Liquidity Supply in the Corporate Bond Market

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ABSTRACT

This paper examines dealer inventory capacity, or liquidity supply, as a driver of liquidity and expected returns in the corporate bond market. We identify shocks to aggregate liquidity supply using data on corporate bond yields and dealer positions. Liquidity supply shocks lead to persistent changes in market liquidity, are correlated with proxies for dealer financial constraints, and have significant explanatory power for

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cross-sectional and time-series variation in expected returns, beyond standard risk factors. Our findings point to liquidity supply by financially constrained intermediaries as a main driver of market liquidity and asset prices.

Liquidity risk is priced in the cross-section of asset returns: average returns are higher for assets more sensitive to aggregate shocks to market liquidity. The liquidity risk premium has been documented in equities (Amihud (2002), Pástor and Stambaugh (2003)), corporate bonds (Lin, Wang, and Wu (2011)), and other asset classes (Sadka (2010)). The mechanisms underlying the liquidity risk premium and aggregate illiquidity, however, are the subject of debate.[1]

This paper provides evidence connecting market liquidity and expected returns to intermediaries' inventory-absorption capacity, or liquidity supply. We propose a new method to identify liquidity supply using the sign restriction that higher liquidity supply leads to a lower price and a higher quantity of liquidity. We apply this method to the corporate bond market. Our liquidity price reflects "noise" in corporate bond yields, or deviations from fitted issuer-level yield curves. Our liquidity quantity indicates how dealers use their balance sheets to provide immediacy. We find that liquidity supply shocks have persistent effects on noise and dealer positions and significant explanatory power for cross-sectional and time-series variation in expected returns.

The corporate bond market is nearly ideal for our purposes. Corporate

[1] Vayanos and Wang (2013) review the literature.

bonds are traded in an over-the-counter market in which trading costs are substantial and fluctuate significantly (Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhütter, and Lando (2012)). In addition, corporate bonds are a significant source of firm financing. The expected return on corporate bonds has been shown to have predictive power for financing flows and real activity (Gilchrist and Zakrajšek (2012), Ma (2019)). Understanding the determinants of corporate bond liquidity and returns is thus of foremost importance.

Studying the links between liquidity and asset prices is challenging because standard liquidity measures are driven not only by dealers' inventory-absorption capacity (Grossman and Miller (1988)), but also by investors' liquidity demand and asymmetric information about the assets traded. To identify shocks to liquidity supply in the corporate bond market, we focus on dealers' absorption of demand imbalances for similar bonds. Investor demand to buy bonds even if they are priced richly (or to sell bonds even if they are priced inexpensively) generates noise in corporate bond yields. Noise compensates dealers for absorbing these demand imbalances. We therefore use noise as our liquidity price.

We measure noise in corporate bond yields using weekly bond-level yield data from 2002 to 2016. Each week, we fit a smooth yield curve for each large issuer of corporate bonds. Our noise measure is the average, across all bonds in our sample, of the divergence between a bond's market yield and the yield curve of its issuer. Because noise captures deviations from issuer-level yield curves, it is unaffected by issuers' credit risk and asymmetries in information about issuers.

Our focus on noise builds on Fontaine and Garcia (2012) and Hu, Pan, and Wang (2013), who study Treasury noise and assume that it is driven by liquidity supply. An increase in noise, however, could reflect a deterioration in liquidity supply or an increase in investors' liquidity demand. To address this concern, we study noise together with the quantity of liquidity provided. To absorb the demand imbalances that give rise to noise, dealers take long positions in bonds that investors want to sell and short positions in bonds that investors want to buy. Thus, as the quantity of liquidity, we use gross positions, the sum of dealers' gross long and gross short positions.

We construct this liquidity quantity using detailed transaction data that allow us to identify dealers.[2] To construct each dealer's position in each bond, we cumulate transactions. We define dealer gross positions as the sum, across bonds and dealers, of the absolute value of each dealer's position in each bond.

Next, we estimate a structural vector autoregression (VAR) model of noise and dealer gross positions. We identify supply shocks as leading contemporaneously to opposite-sign changes in price and quantity, whereas demand shocks lead to same-sign changes in price and quantity.

Our method has several advantages. First, we infer liquidity supply directly from the price and quantity of corporate bond liquidity, rather than using proxies for firm-wide constraints such as dealer firms' leverage. Second,

[2] We focus on primary dealers, the main intermediaries in the corporate bond market and designated counterparties of the Federal Reserve. We list the primary dealers in Internet Appendix Section I. The Internet Appendix is available in the online version of the article on The Journal of Finance website.

our method also identifies aggregate shocks to investor demand imbalances for similar bonds, or liquidity demand. We examine whether liquidity demand shocks have different properties than liquidity supply shocks. Third, our method provides estimates of the persistence of liquidity supply and demand shocks. A shock with persistent effects on liquidity is expected to be more important for asset pricing (Acharya and Pedersen (2005)).

We find that a positive liquidity supply shock is associated with a decrease in noise and an increase in positions that are quite persistent. Liquidity supply shocks are correlated with proxies for dealer inventory capacity such as dealer capital, corroborating our interpretation of the estimated supply shocks. Moreover, liquidity supply shocks capture well episodes of intermediary stress, including key events of the 2007 to 2009 financial crisis. In contrast, liquidity demand shocks are associated with transitory changes in noise and positions, are correlated with lagged corporate bond mutual fund flows and issuance, and do not follow a consistent pattern around stress events. These differences in the properties characterizing liquidity supply and demand shocks suggest that liquidity supply and demand should have different asset pricing implications.

Using a regression approach similar to that of Fama and MacBeth (1973), we find that corporate bonds with returns that are more sensitive to liquidity supply shocks earn higher expected returns, even when controlling for bond-level liquidity and other characteristics.[3] The liquidity supply risk premium

[3]Internet Appendix Section II presents a dynamic equilibrium model that relates liquidity supply and demand shocks to noise, gross positions, aggregate excess returns, and the cross-section of excess returns.

remains significant when controlling for the sensitivity of each bond to well-known liquidity measures (Amihud (2002), Pástor and Stambaugh (2003)), which is consistent with the view that these liquidity measures are driven by factors beyond just liquidity supply. In contrast, we do not find evidence for a liquidity demand risk premium.

Next, we sort corporate bonds into four portfolios based on their exposure to liquidity supply shocks. The difference in average excess returns between the top and bottom portfolios is 0.42% per month with a t-statistic of 3.46. These return differences cannot be attributed to differences in exposure to standard risk factors (Fama and French (1992, 2015), Bai, Bali, and Wen (2019)). These return differences are also not subsumed when risk-adjusting returns using the intermediary capital factor of He, Kelly, and Manela (2017), suggesting that liquidity supply shocks carry information absent from or commingled with other information in the intermediary capital ratio.

We also study time-variation in expected returns for the aggregate corporate bond market. We construct an indicator for whether liquidity has recently been supply- or demand-driven based on lagged supply and demand shocks. Conditional on being in a supply-driven period, dealer gross positions are negatively associated with future aggregate returns. However, conditional on being in a demand-driven period as well as unconditionally, dealer gross positions are not related to future aggregate returns.

Our results provide support for theoretical models in which liquidity suppliers' inventory constraints drive both liquidity and asset prices (Gromb and Vayanos (2018), Kondor and Vayanos (2019)). In these models, liquidity suppliers are marginal investors that exploit, and thereby reduce, price discrepancies due to market segmentation or idiosyncratic trading needs. Similar mechanisms are at the center of models of limits to arbitrage (Shleifer and Vishny (1997)), slow-moving capital (Duffie (2010)), and intermediary asset pricing (He and Krishnamurthy (2013)). Our findings that liquidity supply shocks persistently affect noise and dealer positions and that liquidity supply shocks are priced are consistent with these theories, according to which depleted intermediary capital leads to higher expected returns and therefore allows capital to slowly be replenished.

Our paper contributes to the literature on corporate bond returns and liquidity.[4] Lin, Wang, and Wu (2011) and Bai, Bali, and Wen (2019) find a liquidity risk premium for corporate bonds but do not investigate its economic origin. Bongaerts, de Jong, and Driessen (2017) connect corporate bond returns and equity market liquidity. Bao, Pan, and Wang (2011) and Dick-Nielsen, Feldhütter, and Lando (2012) show that bond-level illiquidity helps explain the cross-section of credit spreads. Friewald and Nagler (2016) find that individual bonds in which dealers have higher net inventory have higher expected returns. More closely related to our paper, Friewald and Nagler (2019) show that proxies for inventory frictions such as aggregate net

[4]For the equity market, prior literature finds mixed evidence on the roles of asymmetric information, investor demand, and dealer constraints in driving the liquidity risk premium and aggregate liquidity. See, for example, Easley, Hvidkjaer, and O'Hara (2002), Duarte and Young (2009), Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010), Karolyi, Lee, and Van Dijk (2012), and Lou and Shu (2017). For arbitrage spreads, the literature points to determinants on both the supply and the demand sides. See, among others, Fleckenstein, Longstaff, and Lustig (2014), Du, Tepper, and Verdelhan (2018), Klingler and Sundaresan (2019), and Jermann (2019).

inventory and the TED spread have explanatory power for the cross-section of credit spreads. Our study differs in that we analyze the cross-section of expected corporate bond returns (not credit spreads) and time-variation in expected aggregate returns. We also connect these analyses to our estimates of supply shocks' persistent effects and demand shocks' transitory effects.

Major changes to corporate bond trading regulations have occurred over the past decade. We find that liquidity supply shocks, on net, were negative during the implementation of the Dodd-Frank and Volcker regulations. Though it is difficult to draw strong conclusions about these regulations from time-series data, our results are broadly consistent with other evidence that recent regulations impaired corporate bond liquidity (Bao, O'Hara, and Zhou (2018), Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018), Dick-Nielsen and Rossi (2018)).

Our approach to identification builds on Cohen, Diether, and Malloy (2007), who develop binary supply and demand proxies for equity short selling. In a similar spirit, Chen, Joslin, and Ni (2018) identify the supply of crash insurance using the correlation between changes in price and quantity. Our paper differs by estimating liquidity supply and demand using a structural VAR with sign restrictions. Goldberg (2020) uses a similar approach but focuses on Treasury noise and real activity.

The remainder of the paper is organized as follows. Section I describes the data and our measures of noise and dealer gross positions. Section II presents the empirical model for disentangling liquidity supply and demand shocks. Section III examines the properties of the estimated liquidity supply and demand shocks. Section IV studies how the liquidity supply and demand shocks are priced in the corporate bond market. Finally, Section V concludes.

I. Data: Noise and Dealer Gross Positions

To identify shocks to liquidity supply by primary dealers in the corporate bond market, we use the price and quantity of liquidity. Motivated by theories of liquidity supply with inventory frictions (Grossman and Miller (1988)), the liquidity price captures temporary price deviations, or noise, in corporate bond yields. The liquidity quantity is dealer gross positions, the aggregate gross long and gross short positions of primary dealers.

A. Noise in Corporate Bond Yields

We compute the noise measure using weekly bond price data from the Merrill Lynch U.S. Corporate Master database for the period 2002 to 2016. For the purpose of computing our noise measure, the Merrill Lynch data have an advantage over transaction data in that end-of-day quotes are provided for all bonds on a daily basis, regardless of whether a transaction occurred for the bond.[5]

The Merrill Lynch database includes corporate bonds with amount outstanding greater than $100 million and remaining time to maturity of at least one year. We limit our sample to dollar-denominated publicly offered bonds with fixed coupons and no embedded options other than make-whole

[5]Appendix A compares overlapping price observations from Merrill Lynch and TRACE and shows that the noise measure is unlikely to be significantly affected by the use of quotation data.

call provisions.[6] To estimate issuer-level yield curves reliably, we further focus on issuers with at least seven bonds outstanding in a given week. These filters result in a sample that comprises 4,933 bonds issued by 330 firms.[7]

In the Svensson (1994) model, the n-period instantaneous forward rate is

$$f(n) = \beta_0 + \beta_1 \exp(-n/\tau_1) + \beta_2 (n/\tau_1) \exp(-n/\tau_1) + \beta_3 (n/\tau_2) \exp(-n/\tau_2), \quad (1)$$

where n denotes time to maturity and $\theta = \{\beta_0, \beta_1, \beta_2, \beta_3, \tau_1, \tau_2\}$ is a set of model parameters to be estimated.

For any θ, the forward rate curve can be used to calculate a zero-coupon yield curve. Using this zero-coupon yield curve, one can compute the model-implied price of a bond as the sum of the present values of its cash flows (coupons and principal). We denote the model-implied price of bond k by $P_k(\theta)$ and the model-implied yield by $ytm_k(\theta)$.

Let $K_{j,t}$ be the number of bonds of issuer j available for curve-fitting in week t. The market or observed price of bond k is denoted by $P_{k,t}$ for $k \in (1, 2, ..., K_{j,t})$. For each week t and issuer j, we estimate the parameters

[6]A large fraction of corporate bonds have a make-whole call provision. We include such bonds in our sample because, during the sample period, the strike price of make-whole options is typically set such that these options are never in-the-money. Elsaify and Roussanov (2016) argue that make-whole options are designed in this way to facilitate the issuer's cash management.

[7]Because we focus on large issuers in estimating noise, the sample of firms used to construct noise is smaller than the TRACE sample used to construct the liquidity quantity measure. Appendix A presents evidence suggesting that differences in these samples are unlikely to meaningfully affect our results.

$\theta_{j,t}$ by minimizing the weighted sum of squared deviations between model-implied and market prices,

$$\hat{\theta}_{j,t} = \arg\min_{\theta} \sum_{k=1}^{K_{j,t}} \left(\left(P_{k,t} - P_k\left(\theta\right) \right) \times \frac{1}{D_{k,t}} \right)^2, \tag{2}$$

where $D_{k,t}$ is the Macaulay duration of bond k. To estimate the parameters reliably, we set β_3 to zero when there are fewer than 15 bonds, effectively estimating the Nelson-Siegel curve for these issuers.[8]

We define aggregate noise in week t as the root-mean-squared difference between the model-implied yield and the market yield,

$$p_t = \sqrt{\frac{1}{K_t} \sum_{k=1}^{K_t} \left(ytm_{k,t} - ytm_k(\theta_{j,t}) \right)^2}, \tag{3}$$

where K_t is the total number of bonds used for curve-fitting in week t, $ytm_{k,t}$ is the market yield of bond k, and $ytm_k(\theta_{j,t})$ is the model-implied yield. Following Hu, Pan, and Wang (2013), we remove an observation from the construction of the noise measure if the observed yield $ytm_{k,t}$ is four standard deviations (calculated using all bonds each week) away from the model yield. The resulting time series of aggregate noise is shown in Figure 1, Panel A.

