Intermediary Leverage Shocks and Funding Conditions

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Abstract

The leverage of financial broker-dealers responds to demand- and supply-like shocks. Supply shocks relax their funding constraint and raise leverage, while demand shocks also raise leverage but tighten the constraint. The shocks play opposite roles in financial markets. Leverage supply shocks improve liquidity and carry a positive price of risk, while leverage demand shocks worsen liquidity and carry a negative price of risk. Because of this difference in signs, disentangling the two types of shocks strengthens the evidence for intermediation frictions in asset pricing, resolves some of the existing puzzles, and can help understand the different mechanisms driving broker-dealer leverage.

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Introduction

Financial intermediaries play a central role in the issuance of new securities, offer essential broker-dealer services to large investors and asset managers, and act as market-makers or providers of liquidity in essentially all financial markets. Because their activities span many asset classes and involve complex investment strategies that face low transaction costs, which together contrasts dramatically with the possibilities average investors have, the marginal value of intermediaries' wealth can be one important factor to price several financial assets.[1] Adrian, Etula, and Muir (2014), henceforth AEM, use balance sheet information about financial intermediaries and find strong evidence that the covariance of returns with variations in a measure of leverage can price a wide range of test assets, thus bringing a new perspective to the field of empirical asset pricing. Assets and strategies that perform poorly when intermediaries' marginal value of wealth is high offer higher returns to investors.

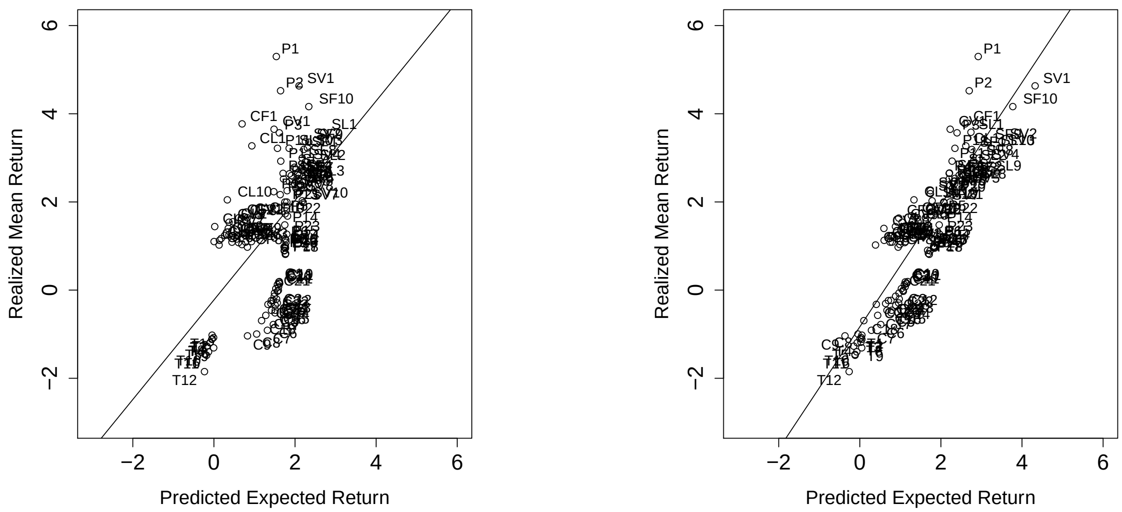
Intuitively, leverage on its own provides a good proxy for intermediaries' marginal value of wealth when funding or leverage constraints are binding. In this case, the marginal value of wealth increases but leverage decreases when funding conditions tighten as intermediaries reduce the level or the risks of the assets that they hold. Therefore leverage is negatively related with the marginal value of wealth. But what if the funding constraints do not bind? It is still likely that leverage may decrease when funding conditions tighten. However, the opposite relationship is also plausible. For instance, a shift in the demand for intermediation by investors wanting to sell assets can lead intermediaries to increase leverage, which tightens their constraints and raises the marginal value of wealth. In this case, leverage will be positively related to the marginal value of wealth. We interpret these two types of movement in leverage as supply and demand shocks, respectively.

To identify these shocks, we combine AEM's measure of intermediaries' leverage and existing proxies for funding conditions together with sign restrictions. The assumptions are that leverage supply shocks correspond to the unexpected increases in leverage that are associated with better funding conditions and, by contrast, that leverage demand shocks

[1] See the detailed survey by Gromb and Vayanos (2010) as well as Geanakoplos (2010); He and Krishnamurthy (2013); Brunnermeier and Sannikov (2014); Kondor and Vayanos (2016).

Figure 1: Leverage Demand and Supply Shocks in Asset Pricing

(a) Raw Leverage and Market Returns **(b)** Leverage Demand and Supply Shocks



Realized and fitted mean excess returns to 3 × 10 portfolios of equities and 3 × 10 portfolios of corporate bonds sorted on β^{illiq}, β^{σ} and $\beta^{\Delta\text{FUND}}$, labeled L, V and F, respectively and ordered from 1 to 10; 2×6 portfolios of recently issued and of old Treasury bonds with different maturities, labeled T and ordered from 1 to 12; and 2 × 27 unlevered call and put options, labeled C and P, respectively. Panel (a) shows results using market returns and leverage. Panel (b) shows the results using leverage demand shocks and leverage supply shocks identified with sign restrictions. Each model is estimated with no intercept $E(R^e) = \beta_i \lambda_i$ and we draw a 45-degree line. Adding the market returns as a factor in Panel (b) does not change the results.

correspond to unexpected increases in leverage that are associated with costlier funding conditions.[2]

Using these shocks for pricing assets, we show how important it is to disentangle leverage demand and leverage supply shocks. Figure 1 illustrates our message. Panel (a) shows the realized and fitted mean returns for Treasury bonds, corporate bonds, equities and options from a model that uses market returns as well as changes in broker-dealers' raw leverage. We also draw the 45-degree line that would arise if the fit were perfect. Panel (b) shows the same results but from a model that uses both leverage demand and supply shocks that

[2]The proxy for funding condition is the first principal component of the three measures used in the literature. This mitigates the effect of any noise that is introduced by each measure. Section B provides the details.

are identified with sign restrictions. Contrasting these two panels, we see that disentangling the two types of leverage shocks substantially improves the fit. We find that both estimates are statistically significant: the prices of risk are 2.0 and -2.2 percent annually for leverage supply and demand shocks, respectively. Disentangling these shocks does not imply a loss of parsimony because we cannot reject that the sum of the two prices is equal to zero (only their signs differ). The risk exposures are also symmetrical: the correlations between the βs for these two shocks is -0.65. Overall, this suggests that changes in leverage that are due to either demand or supply shocks have opposite implications for financial markets. As we show below, this substantially strengthens the evidence for intermediary asset pricing and resolves some of the puzzles and mixed results noted by AEM and others.[3]

On the way to Figure 1 and other tests, our first step is to provide evidence that the funding constraints are not always binding and that the sign restrictions are plausible. We document that the relationship between leverage and the funding conditions is not linear. When current leverage is high, which is when the constraints are more likely to bind, there is a strong negative correlation between current funding conditions and future leverage. This is the relationship that AEM exploit empirically. By contrast, the correlation is insignificant or positive when leverage is low, which is when the constraints are unlikely to bind and that leverage responds to both demand and supply shocks. Similarly, when current funding conditions are tight, which is also a time when the constraints are likely to bind, we find that current leverage is negatively associated with future funding conditions (sample correlation of -0.25). Again, when current funding conditions are good, the effect is either insignificant or positive. We strengthen this evidence by a more structural approach, whereby we compute the probabilities of the funding constraint being binding across time. We specify a system of demand and supply equations and estimate the probability that the observed leverage corresponds to a constrained supply. This approach provides strong evidence that the funding constraint is not always binding and points to episodes where funding conditions are deteriorating. The natural interpretation for these probabilities is that the intermediaries' leverage that we observe is larger than what is predicted by the estimated supply equation. This would be the case, for instance, if intermediaries accommodate a shift in the demand.

[3] Another debate in the literature is whether a measure of net worth or a measure of leverage should be used in empirical work and whether market or book valuations should be used. Adrian, Moench, and Shin (2014) discuss these issues in detail and argue, based on the results of dynamics asset pricing tests, that leverage is more important than net worth for asset prices and that book value should be used.

The next step is to identify the shocks. For this, we implement the sign restrictions in a vector-autoregressive system of equations for both leverage and the proxy for the funding conditions. We find that both demand and supply shocks play important roles in the variations of leverage over time. The leverage response is stronger after a demand shock but more persistent after a supply shock. Consistent with the reduced-form evidence, the contribution of supply shocks to the variations of leverage is higher when funding conditions are tight.

Then, we check the implications of leverage shocks in asset-pricing tests. For instance, underlying Panel (b) of Figure 1, the price of risk is positive for leverage supply shocks and negative for leverage demand shocks. The estimates have the right sign for each individual asset class, with the exception of one estimate that is not significant. We also find that the magnitudes of the estimates are very close for both types of shocks (in absolute value). This is a pervasive feature in our results that arises because the betas for the demand shocks are highly negatively correlated with the betas for the supply shocks. This tells us that a unit change in leverage has a similar impact on returns, whether this is due to a demand or a supply shock, but the sign is different.

Precision varies when considering different asset classes. Exposure to leverage demand shocks is estimated with more precision and the goodness of fit is better for equities and options, while exposure to supply shocks is estimated with more precision for bonds. This is also reflected in the changing signs of the price of risk for raw leverage: the estimate is negative for equities and options but positive for bonds. In a joint test across asset classes, the estimate is positive for raw leverage but the statistical evidence is weak. This is in line with the finding by He, Kelly, and Manela (2017) that estimates of the price of leverage risk appear to vary across asset classes.

We revisit the tests in AEM that are based on Fama-French and momentum equity portfolios as well as Treasury bonds. For leverage shocks, we confirm their results in our sample. A simple model using the leverage factor explains 88 percent of the cross-section of portfolio returns with a positive and significant price-of-risk estimate. Consistent with this result, we find that leverage supply shocks play a bigger role in this set of test assets. Similar to AEM, the average returns of some of the momentum portfolios cannot be attributed to their exposures to either the risk of the leverage demand or leverage supply shocks.

Finally, we verify the prediction by Brunnermeier and Pedersen (2009) that intermediaries' marginal value of wealth drives asset liquidity and, therefore, expected returns. We find that both demand and supply shocks influence market liquidity but in opposite directions. Leverage supply shocks have a significant positive impact on market liquidity while leverage demand shocks have a significant negative impact. In both cases, the impact is highest for the least liquid portfolios and decreases with a monotonous pattern for the more liquid portfolios. In Section IIIB, we show that this symmetrical pattern explains a puzzle AEM identified where the leverage ratio essentially appears unrelated to market illiquidity.

Literature

Following the financial crisis, an empirical literature has emerged that connects intermediaries' balance sheets to asset pricing. One underlying theme is that the intermediaries' marginal value of wealth offers a basis to price assets in several markets, not that of the households' or some other representative investors. One strand of this literature highlights the connection between an apparent increase in arbitrage opportunities with an increase in the associated risk premia. Krishnamurthy (2010) provides evidence on mortgage-backed securities for the period 2007-2009. Fontaine and Garcia (2012) connect the spread of old seasoned Treasuries with risk premia across several fixed-income securities. Frazzini and Pedersen (2014) connect a higher T-bill-Eurodollar (TED) spread with low contemporaneous returns of betting-against-betas strategies. Mitchell and Pulvino (2012) and Hu, Pan, and Wang (2013) provide similar evidence in the hedge fund industry and for exchange rates. In each case, one apparent mispricing between securities of similar risk levels is interpreted as reflecting tighter limits to the arbitrage financial intermediaries usually provide.

A second strand of the empirical literature builds on the insight that, if intermediaries matter, then building a stochastic discount factor (SDF) that prices many assets well should start with proxies for the intermediaries' marginal value of wealth. Gabaix, Krishnamurthy, and Vigneron (2007) examine the mortgage-backed securities market in this light and show that the risk of homeowner prepayment carries a positive risk premium. As discussed above, Adrian, Etula, and Muir (2014) use shocks to the leverage of securities broker-dealers. He, Kelly, and Manela (2017) instead use shocks to broker-dealers' capital ratio and provide evidence for the pricing of additional assets, including corporate and sovereign bonds, derivatives, commodities, and currencies. We find that leverage shocks are also consistently priced across several markets once demand and supply shocks are disentangled.

These two strands of literature are related. Movements in both the prices and the quantities of holdings influence the balance sheets of financial intermediaries. Leverage can increase as a result of a shift in intermediaries' risk-taking, a supply shock that also loosens the limits to arbitrage between the prices of similar assets. However, leverage can also increase due the losses that intermediaries register on the assets they hold or as a result of a shift in the demand for intermediation. In other words, there is a need to separate supply and demand shocks from data on prices and quantities.

Froot and O'Connell (1999) identify shocks by using prices and quantities in the catastrophe reinsurance market. Following a natural disaster, the insures' capital buffer is initially depleted, new policies are sold at higher prices and the demand for reinsurance falls. Once buffers are rebuilt, prices reverse to a lower level and sales increase. In this case, the most likely interpretation is that the pattern of price changes across contracts with different risk exposures shows that a shift in the supply of insurance follows a natural disaster. The alternative interpretation in terms of demand shifts, say because clients update the probability of a disaster, is not supported in the price data. Du, Tepper, and Verdelhan (2018) use banking regulations of quarter-end capital requirements to identify shocks underlying large covered interest parity (CIP) deviations.

Du, Hébert, and Huber (2019) examine an SDF that combines CIP violations with the intermediary manager's returns on wealth.[4] They find that the CIP factor contains information that is either not incorporated into the intermediary factor or that the factor captures similar information more precisely. We document that the relationship between leverage and the funding conditions is not linear: there is a strong negative correlation when current leverage is elevated but a small or positive correlation when leverage is low. We use this fact to identify leverage demand and supply shocks based on sign restrictions.

In a closely related paper, Goldberg and Nozawa (2019) disentangle supply and demand shocks in changes to the quantity of liquidity intermediaries provide in the corporate bond market. They conclude that supply shocks are a main driver of the prices and market liquidity of corporate bonds. Although our approach to disentangling shocks is slightly different, we also find that supply shocks to intermediaries' leverage play a larger role to explain corporate bond returns.[5] We build on and expand this result by showing that both demand and supply

[4]Du, Hébert, and Huber (2019) relate their work to Gârleanu and Pedersen (2011), who add a security's margin times the general funding cost to a consumption-based asset-pricing model, but they measure the shadow value of the constraint using CIP deviations and they use Epstein-Zin preferences instead of log utility, which implies that the covariance risk with the CIP deviations is priced.

[5]Goldberg and Nozawa (2019) combine broker-dealers' trading positions with deviations of bond yields from a fitted curve. We combine the aggregate broker-dealer leverage used in AEM with the principal component from several measures of funding conditions.

shocks are important to understanding the impact of intermediaries' leverage on returns in a cross-section of assets and by showing that both leverage supply and demand shocks affect the liquidity of stocks.

Sign restrictions are also used more broadly in macro-finance. Goldberg (2019) studies how dealers' supply of liquidity in the Treasury market influences the aggregate illiquidity of other asset markets and aggregate real activity in the US economy. Arias, Caldara, and Rubio-Ramirez (2019) use sign restrictions to study the effects of monetary policy shocks in structural VARs. Cieslak and Pang (2020) disentangle monetary news, growth news and risk-premium shocks based on sign restrictions by exploiting stocks and bonds' different exposures to these shocks. Uhlig (2017) highlights the key issues in the use of sign restrictions for the purpose of identifying shocks.

