Market Maker Inventories and Liquidity

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April 10, 2007

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We thank the New York Stock Exchange (NYSE) for providing data. We thank Yakov Amihud, Carole Comerton-Forde, Robin Greenwood, Marios Panayides, Lubos Pastor, Avanidhar Subrahmanyam, Dimitri Vayanos, Vish Viswanathan, and seminar participants at the Federal Reserve Bank of New York, the Office of Economic Analysis of the U.S. Securities and Exchange Commission, the University of Toronto, and the University of Washington for helpful comments. Hendershott gratefully acknowledges support from the National Science Foundation. Part of this research was conducted while Hendershott was the visiting economist and Moulton was a senior economist at the NYSE. The opinions expressed in this paper do not necessarily reflect those of the members, officers, or directors of the NYSE.

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Abstract

Traditional microstructure models predict that market makers' inventory positions do not impact liquidity (the bid-ask spread). Models with limited market maker risk-bearing capacity predict that larger inventories negatively impact overall liquidity and the effect is greater for more volatile stocks. Using 11 years of NYSE specialists' inventory data, this paper tests these theoretical predictions. We find that larger inventory positions lead to lower liquidity both at the market level and at the market maker's firm level. We also find that the impact of inventories is larger for the liquidity of high-volatility stocks and for smaller market making firms. Finally, we confirm a prediction of models both with and without limited risk-bearing capacity: Inventory positions affect the relative liquidity for stock buyers versus sellers.

1. Introduction

Liquidity plays an increasingly important role in financial economists' understanding of how traders and institutions affect asset prices (Amihud, Mendelson, and Pedersen (2006)). Traditional microstructure models link an asset's volatility and a market maker's risk aversion to trading costs, i.e., liquidity (Stoll (1978), Ho and Stoll (1981, 1983), and Mildenstein and Schleef (1983)). However, such models do not predict a link between liquidity and the level of a market maker's position (level of their inventory). In addition to asset volatility and risk aversion, recent theoretical works by Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2006) suggest that limited risk-bearing capacity—an inability to take a position beyond a certain size—implies that market-maker positions impact overall liquidity, i.e., the common component of liquidity in all stocks.[1] While all stocks exhibit commonality, inventory effects are greater for more volatile securities, often referred to as a flight to quality. In this paper, we find support for the predictions of the Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2006) models. In addition, we find support for a prediction that is common to both traditional models and models with limited risk-bearing capacity: Market maker inventory positions shift the relative costs of buying versus selling.

We use 11 years of daily New York Stock Exchange (NYSE) specialists' inventory data to examine how the amount of risk assumed by market makers impacts future daily liquidity. At a single point in time, the aggregate inventory position across market makers (specialists) measures the amount of risk market markers have taken on. Larger inventories, whether long or short, imply greater risk exposure and, therefore, less available risk-bearing capacity. Similarly, the inventory positions across all market makers working for the same market-making firm measures the risk exposure for that firm. The available risk-bearing capacity of specialist firm is its total capital less the committed capital. Therefore, higher levels of committed capital negatively correlate with available risk-bearing capacity of that firm.

NYSE specialists are net long in aggregate over 94 percent of days in our sample period, and their inventories are positively skewed. Specialists trade against order flow, implying that their inventories are negatively correlated with recent market returns. Together these facts indicate that negative returns are associated with both increased capital exposure and losses by specialists. Consistent with past work on stock market liquidity—Chordia, Roll, and Subrahmanyam (2001), Chordia, Sarkar, and Subrahmanyam (2005), and Hameed, Kang, and Viswanathan (2006)—we show that volatility and negative market returns lead to lower liquidity. In addition, high inventories, our proxy for available lower risk-bearing

[1] Amihud and Mendelson (1980) incorporate limited risk-bearing capacity in the form of position limits. Arbitragers also act as market makers by supplying liquidity to other traders. Limited risk-bearing capacity is central to most limits of arbitrage arguments.

capacity, lead to lower liquidity. This is true both at the market level and at the individual specialist-firm level. The impact of inventories on liquidity is larger for smaller specialist firms.

To test additional predictions of the theoretical models, capture the dynamics of inventories, volatility, returns, and liquidity, and better control for potential changes in the trading environment, we estimate a vector autoregression (VAR). The VAR shows that a shock to inventories decreases liquidity. Positive shocks to volatility and negative shocks to liquidity lead to lower inventories. These latter findings are consistent with two additional aspects of the Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2006) models: i) higher volatility predicts less available risk-bearing capacity; and ii) market makers are less willing to take on inventory when liquidity falls, as they try to avoid potential liquidity spirals due to limited available risk-bearing capacity.

