

What drives liquidity? Identifying shocks to market makers' supply of liquidity and their role in economic fluctuations

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November 2015

Abstract

In a market-based financial system, market makers' supply of liquidity can be important for market functioning and, potentially, asset prices and business cycles. Using a structural model, I study the effects of shocks to broker-dealers' supply of liquidity, while controlling for the demand for liquidity and generic financial-conditions shocks. I identify a shock to broker-dealers' supply of liquidity using sign restrictions consistent with a theoretical model of dealer intermediation. I focus on the Treasury market: if broker-dealers are foregoing profitable market-making opportunities in the Treasury market, they are likely also doing so in other markets. Correspondingly, I find that a positive supply shock leads to higher equity market prices, real economic activity, and inflation, and lower uncertainty. I also find that liquidity supply and demand shocks both play significant roles in explaining variation in market-making activity and the price of liquidity. The structural model permits an analysis of historical episodes: the 2007-2009 financial crisis, for example, is characterized by large negative shocks to liquidity supply as well as moderate-sized negative equity-market shocks and positive liquidity-demand shocks.

*Federal Reserve Board. The views expressed here are those of the author and need not represent the views of the Federal Reserve Board or its staff. I am grateful for helpful feedback from seminar participants at Georgetown University. Charles Ahlstrom, Amy Lorenc and Michael Ng provided excellent research assistance. This work is preliminary; please do not circulate without permission of the author. Contact: jonathan.goldberg@frb.gov.

The 2007-2009 financial crisis renewed interest in the constraints faced by financial intermediaries and how these constraints affect business cycles and asset prices. The crisis also triggered debate about how intermediary balance sheet quantities or other measures of intermediation capacity should influence monetary policy. More recently, episodes of heightened financial market volatility – including the Flash Crash of 2010 and the Taper Tantrum in the summer of 2013 – have led policymakers and market participants to ask whether such episodes are symptomatic of a lower-frequency deterioration in intermediaries’ risk-bearing capacity.¹

However, it is not clear how to measure the supply of financial intermediation. The size of financial-intermediary balance sheets, for example, is influenced not only by intermediaries’ risk-bearing capacity, but also by the demand for financial intermediation from households, businesses and investors. Moreover, reverse causality complicates any attempt to gauge the effects of intermediation supply shocks on real economic activity or asset prices.

In this paper, I propose a new method of identifying shocks to the intermediation capacity of an important group of financial intermediaries, securities broker-dealers. Broker-dealers have important roles in a market-based financial system: making markets for tradeable assets; originating securities; and lending against securities. I focus on the Treasury market in order to identify shocks to the supply of liquidity across a broad range of asset markets: if broker-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 a structural vector autoregression (VAR), I extract a probability distribution over the time series of shocks to broker-dealers’ supply of liquidity. The VAR includes measures of market liquidity, market-making activity, equity-market and interest-rate uncertainty, and excess equity market returns. Identification comes from choosing measures of market liquidity and market-making activity such that only shocks to broker-dealers’ intermediation capacity lead to opposite-sign changes in the price of market liquidity and the quantity of market making activity. The price of market liquidity included is a measure of the noise in Treasury 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. The quantity of market liquidity included is the sum of broker-dealers’ gross long and short positions in Treasury securities. A positive shock to broker-dealers’ supply of liquidity is defined as one that leads to a decrease in Treasury yield noise and an increase in broker-dealer gross positions. Crucially, I argue that macroeconomic shocks (such as technology, uncertainty, risk sentiment, monetary policy, and markup shocks) would not have opposite-signed effects on Treasury yield noise and broker-dealer gross positions. In particular, I develop a theoretical model of dealer intermediation consistent with this identification assumption.

In addition, I control for generic shocks to financial conditions. In the benchmark specification, only a liquidity supply shock and a liquidity demand shock are identified; the model contains other

¹For 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).

shocks, but these do not have an assigned structural interpretation. To guard against mistaking generic changes in broad financial market conditions for liquidity supply or demand shocks, I show that my results are robust to estimating the model while identifying additional generic financial conditions shocks. The first additional shock is an interest rate volatility shock. The second additional shock is an equity market shock that leads to higher equity market uncertainty and, on impact, negative excess equity returns. The liquidity supply and demand shocks are required to be orthogonal to these shocks.

In the theoretical model, clients trade two bonds with the same remaining maturity. If the clients were able to trade with each other, the two bonds would have the same price. However, the model features segmented markets, as in Gromb and Vayanos (2002) and Gromb and Vayanos (2010); there are two types of clients and each type is able to trade only one of the bonds. Hence, if there are potential gains from trade, those gains can only be obtained by trading through a dealer. For example, if one type of client seeks to sell and the other to buy, the dealer could take the opposite side of each trade. However, market making by dealers involves risk: there is a positive probability that prior to the bond 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 bonds trade for different prices. This noise in bond prices compensates the dealer for bearing the risk associated with intermediation. A positive shock to dealers' risk aversion – or to the probability of forced closing out of dealers' positions – leads to greater dispersion in prices; also, there is a decrease in the sum of dealers' gross long and short positions. A positive shock to the clients' trading needs also leads to an increase in the dispersion of prices; however, the sum of dealers' gross long and short positions increases. Moreover, shocks to the mean or variance of the interest rate have no effect on the sum of gross positions or the dispersion of bond prices. In the model, if dealers seek to increase their net exposure to the interest rate risk associated with the bonds, they do so by increasing their long positions and decreasing their short positions; the sum of their gross long and short positions does not change. These results are used in the empirical model to identify the liquidity supply and liquidity demand shock. In the theoretical model, I also show that other sign restrictions that might seem plausible *a priori* in fact do not hold in the theoretical model. For example, although a positive shock to dealers' risk aversion leads to a decrease in the sum of dealers' gross long and short positions, it is not necessarily true that both gross long and gross short positions will each decrease.

I present a new fact about Treasury market intermediation that motivates the theoretical model. Using data on dealer-level securities holdings, I show that dealers simultaneously hold long and short positions in Treasury securities with similar remaining maturity – and that such holdings, in aggregate, account for a large share of dealers' gross positions.

Using the VAR, I find that shocks to broker-dealers' supply of liquidity and shocks to the demand for Treasury market liquidity are both important in explaining variation in market-making activity and the price of liquidity in the Treasury market. For the noise measure, liquidity supply shocks explain about one-third of forecast error variance at horizons of up to one year; demand shocks

explain about 15 percent. Nonetheless, these shocks have very different impacts on business cycles and asset prices. A positive shock to broker-dealers' supply of liquidity leads to an increase in industrial production, non-farm payrolls and consumer prices, and a decrease in unemployment; it also leads to a decrease in equity-market and interest-rate uncertainty and an increase in cumulative excess equity market returns. In contrast, positive shocks to liquidity demand have no effects on real activity, consumer prices or asset prices. Impulse responses of real activity are calculated via a Bayesian approach that reflects uncertainty about the time series of shocks to liquidity supply and demand.

The model allows an analysis of historical episodes. For example, the model sees the 2007-2009 financial crisis as a time of large negative shocks to the supply of liquidity, as well as moderate-sized equity-market shocks and liquidity-demand shocks. The model attributes about one-quarter of the increase in equity-market near-term implied volatility (measured by the VIX) during the crisis to liquidity supply shocks, with the equity market shock playing a slightly smaller role and liquidity-demand shocks playing no role. Russia's 1998 default and devaluation and the subsequent collapse of Long-Term Capital Management is also characterized by large negative liquidity supply shocks. However, some episodes of financial market stress, such as creditor negotiations with Greece in the spring of 2010, are associated with only modest negative liquidity supply shocks. In addition, liquidity supply shocks are characterized as playing no role in several notable financial market events, including the devaluation of the Mexican peso in December 1994 and the aftermath of the debt ceiling debate in 2011.

The distinctive feature of this paper is its approach to dealing with the endogeneity of intermediary balance sheets, market liquidity, asset prices and real activity. Hu, Pan and Wang (2013) examine a measure of the noise in Treasury yields and show that it helps price the cross section of hedge funds returns and carry trade returns; however, Hu, Pan and Wang (2013) stops short of disentangling shocks to supply and demand.² Adrian and Shin (2010) uses VARs with recursive identification to study the response of real activity to a shock to broker-dealer asset growth; Adrian and Shin (2009) and Adrian and Shin (2010) regress changes in real activity on lagged changes in intermediary balance sheet quantities. Examining specialist inventory of equities, Comerton-Forde et al. (2010) find that aggregate market-level and specialist firm-level 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.³ Hameed, Kang and Viswanathan (2010) show that negative equity market returns are associated with a subsequent decrease in market liquidity, especially during times of tightness in

²More specifically, high expected returns for assets that covary positively with the noise measure do not necessarily tell us whether the *supply* of market liquidity is a priced risk factor. Another difference between this paper and Hu, Pan and Wang (2013) is that in this paper, liquidity supply shocks can drive equity returns and are required to be orthogonal to the generic financial conditions shocks. Hu, Pan and Wang (2013), rather than using a VAR, strips out the effects of broad financial conditions by regressing the noise measure on measures of financial conditions and testing whether the residual can help price the cross section of hedge fund or carry trade returns.

³Comerton-Forde et al. (2010) provides additional evidence that specialist financial constraints explain their results by showing that the relationship between spreads and specialist positions is weaker after specialist mergers, suggesting that deep pockets ease financial constraints.

the funding market.⁴

The approach to identification in this paper is complementary to the approaches in Fontaine and Garcia (2012)'s approach. Fontaine and Garcia (2012) extract an illiquidity factor from an affine term structure model; the liquidity factor helps explain differences in Treasury prices that can be attributed to the ages of the bonds. They study the supply of liquidity by regressing shadow-banking assets on the illiquidity factor, using the aggregate quantity of residential and commercial mortgages as an instrumental variable; they argue that this is a valid instrumental variable for the pre-crisis period, if not the post-crisis one. Fontaine and Garcia (2012) find that shadow-bank asset growth increases by 7.2 percent in response to a one standard deviation increase in illiquidity. In addition, the supply and demand sign restrictions in this paper have some similarity to the identification approach used in Cohen, Diether and Malloy (2007). That paper studied the relationship between shorting demand and subsequent stock returns; they identify an increase in shorting demand as having occurred when the cost of shorting (the loan fee) and the quantity of shorting (the percentage of shares on loan) a given stock both increase.

Other related papers include Jiménez et al. (2014) and Abbassi et al. (forthcoming). Jiménez et al. (2014) shows that a lower short-term interest rate leads poorly capitalized banks in Spain to grant more loan applications to ex ante risky firms, relative to highly capitalized banks; identification is bolstered by monetary policy in Spain reflecting Euro area conditions rather than specifically Spanish ones. Abbassi et al. (forthcoming) finds that, during the financial crisis, German banks with higher trading expertise increased their investment in securities and decreased their supply of credit to non-financial firms, relative to other banks.

This paper is also related to the literature on the asset pricing effects of idiosyncratic changes in security supply stemming from government policy (Lou, Yan and Zhang (2013) and D Amico and King (2013)). Dealers' (or arbitrageurs') limited risk bearing capacity appears to be important in explaining such effects.

