dynamic model, the average returns $E_T[xR_{i,t}u_t]$, the covariances $E_T[xR_{i,t}u_t]$ and the coefficient C. We use a block bootstrap to deal with potential serial correlation and heteroscedasticity of unknown form. Details of the bootstrap are available in Appendix C.[10]

D. Measures of Leverage and Funding Conditions

We select a measure of leverage, an instrument and a cross-section of test assets to implement the estimation procedure described above. We follow AEM and compute the broker-dealers' leverage LEV using quarterly data from the Federal

[10] Estimation of the VAR and of the reduced-form regressions within the GMM framework may improve efficiency but we prefer the simplicity and robustness of the linear regression and we elect to develop a bootstrap procedure to improve the finite-sample inference.

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 financial assets and liabilities.

Next, we construct an instrument that satisfies three requirements. First, in the context of our model, a valid instrument must exhibit a pattern of covariances with returns that aligns with the cross-section of average returns (i.e., $|c_z| > 0$ in Equation 13). Second, it must be that we can plausibly sign the correlation of this instrument with leverage shocks (i.e., $a_s, a_d > 0$). These first two requirements are technical in nature. The last requirement is that the instrument together with leverage are a price and quantity pair that can be plausibly interpreted in terms of demand and supply shocks.

We combine three well-established proxies for funding conditions, building on a strand of literature going back to the pioneering work of Gromb and Vayanos (2002) and Longstaff (2004) and more recently of Du, Hébert, and Huber (2022).[11] We focus on three proxies derived from the US Treasury markets.[12] First, we use the well-known TED spread: the spread between the EuroDollar LIBOR rate and the T-bill rate. Frazzini and Pedersen (2014) use it in regressions to test for a link

[11]Du, Hébert, and Huber (2022) make clear that any generic measure of no-arbitrage deviations can also help in pricing the cross-section of asset returns in combination with measures of leverage or intermediaries' wealth. While they use CIP violations in empirical analysis, we select other measures that span a longer time period and our results support their prediction.

[12]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).

between funding conditions and the betting-against-beta factor in the U.S. Second, we rely on a well-accepted measure that aggregates deviations of individual bond yields from a smooth parametric curve and that was introduced by Hu, Pan, and Wang (2013) to conduct asset pricing tests across hedge funds and currencies returns. Goldberg (2020) and Goldberg and Nozawa (2021) implement a similar measure in the market for Treasury and corporate bonds, respectively. 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 and test its predictive content for risk premia across several securities markets. We label these three proxies TED, HPW and FG, respectively.

Figure 1 around here.

These proxies exhibit important commonalities despite differences in their construction. Panels (A)-(C) of Figure 1 plot the monthly time series in our sample, between January 1986 and December 2021, showing that they share the same peaks and troughs. The TED proxy features peaks following the crash of 1987, at the beginning of 2000, during the financial crisis of 2008 and, of course, during the COVID-19 financial crisis. 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 the very high 2008 peak makes some of them harder to distinguish.[13]

[13]The TED proxy has a correlation of 0.54 and 0.53 with FG and HPW, respectively, while the correlation between FG and HPW is 0.29. The correlations are not driven by the 2008 financial

We extract the first principal component from these three measures and label this proxy for funding conditions $FUND$, we set its sign such that a higher value of $FUND$ indicates higher marginal value of wealth, and we set $Z_t = FUND_t$. We expect that the principal component can extract a more precise signal of the funding conditions than any of the individual proxies. Fontaine, Garcia, and Gungor (2016) show that the funding conditions proxy $FUND$ is priced and, therefore satisfies the first necessary condition for identification. In addition, we can plausibly sign the relationship between these measures, on the one hand, and leverage demand and supply shocks, on the other hand. The idea behind each measure is that the wedge between the prices of assets with identical cash-flows can proxy for the intermediaries' marginal value of wealth and, therefore, exhibit positive correlations with demand shocks but negative correlations with supply shocks.[14] This link with the marginal value of wealth also means that a proxy for funding conditions together with a measure of leverage makes a price-quantity pair.

E. 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 portfolios of securities sorted on betas with respect to three types of risk. We use equally-weighted returns for portfolios of options or bonds

crisis. After the crisis, the TED proxy has a correlation of 0.26 and 0.48 with FG and HPW, respectively, and the correlation between FG and HPW is 0.30.

[14] In a model that shares several features with Brunnermeier and Pedersen (2009), for some securities i and j that have identical cash flows but different margins m_i and m_j, Gârleanu and Pedersen (2011) show that the wedge between the expected returns μ_i and μ_j is given by $|\mu_i - \mu_j| = \phi(m_i + m_j)$.

but we use value-weighted returns for portfolios of equities. Appendix D provides more details about the test assets.

Equities and corporate bonds We use the following betas to sort equities and corporate bonds into decile portfolios:

$$\beta_i^{\Delta Illiq} = \frac{cov(\Delta Illiq_m, xR_i)}{var(\Delta Illiq_m)} \quad \beta_i^{\Delta\sigma} = \frac{cov(\Delta\sigma_m, xR_i)}{var(\Delta\sigma_m)} \tag{18}$$

$$\beta_i^{\Delta FUND} = \frac{cov(\Delta FUND, xR_i)}{var(\Delta FUND)},$$

where Δ is the first-difference operator, $Illiq_m$ is the stock market illiquidity and σ_m is the stock market volatility. 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. Acharya and Pedersen (2005) also use theoretical considerations to build three sets of β-sorted portfolios representing different forms of liquidity risk. The equity portfolios sorted on illiquidity and volatility betas span period from 1986 to 2021 and the portfolios sorted on funding betas span a shorter period from 1989 to 2021.

Table A1 in the Appendix provides summary statistics, where we report the average returns, illiquidity, volatility, market capitalization, and ex-ante beta estimates for equity portfolios. Sorting on the betas tend to produce a U-shaped patterns in volatility and illiquity across portfolios and inverted U-shaped patterns in market capitalization. However, sorting on these betas create similar monotonic patterns in the illquidity-, volatility-, and funding-betas across portfolios, except in some cases for the extreme portfolios with lowest returns. These broad similarities are consistent with the prediction, in the model of Brunnermeier and Pedersen (2009), that these covariances 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.

Options For options, we use portfolios of unlevered S&P index call and put options with different strike prices and maturities from Constantinides et al. (2013), who show that pricing unlevered options returns remains challenging, especially for puts, but that a proxy for illiquidity goes a long way toward reducing pricing errors. The series are available from 1986Q2 to 2021Q4.[15]

Treasuries For Treasury bonds, we compute returns for bonds with maturities of 2, 3, 4, 5, 7 and 10 years using security-level data available from the Center for Research on Securities Prices (CRSP). For each month and each maturity category, we select 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. These bonds have different interest-rate 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 repeat the same procedure. Finally, we aggregate the monthly bond returns over each quarter during the sample from 1986Q2 to 2021Q4. This creates a panel of returns for twelve bonds.

[15] We thank Alexi Savov for providing us with the code to update the option portfolios.

III. Leverage Shocks in Securities Markets

The model presented in Section 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 positive for supply shocks and negative for demand shocks. We will test these predictions across several asset classes, but first we describe the structural shocks that we recover.

A. Leverage Shocks

Impulse responses Both supply and demand shocks play significant roles in the dynamics of leverage. The contemporaneous impacts of the shocks on LEV and $FUND$ is given by the matrix $\hat{A}$, with 95-percent bootstrap confidence intervals:

$$\hat{A} = \begin{bmatrix} \begin{matrix} 0.58 \\ (0.27, 0.77) \end{matrix} & \begin{matrix} -0.34 \\ -(0.55, 0.02) \end{matrix} \\ & \\ \begin{matrix} 5.16 \\ (2.03, 8.35) \end{matrix} & \begin{matrix} 3.87 \\ (0.78, 7.46) \end{matrix} \end{bmatrix}, \tag{19}$$

where the signs of a_s and b_s of the initial responses in the second column are given by construction but the magnitudes are estimated from the data. Both the sign and magnitude of the responses a_d and b_d in the first column are estimated, and the signs are consistent with the interpretation of $FUND$ and LEV as a price-quantity pair.

Figure 2 around here.

The impulse response functions translate the parameter estimates $\hat{\Phi}$ and $\hat{A}$ in economically meaningful results. Panels (A)-(B) of Figure 2 show the future responses of leverage to current supply and demand shocks, respectively, scaled in units of standard deviations. We find that a one-standard-deviation supply shock raises leverage by 0.35 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 close to 0.5 standard deviation and the effect disappears after about one year. Goldberg (2020) as well as Goldberg and Nozawa (2021) also 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. Panels (C)-(D) shows the responses of the funding conditions proxy. A one-standard-deviation supply shock lowers $FUND$ by 0.2 standard deviation, the effect disappears after about one year but the estimates are relatively less precise. A one-standard-deviation demand shock increases $FUND$ by 0.4 standard deviation and the effect disappears after more than two years.

Historical decomposition We report in Figure 3 a decomposition of the leverage innovations $LEV_{t+1} - E_t[LEV_{t+1}]$ into the demand and supply components. We find that both leverage shocks played important roles around periods of stress in financial markets. Negative supply shocks occurred with positive demand shocks, both contributing to worsen funding conditions, around the 1987 stock market crash, around the year 2000 millenium market stress, as well as during the COVID-19 financial crisis in 2020. The leverage demand shock that we estimate in the first quarter of 2020 appears small and may reflect the large and successful financial support interventions by the fiscal and monetary authorities.

Figure 3 around here.

Positive demand shocks are also apparent during periods with small or positive supply shocks: around the 1994 bond market downturn, in 1998 following the LTCM collapse and the Russian default, and during the period of the financial crisis (2007 to 2008), which exhibits a huge spike in the third quarter of 2008. The large Fed interventions kept funding conditions afloat during that period, which may explain the positive supply shocks that we estimate 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 to 2003). They occurred together with positive demand shocks in the former period and negative demand shocks in the latter. This resulted in higher leverage mostly due to supply shifts and was associated with improved funding conditions in both periods (see also Figure 1).

Robustness One important question is whether the structural shocks that we recover are sensitive to the choice of the instrument. In Table A2 of the appendix, we report the correlations between leverage shocks recovered with $FUND$, with $FUND$ in the more general model with an additional market shock, or with the average of TED, FG and HPW instead of the principal components. The correlations range between 0.79 and 0.99 for leverage demand shocks and between 0.64 and 0.98 for leverage supply shocks, except when using HPW which exhibits a few instances with a lower correlation.

B. Leverage Shocks in Asset Pricing Tests

Asset pricing—baseline results Panel (A) of Figure 4 reports the bootstrap distribution for the price of risk from the estimated model with a dashed vertical line indicating the sample estimate $\hat{\lambda} = 2.12$. The estimate is statistically significant with a 95% confidence interval $[1.4, 3.6]$, the distribution's center is located close to the sample estimate and some asymmetry is visible, which underlies the merit of using a bootstrap procedure (instead of an asymptotic normal distribution). Figure A3 in the appendix reports results for the model extended with one source of aggregate risk uncorrelated with leverage shocks. We find a similar and significant price of risk for leverage shocks, a similar fit, and a small and statistically insignificant price of risk associated with the additional uncorrelated shocks.

Figure 4 around here.

Figure 5 illustrates how important it is to disentangle the two sources of leverage risk. Each panel in this figure reports the fitted values associated with a given asset pricing model together with the 45-degree line that would arise if the fit were perfect. Panel (A) reports the results using the disentangled supply and demand leverage shocks from the estimated econometric model with symmetric prices of risk. Panel (B) reports results of a regression model that uses the market returns together with the raw leverage innovations from the VAR. We keep the same number of pricing factors across models in these panels, but note that our model of interest has a more parsimonious cross-section equation with only one price-of-risk parameter.

Figure 5 around here.

Contrasting both panels, we can see the improvement in fit due to disentangling leverage shocks: the $\bar{R}^2$ increases from 84 to 92% despite using a more parsimonious model. We can use the bootstrap procedure to gauge the statistical precision of this result. Panel (B) of Figure 4 reports the bootstrap distribution for the adjusted $\bar{R}^2$ from our baseline model, showing a confidence interval that ranges between 78 and 98%. The $\bar{R}^2$ value obtained with a model that combined raw leverage innovations and the market returns is narrowly within this interval, but much of the fit is due to the presence of the market factor. In the next section, we show that the $\bar{R}^2$ is substantially lower when using leverage alone.

These baseline results from the econometric model provide strong evidence that intermediaries' leverage is an important source of risk and that it is compensated in financial markets. Separating leverage innovations into supply- and demand-sided disturbances that have opposite correlations with funding conditions and opposite effects in financial markets offers an accurate picture of the risks-returns relationship across bonds, stocks and options. Leverage supply and demand shocks help explain a large share of the cross-section dispersion of returns across the three markets. These results will follow through in other tests across diverse asset classes.

Asset pricing—Fama-Macbeth regressions We now use two-stage regressions to provide a detailed and transparent comparison with asset pricing models that use the raw leverage, where we follow the calculations in AEM to obtain the leverage factor.[16] We first compare with regression results based on the leverage demand shocks or leverage supply shocks, separately, or together with symmetric prices of risk. This will show that both types of shocks are important. We then extend the comparison across models that include the market returns as one of the

[16]We normalize the leverage factor to have zero mean and unit variance like the structural shocks. Results are very similar if we use the leverage innovations from the estimated VAR.

pricing factors, as suggested by AEM, to confirm that our results are not subsumed by including the market.

Table I around here.

Table I reports the price-of-risk estimates based on the stock, option and bond portfolios, jointly, from asset pricing models that exclude a constant in the second-stage regression. 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 report the t-test statistics based on Shanken (1996) standard errors. However, we take the structural shocks as given and, from now on, we ignore the sampling uncertainty due to the estimation of the VAR parameters, in the case of the demand and supply shocks, or due to the seasonality adjustments, in the case of the leverage. We also take out a balanced panel when many asset classes are combined.

We report a 95% confidence interval for the uncentered $\bar{R}^2$ measure of fit in the second-stage regression, which follows the recommendation and methodology in Lewellen, Nagel, and Shanken (2010). This confidence interval cannot be directly compared with the bootstrap interval obtained in the full model and, in addition, it is not clear if one should be narrower than the other. On the one hand, estimation of the full model generates additional sampling variability due to the estimation of the VAR. On the other hand, the structural shocks are re-estimated in the full model as the returns vary across bootstrap samples, while the factor loadings are fixed in the LNS bootstrap procedure.

In Column (1), we report the results using the leverage factor ΔLEV alone. The price of leverage risk is positive and statistically significant but one order of magnitude smaller than AEM's estimates, The $\bar{R}^2$ measure of fit is 8% with a wide confidence interval ([2, 37]). Overall, the evidence is consistent with the message in AEM but weaker, most likely because we used different test assets and a different sample period. In Section IV, we revisit AEM test assets and reconcile the results with our key messages.

Columns (2)-(3) of Table I report the results based on the leverage supply and leverage demand shocks taken separately. The price of risk is positive for supply shocks, negative for demand shocks, as expected and significant in each case, consistent with our baseline results. The measures of fit are essentially the same with almost identical confidence intervals, and close to what we find in Figure 5. This pattern is due to a high but negative correlation between the returns betas for supply and demand shocks, which we explore in Section C.[17]

Column (4) combines the demand and supply shocks, imposing the symmetry constraint $\lambda_s = -\lambda_d$. To implement the symmetry restriction in the second-stage regression, we estimate the price of risk for the difference $\beta_s - \beta_d$. The price-of-risk estimate is significant, close to the structural model estimate (2.02 vs 2.12) and within the bootstrap distribution in Figure 4. The difference between the two estimates arises because we use a balanced panel in the two-stage regression but the unbalanced panel in the model estimation.[18] The $\bar{R}^2$ is essentially unchanged

[17]It may seem intuitive to use the shocks e^d and e^s in a two-stage regression and test whether the unrestricted price-of-risk estimates are symmetric. However, the population values in this regression are the same as the price-of-risk parameter in the model because we used symmetry to identify these shocks. This can be checked empirically using the bootstrap procedure under the maintained hypothesis that the symmetric model is correctly specified. We show in Figure A2B that the bootstrap distribution for the estimate of $\lambda_d + \lambda_s$ is centered on zero, as expected, and that our estimate falls on the 22nd percentile.

[18]The balanced panel is shorter than the full sample that we use to estimate the structural

in Column (4) relative to Column (2) or (3), the confidence interval is narrower ([85,99]) but the magnitude of the price-of-risk estimate decreases relative to when we use only one type of shocks. Again, this happens because the supply and demand returns betas are correlated so that ignoring either the demand or the supply shocks in Columns (2)-(3) creates an upward omitted-variable bias but leaves the fit unchanged.

In Columns (5)-(8), we report similar results for models that include the market returns, following one recommendation in AEM. We follow Lewellen, Nagel, and Shanken (2010) and include the market returns among the test assets to discipline its price-of-risk estimate. Column (5) shows that the price of risk for raw leverage is lower and insignificant with this set of test assets. The fit increases considerably to 87 percent when we include the market returns and the confidence interval is [71, 98]. Columns (6)-(8) show that including the market returns in the asset pricing model with demand or supply shocks yields similar price-of-risk estimates. This suggests that market risk is priced, as expected, but that market betas contribute little to the fit once we already include leverage demand and supply shocks. This is supported by the observation that the fit and the $\bar{R}^2$ confidence intervals improve only marginally. Columns (9)-(12) confirm this intuition by using univariate β's in the second-stage regression, following Cochrane (2009) and Gospodinov and Robotti (2021). Column (9) shows that the univariate market betas yield a significant estimate for the price of market risk when combined with the leverage factor. However, when combined with leverage demand or supply shocks, we find a smaller and statistically insignificant price of market risk (the

model. This causes the correlation between demand and supply shocks to differ from zero in sub-samples, which causes small differences in the betas estimate from the first stage.

R^2s are mechanically identical with univariate betas)

Weak instruments One important concern is that the reduced-form regressions used as one of the moment conditions to estimate the econometric models is based on weak pricing factors. In such a case, the $\tilde{\beta}$ matrix would be ill-conditioned and could contaminate our results, since $\beta_i = A^\top \tilde{\beta}_i$ would also be ill-conditioned. The main concern is whether the reduced-form β estimates are jointly close to zero. A F-test of the null of $\beta_i = 0$ equation-by-equation rejects for 105 of the test assets (roughly 85% of the test assets) at the 5% level with a p-value below 1% in most cases, and the joint test of the null of zero for all equations jointly yields a p-value that is numerically indistinguishable from zero. We are not concerned with the possibility that the β_is are (nearly) collinear since we estimate the model with symmetric prices of risk and without a constant in the cross-section regression.

Given these results, one essential identification condition in our model is that the price of risk for the instrument $FUND$ must be different from zero. In Panel (A) of Figure A2 of the appendix, we report the bootstrap distribution of this reduced-form price of risk. We find the point estimate $\hat{c}_z = -1.19$ and the 95-percent bootstrap confidence is $[-2.2, -0.7]$.