Existing results show strong illiquidity commonality across securities (Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Chordia, Sarkar, and Subrahmanyam, 2005), or that illiquidity increases with the volatilities of securities to compensate market-makers, either for their inventory risk or for their losses to better-informed investors (Benston and Hagerman, 1974; Stoll, 1978; Glosten and Milstom, 1985; Grossman and Miller, 1988; Pagano, 1989). We show that both leverage supply and demand shocks connect intermediaries' balance sheets with market illiquidity but with opposite signs. Other results show that the risk premium increases with the level of illiquidity in a cross-section of equities (Amihud and Mendelson, 1986; Amihud, 2002; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005). As predicted in models with intermediaries, we find that leverage supply shocks bear a positive price of risk and leverage demand shocks bear a negative price of risk when assets are sorted on their level of illiquidity risk.

The rest of the paper is organized as follows. Section I reviews the theoretical underpinnings of our approach, introduces the data and provides reduced-form evidence for the non-linear relationship between leverage and funding conditions. Section II provides the construction and stylized facts about leverage demand shocks and leverage supply shocks. Section III studies how the risks of leverage demand and supply shocks influence the risk premia in securities markets. The conclusion summarizes the main results and discusses potential avenues for future research. An appendix provides details about the data sources and the construction of the portfolios that we use in our tests.

I Leverage and Funding Conditions

A Leverage and the Funding Constraint

Brunnermeier and Pedersen (2009) provide a simple framework to understand how leverage can be linked to the intermediaries' marginal value of wealth through the funding conditions. In this model, specialized traders intermediate between investors who demand immediacy and financiers who provide funds. The specialized traders are risk neutral but they must collateralize margin constraints imposed by financiers separately for each asset, ruling out cross-margining between the positions in different assets (netting). Therefore, the intermediaries' marginal value of wealth is given by the shadow price ϕ of the margin constraint. In other word, the intermediary's marginal value of wealth is connected to how tight the funding conditions are. In equilibrium, the illiquidity $|\Lambda_1^i|$ of any asset i that these traders intermediate is proportional to ϕ,

$$|\Lambda_1^i| = m^i(\phi - 1), \tag{1}$$

where m^i denotes the margin requirement for asset i, and the risk premium of asset i is given by:

$$E_0\left[R_1^i\right] = -\frac{Cov_0\left[\phi, R_1^i\right]}{E_0\left[\phi\right]}, \tag{2}$$

so that the shadow price ϕ also drive risk premium. For simplicity, there is no other source of aggregate risk in this model, where R_1^i is the net return $p_1/p_0 - 1$. and the risk premium depends on the covariance of this payoff with ϕ.

Can we use equations like (1) and (2) to test for or quantify the role of intermediaries' marginal value of wealth in asset markets? One obvious challenge is that we do not observe ϕ directly. But AEM note that "because funding constraints at time-one are always binding, leverage directly measures such constraints and hence measures the marginal value of wealth". With this powerful identification assumption, one can use balance sheet information about leverage in empirical applications to pin down ϕ. For instance, AEM provides several tests based on the identification $\phi \approx a - b\ln(LEV)$, where LEV is a measure of broker-dealer leverage.[6]

[6]Another approach would be to use the margins m_i in empirical tests. However, margin changes are typically too infrequent or hidden to the econometrician. Jylhä (2018) uses changes to Regulation T's

This approach provides a supply-side interpretation of leverage as the quantity of intermediation supplied by the broker-dealers. The leverage decision by intermediaries pins down the quantity of intermediation for two reason. First, leverage does not respond to demand shocks if the funding constraint always binds, as we just discussed. Leverage only increases when market conditions loosen the constraint. Second, Adrian and Shin (2010) show that intermediaries manage the size of their balance sheet primarily by actively varying leverage (mainly through repos and reverse repos). Therefore, asset growth and leverage growth are positively related and broadly aligned along the 45° line. For instance, when the value of the marked-to-market assets increases and the leverage will decrease if it was not actively managed by the intermediaries.

But what if intermediaries' constraints are not always binding? In this case, leverage will be determined by supply as well as demand factors, which means that leverage would not proxy for the funding conditions and the marginal value of wealth of intermediaries. Indeed, supply and demand will both lift leverage but they will have opposite implications for the intermediaries' marginal value of wealth. After a supply shift, leverage and funding conditions move in opposite directions. These leverage supply shocks should carry a positive price of risk because intermediaries' leverage increases while the marginal value of wealth declines.[7] Following a demand shift, leverage and funding conditions move together, because a broker-dealer increases its leverage to match higher investors' demand. These demand shocks should carry a negative price of risk, since in this case its marginal value of wealth increases.

Therefore, the case where the constraints are not always binding is important because these two types of shocks will have different implications for the signs of the prices of risk in asset pricing tests. Regressions of returns or price impact on changes in leverage will produce mixed evidence if the supply and demand shocks are not separated from each other. The regression coefficients may be positive or negative depending on which type of shock is the most prevalent, which may vary over time, across countries and across asset classes. This distinction between supply and demand shocks may explain some of the mixed asset pricing evidence in the financial intermediaries' empirical literature.

Federal Reserve's requirements for initial margins between 1934 and 197 to study changes in the slope of the security market line but does not attempt to identify shocks to intermediaries' marginal value of wealth.

[7] This is the only relevant type of shock if funding constraints are always binding, as assumed by AEM. The constraints always bind when intermediaries have log utilities. The prediction about the price of risk also relies on the assumptions that intermediaries are active traders in all asset markets and there is a degree of homogeneity in the pricing kernels of individual financial intermediaries (He and Krishnamurthy, 2018).

A priori, how plausible is it that the constraints are typically not binding? Generally speaking, the constraints are not binding whenever intermediaries weight inter-temporal considerations. For instance, Liu, Longstaff, and Mandell (2006) study the portfolio problem of traders facing margin constraints and that have access to arbitrage opportunities that vary over time, for instance the ability to buy and quickly resell the same asset in two different markets. With risk-neutral preference over terminal wealth, it is often optimal to invest less than the maximum allowed by the constraint. This arises when the arbitrage opportunities are very persistent and/or volatile. In equilibrium, Du, Hébert, and Huber (2019) also find that the constraints do not bind when intermediaries with Epstein-Zin preferences anticipate higher profits in the future.

B A Measure of Funding Conditions

Therefore, our first task is to establish empirically whether funding constraints are always binding or not. To do that we need another proxy for funding conditions that we can use to tell when leverage increases because of supply factors (beclooser funding conditions) or demand factors (tighter funding conditions). For this purpose, we build on a strand of the literature that uses the wedge between the valuations of assets with identical cash-flows as a proxy for the intermediaries' marginal value of wealth. This is an approach that goes back to the pioneering work of Gromb and Vayanos (2002) or Longstaff (2004). In a model that shares several features with Brunnermeier and Pedersen (2009) but where some securities i and j have identical cash flows, Gârleanu and Pedersen (2011) show that when arbitrageurs use a long-short strategy, then the wedge between the expected returns μ_i and μ_j depends on the shadow price of the funding constraint:

$$|\mu_i - \mu_j| = \phi(m_i + m_j). \tag{3}$$

An established literature uses this approach to build proxies for funding conditions and test some of the important theoretical predictions about the roles of the constraints intermediaries face. In practice, we will use the principal component of three well-established measures derived from the US Treasury markets. First, we use the well-known and often-used TED spread: the spread between the EuroDollar LIBOR rate and the T-bills rate. Frazzini and Pedersen (2014) use it in regressions to test for a link between funding conditions and the U.S. betting-against-beta factor.[8] Second, we use a leading example provided by Hu, Pan, and Wang (2013), who construct their measure by aggregating small deviations of individual bond yields from a smooth parametric curve. They use this proxy in asset pricing tests across hedge funds and currency carry trades. Third, we use the measure from Fontaine and Garcia (2012), who extract a proxy from a panel of pairs of U.S. Treasury securities using a dynamic term structure model. They use this proxy to test for its predictive content for risk premia across several securities markets. There are many reasons why the Treasury market may be the place par excellence to measure funding conditions. First, broker-dealers play a central role in this market. Second, these bonds are the dominant collateral instruments for broker-dealer to manage short-term funding needs (Adrian and Shin, 2010). Third, investors' flight to quality is directed towards the Treasury market during crises. While Treasury bonds with nearby maturities have essentially the same fundamental values, captured by the same few interest rate factors, small gaps open and widen in times of funding stress.

We collect and label these three proxies TED, HPW and FG, respectively. Overall, these proxies exhibit important commonalities despite the differences in their construction. Panels (a)-(c) of Figure 2 plot the monthly time series of these proxies in our sample, between January 1986 and December 2015, showing that they share the same peaks and troughs. The TED proxy features peaks following the crash of 1987, at the beginning of 2000 and, of course, during the recent financial crisis of 2008. There are two other smaller peaks during the European sovereign debt crisis. The FG proxy shares the same peaks, although the ranking of peaks can differ. For instance, the 1994 events and the European debt crisis exhibit higher peaks based on this proxy. The HPW proxy also shares many of the same peaks, but they are not always easy to see next to very high peak of the 2008 crisis. The TED proxy has a correlation of 0.30 and 0.58 with FG and HPW, respectively, while the correlation between FG and HPW is 0.51.[9]

C Do the Funding Constraints always Bind?

In the following, we combine information about funding conditions and about leverage. We use monthly data to construct the principal component of funding conditions proxies,

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

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

which we label $FUND$, and we set its sign such that a higher value of $FUND$ indicates times with wide price differences between nearly identical securities. Using the average instead of the first principal component across proxies does not qualitatively change the results. We expect both approaches can extract a more precise signal of the funding conditions. We then construct LEV as in AEM to measure the leverage of U.S. brokers-dealers.[10]

Using $FUND$ and LEV we will provide several lines of evidence that the constraints of intermediaries do not always bind. First, we simply inspect whether these variables tend to move in opposite direction. Second, we look at a reduced-form evidence test for the hypothesis that the constraints are always binding. Third, and finally, we provide estimates for the probabilities that the constraint is binding at each point in time based on a demand and supply system, where the quantity variable will be the aggregate leverage and the price variable the measure of funding conditions FUND.

(i) Changes in leverage and funding conditions Figure 2 shows the first difference in the funding measure $\Delta FUND_t$ and in the leverage measure $\Delta FUND_t$. If the funding constraints always bind, these two variables should tend to move in opposite directions. However, we can easily identify a few significant dates where the leverage and funding conditions move in the same direction. For instance, in the second quarter of 2008 when leverage increases during one of the most severe tightenings in funding conditions. Overall, ΔLEV_t and $\Delta FUND_t$ move in the same direction in 58 percent of all observations and they move in opposite directions in 42 percent of all observations. The correlation is positive but close to zero.

(ii) A reduced-form look at the evidence One way to test whether the constraints are always binding is to estimate the following predictive regressions:

$$LEV_{t+h} = \beta_h + \beta_{f,h} FUND_t + \beta_{l,h} LEV_t + \beta_{\times,h} FUND_t \times LEV_t + \epsilon^{(l)}_{t+h} \quad (4)$$

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

where h is the forecast horizons, in quarters, and $\epsilon_{t+h}^{(\cdot)}$ is a forecast error.[11] If the constraints are always binding, the partial effect of funding conditions on leverage should be negative, $\beta_{f,h} < 0$), and unrelated to the current leverage the relationship the coefficient, $\beta_{\times,h} = 0$. Otherwise, if the constraints are not always binding, the theory predicts how that partial effect depends on the current leverage in Equation (4). Consider periods when current leverage is high. Then, we expect that tighter funding conditions lead to lower leverage because these are periods where the constraint binds. If the constraints are exactly binding but leverage is high, the partial effect of $FUND_t$ on future leverage should be negative on average, because of the asymmetry across the possible changes to leverage. Contrast this case with periods when leverage is low and where tighter funding conditions may lead to lower leverage after a supply shift and to higher leverage after a supply shift. If both types of shift are equally likely in the data, then the estimated partial effect of $FUND_t$ should be close to zero. The interaction term $FUND_t \times LEV_t$ plays an essential role to capture how the partial effect changes with the level of leverage. Our test asks whether the coefficient $\beta_{\times,h}$ is different from zero and, if not, we expect the estimate to be negative: a higher level of the leverage lowers the partial effects.

Panels (a) of Figure 4 shows that the $\bar{R}^2$s is 68 percent when predicting LEV_{t+h} when $h = 1$ and it gradually declines to around 20 percent when $h = 8$. Panel (b) shows that the estimates of the interaction coefficients $\beta_{\times,h}$ are negative for every horizon up to 8 quarters ahead, as expected, and significant at horizons up to 6 quarter. In all cases, we checked that the estimates of $\beta_{f,h}$ and $\beta_{\times,h}$ that determine the partial effect of interest in Equation (4) are jointly significant.[12]

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

[11] Estimating (4) separately for each horizon implies that the inference is not efficient, relative to estimating a dynamic VAR model, but the estimator is more robust and is not encumbered by a specification of the time-series dynamics. This approach complements the dynamic approach that we undertake below.

[12] We standardize every variable and we estimate the regressions using ordinary least squares. The coefficient of LEV on its own lag is 0.7 for $h = 1$ and remains significant up to 8 quarters ahead.

Panel (d) of Figure 4 reports the time-series of this partial effect, which is given by $\beta_{f,h} + \beta_{\times,h} LEV_t$. The partial effect is a linear transformation of LEV_t by design, but the level, the scale and the size are estimated from the data. As expected, the partial effect is negative and large around some significant historical events: the Mexican crisis of 1994, the dot.com bubble of 2001 and of course the financial crisis of 2008. However, for most of the sample the partial effect is close to zero and alternate between positive and negative values.

Overall, there is strong evidence that funding constraints of financial intermediaries are not always binding. We observe that when the funding constraints are likely to bind, the relationship is negative and supply shocks appear to dominate changes in leverage. Most of the time, however, the relationship is small or even positive and both supply and demand shocks seem to drive leverage.

(iii) A Structural Look at the Evidence We specify a system of demand and supply functions where LEV will represent the quantity variable, $FUND$ the price variable and where we can estimate the probability that the intermediation supply is constrained. The presence of a constraint introduces a challenge in this demand and supply system: the relationship between the observed leverage and its determinants changes when the system moves between the constrained and unconstrained states. We build on existing econometric models to address this challenge while preserving the simplicity of estimation by least squares. This demand and supply system is symbolically represented with the following equations:

$$\begin{aligned} S_t &= \beta_0 Z_t + \beta_1 P_t + v_t \\ D_t &= \alpha_0 X_t + \alpha_1 P_t + u_t \\ Q_t &= \min(D_t, S_t), \end{aligned} \tag{5}$$

where Q_t is the quantity, P_t is the price, X_t and Z_t are exogenous variables and the residuals $u_t \sim N(0, \sigma_u)$ and $v_t \sim N(0, \sigma_v^2)$. The short-hands Q and P for LEV and $FUND$, respectively, are useful to keep the exposition lighter in the following. For instance, the probability that the observation LEV_t is constrained is given by:

$$\begin{aligned} \pi_t &= pr(S_t < D_t) = pr(\beta_0 Z_t + \beta_1 P_t + v_t < \alpha_0 X_t + \alpha_1 P_t + u_t) \\ &= pr(v_t - u_t < \alpha_0 X_t - \beta_0 Z_t + (\alpha_1 - \beta_1) P_t \\ &= \int_{-\infty}^{(\alpha_0 X_t - \beta_0 Z_t + (\alpha_1 - \beta_1) P_t)/\sigma} \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du, \end{aligned} \tag{6}$$

since $v_t - u_t$ is normally distributed with variance $\sigma^2 = \sigma_v^2 + \sigma_u^2$.