[Insert Fig. 1 near here]

[8]Internet Appendix Section III provides examples of fitted yield curves and market yields. Internet Appendix Section III also sorts bonds into five maturity buckets and shows that fitting errors are similar across buckets, suggesting that the Nelson-Svensson-Siegel curve is sufficiently flexible to capture the term structures of corporate bond yields.

B. Dealer Gross Positions

We construct dealer gross positions using transaction data. We focus on primary dealers, the designated trading counterparties of the Federal Reserve Bank of New York listed in Section I of the Internet Appendix. Primary dealers are at the center of market-making and thus their gross positions are informative about the amount of liquidity provided in the corporate bond market. Primary dealers as a group maintain a market share (by transaction volume) of around 70% throughout the sample period.

To construct dealer gross positions in corporate bonds, we use a regulatory version of the Trade Reporting and Compliance Engine (TRACE) database, obtained from FINRA. Regulatory TRACE is similar to the publicly available TRACE except that the volume for large trades is uncapped and the dealers in each trade are identified by name. Using this identifier, we aggregate trades for each dealer-bond each week to construct the weekly trading flow. Then we cumulate weekly flows to estimate each dealer's net position in each bond. To capture dealers' market-making activities, we discard positions if they are not closed within a four-week window using the last-in first-out method. Goldstein and Hotchkiss (2020) report that nearly 60% of paired roundtrip trades are completed within a day; for those that take more than a day, the weighted average holding period of a bond for dealers is 24 days.[9] Table I illustrates the construction of our inventory measure for a hypothetical bond.

[Insert Table I near here]

[9]Because of the four-week window, the sample period starts in August 2002, one month after the TRACE data begin in July 2002.

Because some primary dealers have multiple dealer subsidiaries, we aggregate to the level of the primary dealer holding company. To mitigate possible measurement error, we remove weekly flows greater than one-third of the bond's amount outstanding. We also remove flows for bonds issued less than one month ago, because part dealers' sales likely represents sales of the remaining bonds underwritten in the primary market.[10] We also ensure that there are no positions in bonds that have matured.

For consistency with our construction of aggregate noise, we limit the sample to dollar-denominated publicly offered bonds with fixed coupons and no embedded options other than make-whole call provisions. We do so by merging TRACE data with data on bond characteristics from Mergent FISD. After applying these filters to TRACE, we obtain a sample of 18,938 bonds issued by 4,454 firms over 753 weeks, which we use to construct gross positions.

Our quantity measure Q_t for week t is the sum of the absolute value of dealer positions in each bond. Let $Q_{d,k,t}$ denote dealer d's position in bond k in week t. Aggregate dealer gross positions are given by

$$Q_t = \sum_k \sum_d |Q_{d,k,t}| \,. \tag{4}$$

Equation (4) accounts for the fact that a dealer's position in a given bond $Q_{d,k,t}$ can be negative. Asquith, Au, Covert, and Pathak (2013) show that the cost of borrowing corporate bonds to short is comparable to that for

[10] In Section IV of the Internet Appendix, we find that including flows for recently issued bonds does not significantly alter the gross positions measure.

stocks. Data from the Federal Reserve's Weekly Report of Dealer Positions (FR-2004) also show that primary dealers have substantial short positions in corporate bonds.[11] Accordingly, we do not remove observations if $Q_{d,k,t}$ is negative. We scale the aggregate quantity measure Q_t by the consumer price index excluding food and energy to express it in 2005 dollars.

Panel B of Figure 1 plots the time series of dealer gross positions with and without seasonal adjustment. We find that gross positions exhibit strong seasonality, falling at the end of calendar quarters, and thus we seasonally adjust the series using the ratio to moving average method. We use the logarithm of the seasonally adjusted series in the analysis below.[12]

The average maturity of the bonds used to construct gross positions is stable over time, averaging 8.9 years with a standard deviation of 0.31 years. Aggregate gross positions in investment-grade (IG) bonds as a share of all gross positions is 59% on average, with a standard deviation of 4%. Moreover, aggregate gross positions in IG bonds and in high-yield (HY) bonds are highly

[11]From April 2013, when the FR-2004 corporate bond data begin, the correlation between our measure of dealer gross positions, Q_t, and dealer gross positions reported in FR-2004 is 0.58. The correlation is imperfect in part because the FR-2004 data include commercial paper and bonds with embedded options, and are reported on a fair-value basis rather than at book value. Unfortunately, prior to April 2013, the reporting category "corporate bonds" did not separate corporate bonds from non-agency mortgage-backed securities.

[12]Let $Q_{t,MA}$ be the moving average over the past 52 weeks, $Q_{t,MA} = \frac{1}{52}\sum_{m=1}^{52} Q_{t-m}$. We compute the ratio to moving average, $RMA_t = Q_t/Q_{t,MA}$, and the mean ratio $\overline{RMA}_w$ for each week $w \in \{1, ..., 52\}$. The seasonally adjusted quantity for the w-th week in a year is given by $Q_w^{s.a.} = Q_w/\overline{RMA}_w$.

correlated (correlation coefficient of 0.74). Thus, the composition of dealer gross positions is relatively stable over time.

C. Properties of Noise and Gross Positions

Table II presents summary statistics for noise and dealer gross positions. Seasonally adjusted dealer gross positions are $22.0 billion on average, with a standard deviation of $3.4 billion. Noise is 13.8 bps, on average, with a standard deviation of 8.2 bps.

[Insert Table II near here]

Table II reports the correlation between noise and dealer positions, both in levels and changes. If noise is driven only by fluctuations in liquidity supply, one would expect a negative relation between noise and dealer positions, in both levels and changes. In the data, the correlation in levels is -0.57 while weekly changes are essentially uncorrelated, which suggests that both supply and demand are important in driving noise and gross positions.[13]

Table II also shows the correlations of noise and positions with three well-known measures of corporate bond illiquidity: Amihud illiquidity, the imputed roundtrip cost of Feldhütter (2012), and the Bond-CDS basis from JP Morgan.[14] As expected, noise is positively correlated with each measure

[13]The difference between the correlation in levels and the correlation in changes suggests that liquidity supply shocks may have more persistent effects than liquidity demand shocks, a possibility that we investigate in Section III.B.

[14]The Amihud and imputed roundtrip cost measures are computed each week using a three-month rolling window; the time series for each measure is the median across

of illiquidity, with correlations between 0.5 and 0.9. We also find that our liquidity quantity measure is negatively correlated with each illiquidity measure (with correlations around -0.6). However, noise and dealer positions are not perfectly correlated with the standard illiquidity measures. This lack of correlation is to be expected because these other liquidity measures are also likely affected by various types of liquidity demand, asymmetric information, asset volatility, and, in the case of the Bond-CDS basis, factors specific to the derivatives market. To further highlight the differences between our liquidity supply and demand measures and standard measures of illiquidity, some specifications of our asset pricing tests in Section IV.A control for betas with respect to standard illiquidity measures.

Figure 1 shows the time series of our liquidity price and quantity measures. At the beginning of the sample, gross positions increased from around \$15 billion to near \$25 billion, after which they remained fairly stable until 2006. Gross positions then declined in 2007 as the financial crisis began and fell below \$15 billion following the collapse of Lehman Brothers. Gross positions recovered over the 2009 to 2011 period but have declined on balance since then. Noise spiked during the financial crisis and declined afterwards. It also went up somewhat in late 2015 amid concerns related to China and a selloff in oil markets.

An advantage of our noise measure is that it does not depend on transaction-level data and thus is not directly affected by changes in the nature of transactions, such as trade size or features of transactions unob-

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corporate bonds in TRACE. Regarding the Bond-CDS basis, see Bai and Collin-Dufresne (2019).

servable to the researcher. The downward trend in transaction-based illiquidity measures during the post-crisis period in Figure 1 may reflect changes in average trade size, for example, rather than an actual improvement in market liquidity (Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018)).

In Internet Appendix Section V we estimate dealer-level panel regressions of dealer gross positions on proxies for dealer financial constraints, controlling for time and dealer fixed effects. We find that higher dealer equity capital and lower CDS spreads are associated with increased gross positions, consistent with our assumption that dealer gross positions contain information about dealers' inventory absorption capacity.

D. Other Data

In Section IV, we study whether liquidity supply risk and liquidity demand risk help explain the cross-section of corporate bond returns. To do so, we merge month-end bond prices from TRACE with bond characteristics from the Mergent FISD database. Following Bessembinder, Kahle, Maxwell, and Xu (2009), we use the volume-weighted average price for institutional transactions with volume greater than \$100,000. Construction of monthly bond returns follows Bai, Bali, and Wen (2019).[15] Specifically, we define the

[15] We treat the bond price as a month-end observation if the trade occurs in the last week of the month. If there is more than one daily price observation in the week, we use the last observation as the month-end price. For bond-month pairs without a price observation in the last week, we use the first observation in the following week.

return on bond k in month t as

$$R_{k,t} = \frac{P_{k,t} + AI_{k,t} + Coupon_{k,t}}{P_{k,t-1} + AI_{k,t-1}} - 1, \tag{5}$$

where $P_{k,t}$ is a month-t clean price, $AI_{k,t}$ is accrued interest, and $Coupon_{k,t}$ is the coupon paid in month t. When calculating returns, we remove price observations below \$5 or above \$1,000, and we remove bonds with remaining time to maturity of less than one year.

As before, we focus on U.S. corporate bonds with no embedded options other than make-whole call options. To measure the aggregate return on corporate bonds, we use the Merrill Lynch total return index.

II. Identifying supply and demand shocks

A. *Sign Restrictions*

Our approach to identifying liquidity supply and demand shocks is based on two assumptions. First, we assume that a positive liquidity supply shock is associated with a decrease in noise and an increase in dealer gross positions. Second, we assume that a positive liquidity demand shock leads to an increase in both noise and dealer gross positions.

These assumptions reflect basic economic intuition about supply and demand. To further motivate our assumptions, in Internet Appendix Section II we present a dynamic general equilibrium model with time-varying dealer constraints and demand imbalances due to Grossman and Stiglitz (1980) noise traders (so-called "liquidity traders"). In the model, time-variation in intermediary constraints and noise traders' demand generates changes in noise and dealer gross positions consistent with our identification assumptions. In addition, the model generates qualitative and quantitative predictions relating liquidity supply and demand to the cross-section of expected returns and expected aggregate returns.

B. Empirical Model

We identify liquidity supply and demand shocks using a VAR with standard supply and demand sign restrictions (Uhlig (2017)). Denote the vector of noise and dealer gross positions by $Y_t = \begin{pmatrix} p_t & q_t \end{pmatrix}'$. The VAR is given by

$$Y_t = b + B_1 Y_{t-1} + B_2 Y_{t-2} + ... + B_L Y_{t-L} + \xi_t, \tag{6}$$

where B_i is a 2×2 matrix of coefficients for $i \in (1, ..., L)$, b is a 2×1 vector of constants, and ξ_t is the reduced-form residual, a 2×1 vector with covariance matrix $E[\xi_t \xi_t'] = \Sigma$.

Denote the mapping from orthonormal fundamental shocks v_t to the residual ξ_t by the rotation matrix A, with $\xi_t = A v_t$. To identify the structural shocks, we impose the following sign restrictions on the matrix A,

$$\begin{pmatrix} \xi_t^p \\ \xi_t^q \end{pmatrix} = \underbrace{\begin{pmatrix} - & + \\ + & + \end{pmatrix}}_{A} \begin{pmatrix} v_t^s \\ v_t^d \end{pmatrix} \tag{7}$$

so that the first element of v_t corresponds to a supply shock and the second element corresponds to a demand shock. The sign restrictions on the first column of A correspond to our assumption that an increase in liquidity supply is associated with lower noise and higher dealer positions. The sign restrictions on the second column of A correspond to our assumption that an increase in liquidity demand is associated with an increase in both noise and dealer positions. Using these identification assumptions, we can identify A and uncover the supply and demand shocks from $v_t = A^{-1}\xi_t$.

We estimate the model using the pure-sign-restrictions approach of Uhlig (2005). In estimating the reduced-form VAR, we use a weak Normal-Wishart prior with the lag length ($L = 2$) chosen according to the Bayesian Information Criterion.

To estimate the model, we take 100 draws from the posterior over B and Σ and, for each of these draws, 100 draws of an orthonormal matrix Z that is drawn uniformly from the unit circle. We therefore use a total of 10,000 draws of parameters. Draws of Z are obtained using QR factorization. The candidate rotation matrix is the product $A_m = CZ_W$, where C is the lower-triangular Cholesky decomposition of the draw of Σ. If A_m satisfies the sign restrictions in (7), we keep the draw, whereas if it does not satisfy the restrictions, we discard it. In the following analysis, we report the mean of the structural shocks, computed across the draws that we retain.

III. Properties of Liquidity Supply and Demand Shocks

In this section, we discuss the properties of our estimated liquidity supply and demand shocks and the estimated effects of these shocks on noise and dealer gross positions.

A. *Time Series of Liquidity Supply and Demand Shocks*

We start by describing the historical behavior of the supply and demand shocks identified by our methodology. Figure 2 shows the pointwise mean of the cumulative sum of the liquidity supply shocks, $\sum_{j=1}^{t} v_j^s$.

[Insert Fig. 2 near here]

The supply shocks capture episodes of stress in the corporate bond market as well as more general episodes of intermediary stress. Liquidity supply fell sharply in 2007 following the suspension of redemptions at Bear Stearns hedge funds, which marked the start of the financial crisis, and after the failure of Lehman Brothers. Liquidity supply also declined during the European fiscal crisis in late 2011 and after the "taper tantrum" in 2013, when interest rates rose as the Federal Reserve considered when to reduce its purchases of long-term assets.

