An Empirical Analysis of Stock and Bond Market Liquidity

Tarun Chordia
Emory University

Asani Sarkar
Federal Reserve Bank of New York

Avanidhar Subrahmanyam
University of California at Los Angeles

This article explores cross-market liquidity dynamics by estimating a vector autoregressive model for liquidity (bid-ask spread and depth, returns, volatility, and order flow in the stock and Treasury bond markets). Innovations to stock and bond market liquidity and volatility are significantly correlated, implying that common factors drive liquidity and volatility in these markets. Volatility shocks are informative in predicting shifts in liquidity. During crisis periods, monetary expansions are associated with increased liquidity. Moreover, money flows to government bond funds forecast bond market liquidity. The results establish a link between "macro" liquidity, or money flows, and "micro" or transactions liquidity.

A number of important theorems in finance rely on the ability of investors to trade any amount of a security without affecting the price. However, there exist several frictions,[1] such as trading costs, short sale restrictions, and circuit breakers, that impact price formation. The influence of market imperfections on security pricing has long been recognized. Liquidity, in particular, has attracted a lot of attention from traders, regulators, exchange officials and academics.

Liquidity, a fundamental concept in finance, can be defined as the ability to buy or sell large quantities of an asset quickly and at low cost. The vast majority of equilibrium asset pricing models do not consider trading and thus ignore the time and cost of transforming cash into

We are grateful to an anonymous referee and Cam Harvey (the editor) for providing insightful and constructive comments on earlier drafts of this article. We also thank Michael Brennan, Arturo Estrella, Michael Fleming, Clifton Green, Joel Hasbrouck, Charlie Himmelberg, Eric Hughson, Charles Jones, Ken Kuttner, Stavros Peristiani, Raghu Rajan, Anthony Rodrigues, René Stulz, Ross Valkanov, and seminar participants at the SFS/Kellogg conference on Investment in Imperfect Capital Markets for helpful comments and/or for encouraging us to explore these issues. We also appreciate Michael Emmet for excellent research assistance. The views expressed here are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of New York or the Federal Reserve System. Any errors are the authors' alone. Address correspondence to: Asani Sarkar, The Federal Reserve Bank of New York, New York, NY 10045, or e-mail: asani.sarkar@ny.frb.org.

[1] See Stoll (2000).

The Review of Financial Studies Vol. 18, No. 1
doi:10.1093/rfs/hhi010 Advance Access publication November 3, 2004

financial assets or vice versa. Recent financial crises, however, suggest that, at times, market conditions can be severe and liquidity can decline or even disappear.[2] Such liquidity shocks are a potential channel through which asset prices are influenced by liquidity. Amihud and Mendelson (1986) and Jacoby, Fowler, and Gottesman (2000) provide theoretical arguments to show how liquidity impacts financial market prices. Jones (2001) and Amihud (2002) show that liquidity predicts expected returns in the time series. Pastor and Stambaugh (2003) find that expected stock returns are cross-sectionally related to liquidity risk.[3]

Until recently, studies on liquidity were focused principally on its cross-sectional determinants, and were restricted to equity markets [e.g., Benston and Hagerman (1974) and Stoll (1978)]. As more data has become available, recent work has shifted focus on studying time-series properties of liquidity in equity markets as well as in fixed-income markets. Hasbrouck and Seppi (2001), Huberman and Halka (2001), and Chordia, Roll and Subrahmanyam (2000) document commonality in trading activity and liquidity in the equity markets. Chordia, Roll, and Subrahmanyam (2001) study daily aggregate equity market spreads, depths and trading activity over an extended period to document weekly regularities in equity liquidity and the influence of market returns, volatility, and interest rates on liquidity. For U.S. Treasury Bond markets, Fleming (2003) examines the time series of a set of liquidity measures, Huang, Cai, and Wang (2001) relate liquidity to return volatility, while Brandt and Kavajecz (2002) study the relationship between liquidity, order flow, and the yield curve. Fleming and Remolona (1999) and Balduzzi, Elton, and Green (2001) analyze returns, spreads, and trading volume in bond markets around economic announcements.

To date, the literature on stock and bond market liquidity has developed in separate strands. There is good reason, however, to believe that liquidity in the stock and bond markets covaries. Although the unconditional correlation between stock and bond returns is low [Campbell and Ammer (1993)], there are strong volatility linkages between the two markets [Fleming, Kirby and Ostdiek (1998)], which can affect liquidity in both markets by altering the inventory risk borne by market-making agents [Ho and Stoll (1983) and O'Hara and Oldfield (1986)]. Second, stock and bond market liquidity may interact via trading activity. In practice, a number of asset allocation strategies shift wealth between

[2] "One after another, LTCM's partners, calling in from Tokyo and London, reported that their markets had dried up. There were no buyers, no sellers. It was all but impossible to maneuver out of large trading bets." — *Wall Street Journal*, November 16, 1998.

[3] Note that Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan, Chordia and Subrahmanyam (1998), Jones (2001), and Amihud (2002) view liquidity in a transaction costs context, while Pastor and Stambaugh (2003) relate liquidity risk to expected stock returns.

stock and bond markets.[4] A negative information shock in stocks often causes a "flight to quality" as investors substitute safe assets for risky assets.[5] The resulting outflow from stocks into Treasury bonds may cause price pressures and also impact stock and bond liquidity. In other situations, stock and bond order flows may be complementary. For example, if the Federal Reserve pursues an expansionary monetary policy, the increase in funds could cause higher order inflows into both stocks and government bonds and potential changes in their liquidity. Further, systematic wealth or informational shocks could induce positively correlated trading activity across equity and fixed income securities, and, in turn, cause comovements in liquidities across these markets. Overall, the preceding discussion implies that liquidity can exhibit comovement across asset classes and can also be driven by common influences such as monetary shocks.

Motivated by these observations, in this article we study the joint dynamics of liquidity, trading activity, returns, and volatility in stock and U.S. Treasury bond markets. While the extant literature has examined the dynamic interaction of liquidity and returns in stock markets [Hasbrouck (1991)] and time-varying liquidity in Treasury bond markets [Krishnamurthy (2002)], the intertemporal interactions of liquidity proxies with returns and volatility across these asset classes have not been examined. Our structural model allows us to distinguish the relative importance of order flow and return variability in affecting liquidity as well as price formation in the stock and Treasury bond markets.

We also seek to identify primitive factors that generate order flow in stock and bond markets and, possibly, induce correlated movements in liquidity. We examine the notion [Garcia (1989)] that the monetary stance of the Fed can affect liquidity by altering the terms of margin borrowing and alleviating borrowing constraints of dealers, and also consider the idea that fund flows into stock and bond markets can affect trading activity and thereby influence liquidity. Earlier work has analyzed the effects of monetary policy and fund flows on financial markets, but has not directly addressed their impact on liquidity. For example, Fleming and Remolona (1997) and Fair (2002) document that monetary shocks are associated with large changes in bond and stock prices. For fund flows, Edelen and Warner (2001) and Boyer and Zheng (2002) show a positive association between aggregate flow and concurrent market returns, while Goetzmann and Massa (2002) document that fund flows affect price

[4] See, for example, Ammann and Zimmermann (2001) and Fox (1999) for practical considerations, and Barberis (2000) or Xia (2001) for more academic studies.

[5] "When stocks are expected to show weakness, investment funds often flow to the perceived haven of the bond market, with that shift usually going into reverse when, as yesterday, equities start to strengthen." John Parry, *The Wall Street Journal*, August 1, 2001, p. C1.

formation in equity markets. These findings indicate that fund flows and monetary factors can affect returns and volatility in addition to liquidity. Therefore, we explore the interaction of monetary factors and fund flows with liquidity, returns, volatility, and order flow. Our analysis thus allows us to link microstructure liquidity (in the sense of transaction costs) and "macro liquidity" (in the sense of fund flows between sectors of the economy).

The results indicate that the time-series properties of stock and bond liquidity possess similarities, such as common calendar regularities. There are cross-market dynamics flowing from volatility to liquidity. Further, we find that the correlations in liquidity and volatility innovations between bond and stock markets are positive and significantly different from zero, pointing to common influences across the markets.

Innovations to net borrowed reserves are contemporaneously associated with increased liquidity and also have modest ability to predict liquidity during periods of crises, suggesting that monetary loosening is associated with increased liquidity. We also find that innovations to flows to the stock and government bond sectors play a key role in forecasting liquidity. Overall, our results support the notion that money flows (in the form of bank reserves and mutual fund investments) account for part of the commonality in stock and bond market liquidity.

The rest of the article is organized as follows. Section 1 describes how the liquidity data is generated, while Section 2 presents basic time-series properties of the data and describes the adjustment process to stationarize the series. Section 3 performs daily vector autoregressions (VARs). Section 4 presents the analysis of monetary policy and mutual fund flows. Section 5 concludes.

1. Liquidity and Trading Activity Data

Bond and stock liquidity data were obtained for the period June 17, 1991, to December 31, 1998. The sample period reflects the availability of tick-by-tick Treasury bond data, obtained from GovPX Inc., which covers trading activity among primary dealers in the interdealer broker market. The stock data sources are the Institute for the Study of Securities Markets (ISSM) and the NYSE TAQ (trades and automated quotations). The ISSM data cover 1991–1992 inclusive while the TAQ data are for 1993–1998. We use only NYSE stocks to avoid any possibility of the results being influenced by differences in trading protocols between NYSE and Nasdaq.

Our principal focus in this article is on analyzing the drivers of stock and bond liquidity measures that have been the focus of attention in the previous literature, viz., quoted spreads and market depth. Based on earlier literature [e.g., Amihud and Mendelson (1986), Benston and

Hagerman (1974), and Hasbrouck (1991)], we take these drivers to be returns, return volatility, and trading activity. We use order imbalances as measures of trading activity, rather than volume, because our view is that imbalances bear a stronger relationship to trading costs as they represent aggregate pressure on the inventories of market makers [see Chordia, Roll, and Subrahmanyam (2002)]. Below we describe how we extract liquidity measures from transactions data. Since imbalance measures are from transactions databases as well, they are also described in the following subsection.

1.1 Measures of bond liquidity and order imbalance

GovPX Inc. consolidates data from the primary brokers and transmits the data in real time to subscribers through on-line vendors. The service reports the best bid and offer quotes, the associated quote sizes, the price and amount (in million dollars) of each trade, and whether the trade is buyer or seller initiated. The time of each trade is also reported to the second. The GovPX data pertains to interdealer trades only.

We use trading data for on-the-run Treasury notes with 10 years to maturity since we want to capture liquidity in relatively long-term fixed income markets.[6] Furthermore, although on-the-run securities are a small fraction of Treasury securities, they account for 71% of activity in the interdealer market [Fabozzi and Fleming (2000)]. In addition, we do not analyze the 30-year Treasury bond, since the GovPX data captures a smaller and variable fraction of aggregate market activity for this bond, and because a major broker, Cantor Fitzgerald/eSpeed, does not report its data.[7]

The bond liquidity measures are based on data from New York trading hours (7:30 A.M. to 5:00 P.M. EST). We construct the following measures of bond liquidity:

QSPRB: The daily time-weighted average quoted bid-ask spread, calculated as the difference between the best bid and best ask per \$100 par value.[8]

DEPB: The posted bid and ask depth in dollar terms, averaged over the trading day.

DEPB is only available starting from 1995.

[6] We repeat the analysis with two- and five-year notes and find that the main results are unchanged. Details are available from the authors.

[7] Fleming (2001) provides a detailed account of the format of GovPX data, while Boni and Leach (2001) document the share of GovPX in the aggregate bond market volume.

[8] We delete quotes associated with transactions that are reported as having occurred on days on which the bond market was officially closed. These quotes and transactions are presumably a result of lags in reporting (e.g., they may have actually occurred on the immediately preceding business day). In the absence of a reliable way to account for these quotes, we omit them from the sample.

OIBB: Defined as the dollar value of buys less the dollar value of sells each day, divided by the total dollar value of buys and sells (recall that GovPX data indicate whether a trade is buyer or seller initiated; hence, trades can be signed directly).

Note that since bond data is from the interdealer market, the imbalance measures represent interdealer order imbalances. It is highly likely, however, that interdealer order imbalances arise in response to customer imbalances as dealers lay off customer orders in the dealer market. Interdealer imbalances thus are likely to represent an estimate, albeit a noisy one, of customer imbalances.

In order to obtain reliable estimates of the bid-ask spread, the following filters are used:

1. Bid or offer quotes with a zero value are deleted.
2. A quoted bid-ask spread that is negative or more than 50 cents per \$100 par value (a multiple of about 12–15 times the sample average) is deleted.

1.2 Stock liquidity and order imbalance data

Stocks are included or excluded during a calendar year depending on the following criteria:

1. To be included, a stock had to be present at the beginning and at the end of the year in both the Center for Research in Security Prices (CRSP) and the intraday databases.
2. If the firm changed exchanges from Nasdaq to NYSE during the year (no firms switched from the NYSE to the Nasdaq during our sample period), it was dropped from the sample for that year.
3. Because their trading characteristics might differ from ordinary equities, assets in the following categories were also expunged: certificates, American depository receipts, shares of beneficial interest, units, companies incorporated outside the United States, Americus Trust components, closed-end funds, preferred stocks, and real estate investment trusts.
4. To avoid the influence of unduly high-priced stocks, if the price at any month-end during the year was greater than \$999, the stock was deleted from the sample for the year.

Intraday data were purged for one of the following reasons: trades out of sequence, trades recorded before the opening or after the closing time, and trades with special settlement conditions (because they might be subject to distinct liquidity considerations). Our preliminary investigation revealed that auto-quotes (passive quotes by secondary market dealers) have been eliminated in the ISSM database but not in TAQ. This caused the quoted spread to be artificially inflated in TAQ. Since there is no reliable way to filter out auto-quotes in TAQ, only BBO (best bid or offer)-eligible primary market (NYSE) quotes are used. Quotes established before the opening of the market or after the close were discarded. Negative bid-ask spread quotations, transaction prices, and quoted depths were discarded. Each bid-ask quote included in the sample is matched to a transaction; specifically, following Lee and Ready (1991) any quote less than five seconds prior to the trade is ignored and the first one at least five seconds prior to the trade is retained.

For each stock we define the following variables:

QSPRS: The daily average quoted spread, that is, the difference between the ask and the bid quote, averaged over the trading day.

DEPS: Average of posted bid/ask depth in dollars (i.e., share depth multiplied by the posted ask/bid prices), averaged over the trading day.