Symmetry The symmetry assumption selects one point in the set of parameters satisfying the sign restrictions. Here, we explore this sign-identified set where the prices of risk are not symmetric and find that our core messages hold. Across most of the set, the prices of risk keep the same signs, their magnitudes remain within the confidence interval obtained for the symmetric case, and the dispersions of betas for each type of shocks have comparable scales. Therefore, disentangling demand and supply-sided effects remains essential to understand the source of leverage risks.

We index the model parameters across the identified set with the superscript j.[19] Panel (A) of Figure 6 shows $\lambda_s^{(j)}$ and $\lambda_d^{(j)}$ with values reported on the right and left y-axis, respectively, against $\lambda_d^{(j)} + \lambda_s^{(j)}$ on the x-axis, which measures the asymmetry. The ranges for these parameters are $-\lambda_d^{(j)} \in [0.4, 2.9]$ and $\lambda_s^{(j)} \in [0.7, 3.0]$, respectively, which we can heuristically compare with the statistical confidence interval $\hat{\lambda} \in [1.4, 3.6]$ obtained in the symmetric model.

Figure 6 around here.

While the results show that the signs and magnitude of the prices of risk are robust across the identified set, we also find that our data is largely uninformative about the degree of asymmetry. Using the matrices $A^{(j)}$, we recover series of structural shocks in each case and run two-stage regressions to evaluate if the prices of risk that we recover are "far" from symmetric. For completeness, Panels (A)-(B) of Figure A4 in the appendix report the distributions of the estimates $\hat{\lambda}_d^{(j)}$ and $\hat{\lambda}_s^{(j)}$. As expected, the estimates have the expected sign in every case. Panel (C) shows that the value $\hat{\lambda}_d^{(j)} + \hat{\lambda}_s^{(j)}$ ranges from around -2 to +3 and that the distribution is essentially flat. Panel (D) shows that only a small proportion of the Shanken t-statistics for a test that this sum is zero exceeds the 1.96 cutoff value that would indicate a rejection of symmery.[20] The flat distribution and the low t-statistics

[19]We start with 2×2 orthonormal rotation matrix $\Gamma^{(j)}$ indexed with $j \in [0, 2\pi]$ and such that $A^{(j)} = A(\Gamma^{(j)})^{-1}$ satisfies the sign restrictions. Then, $\lambda^{(j)} = \Gamma^{(j)}\lambda$ and $\beta^{(j)} = \Gamma^{(j)}\beta$.

[20]We use the GMM framework to derive standard errors à la Shanken that account for the symmetry restriction. See Section 12 in Cochrane (2009). This ignores the sampling variability due to the VAR and likely over-estimates the statistically significance of the sum.

suggest that the cross-section of returns is not informative about the degree of asymmetry.

Nonetheless, allowing for asymmetry changes the interpretation of some of the results. Panel (B) of Figure 6 reports the cross-section dispersions of $\beta_{i,d}^{(j)}$ and $\beta_{i,s}^{(j)}$ on the y-axis against the asymmetry on the x-axis. We find that, as one of the prices of risk increases relative to the other, the dispersion of the corresponding betas is also higher, which mechanically increases the role played by one of the shocks in explaining the cross-section of returns. Panel (C) reports the leverage loadings $b_d^{(i)}$ and $b_s^{(i)}$ and Panel (D) reports the funding conditions loadings $a_d^{(i)}$ and $a_s^{(i)}$ across the identified set. These results show that a very high degree of asymmetry can generate counter-intuitive implications. If leverage supply shocks are given the largest weight in explaining asset returns, then the model implies that supply shocks play no role in the variations of broker-dealers leverage, which is at odds with AEM as well as with economic intuition. At the other extreme, if leverage demand shocks are given the largest weight, then the model implies that leverage supply shocks play no role in the variations of the funding conditions instrument. To summarize, the cross-section of returns is largely uninformative about the degree of asymmetry but a very high asymmetry in either direction seems to produce counterintuitive implications. Additional data and deeper economic modelling will be necessary in future research to bear on this question.

Other Equity Portfolios We have used value-weighted stock portfolios sorted on exposures to illiquidity, volatility and funding liquidity risks. This strategy is grounded in theory but it differs from traditional test portfolios from the equity market. Table A3 in the appendix repeats the main joint asset pricing tests but with different portfolios of stocks, keeping other test assets unchanged. Using these portfolios, which have not been used in estimating the leverage shocks, is a form of out-of-sample asset pricing test. We find similar estimates of the prices of risk for leverage supply and demand shocks when using (i) the Fama-French portfolios sorted on size, value, profitability and investment (Fama and French, 2015), (ii) equal-weighted versions of the portfolios sorted on illiquidity, volatility and funding conditions betas, and (iii) portfolios sorted on the level of illiquidity and volatility instead of betas (Appendix D.3 explains the construction of these portfolios). In every case, the leverage supply and demand shocks offer substantial improvements relative to a two-factor model with ΔLEV and the market factor. To illustrate the improved fit, Figure A5 in the appendix repeats the analysis in Figure 5 in the main text but substituting the Fama-French portfolios for stocks.

C. Leverage Shocks in Asset Pricing—Individual Asset Classes

In this section, we analyze results separately for each of the three asset classes—equities, bonds and options—to verify the implications spelled out in Section A. We check that the price of risk for leverage shocks has a similar magnitude when estimated separately in each asset class and that the estimates fall within the baseline bootstrap distribution in Figure 4. We also confirm the prediction that the returns betas of leverage demand and supply shocks are negative and positive, respectively. While this was not a prediction of the model, we document that the leverage demand and supply betas are strongly negatively correlated.

Equities The first two columns of Table II report the estimation results for the equity portfolios. In Column (1), we report results based on the combination of raw leverage shocks and the market returns. The price of risk for the raw leverage factor is positive, but smaller than in Table I and statistically insignificant based on the Shanken t-statistic. The combination with the market returns produces a good measure of fit with a narrow confidence interval. In Column (2), we report results based on demand and supply shocks with symmetric prices of risk. The estimate is 2.04, which is close to the baseline result in Table I, and statistically significant.

Table II around here.

We now check whether the returns betas of leverage demand and supply shocks have the expected signs. Panel (A) of Figure 7 reports a scatter plot of the leverage demand-shock betas on the y-axis and the leverage supply-shock betas on the x-axis. The individual supply-shock betas are positive and the demand-shock betas are negative, as expected. In addition, the sample correlation between the estimated betas is -0.89. This marked correlation 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 correlation also explains why using only supply or demand shocks in asset pricing regressions produces inflated estimates relative to using both shocks in the same regression: excluding one or the other source of risk means that the regression exhibits a classical omission bias but a similar fit. The elevated correlation also implies that unrestricted price-of-risk estimates in a model with both shocks will produce imprecise and uninformative inference.

Figure 7 around here.

Bonds We report the analogous results for corporate and Treasury bonds in Columns (3)-(4) of Table II. The raw leverage shocks produce a positive price of risk that is statistically significant based on the Shanken standard errors and a 78% $\bar{R}^2$ that has a relatively wide confidence interval ([58, 93]). The symmetric price-of-risk estimate for demand and supply shocks is 2.04, significant and close with the baseline result. This parsimonious model offers a better fit and a narrower $\bar{R}^2$ confidence interval.

We report a scatter plot of bond betas in Panel (B) of Figure 7. The leverage supply and demand betas have the expected signs and, like for the equity portfolios, they are closely and negatively correlated (-0.74), which means that riskier corporate bond portfolios tend to have the larger leverage supply betas and the more negative leverage demand betas.

Options Columns (5)-(6) of Table II report the analogous results for the option portfolios. In Column (5), we find that the price-of-risk estimate for raw leverage shocks is negative, unlike bonds and equities, and insignificant. In Column (6), we find a significant price-of-risk estimate for demand and supply shocks, 2.22, which is close to the baseline result. We report in Panel (C) of Figure 7 the leverage demand and supply betas, showing that they have the expected signs in every case and exhibit a strong negative correlation, like for bonds and equities.

Other test assets—HKM 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 estimate the price of risk for leverage demand and supply shocks in each asset class with 2-stage regressions that exclude a constant, include market returns and impose the symmetry. The estimates are reported in Table III. We can observe that the price of leverage supply and demand shocks exhibits the expected sign, is significant and has a similar magnitude across equities, US bonds, sovereign bonds, options and CDS. However, the estimates are statistically indistinguishable from zero in commodities and foreign exchange. Like in our baseline results, we conclude that these test assets provide no evidence against the implication for the sign of the price of leverage risk.

Table III around here.

Figure A6 in the appendix reports average and fitted returns associated with the leverage supply and demand shocks in Panel (A) and those associated with the raw leverage factor and market returns in Panel (B). We exclude the commodity test assets for clarity, since we already know from Table III that leverage shocks provide a poor fit for this asset class. 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 also align with 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. Figure 2 from HKM shows large pricing errors for the commodities portfolios, a few of the options and currencies portfolios, and one extreme FF portfolio of small growth firms.[21]

[21] One natural question is whether the equity capital ratio could be used to extract demand and supply shocks. We find that this approach struggles to identify demand shocks: the supply shocks

Summary We see that leverage demand and supply shocks produce consistent estimates with the same sign, similar magnitudes, and a good fit across classes, with a few instances where the evidence is statistically insignificant. 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 between betas 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.

D. 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 mixed evidence for the price of raw leverage risk. The price of risk estimate was negative for options, positive for bonds and equities, and sometimes insignificant. Instead, we verify that the different signs for the betas and the price of risk of raw lever-

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that we recover in this way explain essentially all the variance of the capital ratio. In addition, if we project the capital ratio forecast errors on the supply, demand shocks and aggregate shocks recovered using the broker-dealers leverage, we find that the demand shocks are insignificant, the supply shocks explain around 10 percent of the variance, and consistent with the main conclusion of Gospodinov and Robotti (2021), we find that the market returns explains the largest share of the variations in the capital ratio. While the equity capital ratio is the reciprocal of the leverage ratio, HKM suggested that these differences 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.

age shocks across asset markets can be explained by the underlying patterns in leverage demand and supply betas, as predicted in Section I. Therefore, the results using raw leverage shocks are consistent with the predictions that intermediaries play a key role in asset pricing. Siriwardane, Sunderam, and Wallen (2022) suggest the leverage betas can differ substantially across asset classes because of a segmentation between the funding sources or the balance sheets of intermediaries that are involved across asset classes.

The leverage betas Equation (6) 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:

$$\beta_{i,l} = \left(\sigma_l^2\right)^{-1}\left(b_d\beta_{i,d} + b_s\beta_{i,s}\right).$$

Therefore, the pattern of demand and supply betas $\beta_{i,d}$ and $\beta_{i,s}$ across portfolio sorts and asset classes reveals interesting differences and helps understand why the sign of the raw leverage betas $\beta_{i,l}$ flip sign.

Table IV around here.

In the first four columns of Panel (A) in Table IV, we report the average beta values for the three sets of equity portfolios and for all equity portfolios taken together. In the next four columns, we report the averages for the three sets of corporate bonds portfolios and for all bond portfolios together. Finally, in the last three columns, we report the averages for call, put and all options taken together. As expected, the leverage demand and supply shocks have negative and positive betas in every case. Within bonds, the supply betas tend to be larger than the demand betas, which is consistent with a greater role of dealers in the over-the-counter bond market and in line with the results from Goldberg and Nozawa (2021) who show that dealers' bonds inventory supply shocks help explain expected returns. Within the portfolios of options, the demand returns betas tend to be larger than the supply returns betas, which is consistent with results from Gârleanu, Pedersen, and Pothesman (2009) who show that demand pressure effects on dealers' inventory contribute to explain well-known pricing puzzles for index options.

In the last two rows of Panel (A), we report the sign implied from the model for the returns betas of raw leverage innovations and the sign in univariate regressions. The predicted sign is correct across all bond portfolios, where relatively large supply returns betas tend to produce positive returns betas for raw leverage. The predicted sign is also correct across options, where by contrast the relatively high demand returns betas produces negative returns betas for raw leverage. Therefore, bonds tend to exhibit positive returns and options tend to exhibit negative returns when intermediaries' leverage increases. The results are also consistent across portfolios of stocks, in which case the demand betas are also more dispersed. However, we expect that the precise mix of leverage demand and supply betas can vary with the specifics of the sorting strategies used by researchers.

Figure 8 around here.

The leverage price of risk Equation (7) led to the additional prediction that the raw leverage price of risk is determined by the dispersions and correlations of the leverage supply and demand betas. We repeat this equation here for convenience:

$$\lambda_l = c\lambda_s \left(b_s \omega_s^2 - b_d \omega_d^2 + (b_d - b_s)\omega_{ds} \right),$$

where $c\lambda_s > 0$ and λ_l is the price of raw leverage risk. In the data, the covariance ω_{ds} between demand and supply betas is negative but $\hat{b}_d \approx \hat{b}_s$. Therefore, we expect the price of raw leverage risk to be determined by the dispersions of the supply and demand betas.

To check this prediction, we estimate the price of risk $\hat{\lambda}_l^{ols}$ for raw leverage with OLS separately for each asset class and then check if the dispersions of the demand and supply betas from the econometric model can explain the regression estimates *within* this class. Panel (B) of Table IV reports the dispersions ω_d^2 and ω_s^2 as well as the covariance ω_{ds} for equity, bond and option portfolios separately. We report on the last two rows the sign of $\hat{\lambda}_l$ implied by Equation (7) and the sign recovered based on OLS for each asset class. Leverage demand betas have a wider dispersion across options and equities implying a negative price of risk for raw leverage. In the bond market the leverage supply betas tend to have a wider dispersion implying a positive price of risk. Figure 8 reports a scatter plot of the model-implied and regression estimates across asset classes, together with the 45-degree line (dashed blue) that would result if the fit was perfect. The 45-degree line produces a good fit, as measured by an uncentered R^2 of 45%, and the signs agree in every asset class.

E. Leverage Shocks and Stock Market Liquidity

AEM put forward the puzzling fact that changes in leverage are largely uncorrelated with changes in stock market liquidity. This is a puzzle because of the theoretical prediction, for example, in Brunnermeier and Pedersen (2009), that liquidity and intermediaries' leverage move in tandem. In this section, we extend the econometric model from Section I to help understand the relationship between leverage and measures of market liquidity.

We assume that the illiquidity Λ_i of asset i is proportional to the intermediaries' marginal value of wealth ϕ, as follows:

$$\Lambda_i = \delta_i(\phi - \gamma), \tag{20}$$

where δ_i is a positive parameter and the illiquidity Λ_i corresponds to the notion of price impact. Equation (20) builds on a central implication in the equilibrium model of Brunnermeier and Pedersen (2009).[22] Given Equations (2) and (20), the population coefficients in a regression of illiquidity on the demand and supply shocks are positive and negative, respectively, as follows:

$$\frac{\mathrm{Cov}(e^d, \Lambda_i)}{\mathrm{Var}(e^d)} = -\frac{\mathrm{Cov}(e^s, \Lambda_i)}{\mathrm{Var}(e^s)} = \alpha\delta_i. \tag{21}$$

Note that this symmetry follows from Equation (20) and that it is distinct from the symmetry of the prices of risk that we used for identification of the model. From Equation (1), we also have that regressions of the illiquidity on raw leverage

[22] In Brunnermeier and Pedersen (2009), the parameter δ_i can be interpreted as the margin requirement. Along this line, Jylhä (2018) analyzes how the infrequent changes to Federal Reserve's Regulation T requirements for initial margins between 1934 and 1974 impact the slope of the security market line.

will produce a population coefficient given by:

$$\frac{\mathrm{Cov}(LEV, \Lambda_i)}{\mathrm{Var}(LEV)} = (b_d - b_s)\alpha\delta_i. \tag{22}$$

Therefore, we get two final implications of the model:

IMPLICATION 3: *If the intermediaries' leverage and marginal value of wealth and the asset illiquidity are driven by demand and supply shocks e^d and e^s as in Equations (1)-(2) and (20), then:*

i. Equation (21): the coefficients in a regression of illiquidity on demand and supply shocks yield positive and negative signs, respectively.

ii. Equation (22): the sign of coefficients in a regression of illiquidity on leverage innovations is determined by $(b_d - b_s)$.

One way to check the prediction is to estimate the coefficients of leverage demand and supply shocks in regressions of market liquidity. To run this test, we construct 10 portfolios of stocks sorted on illiquidity by using the Amihud ratio as a proxy. We also construct 10 portfolios of stocks sorted on volatility, measured with the standard deviation of daily returns over the last quarter (see Appendix D.3). In both cases, we start with the same stocks that were used to form the beta portfolios in Table A1. The first set of portfolios exploits the predictions that the 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 volatile on average (Brunnermeier and Pedersen, 2009, pp. 20-21). Using both sets of portfolios adds power to the test.

Table A4 in the Appendix 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 but smaller capitalization. The pattern is almost monotomic across portfolios. Similarly, the more volatile portfolios exhibit lower liquidity and smaller market capitalization. As in Table A1, illiquidity and volatility are also closely related with the covariances. We find a common monotonous pattern in the illiquidity betas, volatility betas and funding betas: portfolios that are more volatile or less liquid have larger, more negative betas.

Table V shows results from the regressions of the changes in the portfolios' Amihud illiquidity ratio on one of the leverage shocks. We include the market returns in each case but we do not report the corresponding estimates. Row I reports the coefficients for liquidity sorts and Row II for volatility sorts. In Panels (A), we first ask whether the portfolios' illiquidity responds to changes in the leverage supply and demand shocks. The coefficients on the supply shocks have the right sign in every case and they exhibit a clear a clear monotonic pattern: the estimated effects are larger for the least liquid and the more volatile portfolios. In Panel (B), we report the results from regressions on the leverage demand shocks. Most of the estimates have the right sign, they exhibit a loose monotonic pattern and they are systematically lower than in the case of leverage supply shocks.

Table V around here.

Next, Panel (C) reports results based on the raw leverage shocks. We find that the coefficients estimate are negative and monotonic but small and never statistically significant at the 5% level for every portfolio, which is consistent with the results reported by AEM. Looking vertically across Table V, we see that one reason why the coefficients on the raw leverage shocks are negative is the mixing of the significant negative effect of supply shocks on illiquidity with the smaller but positive effect of demand shocks.

Therefore, the decomposition of leverage into supply and demand shocks sheds a light on the puzzle raised in AEM. Disentangling the leverage supply shocks establishes that they are associated with improved market liquidity across the portfolios. We leave for future research to explore why the leverage demand shocks that we recover exhibit a weak relationship with market liquidity. One potential reason may be a nonlinear relationship between market liquidity and leverage demand shocks. While the regressions measure a small average effect across the sample, the effect of relatively large demand-sided shocks may be significant, especially in our sample that includes the 2008-2009 financial crisis and the 2020 COVID crisis. This potential asymmetry or nonlinearity may in turn reveal evidence that more than one mechanism underpin leverage demand shocks but that these mechanisms may generate different implications for market liquidity. For instance, shifts in the intermediaries' demand for funds or shifts in the investors' demand for immediacy would be amalgamated in our demand shocks but may have opposite implications for market liquidity.