1 Limits to market-making

A dealer facilitates the buying and selling of securities for clients, including by buying and selling securities for the dealer's own account.⁵ For example, when faced with a surge of clients seeking to sell a security, dealers often absorb the selling pressure: the dealers buy the securities from their clients, building up inventory that they sell off once the selling pressure has subsided, as modeled in Weill (2007). In doing so, dealers provide liquidity and can reduce gaps between market prices and fundamental values. Of course, providing liquidity is typically risky.

Dealer intermediation in the Treasury market takes many forms, including taking on interest rate risk when clients are seeking to shed it and simply matching buyers and sellers among one's

⁴For a review of the empirical literature on market liquidity through the lens of theory, see Vayanos and Wang (2012).

⁵Dealer firms generally make markets in securities by offering to buy and sell securities on a continuous basis; they also often run matched books of repurchase agreements and originate securities. For a legal definition of dealers, see the Security Exchange Act of 1934.

clients. However, sometimes clients need to trade different securities of similar maturity; in this case, the buyer and seller cannot be directly matched, but the dealer can stand between them, going long the security that one client seeks to sell and going short the security another client seeks to buy. Of course, the dealer will demand compensation – for example, in the form of a low price on the security she is buying from a client and a high price on the one she is selling short. This may in part explain the observed noise in Treasury prices.

When the supply of market liquidity is plentiful (or when the demand for liquidity in the Treasury market is low), the yield on any given Treasury bonds tends to closely in line with what one would expect given the yields on other Treasury bonds. However, as shown by Hu, Pan and Wang (2013), during stress episodes, significant deviations from the yield curve are observed.

Figure 1 shows the yields on different Treasury securities during a “normal” day in 2015 as well as one day during the financial crisis. On the “normal” day, there was little noise in Treasury yields: the yield curve obtained by plotting the yields on individual Treasury securities was fairly smooth. In contrast, yields on the other day were quite noisy. Note that the yields are constructed using only the “bid” price – and hence variations in noise should not reflect variations in bid-ask spreads.⁶

One potential concern is that this noise could be driven by differences in coupons among bonds with similar maturities. To address this concern, on a day-by-day basis, I estimate a smooth yield curve, using the Svensson (1994) yield curve model, as in Gürkaynak, Sack and Wright (2007) and Hu, Pan and Wang (2013). That is, each day, I fit a yield curve with the Svensson (1994) model of instantaneous forward rates, given by:

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

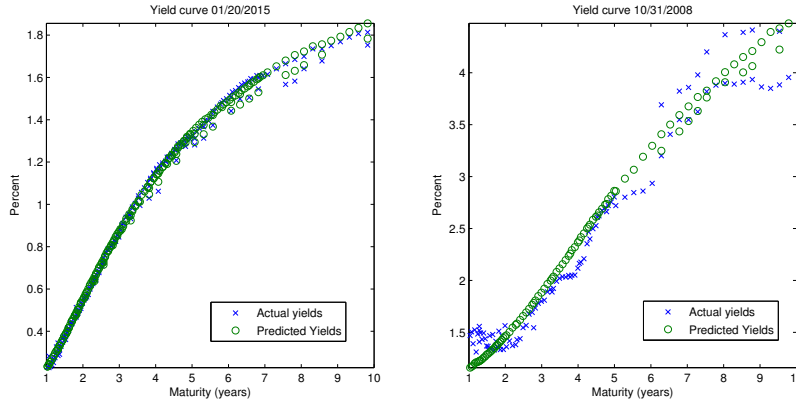
where n is the maturity and the parameters are given by $(\beta_0, \beta_1, \beta_2, \beta_3, \tau_1, \tau_2)$. The parameters are chosen to minimize a weighted sum of squared differences between prices and predicted prices, where the weights are the squared inverse of the securities’ duration. In predicting prices, I take into account all the cashflows associated with a given bond; that is, both coupon payments and the final payment of principal. As shown in Figure 1, the predicted yields are fairly smooth and do not explain the noise in the yield curve.

Next, I examine whether dealers actually make markets by absorbing discrepancies in supply and demand for bonds with similar remaining maturity. To do so, I examine data on dealers’ long and short holdings of Treasury securities from the Weekly Report of Dealer Positions, or FR 2004A. On the FR 2004A, primary dealers report, on a weekly basis, the amounts of their long and short positions in Treasury securities, according to the remaining time to maturity of the securities. For example, each dealer reports the values of their long positions and short positions in Treasury securities with remaining maturity of “more than 2 years but less than or equal to 3 years.” Primary dealers are the trading counterparties of the Federal Reserve Bank of New York and play a significant role in Treasury markets.⁷

⁶The data come from the Price Quote System (PQS) or the New Price Quote System (NPQS).

⁷Primary dealers are required to consistently participate in open-market operations conducted by the Fed as well

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



The left panel shows bond yields and predicted yields on a non-crisis day, January 20, 2015. The right panel shows bond yields and predicted yields on a crisis day, October 31, 2008.

Figure 3 shows the aggregate gross long and short Treasury positions of dealers. The average gross long position since July 2001 was \$192 billion and the average gross short position was \$235 billion.

Next, I examine whether dealers hold long and short positions in Treasury securities of similar remaining maturity. Denote the long position of dealer $i \in I$ in maturity bucket $j \in J$ at time t by $l_{i,j,t}$. Similarly, denote its short positions in the same maturity bucket by $s_{i,j,t}$. I refer to long and short positions held by the same dealer in securities of similar remaining maturity as matched positions. The aggregate size of matched positions is given by:

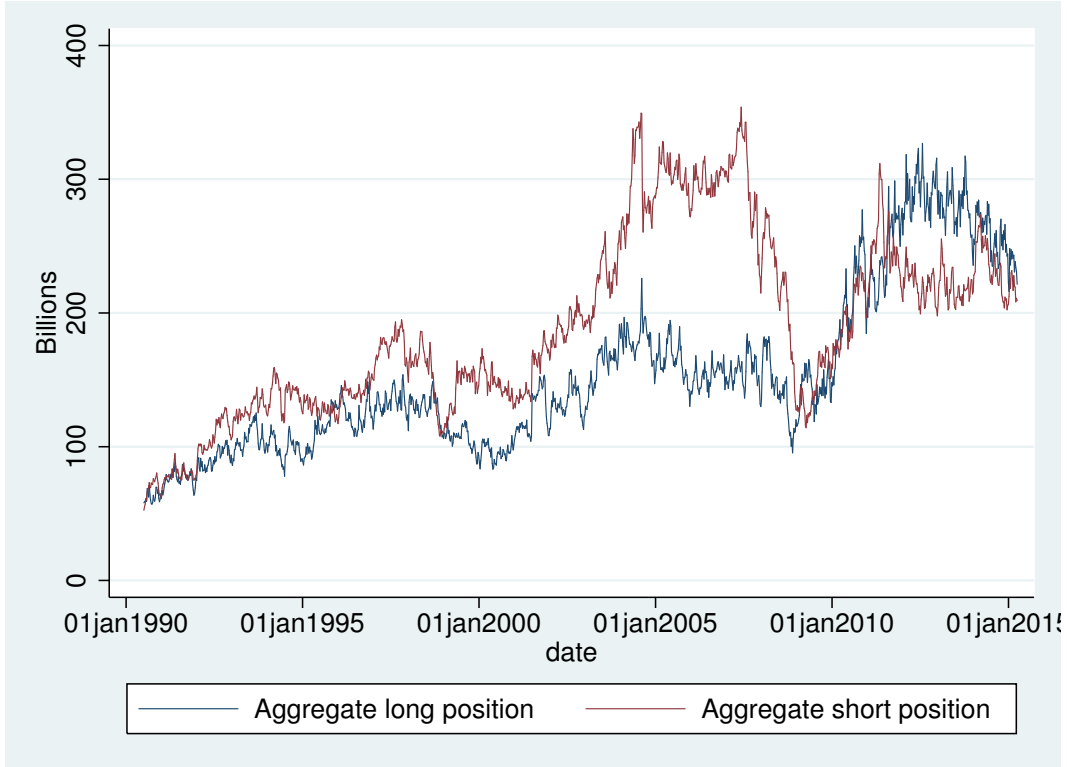
$$\sum_{i \in I} \sum_{j \in J} \min \{l_{i,j,t}, s_{i,j,t}\} \quad (2)$$

Figure 3 shows two different measures of dealers' aggregate matched positions. Two measures are shown because the maturity buckets on the FR 2004A have changed over time. From April 2013 onward, there are six maturity buckets for nominal Treasury notes and bonds; the average bucket size for remaining maturities of less than 11 years is 2.2 years. From July 2001 onward, there are four maturity buckets that nest the narrower buckets that begin in April 2013; the average bucket size for remaining maturities of less than 11 years is 3.7 years. The figure also shows the sum of aggregate gross long and short positions, defined as:

$$\frac{1}{2} \sum_{i \in I} \sum_{j \in J} (l_{i,j,t} + s_{i,j,t})$$

The average aggregate size of matched positions between July 2001 and July 2015 is about \$128 billion. Also, the maturity-matched portfolio size calculated using six buckets (from April 2013 onward) is very close to and highly correlated with the maturity-matched portfolio size calculated as auctions of U.S. government debt.

Figure 2: **Aggregate dealer long and short positions in Treasury securities**



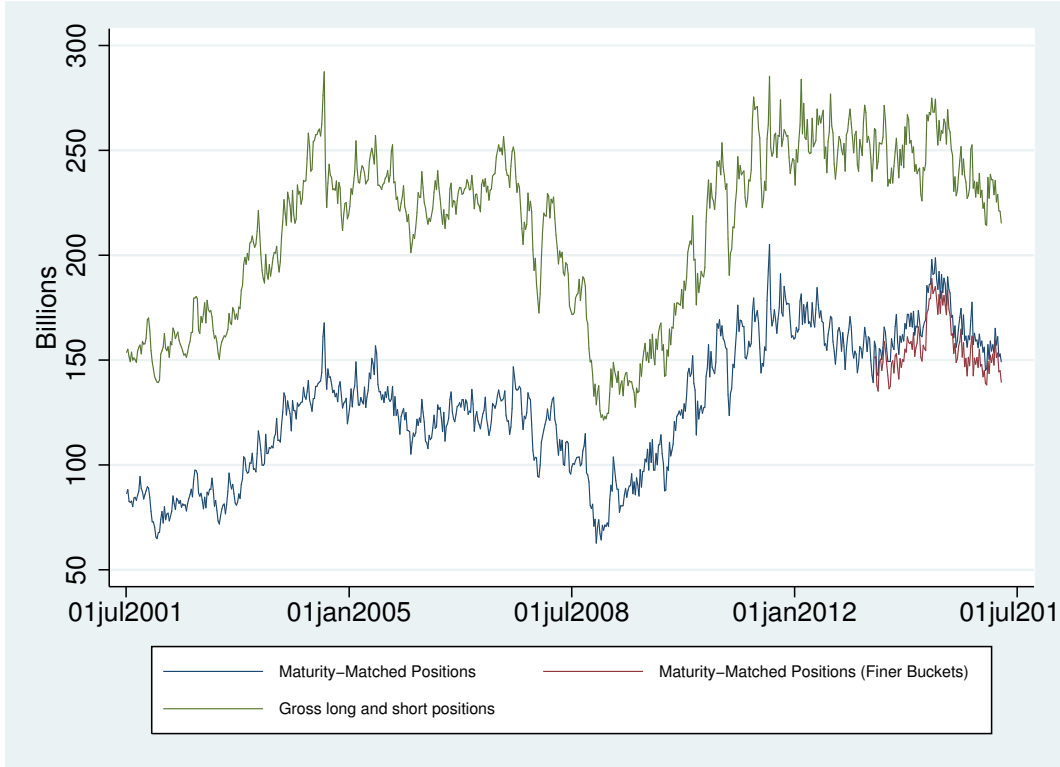
using four buckets. From April 2013 onward, the average maturity-matched portfolio size using six buckets is \$156 billion, versus an average size of \$166 billion when calculated using four buckets; the correlation is 0.98. This suggests that it is common for a given dealer to simultaneously hold long and short positions in Treasury securities with similar remaining maturity, and that these positions are large in value, both in absolute terms and relative to dealers’ aggregate long and short positions.

