The Supply of Liquidity and Real Economic Activity*

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Abstract

This paper identifies shocks to the supply of liquidity by dealer firms and investigates their effects on real economic activity. First, I develop a simple theoretical model of dealer intermediation; then, in a structural VAR model, I use sign restrictions derived from the theoretical model to identify liquidity supply shocks. Liquidity supply shocks that are orthogonal to information contained in macroeconomic and asset price variables have considerable predictive power for economic activity. Moreover, positive liquidity supply shocks cause large and persistent increases in real activity.

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Real economic activity depends—in several ways—on the availability of liquidity in securities and derivatives markets. An important share of business, household and governmental spending is financed through the origination of securities. Real economic activity is also supported by the use of securities and derivatives markets to hedge risks. Thus, the supply of liquidity in securities and derivatives markets should be predictive of real economic activity. This view helps explain why policymakers and market participants were closely attuned to the disappearance of liquidity in securities and derivatives markets during the recent financial crisis.

However, there is no empirical evidence regarding whether the supply of liquidity in securities and derivatives markets predicts real activity. It is difficult to measure fluctuations in the supply of liquidity. Consider haircuts required to borrow against securities or the size of intermediaries' balance sheets. These measures are driven by many factors besides liquidity supply. For example, haircuts on risky assets could rise simply because the underlying collateral became riskier. Similarly, the size of intermediaries' balance sheets is affected by the demand for liquidity. Thus, an increase in haircuts or a decrease in the size of intermediaries' balance sheets are not prima facie evidence of a reduction in liquidity supply.

In this paper, I focus on the supply of liquidity by an important group of financial intermediaries: primary dealers. Primary dealers are the trading counterparties of the Federal Reserve Bank of New York in its implementation of monetary policy. They are generally large financial institutions that intermediate a wide range of securities and derivatives markets.[1]

I use a new method of identifying shocks to the supply of liquidity. I

[1] A list of the firms designated as primary dealers as of September 2016 can be found in Appendix A.

accomplish this goal in two steps. First, I develop a stylized theoretical model of dealer intermediation; this model shows how shocks to the supply of liquidity can be identified using a sign restriction on the impulse responses to such shocks. Second, I use this sign restriction in a structural vector autoregression to estimate the time series of shocks to the supply of liquidity by primary dealers.

In the theoretical model, investors trade two securities with the same payoff. If the investors were able to trade with each other, the two securities would have the same price. However, the model features segmented markets, as in Gromb and Vayanos (2002); there are two types of investors and each type is able to trade only one of the two securities. Hence, potential gains from trade can only be realized by trading through a dealer. For example, if one type of investor seeks to sell and the other to buy, the dealer could take the opposite side of each trade. However, market making by intermediaries involves risk: there is a positive probability that prior to the security prices converging, the dealer will be forced to close out her positions at uncertain prices. As a result, prior to a possible liquidation event, the securities trade for different prices. This noise in security prices compensates dealers for the risk associated with intermediation. An increase in dealer risk aversion leads to greater price dispersion; also, the sum of dealers' gross long and short positions declines. A positive shock to the investors' trading needs also leads to greater price dispersion; however, dealer gross positions rise.

Next, building on the theoretical model, I construct two key inputs for the empirical model: measures of the noise in prices and dealer gross positions in the Treasury market.[2] I focus on the Treasury market in order to identify

[2]One challenge in bringing the theoretical model to the data is that the Treasury market is a complicated market with specific institutional features that must be addressed. In the

shocks to primary dealers' supply of liquidity across a broad range of markets. There are several reasons that I focus on the Treasury market. First, the data available for the Treasury market allows the construction of intermediation measures suggested by the theoretical model. Second, the Treasury market is a central market with wide participation by primary dealers. I link intermediation in the Treasury market to intermediation in other asset markets under the assumption that if primary dealers are foregoing profitable, interest-rate-neutral trades in the U.S. Treasury market, they are also likely to be foregoing opportunities with high risk-adjusted expected profits in other markets.

Using the Treasury market as a laboratory to extract information about dealers' supply of liquidity in a broad set of markets is supported by a number of strands of empirical research. A large literature shows that time-variation in liquidity is correlated across assets and markets.[3] In addition, He, Kelly and Manela (2015) demonstrate that primary dealers' equity capital ratio is a priced risk factor in a wide variety of markets; Adrian, Etula and Muir (2014) show that the leverage of securities broker-dealers alone can explain a remarkable share of variation in expected returns of many equity and Treasury portfolios. These findings suggest that there is a common component to dealer risk-taking in many different markets. Moreover, Treasury market noise can help explain the cross section of hedge fund and carry trade returns (Hu, Pan and Wang (2013)) and variation across countries in the performance of

theoretical model, there are two securities with the same payoff and the same maturity; in the actual Treasury market, there are hundreds of bonds that vary in maturity. Thus, to measure the noise in bond prices, on a day-by-day basis, I estimate a smooth yield curve for nominal Treasury securities; I summarize the noise in Treasury prices by calculating the root mean squared error.

[3]Regarding the correlation of liquidity across stocks, see Chordia, Roll and Subrahmanyam (2000) and Hasbrouck and Seppi (2001). Regarding the correlation of liquidity in equity and bond markets, see Chordia, Sarkar and Subrahmanyam (2005) and Bao, Pan and Wang (2011).

betting-against-beta strategies (Malkhozov et al. (2016)). These results imply that the availability of liquidity in the Treasury market is informative about broader financial market conditions.

During the financial crisis, Federal Reserve officials used the Treasury market—as this paper does—to extract signals about the supply of liquidity more broadly. During the December 15-16, 2008 Federal Open Market Committee meeting, discussing why asset-backed securities (ABS) had fallen in price, a policymaker pointed to the spread between yields for on-the-run Treasury securities (which have been issued recently and are typically the most liquid) and off-the-run Treasury securities:

> I think there's pretty good evidence that there are liquidity strains in the market, beyond just credit strains, impinging on the price of these securities [ABS]. One piece of evidence I would cite is the difference between on-the-run and the off-the-run Treasury security rates, which have gapped out by 40 or 50 basis points... The unwillingness of people—by "people" I mean market makers—to take positions and to do trades—their caution—is affecting the pricing of all kinds of securities well beyond the credit risk, and obviously there's no difference in the credit risk in on-the-run and off-the-run Treasury securities.[4]

At the October 28-29, 2008 FOMC meeting, a Fed official highlighted "a sharp diminution of trading and liquidity in the Treasury securities market" and noted, "The fact that there are severe market-functioning problems in the asset class that is in greatest demand—Treasuries—underscores the scope and

[4]Don Kohn, Transcript of the meeting of the Federal Open Market Committee, December 15-16, 2008.

severity of the markets' broader dysfunction."[5]

Using Treasury market data and a structural vector autoregression (VAR), I estimate the time series of shocks to dealers' supply of liquidity. In the VAR, a positive liquidity supply shock leads to a decrease in noise and an increase in gross dealer positions that are persistent, statistically significant and economically large. Correspondingly, I find that liquidity supply shocks are important for explaining variation in the noise in Treasury prices and the size of dealers' gross positions. For the noise measure, liquidity supply shocks explain about one-half of forecast error variance at short and long horizons; for dealer gross positions, liquidity supply shocks explain about three-quarters of forecast error variance.

This exercise builds on earlier papers that used VARs to identify shocks to dealer intermediation and their effects. Adrian and Shin (2010) identify a dealer shock recursively, by allowing it impact broker-dealer asset growth on impact but restricting it to have no immediate effect on residential investment or inflation. Examining specialist inventory of equities, Comerton-Forde et al. (2010) find that bid-ask spreads widen during periods when specialists have large positions or lose money; Comerton-Forde et al. (2010) also uses a VAR with recursive identification to study the response of bid-ask spreads to inventory and revenue shocks. In contrast, in this paper, liquidity supply shocks are identified using sign restrictions on impulse responses; the specific variables included in the VAR and the sign restrictions are chosen based on a theoretical model of dealer intermediation.

This approach to identifying liquidity supply offers advantages over earlier work on Treasury market liquidity. For example, Hu, Pan and Wang (2013)

[5]William Dudley, Transcript of the meeting of the Federal Open Market Committee, October 28-29, 2008.

assume that variation in noise in Treasury prices is attributable to liquidity supply, but they do not formally identify liquidity supply shocks. Fontaine and Garcia (2012) also use the Treasury market to identify the supply of liquidity across markets. To investigate the effect of liquidity supply on broader securities market intermediation activity, they regress shadow-banking assets on a measure of Treasury market liquidity, using the aggregate quantity of mortgages as an instrumental variable. Their approach relies on the assumption that the aggregate quantity of mortgages is uncorrelated with any other determinants of liquidity supply; this exclusion restriction is a strong assumption, even in the pre-crisis sample period they consider.

Next, I provide evidence about whether the estimated liquidity supply shocks are associated with fluctuations in liquidity supply in asset markets besides the Treasury market. To do so, I use the Senior Credit Officer Opinion Survey (SCOOS). This survey asks primary dealers about securities financing and over-the-counter (OTC) derivatives transactions, as well as liquidity conditions in several fixed-income markets. I find that increases in liquidity supply—as estimated using sign restrictions on noise and dealer holdings in the Treasury market—are associated with primary dealers offering looser terms to investors on securities financing and OTC derivatives transactions, as well as improved liquidity and market functioning in fixed income markets outside the Treasury market.