OIBS: The daily order imbalance (the dollar values of shares bought less shares sold each day, as a proportion of the total dollar value of shares traded).[9]

Our initial scanning of the intraday data revealed a number of anomalous records that appeared to be keypunching errors. Thus we applied filters to the transaction data by deleting records that satisfied the following conditions:[10]

1. quoted spread >\$5;
2. effective spread/quoted spread >4.0;
3. proportional effective spread/proportional quoted spread >4.0;
4. quoted spread/midpoint of bid-ask quote >0.4.

These filters removed less than 0.02% of all stock transaction records. The above variables are averaged across the day to obtain stock liquidity measures for each day. To avoid excessive variation in the sample size, we required stocks to have traded for a minimum of 100 days in a year to be included in the sample for that year. Days for which stock return data was not available from CRSP were dropped from the sample. We also dropped September 4, 1991, from our sample because of transparent reporting errors; specifically, ISSM recorded only quotes, but no transactions on this day.

[9] The Lee and Ready (1991) method was used to sign trades. Of course, there is inevitably some assignment error, so the resulting order imbalances are estimates. Yet, as shown in Lee and Radhakrishna (2000), and Odders-White (2000), the Lee/Ready algorithm is accurate enough as to not pose serious problems in our large sample study.

[10] The proportional spreads in condition 3 are obtained by dividing the unscaled spreads by the midpoint of the prevailing bid-ask quote. Further, the effective spread is defined as twice the absolute distance between the transaction price and the midpoint of the prevailing quote. While the results using effective stock spreads are qualitatively similar to those for quoted spreads, we do not report these, both for reasons of brevity and because effective spreads are not defined in the bond market.

The daily dollar trading volume is obtained from CRSP. The daily spread measures are first averaged within the day for each stock, then averaged value-weighted across stocks (with market capitalization as of the end of the previous year used to calculate weights) to obtain the aggregate market liquidity measures that we use in this study (for convenience we use the same variable names for the aggregate liquidity and volume measures).

2. Basic Properties of the Data

2.1 Summary statistics

We now present summary statistics associated with liquidity measures for stock and bond markets. Table 1 presents the levels of quoted spreads and absolute values of proportional order imbalances for stocks and bonds. Since the reduction in tick sizes of U.S. stocks on June 24, 1997, had a major impact on bid-ask spreads [see Chordia, Roll, and Subrahmanyam (2001)], we provide separate statistics for the periods before and after the change. The average quoted spread is \$0.027 per \$100 par value for bonds and \$0.186 per share for stocks. The median

Table 1
Levels of stock and bond market liquidity

	Mean	SD	Median	CV	Mean	SD	Median	CV
(a) Bid-ask spread and order imbalance								
	June 17, 1991–June 23, 1997 (No. of observations: 1503 for bonds and 1502 for stocks)				June 24, 1997–December 31, 1998 (No. of observations: 380 for bonds and stocks)			
QSPRB	0.027	0.007	0.026	25.139	0.022	0.009	0.020	42.177
ABS OIBB (%)	0.135	0.115	0.107	85.656	0.131	0.095	0.113	72.614
QSPRS	0.186	0.015	0.183	8.256	0.129	0.009	0.128	6.948
ABS OIBS (%)	0.062	0.044	0.054	71.311	0.072	0.040	0.072	55.833
(b) Market depth								
	January 1, 1995–June 23, 1997 (No. of observations: 619 for bonds and stocks)				June 24, 1997–December 31, 1998 (No. of observations: 380 for stocks and bonds)			
DEPB (\$ millions)	6.388	1.601	6.096	25.066	7.349	2.151	6.980	29.269
DEPS (\$ millions)	0.634	0.074	0.634	11.736	0.333	0.047	0.335	13.959

Bond liquidity estimates are based on the time-weighted daily mean of the best bid and ask offer quotes by dealers on the 10-year Treasury note, as reported in the GovPX data set. The stock liquidity series are constructed by first averaging all transactions for each individual stock on a given trading day and then constructing value-weighted averages for all individual stock daily means that satisfy the data filters described in the text. QSPR stands for quoted spread, OIB for the order imbalance, and DEP for dollar depth. OIB is measured as the dollar value of buy trades minus the dollar value of sale trades, divided by the total dollar value of trades. The suffixes B and S refer to bond and stock variables, respectively, and ABS is the notation for absolute value. The stock data series excludes September 4, 1991, on which no trades were reported in the transactions database. The mean, median, standard deviation (SD), and the coefficient of variation (CV) is reported for each measure. The sample period spans the period June 17, 1991 to December 31, 1998, except for bond depth, data for which is from January 1, 1995, to December 31, 1998.

spread measures are almost the same as the means suggesting little skewness in the daily distribution of liquidity. The daily absolute imbalance in percentage terms is 14% for bonds and about 6% for stocks. Consistent with previous results, stock spreads are lower after the tick size change. For reasonable ranges of stock prices (e.g., between $10 and $100), proportional bond spreads appear to be lower than proportional stock spreads. This is possibly due to the fact that the minimum tick size is smaller in the bond market. More fundamental information-based reasons can also account for smaller bond spreads. U.S. Treasury bond prices are impacted by broad macroeconomic information shocks, such as inflation, monetary policy, and unemployment, and adverse selection is unlikely to be a major issue in bond markets. Adverse selection is likely to be far more important in individual stocks due to private information about idiosyncratic shocks.[11] Moreover, recall that the bond data pertains to the interdealer trades only. Thus, the bond spreads that we see are those for the wholesale market.

Figure 1 plots the time series for bond and stock quoted spreads. As can be seen, the bond spread series shows a structural shift in late 1998, probably due to the Russian default crisis. Stock quoted spreads show a steady decline prior to the tick size change, with a substantial drop around the time of the tick size change. In the next subsection, we adjust our raw data for these and other regularities that could cause nonstationarities in our series.

Table 1*b* presents summary statistics for depth for the subperiod for which bond depth is available (1995–1998). Consistent with Chordia, Roll and Subrahmanyam (2001), stock depth is lower after the tick size change, a result that is confirmed by a formal test of differences in means. Note that in the bond interdealer market the size of the trades are negotiated and thus the posted depth may be smaller than the actual depth. However, as long as quoted depth understates actual depth by a fairly constant proportion, all our inferences for depth will retain their validity.

2.2 Adjustment of time-series data on liquidity, imbalances, returns, and volatility

Our goal is to explore the dynamic relationships between liquidity, price formation, and trading activity, across stock and bond markets. We seek to ascertain the extent to which day-to-day movements in liquidity are caused by returns, order imbalances, and return volatility. Returns and return volatility in both markets are obtained as the residual and the absolute value of the residual, respectively, from the following

[11] The stock market spread is an average of the individual stock spreads and is thus likely to be affected by adverse selection.

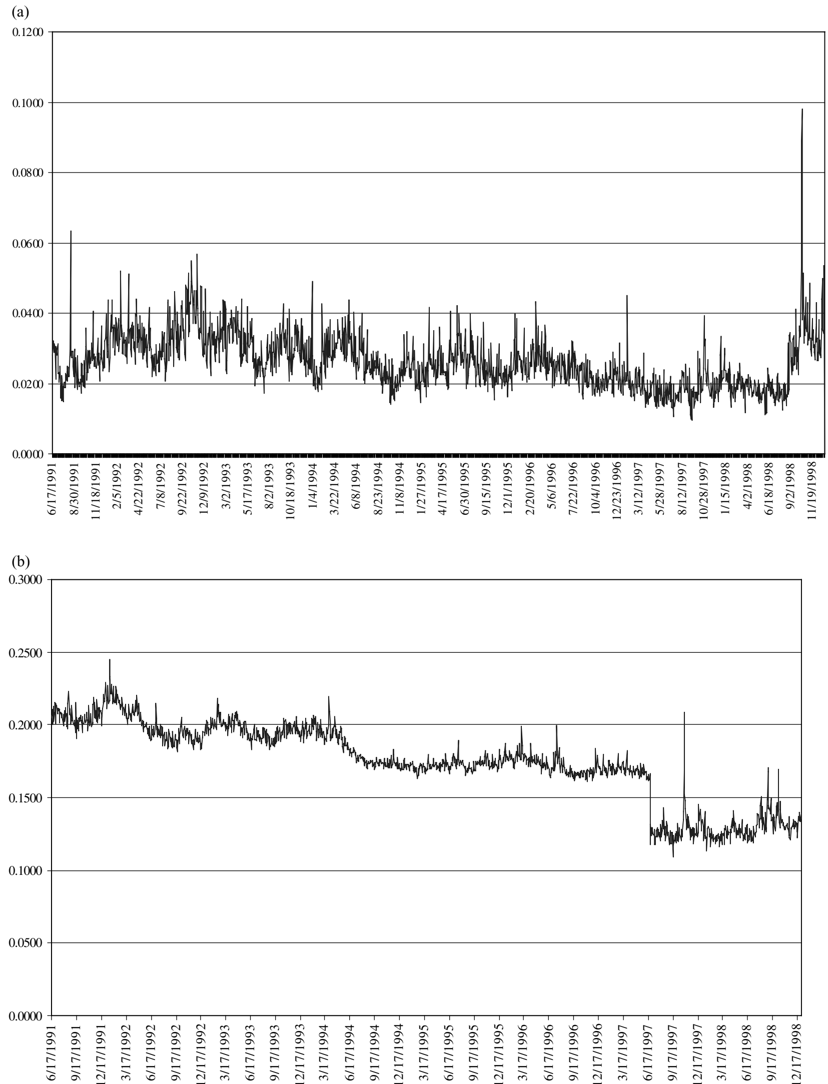

Figure 1
The quoted bid-ask spread: unadjusted series
(a) The quoted bid-ask spread in the 10-year Treasury note market. (b) The quoted bid-ask spread in the stock market.

regression [see Schwert (1990), Jones, Kaul, and Lipson (1994), and Chan and Fong (2000)]:

$$R_{it} = a_1 + \sum_{j=1}^{4} a_{2j} D_j + \sum_{j=1}^{12} a_{3j} R_{it-j} + e_{it}, \tag{1}$$

where D_j is a dummy variable for the day of the week and R_{it} represents the daily return on the Lehmann Brothers' bond index or on the CRSP value-weighted index.

We now adjust the raw data for deterministic time-series variations. All the series, returns, order imbalance, spreads, depths, and volatility in both markets are transformed as follows. Following Gallant, Rossi, and Tauchen (1992), we regress the series on a set of adjustment variables:

$$w = x'\beta + u \quad \text{(mean equation)}. \tag{2}$$

In Equation (2), w is the series to be adjusted and x contains the adjustment variables. The residuals are used to construct the following variance equation:

$$\log(u^2) = x'\gamma + v \quad \text{(variance equation)}. \tag{3}$$

The variance equation is used to standardize the residuals from the mean equation and the adjusted w is calculated in the following equation,

$$w_{\text{adj}} = a + b[\hat{u}/\exp(x'\gamma/2)], \tag{4}$$

where a and b are chosen such that the sample means and variances of the adjusted and the unadjusted series are the same.

The following adjustment variables are used:

1. Four day-of-the-week dummies for Monday through Thursday; since there may be day-of-the-week effects in liquidity, returns, and volatility.
2. Eleven month of the year dummies for February through December.
3. A dummy for holidays set such that if a holiday falls on a Friday then the preceding Thursday is set to 1, and if the holiday is on a Monday then the following Tuesday is set to 1, and if the holiday is on any other weekday then the day preceding and following the holiday are set to 1; this is intended to capture the fact that trading activity declines substantially around holidays.
4. A time trend and the square of the time trend to remove any long-term trends that we are not seeking to explain.
5. Three crisis dummies, where the crises are: the bond market crisis (March 1, 1994, to May 31, 1994), the Asian financial crisis (July 2 to December 31, 1997), and the Russian default crisis (July 6 to December 31, 1998). The dates for the bond market crisis are taken from Borio and McCauley (1996). The starting date for the Asian crisis is the day that the Thai baht was devalued; dates for the

Russian default crisis are obtained from the Bank for International Settlements.[12]

6. Dummies for the day of and the two days prior to macroeconomic announcements about GDP, employment, and inflation in the bond market; this is intended to capture portfolio balancing around public information releases.
7. A dummy for the period after the tick size change in the stock market.
8. A dummy for September 16, 1991, where for some reason, ostensibly a recording error, only 248 firms were recorded as having been traded on the ISSM dataset whereas the number of NYSE-listed firms trading on a typical day in the sample is over 1100.

Table 2 presents the regressions coefficients from the mean equation (2). For the sake of brevity, we do not present results for the variance equation (3); however, these are available upon request. Consider the bond and stock quoted spreads in Table 2*a*. During our sample period, both spreads are higher on Fridays and around holidays. The bond spread is lower from July to September and higher in March, April, and October relative to January. The stock spread is lower in March and in May through December relative to the remaining months. As expected, spreads are generally higher during the three crisis periods and during the Russian default crisis in particular. The bond spread decreases over the sample period. Interestingly, the stock spread decreases before the tick size change but displays an increasing trend since that time. The bond spread is higher on the day of the employment announcement but lower during the two days preceding the announcement. Finally, the stock spread is significantly lower on September 16, 1991, when, as mentioned previously, only 248 firms are recorded as having traded. These 248 firms are large firms that tend to have the lowest spreads.

The results for bond and stock depths (also in Table 2*a*) show that bond depths are lower around holidays, higher from Tuesday to Thursday relative to Friday, and higher in February and July through September relative to January. In addition, the stock depth is lower on holidays and lower in December and January relative to the rest of the year. In both markets, depth decreases during the Russian and the Asian crises, suggesting that liquidity providers step back during periods when the market is under stress; the stock depth also decreases during the bond market crisis (when bond depth data is not available). There is weak evidence that depth has increased over time for bonds and strong evidence that it has increased during the pre-tick size change period for stocks. However, stock depth has been on a downward trend since the tick size change.

[12] "A Review of Financial Market Events in Autumn 1998," CGFS Reports No. 12, October 1999, available at http://www.bis.org/publ/cgfspubl.htm.