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. 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. This case is consistent with the econometric model in Section A if the demand shocks e^d drop out from the specification for leverage in Equation (1). Then, as in AEM, the projection of ϕ on LEV only reveals the supply shocks, $\phi \approx a - b \times LEV$, Equation (6) associates the time-series betas for leverage with the positive betas of supply shocks, and Equation (7) predicts that the cross-sectional regression recovers a positive price of risk. Based on this prediction, AEM provide important evidence supporting intermediary asset pricing.

In Table VI, we check whether the leverage supply and demand shocks display significant prices of risk in the test assets used by AEM (FF25 size and book-to-market portfolios, 10 momentum portfolios and 6 Treasury bonds). In Column (1), we obtain that the raw leverage factor produces a significant positive estimate for the price of risk across, as in AEM, but a lower $\bar{R}^2$, most likely because our sample periods differ. In Columns (2)-(3), we find that the leverage supply and demand shocks produce price-of-risk estimates that have the expected signs and improve the fit of this cross-section of returns. In Column (4), we combine both types of shocks and impose the symmetry between the prices of risk, and find an estimate of 1.9, close to our baseline estimate, and statistically significant. In Columns (5)-(8), we add a constant to these regressions. The results remain essentially unchanged. The leverage factor produces a positive estimate to the relatively wide dispersion of supply betas across these test assets.

Table VI around here.

The evidence is consistent with intermediation models in which the leverage constraints typically do not bind. 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. From a theoretical perspective, Du, Hébert, and Huber (2022) also find that the constraints do not bind when intermediaries with Epstein-Zin preferences weigh inter-temporal considerations and may anticipate higher profits in the future.

In Appendix F, we provide additional empirical evidence with reduced-form and structural approaches that intermediaries funding constraints are not always binding. One observation supporting this conclusion is that across the sample, ΔLEV_t and $\Delta FUND_t$ move in opposite directions in 42% of the sample, which is what we expect if the constraints are binding but move in the same direction in 58% of the sample, which can happen if the constraint is not binding, including in the Fall of 2008 when we estimate the largest demand shock in our sample. The dynamics of leverage shocks yield two other supportive observations. In the sub-sample where the current values of $FUND$ are elevated and the funding conditions are tight, we find (i) that the dispersion of supply shocks is substantially higher and (ii) that leverage exhibits a stronger response to funding conditions. Both observations are consistent with the prediction that the constraint is more likely to be binding, and that supply shocks are more prevalent, when funding conditions are tight. Finally, based on a structural system of constrained simultaneous equations, Figure A9 reports the period-by-period probability that the funding constraints are binding. Reassuringly, and consistent with the prediction that only supply shocks influence leverage when the constraints are binding, the periods where the estimated probabilities are close to zero are also periods when we extract relatively large leverage demand shocks in our baseline VAR results. Overall, the evidence supports a framework similar to the one proposed by Du, Hébert, and Huber (2022) where intertemporal considerations enter the leverage decisions and in which the leverage constraints do not always bind.

V. Conclusion

We offer an econometric model where the intermediaries' leverage and marginal value of wealth are driven by supply and demand shocks. Supply-sided shocks relax the funding constraint and lead to a higher leverage. Demand-sided shocks also lead to higher leverage but tighten the funding constraint. We use the asset pricing implications to separately identify these two types of shocks in the data. The evidence confirms that leverage demand and supply shocks carry a consistent price of risk across asset classes. Our findings imply that the price-of-risk estimate for raw leverage changes signs across markets because it mixes the opposite influences of both types of shocks. Overall, the results confirm the importance of financial intermediaries' balance sheets to understand the pricing of assets. More work is needed to distinguish and quantify the channels of leverage supply and leverage demand shocks, respectively, and why the relative importance of exposures to leverage demand and supply shocks can vary across financial markets.

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Table I. Asset-pricing Tests—All Test Assets

Asset pricing models estimated with two-stage Fama-MacBeth regressions for portfolios of value-weighted equities, corporate and Treasury bonds, and options. The coefficients λ_l, λ_s, λ_d are the prices of the raw leverage shock, leverage supply shock, and leverage demand shock, respectively, λ is the price of risk for supply and demand leverage shocks imposing $-\lambda_s = \lambda_d$, and λ_m is the price of risk for the market returns, all reported as percent per year. Columns (1)-(4): single-factor models. Columns (5)-(8): two-factor models with multivariate first-stage betas. Columns (9)-(12): with univariate first-stage betas. Columns (5)-(12): the market returns are also included as a test asset. Shanken-corrected t-statistics in parentheses. The $\bar{R}^2$ confidence intervals CI in square brackets follow Lewellen, Nagel, and Shanken (2010). The R^2s in columns (9)-(12) are identical to those in columns (5)-(8).

	One Factor Models				Multivariate Betas				Univariate Betas			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
λ_l	4.56				1.17				1.11			
	(2.45)				(1.43)				(1.32)			
λ_s		4.05				2.73				2.61		
		(2.56)				(3.28)				(2.78)		
λ_d			-4.47				-2.87				-2.76	
			(-2.38)				(-2.47)				(-2.19)	
λ				2.02				1.77				1.85
				(2.91)				(3.39)				(4.10)
λ_m					10.16	9.34	8.61	8.64	9.71	4.42	4.45	2.38
					(3.30)	(3.00)	(2.79)	(2.79)	(2.81)	(1.07)	(1.05)	(1.33)
$\bar{R}^2$	7.9	90.5	88.6	93.1	86.8	92.7	90.0	93.3	—	—	—	—
LNS CI	[2, 37]	[80, 99]	[76, 98]	[85, 99]	[71, 98]	[84, 99]	[78, 99]	[85, 99]	—	—	—	—

Table II. Asset-pricing Tests—Individual Asset Classes

Asset pricing models estimated with two-stage Fama-MacBeth regressions for portfolios of value-weighted equities, corporate and Treasury bonds, and options, separately. The coefficient λ_l is the price risk of the raw leverage shock, λ is the price of risk for supply and demand leverage shocks imposing $-\lambda_s = \lambda_d$, and λ_m is the price of risk for the market returns, all reported as percent per year. Market returns are also included as a test asset. Shanken-corrected t-statistics are reported in parentheses. The LNS CI $\bar{R}^2$ confidence interval follows Lewellen, Nagel, and Shanken (2010).

	Equities		Bonds		Options	
	(1)	(2)	(3)	(4)	(5)	(6)
λ_l	1.57		3.78		-11.51	
	(1.24)		(2.40)		(-1.38)	
λ		2.04		2.04		2.22
		(2.85)		(3.72)		(2.55)
λ_m	10.91		16.51		1.41	
	(3.45)		(3.60)		(0.24)	
$\bar{R}^2$	98.3	90.4	78.3	94.3	96.1	93.3
LNS CI	[96, 100]	[75, 99]	[58, 93]	[87, 99]	[90, 100]	[83, 99]

Table III. Asset-pricing Tests—HKM test assets

Asset pricing models estimated with two-stage Fama-MacBeth regressions for the test assets in HKM without a constant in the second-stage regression and with symmetric prices of risk of leverage supply and demand shocks. The coefficient λ is the price of risk for supply and demand leverage shocks imposing $-\lambda_s = \lambda_d$, and λ_m is the price of risk for the market returns, all reported as percent per year. The market returns factor is included as a risk factor and a test asset. Shanken-corrected t-statistics are reported in parentheses.

	FF	BND	SOV	OPT	CDS	COM	FX	ALL
λ	1.84	3.83	3.46	7.19	1.38	0.41	-2.39	1.10
	(1.75)	(3.02)	(1.89)	(1.94)	(1.66)	(0.53)	(-0.81)	(1.29)
λ_m	6.32	4.79	7.13	10.09	5.18	2.34	6.85	3.65
	(1.78)	(1.32)	(1.56)	(2.10)	(0.95)	(0.49)	(1.89)	(0.56)
$\bar{R}^2$	87.5	82.5	90.0	93.7	55.2	-3.9	24.3	36.9

Table IV. Price of Leverage Risk and Dispersions in Betas

The estimates $\overline{\beta}_d$ and $\overline{\beta}_s$ are the sample averages of the leverage demand and supply shocks betas, $\hat{\beta}_{i,d}$ and $\hat{\beta}_{i,s}$ respectively, in the cross-sections of test assets. The last two rows report the signs of the average leverage betas implied by the model in univariate regressions of returns on leverage LEV and in the data. The estimates ω_d^2, ω_s^2 and ω_{ds} are the sample variances and covariances of the demand and supply shocks betas, in the cross-sections. The last two rows report the signs of the leverage price of risk implied by the model ($\hat{\lambda}_l$) and in the data ($\hat{\lambda}_l^{ols}$).

Panel A. Sample averages of betas in different cross-sections of assets

	LIQ	VOL	FND	All	CBL	CBV	CBF	All	CALL	PUT	All
$\overline{\beta}_d$	-1.95	-2.27	-2.16	-2.13	-0.76	-0.77	-1.15	-0.65	-0.84	-2.57	-1.70
$\overline{\beta}_s$	2.59	2.83	2.88	2.77	1.87	1.89	1.35	1.22	0.97	2.15	1.56
$\overline{\beta}_l$	−	−	−	−	+	+	−	+	−	−	−
$\overline{\beta}_l^{ols}$	−	−	−	−	+	+	−	+	−	−	−

Panel B. Sample dispersions of betas in different cross-sections of assets

	LIQ	VOL	FND	All	CBL	CBV	CBF	All	CALL	PUT	All
ω_d^2	0.66	1.75	1.65	1.28	0.11	0.23	0.32	0.32	0.29	0.32	1.06
ω_s^2	0.27	1.04	1.22	0.80	0.34	0.34	0.72	0.96	0.08	0.06	0.42
ω_{ds}	-0.35	-1.27	-1.28	-0.91	-0.15	-0.25	-0.43	-0.45	-0.14	-0.12	-0.65
$\hat{\lambda}_l$	−	−	−	−	+	−	+	+	−	−	−
$\hat{\lambda}_l^{ols}$	−	−	−	−	+	−	+	+	−	−	−

Table V. Leverage Shocks in Illiquidity Regressions

Panel (A): Estimates of the coefficients on leverage supply shocks. Panel (B): Estimates of the coefficients on leverage demand shocks. Panel (C): Estimates of the coefficients on ΔLEV. 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 parentheses.

Panel A. $\Delta illiq_{i,t} = a + b_i e_t^s + c_i xR_{t,m} + e_t$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
I	-42.844	-3.386	-0.263	-0.088	-0.034	-0.016	-0.009	-0.005	-0.002	-0.001
	(-1.79)	(-1.82)	(-3.07)	(-3.72)	(-3.37)	(-2.88)	(-2.99)	(-2.49)	(-2.29)	(-2.40)
II	-4.554	-0.800	-0.139	-0.067	-0.021	-0.018	-0.008	-0.004	-0.004	-0.001
	(-1.48)	(-1.85)	(-2.36)	(-2.91)	(-3.59)	(-2.50)	(-2.61)	(-3.47)	(-1.72)	(-0.57)

Panel B. $\Delta illiq_{i,t} = a + b_i e_t^d + c_i xR_{t,m} + e_t$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
I	2.633	-0.700	0.017	0.013	0.004	0.001	0.000	0.000	0.000	0.000
	(0.17)	(-0.63)	(0.16)	(0.35)	(0.27)	(0.16)	(-0.03)	(-0.14)	(-0.44)	(-0.16)
II	0.296	-0.177	-0.009	-0.001	0.000	-0.002	-0.001	0.000	0.000	0.000
	(0.13)	(-0.68)	(-0.21)	(-0.02)	(-0.01)	(-0.28)	(-0.23)	(0.06)	(-0.01)	(-0.09)

Panel C. $\Delta illiq_{i,t} = a + b_i \Delta LEV_t + c_i xR_{t,m} + e_t$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
I	-19.588	-1.975	-0.121	-0.033	-0.013	-0.007	-0.004	-0.002	-0.001	0.000
	(-1.04)	(-1.35)	(-1.42)	(-1.24)	(-1.26)	(-1.44)	(-1.78)	(-1.68)	(-1.62)	(-1.53)
II	-0.696	-0.374	-0.057	-0.032	-0.012	-0.009	-0.006	-0.002	-0.003	-0.001
	(-0.26)	(-1.08)	(-1.15)	(-1.69)	(-1.86)	(-1.44)	(-2.34)	(-2.05)	(-1.50)	(-0.54)

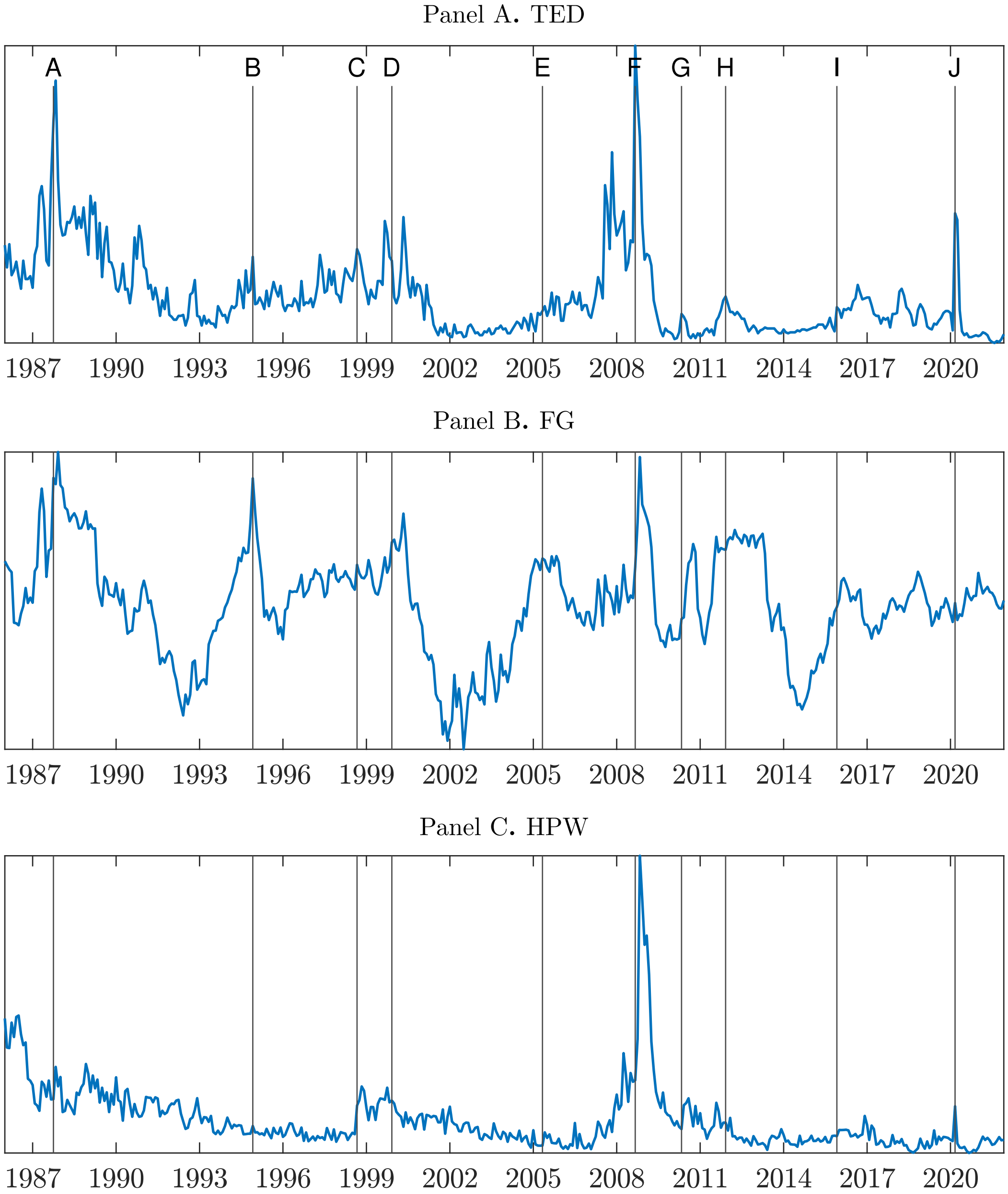
Table VI. Asset-pricing Tests— Adrian, Etula, and Muir (2014)

Asset pricing models estimated with 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. The coefficients λ_l, λ_s and λ_d are the prices of risk of the raw leverage shock, leverage supply shock, leverage demand shock, and λ is the price of risk for supply and demand leverage shocks with a symmetry restriction. Shanken-corrected t-statistics in parentheses. Note that reported $\bar{R}^2$ are computed as non-centered for ease of comparison.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
int.					5.66	-0.20	2.63	0.31
					(1.65)	(-0.40)	(2.53)	(0.70)
λ_l	6.16				3.90			
	(2.64)				(3.01)			
λ_s		3.25				3.32		
		(2.11)				(2.21)		
λ_d			-4.54				-3.13	
			(-1.68)				(-1.67)	
λ				1.86				1.80
				(2.20)				(2.17)
$\bar{R}^2$	23.6	86.3	68.0	82.4	69.2	86.4	71.8	82.0

Figure 1. Funding Conditions Proxies

Panel (A): *TED* spread measure. Panel (B): *FG* funding conditions measure from Fontaine and Garcia (2012). Panel (C): *HPW* noise measure from Hu, Pan, and Wang (2013). Monthly data, 1986-2021.



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, (J) COVID-19 financial crisis.

Figure 2. Impulse Response Functions

Impulse responses of LEV_{t+h} and $FUND_{t+h}$ to identified leverage supply e_t^s and demand shocks e_t^d at horizons $h = 1 \ldots 20$ quarters on the y-axis with 95 percent bootstrap confidence intervals in dashed blue lines and re-scaled in units of standard deviations of each variable of interest on the x-axis.