Brunnermeier and Pedersen (2006) show how limited risk-bearing capacity has a differential impact on high- and low-fundamental-volatility stocks. They use the term "flight to quality" to refer to the result that the liquidity differential between high- and low-fundamental-volatility securities is bigger when market makers have taken on larger positions.[2] We test this prediction by examining the relation between inventories and the liquidity of high- and low-volatility stocks. Supporting the theoretical prediction, the liquidity of high-volatility stocks is more sensitive to larger inventories (less available risk bearing capacity) than is the liquidity of low-volatility stocks. Brunnermeier and Pedersen (2006) also predict that large market maker positions should increase commonality of liquidity across stocks. The common directional effect of inventories for high-volatility stocks and low-volatility stocks supports the idea that limited risk-bearing capacity contributes to liquidity commonality.

In contrast to the above results, microstructure models without limited risk-bearing capacity, e.g., Stoll (1978), Ho and Stoll (1981, 1983), and Mildenstein and Schleef (1983), predict that inventories do not impact the width of the bid-ask spread. However, these models do predict that inventories shift the spread around the true asset value: The more positive an inventory position, the closer the ask price is to the true value and the farther the bid price is from the true value. The intuition behind this prediction is that the market maker wants to reduce the risk of his inventory position. If he is long, he reduces risk by inducing investors to buy more than sell. He does this by making buying cheaper (relative to the true value) and selling more expensive. A short inventory position has the opposite effect as the market maker wants to induce investors to sell by making selling cheaper. This prediction is also present in models with limited risk-bearing capacity. We test this prediction using the relative distance of buy and sell transaction prices from a standard estimate of the true value, the midpoint of the quoted bid and ask prices five

[2] Flight to quality is also present in Pastor and Stambaugh (2003).

minutes after a trade. Consistent with the theory, larger positive inventories make buying cheaper than selling, while smaller positions make selling cheaper than buying.[3]

The remainder of the paper is organized as follows. Section 2 reviews related literature. Section 3 provides a general description of our data and sample. Section 4 shows the basic relation between limited market maker risk-bearing capacity and market liquidity. Section 5 investigates the dynamic relations among inventories, volatility, returns, and liquidity. Section 6 studies the role of capital constraints in flight to quality and liquidity commonality. Section 7 explores the predictions of market microstructure models without capital constraints regarding inventories and the relative costs of buying and selling. Section 8 concludes.

2. Related Literature

Models in which market makers with inventory considerations determine the bid and ask prices typically make two predictions: inventory affects the bid-ask prices, but not the width or distance between the two prices.[4] The latter prediction of spreads being independent of inventories arises in these models from the implicit assumption that, while the market maker is risk averse, he can take on unlimited risk. The result that bid and ask prices are individually sensitive to inventories, but the spread is not, is due to the market maker's attempting to reduce his inventory toward a desired level. If the market maker is long (short), both the bid and ask prices are lowered (raised) relative to the security's true value to induce other traders to buy (sell).

Models in which market makers (or arbitrageurs who act as de facto market makers) have limited risk-bearing capacity (Amihud and Mendelson (1980), Gromb and Vayanos (2002), and Brunnermeier and Pedersen (2006)) predict that inventory levels affect bid-ask spreads.[5] In these models larger inventory positions—further from the market maker's target position—lead to lower liquidity and wider spreads. Inventories impact the relative costs of buying and selling in models with and without limited risk-bearing capacity; both predict that incoming trades that reduce the market maker's inventory are less expensive than trades that increases a market maker's position. Another prediction of the Gromb and

[3] Specialists are normally long so that inventories close to zero are considered below target levels. If other liquidity suppliers are also long on average and follow trading strategies that are correlated with specialists, then our inventory measure is a proxy for all liquidity suppliers' available risk-bearing capacity. See Boehmer and Wu (2006) for evidence on relations among signed trading activity by different market participants at the NYSE.

[4] See Stoll (1978), Ho and Stoll (1981, 1983), and Mildenstein and Schleef (1983).

[5] The study of market makers' limited risk-bearing capacity harkens back to market microstructure's theoretical beginnings. Perhaps the first academic market microstructure paper (Garman (1976)) investigates market makers' inventories in the context of a gambler's ruin problem.

Vayanos and Brunnermeier and Pedersen models is that market maker's (or arbitrageur's) wealth affects liquidity. Unfortunately, without data on the specialist firms' balance sheets it is not possible to directly test whether or not the specialist firms are capital constrained. Testing predictions related to inventory positions does, however, highlight the importance of limited risk-bearing capacity, which is one part of capital constraints.

