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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. Specifically, leverage supply shocks that relax broker-dealers' funding constraints increase leverage, liquidity, and returns and carry a positive price of risk, while leverage demand shocks also increase leverage but reduce liquidity and 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.

LARGE FINANCIAL INTERMEDIARIES PROVIDE BROKER-DEALER services to large investors and asset managers and provide liquidity across several markets. Moreover, they are central in the issuance of new securities. Because the activities of intermediaries span complex investment strategies across essentially all financial markets, in stark contrast to the limited investment options available to households, the marginal value of intermediaries' wealth may determine the compensation for risk. In a seminal paper, Adrian, Etula, and Muir (2014, AEM), show that a measure of leverage from broker-dealers' aggregate balance sheet is a good proxy for intermediaries' marginal value of wealth and that the covariance of asset returns with leverage can help explain expected returns. Consistent with this view, prior evidence shows that assets

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and strategies that perform poorly when intermediaries' marginal value of wealth is high offer larger returns to investors.[1]

However, other results raise questions about the centrality of intermediaries for asset pricing. First, while the asset pricing results of AEM are consistent with well-established models of intermediation frictions (Brunnermeier and Pedersen (2009)), AEM note that leverage appears to be largely uncorrelated with proxies for market liquidity, which runs counter to a key theoretical prediction of these models. Second, in a study that extends intermediation frictions to several asset classes, He, Kelly, and Manela (2017) find that estimates of the price of risk for leverage can switch signs between asset classes.

One reason empirical work yields weak or mixed estimates may be that the leverage decision is driven by both demand-side and supply-side considerations. In a framework such as Brunnermeier and Pedersen (2009), intermediaries face (i) customers that demand immediacy and (ii) financiers that supply them with funds. On one hand, leverage may increase because a change in the supply of funds made available by financiers leads funding conditions to improve, in which case the marginal value of intermediaries' wealth declines. On the other hand, leverage can increase because a change in the demand for immediacy by investors wanting to sell assets leads funding conditions to tighten, in which case, the marginal value of intermediaries' wealth rises. Both types of change can lead to an increase in intermediaries' leverage but with opposite effects on the intermediaries' marginal value of wealth and potentially, in turn, 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]

Our paper's first main contribution is to show that shocks to broker-dealers' aggregate leverage, once separated into demand-side and supply-side shocks, carry consistent prices of risk across a broad range of financial markets. We further show that disentangling demand and supply shocks can rationalize changes in the sign on the price of AEM's raw leverage risk across asset classes. Finally, we show that the separation of demand and supply shocks can help explain the weak correlation between raw leverage and market liquidity. Overall, disentangling demand and supply shocks considerably strengthens evidence of a central role for intermediaries in asset pricing and paves the way for more work to understand mechanisms underpinning demand- and supply-side frictions.

To analyze leverage shocks, we introduce an econometric model in which demand-side variations in intermediaries' leverage are captured by one shock and supply-side variations in intermediaries' leverage are captured by a separate shock. We interpret supply shocks as shifts in the supply of funds

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

[2] In Section VI of the Internet Appendix, we report empirical evidence from reduced-form and structural approaches, indicating that intermediaries' funding constraints are not always binding. The Internet Appendix is available in the online version of the article on *The Journal of Finance* website.

by financiers and demand shocks as shifts in the demand for immediacy by clients. While both shocks can increase leverage, they shift the marginal value of wealth in opposite directions. This interpretation combines within leverage demand shocks potential shifts in intermediaries' demand for funds or supply of immediacy.

To identify the two shocks, we combine a measure of leverage with an instrument that is correlated with the supply and demand shocks. We first restrict the sign of the effect that each type of shock has on leverage and the instrument within a vector autoregression (VAR) system. This procedure identifies a set of potential structural parameters that has one degree of freedom. To achieve point identification, we then assume that the prices of risk for the leverage demand and supply shocks are symmetric. This yields 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, 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-side or demand-side variation. The cross-section of asset returns will therefore be determined by the patterns of the demand and supply betas. With asymmetric prices of risk, our core message remains the same and the fit of asset returns is identical, but interpretation of some of the results changes. Asymmetry mechanically gives greater weight 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 in which either demand shocks or supply shocks clearly dominate.

Empirically, for leverage, we use AEM's measure of broker-dealers' aggregate leverage and, as an instrument, we use a proxy for intermediaries' funding conditions.[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 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 separately on their sensitivity to market illiquidity, market volatility, and funding conditions. Finally, we include portfolios of equities constructed using the same sorts. These sorts are motivated by the predictions in Brunnermeier and Pedersen (2009) linking securities' returns with illiquidity, volatility, and funding conditions.

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

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 discusses conditions for the validity of this proxy in the context of our econometric model. Section III verifies these conditions in our results.

Our pricing model that disentangles leverage demand and supply shocks receives strong empirical support. The estimated betas for the demand and supply shocks have negative and positive signs, as expected. More importantly, we show that the betas with respect to raw leverage can switch signs because they mix demand and supply exposures. In particular, we find relatively large leverage supply betas for bonds, which explains the negative betas that we obtain for raw leverage, and 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 an R^2 of 92% across our equity, bond, and option portfolios, when excluding a constant. The model shows that the price of risk for raw leverage can change sign across asset classes because the demand and supply betas have different dispersions. The price of risk for raw leverage is negative for options, where the demand betas have a wider dispersion, but tends to be positive for bonds, where the supply betas are more dispersed. In contrast, the symmetric price of risk for the leverage demand and supply shocks remains significant, with the same sign and similar magnitude when estimated separately for bonds, equities, and options, and consequently when all test assets are considered together. We conclude that exposures of asset returns to variations in aggregate leverage, as measured by either demand or supply betas, are priced consistently across markets: Assets with similar leverage risks offer similar average returns.

Our conclusions are largely unchanged when we use traditional Fama-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 risk for raw leverage. This sign is consistent with our model prediction because supply shock betas have relatively large dispersion across AEM's test assets. We further find robust signs for the price of demand and supply shocks across the larger set of asset classes considered by He, Kelly, and Manela (2017), which includes sovereign bonds, credit derivatives, commodities, exchange rates, the Fama-French 25 portfolios, government and corporate bonds, and equity derivatives.

Disentangling leverage demand and supply shocks can also help us understand variations in market liquidity. We verify the theoretical prediction of Brunnermeier and Pedersen (2009) that intermediaries' marginal value of wealth is a significant determinant of variations in market liquidity. We find that leverage supply shocks have a significant positive correlation with market liquidity. The effect 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). Combining 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 on 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 financial intermediaries' marginal value of wealth. As discussed above, AEM include the leverage of securities broker-dealers as a proxy. He, Kelly, and Manela (2017) instead use the capital ratio of primary dealers' holding companies and analyze a broader set of asset classes. In this paper, we distinguish between the roles of leverage demand and supply shocks to deepen our understanding of the central role intermediaries' leverage plays in asset pricing.

A broader literature studies demand or supply channels in the determination of asset prices but does not focus on the role of intermediaries. For instance, Liu, Whited, and Zhang (2009) emphasize the effect of firms' demand for capital on stock prices. Koijen and Yogo (2019) argue that stock returns are explained largely 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 quantity decisions, we focus on both the demand for and supply of 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 U.S. corporate bond market, respectively. Like these papers, we find that leverage supply shocks play a larger role in the bond markets. Hanson, Malkhozov, and Venter (2024) document that both demand and supply shocks help explain swap spreads. One of our key methodological contributions, relative to existing work on the effects of demand and supply shocks, is to rely on asset pricing implications to achieve point identification of the shocks.[6]

The studies above 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 U.S. 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 exchange rates. Du, Tepper, and Verdelhan (2018) study the persistent deviations from covered interest rate parity (CIP). In a closely related paper, Du, Hébert, and Huber (2022) show that these measures of apparent mispricing complement information about intermediaries' wealth or leverage in asset pricing tests when intertemporal considerations enter

[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 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).

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 vary across asset markets. This finding is in line with Haddad and Muir (2021), who ascribe a greater share of the variation in aggregate risk premia to intermediaries in asset classes in which households are less active, and with Siriwardane, Sunderam, and Wallen (forthcoming), who show that intermediation frictions differ across markets because of segmentation in funding markets.

Our results also relate to existing work showing strong illiquidity commonality across securities (Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001)), or showing a positive relation between illiquidity and the volatility of securities, to compensate market makers for their inventory risk or for their losses to better informed investors (Benston and Hagerman (1974), Stoll (1978), Glosten and Milstom (1985), Grossman and Miller (1988), Pagano (1989)). We show that leverage supply shocks connect intermediaries' balance sheets with market illiquidity but with opposite signs. Prior work shows 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.