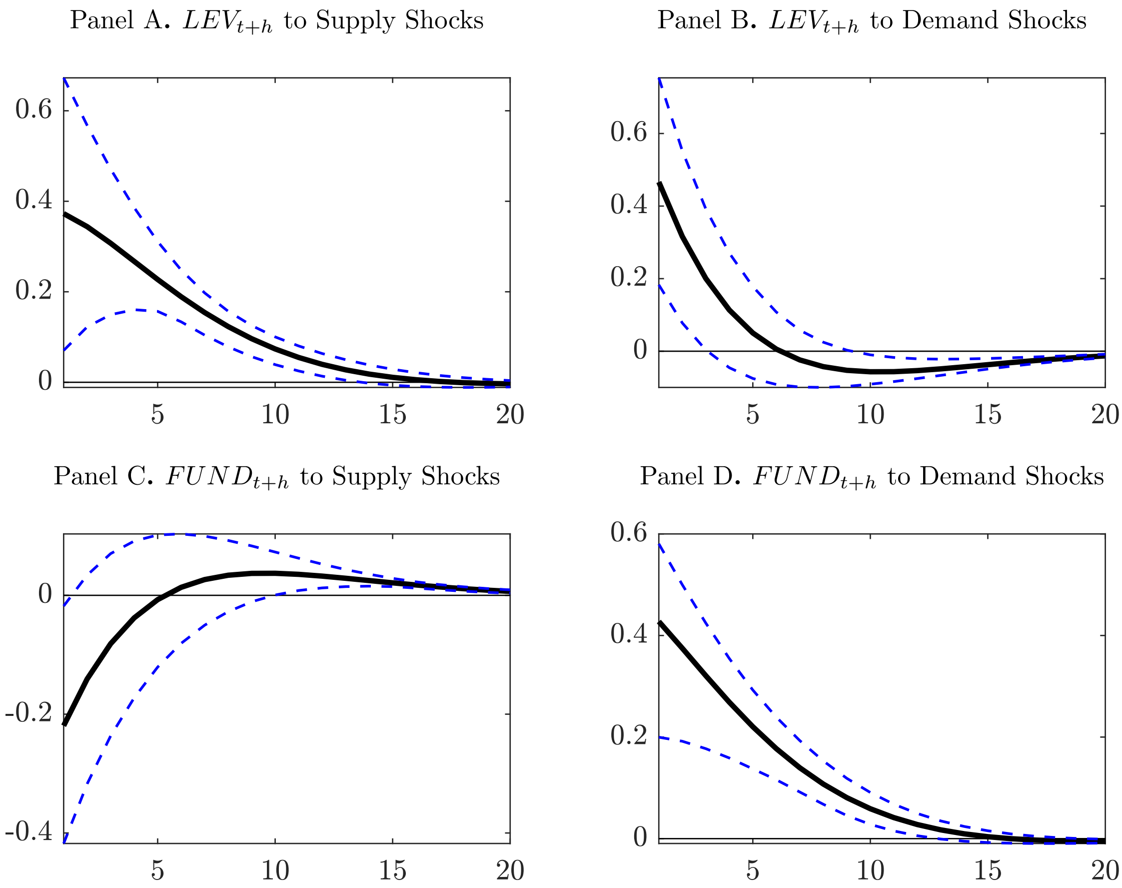
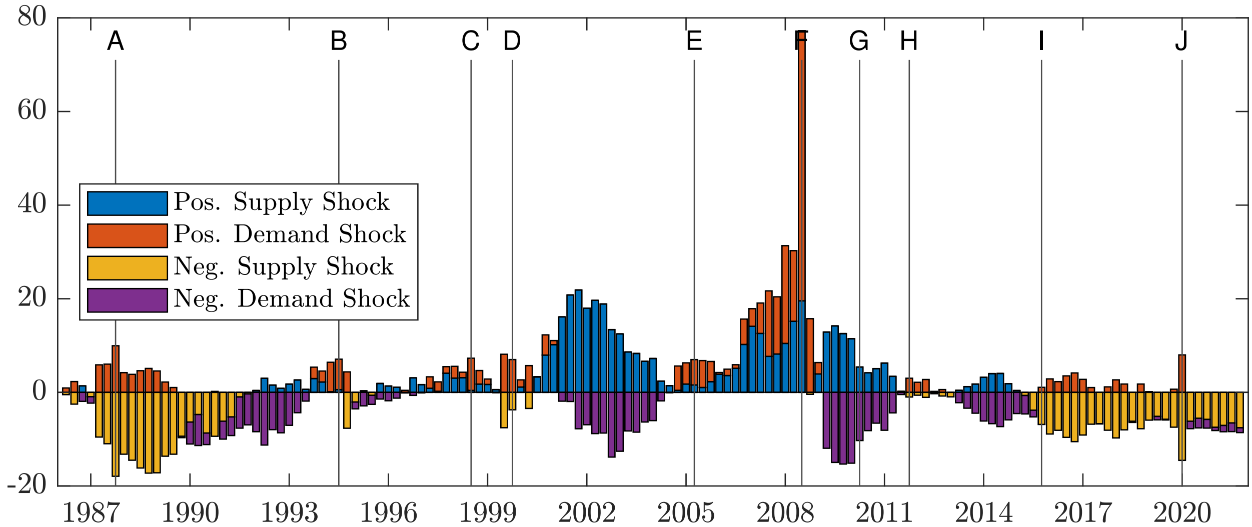


Figure 3. Historical Decomposition

Decomposition of leverage forecast errors in terms of leverage demand and supply shocks from the econometric model identified with sign and asset pricing restrictions. See Section I for a description of the model and Section II for details of the estimation. Quarterly data, 1986Q2-2021Q4.

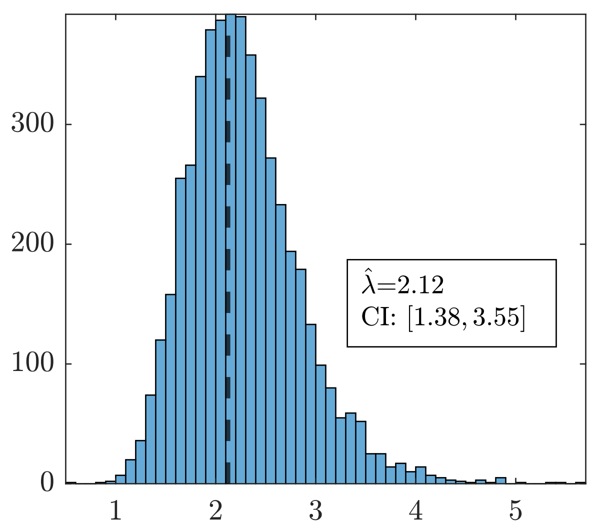


Note: (A) 1987 stock market crash, (B) 1994 bond market massacre, (C) LTCM bailout, (D) Turn of the millenium, (E) Ford & GM downgrades, (F) 2008 financial crisis, (G) First Greece bailout, (H) Second Greece bailout, (I) Oil & China sell-off.

Figure 4. Price of Leverage Demand and Supply Risks

Panel (A): bootstrap distribution of the price of risk λ of leverage demand and supply shocks from the econometric model identified with sign and asset pricing restrictions. Panel (B): bootstrap distribution for the uncentered $\bar{R}^2$. See Section I for a description of the model and and Section II for details of the estimation. See Appendix C for the bootstrap procedure.

Panel A. $\hat{\lambda}$



Panel B. $\bar{R}^2$

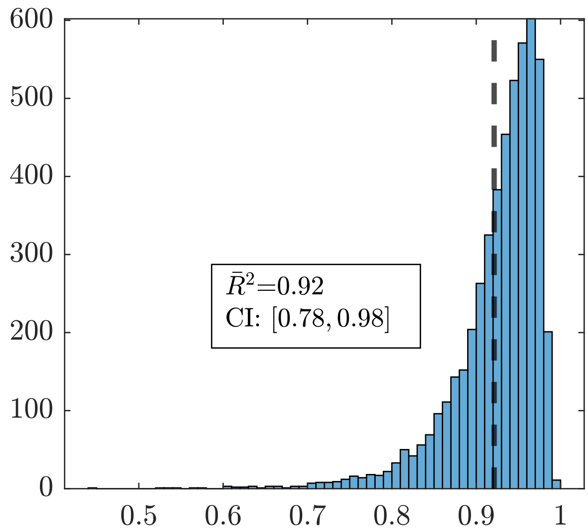
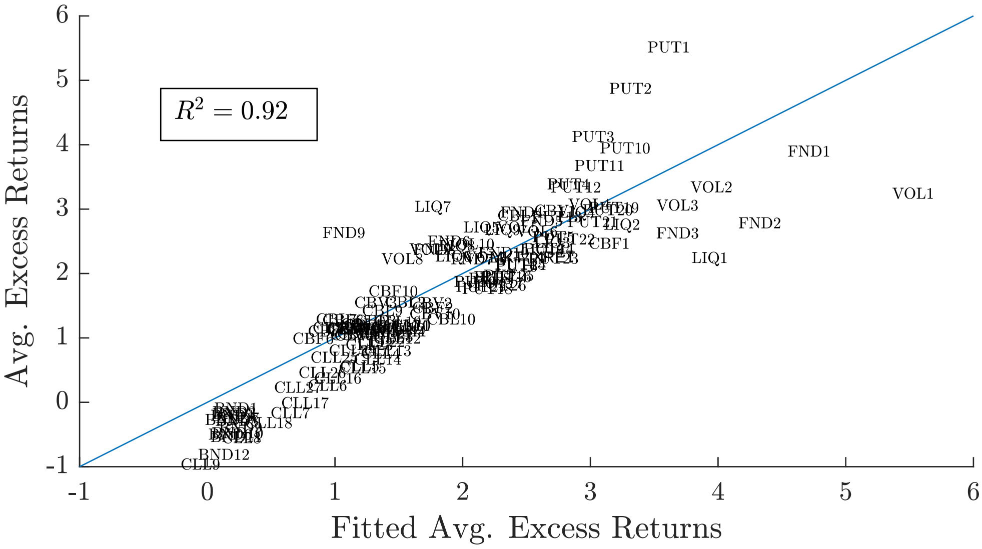


Figure 5. Leverage Demand and Supply Shocks in Asset Pricing

Realized and fitted mean excess returns of 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 leverage demand and leverage supply shocks. Panel (B): results using market returns and the leverage factor from AEM. Each model is estimated in two-stage regressions with no intercept and we draw a 45-degree line.

Panel A. Leverage Demand and Supply Shocks



Panel B. Raw Leverage and Market Returns

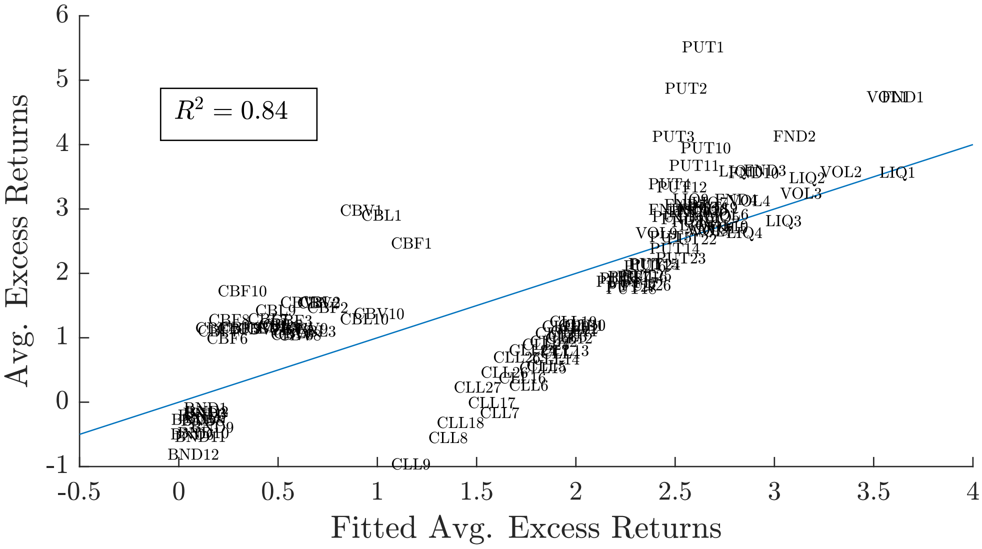


Figure 6. Set of Identified Parameters

Set of parameters satisfying the identification restriction but not imposing symmetry. Panel(A): prices of risk λ_d and λ_s. Panel (B): the dispersions ω_d and ω_s in the cross-section of $\beta_{i,d}$ and $\beta_{i,s}$. Panel (C): LEV loadings b_d and b_s. Panel (D): $FUND$ loadings a_d and a_s.

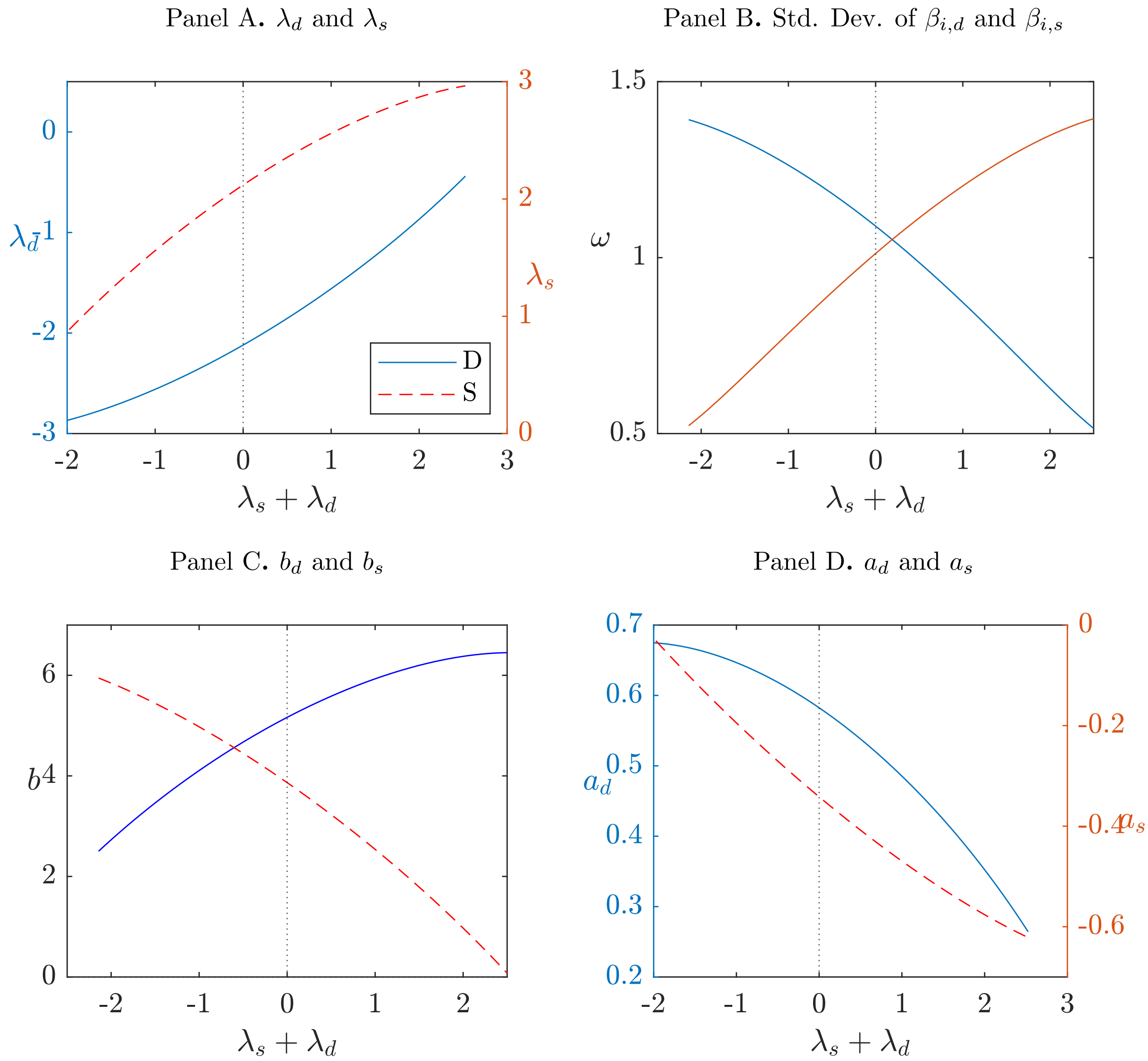


Figure 7. First-Stage β Estimates—Leverage Demand and Supply Shocks

First-stage β estimates of leverage supply and demand shocks in single-factor models based on the leverage demand and supply shocks, reported on the y-axis and the x-axis, respectively. Panel (A): equity portfolios labeled LIQ, VOL and FND. Panel (B): Treasury bonds and corporate bond portfolios labeledCBL, CBV, CBF, and BND. Panel (C): unlevered options portfolios labeled PUT and CLL.

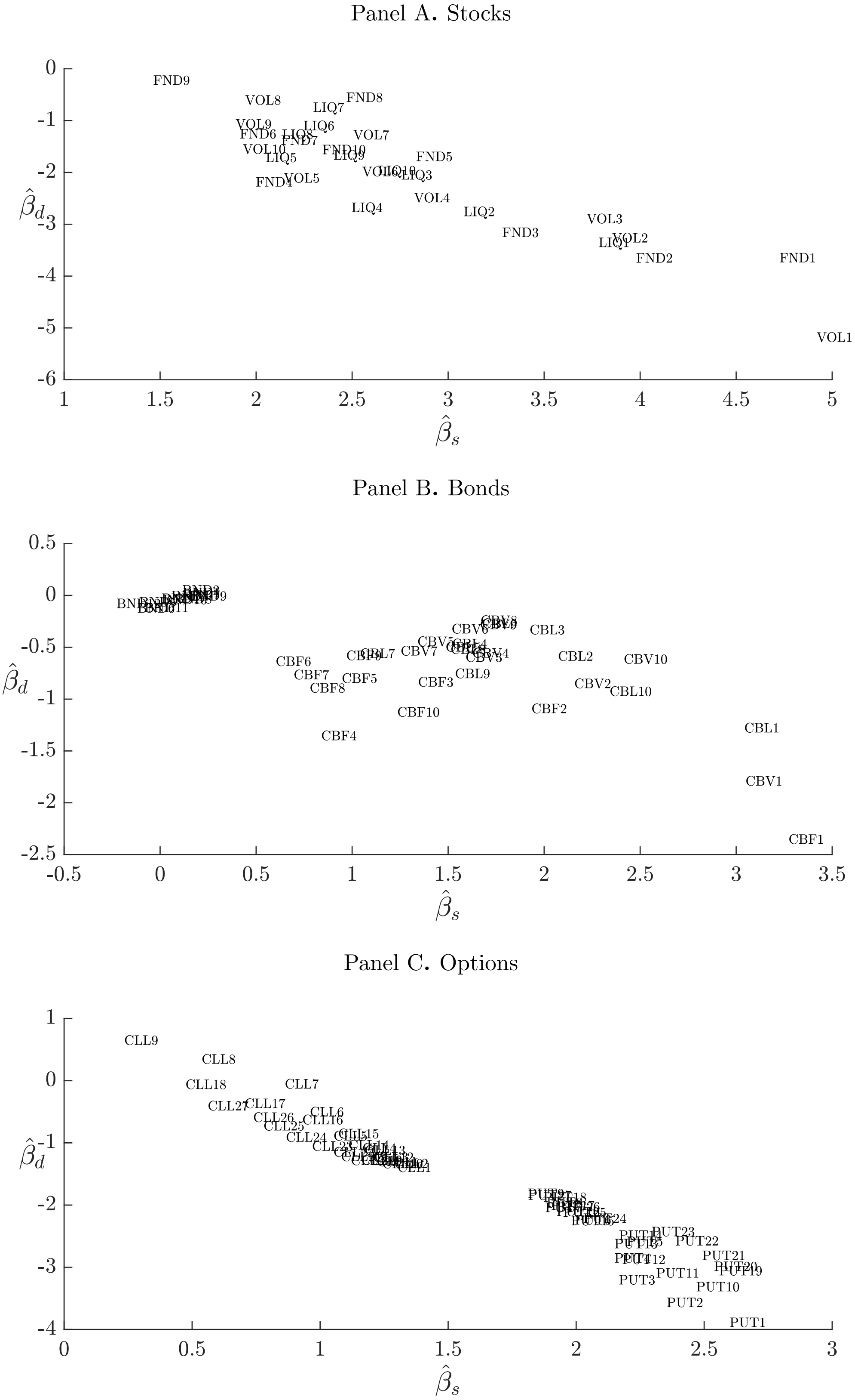
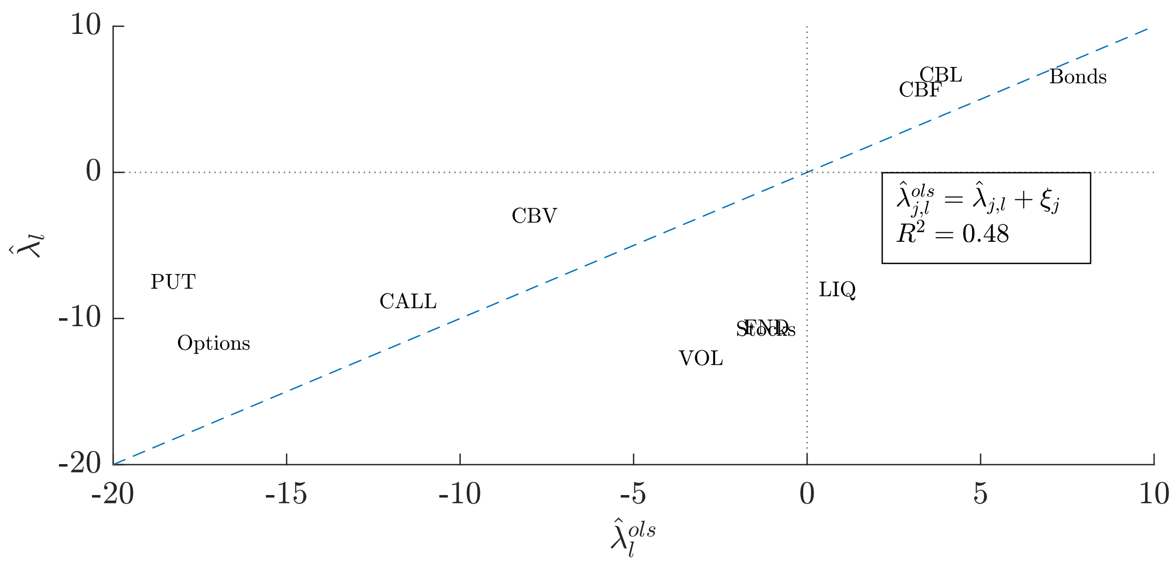