If the empirical model indeed identifies shocks to liquidity supply across a broad range of markets, it is plausible that these shocks predict macroeconomic outcomes. Thus, I study the predictive content of liquidity supply shocks for real economic activity. To do so, I use two different approaches. First, I run standard forecasting regressions for different measures of real economic activity, in which growth in real activity is predicted by current and lagged

growth, as well as current and lagged liquidity supply shocks. Second, I use a vector autoregression that includes measures of real activity and financial conditions, such as interest rates, inflation and equity market returns. In this second approach, a liquidity supply shock is defined as one that leads, on impact, to a rise in noise and fall in dealer gross positions; it is also required to have no effect, on impact, on real activity and financial conditions. I find that a positive liquidity supply shock is expansionary, leading to a fall in unemployment and a rise in industrial production; the cumulative stock return is positive, option-implied stock market volatility falls and the real federal funds rate rises.

Using both approaches, liquidity supply shocks are significant predictors of real activity. This relationship is economically meaningful. In the forecasting exercise, a one standard deviation shock to current liquidity supply is associated with a decrease in unemployment over the following 12 months of about 0.2 percentage points; the associated increase in industrial production is 0.7 percentage points.

The empirical model allows an analysis of historical episodes. I find that a number of stress episodes are well captured by the estimated liquidity supply shocks. For example, liquidity supply shocks were negative, on balance, during stress episodes associated with: the Russian default and the collapse of the Long-Term Capital Management hedge fund; the suspension of redemptions from Bear Stearns hedge funds in the summer of 2007, an event that marked the beginning of the financial crisis; the collapse of Lehman Brothers in 2008; and flare-ups of the European fiscal crisis in 2010 and 2011. In contrast, liquidity supply shocks were positive, overall, during the economic boom of the mid-2000s and the run-up to the financial crisis.

Related literature

My paper can help interpret the literature on the asset pricing implications of the co-movement in liquidity across assets. Aggregate illiquidity is a priced risk factor in a broad range of asset markets.[6] Two possible channels through which aggregate illiquidity might explain asset returns are: (i) investors may value liquidity per se and be willing to pay a premium for assets that have high returns or are liquid when liquidity is scarce; and (ii) aggregate illiquidity may track fluctuations in real activity, making illiquidity priced because illiquidity is associated with poor real economic performance. The existing literature does not clarify which channel leads investors to price liquidity risk. Although I do not address this question directly, the results in my paper are consistent with the second channel being potentially important.

My paper also provides new empirical evidence in support of recent theoretical research on intermediary asset pricing and business cycles. For example, He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014) develop models in which asset prices are determined by the risk-bearing capacity of experts or financial specialists, who thereby also affect real activity. Consistent with such theories, He, Kelly and Manela (2015) and Adrian, Etula and Muir (2014) demonstrate the usefulness of dealer balance sheet quantities for asset pricing. In this paper, I provide complementary empirical evidence, by showing how liquidity supply affects real economic activity.

In addition, my paper is related to studies of recent episodes of financial market volatility, such as the Flash Crash of 2010. Such episodes have led

[6]Papers showing that liquidity risk is priced include: Pástor and Stambaugh (2003) and Acharya and Pedersen (2005), for the stock market; Lin, Wang and Wu (2011), for corporate bonds; Sadka (2010), for hedge funds; and Franzoni, Nowak and Phalippou (2012), for private equity. For a review of the literature on market liquidity, see Vayanos and Wang (2012).

policymakers and market participants to ask whether such episodes are symptomatic of a lower-frequency deterioration in liquidity supply.[7]

1 A simple model of noise in security prices

This section develops a model of security prices and dealer positions. In the model, there are two securities that represent claims to the same long-term cash flow. However, the securities trade in segmented markets, potentially at different prices; dealers hold long and short positions in the securities to partially overcome market segmentation. The noise in the security prices compensates dealers for making markets.

There are: two investors, A investors and B investors; two securities, A securities and B securities; and three periods, t=1, 2, 3. A and B securities represent a claim to an uncertain cash flow v in period 3.[8]

In period 1, A and B investors have complementary trading needs: A and B investors receive endowment shocks in period 3 that are equal in magnitude but opposite in sign and these endowment shocks are correlated with the cash flow v. However, the markets are segmented: investor A is only able to trade A securities and investor B is only able to trade B securities.[9] Hence, gains

[7]For an analysis of such episodes, see: Kirilenko et al. (2014) (Flash Crash); Joint Staff Report (2015) (volatility on October 15, 2104); Khandani and Lo (2011) (Quant Crash); and Adrian et al. (2013) (Taper Tantrum). Market participants and policymakers have in recent years engaged in a lively debate about the supply of market liquidity; see Dudley (2015) and Schwarzman (2015).

[8]It is straightforward to slightly modify the model to allow the securities to be interpreted as Treasury bonds. Specifically, add a fourth period to the model, in which the securities mature with known value equal to one. Assume there is a perfectly elastic supply of central bank reserves at the exogenous interest rate and that the interest rate between periods 3 and 4 is a random variable R revealed in period 3. Then $v = \frac{1}{R}$.

[9]Examples of investors that are willing to trade only a particular security include, per Pedersen (2015), "price-insensitive insurance companies who need [a given bond] for a specific reason." A related example is an investor who owns a particular security and no longer

from trade between the investors can only be realized by trading through a dealer. Market making by dealers involves risk: in period 2, intermediaries may be forced to liquidate their positions at uncertain prices. As a result, unless dealers are risk neutral, the securities will trade at different prices.

i-investors, with $i \in \{A, B\}$, can trade only in the i-bond and money. Dealers can trade in both markets and money.[10] Financial markets are competitive. At $t = 1$, investors and dealers trade in the i-markets. The period-t price of the i-security is $p_{i,t}$. The gross interest rate is normalized to one. The A and B securities each have net supply g.

The mean of the cash flow v, conditional on period 1 information, is denoted by μ. The variance is denoted by σ. That is,

$$E[v] = \mu$$

and

$$Var[v] = \sigma.$$

The cash flow v is revealed in period 2. Also, with probability λ, dealers are forced to liquidate their positions at uncertain prices: $p_{i,2} = v + \epsilon_i$, where ϵ_A and ϵ_B have variance σ_ϵ.

i-investors have mean-variance preferences over period-3 wealth w_i. That is, i-investors maximize $E[w_i] - \frac{1}{2\gamma} Var[w_i]$, where γ is i-investors' risk tol-

wants the associated risk may not be willing to shed that risk by going short a different security with the same payoff; she simply wants to sell, even if doing so is more expensive. Alternatively, consider a sophisticated investor who has shorted a particular security by obtaining the security on loan and then selling it; when the investor wants to close out the trade, she needs to buy back that particular security in order to return it to the lender of the security.

[10] In an appendix (available upon request), I modify the model to include non-dealer intermediaries that, like dealers, are able to trade in both securities markets; I show that the main results of the model still hold.

erance.[11] Dealers also have mean-variance preferences. The risk tolerance of dealers is denoted by γ_D. This risk tolerance γ_D is a proxy for liquidity supply.

The i-investors have a motivation to hedge. In particular, $e_A = -e_B$ and $Cov(v, e_A) = u > 0$.

I denote the period-1 position of dealers in the i-security by x_i; the period-1 position of the i-investor in the i-security is y_i. I denote the period-1 risk premia by ψ, where the i-th element of ψ is:

$$\psi_i = \mu - p_{i,1} \tag{1}$$

At $t = 3$, i-investors receive endowment e_i.

The cash flow v, the liquidation price shocks ϵ_A and ϵ_B, and the realization of the liquidation event are mutually independent. Also, the liquidation price shocks ϵ_A and ϵ_B, the realization of the liquidation event and the endowment e_A are mutually independent.

Define

$$g^* = \left(1 + \frac{2\gamma\sigma}{\gamma_D\sigma + \gamma\lambda\sigma_\epsilon}\right)\frac{u}{\sigma} > 0.$$

I assume that $|g| < g^*$. This assumption guarantees that, in equilibrium, the dealer has a strictly positive position in security B and a strictly negative position in security A, consistent with the role of a marketmaker.

Equilibrium. For dealers, the variance-covariance matrix of the payoffs associated with the A and B securities is given by:

$$\Omega = \begin{bmatrix} \sigma + \lambda\sigma_\epsilon & \sigma \\ \sigma & \sigma + \lambda\sigma_\epsilon \end{bmatrix} \tag{2}$$

[11] Without loss of generality, i-investors and dealers have zero initial wealth.