The paper is organized as follows. In Section I, we draw implications from an econometric model in which intermediaries' leverage and marginal value of wealth are driven by supply and demand disturbances. Section II explains how we estimate supply and demand shocks to leverage using measures of funding conditions and leverage. Section III analyzes how leverage demand and supply shocks influence risk premia across several asset classes. In Section IV, we review AEM's seminal results through the lens of our econometric model. The results highlight the need for further research on the mechanisms underlying leverage supply and demand shocks. The Internet Appendix contains proofs, describes the data, and provides supplemental results.

I. An Econometric Model of Leverage Shocks

We develop an econometric asset pricing model in which intermediaries' leverage and marginal value of wealth are influenced by demand and supply disturbances that are priced in financial markets. We show that the patterns of demand and supply return betas determine the estimated price of risk for aggregate raw 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 in which specialized traders, or speculators, provide intermediation between customers and financiers. The customers are investors that arrive to the markets sequentially and demand immediacy, in the spirit of Grossman and Miller (1988). The intermediaries smooth price fluctuations, thereby providing market liquidity. The intermediaries also interact with financiers that provide funding against margins, but face constraints whereby long positions cannot be netted against short positions. In this class of models, as AEM note, variation in leverage plays a central role for asset pricing in equilibrium.[7]

In our econometric model, 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 suppress the time subscripts for parsimony in this section but we introduce them in the empirical analysis. The shocks e^d and e^s are independent with zero mean and unit standard deviation. The superscripts d and s indicate that there are two types of shocks—demand shocks and supply shocks, respectively—but these labels are devoid of economic content based on equation (1) alone.

We model intermediaries' marginal value of wealth ϕ as

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

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-side disturbances, respectively. The demand-side shock e^d increases leverage and the marginal value of wealth, for example, when investors' order imbalances increase. The supply-side shock e^s increases leverage but decreases the marginal value of intermediaries' wealth, for example, when intermediaries' funding conditions improve. The magnitudes of α_d and α_s determine the relative contributions of demand- and supply-side disturbances to the variation in the marginal value of wealth, ϕ. In a robustness check, we add to the pricing kernel a source of aggregate risk that is unrelated to leverage.

Financial assets indexed by i earn 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. Based on the interpretation of the demand and supply shocks, we expect $\beta_{i,d} < 0$ and $\beta_{i,s} > 0$ for risky assets. We assume that the intermediaries price financial assets and that their

[7] A role for leverage emerges when raising new equity is costly or takes time. Adrian and Shin (2010a) show that intermediaries in the United States manage the size of their balance sheet primarily by actively adjusting leverage, mainly through repos and reverse repos, with equity being the slow-moving variable. Leverage and total assets therefore 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.

marginal value of wealth spans the pricing kernel,

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

which is a defining relation in the intermediary asset pricing literature. Equations (1) to (4) pin down the expected returns $E[xR_i] = \mu_i$ in equation (3) according to

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

where $\lambda_d = -\alpha_d \gamma^{-1}$, $\lambda_s = \alpha_s \gamma^{-1}$, $\beta_i^\top = [\beta_{i,d} \quad \beta_{i,s}]$, $\lambda^\top = [\lambda_d \quad \lambda_s]$, and we get the following model implication that we will test in Section III.

IMPLICATION 1: *If 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) to (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

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

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

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

The opposite effects of leverage demand and supply shocks also determine the estimate of the price of risk for leverage. 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 and 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 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 $\Omega = \mathrm{Var}(\beta_i)$. Equation (7) shows that the sign of λ_l depends on the dispersion in the demand and supply betas and their correlation.

This discussion leads to the following model implication that we will also 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 $\beta_{i,l}$ are a weighted average of the demand and supply betas.*
- *(ii) Equation (7): the price of leverage risk λ_l is determined by the dispersion in the demand and supply betas, as well as their correlation.*

II. Identification, Data, and Estimation

We take the model described in the previous section to the data and test its asset pricing implications. In this section, we describe our identification strategy, 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 an additional 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 the funding conditions that intermediaries face, and Section E describes the test assets used in estimation.

A. Identification

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 $a_d, a_s > 0$. 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, provided 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 variation in both the innovations and the shocks:

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

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 difficulty in achieving point identification is to find and exploit an additional economic restriction to recover the parameters and, in turn, the shocks. A long-standing identification strategy in macroeconomics is to restrict one of these parameters to zero, which implies that one of the variables 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 of the model. We include a detailed derivation in Section I of the Internet Appendix. The idea is to first rewrite 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 (OLS) regressions of returns on the innovations is given by $\beta_i = A^{\top}\tilde{\beta}_i = A^{-1}E\,[xR_i u]$.[8] Substituting in equation (5) yields

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

where the coefficient $C = [c_z\ c_l]^{\top}$ can be recovered from a cross-sectional regression of average returns $E\,[xR_i]$ on the covariances $E\,[xR_i u]$ between individual returns and the reduced-form innovations, provided the covariances are not collinear. 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 an economic assumption linking the prices of risk to identify the model: $\lambda_s = -\kappa\lambda_d$, where $\kappa > 0$ to be consistent with equation (2).[9] This results in turn in the following restriction on the parameters of A in terms of the data,

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

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

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

[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 shock, as in AEM.

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 the betas across demand and supply. The identification assumptions and the closed-form solutions for the structural parameters of the A matrix are stated below.

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

$$a_d = \frac{\sigma_z^2 \varphi_a}{2a_s} \qquad a_s = \sigma_z \sqrt{\frac{1 \pm \sqrt{1-\varphi_a^2}}{2}},$$

$$b_d = \frac{\sigma_l^2 \varphi_b}{2b_s} \qquad b_s = \sigma_l \sqrt{\frac{1 \pm \sqrt{1-\varphi_b^2}}{2}}, \tag{14}$$

where $\varphi_a, \varphi_b \leq 1$ depend on the moments $\mathrm{Var}(u)$ and C (see Section I of the Internet Appendix).

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 a 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 an important role and offer further support for intermediary asset pricing. In the empirical analysis below, we explore how some other model implications vary around the symmetry case and check that our core conclusion remains unchanged.

The symmetry restriction is needed because we cannot separately identify the contributions of each type of shock to the variance of the stochastic discount factor ϕ from the structural betas using the observed dispersion in returns, $\overline{xR}_i = \beta_i^\top \lambda$, alone. Assuming symmetry means that demand and supply shocks have equal contributions to the variance of the stochastic discount factor and therefore that the dispersion in 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 shock and shifts the relative dispersions in the betas, but it also results in the same fit of the price of raw leverage risk λ_l and 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, in which case, 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 return equation for every asset, including the market return xR_m. This more general model can therefore 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 the new aggregate shock captures risks that are uncorrelated with 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 (Section II of the Internet Appendix).

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

The assumption that the demand and supply shocks are uncorrelated is common in a large literature that attempts to separate demand- and supply-side shocks. This assumption 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 shock. We do not claim, however, that some of the true shocks affecting the economy only influence demand for intermediation and that others only influence its supply. A given shock or set of shocks is likely to drive the decisions of households, firms, lenders, and dealers at the same time and may influence leverage through both demand and supply mechanisms.

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

C. Estimation

We specify a parsimonious VAR model to account for the predictable variations in leverage and the instrument, so we can recover the covariance matrix of the unpredictable innovations. Introducing the time subscript t, 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 using OLS and recover the forecast errors $\hat{u}_{t+1}$ and their covariance matrix $\hat{\Sigma}_u$.

We next recover the coefficient $\hat{C}$ in equation (12) from a cross-sectional OLS 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. The results continue to hold 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 accounts for sampling variation 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 address potential serial correlation and heteroskedasticity of unknown form. Details of the bootstrap are available in Section III of the Internet Appendix.[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. Following AEM, we use quarterly data from the Federal Reserve Flow of Funds (Table L.129) to compute the broker-dealers' aggregate leverage LEV, as the ratio of broker-dealers' total financial assets (the sum of the value of long and short positions in securities for every broker-dealer), to broker-dealers' book equity (the difference between financial assets and liabilities).

We next 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 the case 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

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

the instrument together with leverage form a price and quantity pair that can be plausibly interpreted in terms of demand and supply shocks.

Building on a literature going back to the pioneering work of Gromb and Vayanos (2002) and Longstaff (2004) and more recently to Du, Hébert, and Huber (2022),[11] we construct a proxy for funding conditions based on three measures that come from the U.S. Treasury markets.[12] First, we use the well-known TED spread, that is the spread between the EuroDollar LIBOR rate and the T-bill rate. Frazzini and Pedersen (2014) use this measure to test for a link between funding conditions and the betting-against-beta factor in the United States. Second, we rely on the commonly used measure of Hu, Pan, and Wang (2013) that aggregates deviations of individual bond yields from a smooth parametric curve. The authors introduce this measure to conduct asset pricing tests across hedge funds and currency returns. Goldberg (2020) and Goldberg and Nozawa (2021) employ a similar measure in the markets for Treasury and corporate bonds, respectively. Third, we include a measure from Fontaine and Garcia (2012) that extracts a proxy from a panel of U.S. Treasury securities using a dynamic term structure model. The authors use this measure to test the model's predictive content for risk premia across several securities markets. We label these three measures TED, HPW, and FG, respectively.