Figure 8. Price of Leverage Risk

Scatter plot of estimates for the price of raw leverage risk $\lambda_{i,l}$ across different test assets. X-axis: $\hat{\lambda}^{ols}_{i,l}$ estimates from the second-stage OLS regressions. Y-axis: $\hat{\lambda}_{i,l}$ estimate from the econometric model of Section II. Dashed line: the 45-degree line which would correspond to an exact fit. We also report the R^2 for the exact-fit regression $\hat{\lambda}^{ols}_{j,l} = \hat{\lambda}_{j,l} + \xi_j$



Note: 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 Treasuries, CBV, CBL, CBF and BND; Options group PUT and CLL. See Appendix Section D.

Appendix A.

Online Appendix for Intermediary Leverage Shocks and Funding Conditions

Jean-Sébastien Fontaine, René Garcia and Sermin Gungor[23]

A. *Identification*

The restrictions $\text{Var}(u) = \text{Var}(Z) = AA^{\top}$ are given by:

$$\begin{aligned} \sigma_z^2 &= a_d^2 + a_s^2 \\ \sigma_l^2 &= b_d^2 + b_s^2 \\ \sigma_{zl} &= a_d b_d - a_s b_s. \end{aligned} \tag{A1}$$

The two variance restrictions are equivalent to:

$$\begin{aligned} a_d &= \sigma_z \cos(\theta_a) \quad & a_s &= \sigma_z \sin(\theta_a) \\ b_d &= \sigma_l \cos(\theta_b) \quad & b_s &= \sigma_l \sin(\theta_b), \end{aligned} \tag{A2}$$

and the covariance restriction is equivalent to:

$$\rho_{zl} \equiv \frac{\sigma_{zl}}{\sigma_z \sigma_l} = \cos(\theta_a)\cos(\theta_b) - \sin(\theta_a)\sin(\theta_b) = \cos(\theta_a + \theta_b). \tag{A3}$$

This restriction allows to express one of the pair of parameters in θ in terms of the other, say θ_b, leading to a one-dimensional set of values for θ_a indexing the set of parameters identified by the sign restrictions. The scalar asset pricing restriction pins down identification. Recall that the reduced-form prices of risk are given by:

$$C = \begin{pmatrix} c_z \\ c_l \end{pmatrix} = (A^{-1})^T \lambda = \frac{1}{\Delta} \begin{pmatrix} b_s & -b_d \\ a_s & a_d \end{pmatrix} \begin{pmatrix} \lambda_d \\ -\kappa \lambda_d \end{pmatrix},$$

where $\lambda = [\lambda_d \ \lambda_s]^T$ with the restriction $\lambda_s = -\kappa \lambda_d$. It leads to the following:

$$\frac{c_l}{c_z} = \frac{a_s - \kappa a_d}{b_s + \kappa b_d} = \frac{\sigma_z(\sin(\theta_a) - \kappa \cos(\theta_a))}{\sigma_l(\sin(\theta_b) + \kappa \cos(\theta_b))}.$$

Grouping moments from the data on the left-hand side, we obtain:

$$\varrho_{zl} \equiv \frac{\sigma_l}{\sigma_z} \frac{c_l}{c_z} = \frac{\sin(\theta_a) - \kappa \cos(\theta_a)}{\sin(\theta_b) + \kappa \cos(\theta_b)}, \tag{A4}$$

Developing the numerator of equation (A4) and using equation (A3), we obtain:

$$\sin(\theta_a) - \kappa \cos(\theta_a) = \sin(\theta_a + \theta_b)\left[\cos(\theta_b) - \kappa \sin(\theta_b)\right] - \rho_{zl}\left[\sin(\theta_b) + \kappa \cos(\theta_b)\right] \tag{A5}$$

[23]Citation format: Fontaine, Jean-Sébastien, René Garcia, and Sermin Gungor, Internet Appendix to "Intermediary Leverage Shocks and Funding Conditions", Journal of Finance [DOI STRING]

Plugging this expression in equation (A4) one obtains:

$$(\varrho_{zl} + \rho_{zl}) [\sin(\theta_b) + \kappa \cos(\theta_b)] = \sin(\theta_a + \theta_b) [\cos(\theta_b) - \kappa \sin(\theta_b)] \tag{A6}$$

Raising both sides of equation (A6) to the square and developing both sides we arrive after some algebraic and trigonometric manipulations at:

$$\varphi_b \equiv \kappa \sin(2\theta_b) - \sin(\theta_b)^2(\kappa^2 - 1) = \frac{1 - \rho_{zl}^2 - \kappa^2 (\varrho_{zl} + \rho_{zl})^2}{1 - \rho_{zl}^2 + (\varrho_{zl} + \rho_{zl})^2}. \tag{A7}$$

Similarly, we can define: $\varphi_a \equiv \kappa \sin(2\theta_a) - \sin(\theta_a)^2(\kappa^2 - 1)$ with the following relation between φ_a and φ_b:

$$\varphi_a = \kappa^2 - \varrho_{zl}^2(\kappa^2 + \varphi_b) \tag{A8}$$

Setting κ to 1 for the symmetric case we obtain the following solutions for φ_b and φ_a that we use to solve for the four unknowns $\sin(\theta_a), \cos(\theta_a), \sin(\theta_b), \cos(\theta_b)$ in terms of the data.

$$\boxed{\varphi_b \equiv \sin(2\theta_b) = \frac{1 - \rho_{zl}^2 - (\varrho_{zl} + \rho_{zl})^2}{1 - \rho_{zl}^2 + (\varrho_{zl} + \rho_{zl})^2}.} \tag{A9}$$

Then we turn to $\sin(2\theta_a)$, rewriting equation (A8) as $\sin(2\theta_a) = 1 - \varrho_{zl}^2(1 + \varphi_b)$, and solving for $\sin(2\theta_a)$ yields:

$$\boxed{\varphi_a \equiv \sin(2\theta_a) = \frac{(1 - \rho_{zl}^2)(1 - 2\varrho_{zl}^2) + (\varrho_{zl} + \rho_{zl})^2}{1 - \rho_{zl}^2 + (\varrho_{zl} + \rho_{zl})^2}.} \tag{A10}$$

Solution The expressions for φ_a and φ_b are functions of the data through ρ_{zl} and ϱ_{zl}. From the definitional relation $\sin(2\theta_a) = 2\sin(\theta_a)\cos(\theta_a) = \varphi_a$, we obtain the quadratic equation for $\sin(\theta_a)$:

$$\sin(\theta_a)^4 - \sin(\theta_a)^2 + \frac{\varphi_a^2}{4} = 0, \tag{A11}$$

and we obtain a similar quadratic equation linking $\sin(\theta_b)$ and φ_b. Therefore, the solution for $\sin(\theta_a)$, $\cos(\theta_a)$, $\sin(\theta_b)$ and $\cos(\theta_b)$ and the corresponding a_d, a_s, b_d and b_s is:

$$\sin(\theta_a) = \pm\sqrt{\frac{1 \pm \sqrt{1 - \varphi_a^2}}{2}} \qquad \cos(\theta_a) = \frac{\varphi_a}{2\sin(\theta_a)}$$

$$\sin(\theta_b) = \pm\sqrt{\frac{1 \pm \sqrt{1 - \varphi_b^2}}{2}} \qquad \cos(\theta_b) = \frac{\varphi_b}{2\sin(\theta_b)}.$$

The restrictions $a_s, b_s > 0$ eliminate the first ambivalent operator $\pm$ and the second $\pm$ can be eliminated by checking the solutions for Equations (A3)-(A4) given in the data.

B. A model with aggregate risk unrelated to leverage

In this section, we derive the identification of leverage demand and supply shocks in a model extended with an additional aggregate shock that does not influence leverage. We assume that the market returns are driven by the three types qof shocks::

$$xR_m = \mu_m + \beta_{m,m}e^m + \beta_{m,d}e^d + \beta_{m,s}e^s, \tag{A12}$$

where $\beta_{m,d} \leq 0$ and $\beta_{m,s} \geq 0$ to be consistent with the interpretation of the leverage demand and supply shocks, while $\beta_{m,m} > 0$ identifies the sign of e^m. The extended model has reduced-form innovations given by:

$$u = \begin{bmatrix} Z - \mu^z \\ L - \mu^l \\ xR_m - \mu_m \end{bmatrix} = \begin{bmatrix} a_d & -a_s & -a_m \\ b_d & b_s & b_m \\ -b_{m,d} & b_{m,s} & b_{m,m} \end{bmatrix} \begin{bmatrix} e^d \\ e^s \\ e^m \end{bmatrix} = \tilde{A}e,$$

with $e = \begin{bmatrix} e^d & e^s & e^m \end{bmatrix}^\top \sim (0, I_3)$ and, therefore, the variance of the innovations is given by:

$$\text{var}[u] = \begin{bmatrix} \sigma_z^2 & \sigma_{zl} & \sigma_{zl} \\ \sigma_{zl} & \sigma_l^2 & \sigma_{mz} \\ \sigma_{ml} & \sigma_{mz} & \sigma_m^2 \end{bmatrix} = \tilde{A}\tilde{A}^\top. \tag{A13}$$

We assume that the additional aggregate shock does not drive leverage or the instrument: $a_m = 0$, $b_m = 0$ and, therefore, Equation (A13) implies:

$$\begin{aligned} \sigma_z^2 &= a_s^2 + a_d^2 \\ \sigma_l^2 &= b_d^2 + b_s^2 \\ \sigma_m^2 &= b_{m,d}^2 + b_{m,s}^2 + b_{m,m}^2 \end{aligned} \tag{A14}$$

as well as

$$\begin{aligned} \sigma_{zl} &= a_d b_d - a_s b_s \\ \sigma_{zm} &= -a_d b_{m,d} - a_s b_{m,s} \\ \sigma_{lm} &= -b_d b_{m,d} + b_s b_{m,s}. \end{aligned} \tag{A15}$$

However, the aggregate shock affects the intermediaries' marginal value of wealth:

$$\phi = \gamma + \alpha_m e^m + \alpha(e^d - e^s),$$

and, following the same reasoning as in Section A, the structural and reduced-form prices of risk are linked by $\lambda = A^\top C$ but with $C^\top = [c_z \; c_l \; c_m]$ where c_m is the price of risk associated with reduced-form market returns innovations. The symmetry restriction $-\lambda_d = \lambda_s$ implies:

$$(a_d - a_s)c_z + (b_d + b_s)c_l = (b_{m,d} - b_{m,s})c_m. \tag{A16}$$

Equations (A14)-(A16) identify the parameters. To derive the solution for the parameters in terms of the moments from the data, we re-write the unknown parameters as trigonometric functions. We have:

$$a = \begin{pmatrix} a_s \\ a_d \\ a_m \end{pmatrix} = \sigma_z \begin{pmatrix} \cos(\phi_a) \\ \sin(\phi_a) \\ 0 \end{pmatrix}$$
$$b = \begin{pmatrix} b_s \\ b_d \\ b_m \end{pmatrix} = \sigma_l \begin{pmatrix} \cos(\phi_b) \\ \sin(\phi_b) \\ 0 \end{pmatrix}$$
$$b_m = \begin{pmatrix} b_{m,s} \\ b_{m,d} \\ b_{m,m} \end{pmatrix} = \sigma_m \begin{pmatrix} \cos(\phi_m) \\ \sin(\phi_m)\cos(\theta_m) \\ \sin(\phi_m)\sin(\theta_m) \end{pmatrix},$$

with $\phi_a \in [0,\pi] \Rightarrow \sin(\phi_a) \geq 0)$, $\phi_b \in [0,\pi] \Rightarrow \sin(\phi_b) \geq 0$, with $\phi_m \in [0,\pi] \Rightarrow \sin(\phi_m) \geq 0$ and $\theta_m \in [0,2\pi]$. Start with the covariance σ_{zl}:

$$\begin{aligned} \sigma_{zl} =& a_d b_d - a_s b_s = \sigma_z\sigma_l\left(\sin(\phi_a)\sin(\phi_b) - \cos(\phi_a)\cos(\phi_b)\right) \\ \Rightarrow \rho_{zl} =& \frac{\sigma_{zl}}{\sigma_z\sigma_l} = -\cos(\phi_a+\phi_b). \end{aligned} \tag{A17}$$

Similarly:

$$\begin{aligned} -\rho_{zm} \equiv& -\frac{\sigma_{zm}}{\sigma_z\sigma_m} = \sin(\phi_a)\sin(\phi_m)\cos(\theta_m) + \cos(\phi_a)\cos(\phi_m) \\ \Rightarrow \cos(\theta_m) =& -\frac{\rho_{zm} + \cos(\phi_a)\cos(\phi_m)}{\sin(\phi_a)\sin(\phi_m)}, \end{aligned} \tag{A18}$$

and:

$$\begin{aligned} \rho_{lm} =& \frac{\sigma_{lm}}{\sigma_z\sigma_m} = -\sin(\phi_b)\sin(\phi_m)\cos(\theta_m) + \cos(\phi_b)\cos(\phi_m) \\ \Rightarrow \cos(\theta_m) =& -\frac{\rho_{lm} - \cos(\phi_b)\cos(\phi_m)}{\sin(\phi_b)\sin(\phi_m)} \end{aligned} \tag{A19}$$

Using Equations (A18)-(A19), we obtain:

$$\cos(\phi_m) = \frac{\rho_{lm}\sin(\phi_a) - \rho_{zm}\sin(\phi_b)}{\sin(\phi_a+\phi_b)},$$

and, since Equation (A17) implies $\sin(\phi_b+\phi_a) = \pm\sqrt{1-\rho_{zl}^2} \equiv \check{\rho}_{zl}$, we have that:

$$\cos(\phi_m) = \frac{\rho_{lm}\sin(\phi_a) - \rho_{zm}\sin(\phi_b)}{\check{\rho}_{zl}}. \tag{A20}$$

Note that we have:

$$\begin{aligned} \cos(\phi_b) &= \cos(\phi_b+\phi_a-\phi_a) = -\rho_{zl}\cos(\phi_a) + \check{\rho}_{zl}\sin(\phi_a) \\ \sin(\phi_b) &= \sin(\phi_b+\phi_a-\phi_a) = \check{\rho}_{zl}\cos(\phi_a) + \rho_{zl}\sin(\phi_a), \end{aligned} \tag{A21}$$

and:

$$\boxed{\cos(\phi_m) = \frac{(\rho_{lm} - \rho_{zm}\rho_{zl})\sin(\phi_a) - \rho_{zm}\check{\rho}_{zl}\cos(\phi_a)}{\check{\rho}_{zl}}},$$

and:

$$\boxed{\sin(\phi_m) = \sqrt{1-\cos(\phi_m)^2}}. \tag{A22}$$

Subsitute $\cos(\phi_m)$ and $\sin(\phi_m)$ in Equation (A18):

$$\boxed{\cos(\theta_m) = -\frac{\breve{\rho}_{zl}\rho_{zm} + (\rho_{lm} - \rho_{zm}\rho_{zl})\cos(\phi_a)\sin(\phi_a) - \rho_{zm}\breve{\rho}_{zl}\cos^2(\phi_a)}{\breve{\rho}_{zl}\sin(\phi_a)\sin(\phi_m)}}$$

$$\boxed{\sin(\theta_m) = \pm\sqrt{1-\cos^2(\theta_m)}}.$$

We can now use Equation (A16) to find ϕ_a:

$$(\sin(\phi_a)\cos(\theta_a) - \cos(\phi_a))\sigma_z c_z + (\sin(\phi_b)\cos(\theta_b) + \cos(\phi_b))\sigma_l c_l = (\sin(\phi_m)\cos(\theta_m) - \cos(\phi_m))\sigma_m c_m$$

Using the definitions: $\varrho_{zl} = \frac{\sigma_l c_l}{\sigma_z c_z}$ and $\varrho_{zm} = \frac{\sigma_m c_m}{\sigma_z c_z}$, we obtain:

$$(\sin(\phi_b) + \cos(\phi_b))\,\varrho_{zl} = (\sin(\phi_m)\cos(\theta_m) - \cos(\phi_m))\,\varrho_{zm} - (\sin(\phi_a) - \cos(\phi_a))$$

and after some tedious algebra, we get:

$$\boxed{\cos^2(\phi_a) = \frac{\left[\frac{(\varrho_{zl}(\breve{\rho}_{zl}+\rho_{zl})+1)}{\varrho_{zm}} + \frac{(\rho_{lm}-\rho_{zl}\rho_{zm})}{\breve{\rho}_{zl}} + \rho_{zm}\right]^2}{\left[\frac{(\varrho_{zl}(\breve{\rho}_{zl}+\rho_{zl})+1)}{\varrho_{zm}} + \frac{(\rho_{lm}-\rho_{zl}\rho_{zm})}{\breve{\rho}_{zl}} + \rho_{zm}\right]^2 + \left[\frac{(\varrho_{zl}(\breve{\rho}_{zl}-\rho_{zl})-1)}{\varrho_{zm}} + \frac{(\rho_{lm}-\rho_{zl}\rho_{zm})}{\breve{\rho}_{zl}} - \rho_{zm}\right]^2}} \tag{A23}$$

and

$$\boxed{\sin(\phi_a) = -\frac{\left[\frac{(\varrho_{zl}(\breve{\rho}_{zl}-\rho_{zl})-1)}{\varrho_{zm}} + \frac{(\rho_{lm}-\rho_{zl}\rho_{zm})}{\breve{\rho}_{zl}} - \rho_{zm}\right]}{\left[\frac{(\varrho_{zl}(\breve{\rho}_{zl}+\rho_{zl})+1)}{\varrho_{zm}} + \frac{(\rho_{lm}-\rho_{zl}\rho_{zm})}{\breve{\rho}_{zl}} + \rho_{zm}\right]}\cos(\phi_a)}, \tag{A24}$$

and we obtain the solutions for $\cos(\phi_b)$ and $\sin(\phi_b)$ from Equation (A21).