1.1 A theory of “noise” in Treasury securities’ prices

Next, I develop a theory of noise in Treasury securities’ prices. Consistent with the data presented above, dealers will make markets by simultaneously taking positions in Treasury securities with similar remaining maturity, in order to facilitate client trading. As in the data, the dealers will sometimes be net short and sometimes be net long. The noise in Treasury securities’ prices compensates dealers for making markets.

In the model, there are two investors, A and B, and two types of bonds, A bonds and B bonds. A and B bonds both mature in period 3. In period 1, traders A and B have complementary trading needs: A traders and B traders receive endowment shocks in period 3 that are equal in magnitude but opposite in sign and these endowment shocks are correlated with interest rates. However, the markets are segmented: trader A is only able to trade A bonds and trader B is only able to trade B bonds. Hence, the traders must satisfy their trading needs through a dealer. Market making by dealers involves risk: in period 2, dealers may be forced to liquidate their positions at uncertain

Figure 3: Maturity-matched positions



prices. As a result, unless the dealer is risk neutral, the securities will trade at different prices.

Outside the model, there are several reasons why dealers’ clients are willing to trade only a particular security. For example, a client who owns a particular bond and no longer wants the associated interest rate risk may not be willing to shed that risk by going short a different bond with similar remaining maturity; 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. Pedersen (2015) gives the example of a purchase by “price-insensitive insurance companies who need [a given bond] for a specific reason.” These observations motivate the assumption of market segmentation.

The model includes three periods, $t=1, 2, 3$. The i -bonds, with $i \in \{A, B\}$, are zero coupon bonds that pay out in period 3. i -investors can trade only in the i -bond and money. Investors and dealers are competitive. At $t = 1$, investors and dealers trade in the i -markets.

The period- t price of the i -bond is $p_{i,t}$. The gross interest rate on cash (or central bank reserves) between period 1 and period 2 is normalized to 1. The interest rate between periods 2 and 3 is R . There is a perfectly elastic supply of central bank reserves at the exogenous interest rates. In period 1, the expected net present value of the bond and the variance of the net present value are given by:

$$E \left[\frac{1}{R} \right] = \mu$$

and

$$\text{Var}\left[\frac{1}{R}\right] = \sigma.$$

At $t = 1$, investors and dealers trade in the i -markets. At $t = 2$, R is revealed. Also, with probability λ , dealers are forced to liquidate their positions at uncertain prices: $p_{i,2} = \frac{1}{R} + \epsilon_i$, where ϵ_A and ϵ_B are independent and have variance $\kappa\sigma$. At $t = 3$, i -investors receive an endowment e_i and consume.

i -investors have mean-variance preferences over period-3 wealth w_i . That is, i -investors maximize $E[w_i] - \frac{\gamma}{2}\text{Var}[w_i]$.⁸ Dealers also have mean-variance preferences, with risk aversion γ_d .

The i -investors have a motivation to hedge. In particular, $e_A = -e_B$ and $\text{Cov}\left(\frac{1}{R_A}, e_A\right) = u > 0$. The A-bond and the B-bond each have net supply g , representing net supply from government issuance less demand from price-insensitive buyers. If the net governmental supply is non-zero, then the dealers' net position will not sum to zero. This is important because it is consistent with the data above on dealer holdings of Treasury securities and because it leads to ruling out certain identification assumptions (i.e., sign restrictions) that might have been plausible *a priori*.

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

$$\psi_i = E\left[\frac{1}{R_i}\right] - p_{i,1}$$

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

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

The vector of dealers' demand is given by:

$$x = \frac{1}{\gamma_d}\Omega^{-1}\psi$$

and the vector of clients' demand is:

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

Market clearing requires that

$$x + y = g$$

Lemma 1. *There are thresholds g_A and g_B such that*

$$x_i > 0 \text{ if and only if } g > g_i$$

⁸Without loss of generality, i -investors and dealers have zero initial wealth.

and

$$-\infty < g_A < 0 < g_B < \infty.$$

Hence, dealers will hold only long positions, only short positions or a mix of long and short positions, depending on the net supply of the bonds, g .

The next lemma investigates the comparative statics of the model.

Lemma 2. *An increase in dealer risk aversion γ_D , the probability of early liquidation λ or the riskiness of liquidation prices κ leads to an increase in the dispersion of bond prices $|p_b - p_a|$ and a decrease in dealers' gross positions $|x_a| + |x_b|$. That is, for example, $\frac{d[|p_b - p_a|]}{d\gamma_d} > 0$ and $\frac{d[|x_a| + |x_b|]}{d\gamma_d} < 0$. An increase in client risk aversion γ or client hedging needs u also leads to an increase in the dispersion of bond prices; however, dealers' gross positions increase. A change in the mean μ or variance σ of the net present value of the bond has no effect on the dispersion of prices or dealers' gross positions. Finally, an increase in bond net supply g has no effect on the dispersion of prices and, if $g \in (g_A, g_B)$ so that dealers have a long position in A and a short position in B , no effect on dealer gross positions.*

In the FR 2004 A data, one observes long and short positions. A plausible additional sign restriction is that a liquidity supply shock reduces both long and short positions. However, this assumption does not hold in the theory model.

Lemma 3. *Define the short position as $s \equiv x_a \mathbf{1}\{x_a < 0\} + x_b \mathbf{1}\{x_b < 0\}$. Depending on the parameters, it is possible that*

$$\frac{ds}{d\gamma_d} > 0$$

or

$$\frac{ds}{d\gamma_d} < 0.$$

Finally, it is useful to compare the equilibrium in the segmented markets model with the outcome of a model without segmented markets, but that is otherwise identical.

Lemma 4. *Suppose that A traders can hold positions in B bonds and B traders can hold positions in A bonds. Then A and B bonds have the same price.*

2 Identifying shocks to broker-dealers' supply of liquidity

Next I estimate a structural model in which I identify shocks to broker-dealers' supply of liquidity. The variables included in the model and the identification assumptions are motivated by the theoretical model of intermediation in the previous section.

The VAR has the following structure:

$$Y_t = b + ct + B_1 Y_{t-1} + B_2 Y_{t-2} + \dots + B_l Y_{t-l} + \xi_t \tag{3}$$

where Y_t is a $(m \times 1)$ vector of endogenous variables, B_t is a $(m \times m)$ matrix, and $E[\xi_t \xi_t'] = \Sigma$.

The variables in Y_t are: a measure of the noise in Treasury yields; dealers' aggregate gross long and short holdings of nominal Treasury coupon securities; the VIX index, the excess equity market return, and the Merrill Lynch Option Implied Volatility Index (MOVE) index. To construct the noise measure, I use data on indicative quotes for the universe of outstanding nominal Treasury coupon securities in the Federal Reserve's PQS/NPQS database. Each day, I fit a Svensson yield curve, given by (1), as described above. I summarize the noise by calculating the root mean squared error for bonds with remaining maturity of between 1 and 10 years. I measure dealers' total gross position in nominal Treasury coupon securities using the FR 2004A. The VIX index is an indicator of near-term equity-market volatility and the MOVE index is an indicator of near-term interest-rate volatility.⁹ All variables except the excess equity market return enter in logs.¹⁰

As in most structural VAR exercises, the goal is to find (part of) a matrix A such that $\xi_t = Av_t$, where v_t are the mutually orthogonal fundamental shocks with $E[v_t v_t'] = I_m$. I refer to the s -th structural shock at time t by $v_{s,t}$. The frequency of the data is weekly. I estimate the model using the pure sign restrictions approach of Uhlig (2005), adapted to a setting in which I identify multiple columns of A . The estimation procedure builds on Mountford and Uhlig (2009) and Kilian and Murphy (2014).

In the benchmark model, the identification assumptions are:

- A1. The impulse responses to a positive shock to broker-dealers' supply of liquidity are (weakly) negative for the noise measure and (weakly) positive for market-making portfolio size, at all horizons $t = 0, \dots, K$.
- A2. The impulse responses to a positive shock to liquidity demand are (weakly) positive for the noise measure and (weakly) positive for gross dealer holdings, at all horizons $t = 0, \dots, K$.

The identification assumptions are motivated by the theoretical model above. I use $K = 12$, so that the shocks are, by assumption, required to have the above-defined effects for one quarter. The motivation for setting $K > 0$ is to ignore shocks with transitory effects on noise and holdings. Later, I examine robustness to different choices of K .

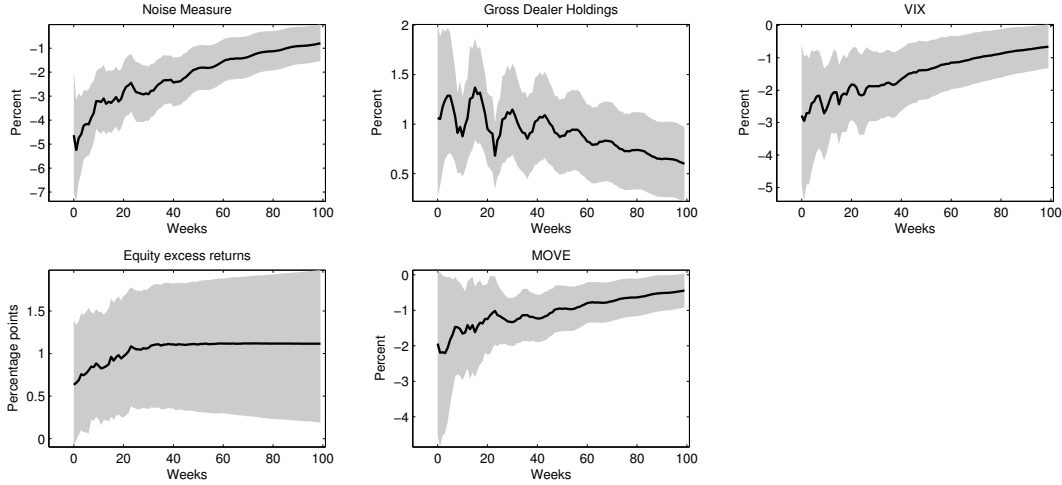
In an alternative specification, I control for a generic shock to financial conditions, identified as follows:

- A3. The impulse responses to a rate risk shock are (weakly) positive for the MOVE, at all horizons $w = 0, \dots, K$
- A4. The impulse responses to a generic equity market shock are (weakly) positive for the VIX, at all horizons $w = 0, \dots, K$, and (weakly) negative for equity-market excess returns on impact.