The benefits of this specification, which is in the spirit of the Tobit model, are its simplicity and the relative ease to estimate the parameters and of the probabilities that supply is constrained. See Maddala and Nelson (1974) and Laffont and Garcia (1977) and references therein for a discussion of this class of models. The variables S_t and D_t can be interpreted as latent indicators of the supply and demand. The last equation says that the observed quantity is given by S_t or D_t, whichever is lowest, because of the presence of the constraint. Effectively, the condition $D_t > S_t$ (or $D_t < S_t$) introduces shifts between two regimes in the behavior of leverage and, especially, its relationship with funding conditions. When the latent supply variable S_t is the lowest and the constraint binds, the quantity of leverage is determined by the supply function. Conversely, when the latent demand variable D_t is lowest, the quantity of leverage is determined by the demand function. There is no strong a priori reason to believe that a constraint acts on the demand. Instead, we have in mind a situation where the observed leverage quantity can be determined by demand factors. The null hypothesis is that this second situation never arises.

The model is complete once we specify the variables included in the supply and demand equations. We include broad indicators of financial conditions in both equations. We include the term structure factors in the demand and supply equations to capture how the strength of economic activity influences the leverage of financial intermediaries. In addition to the term structure factors, the supply equation also includes the money market mutual funds total assets (MMMF), the MMMF allocation to time deposits (MMA1) and the MMMF allocation to Treasury, agency and municipal bonds (MMA2)[13]. The size and allocation of MMMF assets influence the supply of intermediation. Broker-dealers can more easily adjust their leverage when MMMF are larger and when they have smaller allocations to the safest assets. The demand equation includes the aggregate mortgage level and the ratio of the aggregate shadow bank level over the aggregate mortgage level. The mortgage activity and the relative importance of the shadow banking sector are significant sources of demand for intermediation throughout the sample. Estimates of the parameters can be obtained using two-stage least-squares (TSLS) or maximum likelihood, in which case we use the gradients provided by Maddala and Nelson (1974) starting with the TSLS estimates as initial parameter values. The mortgage variable in the demand equation is the instrument

[13] We used the same variables to explain the growth of shadow banking activity in Fontaine and Garcia (2012) in a supply equation.

to estimate the supply equation while the MMMF allocation variables used in the supply equation are the instruments to estimate the demand equation.[14]

The top panel of Figure 5 reports the probabilities that we obtain. There are several episodes when the probabilities are very low, or close to zero. These periods correspond to the same episodes when funding conditions are poor according to $\Delta FUND$ plotted in the bottom panel of the same figure: around the 1987 crash, the 93-94 period of sudden increase in interest rates, around 1998 with LTCM and the Russian crisis, and the European debt crisis of 2011-2012. The probability is also close to zero during the last quarter of 2008, which may be a reflection of the large-scale interventions by the Federal Reserve and the US Treasury, which are unaccounted for in the model. The natural interpretation for these probabilities is that the intermediaries' leverage that we observe is larger than what is predicted by the estimated supply equation. This would be the case, for instance, if intermediaries accommodate a shift in the demand. For our purpose the most important result is that the supply is not constrained over the whole sample period as assumed in Adrian et al. (2014). Of course, this result hinges on the specification choice for the supply equation. However, we checked that the probabilities are very similar if we explicitly use $\Delta FUND$ to classify what period is driven by the demand and the supply. Together with the reduced-form evidence we can confidently proceed to the estimation of the leverage and supply shocks in a vector autoregressive system where the shocks are unpredictable.

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

The results for the demand equation are not as encouraging. The second-stage estimate for $FUND$ is negative but insignificant. The second-stage R^2 is 37 percent and only the ratio of the shadow bank level over the mortgage level appears significant. This difficulty

[14]Using the analytical gradients to search for the highest likelihood produces only modest improvements to the likelihood. In addition, the estimated probabilities are very robust to these small changes in the likelihood. We also estimated other models incorporating the information in $\Delta FUND$ but the results were very similar in terms of probabilities of observing the demand or the supply quantity of leverage.

could be attributed to the low variance of supply shifters in the data or the poor quality of the instruments for supply variations.

II Leverage Supply and Demand Shocks

A Identification with Sign Restrictions

The presence of two types of shocks in the dynamics of leverage can be represented with a parsimonious reduced-form vector autoregression representation,

$$y_{t+1} = a + \phi y_t + u_{t+1}, \tag{7}$$

where $y_t = \begin{bmatrix} FUND_t & LEV_t \end{bmatrix}$, ϕ is a 2×2 coefficient matrix and u_{t+1} is the reduced-form forecast error with covariance matrix Σ_u. Note that we do not include an interaction term $z_t = FUND_t \times LEV_t$ in Equation (7), which contrasts with the approach taken in Equations (4). We make this choice for simplicity and to make clear that our core results do no depend on the inclusion of an interaction term.[15]

The link between u_t and the structural shocks w_t is given by $u_t = B^{-1} w_t$ and, as is well-known, we need restrictions on the B^{-1} impact multiplier matrix to identify its parameter from the reduced-form estimates. In the following, we use the signs of the correlation that each shock generates to identify the structural supply and demand shock, w_t^S and w_t^D respectively. The intuition, as discussed in Section I, is that demand and supply shocks both increase leverage forecast errors but demand shocks tighten funding conditions ($FUND$ increases) while leverage supply shocks loosens funding conditions. Hence, we assume the following signs for the parameters in the B^{-1} matrix :

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

[15]Omitting z as in Equation 7 produces estimates of the parameters in the matrix ϕ that are very different than the estimates obtained from the specification $y_{t+1} = a + \phi y_t + b z_t + u_{t+1}$. However, in this section we are looking to recover the leverage supply and demand shocks. We checked in unreported results that, using the general model that includes one lag of the interaction term, we recover essentially the same shocks (R^2s of 96.1 and 99.3 percent, respectively). Intuitively, the reason is that the variations in z_t lay very close to the line generated by one linear combination of the elements of y_t (R^2 is 81 percent).

where the superscripts S and D designate the demand and the supply shocks. The use of sign restrictions to identify structural VAR models were introduced by Faust (1998), Canova and Nicolo (2002), and Uhlig (2005). The methodology is described in details in Kilian and Lütkepohl (2017). Briefly, the first step is to compute P the unique Cholesky decomposition of Σ_u from the data ($\Sigma_u = P'P$ and P' is a lower triangular) and then to consider potential decompositions $\Sigma_u = P'S'SP$ where S' is drawn from the set of orthonormal matrices (i.e., $S'S = I$). The decomposition given by the matrix $\mathcal{P} = P'S'$ is a solution to the identification problem if it satisfies the required sign restrictions. If that is the case, then we recover the structural shocks, the impulse response functions and the variance decompositions. By simulating many S matrices we obtain a distribution for each of these objects. We report median values.

B Identification Results

(i) Historical decomposition Figure 6 reports the historical decomposition of LEV forecast errors in terms of the underlying structural shocks. Positive leverage supply shocks played an important role in the mid-1990s but especially around 2000-2001 when funding conditions were initially difficult (see Figure 2) and when leverage rapidly increased at the turn of the millennium. Negative supply shocks played an important role around the 1987 stock market crash and around 2010-2011 in the first stages of the European sovereign debt crisis. However, a single positive leverage demand shock played a dominant role behind the increase in leverage at the height of the great financial crisis of 2008.

(ii) Impulse responses and variance decompositions Figure 7 reports the impulse response functions. The signs of the initial responses are given by construction: negative for $FUND$ and positive for LEV. The magnitude and persistence are estimated from the data. A one-standard-deviation supply shock raises leverage by 0.4 standard deviations and the impact dissipates after about two years. The impact of demand shocks is slightly larger but less persistent. A one-standard-deviation shock raises leverage by 0.55 standard deviations but the effect dissipates after about one year.

The variance decompositions in Figure 8 suggest that leverage demand shocks could be playing a slightly bigger role than supply shocks in explaining the variability of LEV, which could be due to the very large demand shock in 2008. Again, based on the confidence intervals, we cannot exclude the fact that both shocks explain a similar share of the variance.

(iii) Distribution of the structural shocks Figure 9 reports the distribution of the leverage demand and supply shocks when the lagged $FUND$ is in the lower third of its distribution and, separately, when the lagged $FUND$ is in the higher third of its distribution. The top two panels compare the distributions of the leverage supply shocks, while the bottom two panels compare two distributions of the leverage demand shocks. The histograms cover a range of ± 3 standard deviations (this range excludes from the figure only one large demand shock in 2008) and also provide summary statistics that are robust to the small sample size: the median measure of central location, the Bowley measure of dispersion and the inter-quantile range measure of skewness (the statistics include every observation).[16]

The distributions are different. When funding conditions are good, both the demand and the supply shocks have negative medians. The supply shocks have a range of 0.83 and a skewness of 0.09 while the demand shocks have a range of 0.62 and a skewness of -0.07. However, when funding conditions are tight, the dispersion of the supply shocks increases substantially. Its range increases from 0.83 to 1.83, while the range of the demand shocks increases from 0.62 to 0.86. We find similar results if we use the lower and higher terciles of LEV to create subsamples. The fact that the supply shocks have a much wider dispersion in these states is consistent with theoretical predictions that supply play a larger role when the leverage constraint is more likely or closer to bind.[17]

III Leverage Shocks in Securities Markets

AEM find that changes to the leverage ratio of primary dealers carry a positive price of risk and, by itself, this source of risk can explain a large share of the variability in a cross-section of stocks sorted on size, value and momentum. This is powerful evidence that intermediation frictions generate risk and require a risk premium. If our identification assumption is valid, then we expect that leverage supply shocks tend to have a positive relationship with returns and carry a positive price of risk in a cross-section of assets. We also expect that leverage demand shocks tend to have a negative relationship with returns and carry a negative price of risk. Overall, we expect the evidence should strengthens that intermediaries' leverage is important to understand asset markets.

[16]See the discussion of these measures in Colacito, Ghysels, Meng, and Siwasarit (2016).

[17]Modeling the variance dynamics explicitly could lead to efficiency gains, but the results would be subject to specification errors. We think of Equation (7) as a robust way to disentangle the leverage supply and demand shocks.

The results support this hypothesis across several asset classes. For the test assets AEM considered, we find that only the supply shocks have a significant price-of-risk estimate, which is consistent with AEM finding that raw leverage shocks have a positive price of risk. Using other test assets, both supply and demand shocks play role and exhibit consistent price-of-risk estimates, but the raw leverage shocks yield mixed evidence. Another feature of the results is reassuring. We find that prices of the risk associated with both demand and supply shocks are also very close, up to their signs. If fact, the returns betas of the demand and supply shocks are also highly negatively correlated: assets with high supply betas tend to have low demand betas. This suggests that identifying the signs of the leverage shocks seems to only change the signs of the betas and of the risk-returns tradeoff but not their magnitudes.

Finally, AEM also point out a lack of correlation between leverage shocks and market liquidity. We verify whether this puzzle disappears once we separate the leverage demand and leverage supply shocks. We find that positive leverage supply shocks are associated with better liquidity but that negative leverage demand shocks are associated with worse liquidity.

A Leverage in Asset-pricing Tests

(i) Test Assets We construct test assets using data from the markets for stocks, corporate bonds, Treasury bonds and index options. These are large financial markets in which intermediaries play an essential role. For stocks, we form portfolios sorted on betas with respect to three types of risk. First, we sort stocks and formed portfolios using betas with respect to changes in aggregate market illiquidity. Second, we sort stocks using betas with respect to changes in aggregate market volatility. Third, we sort stocks using betas with respect to changes in funding conditions. Specifically, the betas are given by:

$$\beta_i^{\Delta\text{Illiq}} = \frac{cov(\Delta\text{Illiq}_m, r_i)}{var(\Delta\text{Illiq}_m)} \quad \beta_i^{\Delta\sigma} = \frac{cov(\Delta\sigma_m, r_i)}{var(\Delta\sigma_m)} \quad \beta_i^{\Delta FUND} = \frac{cov(\Delta FUND, r_i)}{var(\Delta FUND)},$$

where $Illiq_m$ is the stock market illiquidity, σ_m is the stock market volatility and $FUND$ is the funding proxy, as above. Appendix A.2 provides details about the construction of the portfolios. The choice of portfolios is motivated by the theoretical implications put forward by Brunnermeier and Pedersen (2009) that the marginal value of the intermediaries' wealth links returns with illiquidity, volatility and funding liquidity. We also perform asset-pricing tests with standard portfolio sorts in Section (vi) below.

For corporate bonds, we also sort on betas with respect to changes in $Illiq_m$, σ_m and $FUND$, which are estimated using a rolling window of 36 months. We use monthly returns for a cross-section of corporate bonds by merging several data sets: the Lehman Brothers fixed income database, Mergent FISD/NAIC, TRACE, Bloomberg, and Datastream. We closely follow Bai, Turan, and Wen (2015) to merge these data sources and exclude bonds with special features. For Treasury bonds, we compute constant-maturity returns for bonds with maturities of 2, 3, 4, 5, 7 and 10 years, the data for which we obtained from the Center for Research on Securities Prices (CRSP). For each month and each maturity category, we select the most recently issued bond and one other bond that is nearest to each of these maturity points. We use observable bond prices and do not rely on fitted zero-coupon curves. For options, we use the series of unlevered S&P index call and put options with different strike prices and maturities available from Constantinides et al. (2013). They show how challenging it can be to price options returns, especially for puts, but that a proxy for illiquidity goes a long way toward reducing pricing errors. The options data are available until 2011Q4. Because of this, the sample is shorter when we include options among test assets. Note that the cross-sections of Treasury bonds and options are not rich enough to construct beta-sorted portfolios.

(ii) Equities, Bonds and Options Figure 1 in the introduction already summarizes the asset-pricing results for all asset classes jointly. It shows that disentangling leverage demand and supply shocks provides a much improved fit of returns. Table 2 reports the corresponding price-of-risk estimates for these specifications and a few others. Sections (iii)-(v) below analyse each asset class separately.

The first column in Table 2 reports the results using the leverage factor and market returns, as suggested by AEM. We report the t-test statistics based on both the Fama-Macbeth and the Shanken standard errors. We also report a confidence interval for the adjusted $\bar{R}^2$ measure of fit, following the methodology in Lewellen, Nagel, and Shanken (2010). We find that the constant is estimated to be close to zero and statistically insignificant. The estimated price of leverage risk is positive, as in AEM, and significant at the 10 percent level but not at the conventional 5 percent level. Using raw leverage provides a limited fit for the cross-section of returns. In addition, the confidence interval for the $\bar{R}^2$ ranges from 9 to 80 percent. Panel (a) of Figure 1 is useful for visualizing the magnitude of the pricing errors.

The second and third columns of Table 2 report the results using leverage demand and leverage supply shocks, separately. The $\bar{R}^2$ is 68 and 65 percent, respectively. In both cases, it is roughly twice as large relative to using ΔLEV. The confidence interval for the $\bar{R}^2$ is relatively tight in both cases, ranging from around 45 to 85 percent. The constant is not significant in the case of leverage demand shocks. The key message from these two columns is that the price-of-risk estimates are significant at the 1 percent level and have opposite signs. The magnitudes are larger than for ΔLEV: 4.4 and -6.2 for the leverage supply and demand shocks, respectively, compared with 2.4 for leverage. This means that shocks to intermediaries' leverage represent an important source of risk that is associated with compensation in financial markets, but the sign matters. Leverage supply shocks have a positive price of risk and leverage shocks that are due to demand shifts have a negative price of risk.