Gromb and Vayanos (2002) study a model in which arbitrageurs who face margin constraints provide liquidity that benefits all investors. Because the arbitrageurs cannot capture all of the liquidity benefits, they fail to take the socially optimal level of risk. Weill (2006) shows that market makers provide the socially optimal amount of liquidity if they have access to sufficient capital, but undersupply liquidity if capital is insufficient or too costly.

Brunnermeier and Pedersen (2006) construct a multi-asset model linking market makers' funding and market liquidity.[6] They show that when liquidity suppliers take capital-intensive positions, market liquidity is reduced.[7] They also show how limited risk-bearing capacity relates to: liquidity experiencing a flight to quality/liquidity, commonality of liquidity across securities, liquidity co-moving with the market, and volatility impacting liquidity.[8] Our sample of NYSE specialist inventory positions allows us to show how these market makers' limited risk-bearing capacity impacts liquidity and find evidence supporting the Brunnermeier and Pedersen model's additional predictions.

Chordia, Roll, and Subrahmanyam (2001) provide the first study of aggregate stock market liquidity. They show that volatility and negative returns reduce market liquidity. Chordia, Roll, and Subrahmanyam (2000) and Hasbrouck and Seppi (2001) examine co-movement of liquidity across stocks.[9] Coughenour and Saad (2004) extend this by showing that the co-movement in liquidity is higher among stocks traded by the same NYSE specialist firm and that commonality is lower for larger specialist firms. Hameed, Kang, and Viswanathan (2006) more deeply examine the relation between negative returns and liquidity, commonality, and co-movement. By establishing links between limited market maker risk-bearing capacity's relation and overall market liquidity, the liquidity of high-volatility stocks, and the liquidity of low-volatility stocks, we complement these existing papers.

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6 Many of the predictions of the Brunnermeier and Pedersen (2006) model are also obtainable from the Gromb and Vayanos (2002) model. However, Gromb and Vayanos (2002) focus on the welfare implications of arbitrageurs' capital constraints while Brunnermeier and Pedersen (2006) emphasize (as separate results) the predictions we test in this paper.

7 The reduction in market liquidity is more severe if market makers face both funding problems and predation (Attari, Mello, and Ruckes (2005) and Brunnermeier and Pedersen (2005)).

8 There is a related literature on how decreases in asset values lead to lower liquidity; see Hameed, Kang, and Viswanathan (2006) for a detailed discussion.

9 Chordia, Sarkar, and Subrahmanyam (2005) examine market/aggregate liquidity in both the stock and bond markets and establish spillovers and linkages between liquidity and volatility across the asset classes.

Prior data on market maker inventories and trading typically cover relatively short periods of time and/or a limited number of securities.[10] While these limitations prevented testing for the relation between aggregate liquidity and limited market maker risk-bearing capacity at interday horizons, the microstructure literature has been successful in showing that inventories play an important role in intraday trading and price formation.[11] For example, Madhavan and Smidt (1993), Hansch, Naik, and Viswanathan (1998), Reiss and Werner (1998), and Naik and Yadav (2003a) all find support for market makers' controlling risk by mean reverting their inventory positions towards target levels. Hansch, Naik, and Viswanathan (1998) and Reiss and Werner (1998) show that differences in inventory positions across dealers determine which dealers offer the best prices and when dealers trade.

3. Data and Descriptive Statistics

Several data sets are used to construct our sample of daily specialist inventories and liquidity that starts in 1994 and ends in 2004. CRSP is used to identify firms (permno), market capitalizations, closing prices, and returns. Market-wide returns are calculated as the market-capitalization-weighted average across stocks, using market capitalizations lagged six days. Internal NYSE data from the specialist summary file (SPETS) provide the specialist closing inventories for each stock each day. Throughout this paper we refer to the specialist dollar inventory at the end of the NYSE trading day simply as "inventory". The Trades and Quotes (TAQ) master file provides the CUSIP numbers that correspond to the symbols in TAQ on each date and are used to match with the NCUSIP in the CRSP data. We consider only common stocks (SHRCLS = 10 or 11 in CRSP), and we exclude stocks priced over $500. We use only NYSE trades and quotes from TAQ to calculate liquidity measures.

Over our 11-year sample period, 55 different specialist firms operated at the NYSE. The daily number of firms declines from 41 in 1994 to seven in 2004 (see Hatch and Johnson (2002) for a discussion of this consolidation). Each day, we determine the portfolio of stocks assigned to each specialist firm (see Corwin (2004) for a discussion of the allocation of stocks to specialist firms). For our specialist-firm level analyses, we include only the 25 specialist firms that have trading data for at least

10 For examples using NYSE specialist data see Hasbrouck and Sofianos (1993), Madhavan and Smidt (1993), and Madhavan and Sofianos (1998). For examples using London Stock Exchange market maker data see Hansch, Naik, and Viswanathan (1998), Reiss and Werner (1998), and Naik and Yadav (2003a). For futures markets data see Mann and Manaster (1996). For options market data see Garleanu, Pedersen, and Poteshman (2005). For foreign exchange data see Lyons (2001) and Cao, Evans, and Lyons (2006).