Figure 2 also shows the cumulative sum of the liquidity demand shocks, $\sum_{j=1}^{t} v_j^d$. Liquidity demand has not followed a consistent pattern around stress events. For example, it declined following several stress events in the 2007 to 2009 financial crisis and the European fiscal crisis, but it spiked following the collapse of Lehman Brothers.[16]

[16]The cumulative sum of each shock in Figure 2 is approximately zero at the end of the sample period by construction, because a constant is included in the VAR in (6) and the structural shocks are a rotation of the reduced-form shocks.

Figure 2 summarizes changes in liquidity supply and demand over five subperiods in our sample. The definition of subperiods follows Bao, O'Hara, and Zhou (2018): i) the pre-crisis period through June 2007, ii) the crisis period from July 2007 to April 2009, iii) the post-crisis period from May 2009 to June 2010, iv) Dodd-Frank regulation periods from July 2010 to March 2014, and v) the Volcker rule period beginning in April 2014. Although the names of these subperiods are informative, the exact dates on which regulatory changes affected liquidity supply are unknown, making it difficult to attribute the supply shock on a specific date to a specific regulation. Nonetheless, it is informative to see how liquidity supply and demand change, on net, in each subperiod.

During the crisis, both liquidity supply and demand fell, on net, before partly recovering during the post-crisis period. During the Dodd-Frank period, liquidity supply decreased notably while liquidity demand increased. The decrease in liquidity supply occurred mostly during the period in which the debt crisis in Greece deepened, but it is also possible that prospects for tighter regulations on dealer market activity exacerbated the decrease.

During the Volcker period, cumulative supply shocks were negative, on net. The decrease in liquidity supply occurred around the time when a bond mutual fund (Third Avenue) was forced to halt redemptions.[17] Overall, our decomposition shows that liquidity supply falls during periods in which recent banking regulations were introduced, with the effect more pronounced during

[17]Although the Third Avenue fund focuses on HY bonds, the IG and HY markets are closely connected and the same dealers provide liquidity in both markets, which explains why an HY-focused event may have aggregate effects.

times of market stress, consistent with Bao, O'Hara, and Zhou (2018) and Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018).

B. Effects of Liquidity Supply and Demand Shocks

Figure 3 characterizes how noise and dealer gross positions respond to liquidity supply and demand shocks, using the VAR to compute impulse responses. By assumption, both types of shocks lead to a weak increase in dealer gross positions on impact, but the contemporaneous response of noise is positive for a supply shock and negative for a demand shock. Figure 3 shows that on impact, the estimated responses of noise to a supply shock and a demand shock are similar in magnitude. However, the response of noise to a supply shock is highly persistent—the estimated mean response falls by half after only 29 weeks, a measure of half-life. In contrast, the response of noise to a demand shock is transitory. Even at a horizon of four weeks, we cannot exclude an estimate of no effect from the 95% credible interval around the median. The associated half-life is seven weeks. The response of gross positions to a supply shock is also more persistent, compared with the response of gross positions to a demand shock.

[Insert Fig. 3 near here]

The persistent responses of noise and dealer gross positions to a supply shock are consistent with theories of liquidity supply by financially constrained intermediaries (e.g., Gromb and Vayanos (2018)). In these models, following a shock that depletes the capital of liquidity suppliers, market-making returns increase, which allows capital to be slowly replenished. These results are also broadly consistent with existing empirical evidence of slow-moving capital (Mitchell, Pedersen, and Pulvino (2007)). The importance of the persistence of noise's response is highlighted by standard asset pricing theories with illiquid markets (Acharya and Pedersen (2005)), which predict that the asset pricing implications of liquidity shocks depend on their persistence.

The structural VAR also provides estimates of how much of the variability of noise and dealer gross positions, on average, is accounted for by supply shocks as opposed to demand shocks. In Internet Appendix Section VI we address this question using a forecast error variance decomposition. Consider an observer at the end of quarter t using the weekly VAR to predict noise for each week in quarter $t+1$ (we focus on a quarterly frequency here to smooth week-to-week variation). Liquidity supply shocks, on average, account for 60% of the variance in the forecast error (also called the prediction mean squared error). Now suppose the observer uses the VAR to predict noise each week in quarter $t+2$. At this two-quarter horizon, liquidity supply shocks account for 80% of the forecast error variance, reflecting the persistent response of noise to supply shocks. At horizons of three quarters or more, the importance of supply shocks remains large, accounting for roughly three-quarters of forecast error variance.

These results point to the usefulness of the supply-demand decomposition. Liquidity supply shocks have more persistent effects than demand shocks and account for a large share of fluctuations in noise at intermediate and longer-run horizons. However, liquidity demand shocks also have an important role in explaining fluctuations in noise, especially at short horizons.

C. Proxies for Supply and Demand Shocks

An advantage of the identification strategy based on sign restrictions is that we do not use ad-hoc proxies for liquidity supply and demand as our pricing factors. Nonetheless, it is natural to ask how the shocks identified by sign restrictions relate to commonly used proxies for liquidity shocks. To examine the relation, we study the correlation between the structural shocks and several liquidity proxies and we run multivariate regressions of the structural shocks on sets of liquidity proxies. Because we conduct asset pricing tests at a monthly frequency, we estimate correlations and regressions at a monthly frequency as well.[18] To obtain monthly supply and demand shocks, we use the average of each shock within each month.

First, we use proxies for the capital and funding constraints that dealers face, including the intermediary capital ratio of He, Kelly, and Manela (2017), primary dealer CDS spreads, the return on the bet-against-beta strategy of Frazzini and Pedersen (2014), the TED spread, deviations from covered interest parity (CIP) from Du, Tepper, and Verdelhan (2018), and the fraction of agency or "riskless principal" trades.[19] We construct innovations to these

[18]Results of weekly regressions are reported in Internet Appendix Section VII.

[19]He, Kelly, and Manela (2017) calculate primary dealer parent companies' capital ratio using their aggregate market equity and aggregate book value of debt. This ratio is the inverse of leverage and is arguably negatively related with dealer constraints. Stocks that are more sensitive to market returns may have lower expected returns due to short-sale constraints. The bet-against-beta strategy takes long positions in low-beta stocks and short positions in high-beta stocks. A tightening of funding constraints leads, on impact, to lower returns on the bet-against-beta strategy (Frazzini and Pedersen (2014)). The TED spread measures the cost of unsecured funding for banks, which could affect dealer

series using univariate autoregressions.

If liquidity supply shocks capture changes in dealers' inventory absorption capacity, we expect supply shocks to be positively correlated with intermediary capital innovations and the betting-against-beta return, and negatively correlated with innovations to dealer CDS spreads, the TED spread, CIP deviations, and the fraction of agency trades. Table III, Panel A shows that these correlations have the expected sign and are statistically significant. Liquidity supply shocks have a correlation with the intermediary capital ratio innovation of 0.38, and with the dealer CDS spread innovation of −0.25. The estimated correlations between liquidity demand shocks and these six proxies are much smaller in magnitude, are not statistically significant at the 5% level, and do not point overall to a positive or negative relation between demand shocks and changes in dealer constraints.

[Insert Table III near here]

Second, we study two proxies that are expected to be related to liquidity demand: lagged corporate bond mutual fund flows and lagged corporate bond issuance. As reported in Panel B, the correlations between liquidity demand shocks and innovations to lagged fund flows and issuance are positive and statistically significant. Liquidity supply shocks are not correlated with these proxies.

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inventory capacity (Gârleanu and Pedersen (2011)). "Riskless principal" or agency trades are those in which dealers match customers rather than use their balance sheets to provide liquidity (Choi and Huh (2018)).

Third, we examine two proxies that capture broad market conditions. Liquidity supply shocks are negatively correlated with VIX innovations and positively correlated with the lagged return for the aggregate corporate bond market. These correlations are statistically significant and consistent with research for equity markets (Hameed, Kang, and Viswanathan (2010), Nagel (2012)). Liquidity demand shocks are not correlated with VIX innovations or lagged aggregate returns.

We also run kitchen-sink regressions of each structural shock on all 10 proxies and find that the R^2 is 0.25 for the supply shock and 0.14 for the demand shock. The reasonably high R^2 for the supply shock suggests that it could contain information about systematic shocks to dealer inventory capacity. The lower R^2 for the demand shock suggests that investor demand imbalances for similar bonds are likely unrelated to systematic risks.

Overall, these results are consistent with our interpretation of the estimated liquidity supply and demand shocks as capturing, respectively, dealers' inventory capacity and investors' demand imbalances for similar bonds. At the same time, even in the kitchen-sink regressions, the R^2 is well below one, suggesting that well-known proxies capture only part of the variation in liquidity supply and demand. For example, mutual fund flows may be a useful proxy for liquidity demand, but mutual fund flows are likely only one driver of investors' demand imbalances, in part because bond mutual funds hold only a limited fraction of the corporate bond market.[20]

[20] According to the Financial Accounts of the United States, mutual funds held 15% of corporate and foreign bonds issued in the U.S. at the end of 2016.

D. *Discussion*

D.1. Identification

Our approach to identification assumes that noise and dealer gross positions are driven by orthogonal shocks to liquidity supply and demand. The assumption of orthogonality is important for these shocks to have a structural interpretation (Uhlig (2017)).

Three considerations point to the plausibility of our identification assumptions. First, the properties of the estimated supply and demand shocks are consistent with our labeling of the shocks and the orthogonality assumption. The estimated supply shocks are correlated with proxies for intermediary constraints, but demand shocks are not (Section III.C). The estimated demand shocks are correlated with proxies related to investors' liquidity trading needs, but the supply shocks are not. Supply shocks capture well episodes of intermediary stress but demand shocks do not (Section III.A).

Second, our identification assumptions are not required to hold for all types of liquidity, but rather for the particular notion of liquidity we study—the intermediation of investors' cross-sectional demand imbalances that generate noise in issuer-level corporate bond yield curves. Effectively, the demand imbalances that generate noise are spikes in investor demand to buy particular bonds—even if they are priced richly—or to sell particular bonds—even if they are priced inexpensively. It is plausible that unexpected shifts in these demand imbalances are orthogonal to unexpected shifts in liquidity supply.[21]

[21] In our theoretical model, these demand imbalances arise from Grossman-Stiglitz

Third, we impose our sign restrictions only on the contemporaneous responses of noise and gross positions to supply and demand shocks; we do not impose restrictions on the responses at horizons of one week or more. Consequently, while we do require that contemporaneous unexpected shifts in supply and demand be orthogonal, our assumptions permit the drivers of liquidity supply to affect liquidity demand with a lag of one week or more.[22] Empirically, although the signs of the responses to supply and demand shocks are not mechanically restricted except on impact, the signs of the estimated responses one week and beyond are as expected for each shock (Figure 3), consistent with economically distinct shocks that can be labeled supply and demand.

"noise" traders or "liquidity" traders. To illustrate these demand imbalances, Pedersen (2015) cites "price-insensitive insurance companies who need [a particular bond] for a specific reason."

[22]Suppose that a negative shock to liquidity supply leads to an increase, with a lag of one week or more, in investor demand imbalances for particular bonds. Then the sign of the response of gross positions to a supply shock at a horizon of one week or more would be ambiguous (reduced supply would lead to lower positions, all else being equal, while increased demand would lead to higher positions). Because we do not make assumptions about the sign of responses except contemporaneous with each shock, our identification assumptions would not be violated. Our approach is less restrictive than most applications of sign restrictions, which impose restrictions on responses over a long horizon (e.g., Uhlig (2005)).

D.2. Institutional Changes in the Corporate Bond Market

A number of institutional changes have affected the corporate bond market over the sample period. For example, some corporate bonds became available for trading on electronic platforms in addition to traditional telephone-based trading. New technologies may have facilitated matching customers' trades without requiring dealers to commit capital. Our framework would interpret such changes as negative demand shocks because better technology is expected to reduce dealer gross positions and noise. The technological changes observed in the corporate bond market thus suggest that there are determinants of liquidity demand shocks beyond the proxies used in the previous exercise.

Anand, Jotikasthira, and Venkataraman (2017) and Choi and Huh (2018) highlight a related institutional change in recent years, namely, an increase in the provision of liquidity by some "buy-side" institutional investors, which had previously only been present in the market to demand liquidity. Our framework would interpret increased liquidity provision by institutional investors as a decline in liquidity demand. Like technological improvements that facilitate matching, an increase in liquidity provision by buy-side institutional investors is expected to be associated with reduced dealer gross positions and noise.

E. Analysis of Identification using Monte Carlo Simulation

In this section, we verify whether our strategy can recover the underlying structural shocks using simulated data from a Monte Carlo simulation.

Specifically, we generate 1,000 draws of the history of structural shocks, $\{v_t\}$, using an independent standard normal distribution. We then compute the corresponding endogenous variables Y_t using the mean estimate of the structural VAR parameters from the model in Section II.B. For the dm-th draw of simulated structural shocks, we use the resulting endogenous variables Y_t to estimate the structural VAR with sign restrictions and generate the posterior distribution of structural shocks. We compute the mean of structural shocks in the posterior distribution, $\hat{v}_t$, and compute "R^2" for m-th draw of the history of structural shocks as

$$R_m^2 = 1 - \frac{\Sigma_t (\hat{v}_{m,t} - v_{m,t})^2}{\Sigma_t v_{m,t}^2}. \tag{8}$$

If the posterior mean estimates for structural shocks provide an accurate estimate for the true structural shocks, then R^2 should be close to one.

Table IV reports the results of this Monte Carlo simulation. The mean and median R^2 is 0.97 for both supply and demand shocks, implying that the structural shocks identified by imposing sign restrictions on the rotation matrix do indeed closely track the true structural shocks. These simulation results provide additional support for our method of estimating supply and demand shocks.

[Insert Table IV near here]

IV. Asset Pricing

The evidence so far indicates that our liquidity supply shocks lead to persistent changes in noise, are correlated with well-known proxies for intermediary constraints, and well capture episodes of intermediary stress in the corporate bond market. In contrast, our liquidity demand shocks lead to transitory changes in noise, are correlated with proxies for liquidity demand such as lagged mutual fund flows, and do not follow a consistent pattern around episodes of intermediary stress. These results suggest that liquidity supply and demand might have different relations with expected corporate bond returns.

In this section we explore the asset pricing implications of liquidity supply and demand. Sections IV.A and IV.B present evidence on cross-sectional risk premia using bond-level panel regressions and portfolio sorts. In Section IV.C, we examine time-variation in expected aggregate excess returns in the corporate bond market.