Next, we combine the supply and demand shocks together in the same pricing model (always with market returns, for comparability with other columns). The $\bar{R}^2$ is now 88 percent and the confidence interval has been halved; it now ranges from 77 to 94 percent. The price-of-risk estimates have the same signs and they remain significant, though the magnitudes decline somewhat. On a separate line of Table 2, labeled H_0, we report results from a test of the null hypothesis that the prices of risk for leverage demand and supply shocks have the same magnitudes in absolute value. The t-statistic based on Shanken's standard error is only 0.71.

For completeness, the last two column reports the results when using $\Delta FUND$either on its own or together with the leverage demand and supply shocks. On its own, has a significant price of risk and offers a fit that is similar to using both types of leverage shocks together. This is why we can use $FUND$ together with sign restrictions to disentangle the leverage demand and leverage supply shocks. When we combine $\Delta FUND$ with demand and supply leverage shocks, the prices of risk remain significant and essentially unchanged and the fit remains the same.

It is useful to take a step back and think about what this means for leverage risk. Essentially, we split the leverage factor between the two types of shocks that are orthogonal with each other but such that the correlations with funding conditions have opposite signs. Then, for both types of leverage shocks, we compute betas that we put together in a pricing model. This increases the fit from 30 percent when using raw leverage to close to 90 percent when using separate shocks and we find that both types of leverage shocks have significant prices of risk but with opposite signs. The data support the hypothesis that the prices of risk have the same absolute value. It is the difference between the signs of the leverage demand and leverage supply shocks that explain the poor fit and the mixed evidence for raw leverage shocks in some asset-pricing tests. This is a consistent theme across our other results.

(iii) Portfolios of Stocks We now take a separate look at portfolios of stocks. Table 3 provides summary statistics for the equity portfolios. Panel (a) reports the statistics for portfolios sorted on illiquidity betas, labeled from 1 to 10. Portfolio 1 has a large negative beta—it is riskier—and Portfolio 10 has a small positive beta. In fact, the beta for Portfolio 9 is essentially zero, which means that portfolios 9 and 10 either have no exposure to or provide a hedge against illiquidity risk. Overall, the results show a U-shaped pattern for returns, illiquidity and volatility but an inverted U-shaped pattern for market capitalization.

Panel (b) reports the statistics for portfolios sorted on volatility betas. Here again, Portfolio 1 has a large negative beta and Portfolios 9 and 10 have no exposure to or provide a hedge against volatility risk. In this case, the portfolio returns, illiquidity and volatility are mostly downward sloping, while the market capitalization is upward sloping. Larger firms tend to be more liquid, less volatile, to offer a hedge against volatility risk and have lower returns. Panel (c) reports the statistics for portfolios sorted on funding betas. Again, Portfolio 1 has a large negative beta and Portfolio 10 has a positive beta. Portfolios 9 and 10 have no exposure to or provide a hedge against funding risk. Here, again, the returns, illiquidity and volatility exhibit a U-shaped pattern, while market capitalization exhibits an inverted U-shaped pattern.

Taking a step back and looking across Panels (a)-(c), we see that the pattern of the betas is similar whether we sort portfolios on $\beta_i^{\Delta \text{Illiq}}$, $\beta_i^{\Delta\sigma}$ or $\beta_i^{\Delta FUND}$. These strong relations between the beta-sorted portfolios are an empirical manifestation of the theoretical links between market liquidity, volatility and funding liquidity. Since they offer a substantial dispersion in average returns, testing whether these portfolios are well-priced by leverage demand and supply shocks is, therefore, an excellent test of the theoretical pricing implications.

Columns (1)-(4) of Table 4 report the results of the asset-pricing tests for these beta-sorted portfolios of stocks. In the first column, we observe that the price of risk for raw leverage shocks is negative and significant at the 10 percent level based on the Shanken test-statistics. This contrasts with results in Table 2 where the estimated price of risk was positive. Nonetheless, the $\bar{R}^2$ is 90 percent and the confidence interval is tight.

Columns (2) and (3) report results using the leverage supply and demand shocks, separately. Both types of shocks yield price-of-risk estimates with the expected signs. The price of risk for leverage demand shocks is negative and significant at the 1 percent level, based on the Shanken test-statistics. The fit is good and the constant is not significant. The estimate for the leverage supply shocks is positive, as expected, but not significant, the $\bar{R}^2$ is lower relative to the demand shocks and its confidence interval is wider. For completeness, Column (4) reports that the price-of-risk estimate for $\Delta FUND$ is close to -1 percent and significant. In all cases, the price of market risk is reasonably estimated at around 8% and is statistically significant.

Overall, the results suggest that the reason why the raw leverage shocks have a negative price-of-risk estimate is that the effect of the demand shocks is estimated more precisely in stocks. Nonetheless, while the price-of-risk estimate is not significant for supply shocks, both types of shocks achieve a similar fit. This is because their betas exhibit very similar patterns but with opposite signs. To see this, we plot in Figure 10 the betas of the 30 portfolios against the returns of each portfolio in excess of the risk-free rate and adjusted for its exposure to market risk (i.e., we substract the equity premium times the beta from the returns). This confirms that exposures to leverage demand shocks align well with returns. Note that portfolios with relatively high βs with respect to supply shocks (V1 and F10) also have the lowest negative βs with respect to leverage demand shocks, and vice versa (V10, V9 and V8). In this case the cross-sectional correlation between the β estimates is -0.63.

(iv) Portfolios of Bonds Columns (5)-(8) of Table 4 report the results for corporate and Treasury bonds. The price of risk for ΔLEV has a positive sign, which is the opposite of what we found for stocks, and the price of market risk is unreasonably large. The $\bar{R}^2$ is around 60 percent with a confidence interval that spans from 39 to 81 percent.

The estimates are significant, with the expected signs for both the demand and supply shocks. The specification using the supply shock has the highest explanatory power, with an $\bar{R}^2$ of 82 percent, a more precise confidence interval, between 66 and 92 percent, and the estimated price of market risk is economically reasonable. The specification for the demand shock is less satisfying both in terms of its $\bar{R}^2$ and the price of market risk. However, we cannot reject the hypothesis that the prices of risk for both types of shocks have the same magnitude in absolute value (t-statistics: 0.14). For completeness, we report results for $\Delta FUND$. Its price of risk is negative, statistically significant and larger than what we found for equities. The $\bar{R}^2$ is 86 percent and the price of market risk is reasonable.

Our results are consistent with the results of Goldberg and Nozawa (2019) that liquidity supply by financially constrained intermediaries is a main driver of corporate bond prices. Together, these results suggests that the estimate for the price of risk of raw leverage is positive in the bond market because the effects of the leverage supply shocks are estimated more precisely in this market. It also suggests one reason why the estimated price of risk for raw leverage shocks ΔLEV changes signs between the stock and the bond markets. The exposures to leverage demand shocks appear to be measured more precisely in the stock market, while the exposures to supply shocks appear to be measured more precisely in the bond market. Nonetheless, in both markets, the supply shocks have a positive price of risk and the demand shocks have a negative price of risk.

In Figure 11, we plot the betas against their average returns in excess of the risk-free rate where we adjust for the exposure to market risk (i.e., we substract the equity premium times the beta). Similar to what we found for portfolios of stocks, the betas for the demand and supply shocks are highly negatively correlated and, again, the estimates for the prices of risk are very close in absolute value.

In all of the panels, we see a clear separation between Treasury and corporate bonds. Treasury bonds form a cluster with risk-adjusted excess returns of around -5 percent, while corporate bonds form a cluster with returns around or above 5 percent. Treasury bonds carry negative betas with respect to leverage supply shocks and offer a hedge premium. By contrast, Panel (d) shows that using leverage demand shocks does not match the returns to Treasury bonds.

Given this wedge between Treasury and corporate bonds, one might wonder if the same picture emerges if we exclude the Treasuries. In Figure 12, we plot the βs and the mean excess returns estimated for corporate bonds only (excluding Treasury bonds). In panel (a), for ΔLEV, taking out Treasuries results in a slope that is close to zero and large pricing errors for portfolios V1, L1 and F1, those with the highest exposures to risk. However, separating the leverage shocks into supply and demand components, the slopes have the expected signs and the pricing errors are consistent with our other results.

(v) Portfolios of Options Columns (9)-(14) of Table 4 reports the results using the unlevered options returns as test assets. Column (9) shows that the estimate of the leverage price of risk is negative and very large. The fit appears good, since the $\bar{R}^2$ is around 90 percent, but the constant is quite large. Already in Figure 1a, when the estimates are disciplined by the presence of multiple asset classes, we can see that some of the put and call portfolios have the largest pricing errors. By contrast, Figure 1b shows that these pricing errors are substantially reduced when we disentangle leverage supply and demand shocks.

Looking at each type of shocks separately, we see in Column (10) that using only leverage supply shocks exacerbates these distortions. The $\bar{R}^2$ is lower with a wider confidence interval, the constant and the price of risk are very large, yet both estimates are imprecise, and the equity premium estimate is close to 18 percent. We have to conclude that the effects of leverage supply shocks are estimated extremely imprecisely in the option market and that we cannot use these shocks alone in a model to explain option returns. However, Column (11) shows that using leverage demand shocks produces a significant negative price of risk, as expected, a small constant and a good fit; the $\bar{R}^2$ is around 90 percent but this is probably inflated to some extent because we treat options returns in isolation. For completeness, Column (12) shows that funding shocks carry a significant price of risk that is negative, as in the other results.

Finally, Columns (13)-(14) report results using returns on call and put options, separately. It shows that the price of risk for calls is very close to the one obtained with equities, which is consistent with the findings of Constantinides et al. (2013). However, the price of risk for puts is much larger in magnitude and significant. This could reflect the fact that funding constraints can be different for calls and puts. For instance, a higher margin is usually required by the CME for selling naked puts.

(vi) Adrian, Etula, and Muir (2014) Asset pricing Test We conclude by revisiting the asset-pricing tests conducted by AEM. To summarize, they show that the leverage factor explains 77 percent of the cross-section of returns for 25 size and book-to-market portfolios, 10 momentum portfolios and 6 Treasury bonds (see Adrian, Etula, and Muir 2014, Figure 1 and Table III). This model provides a competitive fit relative to a model that includes the Fama-French three factors, the momentum factor and the first principal component of the yield curve. The estimated price of risk for ΔLEV is positive and significant.

We reproduce these results in Table 5 for our sample period from 1989Q2 to 2015Q4 (AEM's sample covers 1968Q1 to 2009Q4). Panel (a) reports the results using market returns as well as one of the raw leverage shocks, the leverage demand shocks or the supply shocks. Panel (b) reports the results in models based on the three Fama-French factors, the momentum factor, and the first principal component of the yield curve.

Our results align with the findings of AEM. The $\bar{R}^2$ of the five-factor model is 93 percent, only slightly higher than what AEM found, and its confidence interval ranges from 79 to 97 percent. The price-of-risk magnitudes for the momentum and book-to-market factors are close to the values obtained by AEM but significantly different from zero, which was not the case in their findings. Turning to a simple model that uses raw leverage, we find that the fit is also competitive in our sample: the $\bar{R}^2$ is 88 percent with an only slightly wider confidence interval (70 to 96 percent).[18] The leverage price of risk is positive and significant. Panel (a) also shows that leverage supply shocks have a positive and significant price-of-risk estimate but that leverage demand shocks have an estimate that is essentially zero. Hence, this suggests that the price of risk for raw leverage shocks is positive because the effect of leverage supply shocks is estimated more precisely for these test assets, relative to leverage demand shocks.

The results in Table 5 also suggest that there is some tension in fitting this set of assets. The constant is significant and the estimated price of market risk tends to be large in every case we report. Figure 1 in AEM shows that the largest pricing errors are associated with MOM10 and MOM1, which are the highest- and lowest-momentum portfolios. The S1B1 portfolio is also badly priced. Our Figure 13a shows that this is also the case in our results, although other momentum portfolios (MOM9 and MOM8) are also badly priced. Panels (c)-(d) of Figure 13 show that these momentum portfolios are even more challenging in models that use either the leverage supply or demand shocks on their own. These portfolios' pricing errors draw a risk-return tradeoff that appears to be orthogonal to the other portfolios.

To better see the tension due to the pricing of momentum portfolios, Table 6 reports the results when using 10 portfolios sorted on momentum, size or value, separately. For momentum, depending on the asset-pricing model, the confidence interval for the $\bar{R}^2$ can be very wide, the constant can be large, and the prices of risk can flip signs, offering a stark contrast with many of the other results that we obtain. For the size portfolios, the constants

[18] In AEM, the $\bar{R}^2$ with and without the market are practically identical. In our case, we always include market returns as a test asset. The price of market risk comes out significant for all models in our sample.

are small and the estimated prices of risk have the expected signs, but the statistical evidence is weak. If anything, the price of risk of leverage demand shocks is estimated more precisely and the $\bar{R}^2$ confidence interval is tighter. Nonetheless, the coefficient for raw leverage is positive and not significant. For the value portfolios, the estimated prices of risk also have the expected signs. In this case, the effects of leverage supply shocks are estimated more precisely. The constant is not statistically different from zero, the price of market risk is reasonable and the $\bar{R}^2$ is 87 percent (confidence interval from 43 to 97 percent).

(vii) Discussion In a joint test with equities, bonds and stocks, both types of leverage shocks carry a large price-of-risk estimate and together deliver a good fit of the dispersion of returns. When looking at individual asset classes in Table 4, we see that at least one of the leverage demand and supply shocks always plays an important role. Because these two types of shocks are associated with higher leverage but since they carry risk prices with opposite signs, this can explain why using exposures to raw leverage shocks seems to carry a negative price of risk in equities but a positive price of risk in bonds.

Another key message from the results is that a positive beta with respect to leverage supply shocks tends to be associated with a negative beta with respect to leverage demand shocks. This high degree of correlation is reassuring since it tells us that identifying different types of leverage shocks does not amount to uncovering new risk factors. The challenge is to identify whether a unit increase in leverage reveals a lower marginal value of intermediaries' wealth and an improved state of the world, or whether it is the other way around. Hence, it is reassuring that, up to correctly signing the effect, the response of the portfolio returns (the $|\beta|$s) is essentially the same and, in fact, the estimated prices of risk for leverage demand and supply shocks in Table 4 are very close in absolute value.

Overall, the results confirm that the leverage demand and leverage supply shocks also have some explanatory power for the most usual size and value portfolios. Yet, the momentum portfolios appear to be a puzzle from the perspective of a model that includes either leverage demand or leverage supply shocks. A momentum or trend-following strategy with a larger positive beta with respect to leverage supply shocks (or a negative beta with respect to leverage demand shocks) has lower average returns. This is the opposite to what we found in every other test. Lewellen, Nagel, and Shanken (2010) also report that momentum portfolios appear anomalous relative to the benchmark models they consider. One conjecture is that momentum strategies exhibit exposure to an omitted risk factor that is correlated with exposure to leverage demand and supply shocks.[19]

B Leverage and Market Illiquidity

We test for the impact of leverage shocks on the illiquidity of stocks. This test is important because it helps us understand the mechanism by which leverage shocks affect investors: through lower liquidity, these shocks make some assets less desirable during bad times. For this purpose, we sort stocks on their market liquidity, measured using the Amihud ratio, in 10 portfolios. We also form 10 portfolios of stocks sorted on their realized volatility over the past six months. The rational for sorting on volatility is the theoretical prediction that the impact of leverage shocks depends on the volatility of a stock. Appendix A.3 details the portfolio construction.