In Figure 1, Panels A to C plot the monthly time series of these measures over our sample period (January 1986 to December 2021) and show that the measures exhibit important commonalities despite differences in their construction. In particular, they share the same peaks and troughs. Focusing first on the TED measure, it features peaks following the crash of 1987, at the beginning of 2000, during the financial crisis of 2008, and during the COVID-19 financial crisis; two smaller peaks can also be seen during the European sovereign debt crisis. The FG proxy shares the same peaks, although the ranking of peaks differs. For instance, the 1994 events and the European debt crisis exhibit higher peaks based on this measure. The HPW measure also shares many of the same peaks, notwithstanding the fact that the very high 2008 peak makes some of the other peaks harder to detect in the figure.[13]

We extract the first principal component from these three measures and label the resulting proxy for funding conditions *FUND*. We sign *FUND* such

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

[12] The Treasury market may be the ideal setting to measure broad funding conditions, as opposed to market-specific conditions, for several reasons. First, investors' flight to quality episodes are directed toward the Treasury market during crises. Second, broker-dealers play a central role in this market. Third, Treasury bonds are the predominant collateral instruments for broker-dealers to manage short-term funding needs (Adrian and Shin (2010b)).

[13] The TED measure has correlations 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 crisis. After the crisis, the TED measure has correlations of 0.26 and 0.48 with FG and HPW, respectively, and the correlation between FG and HPW is 0.30.

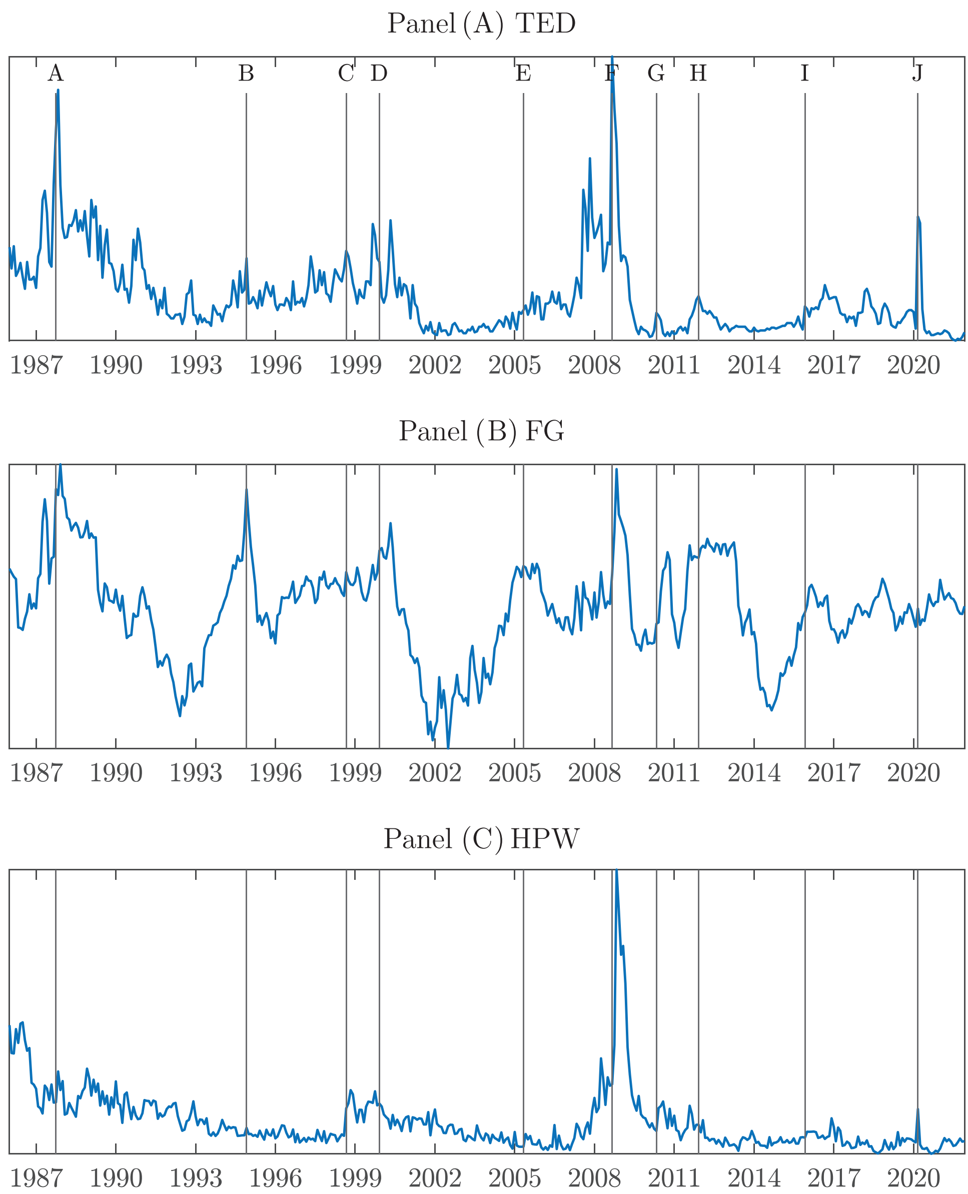

Figure 1. Funding conditions proxies. Panel A: *TED* spread measure. Panel B: *FG* funding conditions measure from Fontaine and Garcia (2012). Panel C: *HPW* noise measure from Hu, Pan, and Wang (2013). Monthly data, 1986 to 2021. Vertical lines denote: (A) 1987 stock market crash, (B) 1994 bond market massacre, (C) LTCM bailout, (D) turn of the millennium, (E) Ford & GM downgrades, (F) 2008 financial crisis, (G) first Greece bailout, (H) second Greece bailout, (I) oil & China sell-off, and (J) COVID-19 financial crisis. (Color figure can be viewed at wileyonlinelibrary.com)

that a higher value indicates a larger marginal value of wealth, and we set $Z_t = FUND_t$. We expect the principal component to extract a more precise signal of funding conditions than any of the component measures. Fontaine, Garcia, and Gungor (2016) show that $FUND$ is priced, and thus it satisfies the first necessary condition for identification. In addition, we can plausibly sign the relationship between FUND on the one hand and leverage demand and supply shocks on the other hand. The idea here is that the wedge between the prices of assets with identical cashflows can proxy for intermediaries' marginal value of wealth, which can 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 and a measure of leverage together form 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 but we use value-weighted returns for portfolios of equities. Section IV of the Internet Appendix provides more details about the test assets.

E.1. Equities and Corporate Bonds

We sort equities and corporate bonds into decile portfolios using the following betas:

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

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

where Δ is the first-difference operator, $Illiq_m$ is stock market illiquidity, and σ_m is stock market volatility. This choice of portfolios is motivated by the theoretical relations proposed by Brunnermeier and Pedersen (2009) between the marginal value of 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 construct three sets of β-sorted portfolios representing different forms of liquidity risk. The equity portfolios sorted on illiquidity and volatility betas span the period 1986 to

[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 $|\mu_i - \mu_j| = \phi(m_i + m_j)$.

2021, while the portfolios sorted on funding betas span the shorter period 1989 to 2021.

Table IA.I in the Internet Appendix reports summary statistics, namely, average returns, illiquidity, volatility, market capitalization, and ex ante beta estimates, for equity portfolios. Sorting on these betas creates similar monotonic patterns in the illiquidity, 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 of Brunnermeier and Pedersen's (2009) model that these covariances are closely related in equilibrium. Overall, the portfolios offer substantial dispersion in average returns and provide an excellent setting for testing demand and supply shocks to leverage.

E.2. Options

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

E.3. 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 plus one other bond that is the closest to each of these maturity points but was issued some time ago. These bonds have different interest rate risk along the maturity dimension 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 procedure. Finally, we aggregate the monthly bond returns over each quarter during the period 1986Q2 to 2021Q4. This procedure yields a panel of returns for 12 bonds.

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 while leverage demand shocks will tend to produce negative returns. The model also implies that the separation of leverage risk into its supply and demand components produces estimates for the price of risk that are positive for supply shocks and negative for demand shocks. We test these predictions across several asset classes. We begin by describing the structural shocks that we recover.

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

A. Leverage Shocks

A.1. Impulse Responses

Supply and demand shocks play significant roles in leverage dynamics. The contemporaneous impacts of the shocks on LEV and $FUND$ are described by the matrix $\hat{A}$, with 95% bootstrap confidence intervals

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

where the signs of a_s and b_s on the initial responses in the second column are given by construction but the magnitudes are estimated from the data. In contrast, both the signs and magnitudes 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.