A. Liquidity Supply Risk Premium: Bond-Level Panel Regressions

We start our analysis by examining the explanatory power of liquidity supply and demand shocks for the cross-section of expected corporate bond returns.

To estimate the liquidity risk exposure of bond k, we estimate the time-series regression

$$R^e_{k,t} = b_{0,k} + \beta_{k,MKT} R^e_{MKT,t} + \beta_{k,s} v^s_t + \beta_{k,d} v^d_t + \epsilon_{k,t}, \tag{9}$$

where $R^e_{k,t}$ is the excess return on bond k, $R^e_{MKT,t}$ is the excess return on the value-weighted corporate bond market portfolio, v^s_t is the estimated liquidity supply shock, and v^d_t is the estimated liquidity demand shock. The frequency is monthly. We obtain monthly liquidity supply and demand shocks by taking an average of weekly shocks within each month and scaling the monthly shocks to have a standard deviation of one. The excess return on bond k is its return less the one-month Treasury bill rate. We estimate (9) using three-year rolling windows (with a minimum of 24 monthly observations) to allow the slope coefficients to vary over time.

The difficulty in precisely estimating time-varying security-level betas is well known. Thus, following Fama and French (1992), we form 10 equally weighted portfolios based on each bond's pre-formation liquidity supply and demand betas from (9). We then estimate the same time-series regression (9) using portfolio returns to obtain post-formation betas. We assign a portfolio's post-formation beta to each bond in the portfolio. This approach allows us to use individual bonds in the asset pricing tests and thus to control for bond-level characteristics.

Using the post-formation betas, we estimate the liquidity supply and demand risk premia using panel regressions,

$$R^e_{k,t+1} = \gamma_0 + \gamma_1 \beta_{k,s,t} + \gamma_3 C_{k,t} + \mu_{k,t+1}, \tag{10}$$

$$R^e_{k,t+1} = \gamma_0 + \gamma_2 \beta_{k,d,t} + \gamma_3 C_{k,t} + \mu_{k,t+1}, \tag{11}$$

where $C_{k,t}$ is a vector of control variables for bond k, which includes the bond's lagged one-month excess return and the logarithms of its Roll illiquidity (used in Bao, Pan, and Wang (2011)), remaining time to maturity, and amount outstanding. We also include six rating dummy variables corresponding to the ratings AA, A, BBB, BB, B, and CCC and below.

An advantage of bond-level panel regressions is that we can easily compute GMM t-statistics for the slope coefficients γ that take into account errors in the first-stage estimation of betas and the cross-sectional and serial correlation in error terms. Appendix B details the construction of the GMM t-statistics. Traditional Fama and MacBeth (1973) regressions generate point estimates for the risk premia γ_1 and γ_2 that are similar to our bond-level regression estimates, because post-formation betas do not vary over time.[23]

In Table V, the first row reports the estimated slope coefficient γ_1 for the liquidity supply beta when (10) is estimated without bond-level controls. The estimated slope coefficient is 0.91% per month, with a t-statistic of 3.05. The positive loading on β_s implies that bonds that decrease in value when there is a decline in dealer liquidity supply are risky and thus earn higher

[23] In our bond-level regression estimates, the portfolio betas are constant but individual bonds shift across portfolios over time based on pre-formation estimates of beta.

returns on average.

[Insert Table V near here]

Row (2) of Table V reports slope coefficients when (10) is estimated using bond-level controls. The estimated slope for the liquidity supply beta remains positive and statistically significant, with a point estimate of 0.42% and a t-statistic of 2.21. Thus, the liquidity supply shock is priced in corporate bonds after accounting for differences in bond characteristics, including credit rating, maturity, and the level of liquidity.

The third and fourth rows in Table V report estimates of the slope coefficient γ_2 for the liquidity demand beta, from (11). The point estimate is negative when controls are excluded and positive when controls are included; with and without controls, we cannot reject the null hypothesis that the liquidity demand risk premium is zero. Thus, we do not find compelling evidence that liquidity demand shocks—shocks to the demand imbalances for similar bonds that give rise to noise—are priced in corporate bonds.

The sensitivity of corporate bond returns to standard measures of aggregate corporate bond illiquidity, including the Amihud and Pástor-Stambaugh measures, has been shown to have explanatory power for expected corporate bond returns (Lin, Wang, and Wu (2011)). Thus, to better understand the information content of our liquidity supply shocks, we run a horse race between liquidity supply shocks and innovations to these standard liquidity factors.

We estimate bond-level panel regressions

$$R^e_{k,t+1} = \gamma_0 + \gamma_1\beta_{k,s,t} + \gamma_2\beta_{k,Amihud,t} + \gamma_3 C_{k,t} + \mu_{k,t}, \tag{12}$$

$$R^e_{k,t+1} = \gamma_0 + \gamma_1\beta_{k,s,t} + \gamma_2\beta_{k,PS,t} + \gamma_3 C_{k,t} + \mu_{k,t}, \tag{13}$$

where $\beta_{k,Amihud,t}$ and $\beta_{k,PS,t}$ are the betas of bond returns with respect to the Amihud (2002) measure and the Pástor and Stambaugh (2003) liquidity factor, respectively. We follow Lin, Wang, and Wu (2011) in constructing aggregate Amihud (2002) and Pástor and Stambaugh (2003) measures for corporate bonds. We normalize the sign of the Amihud measure so that it proxies for liquidity, rather than illiquidity.

Row (5) of Table V reports results from estimating (12) without bond-level controls. The average slope coefficient for the liquidity supply beta is 0.87% with a t-statistic of 3.74, almost unchanged from the previous results. In contrast, the slope coefficient on the Amihud beta has the "wrong" sign, and we cannot reject the null hypothesis of a zero Amihud risk premium.[24] We obtain similar results when including bond-level controls (row (6)) and when repeating this exercise using the Pástor-Stambaugh measure (rows (7) and (8)). These results provide additional evidence of a positive liquidity supply risk premium. The results also suggest that standard liquidity measures, while correlated with our liquidity price and quantity measures, are

[24]Internet Appendix Section IX reports estimates of regressions (12) and (13) excluding the liquidity supply beta $\beta_{k,s,t}$. With and without bond-level controls, the resulting estimated Amihud and Pástor-Stambaugh risk premia are positive, as expected, but not statistically significant.

“contaminated” by other factors that may be priced differently (or not priced at all) in the cross-section of corporate bond returns.

Finally, in the last two specifications in Table V, we replace the liquidity supply beta with the beta with respect to shocks to dealer gross positions, ξ_t^q, the reduced-form residual from (6). To estimate each bond's gross position beta, we use the same process as for the liquidity supply beta and then estimate the liquidity quantity risk premium using the post-formation beta. We find that the estimated price of risk is positive, with a t-statistic of 2.09 when bond-level controls are excluded. This exercise points to the benefits of our supply-demand decomposition: without our empirical framework for disentangling supply and demand, the economic interpretation of the liquidity quantity risk premium is unclear. Viewed through the lens of our framework, dealer gross positions are driven by liquidity supply shocks as well as demand shocks, with the estimated liquidity quantity premium reflecting that supply shocks are priced but demand shocks are not.

B. Liquidity Supply Risk Premium: Portfolio Sorts

To further examine the explanatory power of liquidity supply shocks for expected corporate bond returns, we study the expected returns of portfolios sorted on liquidity supply beta. Using existing factor models, we also study the risk-adjusted expected returns of these portfolios.

We begin with a preliminary exercise, reported in Internet Appendix Section IX, in which we use a univariate quintile sort. This preliminary exercise reveals two important patterns that we account for in our subsequent analysis. First, the average maturity has a U-shaped pattern—it is 11.5 years for the lowest beta quintile, 5.3 years for the middle beta quintile, and 8.2 years for the highest beta quintile. Second, the distribution of liquidity supply betas is skewed to the right. Post-formation supply betas for the five portfolios are -0.08, -0.11, -0.06, 0.05, and 0.36, indicating that the difference in betas between the fourth and fifth quintiles is especially large.

To address differences in maturity uncovered by the univariate sort, we construct 4×5 independently sorted value-weighted bivariate portfolios by liquidity supply beta and remaining time to maturity. We then form the four beta-sorted portfolios for use in our main analysis. The lowest supply-beta-sorted portfolio (portfolio 1) comprises the lowest supply-beta subquartile from each maturity quintile. The highest supply-beta-sorted portfolio (portfolio 4) comprises the highest supply-beta subquartile from each maturity quintile. To obtain more variation in post-formation betas across portfolios, we next divide the top quartile into halves (4L and 4H).

Panel A of Table VI reports the average returns on the supply-beta-sorted portfolios in excess of the one-month T-bill rate. Consistent with the panel regression results in the previous section, the monthly average excess return is lower for the quartile with the lowest supply betas (excess return of 0.30%) than the quartile with the highest betas (excess return of 0.72%). The difference in excess returns, 0.42%, is statistically significant with a Newey-West t-statistic of 3.46. The difference between the lowest quartile and the bonds in the 4H portfolio is even more pronounced, with a difference in average excess returns of 0.75% (t-statistic = 4.06).

[Insert Table VI near here]

Panels F and G of Table VI present characteristics of bonds averaged within portfolios. The post-formation betas for the first and second quartiles are −0.03 and −0.15, respectively, which helps explain why average excess returns for the second quartile (0.28%) are about the same as those for the first quartile (0.30%). Remaining maturity and size do not vary significantly across portfolios. The Roll measure of illiquidity and imputed roundtrip costs have a U-shaped pattern; bonds in the lowest and highest quartiles are more illiquid than the bonds in the middle quartiles. The distribution of ratings is notably different across portfolios. Bonds with higher liquidity-supply betas tend to be lower rated.

Since variation in credit ratings is associated with differences in average returns (Chordia, Goyal, Nozawa, Subrahmanyam, and Tong (2017)), we control for differential risk exposures, including exposure to credit risk, using return-based factor regressions,

$$R^e_{\pi,t} = \alpha_\pi + \Sigma_{j=1}^{J} \beta_{\pi,j} f_{j,t} + \epsilon_{\pi,t}, \tag{14}$$

where $R^e_{\pi,t}$ is the return on portfolio π and $f_{j,t}$, $j \in \{1, \ldots, J\}$, are return-based factors proposed in the literature.

Specifically, we use (i) the five-factor model of Fama and French (2015) supplemented by the TERM (difference in returns between long-term Treasuries and the three-month T-bill) and DEF (difference in returns between a broad corporate bond portfolio and long-term Treasuries) factors from Fama and French (1993), (ii) the five-factor model of corporate bond returns from Bai, Bali, and Wen (2019), (iii) the two-factor intermediary asset pricing model of He, Kelly, and Manela (2017), and (iv) the combination of (ii) and (iii) augmented by the TERM and DEF factors.

Recent research including Chordia, Goyal, Nozawa, Subrahmanyam, and Tong (2017) highlights that risk characteristics constructed specifically for corporate bonds have significant risk premia that cannot be explained by stock market factors. Bai, Bali, and Wen (2019) therefore add four factors to the bond market aggregate return factor, including credit risk (differential return on bonds sorted on credit rating), downside risk (sorted on the second worst return in recent years), liquidity (sorted on the Roll measure), and monthly reversals (sorted on returns in the previous month). Because their five-factor model includes credit risk and liquidity factors, the model is particularly suitable for adjusting for risk exposures in this paper.

We also risk-adjust returns using the He, Kelly, and Manela (2017) two-factor model, where the factors are the equity market return factor and the shock to primary dealer bank holding companies' equity capital ratio, measured using stock prices and book debt. He, Kelly, and Manela (2017) show that their model prices the cross-section of corporate bonds and other intermediated asset classes. Given the positive correlation between the liquidity supply shock and their factor (Section III.C), we examine whether their factor model can explain the differences in excess returns on supply-sorted portfolios.

Panels B to E of Table VI report the intercept from regression (14) using these factor models. The supply-beta-sorted hedge portfolio (the top quartile minus the bottom quartile) has an alpha of 0.52% for the 5+2 factors of Fama and French (1993, 2015), 0.35% for the five factors of Bai, Bali, and

Wen (2019), 0.36% for the two factors of He, Kelly, and Manela (2017), and 0.46% for the kitchen-sink model. These alpha estimates for the hedge portfolio are statistically significantly different from zero except when using the two-factor model of He, Kelly, and Manela (2017), which results in a Newey-West t-statistic of 1.93.

The significant alphas against the five-factor model of Bai, Bali, and Wen (2019) show that bonds with high liquidity supply betas earn higher returns not because of their exposure to systematic credit or overall liquidity risk. Instead, the comovement of bond returns with a particular driver of liquidity—shocks to dealers' inventory-absorption capacity—has unique explanatory power for expected returns.

Adjusting excess returns using the He-Kelly-Manela model somewhat attenuates the alpha estimate for the hedge portfolio, and the point estimate is only marginally statistically significant. Similarly, the point estimate (0.69%) and t-statistic (2.24) for the excess return on the 4H-1 hedge portfolio are lowest when the He-Kelly-Manela model is used, relative to the point estimates from all other factor models shown in Table VI. These results are expected, since dealers' inventory-absorption capacity should be related to their parent bank holding company's equity capital.

Even so, risk-adjusting expected returns using the He-Kelly-Manela model does not subsume the positive excess returns associated with bonds with high exposure to liquidity supply. These results suggest that dealers' inventory capacity is not simply a proxy for their parent bank holding company's equity capital, which underscores the benefits of measuring liquidity supply shocks using dealer positions and bond yields.

C. Time-Varying Expected Aggregate Returns

Intermediary asset pricing models such as He and Krishnamurthy (2013) suggest that dealer balance sheet measures can be informative about time-variation in expected aggregate returns. However, we emphasize that balance sheet quantities such as dealer gross positions are endogenous variables, with dealer gross positions driven by dealers' inventory capacity as well as investor demand imbalances for similar bonds. Accordingly, we study whether dealer gross positions are informative about time-variation in expected aggregate corporate bond returns and whether our supply-demand decomposition has predictive content beyond the information contained in dealer gross positions studied alone.