Table 7 provides quarterly summary statistics on these portfolios. The portfolios are ranked from the least liquid (column 1) to the most liquid (column 10) and from the most volatile to the least volatile. Illiquid portfolios exhibit higher volatility and higher returns but lower capitalization. The pattern is almost monotone across portfolios. The volatility-sorted portfolios exhibit similar patterns between illiquidity, returns and market capitalization.

(i) Raw Leverage Shocks We first consider regressions for the changes in portfolio illiquidity on ΔLEV, including the market returns as a control variable. Panel (a) of Table 8 reports the results for the illiquidity- (Row I) or volatility- (Row II) sorted portfolios. The signs indicate that an increase in leverage will lower illiquidity for almost every portfolio. However, the estimates are never statistically significant. The lack of statistical significance corresponds with the results reported by AEM. Panel (b) of Table 8 reports the results for the regression that uses $\Delta FUND$. We find that the estimated coefficients are large, statistically significant and have the right sign. This result provides early evidence that using funding conditions can help identify the impact that leverage demand and leverage supply shocks have on illiquidity.

(ii) Leverage Demand and Leverage Supply Shocks Table 9 shows the results of illiquidity regressions using supply shocks in Panel (a) and demand shocks in Panel (b). The

[19] Jusselin et al. (2017) show that mixing long-only and trend-following exposures may offer a good tool for tail-risk management and downside protection.

coefficients for the supply shocks are significant, with the right sign in every regression and they exhibit a monotone pattern: the estimates are larger for the least liquid portfolios. Hence, increases in the supply of leverage provide liquidity to the market and lower the illiquidity of the portfolios.

The coefficient estimates for the demand shocks are uniformly positive with magnitudes similar to the case of the supply shocks and significant for the illiquidity-sorted portfolios. An increase in leverage coming from demand decreases the measured market liquidity. Again, there is a monotone pattern: the estimates are larger for the least liquid portfolios. For the volatility-sorted portfolios, the sign is uniformly positive but can be insignificant.

Note that the coefficients on both the demand and supply shocks are very similar, but with opposite signs in the illiquidity regressions. This is a similar pattern to what we found for returns betas in the asset-pricing tests.These results can explain the lack of significance of the coefficients in Table 8 for raw leverage. Using the raw leverage shocks produces insignificant coefficient estimates because these shocks mix leverage demand and supply shocks, which have opposite effects on the market liquidity of stocks. Therefore, the decomposition of leverage into supply and demand shocks sheds some light on the puzzle raised in AEM and provides strong evidence that leverage shocks are related to liquidity and also affect market conditions.

IV Conclusion

In this paper, we relax the identification assumption that intermediaries' funding constraints are always binding. Instead, we use sign restrictions to separately identify two types of shocks in the observed variations of dealers' leverage. One type of shock relaxes the constraint and leads to an increase in the supply of intermediation capital and higher leverage. Another type of shock raises the demand for intermediation capital, which also leads to higher leverage but tightens the constraint. The evidence confirms that leverage supply shocks improve liquidity and carry a positive price of risk but leverage demand shocks worsen liquidity and carry a negative price of risk. Our findings reinforce the importance of financial intermediaries and movements in their balance sheets to understand the pricing of assets. The results also indicate that more work is needed to distinguish and quantify the mechanisms underlying the channels of leverage supply and leverage demand shocks across different asset markets.

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A Appendix

A.1 Data

We extract daily data from CRSP for ordinary common stocks traded on the NYSE or AMEX with prices between \$5 and \$1,000. Nasdaq stocks are excluded to avoid distorting the illiquidity measure (Amihud, 2002). We extract a monthly sample of stock returns with at least 10 observations in a given month. Excluding stocks with too many missing observations reduces the noise when computing stock-level illiquidity or volatility proxies. This exclusion makes our results conservative, since we expect a greater impact of funding shocks for relatively illiquid securities.

A.2 β-sorted Portfolios

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

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

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

(ii) Illiquidity and Volatility Betas Using the same approach, the market illiquidity beta is

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

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

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

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

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

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

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

A.3 Illiquidity and Volatility Sorts

We form 10 portfolios of stocks sorted on the level of illiquidity and volatility, respectively. For a given stock i and day d, we measure its illiquidity by the Amihud ratio $illiq_{id}$ given by: At the end of each year, we form 10 equal-weighted portfolios of stocks sorted on their average Amihud ratio over the previous 6 months. In the case of volatility, we sort stocks on their volatility, which is computed as the standard deviation of returns over the last quarter. We average over six months to mitigate the amplification of noise due to using squared returns. We track these portfolios for one year.

We track the returns, volatility and illiquidity of these portfolios for one year and we form new portfolios using the same procedure at the end of the year. The volatility of a portfolio p is the average of its component stocks. The illiquidity of a portfolio is the median illiquidity of its components,

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

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

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

OLS and TSLS regressions of intermediaries' leverage LEV on funding conditions $FUND$. Panel (b): estimates for the demand equation, including Level, Slope and Curvature factors from the term structure of interest rates, the aggregate mortgage level, and the ratio of the aggregate shadow bank level over the aggregate mortgage level. Panel (a): estimates for the supply equation including Money Market Mutual Funds total assets (MMG), Money Market Mutual Funds allocation to time deposits (MMA1) and Money Market Mutual Funds allocation to Treasury, Agency and Municipal bonds (MMA2). Standard instrumental variables t-statistics in parentheses. End-of-Quarter data (1986:1 to 2015:4).

Panel (a) Supply equation

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

Panel (b) Demand equation

	cst	$FUND$	Level	Slope	Curv.	Ratio	Mrtg	R^2
OLS	69.23	5.38	-6.24	-2.15	2.63	6.70	0.07	
	(4.64)	(4.44)	(-4.23)	(-2.33)	(2.99)	(4.21)	(0.24)	46.72
2SLS	47.69	-0.08	-3.15	0.15	1.65	6.65	0.29	
	(1.93)	(-0.02)	(-0.99)	(0.07)	(1.30)	(3.96)	(0.81)	37.44

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

Cross-sectional tests based on two-stage Fama-MacBeth regressions for portfolios of equities, corporate and Treasury bonds and options. ΔLEV is the leverage factor of AEM, SS and DS are the supply and demand leverage shocks, and $\Delta FUND$ is the proxy for the funding conditions. The market returns MKT are included as a risk factor and a test asset. We use the one-month T-bill rate to compute excess returns. Fama-MacBeth and Shanken-corrected standard errors are reported in parentheses. Bootstrap $\bar{R}^2$ confidence intervals are in square brackets. The row labeled H_0 reports the t-statistics in curly brackets { } for a test of the null hypothesis that the prices of risk of SS and DS have the same absolute value: $\lambda^{DS} = -\lambda^{SS}$. The intercepts and prices of risk are annualized.Quarterly data, 1990Q1–2011Q4 (the sample is shorter because of the unlevered option data).

int	-0.77	-2.16	-0.57	-2.16	-2.18	-2.03
t-FM	(-0.99)	(-2.55)	(-0.68)	(-2.55)	(-2.65)	(-2.60)
t-Sh	(-0.82)	(-1.71)	(-0.38)	(-1.51)	(-1.67)	(-1.41)
ΔLEV	2.39					
t-FM	(2.08)					
t-Sh	(1.76)					
SS		4.40		2.93		3.10
t-FM		(4.31)		(3.00)		(2.99)
t-Sh		(3.03)		(1.90)		(1.72)
DS			-6.19	-4.59		-5.20
t-FM			(-5.61)	(-4.59)		(-5.08)
t-Sh			(-3.36)	(-2.92)		(-2.97)
ΔFUND					-3.90	-4.02
t-FM					(-5.57)	(-5.84)
t-Sh					(-3.78)	(-3.48)
MKT	9.46	8.49	6.29	7.04	7.71	6.48
t-FM	(2.38)	(2.15)	(1.60)	(1.79)	(1.96)	(1.67)
t-Sh	(2.31)	(2.01)	(1.43)	(1.62)	(1.80)	(1.51)
H_0	—	—	—	{0.71 }	—	{0.90}
R^2	31.4	65.1	68.2	88.3	86.0	88.80
$\bar{R}^2$	30.3	64.6	67.8	88.0	85.7	88.44
	[9, 80]	[42, 85]	[47, 85]	[77, 94]	[73, 93]	[77, 95]

Table 3: **Summary Statistics – Equity Portfolios**

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

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

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Return	17.32	14.74	13.56	12.34	13.64	13.56	14.60	13.32	14.31	15.85
Illiqu.	2.91	1.73	1.38	1.15	1.23	1.46	1.43	1.82	1.92	3.51
Volatil.	42.63	36.76	34.40	32.93	31.41	31.03	30.64	29.73	30.75	34.65
Mkt Cap	4.52	5.97	7.33	7.75	9.19	8.64	9.20	9.26	8.49	6.80
$\tilde{\beta}^{\Delta \text{Illiq}}$	-2.81	-1.92	-1.50	-1.23	-1.02	-0.79	-0.56	-0.31	-0.01	0.67
$\tilde{\beta}^{\Delta \text{Vol}}$	-16.13	-12.88	-11.41	-10.68	-10.11	-9.44	-9.44	-8.50	-8.51	-10.43
$\tilde{\beta}^{\Delta \text{FUND}}$	-6.71	-5.80	-4.81	-4.45	-4.57	-3.56	-3.47	-3.31	-3.17	-3.43

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

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Return	20.76	16.71	15.83	15.15	13.14	13.49	11.65	12.49	12.35	11.90
Illiqu.	7.10	3.20	2.32	1.62	1.52	1.23	1.19	0.99	1.05	1.38
Volatil.	43.35	37.18	35.17	32.85	32.43	30.95	30.31	29.33	29.83	33.67
Mkt Cap	1.99	4.06	5.41	7.68	6.76	8.77	8.98	11.80	10.84	10.78
$\tilde{\beta}^{\Delta \text{Illiq}}$	-1.22	-1.03	-1.01	-0.99	-0.89	-0.89	-0.85	-0.84	-0.85	-0.92
$\tilde{\beta}^{\Delta \text{Vol}}$	-39.20	-24.76	-18.59	-14.40	-11.01	-7.91	-4.80	-1.35	2.66	11.21
$\tilde{\beta}^{\Delta \text{FUND}}$	-5.48	-5.08	-4.43	-4.41	-4.15	-4.06	-3.66	-3.83	-3.60	-4.55

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

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

Table 4: **Asset-pricing Tests—Individual Asset Classes**

Cross-sectional tests based on two-stage Fama-MacBeth regressions for portfolios of equities, bonds and options, separately. ΔLEV is the leverage factor of AEM, SS and DS are supply and demand leverage shocks, and $\Delta FUND$ is the proxy for the funding conditions. The market returns MKT are included as a risk factor and a test asset. Fama-MacBeth and Shanken-corrected standard errors are reported in parentheses. Bootstrap $\bar{R}^2$ confidence intervals are in square brackets. Quarterly data, 1990Q1–2015Q4 for stocks, 1989Q2-2014Q4 for bonds and 1986Q2-2011Q4 for options. The intercepts and prices of risk are annualized.

	Equities				Bonds				De-Levered Options				Call	Put
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
int	4.84	1.05	2.62	2.37	0.05	-1.84	-1.26	-2.66	-6.44	-19.91	1.91	1.95	-2.36	-1.03
t-FM	(2.79)	(0.58)	(1.68)	(1.51)	(0.09)	(-3.83)	(-1.98)	(-4.26)	(-3.57)	(-5.38)	(1.71)	(1.75)	(-2.03)	(-0.96)
t-Sh	(2.17)	(0.51)	(1.46)	(1.38)	(0.05)	(-2.12)	(-0.92)	(-2.35)	(-1.29)	(-1.32)	(0.85)	(0.92)	(-1.58)	(-0.38)
ΔLEV	-3.11				5.86				-10.22					
t-FM	(-2.19)				(6.25)				(-5.47)					
t-Sh	(-1.73)				(3.59)				(-2.01)					
SS		2.02				5.68				-15.23				
t-FM		(1.87)				(5.71)				(-6.68)				
t-Sh		(1.66)				(3.33)				(-1.66)				
DS			-2.26				-7.53				-7.01		-3.27	-9.25
t-FM			(-2.37)				(-4.22)				(-5.55)		(-2.51)	(-6.89)
t-Sh			(-2.10)				(-2.01)				(-2.87)		(-2.00)	(-2.86)
ΔFUND				-1.27				-4.55				-5.05		
t-FM				(-2.48)				(-5.14)				(-5.05)		
t-Sh				(-2.33)				(-2.96)				(-2.76)		
MKT	8.11	8.64	8.61	8.18	15.03	9.32	13.13	7.92	6.38	17.83	3.99	5.51	6.19	5.94
t-FM	(2.41)	(2.56)	(2.52)	(2.42)	(3.80)	(2.71)	(3.74)	(2.40)	(1.78)	(4.00)	(1.15)	(1.59)	(1.79)	(1.72)
t-Sh	(2.36)	(2.53)	(2.48)	(2.41)	(2.84)	(2.45)	(3.08)	(2.36)	(1.47)	(1.48)	(1.11)	(1.58)	(1.79)	(1.72)
H_0	—	{0.78}		—	—	{0.14}		—	—	{3.33}		—	—	—
R^2	90.49	85.25	90.48	91.97	62.32	83.04	64.38	86.67	93.79	73.55	93.97	86.68	92.21	95.05
$\bar{R}^2$	89.81	84.20	89.80	91.39	60.44	82.19	62.59	86.00	93.55	72.53	93.73	86.17	91.58	94.65
	[72, 99]	[52, 97]	[67, 98]	[72, 98]	[39, 81]	[66, 92]	[38, 83]	[72, 94]	[88, 98]	[46,86]	[88,97]	[72, 95]	[81, 99]	[89, 98]

Table 5: **Asset-pricing Tests — Size, Book-to-Market, Momentum Portfolios and Treasury Bonds**

Cross-sectional tests based on two-stage Fama-MacBeth regressions for the 25 size and book-to-market-sorted, 10 momentum-sorted portfolios, and 6 new and 6 old Treasury bonds with maturities 2, 3, 4, 5, 7, and 10 years. ΔLEV is the leverage factor of AEM, SS and DS are supply and demand leverage shocks and $\Delta FUND$ is the proxy for the funding conditions, respectively. The market returns MKT is included as a risk factor and a test asset. Fama-MacBeth and Shanken-corrected standard errors are reported in parentheses. Bootstrap $\bar{R}^2$ confidence intervals are in square brackets. Quarterly data, 1989Q2–2014Q4. The intercepts and prices of risk are annualized.