The impulse response functions translate the parameter estimates $\hat{\Phi}$ and $\hat{A}$ into economically meaningful results. In Figure 2, Panels A and B show the future responses of leverage to current supply and demand shocks, respectively, scaled in standard deviation units. We find that a one-standard-deviation supply shock raises leverage by 0.35 of a standard deviation, with the impact dissipating 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 of a standard deviation, with the effect disappearing after about one year. Goldberg (2020) and Goldberg and Nozawa (2021) also find that the initial impacts of demand and supply shocks on dealers' bond market inventories are similar but that the supply shocks are more persistent. Panels C and D show the responses of our funding conditions proxy. We find that a one-standard-deviation supply shock decreases $FUND$ by 0.2 of a standard deviation, with the effect disappearing after about one year, but the estimates are relatively less precise. A one-standard-deviation demand shock increases $FUND$ by 0.4 of a standard deviation and the effect disappears after more than two years.

A.2. Historical Decomposition

In Figure 3, we show 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 have played important roles around periods of financial market stress. Negative supply shocks occurred with positive demand shocks, both contributing to worse funding conditions, around the 1987 stock market crash, the year 2000 millenium market stress, and the COVID-19 financial crisis in 2020. The leverage demand shock that we estimate in the first quarter of 2020 appears

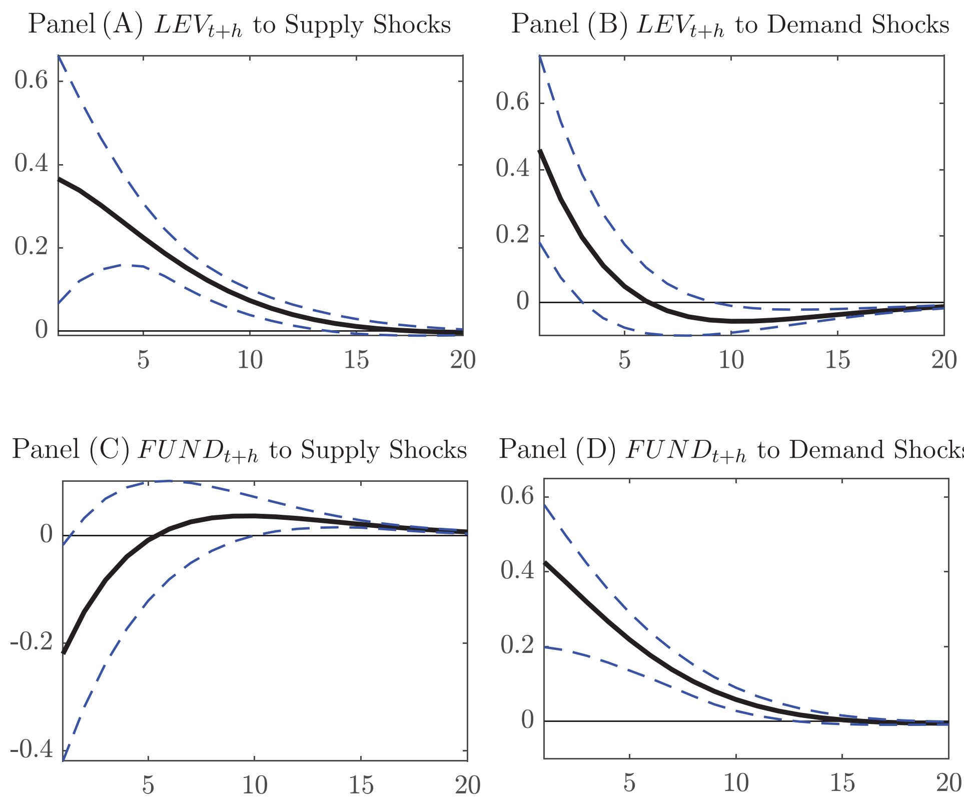

Figure 2. Impulse response functions. This figure plots the impulse responses of LEV_{t+h} and $FUND_{t+h}$ to identified leverage supply shocks e_t^s and demand shocks e_t^d over horizons of $h = 1 \ldots 20$ quarters. The responses, plotted on the y-axis, are accompanied by 95% bootstrap confidence intervals in dashed blue lines. The responses are scaled in units of standard deviations of each variable of interest. (Color figure can be viewed at wileyonlinelibrary.com)

small and may reflect the large and successful interventions by the fiscal and monetary authorities to support financial markets.

Positive demand shocks are also visible during periods with small or positive supply shocks, namely, around the 1994 bond market downturn, in 1998 following the collapse of LTCM collapse and the Russian default, and during the financial crisis 2007 to 2008, which exhibits a huge spike in the third quarter of 2008. The large Fed interventions kept funding conditions stable 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 improved funding conditions in both periods (see also Figure 1).

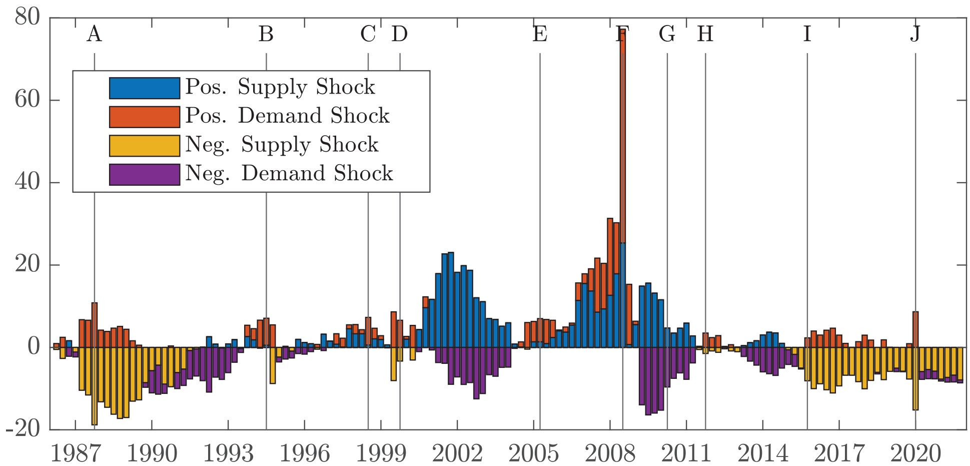

Figure 3. Historical decomposition. This figure decomposes the leverage forecast errors in terms of leverage demand and supply shocks from the econometric model identified with sign and asset pricing restrictions. See Section I for a description of the model and Section II for details of the estimation. Quarterly data, 1986Q2 to 2021Q4. Vertical lines denote: (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, and (I) oil & China sell-off. (Color figure can be viewed at wileyonlinelibrary.com)

A.3. Robustness

An important question that arises is whether the structural shocks that we recover are sensitive to the choice of instrument. In Table IA.II of the Internet Appendix, we report the correlations between leverage shocks recovered with *FUND* alone, with *FUND* in the more general model with an additional market shock, or with the average of *TED*, *FG*, and *HPW* instead of their first principal component. The correlations range between 0.79 and 0.99 for leverage demand shocks and between 0.64 and 0.98 for leverage supply shocks.

B. Leverage Shocks in Asset Pricing Tests

B.1. 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 of $\hat{\lambda} = 2.12$. The estimate is statistically significant with a 95% confidence interval of [1.4,3.6]. The distribution's center is located close to the sample estimate but some asymmetry is visible, which underscores the merit of using a bootstrap procedure (instead of an asymptotic normal distribution). Figure IA.3 in the Internet Appendix shows results for the extended model with one source of aggregate risk that is uncorrelated with leverage shocks. We find a similar and significant price of risk for leverage shocks, similar model

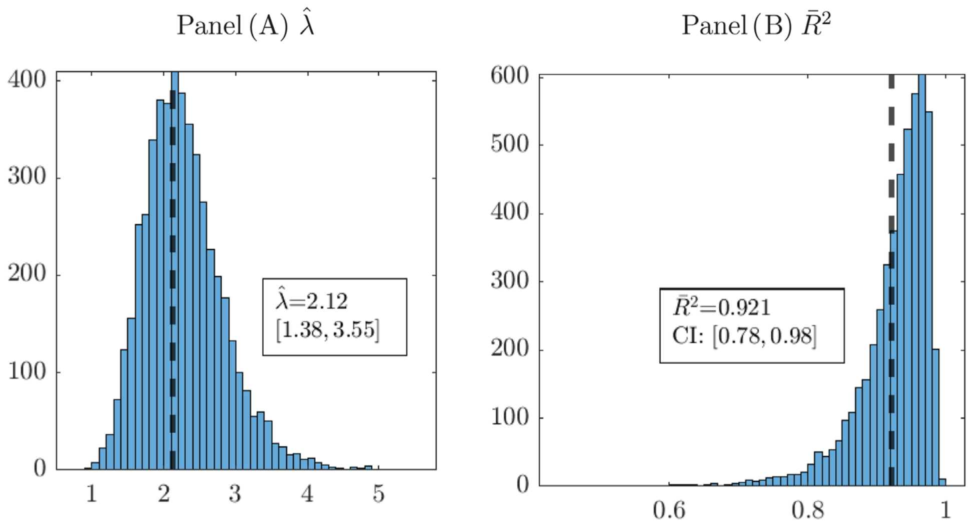

Figure 4. Price of leverage demand and supply risks. Panel A: bootstrap distribution, point estimate and confidence interval of the price of risk λ of leverage demand and supply shocks from the econometric model identified with sign and asset pricing restrictions. Panel B: bootstrap distribution, sample value, and confidence interval for the uncentered $\bar{R}^2$. See Section I for a description of the model and Section II.E for details of the estimation. See Section III of the Internet Appendix for the bootstrap procedure. (Color figure can be viewed at wileyonlinelibrary.com)

fit, and a small and statistically insignificant price of risk associated with the additional uncorrelated shocks.