Table 2
Adjustment regressions for stock and bond liquidity

(a) Bond and stock quoted spread and depth (number of observations: 1882 for bond and stock spread as well as stock depth and 999 for bond depth)

	QSPRB	DEPB	QSPRS	DEPS
Intercept	0.034*	4.941*	0.220*	0.369*
Day of the week				
Monday	−0.409*	0.158	−0.131*	−0.006
Tuesday	−0.467*	0.677*	−0.145*	0.006
Wednesday	−0.372*	0.925*	−0.117*	0.007
Thursday	−0.265*	0.550*	−0.049	0.005
Holiday	0.221*	−0.817*	0.194*	−0.022*
Month				
February	0.116	0.826*	−0.089	0.011**
March	0.226*	−0.018	−0.272*	0.022*
April	0.149*	0.261	−0.120	0.022*
May	0.103	0.336	−0.408*	0.029*
June	−0.016	0.001	−0.656*	0.028*
July	−0.355*	0.771*	−0.738*	0.021*
August	−0.195*	0.537**	−0.836*	0.038*
September	−0.171*	0.812*	−0.990*	0.056*
October	0.171*	−0.182	−0.572*	0.021*
November	0.076	0.042	−0.691*	0.019*
December	0.102	−0.516**	−0.567*	−0.002
Crisis				
Russian crisis July 6, 1998, to December 31, 1998	1.550*	−1.499*	1.366*	−0.049*
Asian crisis July 2, 1997, to December 31, 1997	0.077	−0.605*	0.874*	−0.039*
Bond crisis March 1, 1994, to December 5, 1994	0.229*		0.749*	−0.099*
Tick size change				
Tick size change dummy			−9.452*	0.010
September 16, 1991, dummy			−1.478*	0.193*
Trend				
Time	−0.000	0.002		
Square of Time	−0.000*	0.000**		
Time, pre-tick size change			−0.005*	0.000*
Square of time, pre-tick size change			0.000*	0.000*
Time, post-tick size change			0.004*	0.000*
Square of time, post-tick size change			−0.000*	0.000
Macroeconomic announcements				
GDP	0.152	−0.693	0.048	−0.013
GDP12	0.047	0.130	−0.127	−0.004
EMP	0.154*	−0.375	0.174	−0.011
EMP12	−0.186*	0.423*	0.000	0.008
CPI	0.038	−0.003	0.000	0.009
CPI12	−0.033	0.375*	0.000	0.005

(b) Bond and stock returns and volatility (number of observations: 1882)

	RETB	VOLB	RETS	VOLS
Intercept	0.016	0.187*	0.022	0.574*
Holiday	−3.199	0.027	−15.108	−0.086
Month				
February	−4.882	−0.028	−3.583	0.021
March	−5.667**	−0.010	−10.583	−0.037
April	−0.889	−0.020	−5.083	0.060
May	1.628	−0.019	−2.249	−0.036
June	1.310	−0.024	−13.725	0.014
July	1.426	−0.045*	−0.425	−0.031
August	−0.396	−0.040**	−14.040	−0.069
September	1.405	−0.033	1.655	−0.016
October	−1.518	−0.005	−6.256	0.035
November	−2.439	−0.056*	−3.524	−0.046
December	1.210	−0.048*	1.085	−0.024

Table 2
Continued

	RETB	VOLB	RETS	VOLS
Crisis				
Russian crisis July 6, 1998, to December 31, 1998	0.040	0.087*	−54.751*	0.738*
Asian crisis July 2, 1997, to December 31, 1997	1.078	0.002	−10.577	0.230*
Bond crisis March 1, 1994, to December 5, 1994	−7.841*	0.088*	−8.169	0.162*
Tick size change				
Tick size change dummy			34.664	−0.117
September 16, 1991, dummy			32.890	−0.155
Trend				
Time	−0.006	0.000*		
Square of Time	0.000	0.000*		
Time, pre-tick size change			−0.005	−0.001*
Square of time, pre-tick size change			0.000	0.000*
Time, post-tick size change			−0.453*	0.002**
Square of time, post-tick size change			0.002*	0.000*
Macroeconomic announcements				
GDP	7.567	0.035	−3.832	0.028
GDP12	3.033	−0.005	11.100	0.062
EMP	4.456	0.159*	6.397	0.133*
EMP12	6.216*	−0.019	−4.915	−0.058
CPI	3.117	0.074*	12.833	0.008
CPI12	1.697	−0.015	5.674	−0.005

Bond liquidity estimates are based on the time-weighted daily mean of the best bid and ask offer quotes by dealers on the 10-year Treasury note, as reported in the GovPX data set. The stock liquidity series are constructed by first averaging all transactions for each individual stock on a given trading day and then constructing value-weighted averages for all individual stock daily means that satisfy the data filters described in the text. The sample spans the period June 17, 1991, to December 31, 1998, except for bond depth, for which the sample is January 1, 1995, to December 31, 1998. The stock data series excludes September 4, 1991, on which no trades were reported in the transactions database. QSPR stands for quoted spread and DEP for dollar depth. The suffixes B and S refer to bond and stock variables, respectively. DEP is in \$1 million units for both stocks and bonds. RET is the market return and VOL is the return volatility. The returns used are the Lehman Brothers' aggregate daily bond index returns and the daily CRSP value-weighted index return for stocks. Holiday: a dummy variable that equals one if a trading day satisfies the following conditions, (1) if Independence day, Veterans' day, Christmas, or New Year's day falls on a Friday, then the preceding Thursday, (2) if any holiday falls on a weekend or on a Monday then the following Tuesday, (3) if any holiday falls on a weekday then the preceding and the following days, and 0 otherwise. Monday–Thursday = 1 if the trading day is Monday, Tuesday, Wednesday, or Thursday, and 0 otherwise. February–December = 1 if the trading day is in one of these months, and 0 otherwise. GDP: dummy variable that equals 1 on the day of the GDP announcement and 0 otherwise. GDP12: dummy variable that equals 1 on two days prior to the GDP announcement and 0 otherwise. EMP, EMP12, CPI, CPI12: dummy variables for employment and CPI announcements respectively. The definition of the dummy variables is the same as for GDP announcements. Estimation is done using the Ordinary Least Squares (OLS). The coefficients for spreads and returns are multiplied by a factor of 100. Estimates marked with* and ** are significant at the 5% and 10% level, respectively, or better.

In summary, there are distinct seasonal patterns in stock and bond liquidities. Both stock and bond market liquidities are higher at the beginning of the week compared with Friday, and also higher in the summer/early fall months of July through September compared with the rest of the year. Liquidity in both markets is sharply lower in crisis periods. Liquidity shows an increasing trend over the entire sample for bonds and before the change in the tick size for stocks.

Figure 2 shows the adjusted series for bond and stock quoted spreads. These series appear to be free of long-term trends. To formally test for stationarity, we perform augmented Dickey-Fuller and Phillips-Perron

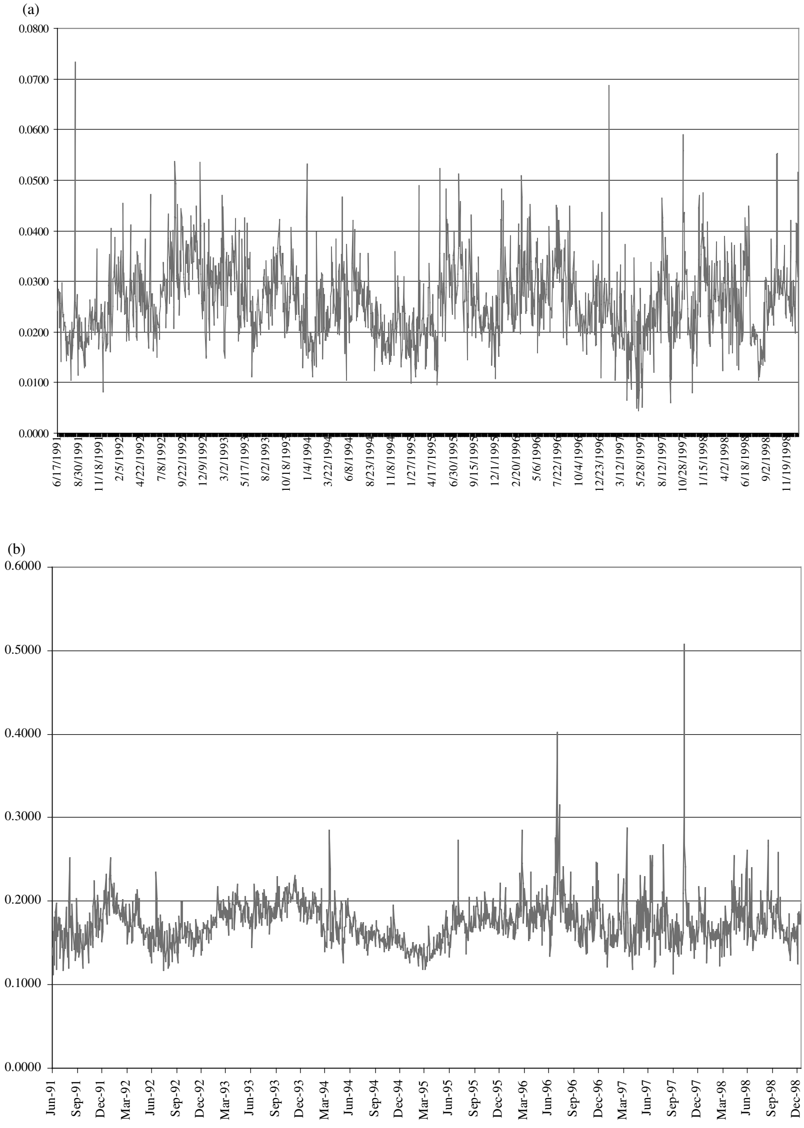

Figure 2
The quoted bid-ask spread: adjusted series
(a) The quote bid-ask spread in the 10-year Treasury note market. (b) The quote bid-ask spread in the stock market.

tests on the adjusted series. We allow for an intercept under the alternative hypothesis and use information criteria to guide selection of the augmentation lags. We easily reject the unit-root hypothesis for every series (including those for return, volatility, and imbalances), generally with p less than .01. Thus, the evidence indicates that all of the adjusted series are stationary.

Next, we briefly discuss the results for returns and volatility, presented in Table 2*b*. Since day-of-the-week effects were incorporated when computing returns and volatility in Equation (1), these effects are omitted from the adjustment regressions. It can be seen that bond and stock returns display little systematic time-series variation. Bond returns are lower in March, lower during the bond market crisis, and higher prior to the employment report. Stock returns are lower during the Russian crisis and show a decreasing trend following the tick size change. Bond volatility is lower in July, August, November, and December relative to January. Stock and bond volatilities are generally higher during crisis periods. Bond volatility shows an increasing trend over the sample period whereas the stock volatility shows a decreasing trend during the pre-tick size change period. Bond and stock volatilities increase on the day of the employment report, while bond volatility also increases on the day of the consumer price index (CPI) report.

Table 3 presents the correlations between the adjusted bond and stock liquidity and imbalance series. The time-series correlation between stock and bond quoted spreads is about 31%. Quoted depths in each market are also positively correlated with each other (about 13%) and are

Table 3
Correlations in stock and bond market liquidity

Returns, volatility, spread, and order imbalance (number of observations: 1882); Depth (number of observations: 999)

	QSPRB	OIBB	DEPB	VOLB	RETB	QSPRS	OIBS	DEPS	VOLS	RETS
QSPRB	1.00									
OIBB	−0.03	1.00								
DEPB	−0.49*	0.00	1.00							
VOLB	0.23*	0.00	−0.14*	1.00						
RETB	−0.10*	0.05*	0.05	−0.04**	1.00					
QSPRS	0.31*	−0.00	−0.21*	0.14*	−0.07*	1.00				
OIBS	−0.03	0.03	0.04	−0.04**	0.25*	−0.12*	1.00			
DEPS	−0.28*	0.06**	0.13*	−0.02	0.08*	−0.57*	0.21*	1.00		
VOLS	0.14*	−0.01	−0.08*	0.22*	−0.02	0.26*	−0.09*	−0.05	1.00	
RETS	−0.08*	0.01	0.05	−0.07*	0.31*	−0.16*	0.79*	0.22*	−0.15*	1.00

This table presents the correlation matrix for the time series of market-wide liquidity and trading activity. All variables have been adjusted for trend, seasonality, and crisis effects, as described in Table 2. Bond liquidity estimates are based on the time-weighted daily mean of the best bid and ask offer quotes by dealers on the 10-year Treasury note, as reported in the GovPX data set. The stock liquidity series are constructed by first averaging all transactions for each individual stock on a given trading day and then constructing value-weighted averages for all individual stock daily means that satisfy the data filters described in the text. QSPR stands for quoted spread, OIB for the order imbalance, and DEP for dollar depth. OIB is measured as the dollar value of buy trades minus the dollar value of sale trades, divided by the total dollar value of trades. RET is the market return and VOL is the return volatility. The returns used are the Lehman Brothers' aggregate daily bond index returns and the daily CRSP value-weighted index return for stocks. The suffixes B and S refer to bond and stock variables, respectively. The sample spans the period June 17, 1991, to December 31, 1998, with the exception of bond depth for which the sample period is January 1, 1995, to December 31, 1998. * denotes significance at the 5% level and ** denotes significance at the 10% level.

significantly negatively correlated with the quoted spreads. Depth in the bond market is negatively related to the quoted spreads in the stock market. While stock order imbalance is highly correlated with stock returns, the correlation with volatility is small. The correlations between the bond imbalance measures and liquidity are small in magnitude, though stock imbalance is moderately correlated with the stock liquidity measures. Volatility in either market is significantly correlated with spreads in both markets. The correlation between volatility in the bond market (VOLB) and the quoted spread in the bond market (QSPRB) is a significant 0.23 and between volatility in the stock market (VOLS) and the quoted spread in the stock market (QSPRS) is 0.26. The cross-market correlations though lower than the within-market correlations are also high. In particular, both the cross-market correlations between volatility and spreads equal 0.14. Thus, volatility seems to be an important avenue through which aggregate bond and stock market liquidity are impacted. It also is worth noting that imbalances are virtually uncorrelated across stock and bond markets. Thus, across all sample days, asset allocational trades that shift wealth from the stock to the bond market and vice versa are not the dominant force driving trading activity across these markets.

3. Vector Autoregresssion

Our goal is to explore the intertemporal associations between market liquidity, returns, volatility, and order imbalances.[13] While univariate relationships between liquidity and the latter three variables have been partially explored in earlier literature, there is good reason to expect bidirectional causality in each case. For example, the familiar notion that liquidity may impact returns through a premium for greater trading costs was first discussed in Amihud and Mendelson (1986). However, returns may also influence future trading behavior, which may, in turn, affect liquidity. For instance, the psychological bias of loss aversion implies return-dependent investing behavior [Odean (1998)] and a wave of trading in one direction sparked by a price change may strain liquidity.