Panel (a) Leverage

int	-2.83	-2.86	-2.84	-2.86
t-FM	(-5.53)	(-5.66)	(-5.38)	(-5.66)
t-Sh	(-3.64)	(-4.54)	(-5.06)	(-5.35)
ΔLEV	4.29			
t-FM	(3.21)			
t-Sh	(2.17)			
SS		2.74		
t-FM		(2.68)		
t-Sh		(2.21)		
DS			0.03	
t-FM			(0.02)	
t-Sh			(0.02)	
ΔFUND				-0.40
t-FM				(-0.52)
t-Sh				(-0.50)
MKT	12.59	8.78	11.70	11.38
t-FM	(3.49)	(2.48)	(3.33)	(3.30)
t-Sh	(3.14)	(2.39)	(3.30)	(3.28)
R^2	87.79	79.76	73.42	73.37
$\bar{R}^2$	87.25	78.86	72.24	72.18
	[70, 96]	[55, 95]	[43, 94]	[43, 94]

Panel (b) Fama-French

int	-2.86	-3.57	-3.80	-3.10
t-FM	(-5.63)	(-9.03)	(-10.11)	(-9.01)
t-Sh	(-5.32)	(-8.32)	(-8.51)	(-7.03)
SMB		1.84	3.22	2.73
t-FM		(0.78)	(1.40)	(1.20)
t-Sh		(0.76)	(1.32)	(1.10)
HML		4.60	5.30	5.38
t-FM		(1.82)	(2.09)	(2.12)
t-Sh		(1.81)	(2.05)	(2.06)
MOM			6.79	7.44
t-FM			(1.96)	(2.15)
t-Sh			(1.92)	(2.10)
PC1				4.64
t-FM				(4.31)
t-Sh				(3.92)
MKT	11.50	10.94	12.27	11.52
t-FM	(3.15)	(3.24)	(3.64)	(3.42)
t-Sh	(3.12)	(3.22)	(3.60)	(3.36)
R^2	73.36	81.88	91.80	92.58
$\bar{R}^2$	72.78	80.70	91.08	91.76
C.I.	[44, 95]	[57, 94]	[76, 96]	[79, 97]

Table 6: **Asset-pricing Tests — Size and Momentum Decile Portfolios**

Cross-sectional tests based on two-stage Fama-MacBeth regressions for ten momentum-, size- and value-sorted portfolios from Ken French's website. ΔLEV is the leverage factor of AEM, SS and DS are supply and demand leverage shocks and $\Delta FUND$ is the proxy for the funding conditions, respectively. The market returns MKT are included as a risk factor and a test asset. Fama-MacBeth and Shanken-corrected standard errors are reported in parentheses. Bootstrap $\bar{R}^2$ confidence intervals are square brackets. Quarterly data, 1990Q1–2015Q4. The intercepts and prices of risk are annualized.

	Momentum				Size				Book-to-Market			
int.	2.71	14.39	6.99	7.48	1.54	-0.07	-0.86	-0.90	3.30	-3.36	1.26	-1.50
t-FM	(1.24)	(3.93)	(4.28)	(4.27)	(1.36)	(-0.08)	(-0.88)	(-0.90)	(1.62)	(-1.69)	(0.69)	(-0.79)
t-Sh	(0.83)	(2.00)	(3.38)	(3.25)	(0.83)	(-0.07)	(-0.79)	(-0.83)	(0.85)	(-0.98)	(0.39)	(-0.49)
ΔLEV	4.21				4.95				6.31			
t-FM	(2.10)				(1.99)				(4.38)			
t-Sh	(1.42)				(1.22)				(2.35)			
SS		-6.29				1.26				5.41		
t-FM		(-2.49)				(0.70)				(4.37)		
t-Sh		(-1.28)				(0.66)				(2.62)		
DS			2.82				-1.88				-5.84	
t-FM			(1.68)				(-1.82)				(-2.86)	
t-Sh			(1.34)				(-1.66)				(-1.65)	
ΔFUND				2.06				-1.20				-3.75
t-FM				(2.05)				(-1.64)				(-3.52)
t-Sh				(1.59)				(-1.53)				(-2.21)
MKT	7.82	5.45	6.84	8.32	7.73	7.05	7.55	7.39	7.13	6.17	3.08	3.52
t-FM	(2.39)	(1.50)	(2.10)	(2.52)	(2.35)	(2.16)	(2.28)	(2.23)	(2.17)	(1.86)	(0.90)	(1.04)
t-Sh	(2.36)	(1.19)	(2.10)	(2.49)	(2.29)	(2.15)	(2.27)	(2.23)	(2.09)	(1.79)	(0.82)	(0.97)
R^2	71.71	87.14	45.05	84.41	93.94	84.65	95.99	94.85	94.72	87.20	27.94	44.21
$\bar{R}^2$	64.64	83.93	31.31	80.51	92.43	80.81	94.99	93.56	93.41	84.00	9.93	30.26
	[5, 92]	[57, 99]	[0, 81]	[31, 99]	[37, 99]	[21, 99]	[66, 99]	[62, 99]	[68, 99]	[43,97]	[0, 71]	[0, 83]

Table 7: **Summary Statistics - Illiquidity and Volatility Portfolios - Quarterly**

Summary statistics for portfolios of stocks sorted on illiquidity and volatility (see Appendix A.3 for the construction of the portfolios). The variables Illiqu., Volatil. and Mkt Cap are the illiquidity, volatility and capitalization across stocks in each portfolio. Quarterly data, 1990Q1 2015Q4.

Panel (a) Illiquidity Sort

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

Panel (b) Volatility Sort

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

Table 8: **Leverage in Illiquidity Regressions**

Panel (a): Estimates of the coefficients on ΔLEV. Panel (b): Estimates of the coefficients on $\Delta FUND$. Row I: Illiquidity regressions for portfolios sorted on illiquidity. Row II: illiquidity regressions for portfolios sorted on volatility. Columns 1-10 are for portfolios with values from high to low. Quarterly data, 1986Q1-2015Q4.

Panel (a) $\Delta illiq_{i,t} = a + b_i \Delta \text{LEV}_t + +c_i \text{MKT}_t + e_t$

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

Panel (b) $\Delta illiq_{i,t} = a + b_i \Delta \text{FUND}_t + c_i \text{MKT}_t + e_t$

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
I	0.46	0.36	0.30	0.31	0.33	0.37	0.38	0.40	0.38	0.39
	(3.34)	(3.41)	(3.05)	(2.83)	(2.64)	(3.06)	(3.33)	(3.57)	(3.55)	(3.80)
II	0.31	0.26	0.23	0.32	0.38	0.24	0.26	0.17	0.12	-0.04
	(2.18)	(2.60)	(2.39)	(3.40)	(2.58)	(1.72)	(2.42)	(1.74)	(1.47)	(0.95)

Table 9: **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. Row I: Illiquidity regressions for portfolios sorted on illiquidity. Row II: illiquidity regressions for portfolios sorted on volatility. Columns 1-10 are for portfolios with values from high to low. Quarterly data, 1986Q1-2015Q4.

Panel (a) $\Delta illiq_{i,t} = a + b_i Supply_t + +c_i \text{MKT}_t + e_t$

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

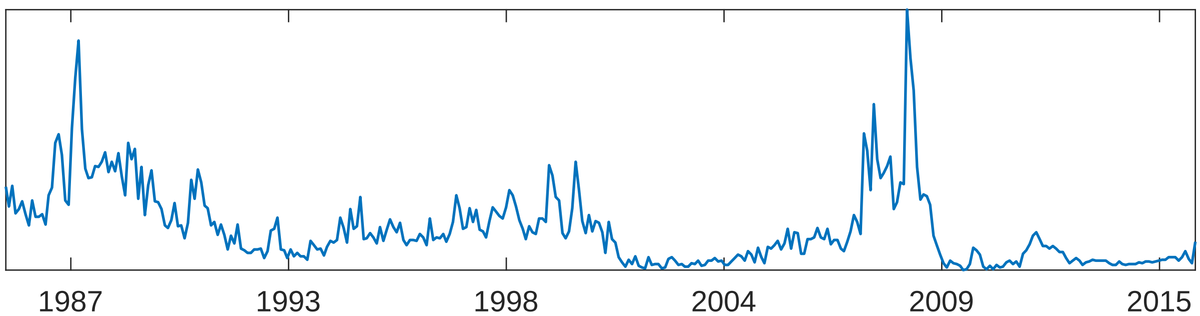
Panel (b) $\Delta illiq_{i,t} = a + b_i Demand_t + c_i \text{MKT}_t + e_t$

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

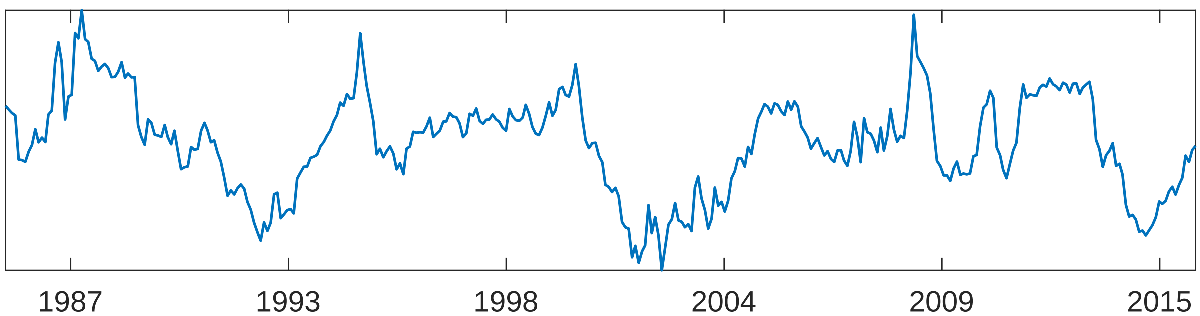
Figure 2: Funding Conditions Proxies

Panel (a): TED spread measure. Panel (b): FL funding conditions measure from Fontaine and Garcia (2012). Panel (c): HPW noise measure from Hu et al. (2013). Monthly data, 1986-2007.

(a) TED proxy



(b) FG proxy



(c) HPW proxy

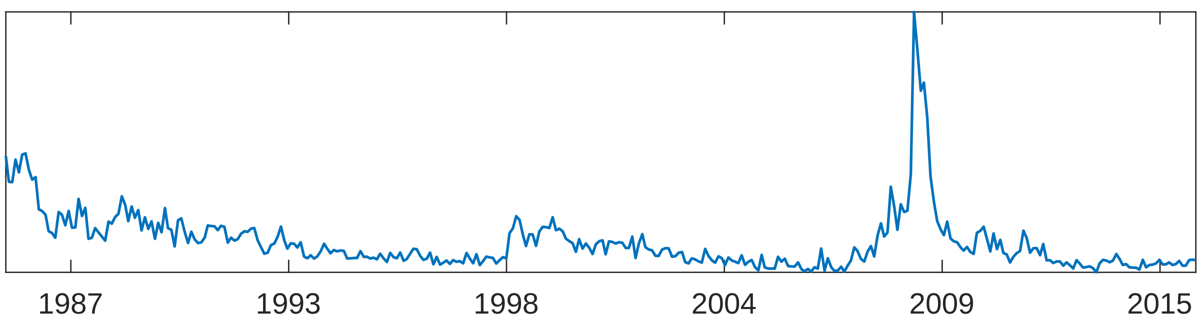


Figure 3: ΔLEV and $\Delta FUND$

Changes in leverage ΔLEV from AEM and changes in funding conditions $\Delta FUND$, compute as the first difference of the first principal component from the other three measures, where both variables are normalized with zero mean and one standard deviation.

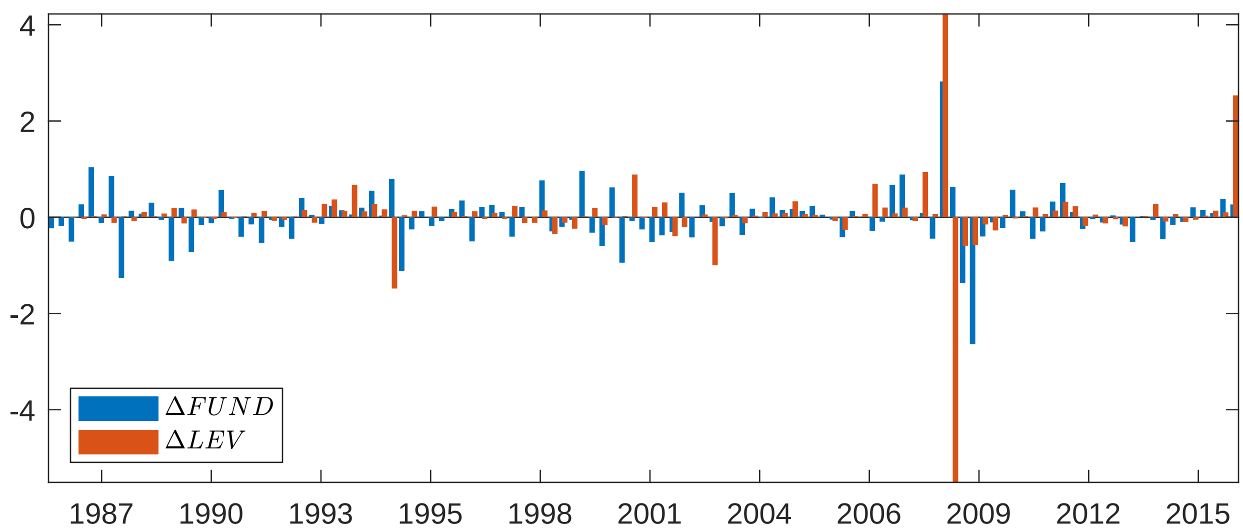
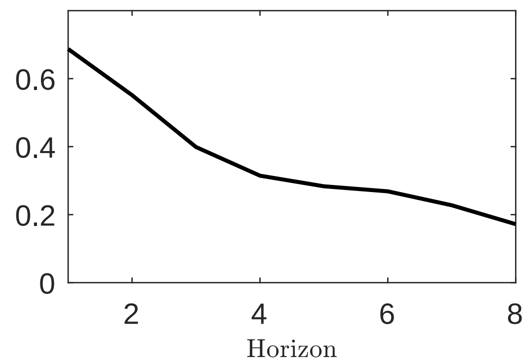


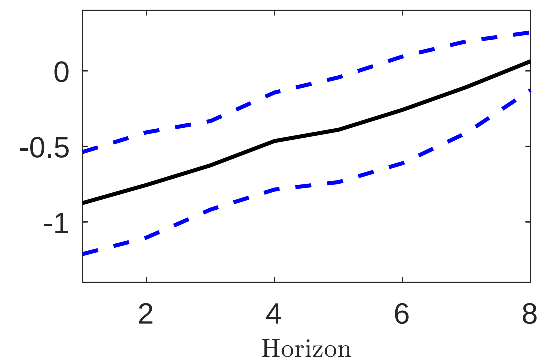
Figure 4: Leverage and Funding Conditions

Results from predictive regressions of LEV_{t+h} on current values of LEV_t, $FUND_t$ and the interaction term $LEV_t \times FUND_t$ for $h = 1 \ldots 8$ quarters (Equation 4 in the text). Panel (a) reports the R^2s. Panel (a) reports estimates of the interaction coefficient $\beta_{\times,h}$ with the 95 percent confidence interval (dashed blue lines). Panel (c) reports the partial effect $\frac{\partial LEV_{t+4}}{\partial FUND_t}$ across different conditioning values of LEV_t. Panel (c) reports the partial effect time-series.