The vector of dealers' demand, $x = [x_A \; x_B]'$, is given by:

$$x = \Omega^{-1}\gamma_D\psi \tag{3}$$

and the vector of investors' demand, $y = [y_A \; y_B]'$, is:

$$y = \frac{1}{\sigma}\left(\gamma\psi - u\begin{bmatrix}1\\-1\end{bmatrix}\right). \tag{4}$$

Market clearing requires that

$$x + y = g \tag{5}$$

There is a unique equilibrium. Define price dispersion as $|p_{B,1} - p_{A,1}|$ and dealer gross positions as $|x_A| + |x_B|$. Then,

$$\frac{|p_{B,1} - p_{A,1}|}{2} = \frac{1}{\gamma_D \frac{1}{\lambda}\frac{\sigma}{\sigma_\epsilon} + \gamma}u$$

and

$$\frac{|x_A| + |x_B|}{2} = \frac{1}{\sigma + \frac{\gamma}{\gamma_D}\lambda\sigma_\epsilon}u$$

Proposition 1. *An increase in dealer risk tolerance γ_D leads to lower price dispersion and higher dealer gross positions. That is, $\frac{d\left[|p_{B,1}-p_{A,1}|\right]}{d\gamma_D} < 0$ and $\frac{d[|x_A|+|x_B|]}{d\gamma_D} > 0$. An increase in investor risk tolerance γ or a decrease in investor trading needs u also leads to lower price dispersion; however, dealer gross positions decrease.*

Proposition 1 reflects the intuition behind the sign restrictions that will be used in the empirical analysis. Only changes in dealer risk tolerance or liquidation risks (the probability of liquidation λ and the riskiness of liquida-

tion prices κ) lead to opposite-signed changes in the dispersion of bond prices and dealer gross positions. Changes in the payoff's mean, denoted by μ, have no effect on price dispersion or dealer gross positions; an increase in its variance, denoted by σ, leads to lower price dispersion and lower gross positions. Changes in the gross supply of securities, denoted by g, have no effect on price dispersion or dealer gross positions. Instead, if gross supply increases, dealers increase their positions in the A and B securities by the same amount, leaving price dispersion unchanged.

2 Data

This section describes the measurement of the noise in Treasury prices and dealer gross positions in the Treasury market. These measures are empirical analogs of the price dispersion and dealer gross position variables from the theoretical model. One challenge in bringing the theoretical model to the data is that the Treasury market is a complicated market. Most notably, in the theoretical model, there are two securities with the exact same payoff; in the actual Treasury market, there are hundreds of bonds that vary in maturity. The construction of the noise and dealer gross position measures takes into account these and other institutional features of the Treasury market.

2.1 Prices

I measure the noise in Treasury prices as in Gürkaynak, Sack and Wright (2007) and Hu, Pan and Wang (2013). On a day-by-day basis, I estimate a smooth yield curve for nominal Treasury securities. This yield curve is used to price each bond available on that day and to calculate the deviation between

the market yield and the predicted yield. The noise measure is obtained by calculating the root mean squared error.

Specifically, I use the Svensson (1994) model of instantaneous forward rates, given by:

$$f(n) = \beta_0 + \beta_1 \exp(-n/\tau_1) + \beta_2 (n/\tau_1) \exp(-n/\tau_1) + \beta_3 (n/\tau_2) \exp(-n/\tau_2) \quad (6)$$

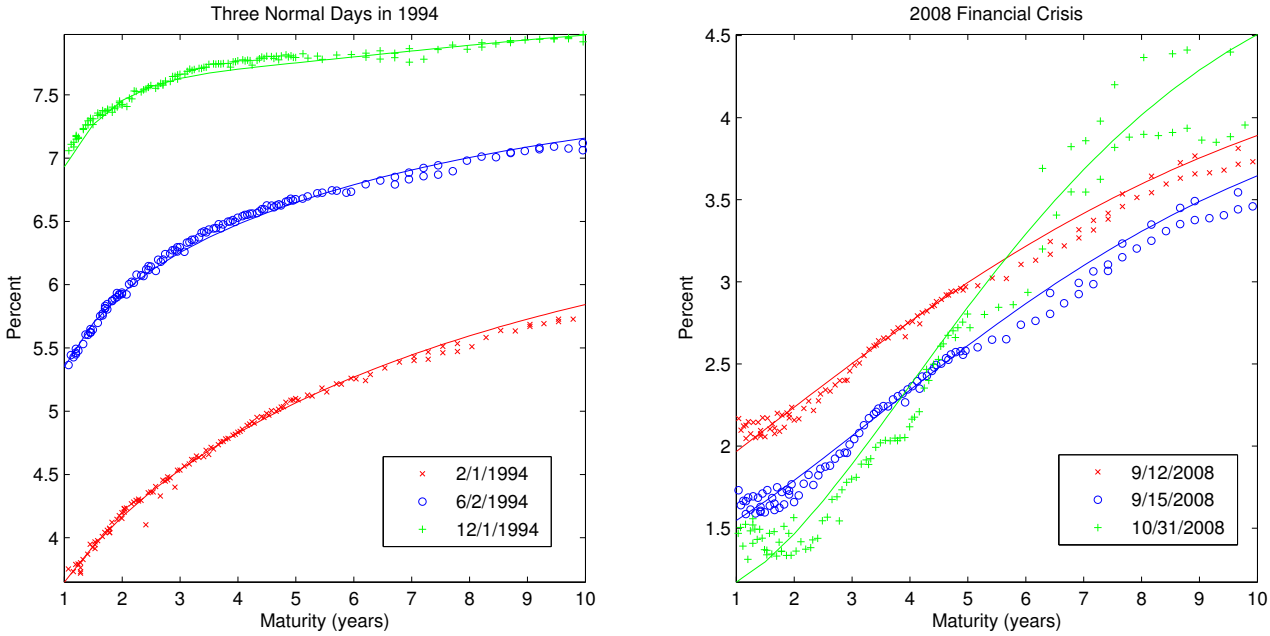
where n is the maturity and the parameters are given by $(\beta_0, \beta_1, \beta_2, \beta_3, \tau_1, \tau_2)$. On each day, I estimate (6) using data on nominal Treasury coupon securities; as in Hu, Pan and Wang (2013), I only include securities with remaining maturity between 1 and 10 years in calculating the noise measure.[12] For each bond, I calculate its predicted price using (6) to discount the entire set of cash flows associated with the bond (i.e., coupon payments and repayment of principal at maturity); I choose the parameters in (6) to minimize the weighted sum of squared differences between actual prices and predicted prices.[13] Data on Treasury prices comes from the Price Quote System (PQS) or the New Price Quote System (NPQS) developed and maintained by the Federal Reserve. Finally, I calculate the noise measure as the root mean squared difference between actual yields and predicted yields.

To illustrate the construction of the noise measure, Figure 1 replicates part of a figure from Hu, Pan and Wang (2013) showing several examples of par-coupon yield curves and market-observed bond yields. The left panel shows three random days in 1994; on these days, fitted yields and market yields were

[12] Coupon securities exclude bills and floating-rate notes. I also exclude Treasury securities with call features and trading in securities that have not yet been issued (the so-called "when issued" market).

[13] As in Gürkaynak, Sack and Wright (2007) and Hu, Pan and Wang (2013), I weigh pricing errors by inverse durations, converting (to a first approximation) pricing errors into yield fitting errors.

Figure 1: **Examples of yield curves and market-observed bond yields**



NOTE. The left panel shows par-coupon yield curves and market-observed bond yields on three random days in 1994; the right panel shows three days surrounding Lehman's default in September 2008. This figure replicates part of a figure in Hu, Pan and Wang (2013); the dates included are the same, but the plots here reflect the data and estimated yield curves used in this paper.

closely, though not perfectly, aligned. The right panel shows three days near the Lehman default in September 2008; on these days, considerable deviations between fitted and market yields were observed. The noise measure itself is shown in Figure 2.

2.2 Quantities

The measure of dealer gross positions is the sum of long and short positions in nominal Treasury coupon securities for all primary dealers.[14] Data on pri-

[14]Significant participation in the Treasury market is a requirement for becoming and remaining a primary dealer.

mary dealers' gross long and short positions in nominal Treasury securities is obtained from the Weekly Report of Dealer Positions, or FR 2004A. Primary dealers are required to report the value of their long and short positions on the FR 2004 A as of the close of business each Wednesday.[15] Positions are reported at fair value under U.S. GAAP; loosely, this means market value. Long and short positions in the same issue are reported net by CUSIP, but long and short positions in different issues are reported gross.

Denote the set of all primary dealers by D and the total gross long position of dealer $d \in D$ at time t by $l_{d,t}$. Similarly, denote dealer d's total gross short positions by $s_{d,t}$. Aggregate dealer gross positions is defined as:

$$\sum_{d \in D} (l_{d,t} + s_{d,t})$$

Figure 2 shows aggregate dealer gross positions. The sample period is July 1990 through October 2016.