Our approach builds on Chen, Joslin, and Ni (2018). First, we estimate

$$R^e_{t+h} \quad = \quad b_0 + b_1 q_t + \eta_{t+h}, \tag{15}$$

where R^e_{t+h} is the h-week return on the aggregate corporate bond market in excess of the T-bill rate.[25] The frequency is weekly, and we estimate (15) separately for $h \in (4, 13, 26, 52)$ weeks. We estimate (15) by OLS and calculate t-statistics using standard errors corrected for overlapping observations following Hodrick (1992). Because aggregate returns were sharply negative during the financial crisis (Figure 4), we report estimates of (15) both excluding and including the financial crisis.[26] Our results are broadly similar

[25] We use the weekly T-bill series from Kenneth French's website and accumulate over h weeks.

[26] As in Figure 2, we define the financial crisis as July 2007 to April 2009, following

when excluding and including the crisis, with supply-driven changes in dealer positions associated with generally larger changes in expected returns in regressions including the crisis.

[Insert Fig. 4 near here]

Table VII, Panel A reports the estimated slope coefficients for q_t and the regression R^2. Excluding the financial crisis, the estimated coefficients for dealer gross positions are negative, indicating that higher dealer gross positions are associated with lower subsequent returns. However, the estimates are statistically significant only at short horizons (4 and 13 weeks). In the full sample, the relation between gross positions and future aggregate returns is not statistically significant at any horizon.

[Insert Table VII near here]

Thus, considered alone, dealer gross positions are at best weakly related to expected aggregate returns. However, the drivers of dealer gross positions—dealers' inventory capacity and investors' demand imbalances for similar bonds—could have different implications for expected aggregate returns. The relation between liquidity supply, liquidity demand, and aggregate returns could therefore be obscured if one uses dealer gross positions alone as a predictor.

Our working hypothesis is that dealer gross positions are more informative about expected aggregate returns at times when liquidity supply shocks have

Bao, O'Hara, and Zhou (2018).

been the primary driver of dealer positions. Because liquidity supply captures inventory capacity, we expect higher gross positions, conditional on positions being primarily supply-driven, to be associated with lower future returns.

To test this hypothesis, we construct a dummy variable D_t indicating whether liquidity demand shocks have been the primary driver over the previous $W \in \{13, 26, 52\}$ weeks. We set D_t equal to one if the absolute value of the cumulative sum of demand shocks over the previous W weeks exceeds the absolute value of the cumulative sum of supply shocks over the same period, that is,

$$D_t = \begin{cases} 1 & \text{if } |\sum_{w=1}^{W} v_{t-w}^{d}| > |\sum_{w=1}^{W} v_{t-w}^{s}|, \\ 0 & \text{otherwise.} \end{cases} \tag{16}$$

We use fairly wide windows W because we are studying the link between risk premia and dealer gross positions, a persistent variable with a period-t level that depends on not only period-t shocks, but also the recent history of shocks.

Figure 4 shows the dealer gross positions and the one-year-ahead aggregate corporate bond return. The gray shaded area corresponds to periods in which supply shocks are more important (i.e., $D_t = 0$). The periods in which supply shocks dominate demand shocks are fairly dispersed over the sample period, especially for shorter W windows. Figure 4 also shows that the categorization of periods as supply- or demand-driven is reasonably consistent for the different W windows used. We estimate our predictive regressions for all three windows W to assess robustness.

To test whether supply-driven gross positions predict bond market returns differently than demand-driven gross positions, we expand (15) as follows:

$$R^e_{t+h} \quad = \quad b_0 + b_{0,D}D_t + b_1 q_t D_t + b_2 q_t(1 - D_t) + cX_t + \eta_{t+h}, \qquad (17)$$

where R^e_{t+h} denotes the h-week excess return, q_t dealer gross positions, D_t the demand-driven indicator from (16), and X_t a vector of control variables. The control variables are the term spread, the dividend-price ratio, the variance risk premium of Bollerslev, Tauchen, and Zhou (2009), and an option-based skewness measure.[27] These control variables have been linked to aggregate risk premia in a variety of markets. The coefficient b_1 captures the relation between gross positions and future returns conditional on demand shocks having been dominant over the previous W weeks. The coefficient b_2 captures the same relation, but conditional on supply shocks having been dominant.

The results from estimating (17) are reported in Table VII using windows of $W = 13$ weeks (Panel B), $W = 26$ weeks (Panel C), and $W = 52$ weeks (Panel D). Each panel reports regressions results both when the controls X_t are excluded from the regression and when they are included.

In regressions excluding the financial crisis, the coefficient b_2 is uniformly negative across specifications and, in most cases, statistically significant at the 5% level. When including the crisis, point estimates for b_2 are generally larger in magnitude. For example, in Panel C1, excluding the crisis, the estimate for b_2 is -19.24 for the one-year forecasting horizon ($h = 52$), implying that a 1% increase in dealer gross positions in a supply-dominated period

[27]Skewness is the difference in implied volatility of at-the-money 30-day S&P500 index options and out-of-the-money options (i.e., moneyness = 0.9) with the same maturity.

corresponds to a decrease in the one-year risk premium of 19.24 bps. The associated t-statistic is -3.59. When including the crisis, the point estimate is -31.36, with a t-statistic of -4.17. Including controls (Panel C2), the estimates of b_2 remain statistically significant, including and excluding the crisis.

In contrast, estimates of b_1, capturing the positions-returns relation conditional on being in a demand-driven period, are generally not statistically significant and smaller in magnitude than the estimates of b_2. The point estimates of b_1 are far from uniform in sign and can vary considerably depending on whether controls are included or not.

The usefulness of the supply-demand decomposition is also illustrated by the improvement in R^2 when allowing the positions-return relation to be conditional on D_t. As shown in Panels A and C1, using a half-year window to define D_t increases the R^2 for the one-year-ahead horizon ($h = 52$) from 0.06 to 0.15, when the crisis is excluded. Including the crisis, R^2 increases from 0.07 to 0.35. Thus, classifying periods as supply- or demand-driven using the estimated supply and demand shocks helps uncover the information about bond risk premia contained in dealer gross positions.

Despite the short time series, we find evidence that supply-driven and demand-driven changes in dealer gross positions have very different implications for time-variation in expected aggregate returns. Higher dealer gross positions predict lower returns only when they are driven mostly by variation in dealers' inventory capacity, not when they are driven mostly by fluctuations in investors' demand imbalances for similar bonds. This result suggests that the asset pricing implications of changes in dealer balance sheets depend on *why* the balance sheet has changed. Our findings regarding time-varying risk premia are consistent with the results of the cross-sectional analysis, in that liquidity supply, but not liquidity demand, is informative about the cross-section of expected returns and time variation in expected aggregate returns.

V. Conclusion

This paper provides an analytical framework for identifying shocks to dealers' liquidity supply by jointly studying price and quantity measures of liquidity. We focus on dealers' use of their balance sheets to accommodate investor demand imbalances for similar bonds. By imposing reasonable sign restrictions on the initial response of the price and quantity of this type of liquidity, we identify shocks to dealers' liquidity supply and shocks to investors' demand imbalances. In particular, a positive supply shock is one that increases dealer gross positions in corporate bonds and decreases noise in issuer-level yield curves.

Although this paper focuses on corporate bonds and primary dealers, our approach to identifying liquidity supply shocks is applicable to other markets and types of intermediaries. For example, our framework could be extended to an even richer cross-section of bonds, such as mortgage-backed securities, to understand the connections across markets with respect to liquidity supply, liquidity demand, and returns.

Our methodology produces liquidity supply shock estimates that are correlated with proxies for intermediary constraints and associated with persistent changes in noise, and that capture episodes of intermediary stress. In contrast, the estimated liquidity demand shocks are correlated with liquidity demand proxies such as mutual fund flows, are associated with transitory changes in noise, and do not follow a consistent pattern around episodes of intermediary stress.

We find that liquidity supply shocks, but not liquidity demand shocks, have important explanatory power for the cross-section of expected corporate bond returns as well as time-variation in expected aggregate returns. Our results provide evidence that dealers' liquidity supply is an important driver of liquidity fluctuations and asset prices, providing empirical support for recent theories connecting dealer inventory constraints to risk premia.

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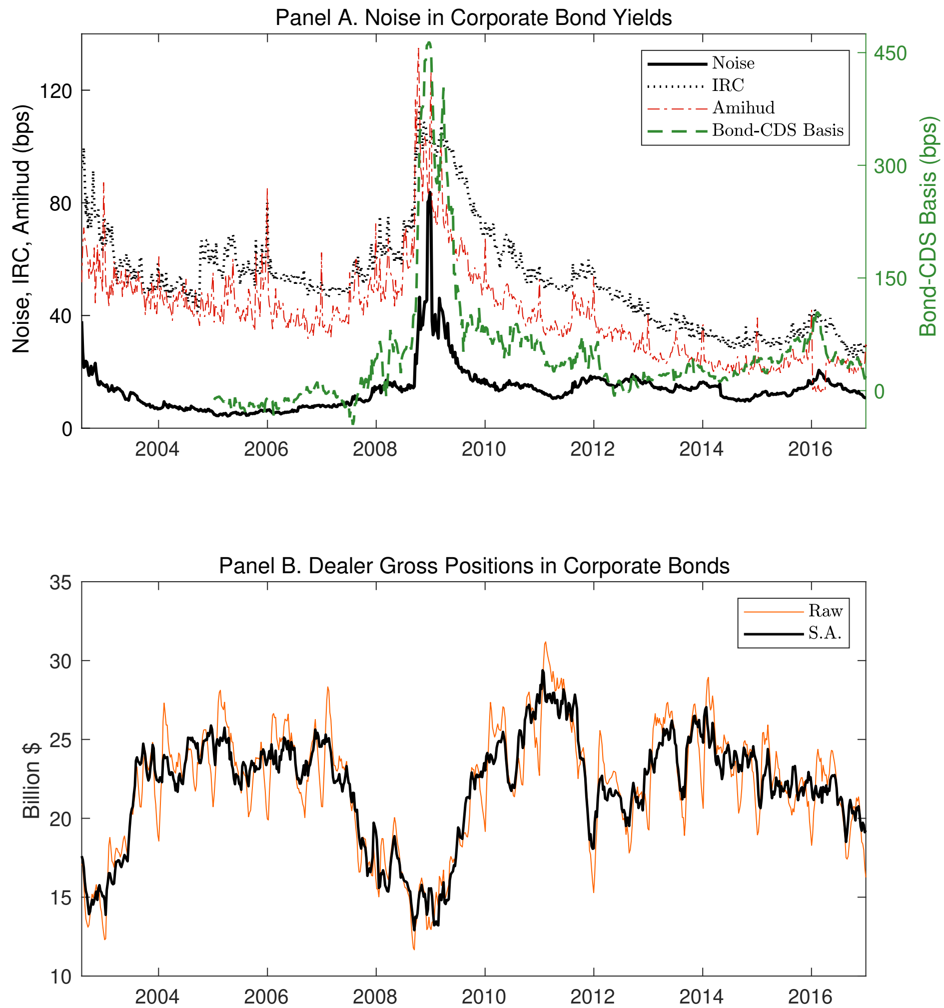

Figure 1. Noise in corporate bond yields and dealer gross positions. The top panel shows a time-series plot of noise in corporate bond yields. For each week t, for each bond in our sample, we calculate a model-implied yield using an issuer-specific fitted Nelson-Siegel-Svensson curve. Aggregate noise in week t is the root mean square deviation between the model-implied yield and the market yield, from equation (3). Three standard measures of illiquidity are also shown: the imputed roundtrip cost (IRC) from Feldhütter (2012), the Amihud price impact proxy, and the Bond-CDS basis. The bottom panel shows a time-series plot of dealer gross positions in corporate bonds, aggregated across primary dealers (equation (4)). Dealer gross positions are constructed from transaction data and are shown without seasonal adjustment (orange line) and with seasonal adjustment (black line). The construction of noise and dealer gross positions is detailed in Sections I.A and I.B, respectively. The frequency is weekly, and the sample period is from August 2002 to December 2016.

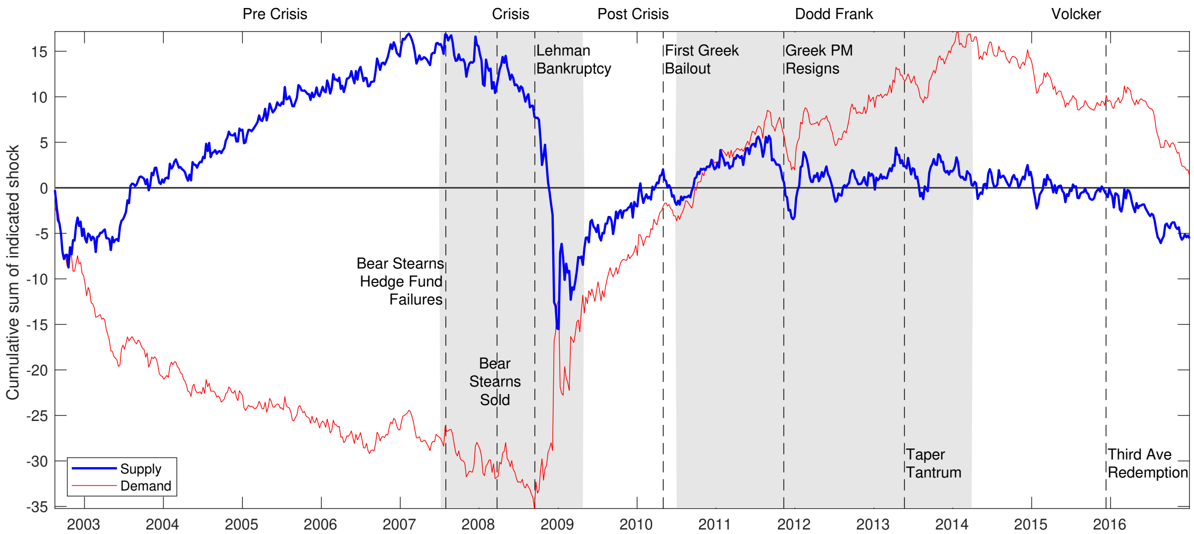

Figure 2. Cumulative sums of liquidity shocks. This figure shows the cumulative sums of shocks to liquidity supply (in blue) and liquidity demand (in red). A positive liquidity supply shock reflects an increase in liquidity supply. The estimation of supply and demand shocks is described in Section II.B. The frequency is weekly, and the sample period is from August 2002 to December 2016. The shaded and unshaded areas mark five periods: the pre-crisis period through June 2007, the crisis period from July 2007 to April 2009, the post-crisis period from May 2009 to June 2010, the Dodd-Frank regulation period from July 2010 to March 2014, and the Volcker rule period beginning in April 2014.