C. *Bootstrap procedure*

We use the following bootstrap procedures.

1. Re-sample $s = T - l - 1$ blocks of length $l = 8$ from the VAR reduced-form residual $\hat{u}_t$. See pp.353-356 in Kilian and Lutkephol (2017) for a detailed discussion of block bootstraps.

2. Construct the bootstrap innovations u_t^* by drawing blocks with replacement, retain the first T observations and set the mean to zero.

3. Construct the bootstrap state variables $y_t^* = [L_t^*\ Z_t^*]^\top$ recursively $y_t^* = \hat{\mu} + \hat{\phi} y_{t-1}^* + u_t^*$ using the starting value $y_0 = E[y_t]$ and the VAR parameter estimates $\hat{\mu}$ and $\hat{\phi}$.

4. Estimate the bootstrap VAR with OLS in the sample $\{y_t^*\}$. Recover the boostrap covariance matrix of the residual Var$(\hat{u}_t^*)$.

5. Correct the small-sample bias in VAR estimates due to the persistence. The persistence estimates are biased downward, which inflates the variance of the residuals

and then deflates the bootstrap distribution of the price of risk.

(a) Re-implement the block bootstrap within each bootstrap sample (i.e., a double-bootstrap).

(b) Compute the bias Ψ_s for each of the following statistics s:

i. the determinant of the covariance matrix $\det(\text{Var}(u))$,

ii. the ratio of the variances σ_z^2/σ_l^2, and

iii. the correlation ρ.

Note: targeting the parameters σ_l^2, σ_z^2 and σ_{12} instead would ignore the correlations between their estimates under the bootstrap measure.

(c) For the determinant and the ratio, the bias is $\Psi_s^* = \overline{\hat{s}}^*/\hat{s}$ and the bias is $\tilde{m}^* = \hat{m}^*/\Psi_m^*$. Using a ratio preserves the positivity and the asymmetry in the distribution. For the correlation, the bias is $\Psi_m^* = \overline{\hat{m}}^* - \hat{m}$ and the correction is $\tilde{m}^* = \hat{m}^* - \Psi_m^*$. Note that $E^*[\tilde{m}^*] = \hat{m}$ by construction.

(d) Construct the corrected covariance matrix $\tilde{\text{Var}}^*(u)$: $\tilde{\sigma}_z^2 = \sqrt{\frac{\det^* \times \text{ratio}^*}{1-\rho^2}}$, $\tilde{\sigma}_l^2 = \frac{\sigma_z^2}{\text{ratio}^*}$ and the covariance from its definition $\tilde{\sigma}_{zl} = \tilde{\rho}\tilde{\sigma}_z\tilde{\sigma}_l$.

(e) Transform the VAR residuals such that they have mean zero and covariance given by $\tilde{\text{Var}}^*(u)$.

6. Re-sample s blocks of length l of returns and returns innovations $\hat{u}_{i,t}$ from the test assets.

7. Construct bootstrap returns returns innovations $u_{i,t}^*$ by drawing blocks with replacement and retaining the first T observations and demeaning to zero under the bootstrap probability measure. Compute the mean $E^*[xR_{i,t}^*]$.

8. Construct the bootstrap returns $xR_{i,t}^* = \hat{\mu}_i^* + \hat{\beta}_i^\top \tilde{u}_t^* + \tilde{u}_{i,t}^*$ using the OLS estimate $\hat{\beta}_i$ from the first-stage regression in the data and the bootstrap value $\hat{\mu}_i^* = E^*[xR_{i,t}^*]$ from the previous step but re-center the bootstrap distribution such that $\overline{\hat{\mu}_i^*} = \hat{\beta}_i^\top \hat{\lambda}$.

9. Recover the bootstrap moment C^*, identify and recover all the structural parameters.

10. Repeat the procedure across B bootstrap samples and construct the distribution of the relevant statistics.

D. *Test Assets*

This section provides more information about the test assets in Section B of the paper. In every case, the sample frequency is quarterly.

D.1. Data

Treasury bonds We compute bond returns with maturities of 2, 3, 4, 5, 7, and 10 years, using security-level data at the monthly frequency from the Center for Research on Securities Prices (CRSP). We select the most recently-issued bond within each maturity category and an additional bond that closely aligns with the maturity points but was issued in the past. We track these selected bonds over the following month to calculate returns and repeat this procedure in subsequent periods. Finally, we aggregate the monthly bond returns on a quarterly basis throughout the sample period spanning from 1986Q2 to 2021Q4, resulting in the creation of twelve labeled bonds (BND1-BND12).

Options We use 54 portfolios of unlevered S&P index call and put options with varying strike prices and maturities. These portfolios are labeled as CLL1-CLL27 and PUT1-PUT27, respectively. The data series for the period from 1986Q2 to 2021Q4 are obtained from Constantinides et al. (2013).

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, Bali, and Wen (2016) to merge these data sources and exclude bonds with special features.[24] The data span the 1989Q2-2021Q4 period.

Equities We use daily CRSP data starting on January 1981 for ordinary common stocks (share codes 10 and 11) traded on the NYSE or AMEX. Nasdaq stocks are excluded following Amihud (2002) and Acharya and Pedersen (2005) because trading volumes include interdealer transactions and distort the illiquidity measure, in contrast to the volumes in NYSE and AMEX. We exclude stocks that have missing price information for more than 200 consecutive trading days during year t, like in the construction of F&F portfolios on Kenneth French's website.

D.2. Beta-sorted Portfolios

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. This strategy creates three sets of ten corporate bond portfolios denoted CBL1-CBL10, CBV1-CBV10 and CBF1-CBF10, where the index 1 and 10 indicates portfolios with securities that have the largest (most negative) and smallest β, respectively.

Equities We estimate betas with respect to changes in $Illiq_m$, σ_m and $FUND$. Every year, we form 3x10 portfolios by sorting on estimated betas and track the portfolios for one year. This strategy creates three sets of ten portfolios denoted LIQ1-LIQ10, VOL1-VOL10, FUND1-FUND10, respectively, where the index 1 and 10 indicates portfolios with securities that have the largest (most negative) and smallest β, respectively.
For a given stock i on day d , we measure illiquidity using the Amihud ratio:

$$illiq_{i,d} = \frac{|R_{i,d}|}{dvol_{i,d}} * 10^6,$$

where $|R_{id}|$ represents the absolute value of the daily stocks return, and $dvol_{id}$ is the trading volume in dollars. This ratio serves as a measure of the price impact of a \$1 million transaction. Goyenko, Holden, and Trzcinka (2009) conclude that this is an

[24] We thank Jun Yang for providing the code based on Chen et al. 2021 to update the panel of corporate bond returns.

accurate proxy for the price impact. The market illiquidity on day d is the mean illiquidity across all stocks:

$$illiq_{mkt,d} = \frac{1}{N}\sum_{i=1}^{N} illiq_{i,d}, \tag{A25}$$

where N is the total number of assets in the market on a given day d.

Betas are computed for each day d and for each stock i as in Frazzini and Pedersen (2014). The illiquidity beta $\hat{\beta}_{i,d}^{\Delta illiq}$ is given by:

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

where $\Delta illiq$ is the daily change in market illiquidity: $\Delta illiq_{mkt,d} = illiq_{mkt,d} - illiq_{mkt,d-1}$; $\hat{\sigma}_i$ and $\hat{\sigma}_{\Delta illiq}$ denote the standard deviation of stock i excess returns and the volatility of the market illiquidity changes, respectively; $\hat{\rho}_{\Delta illiq,i}$ is the correlation between the stock excess returns and market illiquidity changes. Similarly, the market volatility beta is given by:

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

where the volatility $\hat{\sigma}_{\Delta\sigma}$ is the standard deviation of market volatility changes $\Delta\hat{\sigma}_{mkt,d} = \hat{\sigma}_{mkt,d} - \hat{\sigma}_{mkt,d-1}$ and$\hat{\rho}_{\Delta\sigma,i}$ is the correlation between the stock excess return and the market-volatility changes. Volatilities are estimated using the standard deviation of daily log excess returns over a rolling window of the previous 250 trading days. Correlations $\hat{\rho}$ are estimated using overlapping 3-day log excess returns and a rolling window of the previous 1,250 trading days. To reduce noise, a minimum of 120 trading days with non-missing data is required for volatility estimation, and at least 750 trading days of non-missing data for correlation estimation.

We estimated funding liquidity betas for each stock in each month m as:

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

where $\Delta FUND$ is the monthly change in funding liquidity proxy: $\Delta FUND_m = FUND_m - FUND_{m-1}$. The terms $\hat{\sigma}_i$ and $\hat{\sigma}_{\Delta FUND}$ are the volatilities of stock i excess returns and funding liquidity, respectively, and $\hat{\rho}_{\Delta FUND,i}$ is their correlation. We used a rolling window of 36 months for volatilities and 60 months for correlations, requiring a minimum of 20 observations for correlation estimation.

Portfolios are constructed at the end of year t by sorting stocks on estimated betas in ten decile portfolios. We then track the portfolio returns during year $t+1$ using equal- and value-weights. If a stock is delisted that year, it is dropped after its CRSP delist date and its weight is redistributed among the remaining stocks in the portfolio. We aggregate returns to the quarterly frequency and construct quarterly portfolio statistics as follows. The (ex-ante) beta, volatility, and market capitalization of a portfolio are the averages across all stocks in that portfolio. The illiquidity of a portfolio is the median illiquidity across stocks. The illiquidity, market capitalization, and ex-ante beta for each stock are the average of daily values the previous quarter. To control for growth trend in market capitalization and trading activity, we scaled the quarterly illiquidity for each stock by $dvol_{q-1}/dvol_1$, where $dvol_1$ is the dollar value of trading volume in 1985Q4. The volatility of a stock is the standard deviation of daily excess returns in a given quarter. The LIQ

1-10 and VOL 1-10 portfolios are available for the period from 1986Q1 to 2001Q4. The FUND 1-10 portfolios are available from 1991Q1-2021Q4.

D.3. Illiquidity and Volatility Sorts

At the end of each year, starting with the stocks for which the illiquidity and volatility betas computed above are available, we sort stocks at the end of year t on the average level of illiquidity during the last quarter of the year or on the standard deviation of returns during year t in two sets of decile portfolios. We track the portfolios's returns and characteristic as described above.

E. Link with Goldberg (2019)

Section A provides identification restrictions on the elements of the impact matrix A so that they can be estimated from the data. Goldberg (2020) and Goldberg and Nozawa (2021) follow a different strategy to identify liquidity supply and demand shocks in the corporate bond market, exploiting the sign restrictions on the elements of the A matrix to identify a set of parameters (i.e., set identification). The use of sign restrictions to identify structural VAR models was introduced in e.g., Faust (1998) and Uhlig (2005) and it is described in detail in Kilian and Lütkepohl (2017). Uhlig (2017) provides an insightful discussion of its benefits and limitations. Goldberg (2020) and Goldberg and Nozawa (2021), like many others, choose the median parameter from this set. Briefly, the first step is to compute P the unique Cholesky decomposition of $\hat{\Sigma}_u$ from the data ($\Sigma_u = P'P$, with P' lower triangular). The second step is to sample S' from the set of orthonormal matrices $S'S = I$, so that $\hat{\Sigma}_u = P'S'SP$ and the decomposition given by the matrix $P'S'$ is selected if it satisfies the sign restrictions but it is rejected otherwise. The last step calculates $\hat{A}$ as the median value.

F. 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. Second, we check whether the dispersion of supply shocks changes when funding conditions are poor. Third, we look at a reduced-form test for the hypothesis that the constraints are always binding. Fourth, we provide estimates for the probabilities that the constraint is binding at each point in time.

F.1. Changes in Leverage and Funding Conditions

Figure A7 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 56 percent of all observations and they move in opposite directions in 44 percent of all observations. The correlation is positive but close to zero. Overall, this is suggestive that both supply and demand disturbances influence leverage.

F.2. Distribution of the structural shocks

Figure A1 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. 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. The histograms cover a range of ± 3 standard deviations, which excludes one large demand shock in 2008. However, the 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, the supply shocks have a range of 0.74 and a skewness of 0.01 while the demand shocks have a range of 0.74 and a skewness of -0.18. However, when funding conditions are tight, the range of the supply shocks increases to 1.51 and the range of the demand shocks increases to 1.06. We find similar results if we use the lower and higher quantiles 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.[25]

F.3. 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:

$$LEV_{t+h} = \beta_h + \beta_{f,h} FUND_t + \beta_{l,h} LEV_t + \beta_{\times,h} FUND_t \times LEV_t + \epsilon_{t+h}, \tag{A26}$$

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.

[25]Modeling the variance dynamics explicitly may increase efficiency but it would increase the risk of specification errors. We see Equation (17) as a robust quasi maximum likelihood approach to disentangle the leverage supply and demand shocks.

Panel (A) of Figure A8 shows that the estimate of the interaction coefficients $\beta_{\times,h}$ is negative and significant for every horizon up to 8 quarters ahead, as expected. We estimate the regressions using ordinary least squares and standardized variables. The $\bar{R}^2$s is close to 80 percent when $h = 1$ and it gradually declines to around 15 percent when $h = 8$. The coefficient of LEV_{t+h} on its own lag LEV_t remains significant up to 8 quarters ahead. Therefore, there is substantial statistical evidence that the partial effect changes with the level of leverage. Panel (B) of Figure A8 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 $+7$ 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 (A26) separately for each horizon implies that the inference is not efficient, relative to estimating a dynamic VAR model like we do in our baseline results. However, the estimated VAR(1) system in Equation (17) does not include the non-linear effects documented here. We checked in unreported results that, in a model that includes one lag of the interaction term $y_{t+1} = a + \Phi y_t + bz_t + u_{t+1}$, we recover essentially the same shocks. Intuitively, the reason is that the variations in the interaction term z_t lay very close to a line generated by a linear combination of the elements of y_t.

F.4. 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 and supply system is symbolically represented with the following equations:

$$\begin{aligned} S_t =& \beta_0 Z_t + \beta_1 P_t + v_t \qquad D_t = \alpha_0 X_t + \alpha_1 P_t + u_t \\ & Q_t = \min(D_t, S_t), \end{aligned} \tag{A27}$$

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. In our baseline results reported in the main text, we focus on shocks identified based on the signs and the asset pricing restriction because this approach remains agnostic regarding the structure of the supply and demand channels and may be more robust.

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:

$$\pi_t = pr(S_t < D_t) = pr(\beta_0 Z_t + \beta_1 P_t + v_t < \alpha_0 X_t + \alpha_1 P_t + u_t). \tag{A28}$$

Since $v_t - u_t$ is normally distributed with variance $\sigma^2 = \sigma_v^2 + \sigma_u^2$, the probability in Equation (A28) 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. The next section reports the estimated probabilities, while the following two sections provides the details of the specification of the demand and supply equations as well as additional estimation results.

Estimated probabilities We report in Figure A9 the estimated probabilities. When the probability is close one, it is likely that the intermediaries were constrained during that period and changes in leverage captures the effect of supply shifters. When the probability is close to zero, it is unlikely that the intermediaries were constrained, that they were at least partially accommodating demand shifts, and that both demand and supply shocks could be driving leverage.

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, during the European debt crisis of 2011-2012 and around the large volatility spike in the first quarter of 2018. Perhaps surprisingly the probability is also close to zero during the last quarter of 2008, but this could be the reflection of the large-scale interventions by the Federal Reserve and the US Treasury during this quarter, which are unaccounted for in the model. Reassuringly, even though the methodologies differ, the periods where the estimated probabilities are close to zero are consistent with periods when we extract relatively large demand shocks (see the historical decomposition in Figure 3).

The constraint was likely binding with a probability closer to one in the 1994-1998, 2001-2004 and 2010-2011 periods. These periods were associated with improved funding conditions and, therefore, the results suggest a positive shift in the intermediaries' supply decisions that led to a binding constraint. As a robustness check, we checked that these conclusions are robust to the specification of the demand and supply equations that include the direction of the price change ΔP in the system of equations given by (A27) (see Maddala and Nelson (1974) and Laffont and Garcia (1977)).

Supply and demand To complete the demand and supply system in Section F.4, 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.

Estimation Estimates 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 and the CAY in the demand equation are the instruments 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 A5. 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.

The results for the demand equation indicate that the OLS estimates do not always have the right sign and lack significance. The second-stage estimate for $FUND$ is negative and significant. 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, except for the ratio in the 2SLS. 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.

Table A1. Summary Statistics—Equity Portfolios

Summary statistics for 3 × 10 portfolios of stocks sorted on illiquidity, volatility and funding betas, respectively. We report the average ex-anted $\tilde{\beta}^{\Delta \text{Illiq}}$, $\tilde{\beta}^{\Delta\sigma}$ and $\tilde{\beta}^{\Delta \text{FUND}}$, the average equally- and value-weighted quarterly excess returns, $\overline{xR}_i^{ew}$ and $\overline{xR}_i^{vw}$, and the average illiquidity, volatility and market capitalization. A portfolio illiquidity is the median across stocks (× 100), its volatility is the standard deviation, and its capitalization is the average capitalization across stocks (in $ billions).