Next, the impact of volatility on liquidity has been addressed in Benston and Hagerman (1974), the idea being that increased volatility implies increased inventory risk and hence a higher bid-ask spread. In the reverse direction, decreased liquidity could increase asset price fluctuations [see, e.g., Subrahmanyam (1994)]. Further, the predictive relationship between imbalances and liquidity has been addressed in Chordia, Roll, and

[13] We use signed and not absolute imbalances in our study because our view is that unsigned imbalances could be collinear with volatility and thereby obscure the volatility–liquidity relationship. We find, however, that our main results are not sensitive to whether absolute order imbalance is excluded or included in the system; details are available from the authors.

Subrahmanyam (2002), who find that high negative imbalance and high negative return days are followed by return reversals, ostensibly because of strained market-maker inventories or investor overreaction and correction.[14] However, if increased liquidity makes assets more attractive and induces agents to buy these assets, then this may, in turn, influence order imbalances.

There is also reason to believe that cross-market effects across stocks and bonds may be significant. For example, if there are leads and lags in trading activity in response to systematic wealth or informational shocks, then trading activity in one market may predict trading activity, and, in turn, liquidity in another. Similarly, leads and lags in volatility and liquidity shocks may have cross-effects. Thus, if systemic (macro) shocks to liquidity and volatility get reflected in one market before another, then liquidity in one market could influence future liquidity in another. More generally, insofar as the above variables in one market forecast the corresponding variables in the other, the arguments in the previous two paragraphs carry over to cross-market effects as well.

Given that there are reasons to expect cross-market effects and bidirectional causalities, in this section we adopt an eight-equation vector autoregression that incorporates eight variables, four each (i.e., measures of liquidity, returns, volatility, and order imbalances) from stock and bond markets.[15] Thus, consider the following system:

$$X_t = \sum_{j=1}^{K} a_{1j} X_{t-j} + \sum_{j=1}^{K} b_{1j} Y_{t-j} + u_t, \tag{5}$$

$$Y_t = \sum_{j=1}^{K} a_{2j} X_{t-j} + \sum_{j=1}^{K} b_{2j} Y_{t-j} + v_t, \tag{6}$$

where $X\,(Y)$ is a vector that represents liquidity, returns, order imbalance, and volatility in the bond (stock) market. In the empirical estimation, we choose K, the number of lags in Equations (5) and (6) on the basis of the Akaike information criterion and the Schwarz information criterion. Where these two criteria indicate different lag lengths, we choose the lesser lag length for the sake of parsimony. Typically, the slope of the information criterion (as a function of lags) is quite flat for larger lag lengths, so the choice of smaller lag lengths is justified. We now provide estimates from the VAR model that captures time-series movements in stock and

[14] See Chordia and Subrahmanyam (1995) for a simple model of how spread levels depend on inventory.

[15] Hasbrouck (1991), in the latter part of his article, also performs a VAR comprised of stock spreads and trades. However, he uses intraday horizons, whereas we use a daily horizon to look for longer-term causalities.

bond liquidity. We are also interested in examining whether unexpected liquidity shocks are systemic in nature, and an examination of the VAR disturbances allows us to address this issue.

3.1 VAR estimation results

We present results from a VAR with endogenous variables OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRB, and QSPRS. The VAR is estimated with two lags and a constant term, and uses 1880 observations. We first examine the cross-correlations of innovations obtained from the VAR estimation. Unexpected arrival of information, as well as unexpected shocks to investors' liquidity, can cause unanticipated trading needs, and, in turn, unanticipated fluctuations in liquidity. It is of interest to examine whether such fluctuations are correlated across stock and bond markets, both from an academic and a practical standpoint. From an academic standpoint, we would like to know whether liquidity shocks are systemic in nature or unique to a particular market. From a practical standpoint, asset allocation strategies could be designed to take advantage of increased liquidity, for example, if shocks are positively correlated, it suggests contemporaneous execution of orders in both markets on unusually high liquidity days in one market.

Table 4*a* reports the correlation matrix of the VAR innovations. We find that shocks to spreads are negatively associated with returns. This is consistent with the results of Chordia, Roll, and Subrahmanyam (2001), who show that positive market returns are accompanied by decreased spreads. The table also shows that cross-market liquidities and volatilities are positively and significantly correlated. Innovations in stock and bond spreads have a correlation of 0.26, while that between volatility innovations is 0.22; these numbers are statistically different from zero. Innovations in stock and bond depths have a correlation of 0.10 (not reported in the table for brevity), which is also statistically significant. These results indicate that there are contemporaneous commonalities in stock and bond liquidity.

Table 4 also presents pairwise Granger-causality tests between the endogenous variables of the VAR. For the null hypothesis that variable i does not Granger-cause variable j, we test whether the lag coefficients of i are jointly zero when j is the dependent variable in the VAR. In Table 4*b*, the cell associated with the ith row variable and the jth column variable shows the chi-square statistic associated with this test. We focus on the interaction of the quoted spreads with the endogenous variables. Within each market, there is two-way causation between quoted spreads and volatility. Also, the stock return causes the stock spread, although the reverse is not true. However, the Granger test results show little evidence of cross-market causations. For example, there is no evidence of a causal relationship between stock and bond spreads, or between spreads in one

Table 4
Granger causality tests and contemporaneous correlation between VAR innovations

	OIBB	OIBS	VOLB	VOLS	RETB	RETS	QSPRB	QSPRS
(a) Correlations between VAR innovations								
OIBB	1.00							
OIBS	0.03	1.00						
VOLB	−0.01	−0.05**	1.00					
VOLS	0.00	−0.08*	0.22*	1.00				
RETB	0.05*	0.25*	−0.04**	−0.02	1.00			
RETS	0.02	0.80*	−0.08*	−0.15*	0.31*	1.00		
QSPRB	−0.02	−0.06*	0.24*	0.10*	−0.12*	−0.14*	1.00	
QSPRS	−0.01	−0.16*	0.15*	0.23*	−0.08*	−0.24*	0.26*	1.00
(b) Chi-square statistics from Granger causality tests. Null hypothesis: Row variable does not Granger-cause column variable								
OIBB		0.080	1.340	7.745*	3.316	0.234	0.128	0.154
OIBS	1.966		1.217	2.860	3.360	4.047	0.919	2.617
VOLB	0.729	5.954**		1.154	3.458	8.918*	22.156*	0.498
VOLS	8.902*	1.137	2.956		0.084	1.111	4.396	34.167*
RETB	4.337	2.478	9.659*	6.036*		4.849**	3.354	5.492**
RETS	0.481	3.286	1.142	25.525*	1.733		0.014	12.342*
QSPRB	0.451	6.605*	7.616*	2.364	3.301	7.333*		0.737
QSPRS	2.816	1.200	0.721	14.036*	0.380	3.086	2.723	

The table presents results from a VAR with endogenous variables OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRB, and QSPRS. It is estimated with two lags and a constant term, and uses 1880 observations. (a) Correlations between the VAR innovations. (b) Chi-square statistics and *p*-values of pairwise Granger causality tests between the endogenous variables. QSPR stands for quoted spread and OIB for the order imbalance. Bond liquidity estimates are based on the time-weighted daily mean of the best bid and ask offer quotes by dealers on the 10-year Treasury note, as reported in the GovPX data set. The stock liquidity series are constructed by first averaging all transactions for each individual stock on a given trading day and then constructing value-weighted averages for all individual stock daily means that satisfy the data filters described in the text. OIB is measured as the dollar value of buy trades minus the dollar value of sale trades, divided by the total dollar value of trades. RET is the market return and VOL is the return volatility. The returns used are the Lehman Brothers' aggregate daily bond index returns and the daily CRSP value-weighted index return for stocks. The suffixes B and S refer to bond and stock variables, respectively. The sample period spans the period June 17, 1991, to December 31, 1998. *denotes significance at the 5% level and **denotes significance at the 10% level.

market and volatility in the other. The only exceptions are that the bond spread causes returns and order flow in the stock market. Overall, the results in Table 4 indicate that bond and stock market liquidity movements are subject to common influences, but liquidity changes in one market do not "lead" to liquidity changes in the other in an informational sense.

To further understand the dynamic properties of liquidity, we compute impulse response functions (IRFs) for the quoted spreads. The IRF traces the impact of a one-time, unit standard deviation, positive shock to one variable (henceforth, termed simply a "shock" or "innovation" for expositional convenience) on the current and future values of the endogenous variables. Since the innovations are correlated (as shown in Table 4*a*), they need to be orthogonalized. We use the inverse of the Cholesky decomposition of the residual covariance matrix to orthogonalize the impulses.

Results from the IRFs and variance decompositions are generally sensitive to the specific ordering of the endogenous variables.[16] In particular, placing a variable earlier in the ordering tends to increase its impact on the variables that follow it. Thus, in choosing an ordering, one approach is to order the variables according to the order in which they influence the other variables. We note that the price formation process starts with market makers observing an order, and in microstructure theory, information or endowment shocks generally affect prices and liquidity through trading. This suggests an argument for order imbalance to be placed first in the ordering. While the relative ordering of returns, volatility, and liquidity is unclear, we find that the impulse response results are robust to the ordering of these three variables.[17] On the other hand, we find that the relative ordering of the bond and stock spreads does matter. Given these considerations, we initially fix the ordering for endogenous variables as follows: OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRB, QSPRS. Later, we show how the results change when QSPRB is placed after QSPRS.

The contemporaneous correlations in the VAR innovations, reported in Table 4*a*, show that order imbalances mostly have low correlations with the other variables with the exception of OIBS and returns. Since OIB generally has relatively weak effects on liquidity and volatility, we omit its IRFs for brevity; these are available upon request from the authors.

Figure 3*a* illustrates the response of the stock quoted spread to a unit standard deviation shock in the endogenous variables for a period of 10 days. Monte Carlo two standard error bands are provided to gauge the statistical significance of the responses. The figure indicates that the stock quoted spread increases by 0.02 standard deviation units on the first day in response to its own shock, with the response decaying rapidly from day one to day two and more gradually after that. An innovation in stock returns forecasts a reduction in the stock quoted spread while a shock to stock volatility predicts an increase in the stock spread, with the response peaking on the second day. These results are consistent with those of Chordia, Roll, and Subrahmanyam (2001) who show that upmarket moves have a positive effect on the spread, and with models of microstructure which argue that increased volatility, by increasing inventory risk, tends to decrease liquidity.

[16] However, the VAR coefficient estimates (and, hence, the Granger causality tests) are unaffected by the ordering of variables.

[17] In particular, the impulse responses of liquidity to shocks in returns (volatility), and vice versa, are robust to whether we put returns (volatility) before or after liquidity in the VAR ordering, with the exception that when volatility is placed last, bond volatility no longer forecasts stock spreads. In the variance decomposition results, however, the importance of returns and volatility in explaining the forecast error variance of liquidity is reduced when the liquidity variable precedes them in the ordering. Details are available from the authors on request.

There is evidence of cross-market dynamics. In particular, the stock spread responds positively to a shock in the bond spread, and the magnitude is about a quarter of the response of the stock spread to its own shock. An innovation to bond volatility also forecasts an increase in the future stock spread.

Figure 3*b* shows the response of the bond quoted spread to unit shocks in the endogenous variables. The responses are qualitatively similar to

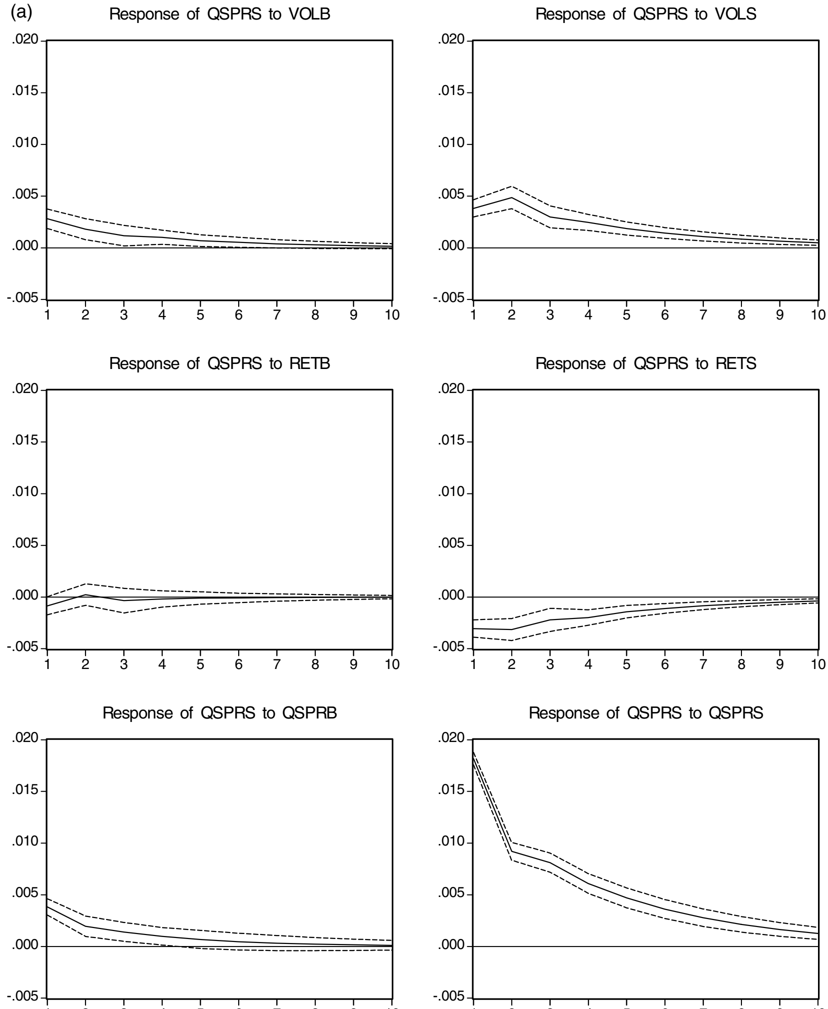

Figure 3
Response of the (a) stock and (b) bond quoted spreads to the endogenous variables, and (c) response of the stock quoted spread to the bond quoted spread and vice versa, when the bond spread is before the stock spread [(a) and (b)] and when the stock spread is before the bond spread (c) in the VAR ordering.