3 Identifying liquidity supply shocks

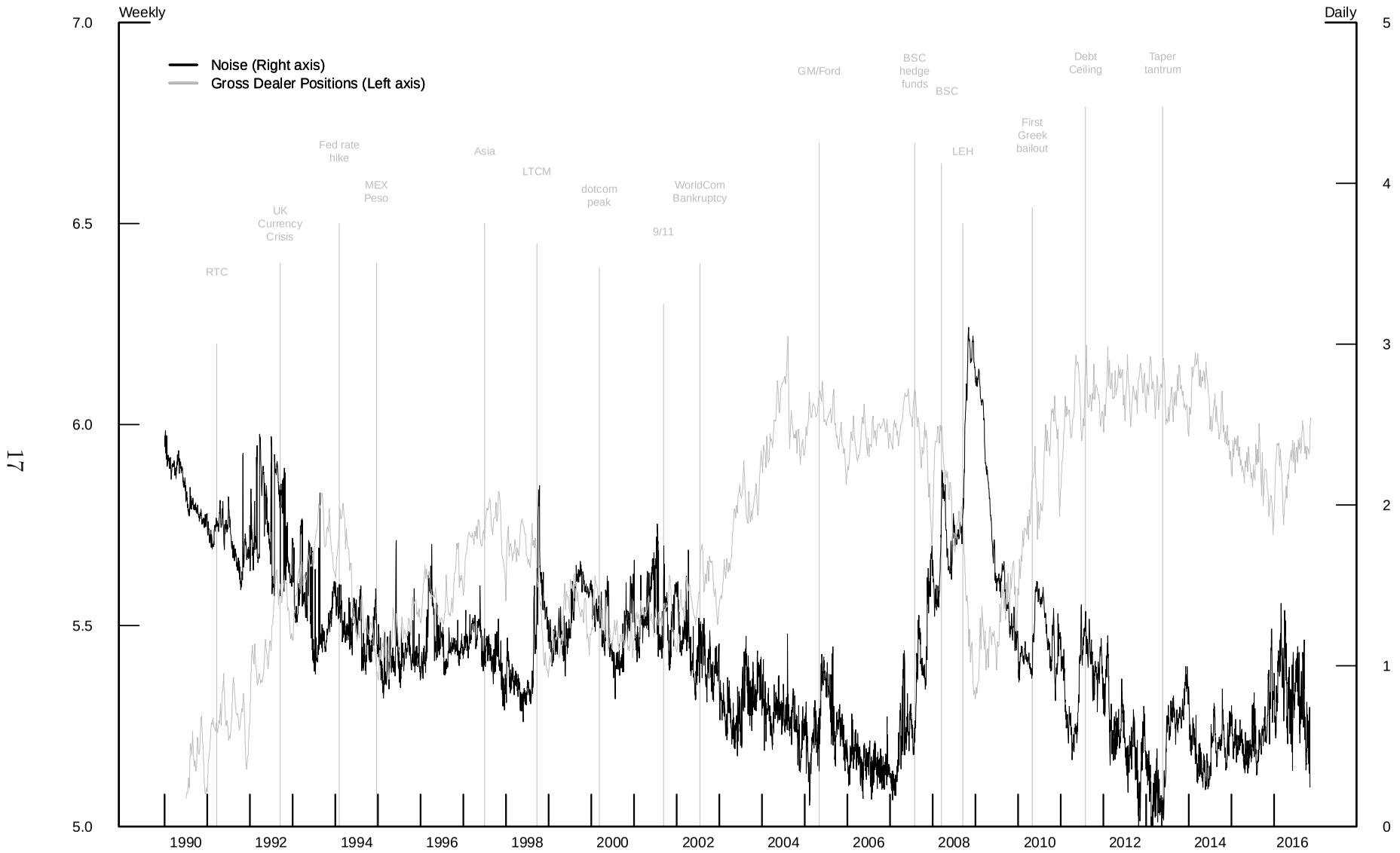
This section uses a structural VAR model to identify shocks to the supply of liquidity. The variables included in the model and the identification assumptions are motivated by the theoretical model in Section 1.

The VAR has the following structure:

$$Y_t = b + ct + B_1 Y_{t-1} + B_2 Y_{t-2} + ... + B_L Y_{t-L} + \xi_t \tag{7}$$

[15] Over the past decade, non-dealer high-frequency trading firms have accounted for a growing share of market making in on-the-run Treasury securities. However, high-frequency trading firms in general carry little inventory overnight.

Figure 2: **Noise and dealer gross positions**



Note: The black line shows the noise in Treasury yields, in log(basis points). The grey line shows dealer gross positions in Treasury securities, in log(billions of dollars). The construction of these measures is described in Sections 2.1 and 2.2, respectively.

where Y_t is a (2 x 1) vector of endogenous variables, B_l is a (2 x 2) matrix, and $E\left[\xi_t \xi_t'\right] = \Sigma$. The variables in Y_t are the noise measure and the dealer gross position measure described in Section 2; both variables enter in logs. The frequency of the data is weekly.[16] I use $L = 26$ lags of the endogenous variables in the VAR.[17]

Denote the mapping from orthonormal fundamental shocks v_t to the residual ξ_t by the matrix A, with $\xi_t = Av_t$. The goal is to identify the column of A corresponding to a liquidity supply shock. I estimate the model using the pure sign restrictions approach of Uhlig (2005).

The identification assumption is:

The impulse responses to a positive liquidity supply shock are, on impact, (weakly) negative for the noise measure and (weakly) positive for dealer gross positions.

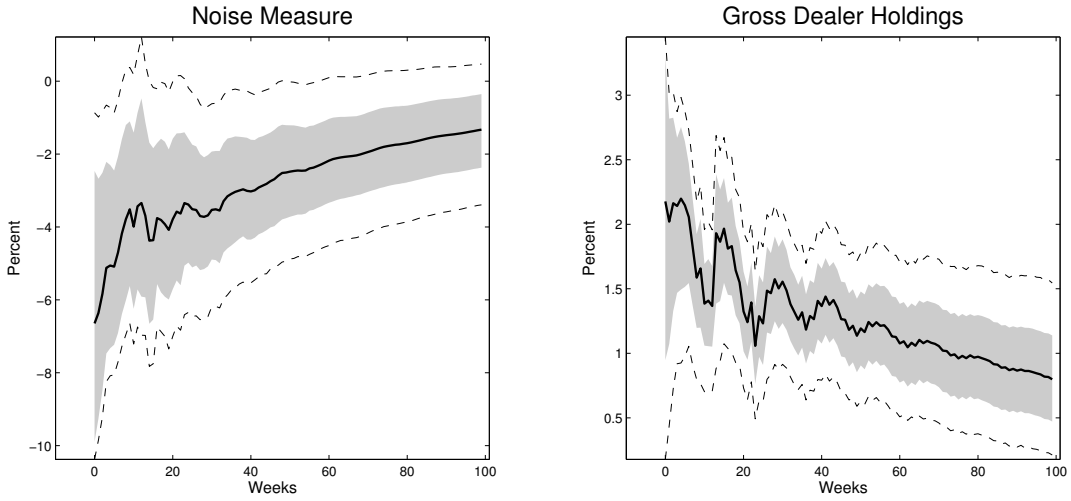
This identification assumption is motivated by Proposition 1. As in Uhlig (2005), I use a weak Normal-Wishart prior. The empirical results are generally stronger if I require the sign restrictions to hold, not only on impact, but also for a sustained period of time afterward; such a strategy is common in the literature on VARs with sign restrictions. However, here I assume only that the sign restrictions hold on impact.

Figure 3 shows the impulse responses to a liquidity supply shock. A positive liquidity supply shock leads to a decrease in noise and an increase in gross dealer holdings that are quite persistent; by assumption, on impact, noise weakly decreases and gross dealer holdings weakly increase.

[16] The noise measure is available at a daily frequency and the dealer gross positions measure is available as of close of business each Wednesday; to obtain a weekly noise measure, I take an average of the noise measure over the week ending each Wednesday.

[17] The results are very similar if the time trend c is excluded from the VAR given by (7) or if the lag length L is halved or doubled.

Figure 3: **Impulse responses to a liquidity supply shock**



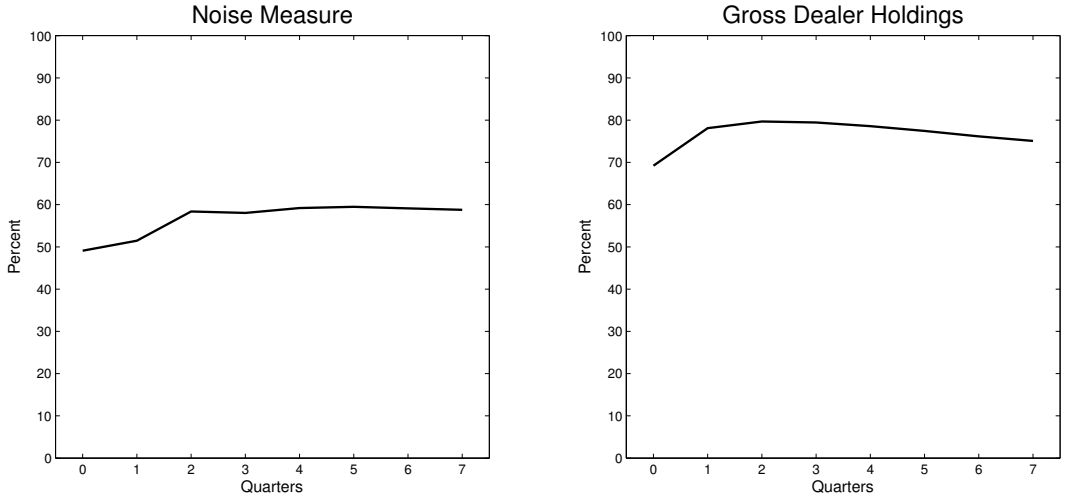
Note: The mean impulse response is shown in black. The shaded area marks a pointwise 68-percent credible interval around the median. The dashed lines mark a pointwise 95-percent credible interval around the median.