⁹The MOVE index is an unweighted average of option-implied volatility calculated from exchange-traded options on 2-year, 5-year, 10-year and 30-year Treasury securities.

¹⁰Data on excess equity market returns are from the website of Ken French.

Figure 4: **Impulse responses to a shock to broker-dealers' supply of liquidity**



Note: The mean impulse response is shown in black. The gray shaded area marks a pointwise 68-percent credible interval around the median. The model is estimated using assumptions A1 and A2. See text for details.

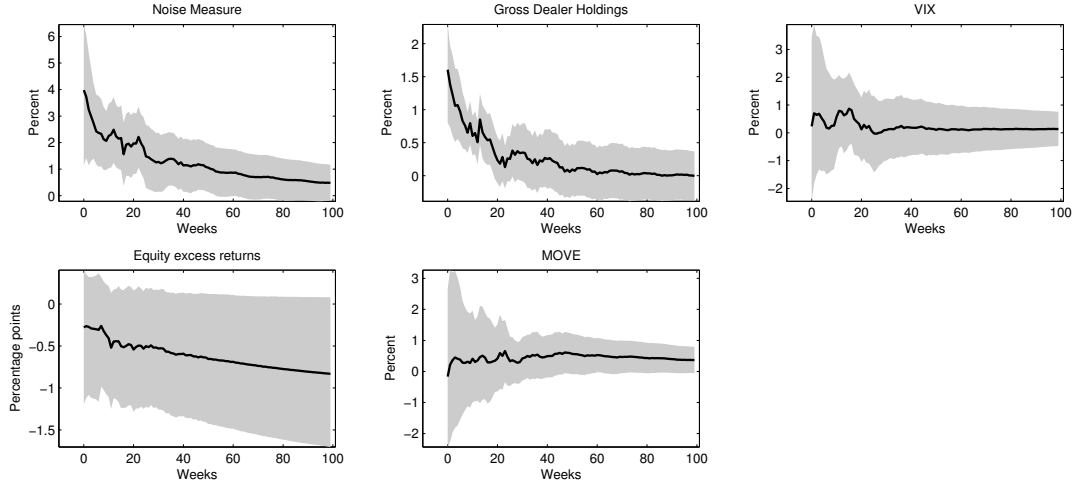
I use $l = 26$ lags of the endogenous variables in the VAR. As in Uhlig (2005), I use a weak Normal-Wishart prior.

Although it may at first seem unobjectionable to assume that supply shocks move price and quantity in opposite directions while demand shocks move price and quantity in the same direction, it is well known that, in a dynamic arbitrage models, an increase in noise trading (or the demand for liquidity) can lead arbitrageurs to pull back from their positions despite the increase in the expected return to the arbitrage trade (see Shleifer and Vishny (1997) and Gromb and Vayanos (2010)). This can occur if positions previously acquired by the arbitrageur are negatively affected by the increase in noise trading, leading to a loss of wealth that prevents the arbitrageur from increasing those positions in response to the demand-driven increase in expected return. In the present setting, one safeguard against this problem is that the shock to liquidity demand is narrowly defined: it is a shock to non-dealers' demand for a specific type of Treasury trading. Presumably, in response to an increase in non-dealers' demand for Treasury trading, individual dealers can shift funds internally to take advantage of the increased market-making opportunity. In addition, by focusing on the noise in Treasury prices, I focus on the demand for idiosyncratic trading: the noise measure excludes the effects of trading pressure that shifts the yield curve up or down or rotates it consistent with changes in the Svensson (1994) parameters.

Figures 4 and 5 show the impulse responses to a shock to broker-dealers' supply of liquidity and a shock to liquidity demand, respectively. A positive shock to the supply of liquidity leads to a decrease in uncertainty measures for equity and Treasury markets and an increase in equity excess returns. In contrast, a positive liquidity demand shock has no effect on these asset prices.

Figure 6 shows the impulse responses to a shock to broker-dealers' supply of liquidity under assumptions A1-A4. In this alternative specification, a rate risk shock and a generic equity market shock are defined as structural shocks, and the liquidity supply shock is required to be orthogonal

Figure 5: **Impulse responses to a shock to the demand for liquidity**



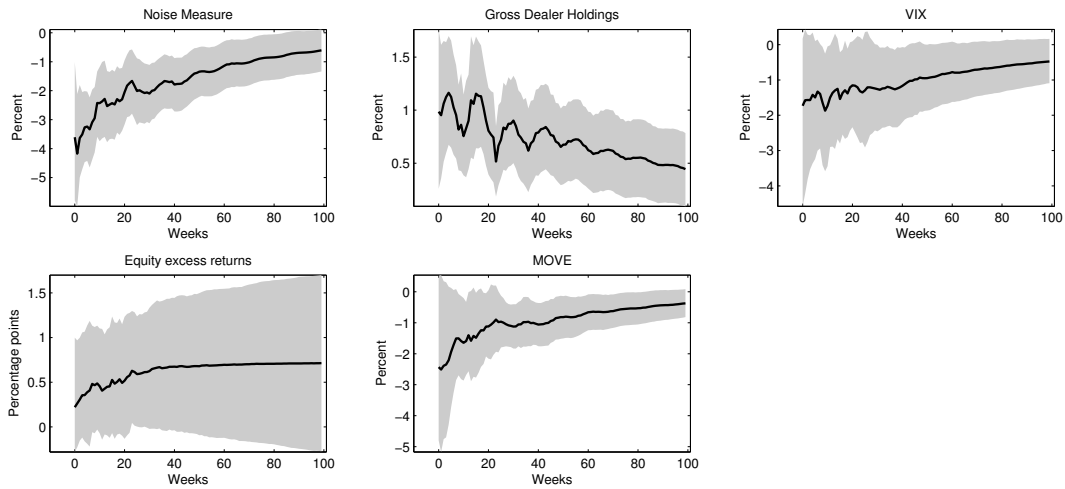
Note: The mean impulse response is shown in black. The gray shaded area marks a pointwise 68-percent credible interval around the median. The model is estimated using assumptions A1 and A2.

to these shocks. The resulting impulse responses are consistent with those in Figure 4, in which only two structural shocks (liquidity supply and demand) were defined. Figures 7 and 8 show the responses to a rate risk shock and a generic equity market shock. Neither shock has an effect, on impact, on noise or dealer holdings. Also, neither leads, at any horizon, to opposite-signed changes in noise and dealer holdings.

Figures 9 show the pointwise mean of the cumulative sum of each structural shock. Figures 11-14 show the cumulative effect of these structural shocks on noise and the VIX. To calculate the cumulative effect of shock s , I first calculate baseline values for Y_{l+1}, \dots, Y_T conditional on Y_1, \dots, Y_l and the assumption that $v_t = 0$ for all t . Next, I draw from the posterior distribution over $v = \{v_t\}_{t=1}^T$ and calculate counterfactual values for Y_{l+1}, \dots, Y_T conditional on Y_1, \dots, Y_l , the drawn values of $\{v_{s,t}\}_{t=1}^T$ and the assumption that $v_{j,t} = 0$ for $j \neq s$ and all t . The difference between the counterfactual values for Y_{l+1}, \dots, Y_T and the baseline values is defined as the cumulative effect of shock s . In Figures 11-14, I show the mean cumulative effect calculated using many draws from the posterior over $v = \{v_t\}_{t=1}^T$.

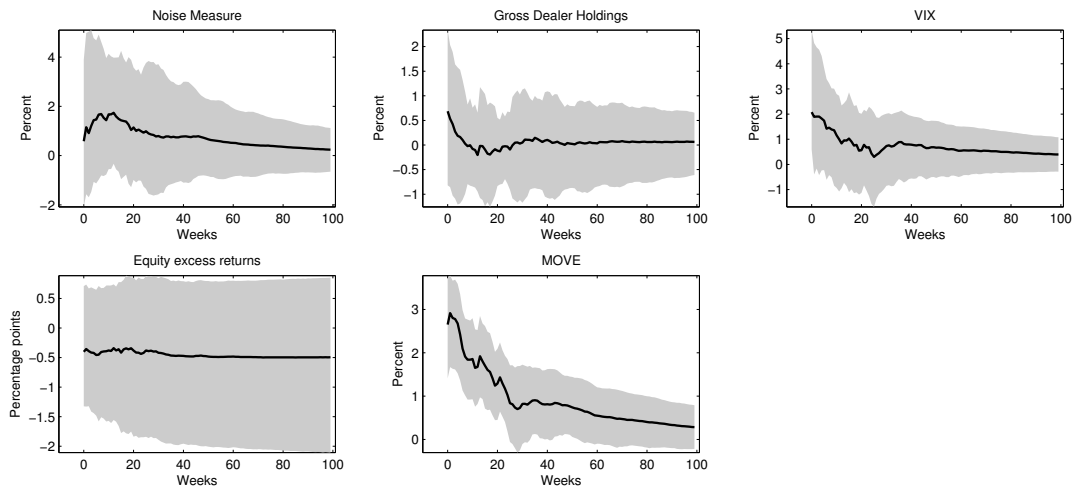
These results allow a decomposition of historical episodes of financial market stress. For example, in 2006 and through the first months of 2007, liquidity supply shocks were positive, overall, even as the housing sector slowed and then began to implode. During this time, the generic equity market shocks were mixed and the liquidity demand shocks were generally positive. In summer of 2007, two large financial institutions suspended redemptions from certain investment funds, and thereafter liquidity supply shocks were, overall, markedly negative for the next 15 months. At the same time, liquidity demand shocks continued to be positive, overall, and a notable positive liquidity demand shock occurred at the time of the near collapse of Bear Stearns in March 2008. Following the bankruptcy of Lehman Brothers in September 2008, liquidity supply shocks and generic equity market shocks were sharply negative, while shocks to liquidity demand were quite muted. The

Figure 6: **Impulse responses to a shock to broker-dealers' supply of liquidity (alternative specification)**



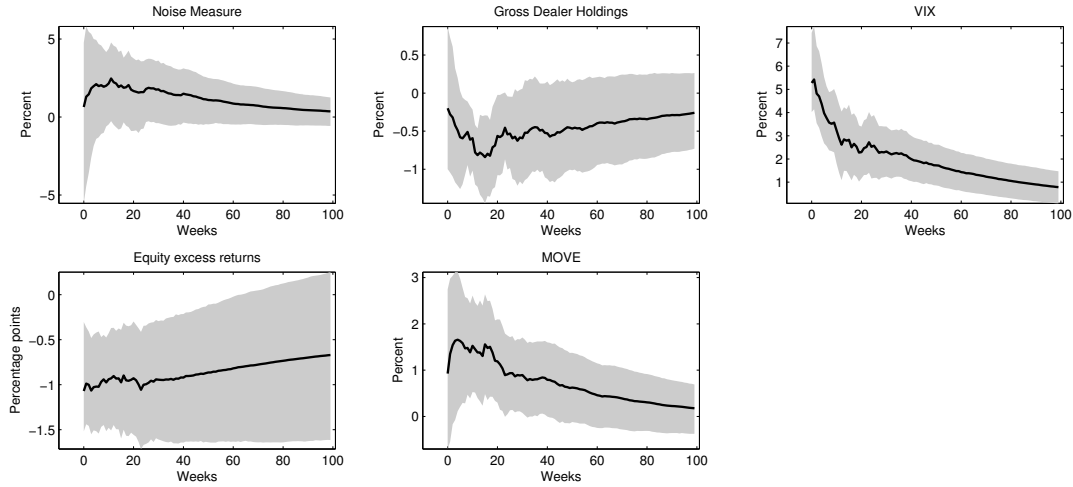
Note: The mean impulse response is shown in black. The gray shaded area marks a pointwise 68-percent credible interval around the median. The model is estimated using assumptions A1-A4. See text for details.