Figure 5 highlights the importance of disentangling the two sources of leverage risk. Each panel in the figure reports the fitted values associated with a given asset pricing model together with the 45° line that would arise if the fit were perfect. Panel A shows the results using the disentangled supply and demand leverage shocks from the estimated econometric model with symmetric prices of risk; Panel B shows results of a regression model that uses market returns together with raw leverage innovations from the VAR. We hold the number of pricing factors constant across the 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.

Comparing the two panels, we can see the improvement in fit due to disentangling the 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 shows the bootstrap distribution for the adjusted $\bar{R}^2$ from our baseline model, with a confidence interval that ranges between 78% and 98%. The $\bar{R}^2$ obtained from a model that combines raw leverage innovations and 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.

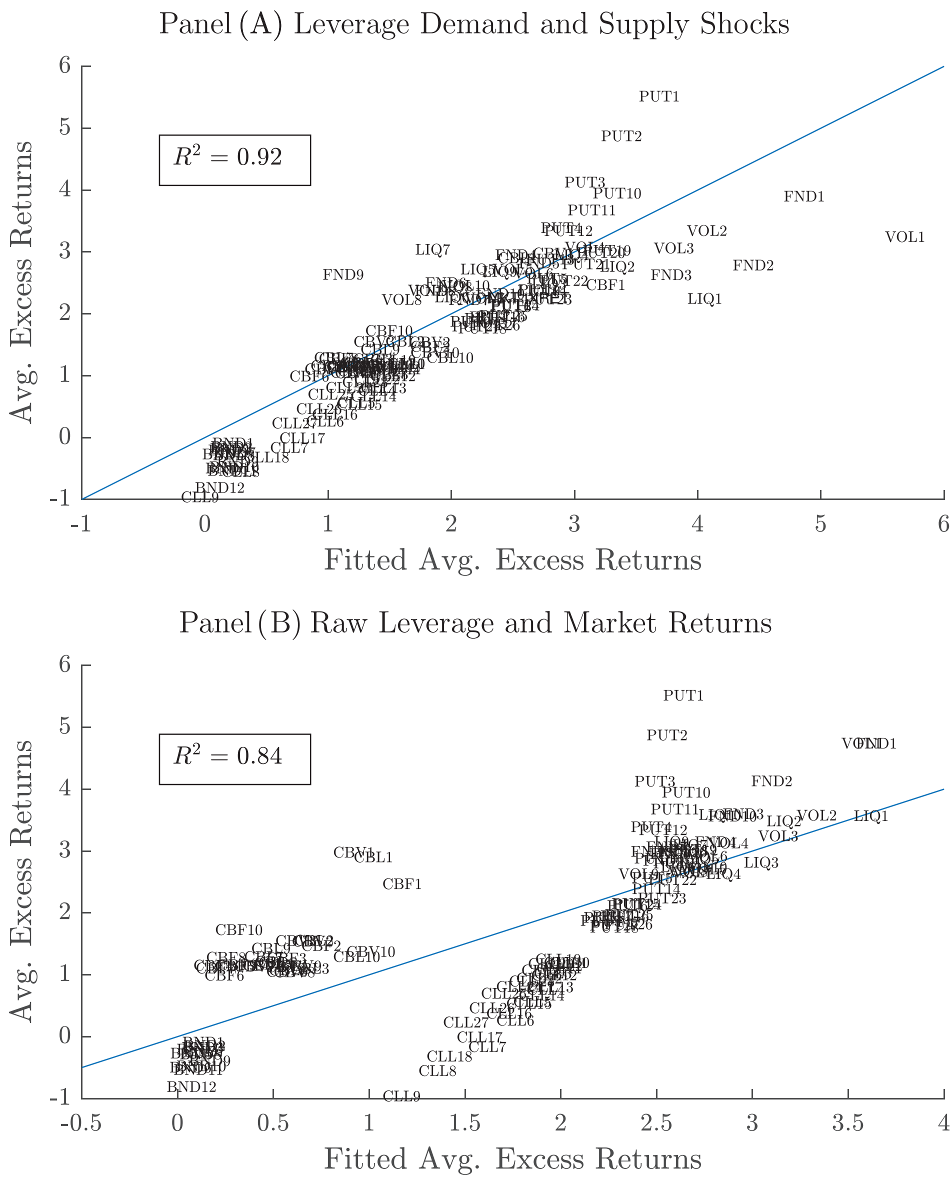

Figure 5. Leverage demand and supply shocks in asset pricing. This figure presents realized and fitted mean excess returns for test around assets and a 45° line to assess the fit, including 3×10 and 3×10 equity and corporate bond portfolios sorted by $\beta^{\Delta \text{illiq}}$, $\beta^{\Delta\sigma}$, and $\beta^{\Delta \text{FUND}}$, labeled as *LIQ*, *VOL*, *FND* (for equities) and *CBL*, *CBV*, *CBF* (for corporate bonds), ordered from 1 to 10, 2×6 portfolios of recently issued and old Treasury bonds with different maturities, labeled as *BND* and ordered from 1 to 12, and 2×27 unlevered call and put options, labeled as *CLL* and *PUT*. Panel A: results using leverage demand and leverage supply shocks. Panel B: results using market returns and the AEM leverage factor. Each model is estimated using two-stage regressions without an intercept. (Color figure can be viewed at wileyonlinelibrary.com)

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

B.2. Asset Pricing—Fama-Macbeth Regressions

We now use two-stage least squares regressions to compare with asset pricing models that use raw leverage, where we follow the calculations in AEM to obtain the leverage factor.[16] We first compare results with those based on leverage demand shocks or leverage supply shocks, separately or together with symmetric prices of risk. This horse race shows that both types of shocks are important. We then extend the comparison across models that include market returns as one of the pricing factors, as suggested by AEM. We confirm that our results are not subsumed by including the market.

Table I reports the price-of-risk estimates based on stock, option, and bond portfolios, jointly, from asset pricing models that exclude a constant in the second-stage regression. In simulations with realistic sample sizes and asset returns distributions, Kroencke and Thimme (2021) show that the zero-intercept restriction can substantially improve statistical power of the test. We report t-test statistics based on Shanken (1996) standard errors. However, we take the structural shocks as given and from here forward ignore sampling uncertainty due to estimation of the VAR parameters, in the case of demand and supply shocks, or due to seasonality adjustments, in the case of the leverage. The regressions are estimated in 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, LNS). Note that this confidence interval cannot be directly compared with the bootstrap interval obtained in the full model. 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 estimation of the VAR. On the other hand, the structural shocks are reestimated 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

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

Table I

Asset-Pricing Tests—All Test Assets

This table presents results of asset pricing models estimated using two-stage Fama-MacBeth regressions for portfolios of value-weighted equities, corporate and Treasury bonds, and options. The coefficients λ_l, λ_s, and λ_d are the prices of the raw leverage shock, the leverage supply shock, and the 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 market returns, all reported as percent per year. Columns (1) to (4): single-factor models; columns (5) to (8): two-factor models with multivariate first-stage betas; columns (9) to (12): two-factor models with univariate first-stage betas; columns (5) to (12): market returns are also included as a test asset. Shanken-corrected t-statistics are in parentheses. The $\bar{R}^2$ confidence intervals (CIs) 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	—	—	—	—
CI	[2,37]	[80,99]	[76,98]	[85,99]	[71,98]	[84,99]	[78,99]	[85,99]	—	—	—	—

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, likely because we use different test assets and a different sample period. In Section IV, we revisit the AEM test assets and reconcile the results with our key messages.

Columns (2) and (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 and negative for demand shocks, as expected, and significant in both cases, 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]

[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 use symmetry to identify these shocks. This can be checked empirically using the bootstrap procedure under the hypothesis that the symmetric model is correctly specified. In Figure IA.2 of the Internet Appendix,

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 versus 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 an unbalanced panel in the model estimation.[18] The $\bar{R}^2$ is essentially unchanged in column (4) relative to column (2) or (3), and 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 shock. Again, this pattern obtains because the supply and demand return betas are correlated, and thus ignoring either demand or supply shocks in columns (2) and (3) creates an upward omitted-variable bias but leaves the fit unchanged.

In columns (5) to (8), we report similar results for models that include market returns, following a recommendation in AEM. Following LNS, we include market returns among the test assets to discipline the 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% when we include the market returns and the confidence interval is [71, 98]. Columns (6) to (8) show that including 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 market betas contribute little to the fit after we include leverage demand and supply shocks. This inference is supported by the observation that the fit and the $\bar{R}^2$ confidence intervals improve only marginally. Columns (9) to (12) confirm this intuition using univariate betas 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 R^2s are mechanically identical with univariate betas.