Figure 4 shows the share of forecast error variance due to the liquidity supply shock. For the noise measure, liquidity supply shocks explain about one-half of forecast error variance at short and long horizons; for gross dealer positions, liquidity supply shocks explain about three-quarters of forecast error variance.

3.1 Estimates of the history of liquidity supply shocks

Figure 5 shows the pointwise mean of the cumulative sum of the liquidity supply shock. Liquidity shocks capture stress episodes well. For example, liquidity supply shocks were negative, on balance: following the series of rate hikes in 1994 and the corresponding increase in long-term interest rates, which caught many investors by surprise; amid the Russian default and the collapse of the Long-Term Capital Management hedge fund; at the end of the 1990s

Figure 4: **Forecast error variance decomposition**



Note: Each plot shows the share of forecast error variance for a given variable due to the liquidity supply shock. The forecast error variance decomposition is calculated by: drawing the parameters of the structural VAR from the posterior distribution; calculating the forecast error variance decomposition at different time horizons for each draw; and then taking the mean across draws and across weeks within a given quarter.

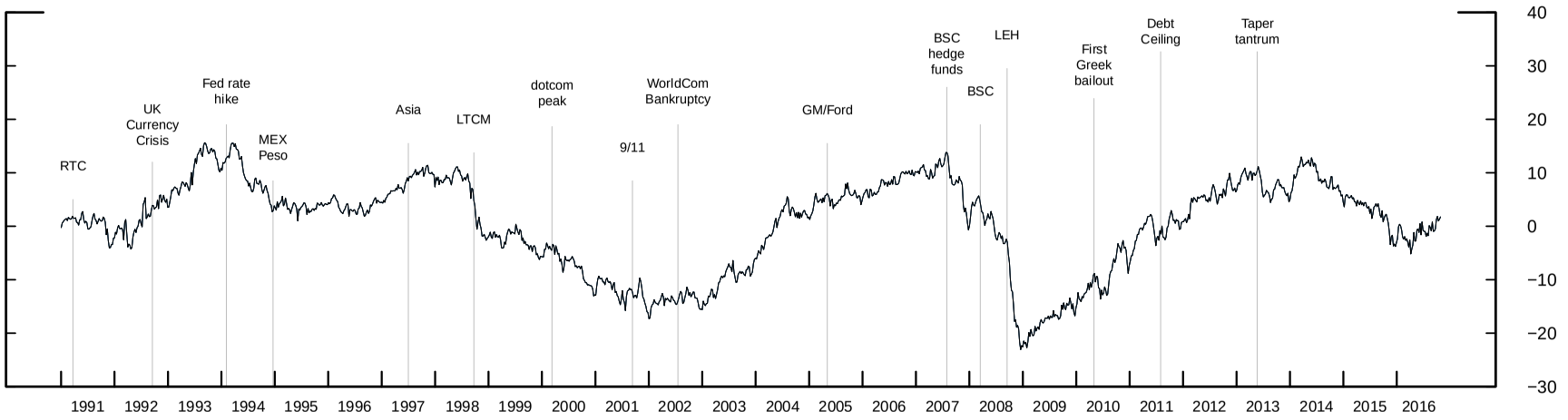
and during the early 2000s, against the backdrop of the dot-com burst and the 9/11 attacks; following the suspension of redemptions from Bear Stearns hedge funds in the summer of 2007, an event that marked the beginning of the financial crisis; after the collapse of Lehman Brothers in 2008; amid flare-ups of the European fiscal crisis in 2010 and 2011; and following the "taper tantrum" in 2013, when interest rates rose as the Federal Reserve considered when to reduce the pace of its purchases of long-term assets. In contrast, liquidity shocks were positive, overall: between 1992 and early 1994, against the background of Federal Reserve decisions to cut interest rates and then maintain rates at low levels; in 1997, amid strong U.S. economic growth and despite the Asian financial crisis; and during the economic boom of the mid-2000s and the run-up to the financial crisis.

Next, I calculate the cumulative effect of liquidity supply shocks on noise and gross dealer portfolios. Specifically, I calculate the cumulative contribution of the liquidity supply shock to noise and gross dealer portfolios based on a historical decomposition of the data. To do so, I first calculate the counterfactual values of noise and gross dealer positions that would obtain, based on the VAR model, if the observed liquidity supply shocks occured, but the other structural shock was always equal to zero. Appendix B shows the estimated effects of the liquidity supply shock on noise and gross dealer portfolios; the construction of these time series is also described.

3.2 Liquidity supply in other asset markets

The method developed here identifies shocks to the supply of a certain type of market liquidity in the Treasury market. I link intermediation in the Treasury market to intermediation in other asset markets under the assumption

Figure 5: **Cumulative sum of liquidity supply shocks**



Note: This panel shows the mean of the posterior distribution of the cumulative sum of shocks to liquidity supply. A positive shock reflects an increase in liquidity supply.

that if dealers are foregoing profitable, interest-rate-neutral trades in the U.S. Treasury market, they are also likely to be foregoing opportunities with high risk-adjusted expected profits in other markets. In this section, I provide evidence supporting this assumption, using the Federal Reserve's Senior Credit Officer Opinion Survey (SCOOS). This survey collects information about conditions in markets for securities financing and over-the-counter (OTC) derivatives; the survey also asks about conditions in a broad range of fixed income markets. The survey is completed by risk officers at primary dealers and has been administered, typically four times per year, since 2010.

In the survey, each dealer is asked to characterize changes during the survey period in the terms offered to investors across the entire spectrum of securities financing and OTC derivatives transactions. Dealers are asked separately about price and non-price terms. An example of looser price terms is a lower financing rate. Examples of looser non-price terms are a lower haircut or weaker covenants. Questions about price and non-price terms are asked separately for a variety of investor types, such as hedge funds or non-financial corporations.

I aggregate responses about price terms for each investor type by calculating the net percentage of dealers indicating easier price terms, where the net percentage is equal to the percentage of dealers that reported easier conditions minus the percentage of dealers that reported tighter conditions. Then, I take an average across investor types of the net percentage easing price terms. Responses about non-price terms are aggregated similarly. Appendix B provides additional detail about variable construction.

Each dealer is also asked to characterize changes in liquidity and market functioning in several fixed income asset classes, such as high-grade corporate bonds and agency residential mortgage-backed securities. I aggregate responses regarding liquidity and market functioning for each asset class by

calculating the net percentage of dealers reporting improved conditions. Then, I take an average across asset classes of the net percentage reporting improved conditions.

Under the assumption linking the Treasury market and other markets, the following hypotheses should hold:

H1. A positive liquidity supply shock is associated with dealers easing terms in a broad range of securities financing and OTC derivatives transactions.

H2. A positive liquidity supply shock is associated with improvements in liquidity and market functioning in a broad range of asset markets.

To investigate H1, I run regressions of the net percentage of dealers easing terms on estimated liquidity supply shocks. The results are reported in Panels A and B of Table 1. I define v_{t_q} as the average value in quarter t_q of the weekly liquidity supply shock from the structural VAR estimated previously. Panel A shows the results for price terms. The first column provides results from regressing the net percentage easing price terms on the contemporaneous quarterly liquidity supply shock, v_{t_q}. The second column provides results from regressing the net percentage easing price terms on the contemporaneous liquidity supply shock and its lag. The coefficients are positive, statistically significant and economically meaningful. The adjusted R^2 when including only the contemporaneous quarterly liquidity shock is 0.27, and this rises considerably when also including one lag of the quarterly liquidity shock. The results for non-price terms, shown in Panel B, are broadly similar. In all cases, I can reject the null hypothesis that the coefficients on the included liquidity supply shocks are jointly equal to zero.

Table 1: Liquidity supply shocks and financial market conditions

Panel A. Price terms in securities financing and OTC derivatives transactions				
	(1)		(2)	
Liquidity supply shock	β	t-stat	β	t-stat
v_{t_q}	0.52	3.32	0.44	3.06
v_{t_q-1}			0.49	3.14
Pr $> W$		0.003		0.001
Adj-R^2		0.24		0.46

Panel B. Non-price terms in securities financing and OTC derivatives transactions				
	(1)		(2)	
Liquidity supply shock	β	t-stat	β	t-stat
v_{t_q}	0.35	2.18	0.27	1.79
v_{t_q-1}			0.50	3.68
Pr $> W$		0.039		0.003
Adj-R^2		0.09		0.31

Panel C. Liquidity and market functioning				
	(1)		(2)	
Liquidity supply shock	β	t-stat	β	t-stat
v_{t_q}	0.49	2.83	0.47	2.39
v_{t_q-1}			0.41	1.83
Pr $> W$		0.009		0.000
Adj-R^2		0.21		0.36

Note: Sample period: 2010q2:2016q2. The dependent variable in Panel A is a measure of the change in price terms offered for securities financing and OTC derivatives transactions; in Panel B, a measure of the change in nonprice terms; and in Panel C, a measure of the change in liquidity and market functioning in fixed income markets. See the text and Appendix C for details. In addition to the listed liquidity supply shocks, each specification also includes a constant. The columns labeled β contain standardized estimates of the OLS coefficients. The row Pr $> W$ provides the p-value for the test of the null hypothesis that the coefficients on the included liquidity supply shocks are jointly equal to zero. t-statistics for each coefficient and these p-values are calculated by estimating the robust covariance matrix.