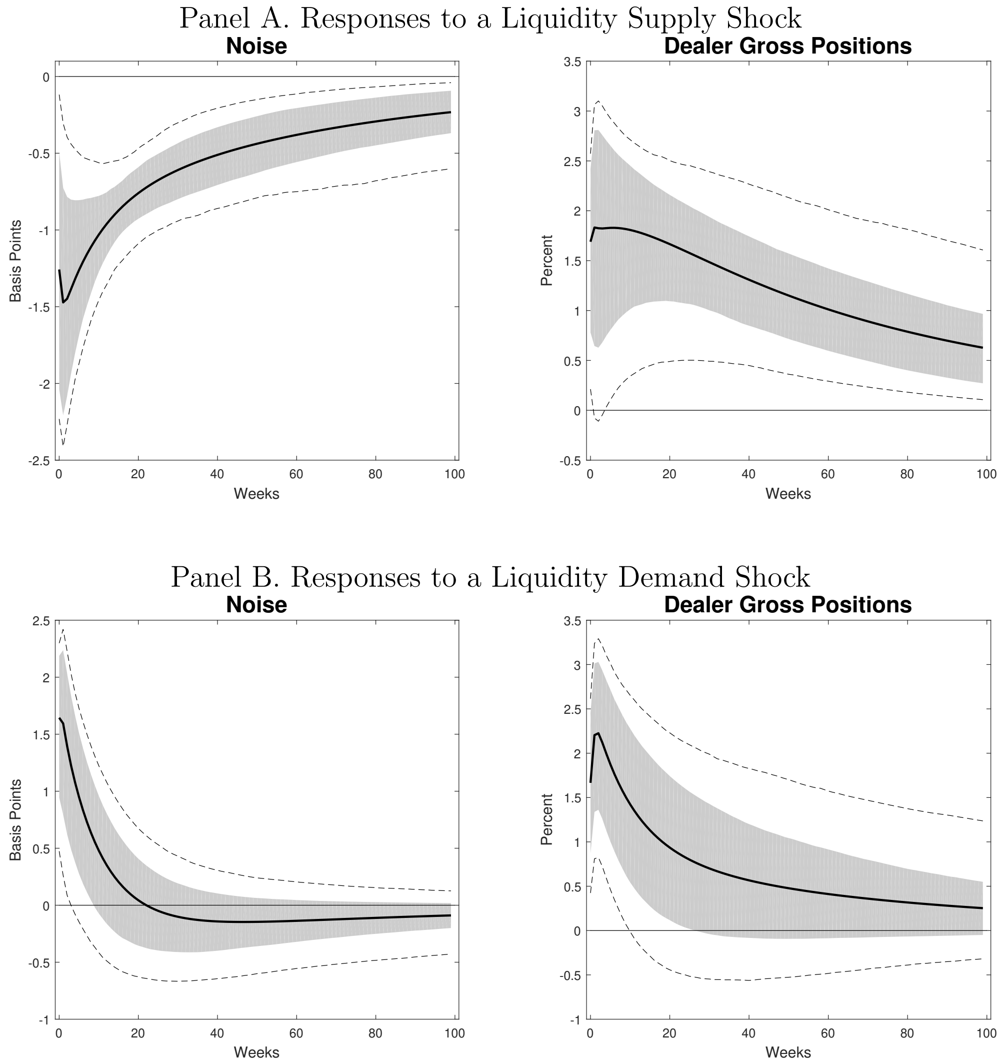

Figure 3. Impulse responses to liquidity supply and demand shocks. The figure shows the impulses of noise and dealer gross positions to a liquidity supply shock (Panel A) and to a liquidity demand shock (Panel B). The mean impulse response is shown in black. The shaded area marks a pointwise 68% credible interval around the median. The dashed lines mark a pointwise 95% credible interval around the median.

Figure 4. Forward aggregate returns and dealer gross positions. The blue line is the one-year-ahead return on the Merrill Lynch corporate bond market index. The red line is demeaned log dealer gross positions. The shaded areas show periods in which dealer gross positions have been primarily driven by liquidity supply shocks, while the unshaded areas show periods in which liquidity demand shocks dominate. Gross positions in week t are classified as driven by liquidity demand if $|\sum_{w=1}^{W} v_{t-w}^{d}| > |\sum_{w=1}^{W} v_{t-w}^{s}|$, otherwise they are classified as driven by liquidity supply.

Table I
Example of the Inventory Construction Method

This table illustrates our method of constructing the inventory of a particular bond for a particular dealer, using artificial data. See Section I.B for details.

Transaction ID	Week	Volume	Extant Transaction Amount					End-of-Week
			1	2	3	4	5	Inventory
1	1	1000	1000					1000
2	2	200	1000	200				1200
3	3	-300	900	0	0			900
4	4	-500	400	0	0	0		400
5	5	100	0	0	0	0	100	100

Table II
Summary Statistics

The table presents summary statistics for the period August 2002 to December 2016. The frequency is weekly. The price variable p_t is noise in corporate bond yields from equation (3). The quantity variable Q_t is aggregate dealer gross positions from equation (4), with $q_t = \log Q_t$. Amihud is the median Amihud (2002) measure, IRC is the median imputed roundtrip cost measure of Feldhütter (2012), and Basis is the Bond-CDS basis from JP Morgan. AR(1) and AR(12) are the autocorrelations at lags 1 and 12, respectively. The sample is weekly from August 2002 to December 2016.

Panel A. Univariate Statistics				
	Mean	Std	AR(1)	AR(12)
Q_t	21.97	3.43	0.99	0.80
q_t	16.89	0.17	0.99	0.80
p_t	13.76	8.23	0.95	0.70
Panel B. Pairwise Correlations in Levels				
	p_t	$Amihud_t$	IRC_t	$Basis_t$
q_t	-0.57	-0.59	-0.55	-0.58
p_t		0.55	0.55	0.90
$Amihud_t$			0.93	0.62
IRC_t				0.65
Panel C. Pairwise Correlations in Weekly Changes				
	Δp_t	$\Delta Amihud_t$	ΔIRC_t	$\Delta Basis_t$
Δq_t	0.13	0.00	-0.01	0.07
Δp_t		0.27	0.13	0.16
$\Delta Amihud_t$			0.60	0.03
ΔIRC_t				0.07

Table III
Structural Shocks and Other Financial Variables

The left side of the table reports the correlation between the liquidity supply shock and the innovation in each financial variable. The right side reports the correlation between the liquidity demand shock and the innovation in each financial variable. t-statistics are also reported. For explanatory variables that are returns (i.e., betting-against-beta return, corporate bond aggregate return), the innovation is defined as the return itself. For all other explanatory variables, the innovation is determined using a univariate autoregression. The frequency is monthly, and the sample period is August 2002 to December 2016. See Internet Appendix Section VIII for detailed variable definitions. Also reported are the R^2s for multivariate regressions of each structural liquidity shock on the indicated explanatory variables.

	Liquidity Supply Shock		Liquidity Demand Shock	
Innovation	ρ	t-stat	ρ	t-stat
Panel A. Balance Sheet and Funding Costs				
Intermediary capital ratio	0.38	(5.40)	−0.02	(−0.28)
Dealer CDS spread	−0.25	(−3.33)	−0.14	(−1.82)
Betting-against-beta return	0.23	(3.12)	−0.13	(−1.65)
TED spread	−0.27	(−3.66)	−0.04	(−0.54)
Covered interest parity (CIP) deviation	−0.31	(−4.30)	0.06	(0.83)
Fraction of agency (riskless) trades	−0.33	(−4.61)	−0.04	(−0.50)
R^2 using all Panel A variables	0.25		0.08	
Panel B. Corporate Bond Issuance and Fund Flows				
Lagged issuance	−0.02	(−0.23)	0.16	(2.15)
Lagged mutual fund flows	−0.11	(−1.45)	0.19	(2.57)
R^2 using all Panel B variables	0.01		0.06	
Panel C. Market Conditions				
VIX	−0.16	(−2.05)	−0.05	(−0.66)
Lagged corporate bond aggregate return	0.16	(2.08)	−0.03	(−0.38)
R^2 using all Panel C variables	0.04		0.00	
R^2 using all explanatory variables	0.25		0.14	

Table IV
Monte-Carlo Comparison of Sign-Identified Structural Shocks with True Values

The table reports the R^2 given by

$$R_m^2 = 1 - \frac{\Sigma_t(\hat{v}_{m,t} - v_{m,t})^2}{\Sigma_t v_{m,t}^2},$$

where $v_{m,t}$ is the true structural shock generated by the m-th run of the Monte Carlo simulation and $\hat{v}_{m,t}$ is the posterior mean structural shock estimated by applying the structural VAR with sign restrictions on the simulated data. The table presents summary statistics for the distribution of R_m^2 across 1,000 simulations. $R_{m,s}^2$ is the R^2 for supply shocks, and $R_{m,d}^2$ is the R^2 for demand shocks.

	Mean	Standard Deviation	Percentile 2.5	16	50	84	97.5
$R_{m,s}^2$	0.97	0.02	0.93	0.96	0.97	0.98	0.99
$R_{m,d}^2$	0.97	0.02	0.93	0.96	0.97	0.98	0.99

Table V
Bond-Level Panel Regressions of Returns on Liquidity Supply and Demand Betas

The table reports average slope coefficient estimates for (10) to (13). Slope coefficients are reported for the bond-level liquidity supply beta $\beta_{k,s,t}$, liquidity demand beta $\beta_{k,d,t}$, Amihud illiquidity beta $\beta_{k,Amihud,t}$, Pástor-Stambaugh illiquidity beta $\beta_{k,PS,t}$, liquidity quantity beta $\beta_{k,q,t}$, and log Roll illiquidity $\log(Roll_{k,t})$. Betas on the right-hand side are post-formation betas that assign portfolio betas to individual bonds. The final column indicates whether remaining time to maturity, log amount outstanding, lagged one-month return, and credit rating dummy variables are included as controls. The estimated coefficients for these control variables are presented in Section IX of the Internet Appendix. Values in parentheses are GMM t-statistics that account for errors in the first-stage estimation of betas and the cross-sectional and serial correlation in errors terms, as detailed in Appendix B. The frequency is monthly, and the sample period is September 2004 to December 2016.

	β_s	β_d	β_{Amihud}	β_{PS}	β_q	log *Roll*	Controls for maturity, size, lagged return, and credit rating
(1)	0.91						No
	(3.05)						
(2)	0.42					0.56	Yes
	(2.21)					(2.31)	
(3)		-0.80					No
		(-0.71)					
(4)		0.31				0.58	Yes
		(0.66)				(2.38)	
(5)	0.87		-0.32				No
	(3.74)		(-0.54)				
(6)	0.36		-0.09			0.56	Yes
	(2.53)		(-0.45)			(2.39)	
(7)	0.87			-1.36			No
	(3.53)			(-0.24)			
(8)	0.39			-0.21		0.56	Yes
	(2.22)			(-0.16)		(2.33)	
(9)					0.02		No
					(2.09)		
(10)					0.01	0.56	Yes
					(2.31)	(2.20)	

Table VI
Average Returns and Alphas for Value-Weighted Portfolios Sorted on the Liquidity Supply Beta

Corporate bonds are independently double-sorted on their supply beta (four categories) and remaining time to maturity (five categories) into 20 portfolios. We take the equal-weighted average across five maturity bins to obtain four beta-sorted portfolios. The highest-beta portfolio is further subdivided into two bins, low (L) and high (H). Returns are monthly and value-weighted, and the sample period is August 2004 to December 2016. Reported are the average returns in excess of the T-bill rate, pre-formation betas (estimated using three-year rolling windows), and post-formation betas. Alphas are reported for different factor models, including Fama and French (2015) augmented with TERM and DEF factors, Bai, Bali, and Wen (2019), and He, Kelly, and Manela (2017).

	1 (low)	2	3	4 (high)	4L	4H	4 - 1	4H - 1
Panel A. Average Excess Returns								
$\bar{R}^e$	0.30	0.28	0.38	0.72	0.49	1.05	0.42	0.75
$t(\bar{R}^e)$	(2.16)	(2.59)	(3.22)	(3.79)	(2.78)	(4.40)	(3.46)	(4.06)
Panel B. Fama-French Five-Factor Model + TERM + DEF								
α	0.02	0.06	0.19	0.54	0.26	0.94	0.52	0.92
$t(\alpha)$	(0.17)	(0.79)	(1.75)	(2.28)	(1.40)	(2.66)	(2.66)	(2.91)
Panel C. Bai, Bali, and Wen Five-Factor Model								
α	-0.13	-0.06	0.02	0.23	-0.04	0.63	0.35	0.76
$t(\alpha)$	(-1.81)	(-2.34)	(0.63)	(2.07)	(-0.67)	(2.64)	(2.07)	(2.59)
Panel D. He, Kelly, and Manela Two-Factor Model								
α	0.15	0.17	0.26	0.51	0.28	0.84	0.36	0.69
$t(\alpha)$	(0.84)	(1.35)	(1.84)	(2.00)	(1.36)	(2.32)	(1.93)	(2.24)
Panel E. He, Kelly, and Manela + Bai, Bali, and Wen + TERM + DEF								
α	-0.14	-0.06	0.07	0.32	0.02	0.76	0.46	0.90
$t(\alpha)$	(-1.21)	(-0.53)	(0.62)	(2.20)	(0.11)	(3.54)	(2.51)	(3.04)
Panel F. Average Characteristics of Bonds								
β_s^{Pre}	-3.18	-0.72	0.49	5.20	2.27	8.24		
β_s^{Post}	-0.03	-0.15	0.01	0.34	0.30	0.47		
Maturity (years)	8.1	7.9	7.9	8.1	8.0	8.2		
Size (million USD)	755.3	852.1	770.5	660.1	677.0	644.1		
Roll (%)	1.04	0.79	0.92	1.43	1.13	1.78		
IRC (%)	0.72	0.63	0.67	0.91	0.77	1.07		
Panel G. Fraction of Credit Ratings								
AA+	11%	14%	8%	2%	3%	1%		
A	36%	43%	35%	17%	23%	10%		
BBB	26%	31%	37%	30%	36%	24%		
HY	26%	12%	19%	49%	38%	60%		

Table VII
Bond Market Aggregate Return Forecasting Regressions

The table reports results for estimating regressions of the form

$$
\begin{aligned}
R^e_{t+h} &= b_0 + b_1 q_t + \eta_{t+h} \\
R^e_{t+h} &= b_0 + b_{0,D} D_t + b_1 q_t D_t + b_2 q_t (1 - D_t) + c X_t + \eta_{t+h}
\end{aligned}
$$

where R_{t+h} is the return between weeks t and $t+h$ for the aggregate corporate bond market, q_t is the logarithm of dealer gross positions, and D_t is a dummy variable equal to one if demand shocks are greater in magnitude than supply shocks over the past $W \in \{13, 26, 52\}$ weeks; see Section IV.C for details. X_t is a vector of control variables: the term spread, the dividend-price ratio, the variance risk premium, and an option-based skewness measure. The sample is weekly from August 2002 to December 2016. t-statistics reported in parentheses are corrected for overlapping observations following Hodrick (1992).