B.3. Weak Instruments

An important concern is that the reduced-form regressions used as one of the moment conditions to estimate the econometric models may be based on weak pricing factors. To the extent that it is true, the $\tilde{\beta}$ matrix may 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. An F-test of the null of $\beta_i = 0$ equation-by-equation rejects this possibility for 105 (roughly 85%) of the test assets at the 5% level

we show 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 model. This causes the correlation between demand and supply shocks to differ from zero in subsamples, which leads to a small difference in the beta estimates from the first stage.

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 IA.2 of the Internet Appendix, we report the bootstrap distribution of this reduced-form price of risk. We find that the point estimate is equal to $\hat{c}_z = -1.19$ and the 95% bootstrap confidence interval is $[-2.2, -0.7]$.

B.4. Symmetry

The symmetry assumption selects one point in the set of parameters satisfying the sign restrictions. Here, we explore the sign-identified set when the prices of risk are not symmetric. We find that our core messages hold. Across most of the set, the signs on the prices of risk do not change, their magnitudes remain within the confidence interval obtained for the symmetric case, and the dispersion in the betas has comparable scale for each type of shock. Therefore, disentangling demand-side and supply-side 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 plots $\lambda_s^{(j)}$ and $\lambda_d^{(j)}$ on the right and left y-axis, respectively, against $\lambda_d^{(j)} + \lambda_s^{(j)}$ on the x-axis, which measures the extent of asymmetry. The ranges for these parameters are $-\lambda_d^{(j)} \in [0.4, 2.9]$ and $\lambda_s^{(j)} \in [0.7, 3.0]$, which we can heuristically compare with the statistical confidence interval $\hat{\lambda} \in [1.4, 3.6]$ obtained in the symmetric model.

While the results show that the signs and magnitude of the prices of risk are robust across the identified set, our data are 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 whether the prices of risk that we recover are "far" from symmetric. For completeness, Panels A and B of Figure IA.4 in the Internet 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 equal to zero exceeds the 1.96 cutoff value that would indicate rejection of symmetry.[20] The flat distribution and the low t-statistics suggest that the cross-section of returns is not informative about the degree of asymmetry.

[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. We then have $\lambda^{(j)} = \Gamma^{(j)}\lambda$ 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 is likely to overestimate the statistical significance of the sum.

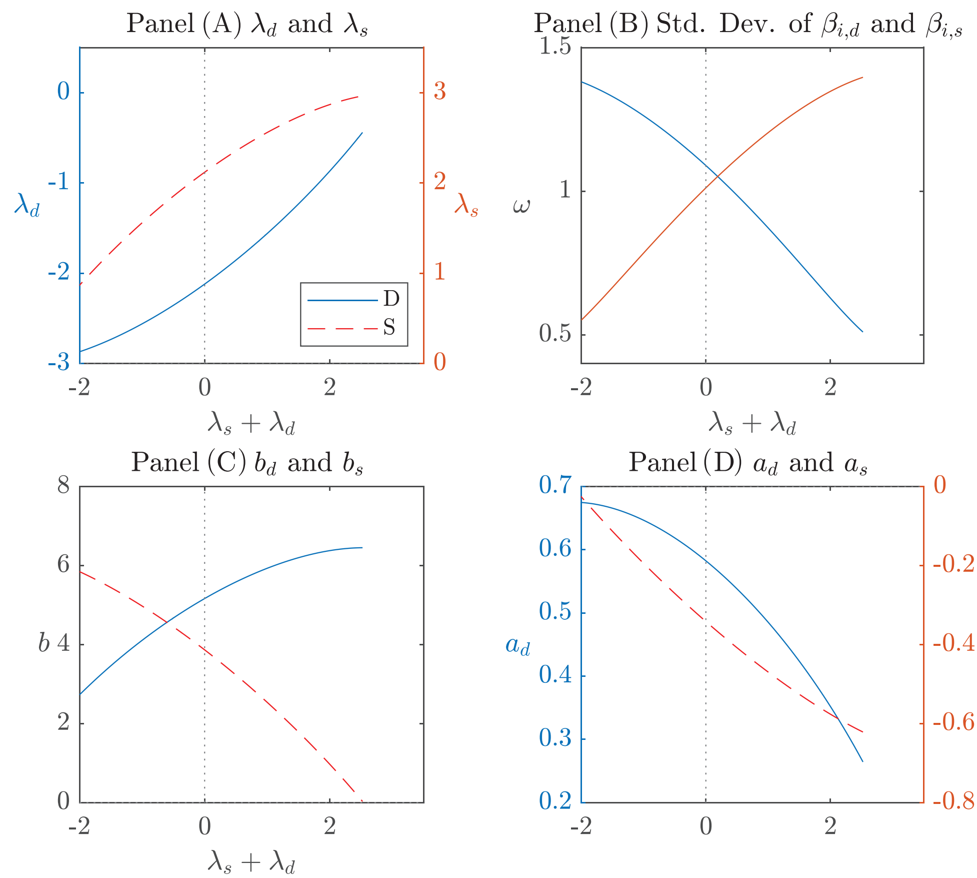

Figure 6. Set of identified parameters. This figure plots the set of parameters satisfying the identification restriction but not imposing symmetry. Panel A: prices of risk λ_d and λ_s. Panel B: the dispersions parameters ω_d and ω_s in the cross-section of $\beta_{i,d}$ and $\beta_{i,s}$. Panel C: *LEV* loadings b_d and b_s. Panel D: *FUND* loadings a_d and a_s. (Color figure can be viewed at wileyonlinelibrary.com)

Nonetheless, allowing for asymmetry changes the interpretation of some of the results. Panel B of Figure 6 plots the cross-sectional dispersion in $\beta^{(j)}_{i,d}$ and $\beta^{(j)}_{i,s}$ on the y-axis against asymmetry on the x-axis. We find that as one of the prices of risk increases relative to the other, the dispersion in 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 $b^{(i)}_d$ and $b^{(i)}_s$ and Panel D reports the funding conditions loadings $a^{(i)}_d$ and $a^{(i)}_s$ across the identified set. As can be seen, a very high degree of asymmetry can generate counterintuitive implications. If leverage supply shocks are given the greatest weight in explaining asset returns, then the model implies that supply shocks play no role in the variation 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 greatest 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 degree of asymmetry in either direction seems to produce counterintuitive implications. Additional data and deeper economic modeling in future research will be necessary to bear on this question.

B.5. Other Equity Portfolios

Thus far, we have used value-weighted stock portfolios sorted on exposures to illiquidity, volatility, and funding liquidity risks. This strategy is grounded in theory but differs from traditional test portfolios from the equity market. Table IA.III in the Internet Appendix repeats the main joint-asset pricing tests but with different portfolios of stocks, keeping other test assets unchanged. Using these portfolios, which are not 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 (Section IV.C of the Internet Appendix explains the construction of these portfolios). In each 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 IA.5 in the Internet Appendix repeats the analysis in Figure 5 in the main text but substitutes the Fama-French portfolios for stocks.

C. Leverage Shocks in Asset Pricing—Individual Asset Classes

In this section, we separately analyze results 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 return betas of leverage demand and supply shocks are negative and positive, respectively. While not a prediction of the model, we further document that the leverage demand and supply betas are strongly negatively correlated.

C.1. 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 market returns

Table II
Asset-Pricing Tests—Individual Asset Classes

This table presents results of asset pricing models estimated using two-stage Fama-MacBeth regressions separately for portfolios of value-weighted equities, corporate and Treasury bonds, and options. The coefficient λ_l is the price of 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 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]

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.

We now check whether the return betas of leverage demand and supply shocks have the expected signs. Panel A of Figure 7 provides a scatter plot of leverage demand-shock betas on the y-axis and leverage supply-shock betas on the x-axis. Supply-shock betas are positive and 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 classic omission bias but similar fit. The elevated correlation also implies that unrestricted price-of-risk estimates in a model with both shocks will lead to imprecise and uninformative inference.