To investigate H2, I run regressions of the net percentage of dealers reporting improved conditions on estimated liquidity supply shocks. The results are reported in Panel C of Table 3. Contemporaneous and lagged quarterly liquidity supply shocks estimated using Treasury market data are associated with improvements in liquidity and market functioning in fixed income markets more generally. For both specifications, I can reject the null hypothesis that the coefficients on the included liquidity supply shocks are jointly equal to zero.

4 Liquidity supply and real economic activity

This section examines the real implications of liquidity supply shocks.

4.1 Predictive power of liquidity supply shocks

I estimate the following forecasting model for real economic activity:

$$g_{t_m \to t_m+h} = \alpha + \sum_{i=0}^{p} \beta_i g_{t_m-i} + \sum_{i=0}^{q} +\gamma_i v_{t_m-i} + \epsilon_{t_m+h} \tag{8}$$

where x_{t_m} is a measure of real activity in month t_m, the forecast horizon is h, and $g_{t_m \to t_m+h}$ is the change in real activity between t_m and t_m+h. The liquidity supply shock is denoted by v_{t_m} and is defined as the average value in month t_m of the weekly liquidity supply shocks from the structural VAR estimated in the previous section; the current value of v_{t_m} and q lags are included in the regression. The forecasting regression also includes g_{t_m}, the change in real activity between t_{m-1} and t_m, and p lags of g_{t_m}. The forecasting regression (8) is estimated by ordinary least squares (OLS). The covariance matrix for the coefficient estimators is calculated according to Hodrick (1992) to take

into account serial correlation in the error term ϵ_{t_m+h} induced by overlapping forecast horizons.

I examine the predictive power of liquidity supply shocks for two measures of real activity: the civilian unemployment rate and industrial production.[18] Table 2 shows the results of this exercise for a 12-month forecast horizon. The first two columns of each table show the results from a baseline specification, which includes as predictors the growth rate in the current month, 11 lags of the growth rate, and the current liquidity supply shock. The second two columns show the results when, in addition, 5 lags of the liquidity supply shock are included. In each case, p-values are reported for the test of the null hypothesis that the coefficients on the liquidity supply shocks included in the regression are jointly equal to zero.

Liquidity supply shocks are statistically significant predictors of both measures of real economic activity. Also, the magnitude of the estimated coefficients indicates an economically significant positive relationship between increases in liquidity supply and real activity. A one standard deviation shock to liquidity supply is associated with a decrease in unemployment over the following 12 months of about 0.2 percentage points; the associated increase in industrial production is 0.7 percent.[19] Including current and lagged liquidity supply shocks improves in-sample fit for both measures.

I also examine the ability of the liquidity supply shocks alone to forecast real activity. Figure 6 shows the actual 12-month ahead growth of each measure of real activity, together with the fitted values from a simple regression of

[18]For the unemployment rate, I calculate the change between any two periods as the difference in the unemployment rate; for industrial production, I use the log-difference.

[19]The standard deviation over the sample period of the 12-month change in the unemployment rate is 1 percentage point. The standard deviation of the 12-month log-difference in industrial production is 4.2 percent.

Table 2: Predictability of real activity

Panel A. Unemployment				
	(1)		(2)	
Liquidity supply shock	β	t-stat	β	t-stat
v_{t_m}	-0.209	4.38	-0.212	4.38
v_{t_m-1}			-0.191	4.22
v_{t_m-2}			-0.184	4.31
v_{t_m-3}			-0.159	4.08
v_{t_m-4}			-0.112	3.37
v_{t_m-5}			-0.090	3.07
Pr > W	0.000		0.004	
Adj-R^2	0.31		0.40	
Memo: Adj-R^2 when excluding all liquidity supply shocks: 0.27				
Panel B. Industrial production				
	(1)		(2)	
Liquidity supply shock	β	t-stat	β	t-stat
v_{t_m}	0.166	3.38	0.168	3.39
v_{t_m-1}			0.167	3.16
v_{t_m-2}			0.132	3.02
v_{t_m-3}			0.084	2.54
v_{t_m-4}			0.059	1.86
v_{t_m-5}			0.020	0.76
Pr > W	0.001		0.021	
Adj-R^2	0.17		0.20	
Memo: Adj-R^2 when excluding all liquidity supply shocks: 0.14				

Note: Sample period: 1991m1:2015m10. The dependent variable is $g_{t\to t+h}$, the change in an indicator of economic activity between t and $t+h$, where h is the forecast horizon. In addition to the listed liquidity supply shocks, each specification also includes a constant, g_t (the change in activity between $t-1$ and t), and 11 lags of g_t; these coefficients are not reported. The columns labeled β contain standardized estimates of the OLS coefficients. The row Pr > W provides the p-value for the test of the null hypothesis that the coefficients on the included liquidity supply shocks are jointly equal to zero. t-statistics for each coefficient and these p-values are calculated by estimating the covariance matrix according to Hodrick (1992).

growth on current and lagged liquidity supply shocks. Note that the liquidity supply shocks are simply a weighted sum of residuals from a VAR of the noise in Treasury yields and dealers' gross positions in Treasury securities – two variables that are not *per se* related to real economic activity but that are used only to extract a signal about liquidity supply. Nonetheless, the liquidity supply shocks are able to forecast important variation in real economic activity, including the improvement in labor market conditions during the recovery from the 1990-1991 recession, the slowdown in economic activity that accompanied the Federal Reserve's interest rate hikes in 1994, the steady growth of the mid-2000s and, in part, the recession associated with the financial crisis.

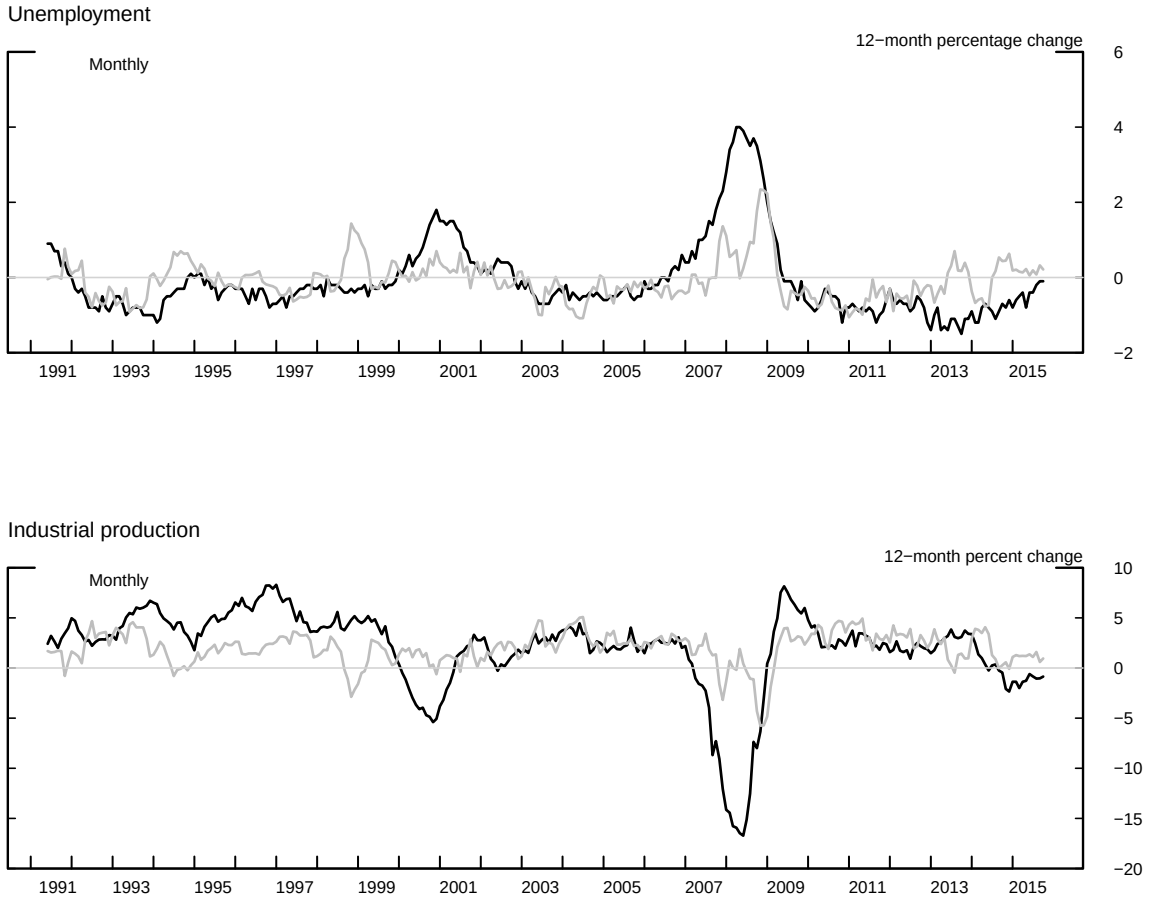
4.2 Business cycle VAR analysis

Next, I use a VAR to model business cycle and financial market variables to further investigate the relationship between liquidity supply shocks and real activity. The VAR includes the unemployment rate, industrial production, core consumer prices, the real federal funds rate, the term spread, the equity market return, stock-market implied volatility, noise and gross dealer positions. The data frequency is monthly. The real activity measures, stock-market implied volatility and the price index enter in log levels.[20]

The identification assumptions are:

[20]The measure of core consumer prices used is the price index for personal consumption expenditures less food and energy. The real federal funds rate in a given month is defined as the average effective federal funds rate during that month less realized inflation, where realized inflation is given by the log-difference between the core consumer price index in period t and its lagged value a year earlier. The term spread is defined as the difference between the ten-year constant-maturity Treasury yield and the two-year constant-maturity Treasury yield. The measure of stock-market implied volatility is the VIX. For noise, gross dealer positions and other variables available at a daily or weekly frequency, I use the monthly average.