	Without Crisis				With Crisis			
Horizon (weeks)	4	13	26	52	4	13	26	52
Panel A. Unconditional Forecasting Regressions								
q	-1.83	-5.60	-8.15	-8.68	0.08	-1.60	-4.79	-10.55
	(-2.06)	(-2.31)	(-1.81)	(-1.48)	(0.08)	(-0.58)	(-0.94)	(-1.18)
$\bar{R}^2$	0.03	0.09	0.09	0.06	0.00	0.01	0.03	0.07
Panel B1. 13 Weeks, Without Controls								
$q * D$	-1.54	-3.28	-4.22	-0.44	0.48	2.19	2.07	3.62
	(-1.49)	(-1.05)	(-0.72)	(-0.05)	(0.47)	(0.66)	(0.34)	(0.32)
$q * (1 - D)$	-2.14	-8.56	-13.89	-20.68	-0.45	-6.89	-14.59	-30.80
	(-1.49)	(-3.41)	(-3.60)	(-3.76)	(-0.31)	(-2.07)	(-2.71)	(-3.74)
$\bar{R}^2$	0.03	0.11	0.12	0.13	0.00	0.08	0.13	0.26
Panel B2. 13 Weeks, With Controls								
$q * D$	-2.42	-5.14	-7.20	-5.61	-0.32	-0.28	-2.34	-4.39
	(-2.29)	(-1.68)	(-1.33)	(-0.75)	(-0.32)	(-0.09)	(-0.42)	(-0.45)
$q * (1 - D)$	-1.34	-5.85	-9.20	-12.47	0.14	-5.11	-11.35	-24.18
	(-0.94)	(-2.38)	(-2.51)	(-2.47)	(0.10)	(-1.54)	(-2.26)	(-3.37)
$\bar{R}^2$	0.12	0.28	0.38	0.56	0.07	0.19	0.31	0.53

Table VII
Bond Market Aggregate Return Forecasting Regressions – Continued

	Without Crisis				With Crisis			
Horizon (weeks)	4	13	26	52	4	13	26	52
Panel C1: 26 Weeks, Without Controls								
$q * D$	-2.04	-4.13	-1.26	1.95	1.86	4.59	8.85	9.92
	(-1.56)	(-1.10)	(-0.19)	(0.21)	(1.37)	(1.12)	(1.21)	(0.73)
$q * (1 - D)$	-1.72	-7.00	-14.58	-19.24	-1.65	-7.65	-18.44	-31.36
	(-1.47)	(-2.81)	(-3.18)	(-3.59)	(-1.47)	(-2.54)	(-3.46)	(-4.17)
$\bar{R}^2$	0.03	0.09	0.15	0.15	0.04	0.13	0.30	0.35
Panel C2: 26 Weeks, With Controls								
$q * D$	-2.97	-6.20	-4.60	-3.26	1.21	2.36	5.32	2.47
	(-2.19)	(-1.64)	(-0.72)	(-0.36)	(0.87)	(0.58)	(0.76)	(0.20)
$q * (1 - D)$	-1.04	-4.61	-10.64	-12.73	-0.94	-5.75	-14.99	-24.97
	(-0.88)	(-1.74)	(-2.32)	(-2.31)	(-0.83)	(-1.87)	(-2.92)	(-3.66)
$\bar{R}^2$	0.12	0.28	0.39	0.56	0.09	0.22	0.43	0.59
Panel D1: 52 Weeks, Without Controls								
$q * D$	-0.65	-0.77	6.67	13.54	3.86	8.63	14.56	16.13
	(-0.39)	(-0.16)	(0.75)	(0.86)	(2.33)	(1.80)	(1.67)	(0.97)
$q * (1 - D)$	-2.13	-6.79	-11.59	-18.23	-2.24	-7.84	-16.85	-29.97
	(-1.92)	(-2.37)	(-2.17)	(-3.06)	(-2.15)	(-2.67)	(-3.16)	(-4.02)
$\bar{R}^2$	0.03	0.10	0.16	0.18	0.12	0.24	0.41	0.38
Panel D2: 52 Weeks, With Controls								
$q * D$	-2.46	-6.10	-2.55	0.15	3.23	6.18	9.92	7.06
	(-1.37)	(-1.22)	(-0.29)	(0.01)	(1.86)	(1.26)	(1.14)	(0.44)
$q * (1 - D)$	-1.49	-4.44	-7.95	-11.88	-1.61	-6.28	-13.83	-24.30
	(-1.33)	(-1.51)	(-1.52)	(-2.07)	(-1.50)	(-2.09)	(-2.66)	(-3.58)
$\bar{R}^2$	0.11	0.28	0.40	0.56	0.15	0.31	0.52	0.59

Appendix A. Robustness of Noise Measurement

A. *Subsample of Bonds Used to Construct Noise*

As detailed in Section I, noise and dealer gross positions are calculated for dollar-denominated, publicly offered, fixed-coupon corporate bonds that have no embedded options other than make-whole call provisions. However, the universe of bonds used to compute noise is smaller than the universe used to compute dealer gross positions, for two reasons. First, we calculate noise using only corporate bonds from large issuers, because the noise measure relies on fitted issuer-level yield curves. Second, we calculate dealer gross positions using TRACE and we calculate noise using Merrill Lynch data; not all bonds included in TRACE are included in the Merrill Lynch data. (As discussed in Section I.A, we use Merrill Lynch data to calculate noise because TRACE prices exist only for bonds that have recently transacted at large volumes, making it difficult to calculate issuer-level yield curves for a large number of issuers.)

Here, we examine how these filters might affect the noise measure. To do so, we divide all bonds used in our analysis into two nonoverlapping subsamples: matched bonds used to calculate noise and unmatched bonds used to calculate dealer gross positions but not used to calculate noise.

First, we consider whether illiquidity for the matched bonds comoves with illiquidity for the unmatched bonds. As shown in Table A.I, Panel A, for three standard illiquidity measures (imputed roundtrip cost, the Amihud measure, and volume), the illiquidity of matched bonds is strongly positively correlated with the illiquidity of unmatched bonds. These correlations are somewhat larger when considering only IG bonds than when considering only HY bonds.

[Insert Table A.I near here]

Second, we consider whether matched bonds are, on average, more or less liquid than unmatched bonds. As shown in Table A.I, Panel B, the subsample used to compute noise consists of more liquid bonds than the subsample not used to compute noise. On average, the bonds used to compute noise have a lower imputed roundtrip cost, a lower Amihud illiquidity measure, and higher transaction volume. The difference in average illiquidity is intuitive, as one would expect the bonds issued by large issuers to be more liquid than those issued by small issuers. However, in our structural VAR in equations (6) and (7), an increase in average noise does not affect our estimates of the slope coefficients or the covariance matrix of the residual, which are the objects of interest.

B. Prices in Merrill Lynch and TRACE Data Sets

In this section, we compare price data from Merrill Lynch and TRACE using month-end overlapping observations from 2002 to 2016. Restricting attention to overlapping observations, we have 229,228 bond-month observations. For each overlapping observation, we calculate the yield-to-maturity using the TRACE price and the Merrill Lynch price.[28]

[28]To calculate the month-end price using TRACE, we follow Bessembinder, Kahle, Maxwell, and Xu (2009) and compute the volume-weighted average price using transac-

For the analysis in Table A.II, we double-sort bonds using five ratings categories and four maturity categories. As shown in Panel A, average yields in the two data sets are very similar, though average yields are slightly higher in the Merrill Lynch data. Differences in the level or slope of yields can be easily accounted for in the Nelson-Siegel-Svensson model.

[Insert Table A.II near here]

We repeat the analysis, conditioning on market conditions being illiquid. To this end, we study the subsample of year-end observations. As shown in Panel B, yields-to-maturity are again similar. The results in Table A.II suggest that Merrill Lynch and TRACE prices, where they are both available, are similar for a variety of maturity and ratings categories, both on average and during times of higher market illiquidity.

tions of $100,000 or more.

Table A.I
Comparison of Samples for Computing Noise and Dealer Gross Positions

Matched bonds are bonds that appear in the TRACE and Merrill Lynch data sets from issuers with at least seven bonds outstanding. Matched bonds are used to compute noise. Unmatched bonds are bonds in TRACE that are included in aggregate dealer gross positions but are not used to compute noise. IRC is the median imputed roundtrip cost of Feldhütter (2012), Amihud is the median Amihud (2002) measure, and Volume is the median dollar trading volume in thousands of U.S. dollars.

			# obs	(%)	IRC	Amihud	Volume
Panel A. Correlation of time series for matched and unmatched bonds, by rating category							
All					0.90	0.91	0.81
IG					0.93	0.94	0.87
HY					0.74	0.65	0.58
Panel B. Number of observations and average values							
All	TRACE	All issuers	1,519,209	100%	0.42	1.40	21,918
		Large issuers	850,191	56%	0.39	1.33	23,132
	ML	All issuers	1,355,919	89%	0.44	1.46	22,349
		Large issuers	548,202	36%	0.35	1.18	23,113
IG	TRACE	All issuers	1,073,921	100%	0.36	1.24	20,674
		Large issuers	738,469	69%	0.35	1.23	21,936
	ML	All issuers	938,862	87%	0.38	1.31	21,192
		Large issuers	500,739	47%	0.34	1.16	22,363
HY	TRACE	All issuers	445,288	100%	0.56	1.72	24,919
		Large issuers	111,722	25%	0.63	1.83	31,041
	ML	All issuers	417,057	94%	0.57	1.74	24,953
		Large issuers	47,463	11%	0.47	1.34	31,027

Table A.II
Comparing Yield-to-Maturity Between Merrill Lynch and TRACE Data

The table reports the average yield-to-maturity (%) for each credit rating and maturity category using overlapping month-end observations in Merrill Lynch and TRACE. The sample period is July 2002 to December 2016.

	Merrill Lynch				TRACE			
Maturity	< 4yr	4-7yr	7-12yr	> 12yr	< 4yr	4-7yr	7-12yr	> 12yr
Panel A. Average, Full Sample								
AAA	3.39	4.03	4.40	4.97	3.31	3.99	4.35	4.96
AA	2.99	3.86	4.55	5.12	2.92	3.81	4.51	5.10
A	2.88	3.76	4.51	5.31	2.82	3.72	4.48	5.29
BBB	3.34	4.28	4.92	5.87	3.28	4.24	4.89	5.85
HY	11.18	9.57	8.12	9.36	11.01	9.44	8.06	9.25
Panel B. End of Year Only								
AAA	3.24	4.24	4.54	4.83	3.08	4.07	4.44	4.78
AA	3.03	3.82	4.55	5.08	2.91	3.72	4.46	5.04
A	2.85	3.83	4.70	5.39	2.74	3.71	4.61	5.33
BBB	4.00	4.50	5.24	6.14	3.86	4.37	5.16	6.11
HY	16.34	11.81	8.86	12.95	16.05	11.70	8.78	12.46

Appendix B. Standard Errors for Cross-Sectional Risk Premia Estimates

This section explains how we calculate Generalized Method of Moments (GMM) standard errors for the risk premia estimates in Section IV.A. Our approach accounts for possible errors in the first-stage estimation of betas and for heteroskedasticity and autocorrelation in the error terms in the second-stage estimation of risk premia.

To begin, for each bond and each month t, we use the bond's returns over the previous 36 months to estimate its liquidity supply and demand betas in (9). We then sort bonds into 10 portfolios according to their estimated beta. We calculate equal-weighted portfolio returns.

In the first stage, using 10 beta-sorted portfolios, we regress excess returns on factors,

$$R^e_{\pi,t} = a_\pi + \beta_{\pi,MKT} R^{e,MKT}_t + \beta_{\pi,s} v^s_t + \beta_{\pi,d} v^d_t + u_{\pi,t}, \tag{B1}$$

where $R^e_{\pi,t}$ is the excess return on portfolio π, a_π is a constant term, and $u_{\pi,t}$ is the residual for portfolio π. Following Fama and French (1992), we assign the equal-weighted portfolio betas, $\beta_{\pi,s}$, to individual bonds in each portfolio.

Equivalently, the portfolio-level time-series regression in (B1) can be written as a pooled OLS regression at the bond level using dummy variables,

$$R^e_{k,t} = aD_{k,t} + \beta_{MKT} D_{k,t} R^{e,MKT}_t + \beta_s D_{k,t} v^s_t + \beta_d D_{k,t} v^d_t + u_{k,t}, \tag{B2}$$

where $a = \left(a_1, \ldots, a_{10} \right)$, $\beta_\xi = \left(\beta_{1,\xi}, \ldots, \beta_{10,\xi} \right)$ for $\xi \in (MKT, s, d)$, $D_{k,t}$ is a 10-by-1 vector of dummy variables, and π's entry of $D_{k,t}$ equals one if bond k belongs to portfolio π in month t, and zero otherwise.

The regressions (B1) and (B2) yield the same estimates for a and β_ξ when the number of bonds in a month, N_t, is constant over time. When N_t varies over time, we can ensure the equivalence by multiplying each observation in month t by $\sqrt{N/N_t}$ where $N = \frac{1}{T}\sum_t N_t$, for both the left- and the right-hand side of (B2).[29] Because the second-stage regression is estimated at the bond level, we use the bond-level regression (B2) to compute standard errors.

In the second stage, to estimate the liquidity supply risk premium, we estimate (10) using a pooled OLS regression. We group the slope coefficients into a vector, $\gamma = [\gamma_0, \gamma_1, \gamma_3]'$.