C.2. Bonds

We report the analogous results for corporate and Treasury bonds in columns (3) and (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 of [58, 93]. The symmetric price-of-risk estimate for demand and supply shocks is 2.04, significant and

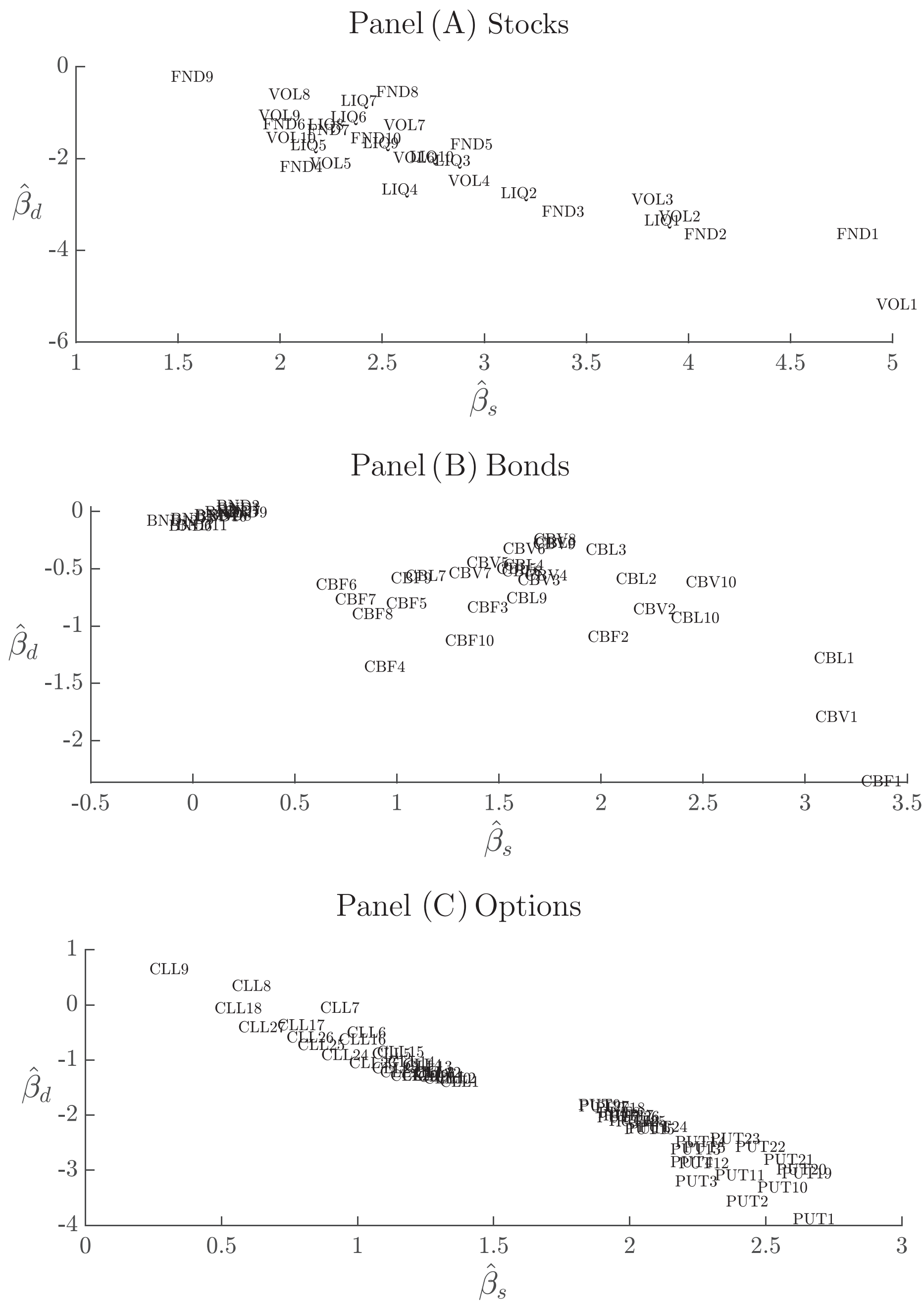

Figure 7. First-stage β estimates. This figure shows first-stage β estimates of leverage supply and demand shocks from single-factor models, with leverage demand shocks reported on the y-axis and leverage supply shocks on the x-axis. Panel A: equity portfolios labeled LIQ, VOL and FND. Panel B: Treasury bonds and corporate bond portfolios labeled CBL, CBV, CBF, and BND. Panel C: unlevered options portfolios labeled PUT and CLL.

Table III

Asset-Pricing Tests—HKM Test Assets

This table presents results from asset pricing models estimated using 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 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

close to the baseline result. This parsimonious model offers a better fit and a narrower $\bar{R}^2$ confidence interval.

Panel B of Figure 7 provides a scatter plot of bond betas. The leverage supply and demand betas have the expected signs and, as for the equity portfolios, are strongly negatively correlated (−0.74), which means that riskier corporate bond portfolios tend to have the larger leverage supply betas and more negative leverage demand betas.

C.3. Options

Columns (5) and (6) of Table II report analogous results for 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. In Panel C of Figure 7, we depict the leverage demand and supply betas. As can be seen, they have the expected signs in every case and exhibit a strong negative correlation, as for bonds and equities.

C.4. Other Test Assets—HKM

He, Kelly, and Manela (2017, HKM) 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 using two-stage regressions that exclude a constant, include market returns, and impose symmetry. The estimates are reported in Table III. We find that the price of leverage supply and demand shocks exhibits the expected sign, is significant, and has a similar magnitude across equities, U.S. bonds, sovereign bonds, options, and credit default swaps (CDS). However, the estimates are statistically indistinguishable from zero in commodities and foreign exchange. As 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.

Figure IA.6 in the Internet Appendix depicts average and fitted returns associated with the leverage supply and demand shocks in Panel A and 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 previous results, the pricing errors are substantially reduced across the board when we separate the raw leverage factor into supply and demand shocks. The results also align with HKM's results that a pricing model based on shocks to intermediaries' equity capital ratio offers a good fit of returns across the 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 Fama-French portfolio of small growth firms.[21]

C.5. Summary

We document that leverage demand and supply shocks produce consistent estimates with the same sign, similar magnitude, and good fit across classes, with only a few instances in which the evidence is statistically insignificant. One key takeaway 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, as 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 leads to a lower marginal value of intermediaries' wealth and better funding conditions or to the contrary.

D. The Sign of Leverage Risk

The consistent positive and negative signs on the prices of risk associated with supply and demand shocks across assets are to be contrasted with the

[21] One natural question that arises 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 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 shocks, demand shocks, and aggregate shocks recovered using broker-dealers' leverage, we find that the demand shocks are insignificant, the supply shocks explain around 10% of the variance, and, consistent with the main conclusion of Gospodinov and Robotti (2021), market returns explain the largest share of the variations in the capital ratio. While the equity capital ratio is the reciprocal of the leverage ratio, HKM suggest that these differences could be due to the fact that (i) their equity ratio uses data on large holding companies while AEM's leverage ratio use data on the subsidiary broker-dealers and (ii) they use the market value of equity while AEM use book value.

mixed evidence on the price of raw leverage risk: The price of risk estimate is negative for options and positive for bonds and equities, and sometimes insignificant. We verify that the different signs for the betas and the price of risk of raw leverage shocks across asset markets can be explained by the underlying patterns in leverage demand and supply betas, as predicted in Section I. The results using raw leverage shocks are therefore consistent with the predictions that intermediaries play a key role in asset pricing. Siriwardane, Sunderam, and Wallen (forthcoming) suggest that leverage betas can differ substantially across asset classes because of a segmentation between funding sources or between the balance sheets of intermediaries involved in the asset classes.

D.1. Leverage Betas

Equation (6) implies that the magnitude and sign of the return betas for the raw leverage factor are determined by the magnitudes of the supply and demand betas for leverage. We repeat this equation here for convenience:

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

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

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

In the last two rows of Table IV, Panel A, we report the sign implied from the model for the return betas of raw leverage innovations and the sign in univariate regressions. The predicted sign is correct across all bond portfolios, where relatively large supply return betas tend to produce positive return betas for raw leverage. The predicted sign is also correct across options, where the relatively high demand return betas produce negative return betas for raw leverage. Bonds therefore tend to exhibit positive returns and options negative returns when intermediaries' leverage increases. The results are also consistent across portfolios of stocks, in which case, the demand betas are

Table IV
Price of Leverage Risk and Dispersion in Betas

In Panel A, the estimates $\overline{\beta}_d$ and $\overline{\beta}_s$ are the sample averages of the leverage demand and supply shock 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. In Panel B, 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 average 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 dispersion 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
$\hat{\lambda}_l$	−	−	−	−	+	−	+	+	−	−	−
$\hat{\lambda}_l^{ols}$	−	−	−	−	+	−	+	+	−	−	−

also more dispersed. However, we expect the precise mix of leverage demand and supply betas to vary with the specifics of the sorting strategies used by researchers.

D.2. Leverage Price of Risk

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

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

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 $\hat{b}_d \approx \hat{b}_s$. We therefore expect the price of raw leverage risk to be determined by the dispersion in the the supply and demand betas.