Figure 7: **Impulse responses to a rate risk shock**



Note: The mean impulse response is shown in black. The gray shaded area marks a pointwise 68-percent credible interval around the median. The model is estimated using assumptions A1-A4. See text for details.

Figure 8: Impulse responses to a generic equity market shock



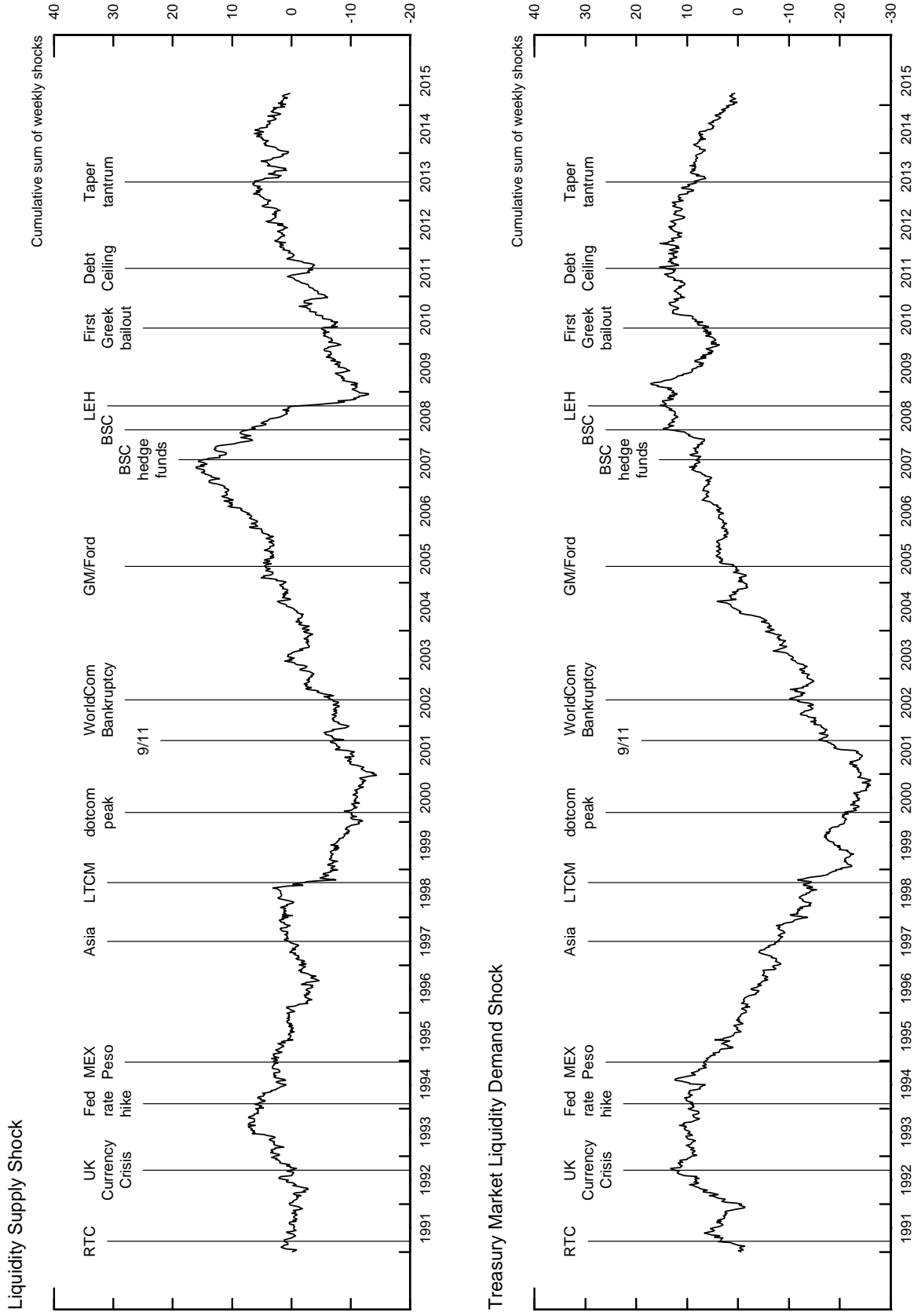
Note: The mean impulse response is shown in black. The gray shaded area marks a pointwise 68-percent credible interval around the median. The model is estimated using assumptions A1-A4. See text for details.

model attributes about one-quarter of the increase in the VIX after Lehman Brothers' bankruptcy to liquidity supply shocks. The liquidity supply shocks and generic equity market shocks turned positive only toward the end of the year, after capital injections into banks under the Capital Purchase Program, the creation of several lender-of-last resort facilities, and a series of rate cuts that brought the federal funds target range to zero.

One can also examine financial market events outside the 2007-2009 financial crisis. Episodes characterized by negative liquidity supply shocks include: Russia's 1998 default and devaluation; the subsequent collapse of Long-Term Capital Management; and the taper tantrum in 2013. Other episodes of financial market stress, such as creditor negotiations with Greece in the spring of 2010, are associated with modest negative liquidity supply shocks. In contrast, liquidity supply shocks are characterized as absent from several notable financial market events, including the aftermath of the debt ceiling debate in 2011 and the Mexican economic crisis that followed the devaluation of the Mexican peso in December 1994.

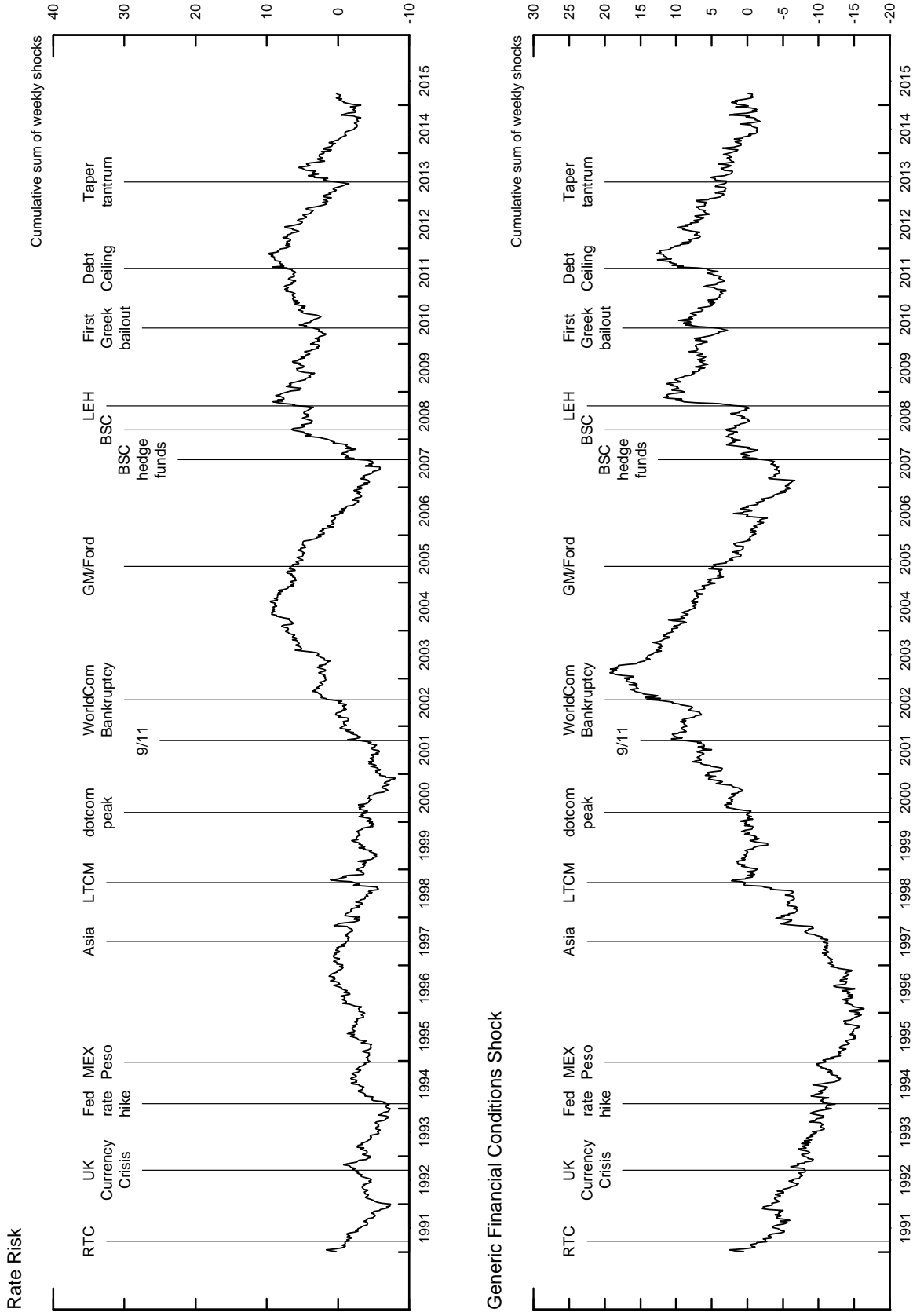
Figure 15 shows the share of forecast error variance that can be accounted for by the liquidity supply shock and the liquidity demand shock. Both shocks are important in explaining variation in market-making activity and the price of liquidity in the Treasury market. For the noise measure, liquidity supply shocks explain about 30 percent of forecast error variance at horizons of up to one year; demand shocks explain about 15 percent. The liquidity supply shocks also explain a significant portion of forecast error variance for equity market excess returns and measures of near-term equity market and bond market uncertainty, while demand shocks play a modest role in explaining these variables.