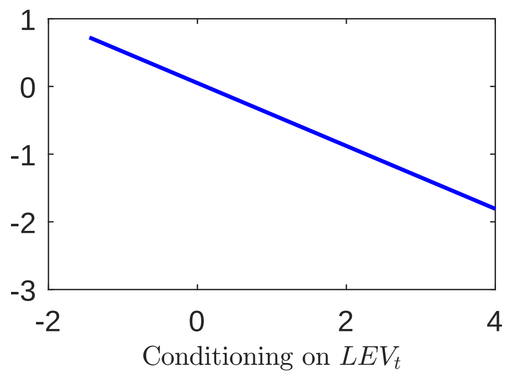
(a) LEV_{t+h} R^2



(b) LEV_{t+h} $\beta_{\times,h}$



(c) $\partial LEV_{t+4}/\partial FUND_t$



(d) $\partial LEV_{t+4}/\partial FUND_t$

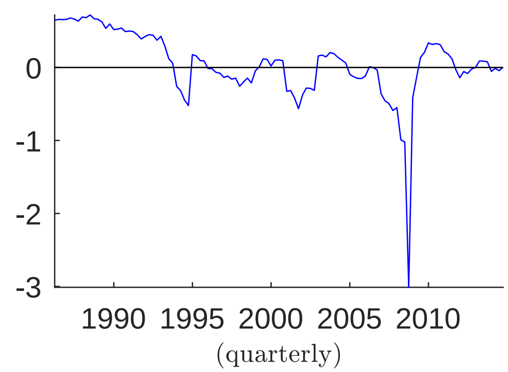
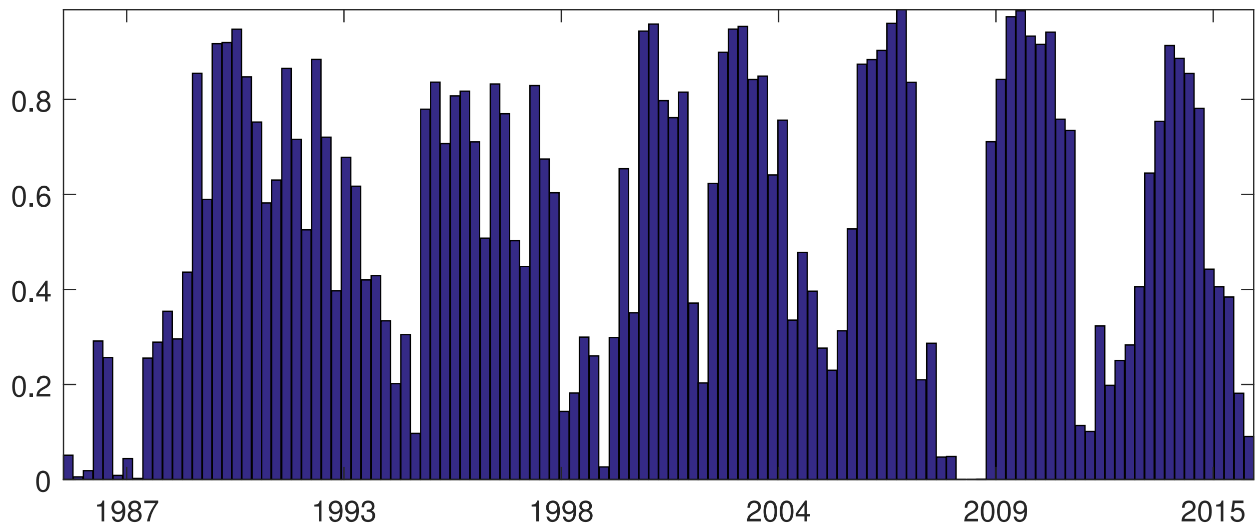


Figure 5: Probabilities of Constrained Intermediation Supply

The probabilities of constrained intermediation supply estimated in the demand and supply system.

(a)



(b) $\Delta FUND$

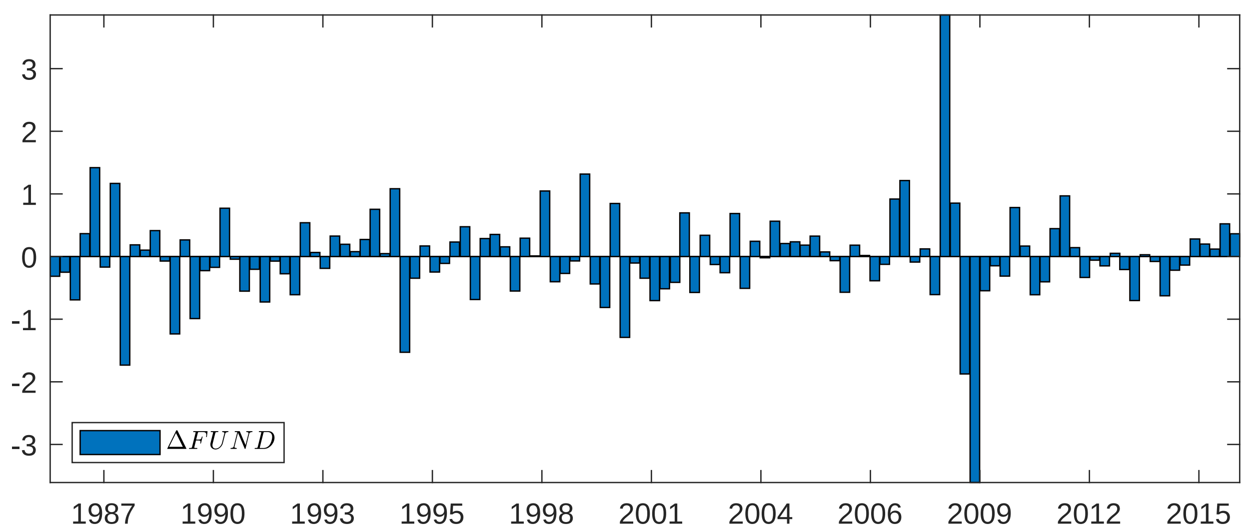


Figure 6: Historical Decomposition

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

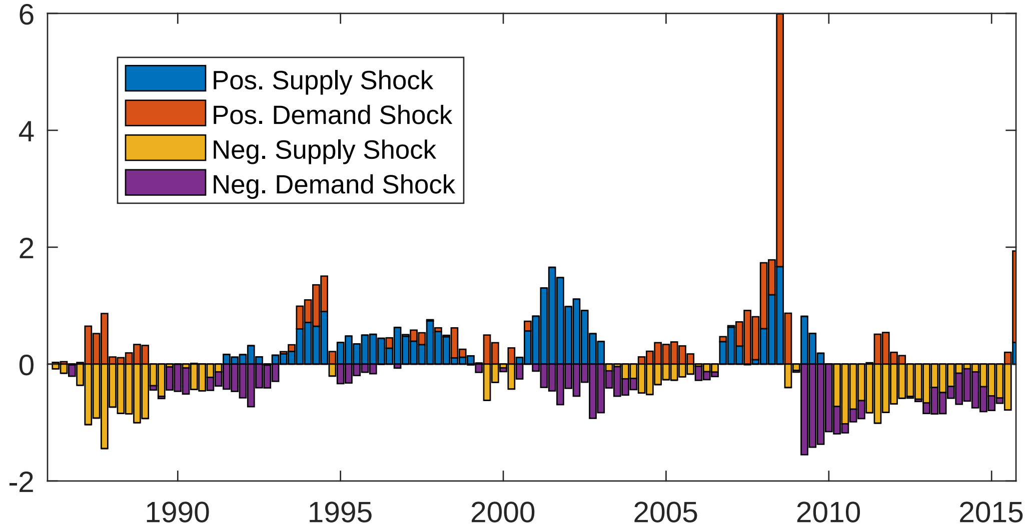
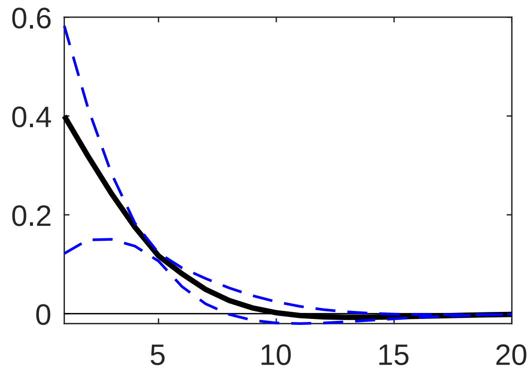


Figure 7: Impulse Response Functions

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

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



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

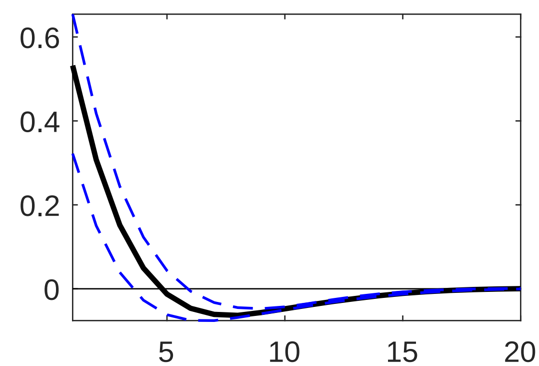
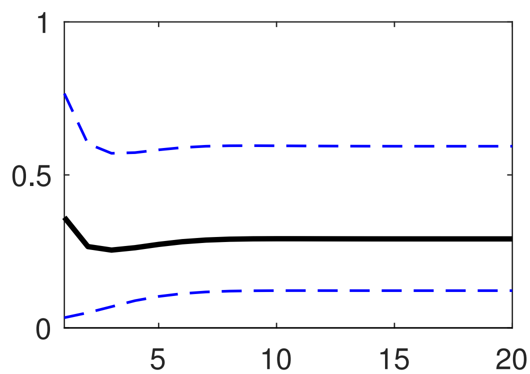


Figure 8: Variance Decomposition

Variance decomposition in terms of leverage demand and leverage supply shocks identified with sign restrictions in a bivariate VAR(1) for LEV_{t+h} and $FUND_{t+h}$ at horizons $h = 1 \ldots 20$ quarters with 95 percent confidence intervals (dashed blue lines).

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



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

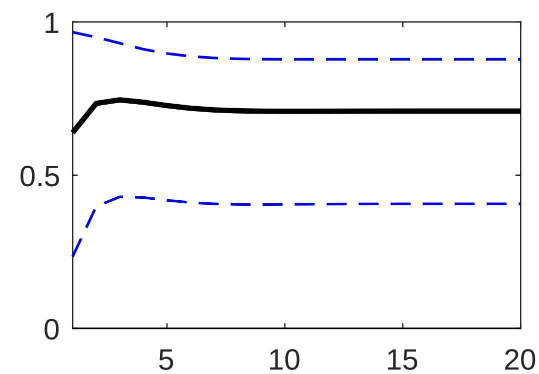
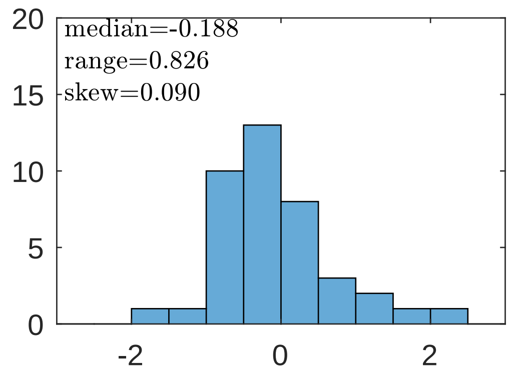


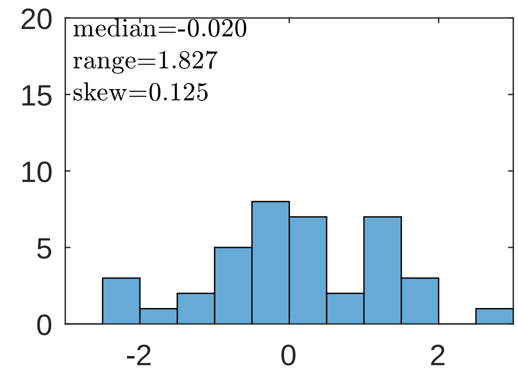
Figure 9: Distribution of Leverage Supply and Demand Shocks

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

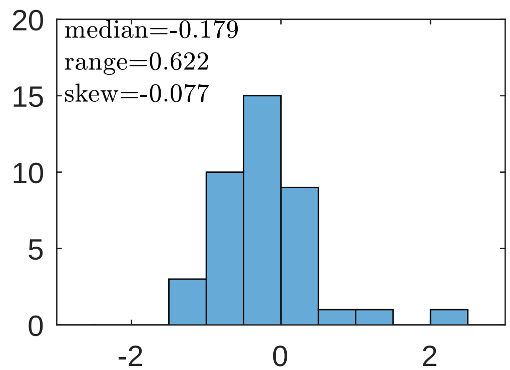
(a) Supply Shocks when $FUND$ is low



(b) Supply Shocks when $FUND$ is Hi



(c) Demand Shocks when $FUND$ is low



(d) Demand Shocks when $FUND$ is Hi

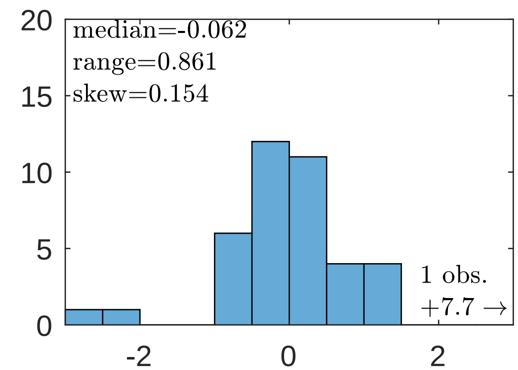


Figure 10: Returns vs Risk Exposures—Equity Portfolios

Panesl (a)-(d): ex-post βs and average portfolio returns in excess of the risk-free rate adjusted for exposures to market risk based on two-factor models where the second factor is one of ΔLEV, $\Delta FUND$, leverage supply shocks or leverage demand shocks, respectively. The test assets are the portfolios of stocks sorted on $\beta^{\Delta \text{Illiq}}$, $\beta^{\Delta\sigma}$, and $\beta^{\Delta FL}$ labeled with "L", "V", and "F", respectively, and numbered from 1 to 10. Quarterly data, 1990Q1–2015Q4. Returns are annualized.