Panel A. $\beta^{\Delta \text{Illiq}}$-sorted Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\overline{xR}_i^{ew}$	3.54	3.18	3.04	3.12	3.10	2.97	2.94	3.11	3.05	3.11
$\overline{xR}_i^{vw}$	2.28	2.82	2.49	3.03	2.81	2.37	3.11	2.44	2.77	2.42
Illiqu.	48.31	5.03	3.23	2.34	1.94	1.90	2.02	2.07	4.01	85.81
Volatil.	18.91	12.24	11.01	10.28	9.72	9.70	9.31	9.75	10.54	14.90
Cap	2.18	5.10	6.19	7.33	8.58	9.17	9.87	9.09	7.69	3.41
$\tilde{\beta}^{\Delta \text{Illiq}}$	-0.38	-0.25	-0.20	-0.17	-0.14	-0.12	-0.10	-0.07	-0.04	0.07
$\tilde{\beta}^{\Delta\sigma}$	-23.93	-16.92	-15.53	-13.68	-12.78	-12.30	-11.72	-11.92	-13.39	-21.41
$\tilde{\beta}^{\Delta \text{FUND}}$	-4.97	-3.80	-3.56	-3.23	-3.22	-3.13	-2.83	-2.65	-2.71	-3.78

Panel B. $\beta^{\Delta\sigma}$-sorted Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\overline{xR}_i^{ew}$	3.55	3.38	3.00	3.34	3.20	2.82	3.06	3.50	2.75	2.53
$\overline{xR}_i^{vw}$	3.30	3.38	3.13	3.17	2.78	2.70	2.31	2.25	2.44	2.54
Illiqu.	158.76	19.05	7.05	3.93	2.56	2.14	1.86	1.56	1.69	4.93
Volatil.	18.10	14.89	12.62	11.20	10.14	9.84	9.23	11.72	8.62	10.52
Cap	0.87	2.53	3.91	5.34	6.66	8.80	9.30	10.81	11.98	8.45
$\tilde{\beta}^{\Delta \text{Illiq}}$	-0.20	-0.17	-0.17	-0.16	-0.13	-0.13	-0.12	-0.11	-0.10	-0.10
$\tilde{\beta}^{\Delta\sigma}$	-53.75	-31.79	-24.16	-18.51	-14.51	-11.46	-7.85	-3.94	0.38	11.03
$\tilde{\beta}^{\Delta \text{FUND}}$	-5.85	-4.81	-4.20	-3.71	-3.30	-3.08	-2.76	-2.25	-1.99	-1.93

Panel C. $\beta^{\Delta \text{FUND}}$-sorted Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\overline{xR}_i^{ew}$	4.09	3.55	3.75	3.46	3.51	3.53	3.10	3.13	3.11	3.97
$\overline{xR}_i^{vw}$	4.11	2.94	2.72	3.10	2.96	2.64	2.29	2.43	2.71	2.54
Illiqu.	111.85	9.16	4.89	3.42	2.93	4.03	3.55	4.15	6.57	20.00
Volatil.	18.92	13.59	11.90	10.72	10.36	10.20	9.24	8.85	9.27	12.48
Cap	1.80	4.16	5.91	7.99	8.82	9.15	9.21	8.91	9.27	4.89
$\tilde{\beta}^{\Delta \text{Illiq}}$	-0.24	-0.20	-0.18	-0.17	-0.16	-0.16	-0.13	-0.14	-0.12	-0.14
$\tilde{\beta}^{\Delta\sigma}$	-27.43	-20.99	-18.18	-15.97	-14.98	-13.93	-13.39	-12.41	-12.75	-15.61
$\tilde{\beta}^{\Delta \text{FUND}}$	-13.27	-7.60	-5.70	-4.32	-3.30	-2.32	-1.29	-0.23	1.35	5.34

Table A2. Correlations between shocks using different instruments

Correlations between structural shocks identified using different instruments in a VAR with leverage. $FUND$ is the funding condition proxy underlying the baseline results in the paper, $FUND+$ combine $FUND$ and the market returns in the VAR, $AVG3$ is the average of the TED, FL and HPW measures. Panel (A) reports correlations between demand shocks. Panel (B) reports correlations between supply shocks.

Panel A. Demand shocks

	PCA3	MKT+PCA3	AVG3	FL	HPW
PCA3	1.00	0.99	0.94	0.89	0.85
MKT+PCA3	0.99	1.00	0.94	0.90	0.85
AVG3	0.94	0.94	1.00	0.90	0.97
FL	0.89	0.90	0.90	1.00	0.79
HPW	0.85	0.85	0.97	0.79	1.00

Panel B. Supply shocks

	PCA3	MKT+PCA3	AVG3	FL	HPW
PCA3	1.00	0.98	0.85	0.76	0.62
MKT+PCA3	0.98	1.00	0.83	0.76	0.59
AVG3	0.85	0.83	1.00	0.64	0.89
FL	0.76	0.76	0.64	1.00	0.29
HPW	0.62	0.59	0.89	0.29	1.00

Table A3. Asset-pricing Tests— Alternative Equity Portfolios

Asset pricing models estimated with two-stage Fama-MacBeth regressions for portfolios of equities, corporate and Treasury bonds, and options. Columns (1)-(4): results using 40 portfolios of equities sorted by size, book-to-market, profitability and investment portfolios as equity portfolios. Columns (5)-(8): results for 30 portfolios sorted by $\tilde{\beta}^{\Delta \text{Illiq}}$, $\tilde{\beta}^{\Delta\sigma}$ and $\tilde{\beta}^{\Delta \text{FUND}}$ as equity portfolios. Columns (9-12): results for 20 portfolios sorted by liquidity and volatility. The coefficient λ_l, λ_s and λ_d are the prices of the raw leverage shock, leverage supply shock, leverage demand shock, and λ is the price of risk for supply and demand leverage shocks with a symmetry restriction. Shanken-corrected t-statistics in parentheses.

	FF Portf.				Beta Portf.				Characteristic Porf.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
λ_l	5.90				4.56				5.08			
	(1.92)				(2.45)				(2.09)			
λ_s		3.69				4.05				3.33		
		(2.52)				(2.56)				(2.51)		
λ_d			-4.50				-4.47				-4.05	
			(-2.27)				(-2.38)				(-2.26)	
λ				1.96				2.02				1.77
				(2.80)				(2.91)				(2.73)
$\bar{R}^2$	13.5	90.3	89.1	93.5	7.9	90.5	88.6	93.1	12.2	88.0	85.9	91.3

Table A4. Illiquidity and Volatility Portfolios—Summary Statistics

Summary statistics for portfolios of stocks sorted on illiquidity and volatility (see Appendix D.3 for the construction of the portfolios). We report the average ex-ante $\tilde{\beta}^{\Delta \text{Illiq}}$, $\tilde{\beta}^{\Delta\sigma}$ and $\tilde{\beta}^{\Delta \text{FUND}}$, the average quarterly equally-weighted and value-weighted excess returns excess returns ($\overline{xR}_i^{ew}$ and $\overline{xR}_i^{vw}$), illiquidity, volatility and market capitalization of each portfolio. The portfolio illiquidity is the median across stocks (× 100), its volatility is the standard deviation of excess returns and its Cap is the average quarter-end capitalization across stocks (in $ billions).

Panel A. Illiquidity Sort

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\overline{xR}_i^{ew}$	3.74	2.52	3.39	3.50	3.27	2.87	3.16	3.01	2.93	2.69
$\overline{xR}_i^{vw}$	3.41	2.84	3.16	3.52	3.22	3.03	3.20	3.08	2.89	2.43
Illiqu.	2532.24	191.63	39.69	14.49	5.93	2.55	1.28	0.62	0.29	0.10
Volatil.	19.43	14.19	14.21	12.76	11.62	10.53	10.28	9.85	8.69	7.83
Cap	0.05	0.18	0.39	0.70	1.14	1.82	2.85	4.96	10.62	45.68
$\tilde{\beta}^{\Delta \text{Illiq}}$	-0.11	-0.18	-0.17	-0.17	-0.16	-0.15	-0.13	-0.12	-0.11	-0.09
$\tilde{\beta}^{\Delta\sigma}$	-28.55	-23.56	-19.55	-16.85	-14.60	-13.07	-11.97	-11.03	-8.98	-6.39
$\tilde{\beta}^{\Delta \text{FUND}}$	-4.28	-4.41	-3.84	-3.41	-3.17	-3.06	-3.22	-3.14	-2.83	-2.53

Panel B. Volatility Sort

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\overline{xR}_i^{ew}$	2.87	3.25	3.16	3.24	3.25	3.21	2.97	3.24	3.00	2.84
$\overline{xR}_i^{vw}$	1.39	2.18	2.40	2.64	2.76	2.66	2.72	2.70	2.67	2.42
Illiqu.	691.50	40.53	12.59	6.11	3.08	2.03	1.47	1.04	1.03	1.29
Volatil.	24.24	16.58	13.85	12.30	11.24	10.36	9.68	8.70	7.47	6.08
Cap	0.38	1.12	1.99	2.98	4.16	5.64	7.68	10.37	13.87	19.81
$\tilde{\beta}^{\Delta \text{Illiq}}$	-0.18	-0.18	-0.17	-0.17	-0.15	-0.14	-0.13	-0.11	-0.10	-0.07
$\tilde{\beta}^{\Delta\sigma}$	-32.53	-23.62	-19.28	-16.56	-14.59	-13.03	-11.61	-9.97	-8.34	-5.38
$\tilde{\beta}^{\Delta \text{FUND}}$	-5.76	-4.55	-4.17	-3.80	-3.49	-3.25	-3.00	-2.63	-2.10	-1.30

Table A5. Leverage Demand and Supply Equations

OLS and TSLS regressions of intermediaries' leverage LEV on funding conditions $FUND$ for the demand and supply equations in the simultaneous system of Section F. Panel (A): the supply equation includes 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): demand equation includes 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	57.24	1.35	-5.40	-1.61	-1.38	0.19	-2.68	0.67	
	(7.07)	(0.55)	(-5.15)	(-2.27)	(-2.61)	(0.58)	(-5.88)	(1.41)	37.36
2SLS	65.21	17.57	-7.92	-4.53	-0.37	0.09	-2.94	0.60	
	(6.54)	(2.06)	(-4.59)	(-2.73)	(-0.47)	(0.23)	(-5.54)	(1.11)	39.87

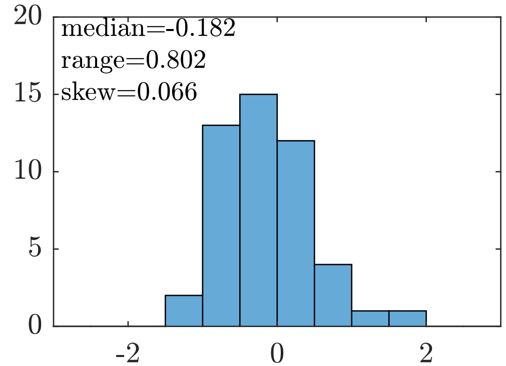
Panel B. Demand equation

	int	FUND	Level	Slope	Curv.	Ratio	Mrtg	CAY	R^2
OLS	3.98	-1.48	-1.26	-0.09	0.78	6.51	0.52	3.44	
	(0.50)	(-0.66)	(-1.59)	(-0.15)	(1.58)	(7.66)	(2.69)	(3.66)	53.18
2SLS	-43.38	-98.37	8.64	14.26	-3.45	1.06	3.26	15.96	
	(-1.50)	(-2.33)	(1.83)	(2.25)	(-1.56)	(0.33)	(2.55)	(2.70)	65.91

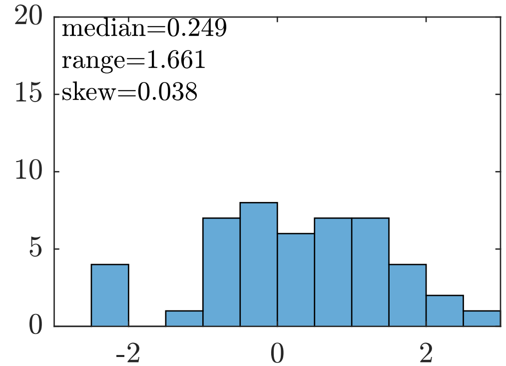
Figure A1. Conditional Distribution of Leverage Supply and Demand Shocks

Distributions of leverage supply and leverage demand shocks from a bivariate VAR(1) for LEV_t and $FUND_t$ in levels identified with sign and asset pricing 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.

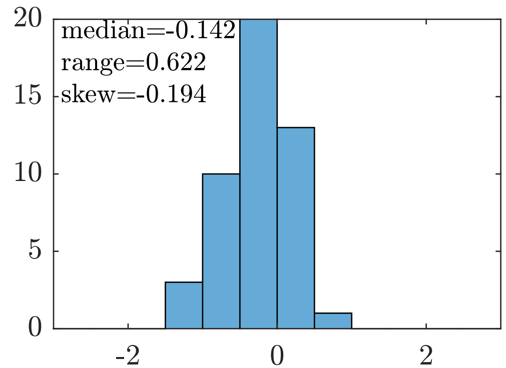
Panel A. Supply Shocks when $FUND$ is low



Panel B. Supply Shocks when $FUND$ is high



Panel C. Demand Shocks when $FUND$ is low



Panel D. Demand Shocks when $FUND$ is high

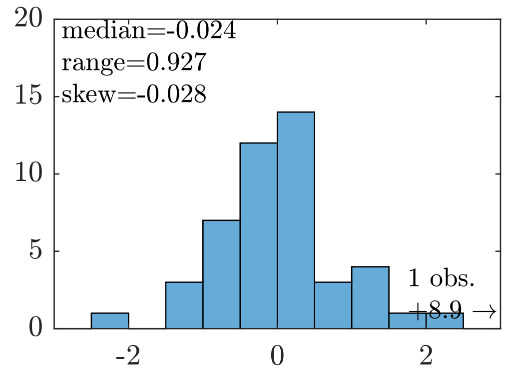
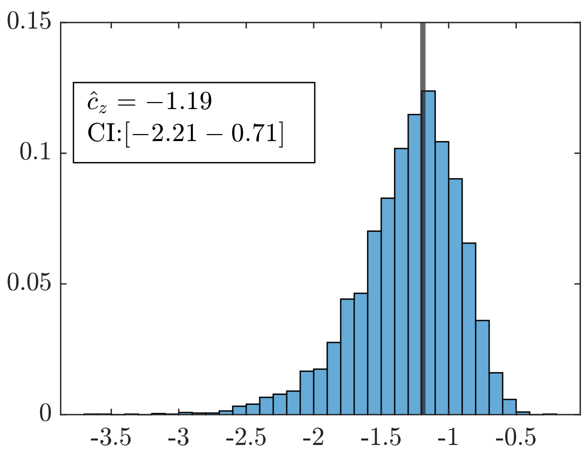


Figure A2. Bootstrap Distributions–Benchmark Model

Panel (A): bootstrap distribution for c_z with the vertical line indicating the sample estimate and CI is the 95 percent confidence interval. Panel (B): bootstrap distribution of $\hat{\lambda}_d + \hat{\lambda}_s$ when both prices of risk are estimated freely with a regression using the bootstrap series of returns and leverage supply and demand shocks in each bootstrap sample using the unbalanced panel as in the original data, with a vertical line indicating the sample estimate and the p-value is the probability mass under the bootstrap measure of outcome to the left of the value obtained in the data. See Section C for details of the Bootstrap procedure.

Panel A. c_z



Panel B. $\hat{\lambda}_d + \hat{\lambda}_s$

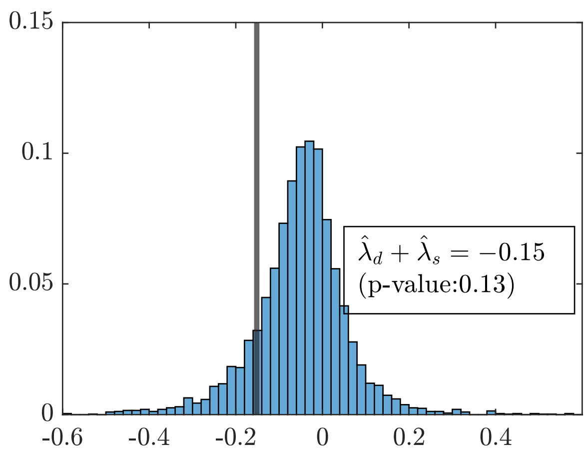


Figure A3. Bootstrap Distributions–Extended Model

Panel (A): bootstrap distribution of the prices of risk λ in the extended model. The vertical line indicating the sample estimate $\hat{\lambda}$ and CI is its bootstrap 95 percent confidence interval. Panel (B): bootstrap distribution of the price of risk λ_m for the shocks e^m that is uncorrelated with leverage demand and supply shocks. Panel (C): bootstrap distribution of the uncentered $\bar{R}^2$. The market risk premium in the extended model is given $E[R_m] = \lambda(\beta_{m,s} - \beta_{m,d}) + \lambda_m \beta_{m,m}$. See Section I for a description of the model and Section E for the list of test assets. See Appendix C for the bootstrap procedure.

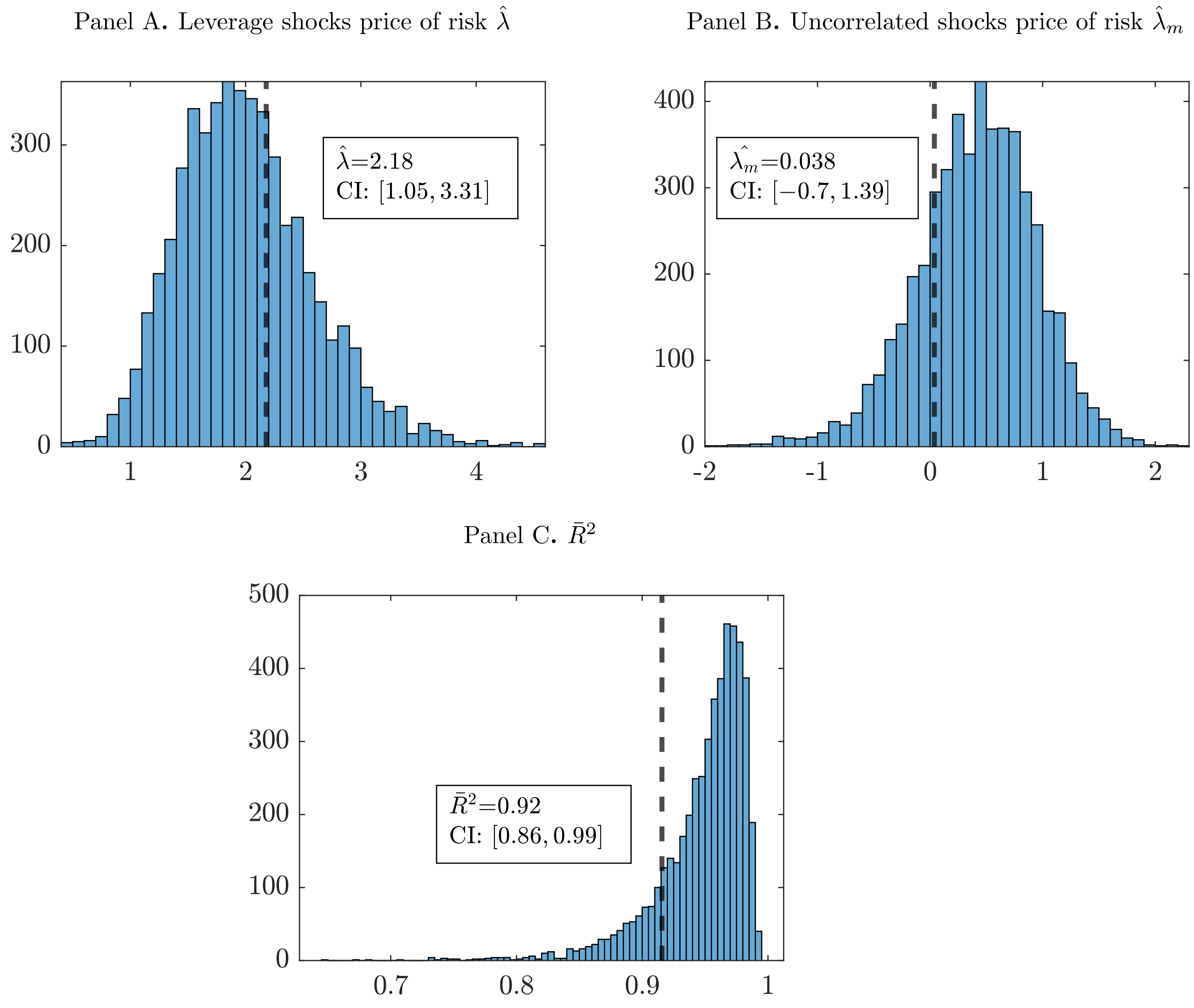


Figure A4. Symmetry in the Set identified with Signs Restrictions

Results across 10,000 series of structural shocks drawn from the set of parameters identified in a VAR with sign restrictions. Panels (A)-(B): two-state regression estimates for the price of risk of leverage demand and supply shocks, respectively, using the same test assets as in our baseline results. Panel (C): the sum $\lambda_s + \lambda_d$. Panel (D): the corresponding Shanken t-stats for a test that the sum is zero. The red bars indicate rejection at the 5% significance level.