Figure 9: Cumulative sum of selected structural shocks



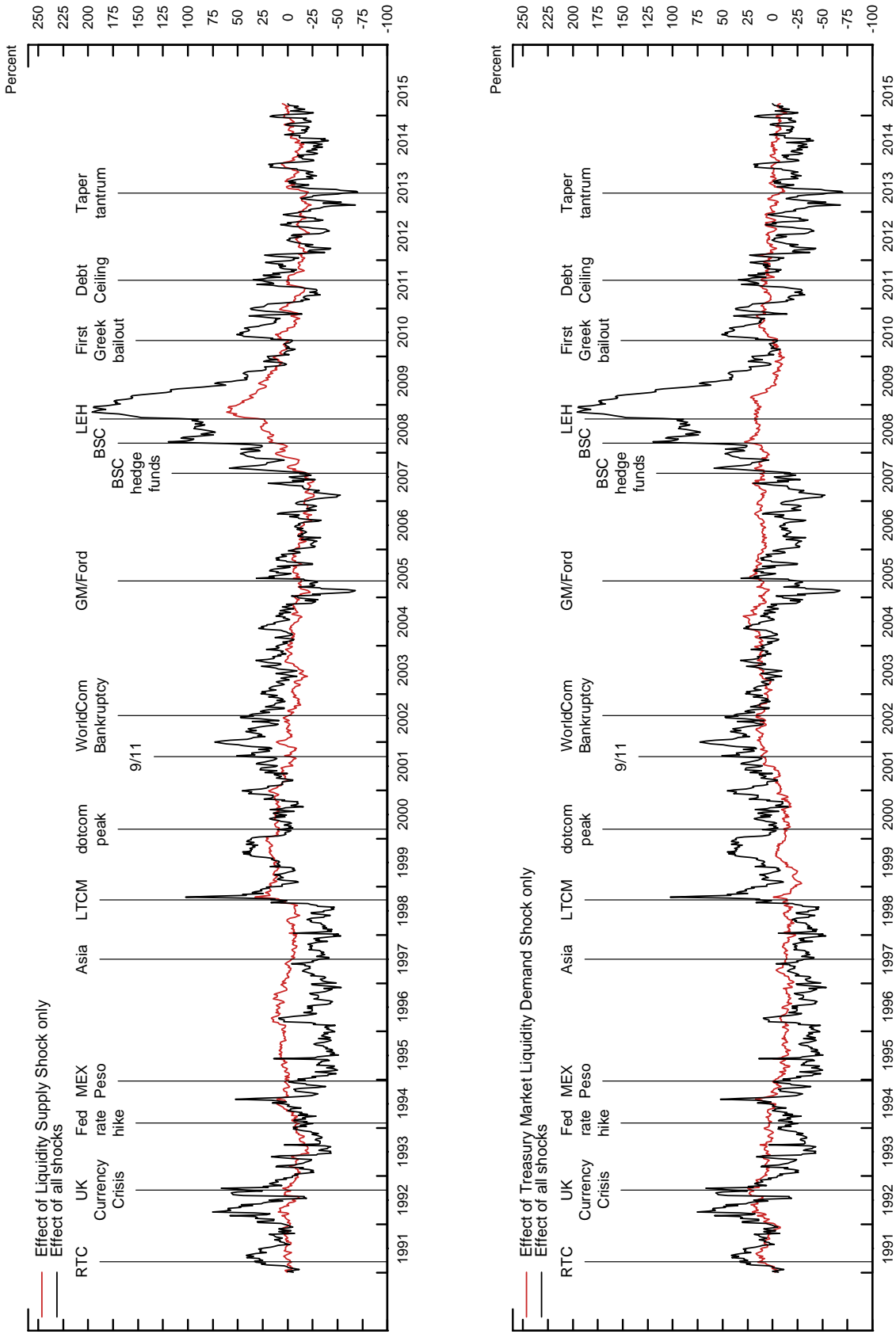
Notes: Each panel shows the mean of the posterior distribution of the cumulative sum of one of the structural shocks. The model is estimated using assumptions A1-A4.

Figure 10: Cumulative sum of selected structural shocks



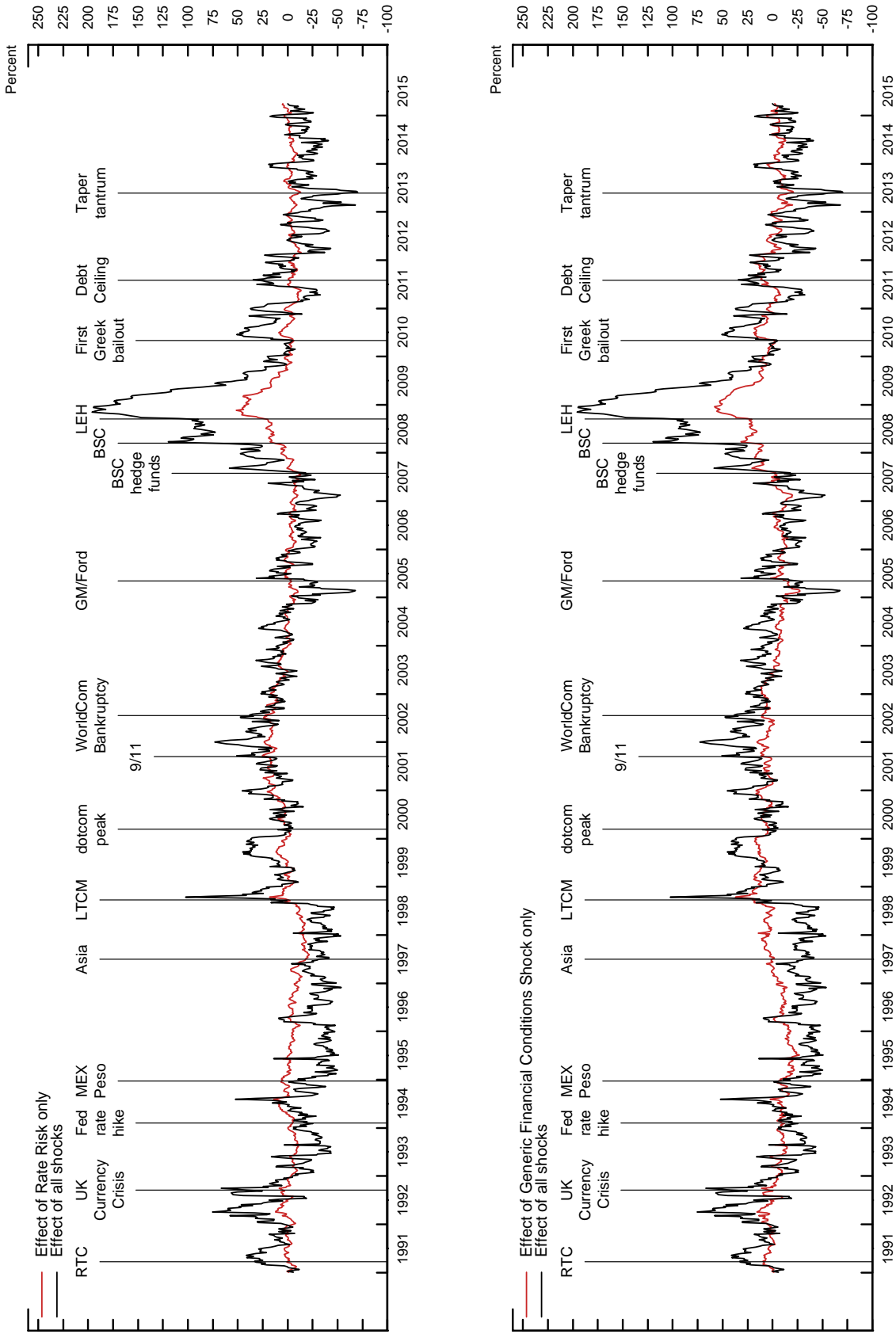
Notes: Each panel shows the mean of the posterior distribution of the cumulative sum of one of the structural shocks. The model is estimated using assumptions A1-A4.

Figure 11: Cumulative effect of structural shocks on the noise measure



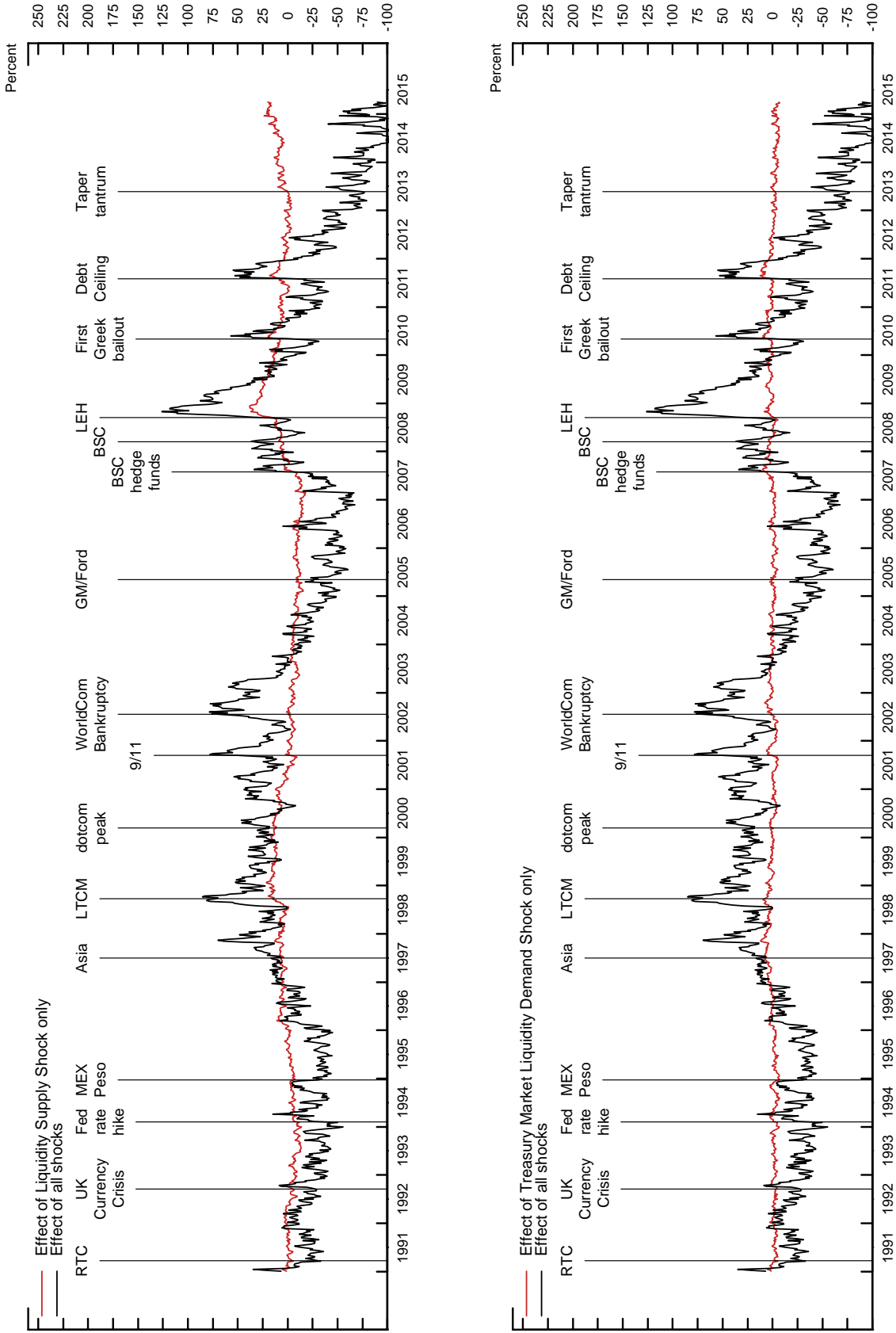
Notes: Each panel shows the mean of the posterior distribution of the cumulative effect of one of the structural shocks. See text for details.