Figure 6: Predictability using only liquidity supply shocks



Note: The black line is actual 12-month ahead growth in nonfarm payroll employment. The grey line is the fitted value from a regression of this variable on the current liquidity supply shock, 5 lags of this shock, and a constant.

1. The impulse responses to a positive liquidity supply shock are, on impact, (weakly) negative for the noise measure and (weakly) positive for dealer gross positions.

2. A liquidity supply shock has no effect, on impact, on all the other variables.

I estimate the model following the algorithm of Arias, Rubio-Ramirez and Waggoner (2016) using a flat prior over the impulse response function parameterization.[21]

Figure 7 shows the impulse responses to a positive liquidity supply shock. By assumption, on impact, noise falls and dealer gross positions rise. As in the small VAR discussed in Section 3, the decrease in noise and the rise in dealer gross positions are economically large and very persistent.

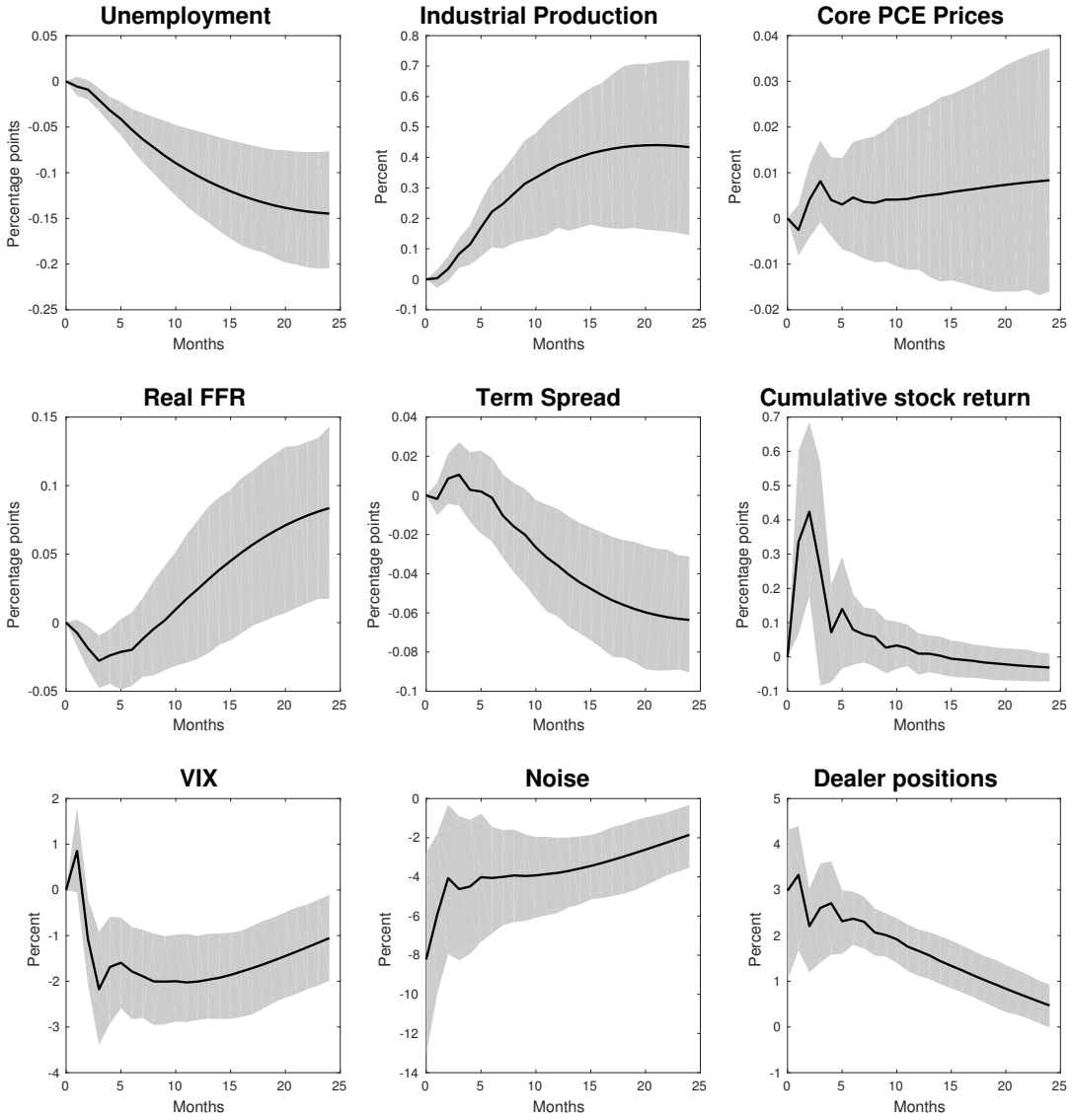
A positive liquidity supply shock is clearly expansionary, with unemployment declining and industrial production rising. The magnitude of the changes in real activity are only somewhat smaller than those in the forecasting exercise summarized in Table 2 , and still economically sizable. The cumulative stock return is positive after a couple of months and near-term stock-market implied volatility (VIX) declines persistently. In response to these developments, with a lag of several months, the real federal funds rate rises. The term spread declines and core consumer prices are unchanged.

5 Conclusion

In this paper, I provide a new method for identifying shocks to liquidity supply. Motivated by a theoretical model of intermediation, I use a structural VAR

[21] I am very grateful to the authors for providing the code for their paper. Note also that this VAR model does not include a time trend, which was included in the VAR in Section 3. The lag length of the VAR is four months.

Figure 7: Response of real activity measures to a liquidity supply shock



Note: The pointwise mean impulse response is shown in black. The shaded area marks a pointwise 68-percent credible interval around the median.

model to identify liquidity supply shocks. In the structural VAR, a positive liquidity supply shock leads to a decrease in the noise in Treasury prices and an increase in gross dealer holdings of Treasury securities. I link intermediation in the Treasury market to intermediation in other asset markets under the assumption that if dealers are foregoing profitable, interest-rate-neutral trades in the U.S. Treasury market, they are also likely to be foregoing opportunities with high risk-adjusted expected profits in other markets.

I study the information content of liquidity supply shocks that is orthogonal to information contained in macroeconomic and asset price variables. Liquidity supply shocks have considerable predictive power for economic activity. Impulse responses from a structural VAR model indicate that positive liquidity supply shocks cause large and persistent increases in real activity.

The identification approach used in the paper could be carried over to quantitative macroeconomic models with explicitly modeled frictions in the financial sector. Such models would be needed to draw normative conclusions regarding policies that affect liquidity supply.

Appendix A: List of primary dealers

Below is the list of firms designated as primary dealers by the Federal Reserve Bank of New York, as of September 2016.

Bank of Nova Scotia, New York Agency
BMO Capital Markets Corp.
BNP Paribas Securities Corp.
Barclays Capital Inc.
Cantor Fitzgerald & Co.
Citigroup Global Markets Inc.
Credit Suisse Securities (USA) LLC
Daiwa Capital Markets America Inc.
Deutsche Bank Securities Inc.
Goldman, Sachs & Co.
HSBC Securities (USA) Inc.
Jefferies LLC J.P.
J. P. Morgan Securities LLC
Merrill Lynch, Pierce, Fenner & Smith Incorporated
Mizuho Securities USA Inc.
Morgan Stanley & Co. LLC
Nomura Securities International, Inc.
RBC Capital Markets, LLC
RBS Securities Inc.
Societe Generale, New York Branch
TD Securities (USA) LLC
UBS Securities LLC
Wells Fargo Securities, LLC

The current list together with historical lists of primary dealers can be found at: https://www.newyorkfed.org/markets/primarydealers.html.

Appendix B: Cumulative effects of liquidity supply shocks

In this appendix, I discuss the cumulative effect of liquidity supply shocks on noise and gross dealer portfolios. Figure B.1 plots the cumulative contribution of the liquidity supply shock to noise and gross dealer portfolios based on a historical decomposition of the data. Consistent with the forecast error variance decomposition shown in Figure 4, liquidity supply shocks account for a large share of the variation in noise and gross dealer portfolios. For example, according to the model, after the Russian default and collapse of the LTCM hedge fund in 1998, liquidity supply shocks drove a rise in noise and a decrease in gross positions.