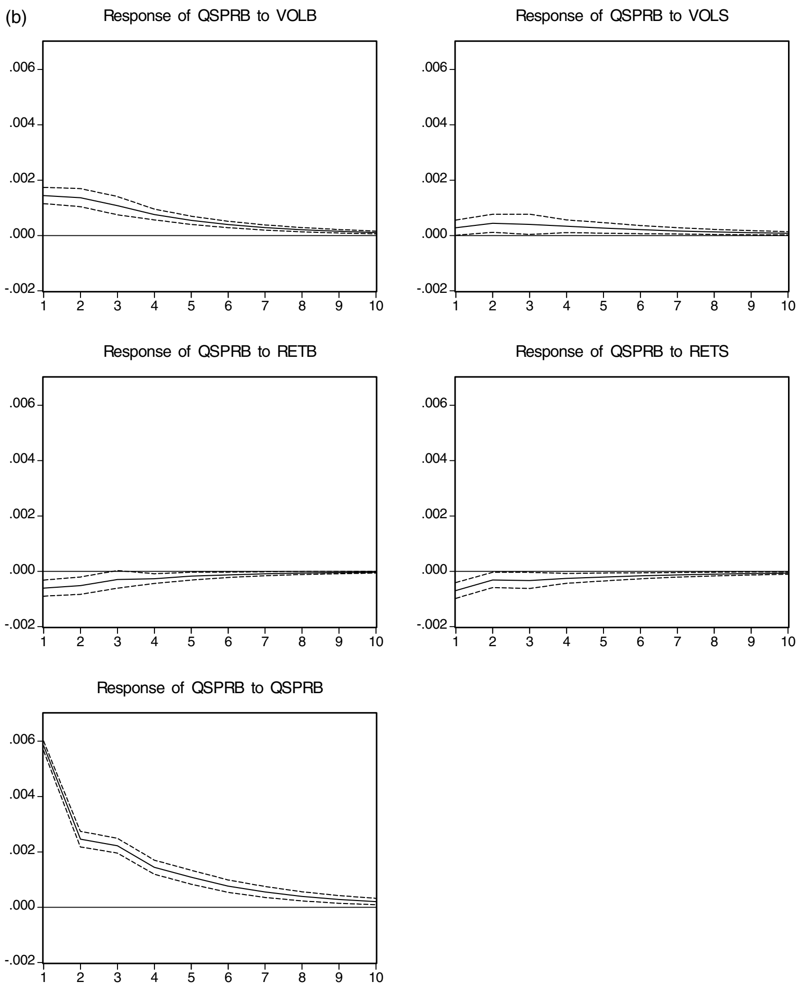

Figure 3
Continued

those for the stock spread. Shock to bond returns are associated with decreases in the future bond spread, and shocks to bond volatility and bond spreads forecast higher bond spreads. Again, there are significant cross-market effects, since a shock to the stock return is associated with a decrease in the bond spread, while innovations to stock volatility have the opposite effect.[18]

[18] In unreported results, we also performed impulse response analyses examining the effect of spreads on the other exogenous variables. While these graphs are omitted for brevity, we find that shocks to spreads forecast an increase in own market volatility, suggesting that there are cross-dynamics between spreads and volatility in both directions.

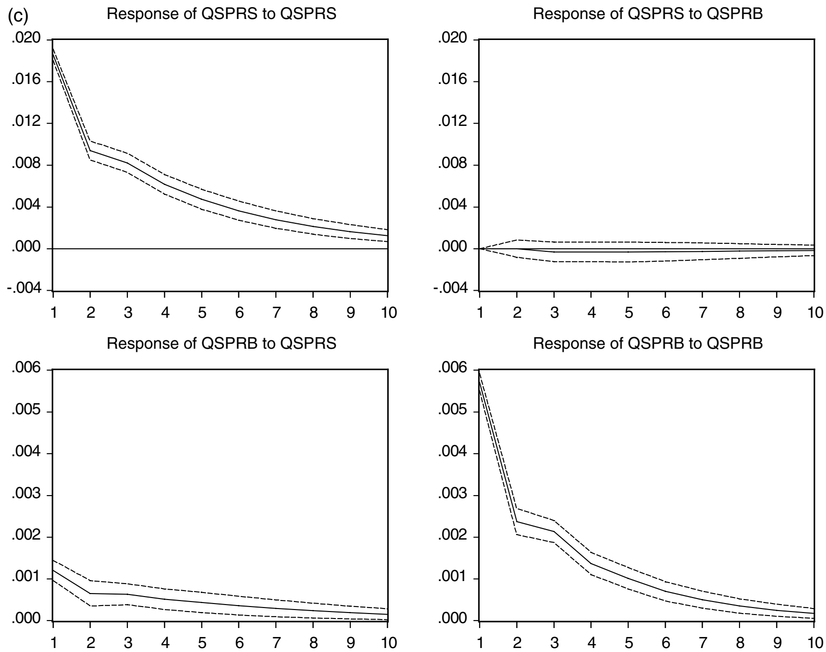

Figure 3
Continued

As an alternative way of characterizing liquidity dynamics, Table 5*a* shows the variance decompositions of bond and stock spreads. For brevity, we present results for forecast horizons of one day and ten days (the forecast standard errors are largely stable beyond the tenth lag). The fraction of the error variance in forecasting the bond spread, due to innovations in the bond spread, is more than 90% at short horizons and declines to reach 84% after 10 days. Bond volatility explains about 6% of the forecast error variance at short horizons, increasing to almost 11% after 10 days. For forecasting the stock spread, innovations in the own-spread are again the most important variable by far. The importance of stock volatility is greater at longer horizons. Bond spreads explain almost 4% of the error variance in stock spreads. These results show that innovations in own-market liquidity explain most of the liquidity dynamics, especially at shorter horizons. Own-market volatility and cross-market liquidity are the other important variables, with the impact of volatility increasing with time. It also is worth noting that in all cases, the forecast standard errors are greater for the longer horizon, suggesting the existence of dynamic structure in the data.[19]

[19] We thank an anonymous referee for pointing this out to us.

Table 5
Variance decompositions of bond and stock quoted bid-ask spread, order imbalance, volatility, and returns

(a) VAR ordered OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRB, and QSPRS
Variance Decomposition (%) of QSPRB and QSPRS

Forecast horizon	Forecast standard error	OIBB	OIBS	VOLB	VOLS	RETB	RETS	QSPRB	QSPRS
QSPRB									
1	0.0061	0.02	0.33	5.58	0.23	1.01	1.36	91.48	0.00
10	0.0077	0.07	0.69	10.68	1.20	1.48	1.48	83.91	0.48
QSPRS									
1	0.0197	0.01	2.44	2.05	3.74	0.18	2.40	3.81	85.35
10	0.0269	0.01	3.01	2.03	8.44	0.13	4.53	3.07	78.79

(b) VAR ordered OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRS and QSPRB
Variance Decomposition (%) of QSPRB and QSPRS

Forecast horizon	Forecast standard error	OIBB	OIBS	VOLB	VOLS	RETB	RETS	QSPRS	QSPRB
QSPRB									
1	0.0061	0.02	0.33	5.58	0.23	1.01	1.36	3.91	87.57
10	0.0077	0.07	0.69	10.68	1.20	1.48	1.48	5.21	79.18
QSPRS									
1	0.0197	0.01	2.44	2.05	3.74	0.18	2.40	89.17	0.00
10	0.0269	0.01	3.01	2.03	8.44	0.13	4.53	81.77	0.08

The table presents the variance decompositions computed from a VAR with endogenous variables OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRB, and QSPRS. It is estimated with two lags and a constant term, and uses 1880 observations. QSPR stands for quoted spread and OIB for the order imbalance. OIB is measured as the dollar value of buy trades minus the dollar value of sale trades, divided by the total dollar value of trades. RET is the market return and VOL is the return volatility. The returns used are the Lehman Brothers' aggregate daily bond index returns and the daily CRSP value-weighted index return for stocks. The suffixes B and S refer to bond and stock variables, respectively. The sample period is June 17, 1991, to December 31, 1998.

In the preceding analysis, we placed QSPRS last in the VAR ordering, thus maximizing the predictive power of the remaining variables. In particular, the result that shocks to the bond spread are informative in predicting stock spreads may be sensitive to the initial ordering. Thus, we repeat our analysis with the following alternative ordering: OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRS, QSPRB. Figure 3*c* reports the IRF results with the new ordering. In contrast to the earlier results, the bond spread responds to the stock spread but the reverse is not true. Table 5*b* shows the variance decomposition results when the bond spread is placed last in the ordering. The contribution of the stock spread in explaining the error variance in bond spreads increases from less than 1% earlier to more than 5% now. On the other hand, the contribution of bond spreads in explaining the error variance in stock spreads is reduced from more than 3% earlier to essentially zero.

An interesting observation, based on the above results, is that when QSPRB is last in the ordering, the response of QSPRS to a shock in QSPRB mirrors the response of QSPRB to a shock in QSPRS when the latter is last in the ordering. There is a plausible economic rationale for this result. Suppose both stock and bond liquidity are impacted by a common macro factor *F*. Then, the mutual responses of stock and bond spreads may simply reflect their common response to the missing factor *F*. In the second half of this article, we explore candidate factors such as monetary shocks and mutual fund flows.

Next, we briefly discuss the interactions of returns and volatility. As mentioned earlier, these results are robust to the relative ordering of returns and volatility in the VAR. The IRFs (not reported) show that volatility in each market is positively related to its own shock, and stock volatility responds positively to bond volatility. In addition, stock returns react positively to shocks in bond returns, while stock volatility decreases after a shock in stock returns. The results generally are consistent with the well-known notions that volatility is persistent and that down-markets are associated with increased volatility [e.g., Schwert (1990)], and also point to significant cross-market effects. Finally, the order imbalance in each market is positively related to its own shock and to shocks in the order imbalance in the other market.

We now repeat the previous analysis using quoted depths instead of quoted spreads in the VAR. Due to unavailability of data, the sample period is from January 1, 1995, to December 31, 1998. Since the results are broadly similar to those for spreads, we describe the results briefly without reporting them. The IRFs show that, within each market, depth decreases in response to a shock to volatility. While shocks to bond returns forecast an increase in stock depth and shocks to bond volatility imply the opposite, the response of bond depth to stock market variables is not statistically significant.

3.2 Summary of daily results

Our results can be summarized as follows. There are significant cross-correlations in liquidity innovations after accounting for the effect of returns and volatility. The impulse response results show evidence that volatility shocks predict liquidity movements both within and across markets. For example, innovations to stock volatility forecast an increase in bond spreads. Furthermore, shocks to volatility in a market forecast a reduction in that market's liquidity. This result is consistent with standard microstructure models such as Ho and Stoll (1983), in which volatility, by increasing inventory risk, has an adverse effect on liquidity.

Volatility in each market is also related to lagged own market volatility as well as the volatility in the other market. Thus, there are significant cross-market effects in volatility. Volatility persistence is observed in both markets. Also, the asymmetric volatility result that volatility decreases in upmarkets and increases in down-markets, obtains in both the stock and bond markets.

The impact of volatility on spreads is economically significant; for example, we find that the effect of a one standard deviation shock to stock volatility on stock spreads aggregates to an annualized amount of $200,000 on a daily round-trip trade of two million shares in the basket of NYSE-listed common stocks, whereas the effect of bond volatility on the stock spread is about half this amount.[20]

We also find that spread innovations and return innovations are negatively correlated, suggesting that liquidity in both stock and bond markets is lower in down-markets, possibly because of strained market-making capacities during periods of market declines. Finally, the results strongly suggest the existence of a missing factor that commonly impacts bond and stock liquidity. The next section seeks to explore such systematic influences.

4. Long-Horizon Variations in Liquidity: The Role of Monetary Policy and Mutual Fund Flows

Thus far we have studied the dynamics of liquidity at the daily level and found significant commonalities in stock and bond market liquidities. The primary goal of this section is to shed light on more primitive drivers of liquidity across these markets, and an ancillary objective is to explore liquidity movements over longer time horizons. What are candidates for macro liquidity drivers? Possibly, systemic shocks that affect portfolio rebalancing needs of investors and market makers' ability to provide liquidity. Motivated by this observation, we now add, in turn, two plausible macro drivers of liquidity to the VAR system.

First, we consider measures of the federal monetary policy stance. A loose monetary policy may increase liquidity and encourage more trading by making margin loan requirements less costly and by enhancing the ability of dealers to finance their positions. Along these lines, while several studies have informally discussed the notion that the Federal Reserve steps in to enhance financial market liquidity by loosening credit constraints during periods of market turbulence,[21] to date there has been no empirical study on the impact of changes in monetary policy on aggregate liquidity in financial markets.[22] Monetary conditions may also affect asset prices through their effect on volatility [Harvey and Huang (2002)],

[20] Our assessments of economic significance in this article are based on the 10-day cumulative impulse response of the spread to a one standard deviation shock in another variable, and on assuming 250 trading days in an year. Taking the total incremental trading cost per million shares traded and multiplying by the number of trading days in an year yields the dollar amount we report.

[21] See Garcia (1989) and "Monetary Policy Report to Congress," *Federal Reserve Bulletin*, March 1995, pp. 219–243.

[22] At 9 A.M. on the day following the 1987 stock market crash, the following statement hit the wires, "The Federal Reserve, consistent with its responsibilities as the nation's central bank, affirmed today its readiness to serve as a source of liquidity to support the economic and financial system."

interest rates, equity cost of capital, or expected corporate profitability. Indeed, Smirlok and Yawitz (1985) and Cook and Hahn (1988) show that an expansionary monetary policy increases stock prices in the short run and thus lowers expected return. Again, however, there could be reverse causality because reduced liquidity and increased volatility, could, in turn, spur the Federal Reserve to soften its monetary stance. For these reason, we add monetary policy as an endogenous variable to our VAR system.

Second, we examine aggregate mutual fund flows into equity and bond markets. Greater money flows from these institutions could lead to decreased liquidity by straining market-maker inventories [see, e.g., Edelen (1999)]. At the same time, in the reverse direction, increased liquidity or decreased volatility of these asset markets could make the assets more attractive and spur mutual fund buying, again justifying the use of fund flows as endogenous variables. In essence, the fund flows analysis examines the impact of a primitive source of order imbalances, namely, buying and selling by financial intermediaries who manage money for individual investors, on price formation and liquidity.