Figure 12: Cumulative effect of structural shocks on the noise measure



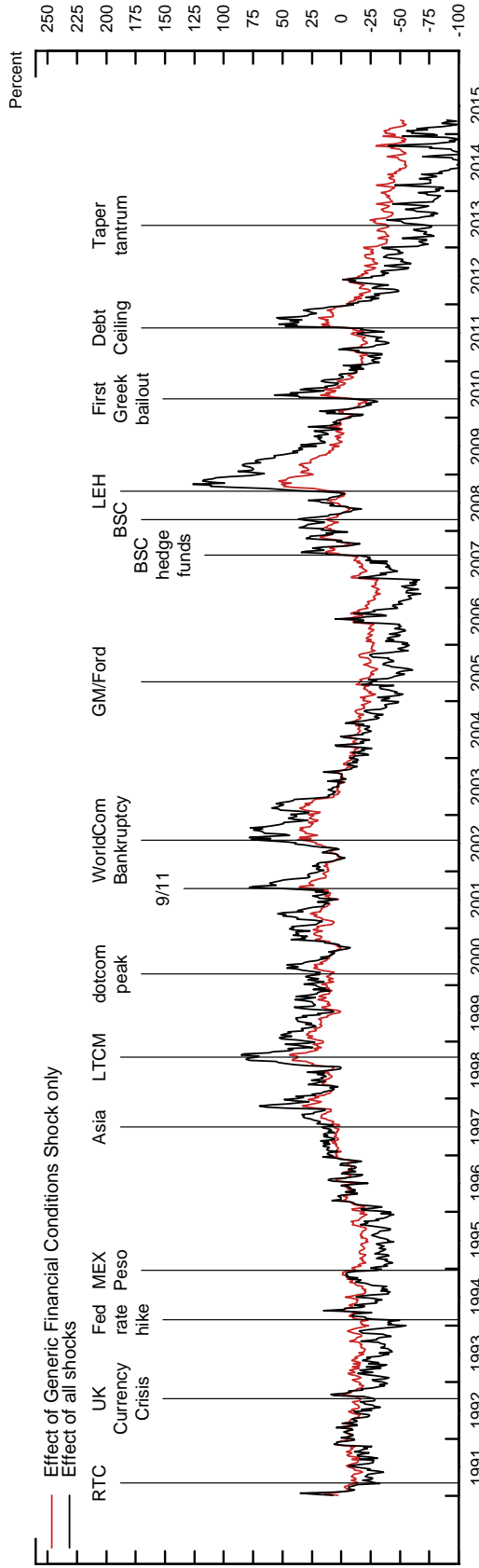
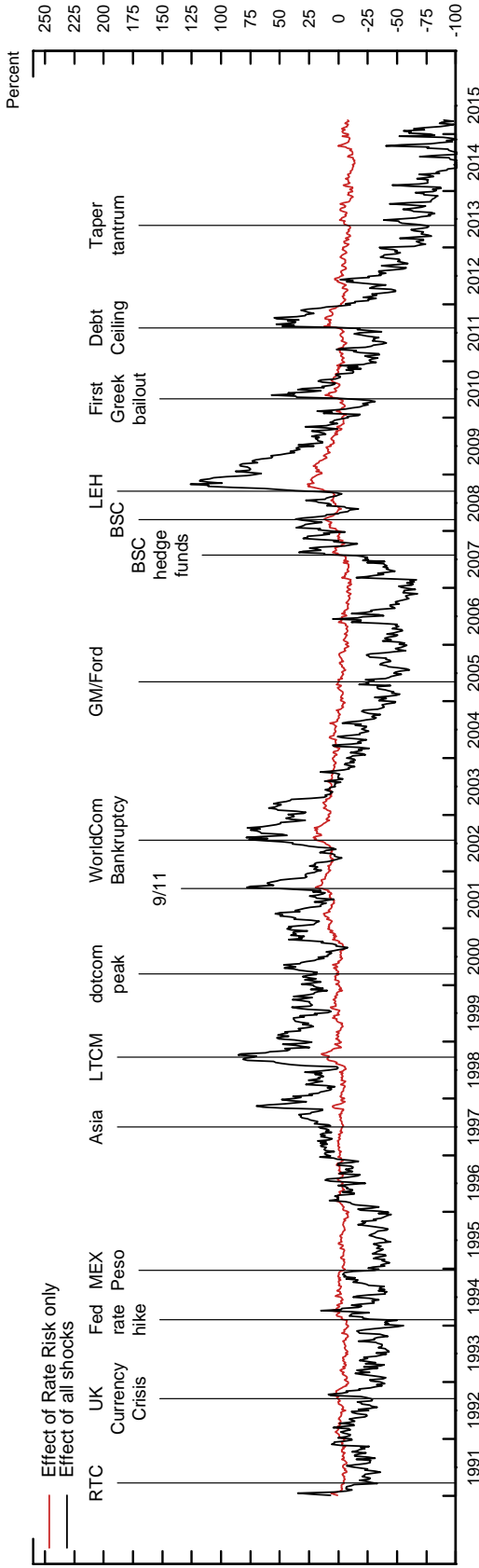
Notes: Each panel shows the mean of the posterior distribution of the cumulative effect of one of the structural shocks. See text for details.

Figure 13: Cumulative effect of structural shocks on VIX



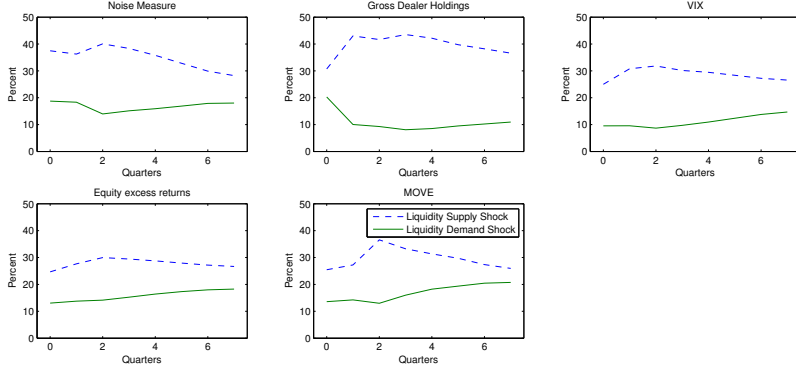
Notes: Each panel shows the mean of the posterior distribution of the cumulative effect of one of the structural shocks. See text for details.

Figure 14: Cumulative effect of structural shocks on VIX



Notes: Each panel shows the mean of the posterior distribution of the cumulative effect of one of the structural shocks. See text for details.

Figure 15: Forecast error variance decomposition of liquidity supply and demand shocks



Note: The forecast error variance decomposition above 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. The model is estimated under A1-A2.

3 Dealer willingness to intermediate and business cycles

In this section, I study the business cycle implications of shocks to dealers' liquidity supply, as well as the other structural shocks identified above. Consider the following model for a measure of real economic activity:

$$\Delta x_{t_m} = \alpha_0 + \sum_{i=0}^l \theta_{s,i} v_{s,t_m-i} + \epsilon_{s,t_m} \quad (4)$$

where x_{t_m} is a measure of real economic activity in month m and v_{s,t_m} is the value of fundamental shock s in month $t_m \in \{1, \dots, T_m\}$. Here, the frequency is monthly, so I calculate v_{s,t_m} by taking an average of the weekly observations of $v_{s,t}$ in each month. Also,

$$\Delta x_{t_m} = \ln\left(\frac{x_{t_m}}{x_{t_m-1}}\right)$$

when x is equal to industrial production or non-farm payrolls and

$$\Delta x_{t_m} = x_{t_m} - x_{t_m-1}$$

when x is equal to unemployment. I also estimate the model using inflation on the left-hand side of (4). Due to the possible presence of serial correlation in the errors ζ_{s,t_m} , I assume that the errors follow an AR(p) process:

$$\rho(L)\epsilon_{s,t_m} = \zeta_{s,t} \sim i.i.d. N(0, h_s^{-1}) \quad (5)$$

where $\rho(L) = (1 - \rho_1 L - \dots - \rho_p L^p)$ is a polynomial of order p in the lag operator. Denote the parameters of the model by $\Gamma = (\alpha_0, \{\zeta_{s,i}\}_{i=0}^l, \{\rho_i\}_{i=1}^p, h_s)$. I use a weak, independent Normal-Gamma prior.

The model given by (4) and (5) is similar to the one used in Kilian (2009) to estimate the impulse responses of measures of real activity to structural shocks estimated using a VAR. Kilian (2009) uses a frequentist approach and addresses serial correlation in the errors ϵ_{s,t_m} using block bootstrap methods. In contrast, I use a unified Bayesian method to estimate the model; this method, unlike Kilian (2009), takes into account that the regressors used in (4) are generated regressors. Although $v_{s,t}$ is unknown, we can draw from the posterior distribution $p(v|Y)$ over $v = \{v_t\}_{t=1}^T$. To draw from the posterior distribution $p(\Gamma|Y,x)$, I first draw v from $p(v|Y)$ and then make draws from $p(\Gamma|x,v)$.¹¹ By repeating this exercise, I obtain a set of draws from $p(\Gamma|Y,x)$.

Under the identifying assumption that there is no feedback within a given month from Δx_{t_m} to v_{s,t_m} , these shocks can be treated as predetermined and $\theta_{s,i}$ is the impulse response to shock s at horizon i . The assumption that v_{s,t_m} is predetermined with respect to monthly changes in real activity and consumer prices is not testable. However, a defense of this assumption can be made similar to that offered by Kilian (2009). To proceed, I estimate an autoregressive model for Δx_{t_m} :

$$\Delta x_{t_m} = \alpha_1 + \sum_{i=1}^p \phi_i \Delta x_{t_m-i} + \eta_{t_m}$$

and calculate the correlation between η_{t_m} and $\zeta_{s,t}$. If an unanticipated increase in liquidity supply were to have a positive effect on the growth of real activity within a month, this would be associated with a positive correlation between these shocks. If an unanticipated increase in the growth of real activity were to generate an increase in liquidity supply within a month, this would also be associated with a positive correlation between \hat{v}_{1,t_m} and $\hat{\eta}_{t_m}$. However, the correlation is low, suggesting that neither channel is important at a monthly frequency. A similar argument can be made for the generic equity market shock and rate risk shock.

The impulse responses calculated using (4) and (5) are shown in Figures 16-18.

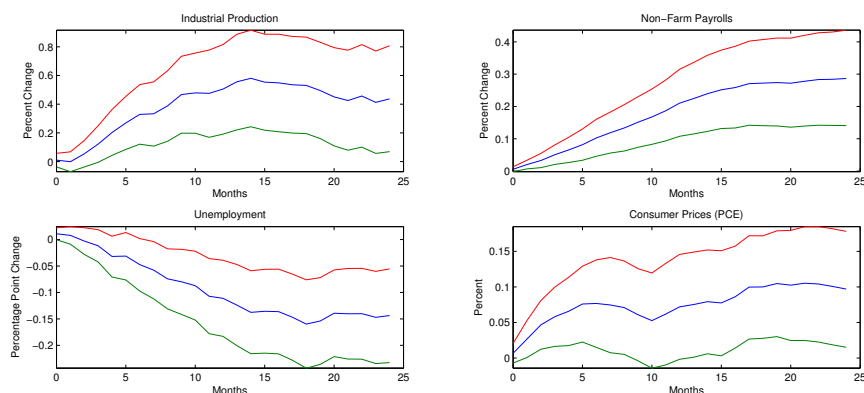
In the next section, I will investigate the robustness of the impulse responses of real activity and inflation under a variety of alternative model specifications.