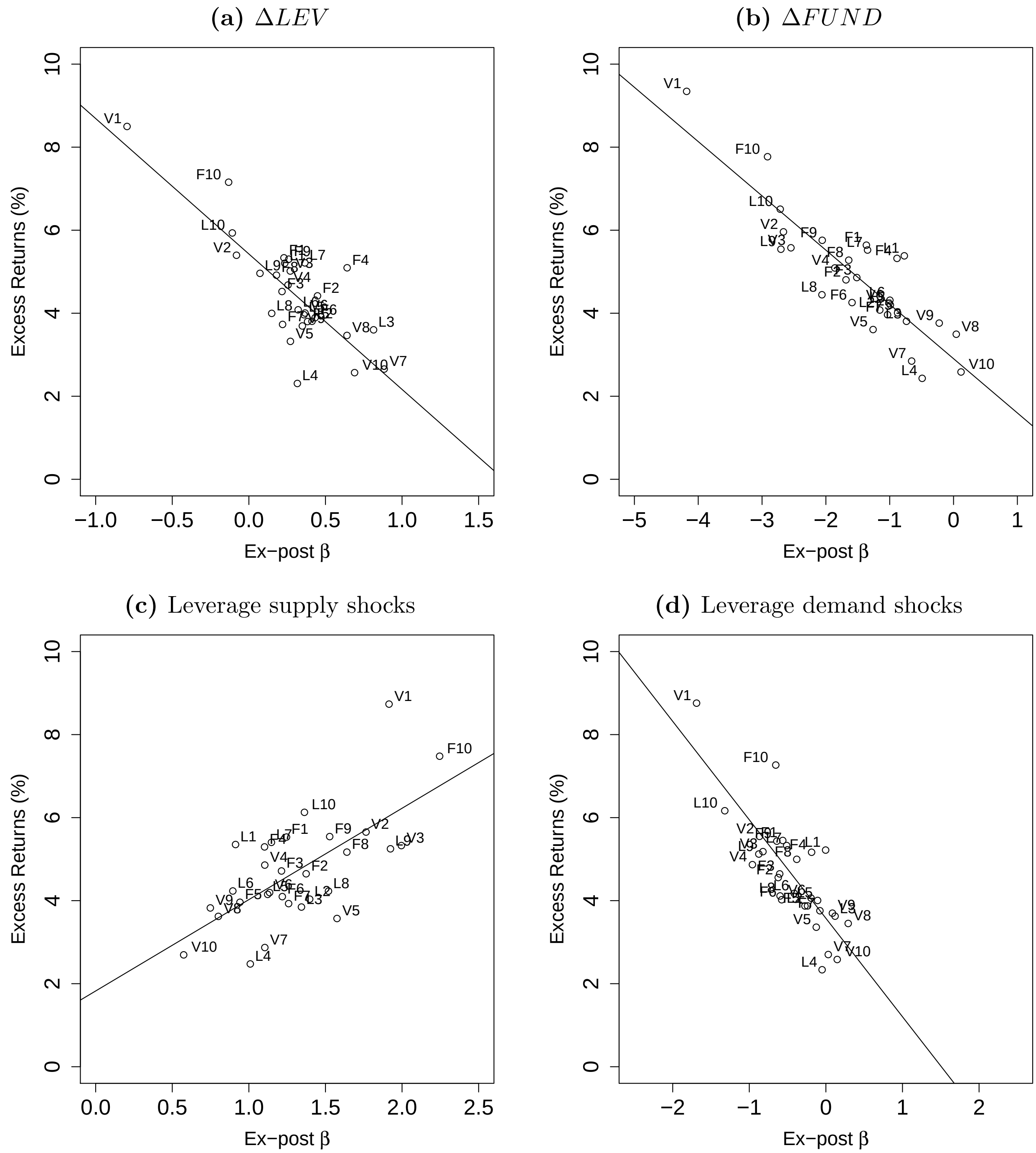
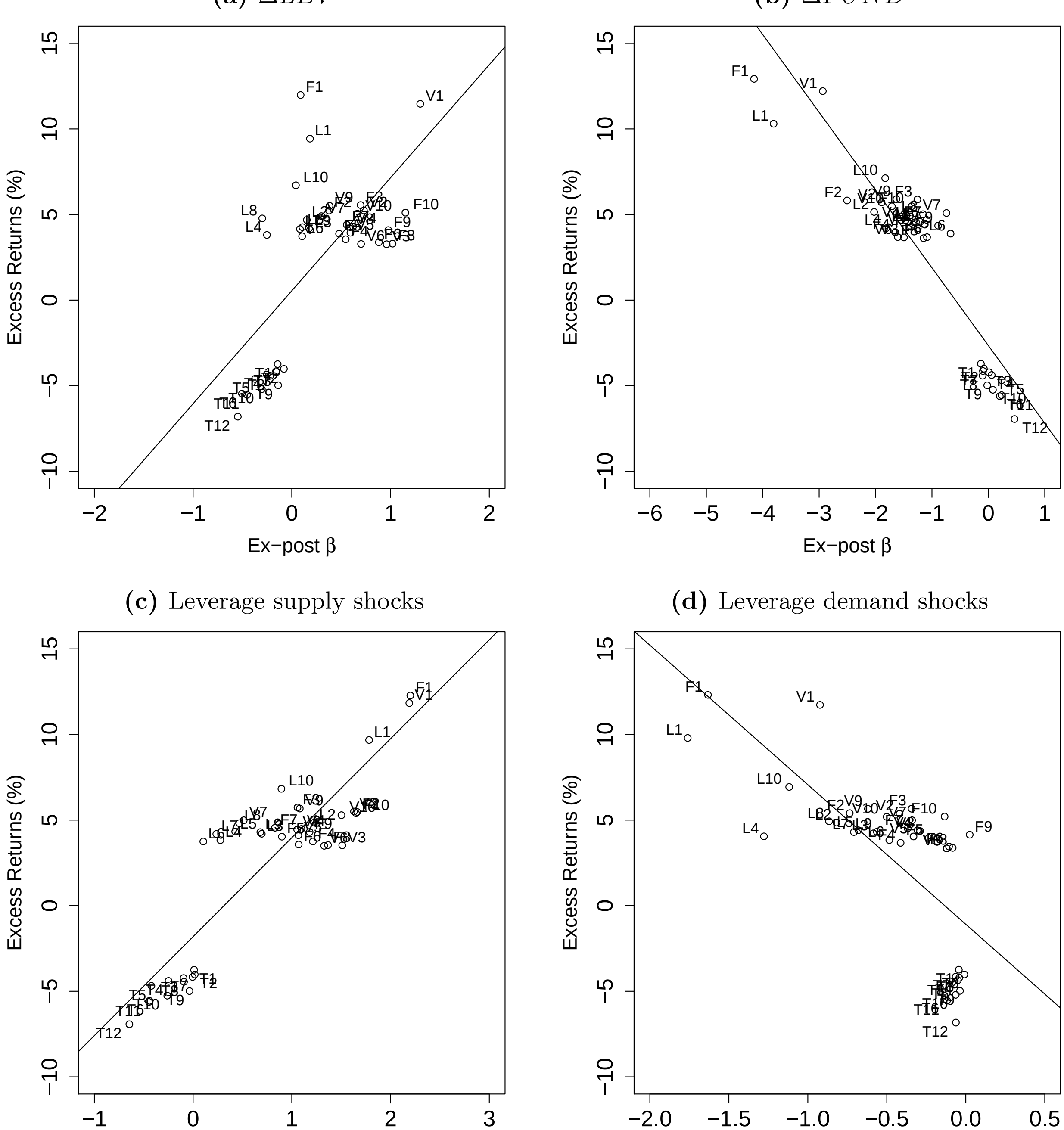


Figure 11: Returns vs Risk Exposures—Bond Portfolios

Panels (a) -(d): ex-post βs and average portfolio returns in excess of the risk-free rate adjusted for exposures to market risk based on two-factor models where the second factor is one of ΔLEV, $\Delta FUND$, leverage supply shocks or leverage demand shocks, respectively. Test assets are the portfolios of corporate bonds sorted on $\beta^{\Delta \mathrm{Illiq}}$, $\beta^{\Delta\sigma}$, and $\beta^{\Delta FL}$, labeled with "L", "V", and "F", respectively, and numbered from 1 to 10, as well as individual newly-issued and seasoned Treasury bonds with maturities of 2, 3, 4, 5, 7, and 10 years, labeled with T1-T6 and T7-T12, respectively. Quarterly data, 1989Q2–2014Q4. Returns are annualized.



(a) ΔLEV **(b)** $\Delta FUND$ **(c)** Leverage supply shocks **(d)** Leverage demand shocks

Figure 12: Returns and Risk Exposures—Corporate Bonds

Panels (a)-(d): ex-post βs and average portfolio returns in excess of the risk-free rate adjusted for exposures to market risk based on two-factor models where the second factor is one of ΔLEV, $\Delta FUND$, leverage supply shocks or leverage demand shocks, respectively. Test assets are the portfolios of corporate bonds sorted on $\beta^{\Delta \text{Illiq}}$, $\beta^{\Delta\sigma}$, and $\beta^{\Delta FL}$, labeled with "L", "V", and "F", respectively, and numbered from 1 to 10. Quarterly data, 1989Q2–2014Q4. Returns are annualized.

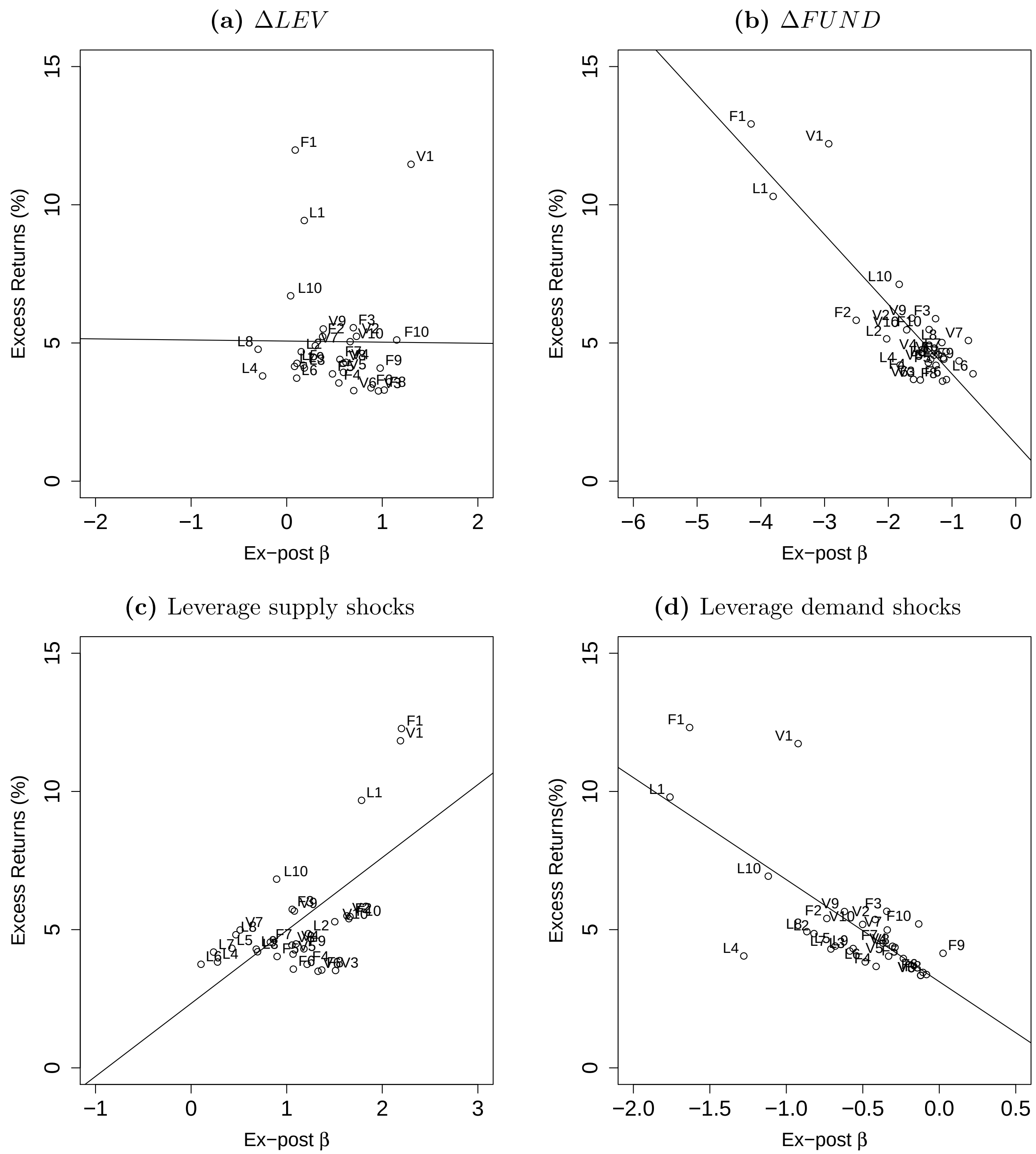
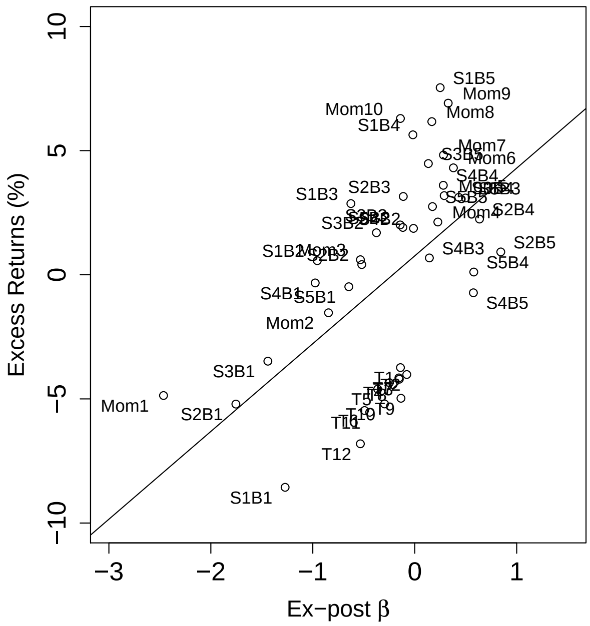


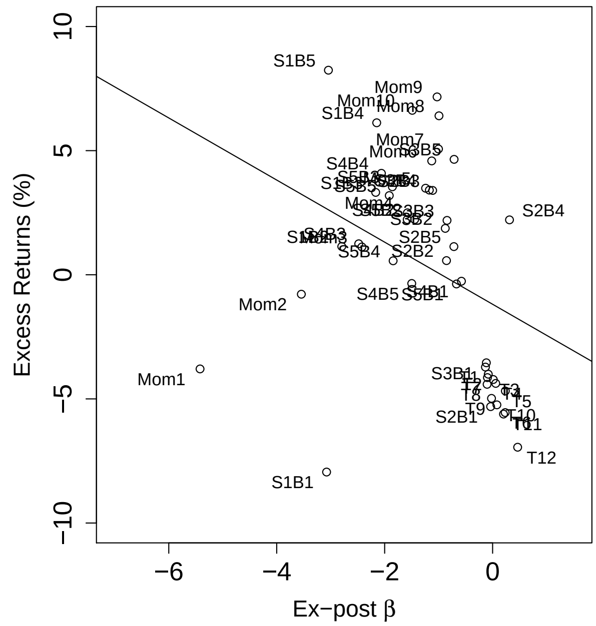
Figure 13: Returns and Risk Exposures — AEM Test Assets

Ex-post βs and average portfolio returns in excess of the risk-free rate adjusted for exposures to market risk based on two-factor models where the second factor is one of ΔLEV, $\Delta FUND$, leverage supply shocks or leverage demand shocks, from Panel (a) to (d), respectively. The test assets include 25 size and book-to-market portfolios (denoted as S1B1 for small and high BTM portflolio and S5B5 for high and low BTM portfolio), 10 momentum portfolios (Mom1 to Mom10), and newly-issued and seasoned Treasury bonds with maturities of 2, 3, 4, 5, 7, and 10 years (denoted as T1-T6 and T7-T12, respectively). The sample period is 1989Q2–2014Q4.

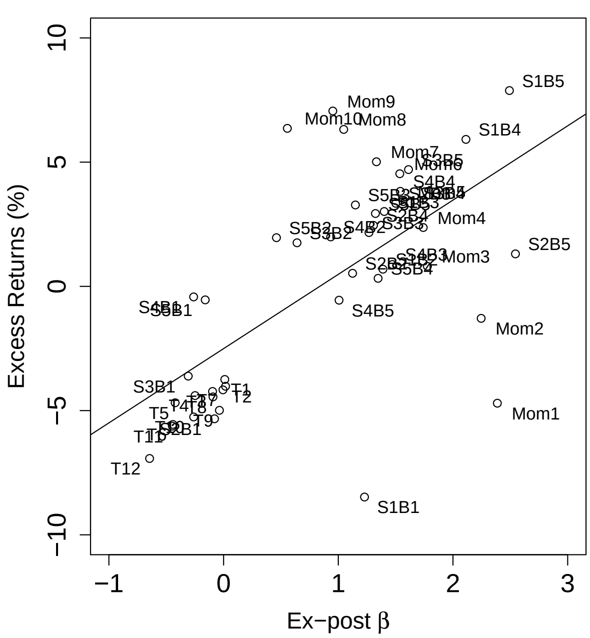
(a) ΔLEV



(b) $\Delta FUND$



(c) Leverage supply shocks



(d) Leverage demand shocks