Unlike the daily liquidity data, the data on mutual funds and borrowed reserves (our primary indicator of monetary tightness) are not available at the daily frequency. Mutual fund flow data is available only monthly while net borrowed reserves are available at a fortnightly frequency. We use biweekly borrowed reserves data from the Federal Reserve and monthly equity and government bond net flows from the Investment Company Institute for our analysis in this section.[23] The analysis of links between liquidity and lower-frequency data on monetary policy and fund flows, of course, has the auxiliary benefit of allowing the exploration of liquidity dynamics over longer horizons than the daily intervals considered in the previous section.

Net borrowed reserves are defined as total borrowings minus extended credit minus excess reserves. Thus, net borrowed reserves represent the difference between the amount of reserves banks need to have to satisfy their reserve requirements and the amount which the Fed is willing to supply. Following Strongin and Tarhan (1990), Strongin (1995), and Christiano et al. (1999), we divide the net borrowed reserves by total reserves and associate higher values of this ratio (which we term NBOR) with increased monetary tightness. These authors argue that innovations to NBOR primarily reflect exogenous shocks to monetary policy. Market participants also use net borrowed reserves as a measure of the Fed's

[23] In this section, returns are computed by compounding the residuals from Equation (1) over the relevant period and volatility is the absolute value of the compounded returns (adjusted for month-of-the-year regularities and trends). Liquidity and imbalance measures are computed by simply averaging the adjusted daily time-series over the relevant time span.

monetary stance.[24] For example, Melton (1985) notes that "... since late 1979, the key link between the Fed and the federal funds rate is the amount of reserves that the banks must borrow from the Fed's discount window. Consequently, the best single indicator of the degree of pressure the Fed is putting on the reserves market is the amount of borrowed reserves."

Another popular monetary policy variable is the surprise in the Fed Funds target changes. Cochrane and Piazzesi (2002) argue that these monetary shocks are ideal measures of unexpected movements in monetary policy. The Federal Reserve periodically changes its target funds rate to signal changes in monetary policy. Since the timing of the target rate changes is typically known, the market forms expectations regarding the target rate change. These expectations can, in principle, be recovered from the prices of the federal funds futures contracts.[25] We compute a variable, FFSUR, as the difference between the target funds rate and its market expectation on days when the Fed changes the target rate.[26] FFSUR is zero on days when the target rate remains the same. FFSUR is further decomposed into negative surprises (NFFSUR) and positive surprises (PFFSUR). NFFSUR indicates a greater-than-expected reduction in the target rate while the reverse is true for PFFSUR.

4.1 Summary statistics

Table 6 presents the biweekly net borrowed reserves, NFFSUR and PFFSUR as well as money flows into equity and bond funds (denoted by EFLOW and BFLOW, respectively) each month. Bond funds experience outflows during our sample period, the reverse is true for equity funds. As with the daily variables, we adjust NBOR, EFLOW, and BFLOW for monthly variations, time trends, and crisis effects. We do not report the coefficients for brevity, but discuss the qualitative results. NBOR is lower from January to March, relative to the rest of the year, and it is increasing over time at a decreasing rate. The crisis coefficients are negative, suggesting a looser monetary policy during crises. EFLOW and BFLOW are both lower in December compared with the rest of the year. EFLOW is also relatively low in the summer months (June to August) and

[24] "In the aftermath of the [September 11] crisis, the Fed pumped tens of billions of dollars into the economy. As a result, the banks' excess reserves soared. But as the financial markets returned to some semblance of normality, the Fed gradually began mopping up much of that excess money. Bank reserves have now fallen back significantly, and in the process, short-term interest rates have moved back up to their intended target level. "Why the Fed Should Stick to Rate Cutting," by Rich Miller, *Business Week*, October 15, 2001.

[25] We are grateful to Ken Kuttner (2001) for providing us with his expectations data.

[26] The target rate changes are dated according to the day on which they became known to the market. As discussed in Kuttner (2001), this corresponded to the day after the decision to change rates until 1994, and to the decision day from February 1994, when the Fed started communicating its intention to change the target on the decision day. The target change on October 15, 1998, occurred between FOMC meetings and was announced after close of the futures markets; hence, the surprise is equal to the new target on the 16th minus the expectations implied by the closing futures rate on the 15th.

Table 6
Net borrowed reserves, federal funds surprises and mutual fund flows

	NBOR	NFFSUR	PFFSUR	EFLOW	BFLOW
Mean	−0.018	−14.069	9.625	11.952	−0.208
Median	−0.017	−10.333	10.833	10.673	−0.415
No. of observations	198	15	8	91	91

The table presents monthly equity mutual fund net flows (EFLOW) and monthly government bond mutual fund net flows (BFLOW). The unit is \$1 billion. Monthly mutual fund data are from the Investment Company Institute. NBOR is equal to the net borrowed reserves divided by the total reserves, where net borrowed reserves equal total borrowings minus extended credit minus excess reserves. Reserves data is from the Federal Reserve. NFFSUR (PFFSUR) is the negative (positive) surprise in the target federal funds rate changes, where the surprise is the target rate minus its market expectations. The unit is in basis points (0.01%). The sample period spans June 17, 1991, to December 31, 1998.

in October. BFLOW decreased during the bond crisis, while EFLOW decreased during the Russian crisis. Finally, BFLOW has been decreasing while EFLOW has been increasing over the sample period.

4.2 Monetary policy

We allow for differential effects of monetary policy during crisis and noncrisis periods in our analysis. It is often argued that substantive changes in monetary policy variables occur primarily in times of financial crises and, in turn, financial markets respond to monetary policy mainly during crises periods. We find that net borrowed reserves declined significantly (by about 33%) in the crisis period relative to the non-crisis period, suggesting a loose monetary stance of the Federal Reserve during periods of financial crises. Several recent articles have suggested that financial crises affect liquidity.[27] For Treasury bonds, Fleming (2001) finds that price impacts and quoted bid-ask spreads are higher during crisis periods. To allow for crisis period effects, we include two variables in our VAR analysis: NBOR_CR, which is simply NBOR multiplied by a crisis dummy, which is one during the three crisis periods identified earlier, and is zero otherwise, and NBOR_NO, which is equal to NBOR everywhere except the crisis periods, where it equals zero. We then estimate a VAR of order one (suggested by the information criterion) using all of the financial market variables, namely, spreads, volatility, returns, and order flow in the two markets, together with NBOR_NO and NBOR_CR.[28]

In our initial VAR, NBOR_CR, and NBOR_NO are first and second in the ordering of the endogenous variables, with the ordering of the other endogenous variables kept the same as in Table 5*a*. The motivation here

[27] See, for example, Greenspan (1999); "Finance and Economics: Alan Greenspan's Miracle Cure," *Economist*, October 24, 1998, pp. 75–76; and "A Review of Financial Market Events in Autumn 1998," CGFS Reports No. 12, October 1999, available at http://www.bis.org/publ/cgfspubl.htm.

[28] Unit root tests performed for all of the lower-frequency series did not reject stationarity.

is that, while financial markets respond to monetary policy, the latter is relatively exogenous to the financial system (e.g., the Federal Reserve does not change borrowed reserves contemporaneously to dampen stock or bond market volatility). There is precedent for putting monetary policy instruments before financial variables in the VAR ordering [Thorbecke (1997)], and anecdotal evidence suggests that monetary policy responds to macroeconomic rather than financial factors.[29] Later, however, we allow for the fact that, during crisis periods, monetary policy may specifically respond to conditions in the financial market.

The correlation matrix of the resulting VAR innovations are reported in Table 7*a*. While there is only a weak correlation between NBOR_NO and the financial market variables, innovations to NBOR_CR are positively correlated with spreads, and the correlation with stock spreads is statistically significant. Thus, there is evidence that loosened monetary policy is contemporaneously associated with increased equity market liquidity during crises. The Granger causality results in Table 7*b* indicate that shocks to NBOR_CR are informative in predicting bond spreads at the 10% level of significance. However, NBOR_NO is not informative in predicting liquidity.

In Table 7*c*, we report the variance decompositions of the stock and bond spreads at the eighth lag (the forecast standard errors were largely stable beyond this lag). For the bond spread, NBOR_CR explains about 4.5% of the variation in the bond spread after two months (or eight biweekly periods), more than the fraction explained by bond volatility. In contrast, NBOR_NO explains less than one-half of 1% of the bond spread. For the stock spread, NBOR_CR explains almost 3% of the variation in the stock spread, lower in magnitude only to the spreads and the stock return. These results are consistent with the view that monetary shocks explain an important part of the common variation in the stock and bond liquidity during crises.

Figure 4 presents the IRFs of the spreads to net borrowed reserves during crisis periods. We find that stock spreads are positively associated with NBOR_CR, suggesting that loosened monetary policy is associated with reduced spreads in the stock market. In unreported results, there is no evidence that any of the other financial market variables are associated with monetary policy.[30]

[29] In a recent speech, Federal Reserve Governor Ben Bernanke states that "... as a general rule, the Fed will do best by focusing its monetary policy instruments on achieving its macro goals — [real] price stability and maximum sustainable employment" (remarks before the New York Chapter of the National Association for Business Economics, New York, NY, October 15, 2002, available at www.federalreserve.gov//boarddocs/speeches/2002/20021015/default.htm). Similar sentiments are expressed by Federal Reserve Chairman Alan Greenspan, at www.federalreserve.gov/boarddocs/speeches/2002/20021219/default.htm.

[30] Monetary statistics (like NBOR) are reported with a lag of about a week. (We are grateful to the anonymous referee for bringing this to our attention.) Thus the data labeled as spanning a particular

Table 7
VAR of net borrowed reserves, bond and stock quoted bid-ask spread, order imbalance, volatility, and returns

(a) Contemporaneous correlation between VAR innovations

	OIBB	OIBS	VOLB	VOLS	RETB	RETS	QSPRB	QSPRS	NBOR_NO	NBOR_CR
OIBB	1.00									
OIBS	0.04	1.00								
VOLB	−0.05	0.15*	1.00							
VOLS	−0.15*	−0.06	0.12**	1.00						
RETB	0.05	0.26*	−0.06	0.08	1.00					
RETS	0.03	0.77*	0.12*	−0.08	0.30*	1.00				
QSPRB	−0.13**	−0.03	0.16*	0.10	−0.16*	−0.12**	1.00			
QSPRS	0.01	−0.16*	0.08	0.13**	−0.09	−0.26*	0.46*	1.00		
NBOR_NO	−0.05	−0.02	−0.01	−0.07	0.08	0.01	−0.05	−0.04	1.00	
NBOR_CR	0.06	−0.06	0.12**	0.08	−0.18*	−0.08	0.08	0.17*	−0.41*	1.00

(b) Chi-square statistics from Granger causality tests
Null hypothesis: Row variable does not Granger-cause column variable

	OIBB	OIBS	VOLB	VOLS	RETB	RETS	QSPRB	QSPRS
NBOR_CR	0.231	0.009	0.017	2.315	0.610	0.231	2.946**	0.517
NBOR_NO	0.005	0.408	1.898	0.603	0.260	1.457	0.001	0.000

(c) Variance decompositions
VAR ordered NBOR_CR, NBOR_NO, OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRB, and QSPRS
Variance decomposition (%) for forecast horizon of 8 biweekly periods

	Forecast standard error	NBOR _CR	NBOR _NO	OIBB	OIBS	VOLB	VOLS	RETB	RETS	QSPRB	QSPRS
QSPRB	0.0055	0.46	83.58	4.48	0.45	1.25	0.33	4.02	1.36	1.08	3.00
QSPRS	0.0201	74.67	12.16	1.83	0.28	1.39	1.59	2.06	1.97	0.68	3.38

(d)
VAR ordered OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRB, QSPRS, NBOR_NO, and NBOR_CR
Variance decomposition (%) for forecast horizon of 8 biweekly periods

	Forecast standard error	OIBB	OIBS	VOLB	VOLS	RETB	RETS	QSPRB	QSPRS	NBOR _NO	NBOR _CR
QSPRB	0.0055	1.11	0.46	3.55	1.17	1.28	2.95	82.86	0.88	2.43	3.32
QSPRS	0.0201	1.42	1.85	2.41	2.06	0.80	3.38	12.35	75.21	0.25	0.27

The table presents results from a VAR with endogenous variables NBOR_NO, NBOR_CR, OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRB, and QSPRS. The VAR is estimated with one lag and a constant term, and uses 196 observations. (a) Correlations between the VAR innovations. (b) Chi-square statistics and *p*-values of pairwise Granger causality tests between net borrowed reserves and financial market variables. (c) The variance decompositions of QSPRB and QSPRS at a forecast horizon of eight two-week periods (four months). NBOR is the ratio of net borrowed reserves to total reserves, where net borrowed reserves equal total borrowings minus extended credit minus excess reserves. NBOR_NO is equal to NBOR, but with the crisis period values set to 0. NBOR_CR is equal to NBOR, but with the normal period values set to 0. The crisis periods are March 1, 1994, to December 5, 1994; July 2, 1997, to December 31, 1997; July 6, 1998; to December 31, 1998. The reserves data is from the Federal Reserve and is at a biweekly frequency. QSPR stands for quoted spread and OIB for the order imbalance. OIB is measured as the dollar value of buy trades minus the dollar value of sale trades, divided by the total dollar value of trades. VOL is the return volatility and RET is the daily market return compounded over the biweekly period. The returns are the Lehman Brothers' aggregate daily bond index returns and the daily CRSP value-weighted index return for stocks. The suffixes B and S refer to bond and stock variables, respectively. The sample period is June 17, 1991, to December 31, 1998. *denotes significance at the 5% level and **denotes significance at the 10% level.