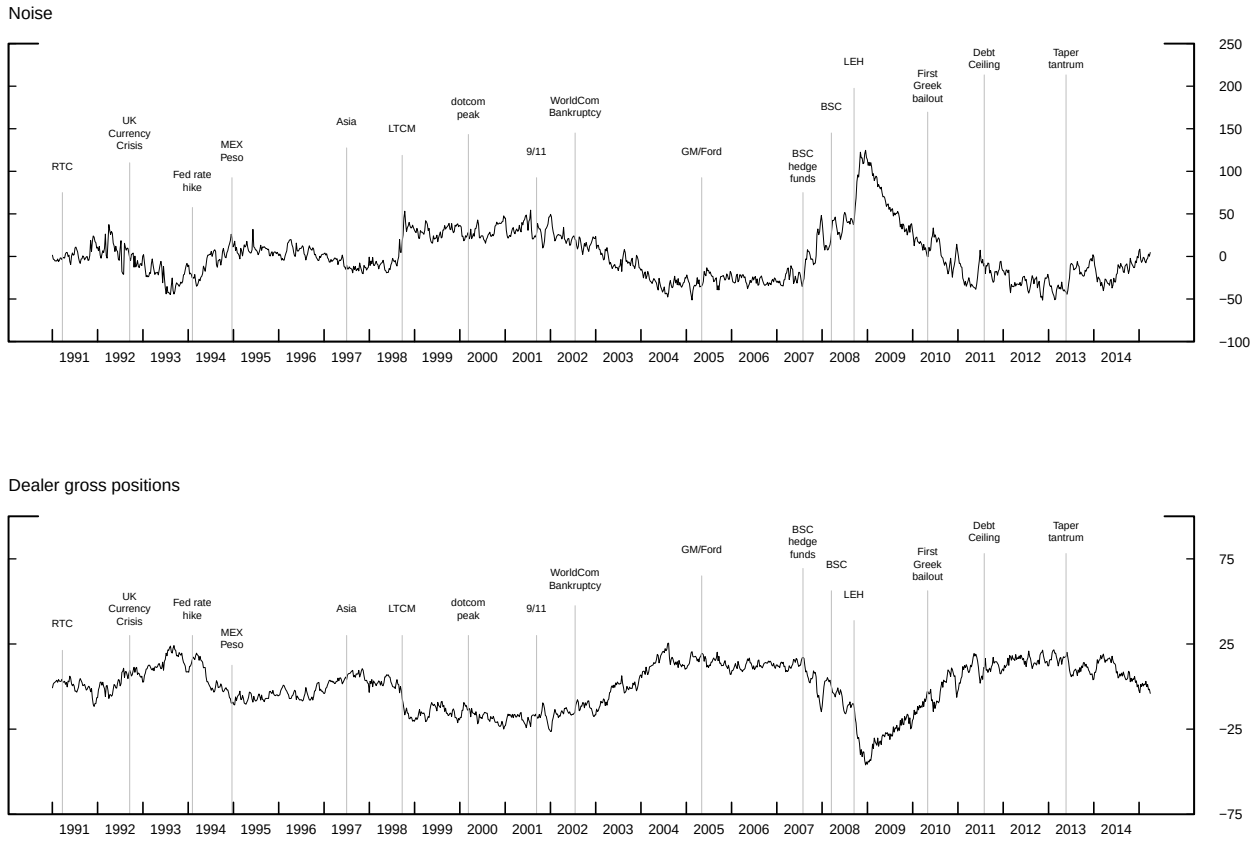
To calculate the cumulative effect of the liquidity supply shock on noise and gross dealer portfolios, I first calculate the counterfactual values of noise and gross dealer positions that would obtain, based on the VAR model, if the observed liquidity supply shocks occured, but the other structural shock was always equal to zero. That is, denote by Y_t^{cf} the counterfactual value of Y_t that would obtain from (7) if $v_t = [v_{dealer,t}\ 0]$' for $t > L$ and v_t is a vector of zeros otherwise. Then, define the effect of liquidity supply shocks on noise and gross dealer portfolios as $\tilde{Y}_{dealer,t}$, where $\tilde{Y}_{dealer,t}$ is the difference between the data, Y_t, and the counterfactual value of Y_t:

$$\tilde{Y}_{dealer,t} = Y_t - Y_t^{cf} \tag{9}$$

The cumulative effect of the liquidity supply shock, $\tilde{Y}_{dealer,t}$, is defined in (9). To calculate $\tilde{Y}_{dealer,t}$ for given parameters of the VAR, I first calculate baseline values for $Y_{l+1}, ..., Y_T$ conditional on $Y_1, ..., Y_l$ and the assumption that $v_t = 0$ for all t. Next, I calculate the counterfactual value Y_t^{cf} by assuming that $v_t = [v_{dealer,t}\ 0]$' for $t > L$ and v_t is a vector of zeros otherwise. The

difference between the counterfactual values for $Y_{l+1}, ..., Y_T$ and the baseline values is equal to $\tilde{Y}_{dealer,t}$. In Figure B.1 , I show the mean effect calculated using many draws from the posterior over the parameters of the VAR.

Figure B.1: **Effect of liquidity supply shocks on noise and dealer gross positions**



Note: Each panel shows the mean of the posterior distribution of the effect of current and previous liquidity supply shocks on the variable indicated.

Appendix C: Senior Credit Officer Opinion Survey

This appendix describes how measures of financial conditions are constructed using data from the Senior Credit Officer Opinion Survey; these measures are used in Section 3.2.

Price and non-price terms in securities financing and derivatives transactions

In the survey, each dealer is asked to characterize changes over a given three month period in the price and nonprice terms that the dealer offers for securities financing and OTC derivatives transactions, for a variety of client types. Regarding price and nonprice terms, the survey instructions say, "In some questions, the survey differentiates between the compensation demanded for bearing credit risk (price terms) and the contractual provisions used to mitigate exposures (nonprice terms)." Questions about price terms follow the pattern of:

> "Over the past three months, how have the price terms (for example, financing rates) offered to Y as reflected across the entire spectrum of securities financing and OTC derivatives transactions changed, regardless of nonprice terms? (Please indicating tightening if terms have become more stringent-for example, if financing rates have risen.)"

where Y is a client type, such as "hedge funds." Questions about non-price terms follow the pattern of:

> "Over the past three months, how has your use of nonprice terms (for example, haircuts, maximum maturity, covenants, cure periods, cross-default positions, or other documentation features) with respect to Y across the entire spectrum of securities financing and

OTC derivatives transactions changed, regardless of price terms? (Please indicating tightening if terms have become more stringent-for example, if haircuts have been increased.)"

I use data on six investor types: hedge funds; non-financial corporations; mutual funds, exchange traded funds, pension plans and endowments; trading real estate investment trusts (REITs); insurance companies; and separately managed accounts (SMAs) established with investment advisors. Time series are available for the first two client types beginning in 2010Q2. Time series are available for the remaining client types beginning 2011Q3.

To create the quarterly measures of price terms used in Table 1, I follow two steps. First, for each client type and each quarter, I aggregate responses regarding price terms by calculating the net percentage of dealers easing terms. This net percentage is equal to the percentage of dealers that reported looser conditions ("eased somewhat" or "eased considerably") minus the percentage of dealers that reported tighter conditions ("tightened considerably" or "tightened somewhat"). Second, for each quarter, I take an average across all client types for which data is available. The quarterly measure of nonprice terms is constructed analogously. Note that the three month periods used in the survey do not correspond to standard quarters; instead, the March survey asks about December through February, and so on. In constructing the liquidity supply measures v_{t_q} used on the right hand side of the regressions reported in Table 1, I calculate averages for a three month period matching the three month period covered in each survey.

Liquidity and market functioning

Dealers are also asked to characterize how liquidity and market functioning have changed over the same three month period in a variety of asset classes.

These asset classes span a large part of the fixed-income universe outside Treasury securities; the security types included play major roles in corporate finance, real estate finance, and household finance. Questions about liquidity and market functioning follow the pattern of:

> "Over the past three months, how have liquidity and functioning in the X market changed?"

where X is an asset class.

I use data on six asset classes: high-grade corporate bonds; residential mortgage backed securities (RMBS) issued by federal agencies; high-yield corporate bonds; commercial mortgage backed securities (CMBS); RMBS not issued by federal agencies; and consumer asset-backed securities (ABS). Time series are available for the first two client types beginning in 2010Q2. Time series are available for the remaining client types beginning 2011Q3.

To create the quarterly measures of liquidity and market functioning used in Table 1, I follow two steps. First, for each asset class and each quarter, I aggregate responses regarding liquidity and market functioning by calculating the net percentage of dealers reporting improved conditions. This net percentage is equal to the percentage of dealers that reported improved conditions ("improved considerably" or "improved somewhat") minus the percentage of dealers that reported a deterioration in conditions ("deteriorated somewhat" or "deteriorated considerably"). Second, for each quarter, I take an average across all asset classes for which data is available.

Changes to the survey questions

The exact client types and asset classes included have varied somewhat since the survey was introduced. I use time series constructed by the Federal Reserve that group the client types included in each survey into the six cat-

egories listed above and that group the asset classes into the six categories listed above.

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