3.1 Robustness and alternative specifications

First, I investigate the sensitivity of the results to alternative assumptions regarding K , the number of periods (in this case, weeks) for which the sign restrictions are required to hold. As shown in Figure 19, the impulse responses of non-farm payrolls to a liquidity shock are very similar for a wide range of values for K . Second, I study an alternative model specification: rather than the two-stage procedure of estimating the structural VAR using only financial variables and then aggregating to monthly frequency to study the response of real activity via (4), I instead aggregate the financial variables to monthly frequency and include a measure of real activity in the VAR given by (3). As shown in Figure 20, the impulse responses to a liquidity shock for the financial variables and for

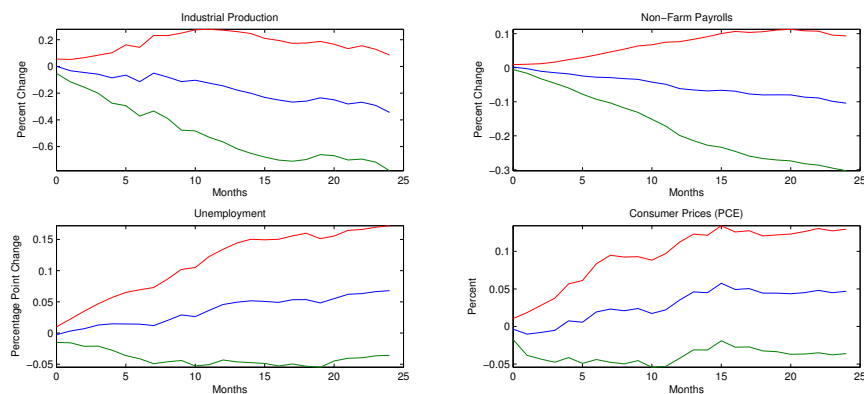
¹¹For a given v , I draw from $p(\Gamma|v,x)$ using Gibbs sampling, with a likelihood based on data from $\{p+1, \dots, T_m\}$. As in Geweke (2005), a draw for (ρ_1, \dots, ρ_L) is retained if and only if the draw implies that ϵ_{s,t_m} is stationary; otherwise, the previously drawn value for (ρ_1, \dots, ρ_L) is retained.

Figure 16: Impulse responses to a liquidity supply shock



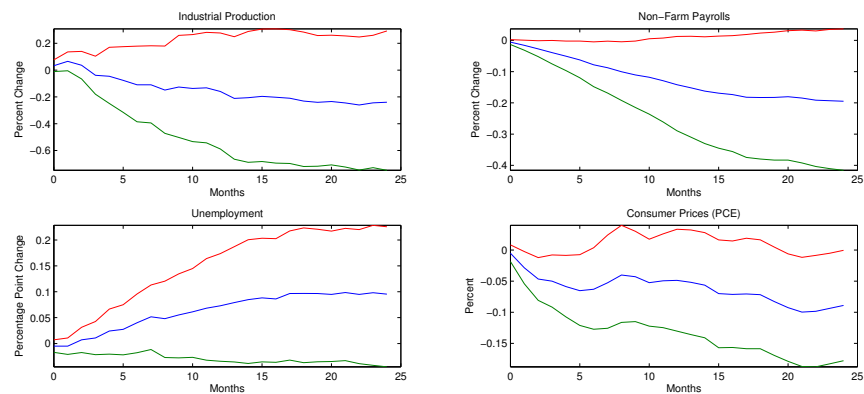
Note: The blue line shows the mean cumulated impulse responses from (4) to a one standard deviation shock to liquidity supply. The red and green lines mark a pointwise 68-percent credible interval around the pointwise median.

Figure 17: Impulse responses to a liquidity demand shock



Note: The blue line shows the mean cumulated impulse responses from (4) to a one standard deviation shock to liquidity demand. The red and green lines mark a pointwise 68-percent credible interval around the pointwise median.

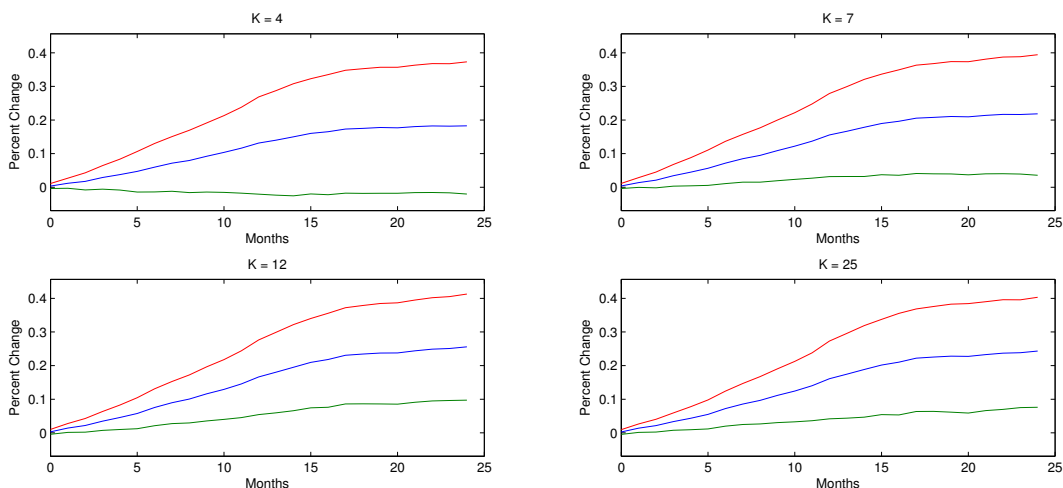
Figure 18: Impulse responses to a generic equity market shock



Note: The blue line shows the mean cumulated impulse responses from (4) to a one standard deviation generic financial-conditions shock. The red and green lines mark a pointwise 68-percent credible interval around the pointwise median.

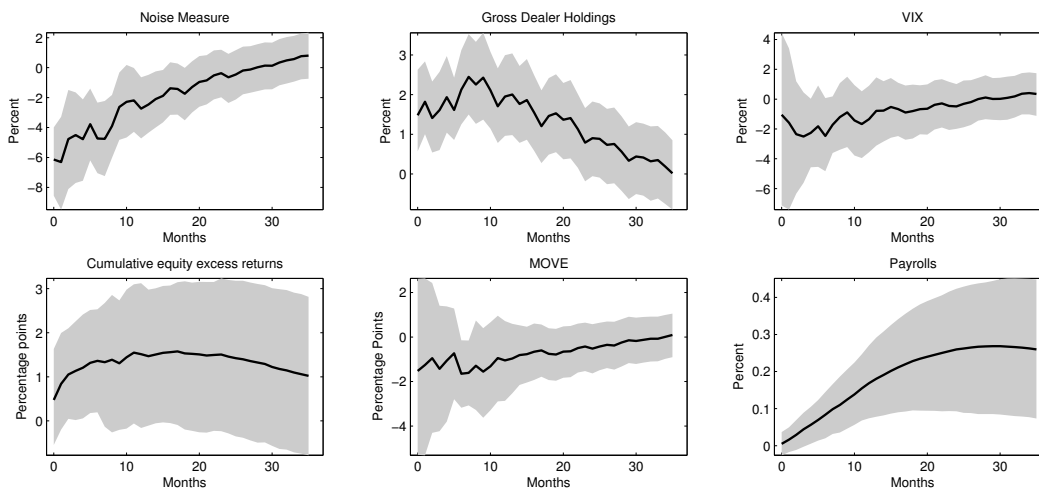
the real activity measure (in this case, payrolls) are very similar to those derived via the two-step benchmark procedure.

Figure 19: **Impulse response of payrolls to a liquidity shock, for $K \in \{4, 7, 12, 25\}$**



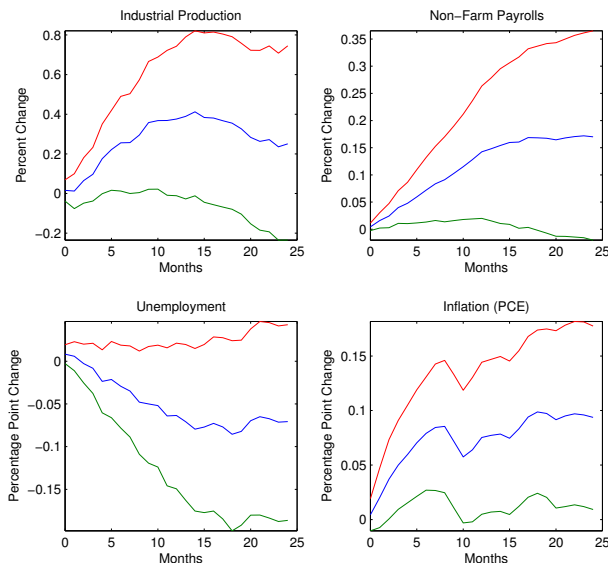
Note: The blue line shows the mean cumulated impulse responses from (4) to a one standard deviation shock to liquidity supply. The red and green lines mark a pointwise 68-percent credible interval around the pointwise median.

Figure 20: **Impulse responses to a liquidity supply shock: VAR at monthly frequency**



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

Figure 21: **Impulse responses to a liquidity supply shock, with term spread included in the first stage**



Note: The blue line shows the mean cumulated impulse responses from (4) to a one standard deviation shock to liquidity supply. The red and green lines mark a pointwise 68-percent credible interval around the pointwise median.

4 Conclusion

A large theoretical literature has examined how constraints facing financial intermediaries can contribute to reduced market liquidity and affect asset prices and the real economy. However, empirically, it is hard to measure the capacity of intermediaries and identify shocks to the supply of intermediation. In this paper, I provide a new method for identifying shocks to supply of market liquidity by broker dealers. Specifically, motivated by a theoretical model of intermediation, I use a VAR model and identify a shock to liquidity supply that is orthogonal to liquidity demand and to generic financial conditions shocks. This method builds on earlier research that stopped short of disentangling shocks to liquidity supply and demand or that used VARs that recursively identified a shock to broker-dealer balance sheets or specialist inventories.

I find that shocks to liquidity supply and liquidity demand both are important in explaining the amount of market-making activity and the price of market liquidity in the Treasury market. However, a positive shock to liquidity supply leads to greater real activity and inflation, as well as higher equity market excess returns and lower equity and bond market uncertainty. In contrast, liquidity demand shocks have little or no effect on real activity, inflation and asset prices. Requiring these shocks to be orthogonal to a generic shock to financial conditions matters, but does not make a large difference in estimates of the impulse responses of real activity to these shocks. These results underscore the importance of the supply of intermediation for understanding business cycles and asset pricing.

The identification approach used in the paper – relying on gross dealer Treasury holdings, a

measure of the noise in prices, asset prices and a set of sign restrictions on impulse response functions – 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 aim to support the supply of financial intermediation.

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