To twist this prediction, we estimate the price of risk $\hat{\lambda}_l^{ols}$ for raw leverage using OLS separately for each asset class and then check if the dispersion in the demand and supply betas from the econometric model can explain the regression estimates *within* this class. Panel B of Table IV reports the dispersion parameters ω_d^2 and ω_s^2 as well as the covariance ω_{ds} separately for equity,

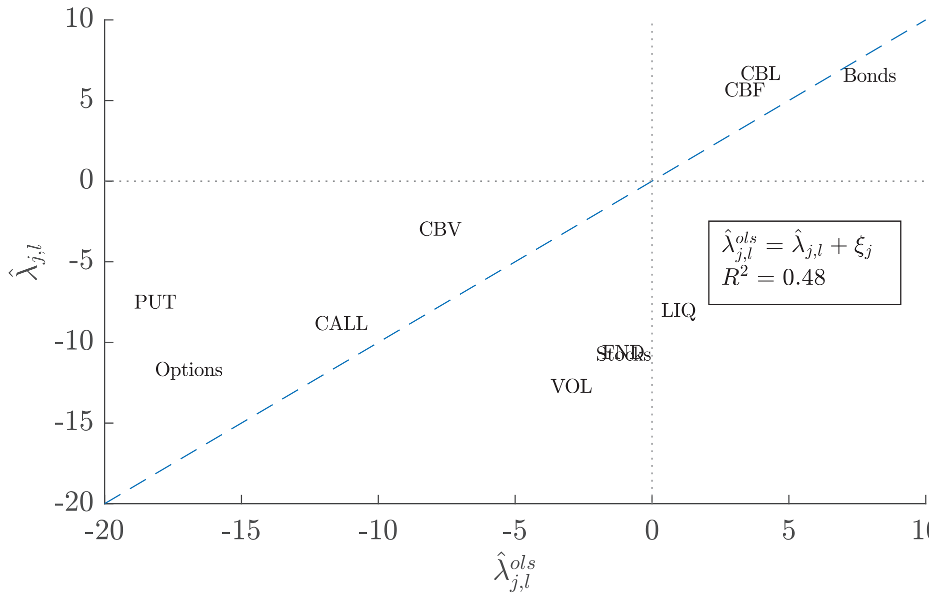

Figure 8. Price of leverage risk. This figure provides a scatter plot of raw leverage risk $\lambda_{j,l}$, across various test assets. The x-axis shows $\hat{\lambda}^{ols}_{j,l}$ estimates from the second-stage OLS regressions, while y-axis displays $\hat{\lambda}_{j,l}$ estimates from the econometric model in Section II. The dashed line represents the 45° line, which would correspond to a perfect fit. We also report the R^2 for the exact-fit regression $\hat{\lambda}^{ols}_{j,l} = \hat{\lambda}_{j,l} + \xi_j$. The asset groups are as follows: PUT and CALL represent unlevered S&P 500 option portfolios for puts and calls, respectively. VOL, LIQ, and FND are three sets of 10 equity portfolios sorted by volatility, illiquidity, and funding risk, respectively. CBV, CBL, and CBF are three sets of 10 corporate bond portfolios sorted by the same criteria. BND represents a set of Treasury bonds. The "Stocks" category combines VOL, LIQ, and FND portfolios, "Bonds" includes CBV, CBL, CBF, and BND, while "Options" consists of PUT and CALL portfolios. For additional details, refer to Section IV of the Internet Appendix. (Color figure can be viewed at wileyonlinelibrary.com)

bond, and option portfolios. The last two rows report 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 wider dispersion, implying a positive price of risk. Figure 8 provides a scatter plot of the model-implied and regression estimates across asset classes, together with the 45° line that would result if the fit were perfect. The 45° 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 note 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 of 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 intermediaries' marginal value of wealth ϕ,

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

where δ_i is a positive parameter and 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,

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

Note that this symmetry follows from equation (20) and is distinct from the symmetry of the prices of risk that we use for identification of the model. From equation (1), we also have that regressions of the illiquidity on raw leverage produce a population coefficient given by

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

This leads to the implication of the model:

IMPLICATION 3: *If intermediaries' leverage and marginal value of wealth and if 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 this prediction is to estimate the coefficients of leverage demand and supply shocks in regressions of market liquidity. To do so, we construct 10 portfolios of stocks sorted on illiquidity using the Amihud ratio as a proxy. We also construct 10 portfolios of stocks sorted on volatility, measured using the standard deviation of daily returns over the last quarter (see Section IV.C of the Internet Appendix). In both cases, we start with the same stocks that were used to form the portfolios sorted on betas. The first

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

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 $\triangle LEV$. Row I: regressions for portfolios sorted on illiquidity. Row II: regressions for portfolios sorted on volatility. Columns (1) to (10) rank portfolios from high illiquidity (or volatility) to low illiquidity (or volatility). Newey-West t-statistics with three lags are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Panel A. $\Delta illiq_{i,t} = a + b_i e_t^s + c_i xR_{t,m} + e_t$					
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. $\Delta illiq_{i,t} = a + b_i e_t^d + c_i xR_{t,m} + e_t$					
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. $\Delta illiq_{i,t} = a + b_i \Delta LEV_t + c_i xR_{t,m} + e_t$					
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)

set of portfolios exploits the predictions that intermediaries' marginal value of wealth drives the commonality in liquidity. The second set exploits the prediction that the sensitivity of market liquidity is larger for securities that are more volatile on average (Brunnermeier and Pedersen, 2009, pp. 20–21). Using both sets of portfolios adds power to the test.

Table IA.IV in the Internet 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 monotonic across portfolios. Similarly, the more volatile portfolios exhibit lower liquidity and smaller market capitalization. The illiquidity and volatility are also closely related with the covariances. We find a common monotonic 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 reports results from regressions of changes in the portfolios' Amihud illiquidity ratio on one of the leverage shocks. Row I reports the coefficients for liquidity sorts and Row II for volatility sorts. In Panel A, we first ask whether portfolios' illiquidity responds to changes in the leverage supply shocks. The coefficients on the supply shocks have the right sign in each case and exhibit a clear monotonic pattern: The estimated effects are larger for the least liquid and more volatile portfolios. In Panel B, we report results from regressions on the leverage demand shocks. Most of the estimates have the right sign and exhibit a loose monotonic pattern, but are systematically lower than in the case of leverage supply shocks.

Next, Panel C reports results based on the raw leverage shocks. We find that the coefficient estimates are negative and monotonic but small and never statistically significant at the 5% level, consistent with the results reported by AEM. Looking vertically across Table V, we see that one reason 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.

The decomposition of leverage into supply and demand shocks therefore sheds light on the puzzle raised in AEM. Disentangling the leverage supply shocks establishes that they are associated with improved market liquidity across all of the portfolios. We leave for future research exploration of 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-side shocks may be significant, especially in our sample that includes the 2008 to 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 generate different implications for market liquidity. For instance, shifts in intermediaries' demand for funds or shifts in investors' demand for immediacy may be combined in our demand shocks and have opposite implications for market liquidity.

IV. AEM's Leverage Results in Perspective

In this section, we review the approach of AEM through the lens of the model developed in Section I. In many existing theoretical models, including the leading example of Brunnermeier and Pedersen (2009), intermediaries' leverage and marginal value of wealth move monotonically 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 of the specification for leverage in equation (1). In this case, 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 six Treasury bonds).

Table VI

Asset-Pricing Tests—Adrian, Etula, and Muir (2014)

This table reports results of asset pricing models estimated using two-stage Fama-MacBeth regressions for the 25 size- and book-to-market–sorted portfolios, 10 momentum-sorted portfolios, and six new and six old Treasury bonds with maturities of 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, the leverage supply shock, the leverage demand shock, and λ is the price of risk for supply and demand leverage shocks with a symmetry restriction. Shanken-corrected t-statistics are in parentheses. Note that the reported $\bar{R}^2$ are computed as noncentered 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

In column (1), we find that the raw leverage factor produces a significant positive estimate for the price of risk, as in AEM, but a lower $\bar{R}^2$, likely because our sample periods differ. In columns (2) and (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 symmetry between the prices of risk. We find an estimate of 1.9, close to our baseline estimate, that is statistically significant. In columns (5) to (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.

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 highly 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 intertemporal considerations and may anticipate higher profits in the future.

In Section VI of the Internet Appendix, 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 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 subsample in which the current values of *FUND* are elevated and funding conditions are tight, we find that (i) the dispersion of supply shocks is substantially higher and (ii) 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 supply shocks are more prevalent, when funding conditions are tight. Finally, based on a structural system of constrained simultaneous equations, Figure IA.9 of the Internet Appendix 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 in which 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 that proposed by Du, Hébert, and Huber (2022) where intertemporal considerations enter leverage decisions and in which leverage constraints do not always bind.

V. Conclusion

In this paper, we develop an econometric model in which intermediaries' leverage and marginal value of wealth are driven by supply and demand shocks. Supply-side shocks relax the funding constraint and lead to higher leverage. Demand-side shocks also lead to higher leverage but tighten the funding constraint. We use these 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 estimated price of risk for leverage changes signs across markets because it is influenced by both types of shocks, the effects of which are in opposite directions. Overall, the results confirm the importance of financial intermediaries' balance sheets for understanding asset pricing. More work is needed to identify and quantify the channels driving leverage supply and demand shocks, and to explain how the relative importance of exposures to leverage demand and supply shocks varies across financial markets.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.