Next, we compute the GMM standard errors for $\hat{\gamma}$, accounting for the cross-sectional and serial correlation in error terms in (10) and estimation errors in $\hat{\beta}_s$ in (B2).

Define the moments

$$f_{k,t}(\theta) = \begin{bmatrix} u_{k,t}F_{k,t} \\ \mu_{k,t} \\ \mu_{k,t}\beta_{k,s,t-1} \\ \mu_{k,t}C_{k,t-1} \end{bmatrix}, \tag{B3}$$

where $\theta \equiv [a', \beta', \gamma']'$ and $F_t \equiv [D'_{k,t}, D'_{k,t}R_t^{e,MKT}, D'_{k,t}v_t^s, D'_{k,t}v_t^d]'$. The moment conditions are

$$g(\theta) = E[f_{k,t}(\theta)] = 0. \tag{B4}$$

[29] We can regard this procedure as a generalization of weighted least square (WLS) estimates. For a regression $y = X\beta + \epsilon$, we can obtain the WLS estimates by $\hat{\beta} = (X'\Omega X)^{-1}X'\Omega y$, where Ω is a diagonal matrix containing a weight for each observation (e.g., N/N_t in this case). The portfolio-level regression treats each monthly observation equally. Thus, in the bond-level regression, an observation in a month with fewer bonds receives more weight than an observation in a month with more bonds.

We estimate the GMM standard errors using the covariance matrix

$$V = D^{-1} S D^{-1\prime}, \tag{B5}$$

where D is the derivative of the moment conditions with respect to θ, and S is the covariance matrix of the moments in (B3).

The covariance matrix S is

$$S = \sum_{l=-\infty}^{\infty} E[f_{k,t}(\theta) f_{k,t-l}(\theta)']. \tag{B6}$$

We estimate S using a Bartlett kernel (Newey and West (1987)). We calculate an empirical counterpart to $E[f_{k,t}(\theta) f_{k,t-l}(\theta)']$ in (B6) using an approach that corrects for cross-sectional correlation and autocorrelation in error terms. To address these issues, our estimator of S is

$$S_T = \sum_{l=-L}^{L} \omega(l) \frac{1}{NT} \sum_{t=1}^{T} \left(\sum_{k=1}^{N_t} f_{k,t}(\theta) \right) \left(\sum_{k=1}^{N_{t-l}} f_{k,t-l}(\theta)' \right), \tag{B7}$$

where and $\omega(l) = (L+1-l)/(L+1)$ is the Bartlett kernel with lag truncation L. By first summing the observations across bonds every month and then squaring the sum, we account for the cross-sectional correlation in $f_{k,t}(\theta)$.

We set the lag truncation for the Newey-West kernel $L = 8$. The choice of $L = 8$ lags reflects the fact that we cannot reject the null of no autocorrelation in the residual (B1) at lags greater than four months. We view $L = 8$ months as a conservative choice, given that the Newey-West kernel assigns lower weights to higher-order autocorrelation terms.

We also estimate the derivative matrix D,

$$
\begin{aligned}
D &= \frac{\partial g(\theta)}{\partial \theta'} \\
&= \left[\begin{array}{cc} \begin{pmatrix} & -E[F_{k,t}F'_{k,t}] & \end{pmatrix} & 0 \\ \begin{array}{cccc} 0 & 0 & \frac{\partial}{\partial \beta_s}E[\mu_{k,t}] & 0 \\ 0 & 0 & \frac{\partial}{\partial \beta_s}E[\mu_{k,t}\beta_{k,s,t-1}] & 0 \\ 0 & 0 & \frac{\partial}{\partial \beta_s}E[\mu_{k,t}C_{k,t-1}] & 0 \end{array} & \begin{pmatrix} \\ -E[\Gamma_{k,t-1}\Gamma'_{k,t-1}] \\ \\ \end{pmatrix} \end{array}\right], \qquad \text{(B8)}
\end{aligned}
$$

where $\Gamma_{k,t} = \begin{pmatrix} 1 & \beta_{k,t} & C_{k,t} \end{pmatrix}'$.

A key input in the derivative matrix is $\frac{\partial}{\partial \beta_s}E[\mu_{k,t}\beta_{k,s,t-1}]$ in the third row, which accounts for the fact that the estimate for γ depends on β_s, which is estimated in the first stage.

We partition V as

$$V = \begin{pmatrix} V^{[11]} & V^{[12]} \\ V^{[21]} & V^{[22]} \end{pmatrix}, \qquad \text{(B9)}$$

where $V^{[22]}$ is the covariance matrix for $\hat{\gamma}$ in the second-stage panel regression (10).

Finally, we estimate $\hat{V}$ using (B5) to (B8). The covariance matrix for $\hat{\gamma}$ is

$$\text{cov}(\hat{\gamma}) = \frac{1}{NT}\hat{V}^{[22]}, \qquad \text{(B10)}$$

and we compute GMM t-statistics based on $\text{cov}(\hat{\gamma})$. The standard errors for liquidity demand and other risk factors are computed analogously.

REFERENCES

Acharya, Viral V, and Lasse Heje Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics* 77, 375–410.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Anand, Ambar, Chotibhak Jotikasthira, and Kumar Venkataraman, 2017, Do buy-side institutions supply liquidity in bond markets? Evidence from mutual funds, Working paper, Syracuse University.

Asquith, Paul, Andrea S. Au, Thomas R. Covert, and Parag A. Pathak, 2013, The market for borrowing corporate bonds, *Journal of Financial Economics* 107, 155–182.

Bai, Jennie, Turan G. Bali, and Quan Wen, 2019, Common risk factors in the cross-section of corporate bond returns, *Journal of Financial Economics* 131, 619–642.

Bai, Jennie, and Pierre Collin-Dufresne, 2019, The CDS-bond basis, *Financial Management* 48, 417–439.

Bao, Jack, Maureen O'Hara, and Xing Zhou, 2018, The Volcker rule and corporate bond market making in times of stress, *Journal of Financial Economics* 130, 95–113.

Bao, Jack, Jun Pan, and Jiang Wang, 2011, The illiquidity of corporate bonds, *Journal of Finance* 66, 911–946.

Bessembinder, Hendrik, Stacey E. Jacobsen, William F. Maxwell, and Kumar Venkataraman, 2018, Capital commitment and illiquidity in corporate bonds, *Journal of Finance* 73, 1615–1661.

Bessembinder, Hendrik, Kathleen M. Kahle, William F. Maxwell, and Danielle Xu, 2009, Measuring abnormal bond performance, *Review of Financial Studies* 22, 4219–4258.

Bollerslev, Tim, George Tauchen, and Hao Zhou, 2009, Expected stock returns and variance risk premia, *Review of Financial Studies* 22, 4463–4492.

Bongaerts, Dion, Frank de Jong, and Joost Driessen, 2017, An asset pricing approach to liquidity effects in corporate bond markets, *Review of Financial Studies* 30, 1229–1269.

Chen, Hui, Scott Joslin, and Sophie Xiaoyan Ni, 2018, Demand for crash insurance, intermediary constraints, and risk premia in financial markets, *Review of Financial Studies* 32, 228–265.

Choi, Jaewon, and Yesol Huh, 2018, Customer liquidity provision: Implications for corporate bond transaction costs, Working paper, Federal Reserve Board.

Chordia, Tarun, Amit Goyal, Yoshio Nozawa, Avanidhar Subrahmanyam, and Qing Tong, 2017, Are capital market anomalies common to equity and corporate bond markets? An empirical investigation, *Journal of Financial and Quantitative Analysis* 52, 1301–1342.

Cohen, Lauren, Karl B. Diether, and Christopher J. Malloy, 2007, Supply and demand shifts in the shorting market, *Journal of Finance* 62, 2061–2096.

Comerton-Forde, Carole, Terrence Hendershott, Charles M. Jones, Pamela C. Moulton, and Mark S. Seasholes, 2010, Time variation in liquidity: The role of market-maker inventories and revenues, *Journal of Finance* 65, 295–331.

Dick-Nielsen, Jens, Peter Feldhütter, and David Lando, 2012, Corporate bond liquidity before and after the onset of the subprime crisis, *Journal of Financial Economics* 103, 471–492.

Dick-Nielsen, Jens, and Marco Rossi, 2018, The cost of immediacy for corporate bonds, *Review of Financial Studies* 32, 1–41.

Du, Wenxin, Alexander Tepper, and Adrien Verdelhan, 2018, Deviations from covered interest rate parity, *Journal of Finance* 73, 915–957.

Duarte, Jefferson, and Lance Young, 2009, Why is PIN priced?, *Journal of Financial Economics* 91, 119–138.

Duffie, Darrell, 2010, Presidential address: Asset price dynamics with slow-moving capital, *Journal of Finance* 65, 1237–1267.

Easley, David, Soeren Hvidkjaer, and Maureen O'Hara, 2002, Is information risk a determinant of asset returns?, *Journal of Finance* 57, 2185–2221.

Elsaify, Amora, and Nikolai Roussanov, 2016, Why do firms issue callable bonds?, Working paper, University of Pennsylvania.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Feldhütter, Peter, 2012, The Same Bond at Different Prices: Identifying Search Frictions and Selling Pressures, *Review of Financial Studies* 25, 1155–1206.

Fleckenstein, Matthias, Francis A. Longstaff, and Hanno Lustig, 2014, The TIPS-Treasury bond puzzle, *Journal of Finance* 69, 2151–2197.

Fontaine, Jean-Sébastien, and René Garcia, 2012, Bond liquidity premia, *Review of Financial Studies* 25, 1207–1254.

Frazzini, Andrea, and Lasse Heje Pedersen, 2014, Betting against beta, *Journal of Financial Economics* 111, 1–25.

Friewald, Nils, and Florian Nagler, 2016, Dealer inventory and the cross-section of corporate bond returns, Working paper, Norwegian School of Economics.

Friewald, Nils, and Florian Nagler, 2019, Over-the-counter market frictions and yield spread changes, *Journal of Finance* 74, 3217–3257.

Gârleanu, Nicolae, and Lasse Heje Pedersen, 2011, Margin-based asset pricing and deviations from the law of one price, *Review of Financial Studies* 24, 1980–2022.

Gilchrist, Simon, and Egon Zakrajšek, 2012, Credit spreads and business cycle fluctuations, *American Economic Review* 102, 1692–1720.

Goldberg, Jonathan, 2020, Liquidity supply by broker-dealers and real activity, *Journal of Financial Economics* 136, 806–827.

Goldstein, Michael A., and Edith S. Hotchkiss, 2020, Providing liquidity in an illiquid market: Dealer behavior in US corporate bonds, *Journal of Financial Economics* 135, 16–40.

Gromb, Denis, and Dmitri Vayanos, 2018, The dynamics of financially constrained arbitrage, *Journal of Finance* 73, 1713–1750.

Grossman, Sanford J., and Merton H. Miller, 1988, Liquidity and market structure, *Journal of Finance* 43, 617–633.

Grossman, Sanford J., and Joseph E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393–408.

Hameed, Allaudeen, Wenjin Kang, and Shivesh Viswanathan, 2010, Stock market declines and liquidity, *Journal of Finance* 65, 257–293.

He, Zhiguo, Bryan Kelly, and Asaf Manela, 2017, Intermediary asset pricing: New evidence from many asset classes, *Journal of Financial Economics* 126, 1–35.

He, Zhiguo, and Arvind Krishnamurthy, 2013, Intermediary asset pricing, *American Economic Review* 103, 732–770.

Hodrick, Robert J., 1992, Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement, *Review of Financial Studies* 5, 357–386.

Hu, Grace Xing, Jun Pan, and Jiang Wang, 2013, Noise as information for illiquidity, *Journal of Finance* 68, 2341–2382.

Jermann, Urban J., 2019, Negative swap spreads and limited arbitrage, *Review of Financial Studies* 33, 212–238.

Karolyi, G. Andrew, Kuan-Hui Lee, and Mathijs A. Van Dijk, 2012, Understanding commonality in liquidity around the world, *Journal of Financial Economics* 105, 82–112.

Klingler, Sven, and Suresh Sundaresan, 2019, An explanation of negative swap spreads: Demand for duration from underfunded pension plans, *Journal of Finance* 74, 675–710.

Kondor, Péter, and Dimitri Vayanos, 2019, Liquidity risk and the dynamics of arbitrage capital, *Journal of Finance* 74, 1139–1173.

Lin, Hai, Junbo Wang, and Chunchi Wu, 2011, Liquidity risk and expected corporate bond returns, *Journal of Financial Economics* 99, 628–650.

Lou, Xiaoxia, and Tao Shu, 2017, Price impact or trading volume: Why is the Amihud (2002) measure priced?, *Review of Financial Studies* 30, 4481–4520.

Ma, Yueran, 2019, Nonfinancial firms as cross-market arbitrageurs, *Journal of Finance* 74, 3041–3087.

Mitchell, Mark, Lasse Heje Pedersen, and Todd Pulvino, 2007, Slow moving capital, *American Economic Review* 97, 215–220.

Nagel, Stefan, 2012, Evaporating liquidity, *Review of Financial Studies* 25, 2005–2039.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Pástor, Luboš, and Robert F Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642–685.

Pedersen, Lasse Heje, 2015, *Efficiently Inefficient: How Smart Money Invests and Market Prices are Determined* (Princeton University Press).

Sadka, Ronnie, 2010, Liquidity risk and the cross-section of hedge-fund returns, *Journal of Financial Economics* 98, 54 – 71.

Shleifer, Andrei, and Robert W Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35–55.

Svensson, Lars E.O., 1994, Estimating and interpreting forward interest rates: Sweden 1992–1994, NBER working paper w4871.

Uhlig, Harald, 2005, What are the effects of monetary policy on output? Results from an agnostic identification procedure, *Journal of Monetary Economics* 52, 381–419.

Uhlig, Harald, 2017, Shocks, sign restrictions, and identification, in Bo Honoré, Ariel Pakes, Monika Piazzesi, and Larry Samuelson, eds., *Advances in Economics and Econometrics: Eleventh World Congress* (Cambridge University Press).

Vayanos, Dimitri, and Jiang Wang, 2013, Market liquidity: Theory and empirical evidence, in George M. Constantinides, Milton Harris, and Rene M. Stulz, eds., *Handbook of the Economics of Finance*, volume 2 (Elsevier).