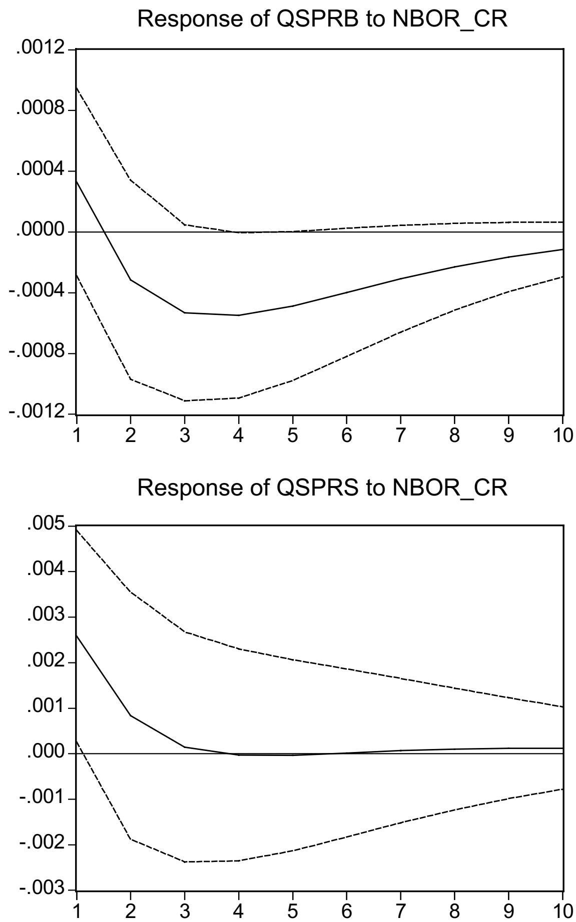

Figure 4
Crisis period response of the bond and stock quoted spread to net borrowed reserves

To allow for the fact that the Federal Reserve may respond to financial markets, especially in times of crisis, we reestimate the VAR with the following alternative ordering: OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRB, QSPRS, NBOR_NO, NBOR_CR. In impulse response graphs that are omitted for brevity, we find that under the new ordering, stock and bond spreads are unresponsive to shocks in NBOR_CR. Table 7*c* shows that, when placed last in the ordering, NBOR_CR

time period is not available to the market till about a week after that time period. We do not lag the NBOR data on the basis that NBOR has a contemporaneous, noninformational effect, for example, by improving the borrowing terms for market makers. The peak or trough at the second lag in the IRFs could be an artifact of the lag in release, however.

explains about 3.5% of the forecast error variance of the bond spread, compared with about 4.5% earlier. The variance decomposition results suggest that NBOR_CR remains an important determinant of bond spreads during crisis periods, equal in magnitude to bond volatility, even under the alternative ordering.

We repeat the analysis after replacing stock and bond spreads with depths in the VAR. Despite the limited number (104) of observations, the results (not shown) are similar to those found with the quoted spreads. In particular, NBOR_CR explains between 4.5% (when it is placed first in the ordering) and 2.5% (when it is placed last) of the forecast error variance of the bond depth.

Monetary policy may, in part, be predictable. In particular, a loosening (tightening) of monetary policy may be followed by further loosening (tightening). This implies that financial market investors are likely to react only to the surprise component in monetary policy. Unfortunately, data on expectations of borrowed reserves is not readily available. As an alternative, and as a robustness check, we use the previously described negative surprises (NSURPRISE) and positive surprises (PSURPRISE) in the federal funds rate. We estimate a VAR of order two (again, as per the information criteria) with NSURPRISE, PSURPRISE, and the financial market variables.

Figure 5 shows the response of spreads to a unit orthogonalized shock to NSURPRISE and PSURPRISE. Stock spreads are lower in response to a shock to NSURPRISE. Furthermore, a unit shock to PSURPRISE is associated with increases in bond spreads. The results are consistent with the notion that a monetary expansion increases liquidity, while monetary tightening has the opposite result. In unreported results, we also find that stock and bond volatility decreases (increases) in response to a shock in NSURPRISE (PSURPRISE). In addition, stock and bond returns decrease in response to a shock to NSURPRISE, perhaps because the market views the higher-than-expected rate cut as a signal of worse-than-expected economic conditions.

As before, we allow for the fact that monetary policy may respond to financial markets, rather than the other way round, by placing NSURPRISE and PSURPRISE last in the ordering. Yet again, we find that the impulse response results are sensitive to the ordering; specifically, unreported IRFs indicate that when the surprise variables are placed last in the ordering, the impulse responses of liquidity to shocks in NSURPRISE and PSURPRISE are no longer significant.

Overall, NBOR innovations during crises are an important determinant in forecasting the error variance in bond liquidity. Similarly, impulse response results indicate that net borrowed reserves and federal fund surprises predict stock and bond liquidity. We cannot draw a strong conclusion regarding the *predictive* effect of monetary policy on liquidity,

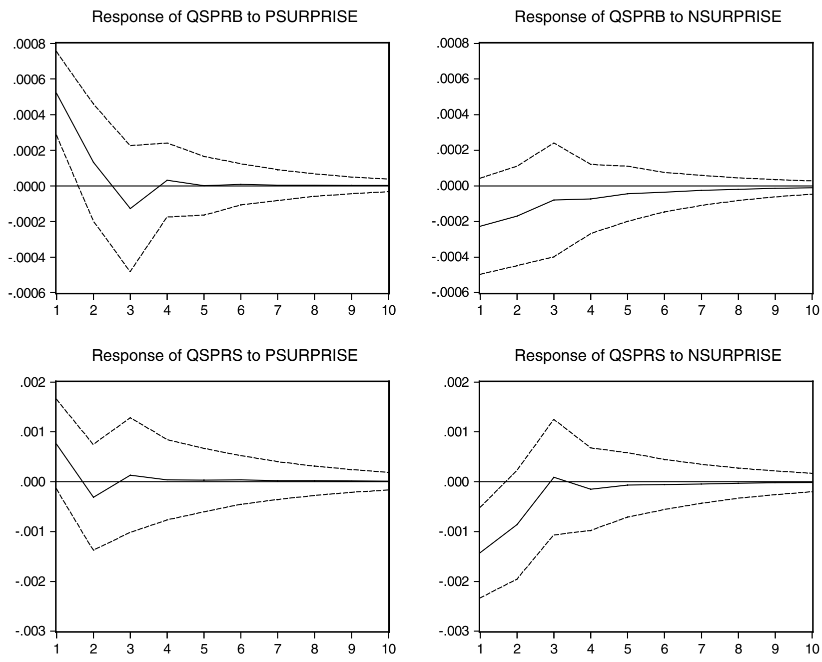

Figure 5
Response of the bond and stock quoted spread variables to negative and positive federal funds surprises

since the impulse responses of the monetary variables are sensitive to the Cholesky ordering. However, *contemporaneous* innovations in crisis-period borrowed reserves are positively and significantly correlated with stock spreads, suggesting that loosened monetary policy is associated with a contemporaneous increase in equity market liquidity during crises.

4.3 Fund flows

We now examine the interaction of mutual fund flows with financial market variables. We estimate a VAR of order one (again suggested by the information criteria) with EFLOW, BFLOW, and the financial market variables. As before, we initially place BFLOW and EFLOW first and second in the ordering, with the remaining variables ordered as before; later, we place BFLOW and EFLOW last in the ordering. Table 8*a* shows that innovations to EFLOW and BFLOW are negatively correlated with each other, and that bond flows are strongly correlated with spreads, but have low correlations with the other variables. Table 8*b* shows that BFLOW Granger causes stock and bond spreads, and the stock return, while EFLOW Granger causes BFLOW, the bond spread, and stock order flow and volatility.

Table 8
Monthly VAR of mutual fund flows, bond and stock quoted bid-ask spread, order imbalance, volatility, and returns

(a) Contemporaneous correlation between VAR innovations

	BFLOW	EFLOW	OIBB	OIBS	VOLB	VOLS	RETB	RETS	QSPRB	QSPRS
BFLOW	1.00									
EFLOW	−0.18**	1.00								
OIBB	0.17	0.11	1.00							
OIBS	0.07	0.32*	0.17	1.00						
VOLB	−0.13	−0.06	0.02	−0.08	1.00					
VOLS	−0.11	−0.22*	−0.23*	−0.14	0.02	1.00				
RETB	0.17	0.08	0.27*	0.39*	−0.13	−0.02	1.00			
RETS	−0.05	0.46*	0.16	0.78*	−0.09	−0.20**	0.39*	1.00		
QSPRB	0.21*	0.04	−0.09	0.02	0.01	0.03	−0.16	−0.05	1.00	
QSPRS	0.30*	−0.13	−0.05	−0.10	0.02	0.31*	−0.11	−0.19**	0.38*	1.00

(b) Chi-square statistics from Granger causality tests
Null hypothesis: Row variable does not Granger-cause column variable

	BFLOW	EFLOW	OIBB	OIBS	VOLB	VOLS	RETB	RETS	QSPRB	QSPRS
BFLOW		0.811	0.511	0.023	0.233	0.001	2.230	3.666**	4.396*	4.651*
EFLOW	3.809**		0.472	9.972*	1.700	5.797*	0.746	2.148	10.442*	0.006

(c) Variance decompositions
VAR ordered BFLOW, EFLOW, OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRB, and QSPRS
Variance decomposition (%) for forecast horizon of four months

	Forecast standard error	BFLOW	EFLOW	OIBB	OIBS	VOLB	VOLS	RETB	RETS	QSPRB	QSPRS
QSPRB	0.0050	21.11	4.82	1.75	0.35	1.37	1.65	3.14	0.32	65.02	0.47
QSPRS	0.0180	7.55	4.22	0.69	0.88	0.20	7.85	2.44	0.55	4.56	71.07

Table 8
Continued

VAR ordered OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRB, QSPRS, EFLOW, and BFLOW

Variance Decomposition (%) for forecast horizon of four months

	Forecast standard error	OIBB	OIBS	VOLB	VOLS	RETB	RETS	QSPRB	QSPRS	EFLOW	BFLOW
QSPRB	0.0050	2.88	0.84	0.43	1.36	3.52	0.94	76.72	0.13	1.70	11.50
QSPRS	0.0180	0.95	0.51	0.30	5.97	2.04	1.81	7.85	77.19	0.13	3.23

The table presents results from a VAR with endogenous variables BFLOW, EFLOW, OIBB, OIBS, VOLB, VOLS, RETB, RETS, QSPRB, and QSPRS. The VAR is estimated with one lag and a constant term, and uses 90 observations. (a) Correlations between the VAR innovations. (b) Chi-square statistics and *p*-values of pairwise Granger causality tests between fund flows and financial market variables. (c) The variance decompositions of QSPRB and QSPRS at a forecast horizon of four months. EFLOW (BFLOW) measures monthly equity (government bond) mutual fund net flows. The data is from the Investment Company Institute and is at a monthly frequency. QSPR stands for quoted spread and OIB for the order imbalance. OIB is measured as the dollar value of buy trades minus the dollar value of sale trades, divided by the total dollar value of trades. RET is the daily market return compounded over the month and VOL is the return volatility. The returns used are the Lehman Brothers' aggregate daily bond index returns and the daily CRSP value-weighted index return for stocks. The suffixes B and S refer to bond and stock variables, respectively. The sample period is June 17, 1991, to December 31, 1998. * denotes significance at the 5% level and ** denotes significance at the 10% level.

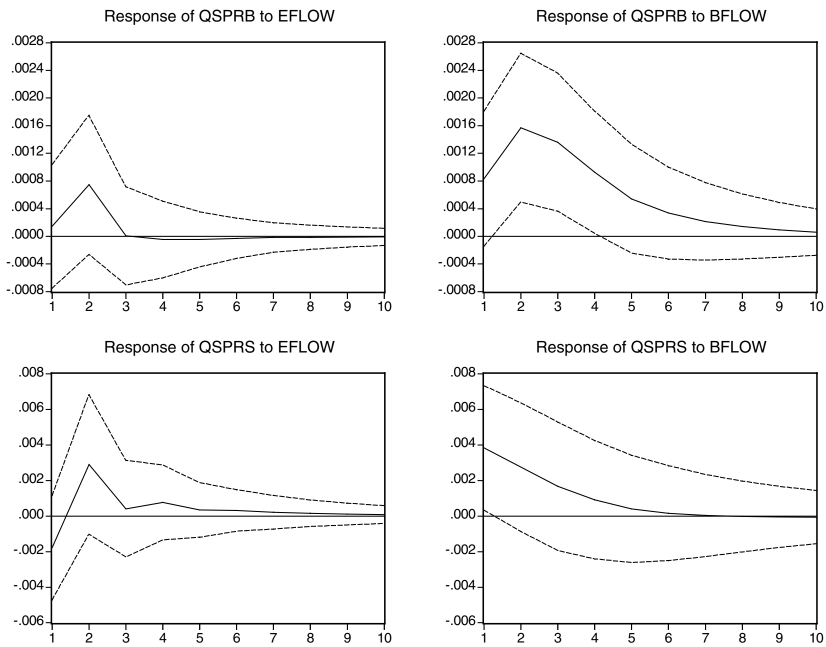

Figure 6
Response of the bond and stock quoted spread to equity and bond fund flows

The response of fund flows to endogenous variables shows (not reported) that equity flows decline in response to a shock in bond returns and bond flows decrease in response to a shock in stock volatility, but otherwise fund flows do not respond to the financial variables. Figure 6 illustrates the impulse response of spreads to a shock in EFLOW and BFLOW. Innovations to equity flows are not informative in forecasting spreads. However, the bond spread increases in response to a shock in bond flows, with the response peaking in the second month. Further, stock spreads respond positively to shocks in bond flows during the first period.[31]

In other unreported impulse responses analyses, we find that in response to a shock to stock flows, stock returns increase. Warther (1995) finds a similar result for weekly data, but finds that returns are uncorrelated with past flows at the monthly level. In addition, equity flows

[31] Mutual fund flow reporting is subject to a delay. For example, fund flow data for a given month is typically reported by the Investment company Institute around the end of the following month. Our view is that flows impact financial markets contemporaneously by straining imbalances and causing price pressures. However, if we also allow for an informational role for fund flows, then the reporting delays may help explain the second lag peaks that are quite ubiquitous in the impulse responses.

initially decrease but later increase in response to a shock in bond flows, and only the increase (after two months) is statistically significant.

The variance decompositions corresponding to four monthly lags, shown in Table 8*c*, are consistent with these results. Innovations in BFLOW account for almost all of the forecast error variance in BFLOW, with stock volatility and bond spreads being the only other variable of importance. BFLOW explains up to 11%, while bond returns explain up to 6% of the error variance in forecasting EFLOW. BFLOW and EFLOW together explain more than 25% of the forecast variance of the bond spread and up to 12% of the error variance of the stock spread. These results are consistent with our claim that fund flows affect liquidity. Volatility remains important in explaining variations in spreads; specifically, stock volatility explains about 10% of the error variance in the stock spread.

Next, we check the robustness of the results by examining variance decompositions and impulse responses obtained from placing EFLOW and BFLOW last in the ordering. Table 8*c* shows that while, as expected, error variances explained by the flow variables decline, they continue to explain a large portion of the forecast error variances in spreads. For example, when BFLOW is placed last, it still explains up to 12% of the error variances in bond spreads, compared with about 21% earlier. Moreover, when EFLOW is last, the contribution of EFLOW to the forecast error variance of stock spreads is about 3%, compared with about 4% earlier. Impulse response analyses (omitted for brevity) show that when BFLOW is last in the ordering, the bond spread increases in response to a shock in BFLOW. When EFLOW is last in the ordering, the stock spread is unresponsive to EFLOW. These results are similar to those obtained when the fund flow variables were first in the ordering. We conclude that bond and equity flows impact future spreads in an economically meaningful way, and this result is robust to the Cholesky ordering.