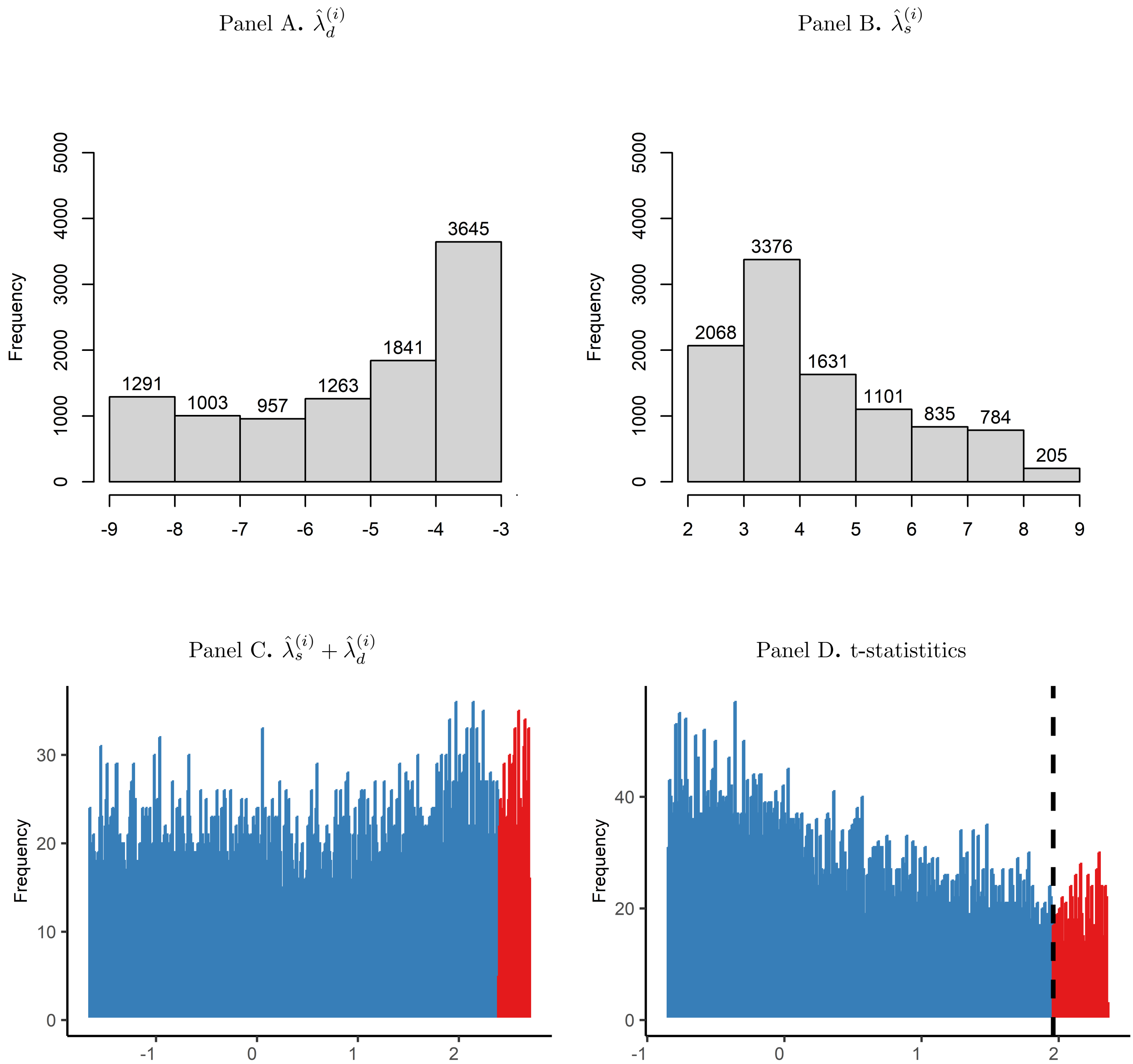
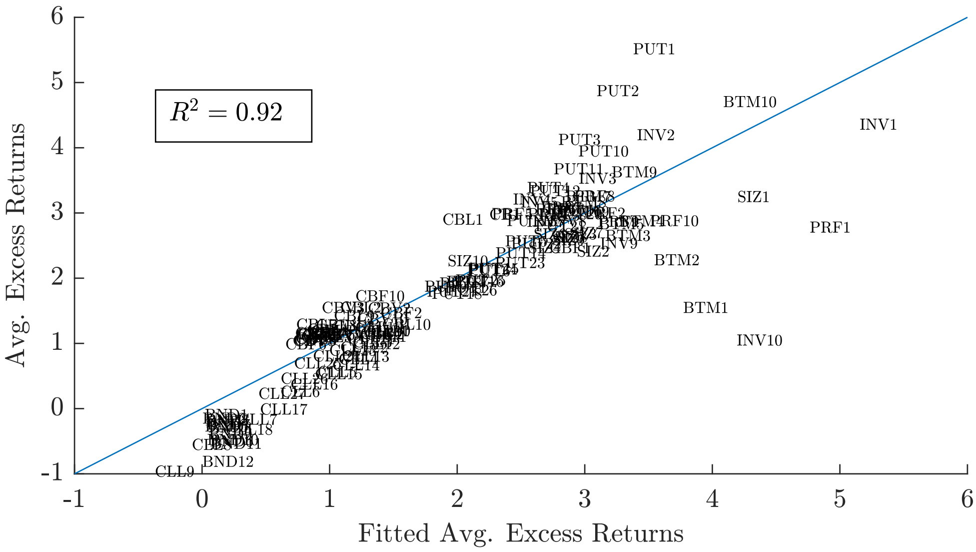


Figure A5. Leverage Shocks in Asset Pricing—Alternative Equity Portfolios

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): results using leverage demand and leverage supply shocks. Panel (B): results using market returns and the leverage factor from AEM. Each model is estimated with no intercept $E(xR_i^e) = \beta_i\lambda_i$ and we draw a 45-degree line.

Panel A. Leverage Demand and Supply Shocks



Panel B. Raw Leverage and Market Returns

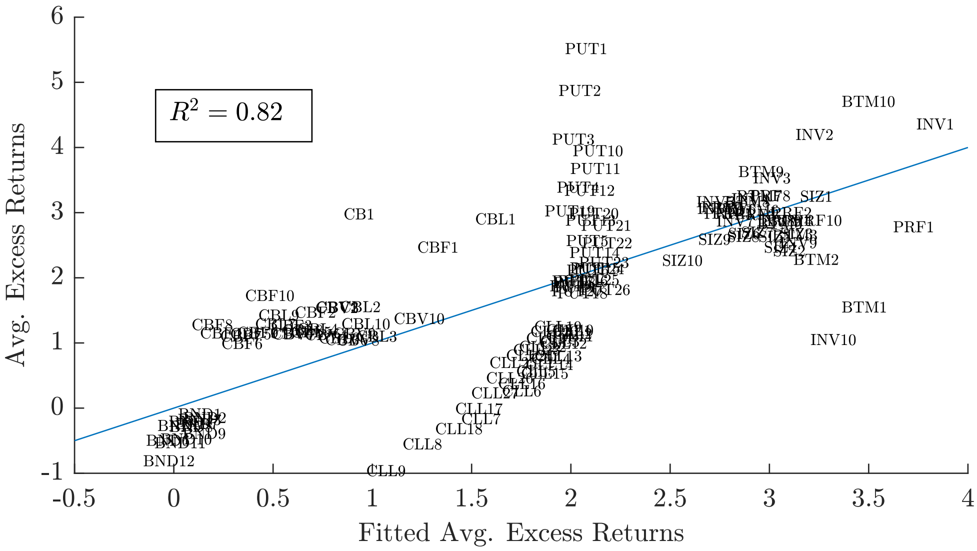
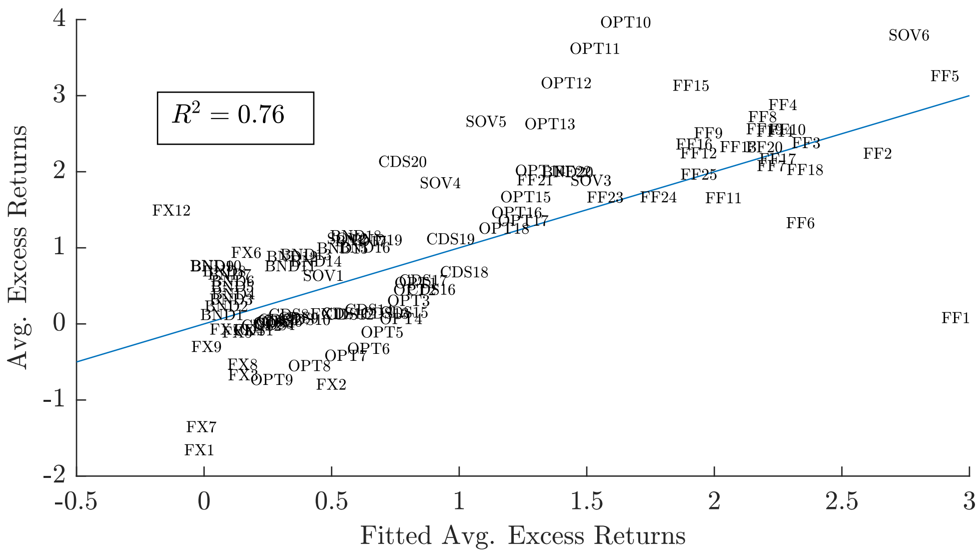


Figure A6. Leverage Shocks in Asset Pricing—HKM Test Assets

Realized and fitted mean excess returns for HKM test assets in sample period: equities (FF), US bonds (BND), foreign sovereign bonds (SOV), options (OPT), CDS, and foreign exchange (FX), but excluding commodities (COM). Panel (A): results using leverage demand and leverage supply shocks. Panel (B): results using market returns and the leverage factor from AEM. Each model is estimated with no intercept $E(xR_i^e) = \beta_i \lambda_i$ and we draw a 45-degree line.

Panel A. Leverage Demand and Supply Shocks



Panel B. Raw Leverage and Market Returns

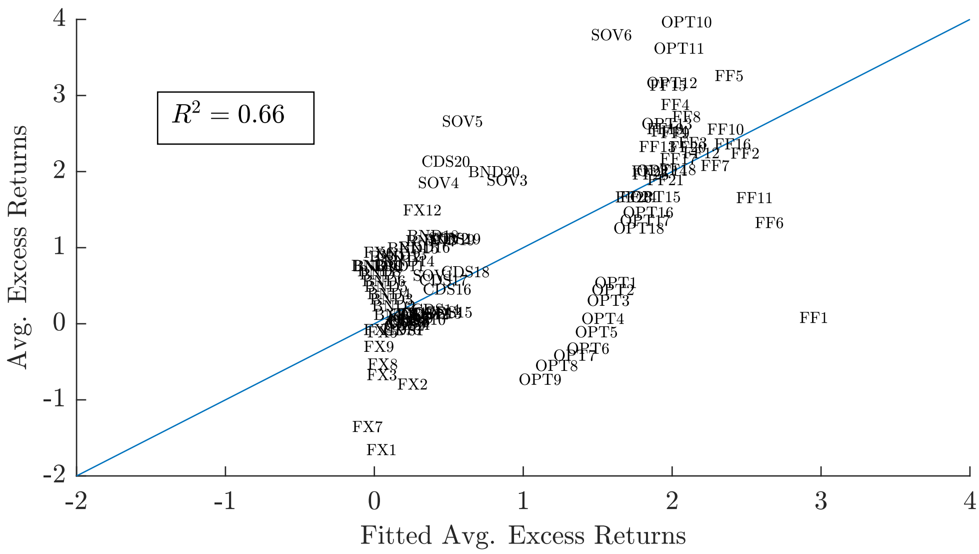


Figure A7. ΔLEV and $\Delta FUND$

Changes in leverage ΔLEV and changes in funding conditions $\Delta FUND$ normalized with mean zero and standard deviation of one. The two series should always move in opposite directions if they are determined by supplys shocks only.

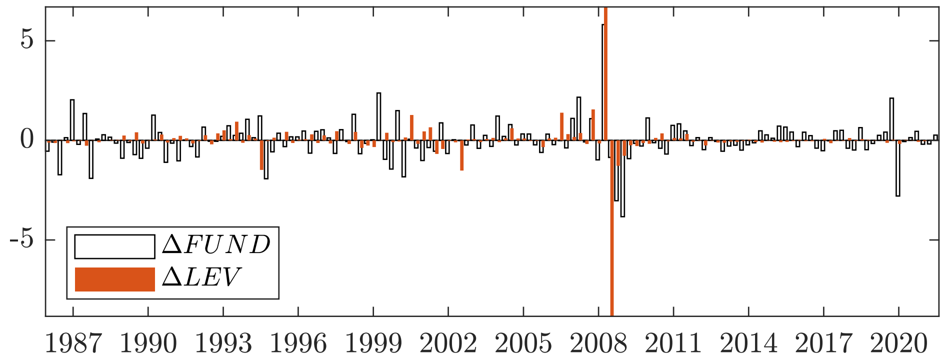


Figure A8. Leverage and Funding Conditions

Predictive regressions of LEV_{t+h} on LEV_t, $FUND_t$ and the interaction term $LEV_t \times FUND_t$ for $h = 1 \ldots 8$ quarters (Equation A26). Panel (A): 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): the partial effect $\frac{\partial LEV_{t+4}}{\partial FUND_t}$ across conditioning values of LEV_t.

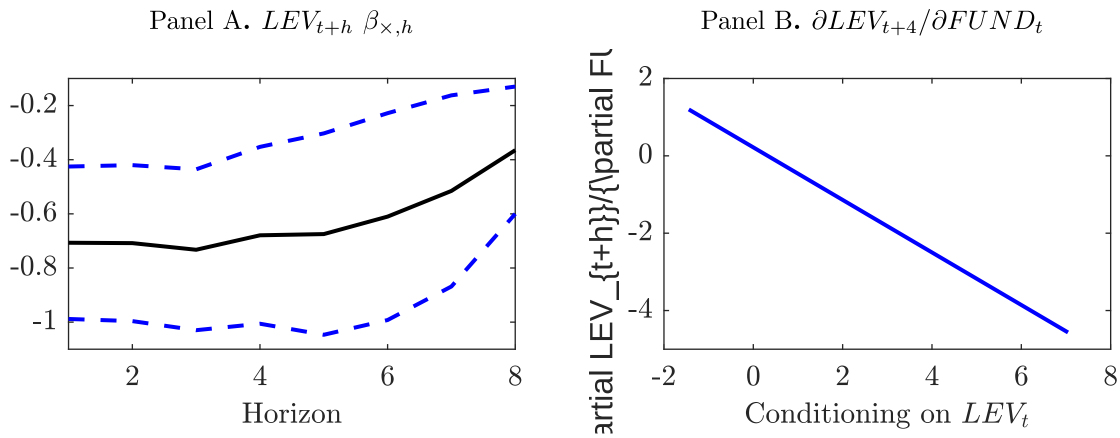
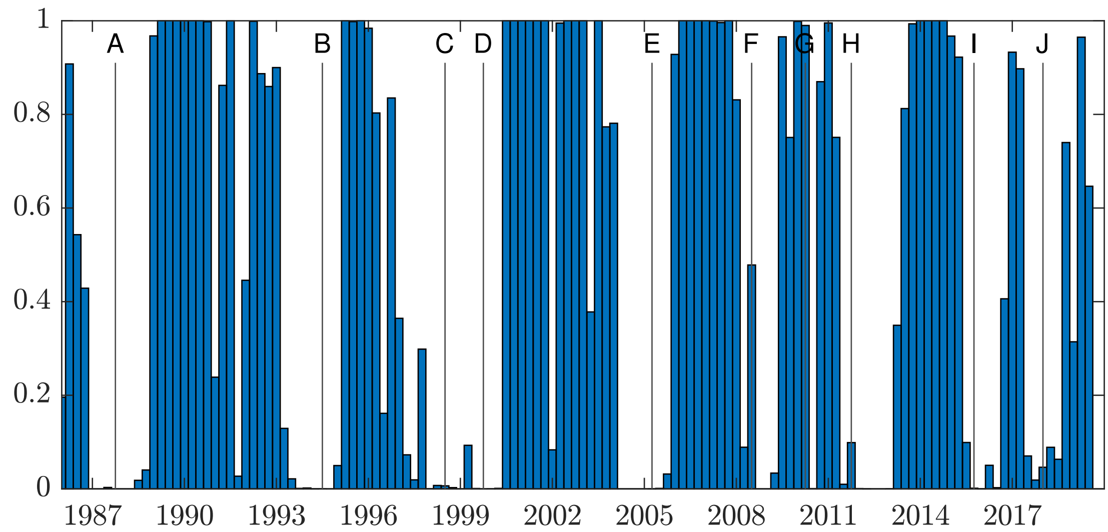


Figure A9. Probabilities of Constrained Intermediation Supply

The probability of constrained intermediation supply estimated in the demand and supply system defined in Equations (A27)-(A28). The sample period matches the availability of the CAY variables. Quarterly data, 1986-2019.



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, (J) 2018 volatility spike "Volmageddon".