4.4 Summary of monetary policy and fund flow results

Our results on monetary policy and fund flows are as follows. When we place the monetary variables first in the ordering (based on the idea that monetary policy targets the macroeconomy and is largely exogenous to financial market variables), our impulse response analyses suggest that monetary easing forecasts increased stock and bond market liquidity during crisis periods. For the whole sample period, unanticipated shocks to the federal funds rate are associated with liquidity as conjectured: unexpected increases in the federal funds rate are associated with an increase in spreads while unexpected decreases have the opposite result. While volatility in both bond and stock markets responds positively (negatively) to positive (negative) federal funds surprises, the effect on stock market volatility is larger. The impulse response results (except for the response of bond volatility to a positive surprise) are sensitive to ordering; specifically, they are insignificant when the monetary variables are placed last in the VAR ordering. However, during crisis periods, innovations to net borrowed reserves are positively correlated with contemporaneous stock spread innovations. Further, crisis period innovations in borrowed reserves are important in explaining the forecast error variance of bond spreads. Overall, the monetary policy appears to have a modest association with financial market liquidity, and that too, only during crisis periods.

We also find that innovations to equity fund flows have modest ability to forecast liquidity, but innovations to bond fund flows significantly forecast increases in bond spreads. We propose that the relatively modest impact of equity fund flows may be due to the fact that our measure encompasses only mutual fund flows, whereas individual investors who directly trade securities form a relatively larger share of the equity market than the bond market. Hence, our measure of equity flows (which ignore trades done by individuals for their own account) may be less accurate than that of bond flows.

From the standpoint of economic significance, we find that a one standard deviation shock to net borrowed reserves during crisis periods (when they are placed first in the ordering) has an annualized impact of about $70,000 on trading costs for a daily trade of two million shares in the basket of NYSE-listed common stocks, while the corresponding impact of a onestandard deviation negative federal funds rate surprise is about $20,000. These numbers appear reasonably substantial. The economic significance of bond fund flows on liquidity is small: A one standard deviation shock to bond flows has an annualized effect of only $7500 on the cost of trading $2 million dollars worth of Treasury bonds per day (in par value). However, stock and bond flows explain a significant fraction of the error variance in forecasting liquidity in both stock and bond markets. We also find that substantial commonality between stock and bond market liquidity continues to exist even at longer horizons; unexpected shocks to these variables are significantly and positively cross-correlated even at biweekly and monthly frequencies.

5. Concluding Remarks

We examine common determinants of stock and bond liquidity over the period 1991 through 1998, and study the effect of monetary shocks and money flows (bank reserves, federal funds rates, and mutual fund investments) on transactions liquidity. Thus, our study promotes a better understanding of the dynamics of liquidity by analyzing liquidity comovements across different asset classes. We also take a step towards linking microstructure liquidity with macro-level liquidity as embodied in money flows, which, in turn, helps enhance our understanding of the factors that drive liquidity across different markets. Our analysis takes on particular significance given the association between variations in liquidity and the cost of capital [Pastor and Stambaugh (2003)], and also has direct implications for predicting and controlling trading costs associated with asset allocation strategies.

Some of our findings are as follows:

- Weekly regularities in stock and bond market liquidities closely mimic each other. Friday is the lowest-liquidity day of the week for both markets. Further, liquidity in both stock and bond markets tends to be higher during the summer/early fall months of July to September.
- Daily innovations in volatility and liquidity explain a large fraction of the error variance in forecasting liquidity, suggesting past volatility and liquidity are the most important variables in forecasting future liquidity.
- Liquidity and volatility shocks are positively and significantly correlated across stock and bond markets at daily horizons, indicating that liquidity and volatility shocks are often systemic in nature.
- An unexpected loosening of monetary policy, as measured by a decrease in net borrowed reserves, is associated with a contemporaneous increase in stock liquidity and has modest ability to forecast liquidity during crises.
- Innovations to bond fund flows are informative in forecasting both stock and bond market liquidity.

Our work suggests a fertile research agenda. Little theoretical work has been done on time-series movements in liquidity, and there is no theory on linking movements in liquidity across equity and fixed-income markets. A model of market equilibrium with endogenous trading across stock and bond markets would seem to be desirable. Furthermore, the theoretical link between monetary policy, fund flows, and stock and bond market liquidity also represents a research issue that has largely remained unexplored. We hope our work serves to stimulate research in these areas.

References

Amihud, Y., 2002, "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects," *Journal of Financial Markets*, 5, 31–56.

Amihud, Y., and H. Mendelson, 1986, "Asset Pricing and the Bid-Ask Spread," *Journal of Financial Economics*, 17, 223–249.

Ammann, M., and H. Zimmermann, 2001, "Tracking Error and Tactical Asset Allocation," *Financial Analysts Journal*, 57, 32–43 (March/April).

Balduzzi, P., E. Elton, and T. Green, 2001, "Economic News and Bond Prices: Evidence from U.S. Treasury Market," *Journal of Financial and Quantitative Analysis*, 36, 523–543.

Barberis, N., 2000, "Investing for the Long Run When Returns are Predictable," *Journal of Finance*, 55, 225–264.

Benston, G., and R. Hagerman, 1974, "Determinants of Bid-Asked Spreads in the Over-The-Counter Market," *Journal of Financial Economics*, 1, 353–364.

Boni, L., and J. Leach, 2001, "Supply Contractions and Trading Protocol: An Examination of Recent Changes in the U.S. Treasury Market," working paper, University of New Mexico, Albuquerque, NM.

Borio, C., and R. McCauley, 1996, "The Economics of Recent Bond Yield Volatility," BIS Economic Paper No. 44, Bank for International Settlements, Basel, Switzerland.

Boyer, B., and L. Zheng, 2002, "Who Moves the Market? A Study of Stock Prices and Investment Cashflows," working paper, University of Michigan, Ann Arbor, MI.

Brandt, M., and K. Kavajecz, 2002, "Price Discovery in the U.S. Treasury Market: The Impact of Orderflow and Liquidity on the Yield Curve," working paper, University of Pennsylvania, Philadelphia, PA.

Brennan, M., and A. Subrahmanyam, 1996, "Market Microstructure and Asset Pricing: On the Compensation for Illiquidity in Stock Returns," *Journal of Financial Economics*, 41, 441–464.

Brennan, M., T. Chordia, and A. Subrahmanyam, 1998, "Alternative Factor Specifications, Security Characteristics, and the Cross-Section of Expected Stock Returns," *Journal of Financial Economics*, 49, 345–373.

Campbell, J. and J. Ammer, 1993, "What Moves the Stock and Bond Markets? A Variance-Decomposition for Long-Term Asset Returns," *Journal of Finance*, 48, 3–37.

Chan, K., and W. Fong, 2000, "Trade Size, Order Imbalance, and the Volatility-Volume Relation," *Journal of Financial Economics*, 57, 247–273.

Chordia, T., R. Roll, and A. Subrahmanyam, 2000, "Commonality in Liquidity," *Journal of Financial Economics*, 56, 3–28.

Chordia, T., R. Roll, and A. Subrahmanyam, 2001, "Market Liquidity and Trading Activity," *Journal of Finance*, 56, 501–530.

Chordia, T., R. Roll, and A. Subrahmanyam, 2002, "Order Imbalance, Liquidity, and Market Returns," *Journal of Financial Economics*, 65, 111–130.

Chordia, T., and A. Subrahmanyam, 1995, "Market Making, the Tick Size, and Payment-For-Order Flow: Theory and Evidence," *Journal of Business*, 68, 543–575.

Cochrane, J., and M. Piazzesi, 2002, "The Fed and Interest Rates: A High-Frequency Identification," *American Economic Review* (Papers and Proceedings of the 2002 AEA meetings), 92, 90–95.

Christiano, L., M. Eichenbaum, and C. Evans, 1999, "Monetary Policy Shocks: What Have We Learned and to What End?," in Taylor, J., and Woodford, M. (eds.), *Handbook of Macroeconomics*, vol. 1, Elsevier Science B.V., Amsterdam, Netherlands, 65–148.

Cook, T., and T. Hahn, 1988, "The Information Content of Discount Rate Announcements and Their Effect on Market Interest Rates," *Journal of Money, Credit and Banking*, 20, 167–180.

Edelen, R., 1999, "Investor Flows and the Assessed Performance of Open-End Mutual Funds," *Journal of Financial Economics*, 53, 439–466.

Edelen R., and J. Warner, 2001, "Aggregate Price Effects of Institutional Trading: A Study of Mutual Fund Flow and Market Returns," *Journal of Financial Economics*, 59, 195–220.

Fabozzi, F., and M. Fleming, 2000, "U.S. Treasury and Agency Securities," in Fabozzi, F. (ed.), *The Handbook of Fixed Income Securities* (6th ed.), McGraw Hill, New York, NY.

Fair, 2002, "Events That Shook the Market," *Journal of Business*, 75, 713–731.

Fleming, J., C. Kirby, and B. Ostdiek, 1998, "Information and Volatility Linkages in the Stock, Bond, and Money Markets," *Journal of Financial Economics*, 49, 111–137.

Fleming, M., 2003, "Measuring Treasury Market Liquidity," *Federal Reserve Bank of New York, Economic Policy Review*, 9, 83–108.

Fleming, M., and E. Remolona, 1997, "What Moves the Bond Market?" *Economic Policy Review*, 3, 31–50 (December).

Fleming, M., and E. Remolona, 1999, "Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information," *Journal of Finance*, 54, 1901–1915.

Fox, S., 1999, "Assessing TAA Manager Performance," *Journal of Portfolio Management*, 26, 40–49.

Gallant, A., P. Rossi, and G. Tauchen, 1992, "Stock Prices and Volume," *Review of Financial Studies*, 5, 199–242.

Garcia, G., 1989, "The Lender of Last Resort in the Wake of the Crash," *American Economic Review*, 79, 151–155.

Goetzmann, W., and M. Massa, 2002, "Daily Momentum and Contrarian Behavior of Index Fund Investors," *Journal of Financial and Quantitative Analysis*, 37, 375–389.

Greenspan, A., 1999, "Risk, Liquidity, and the Economic Outlook," *Business Economics*, 34, 20–24.

Harvey, C., and R. Huang, 2002, "The Impact of the Federal Reserve Bank's open Market Operations," *Journal of Financial Markets*, 5, 223–257.

Hasbrouck, J., 1991, "Measuring the Information Content of Stock Trades," *Journal of Finance*, 56, 179–207.

Hasbrouck, J., and D. Seppi, 2001, "Common Factors in Prices, Order Flows and Liquidity," *Journal of Financial Economics*, 59, 383–411.

Ho, T., and H. Stoll, 1983, "The Dynamics of Dealer Markets Under Competition," *Journal of Finance*, 38, 1053–1074.

Huang, R., J. Cai, and X. Wang, 2001, "Inventory Risk-Sharing and Public Information-Based Trading in the Treasury Note Interdealer Broker Market," working paper, University of Notre Dame, Notre Dame, IN.

Huberman, G., and D. Halka, 2001, "Systematic Liquidity," *Journal of Financial Research*, 24, 161–178.

Jacoby, G., D. Fowler, and A. Gottesman, 2000, "The Capital Asset Pricing Model and the Liquidity Effect: A Theoretical Approach," *Journal of Financial Markets*, 3, 69–81.

Jones, C., 2001, "A Century of Stock Market Liquidity and Trading Costs," working paper, Columbia University, New York, NY.

Jones, C., G. Kaul, and M. Lipson, 1994, "Transactions, Volume, and Volatility," *Review of Financial Studies*, 7, 631–651.

Krishnamurthy, A., 2002, "The Bond/Old-Bond Spread," *Journal of Financial Economics*, 66, 463–506.

Kuttner, K., 2001, "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market," *Journal of Monetary Economics*, 47, 523–544.

Lee, C., and B. Radhakrishna, 2000, "Inferring Investor Behavior: Evidence from TORQ Data," *Journal of Financial Markets*, 3, 83–111.

Lee, C., and M. Ready, 1991, "Inferring Trade Direction from Intraday Data," *Journal of Finance*, 46, 733–747.

Melton, W., 1985, *Inside the Fed*, Dow-Jones Irwin, Homewood, IL.

Odders-White, E., 2000, "On the Occurrence and Consequences of Inaccurate Trade Classification," *Journal of Financial Markets*, 3, 205–332.

Odean, T., 1998, "Are Investors Reluctant to Realize Their Losses?," *Journal of Finance*, 53, 1775–1798.

O'Hara, M., and G. Oldfield, 1986, "The Microeconomics of Market Making," *Journal of Financial and Quantitative Analysis*, 21, 361–376.

Pastor, L., and R. Stambaugh, 2003, "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy*, 113, 642–685.

Schwert, W., 1990, "Stock Market Volatility and the Crash of 87," *Review of Financial Studies*, 3, 77–102.

Smirlok, M., and J. Yawitz, 1985, "Asset Returns, Discount Rate Changes, and Market Efficiency," *Journal of Finance*, 40, 1141–1158.

Stoll, H., 1978, "The Pricing of Security Dealer Services: An Empirical Study of NASDAQ stocks," *Journal of Finance*, 33, 1153–1172.

Stoll, H., 2000, "Presidential Address: Friction," *Journal of Finance*, 55, 1479–1514.

Strongin, S., 1995, "The Identification of Monetary Policy Disturbance: Explaining the Liquidity Puzzle," *Journal of Monetary Economics*, 34, 463–497.

Strongin, S. and V. Tarhan, 1990, "Money Supply Announcements and the Market's Perception of Federal Reserve Policy," *Journal of Money*, *Credit and Banking*, 22, 135–153.

Subrahmanyam, A., 1994, "Circuit Breakers and Market Volatility: A Theoretical Perspective," *Journal of Finance*, 49, 237–254.

Thorbecke, W., 1997, "On stock Market Returns and Monetary Policy," *Journal of Finance*, 52, 635–654.

Warther, V., 1995, "Aggregate Mutual Fund Flows and Security Returns," *Journal of Financial Economics*, 39, 209–235.

Xia, Y., 2001, "Learning About Predictability: The Effects of Parameter Uncertainty on Dynamic Asset allocation," *Journal of Finance*, 56, 205–246.