11 Without directly examining liquidity, Naik and Yadav (2003b) show how the contemporaneous relationship between government bond price changes and changes in market-maker inventories differs when market-maker inventories are very long or very short.

1250 sequential trading days (about five years) and handle a minimum of 20 stocks, to facilitate time-series and cross-sectional analysis. Our specialist firm sample includes over 84% of the stock-day observations used in the market-wide analysis.

Our basic inventory measures are the sum of specialist inventories across all stocks on day t, abbreviated INV_t, and across all stocks handled by specialist firm s, denoted $INV_{s,t}$. Figure 1 graphs the market inventory measure INV_t between 1994 and 2004. The average inventory position over the 11 years is \$196 million, with a range of -\$331 million to \$988 million and a daily standard deviation of \$137 million. Inventory is negative on only 163 of the 2,770 days in our sample, implying that specialists are net long over 94 percent of the time.

[Insert Figure 1 Here]

We construct a daily average liquidity measure across individual stocks for both the market-level and specialist-firm level. Many liquidity measures at the individual stock level come from microstructure studies and are based on the difference between the prices at which investors can sell and buy a given stock. The prices are typically referred to as the bid and ask prices and the difference between them is the quoted spread. On the floor of the NYSE, specialists and floor brokers can offer better prices than the bid and ask, and Chordia, Roll, and Subrahmanyam (2001) show that this often occurs. Therefore, to measure liquidity we use the effective spread, which is the difference between an estimate of the true value of the security (the midpoint of the bid and ask) and the actual transaction price. The wider the effective spread, the more illiquid the stock. The narrower the effective spread, the more liquid the stock. The percentage effective spread for a trade in stock j at time k on day t is defined as:

$$\begin{aligned} ESpread_{j,k,t} &= \text{Percentage Effective Spread for stock } j \text{ at time } k \text{ on day } t \\ &= 2\, I_{j,k,t}\, (P_{j,k,t} - M_{j,k,t}) / M_{j,k,t}\,, \end{aligned}$$

where $I_{j,k,t}$ is an indicator variable that equals one for buyer-initiated trades and negative one for seller-initiated trades, $P_{j,k,t}$ is the trade price, and $M_{j,k,t}$ is the matching quote midpoint of the bid and ask prices. We follow the standard trade-signing approach of Lee and Ready (1991) and use quotes from five seconds prior to a trade for data up through 1998. After 1998, we use contemporaneous quotes to sign trades—see Bessembinder (2003).

To calculate the effective spread (our illiquidity measure) for each stock-day combination, we volume-weight trades throughout the day (i.e., we use the share volume at each time k to weight $ESpread_{j,k,t}$)

$$ESpread_{j,t} \quad = \quad \text{Volume-Weighted Percentage Effective Spread for stock } j \text{ on day } t.$$

Spreads steadily decline over our sample period due to an increase in trading volume and reduction in tick size—see Chordia, Roll, and Subrahmanyam (2001) and Hameed, Kang, and Viswanathan (2006). To control for this decline, we detrend the above volume-weighted percentage effective spread measure for each stock using the following regression:

$$\begin{aligned} ESpread_{j,t} = a_j + \sum_{\delta=1}^{4} b_{\delta,j} DAY_{\delta,t} + \sum_{\mu=1}^{11} c_{\mu,j} MONTH_{\mu,t} + d_j HOLIDAY_t + e_j TICK1_t \\ + f_j TICK2_t + g_j DAYS1_t + h_j DAYS2_t + i_j DAYS3_t + SPR_{j,t}, \end{aligned} \tag{1}$$

where $ESpread_{j,t}$ is the volume-weighted percentage effective spread for stock j on day t as defined above; $DAY_{\delta,t}$ are day-of-the-week dummies for Monday through Thursday; $MONTH_{\mu,t}$ are month-of-the-year dummies for February through December; $HOLIDAY_t$ is a dummy for days around exchange holidays as in Chordia, Sarkar, and Subrahmanyam (2005); $TICK1_t$ and $TICK2_t$ are dummies for the eighth and sixteenth tick-size periods, respectively; $DAYS1_t$ is the number of days from the beginning of the sample; $DAYS2_t$ is the number of days since the tick-size change to sixteenths (June 24, 1997); and $DAYS3_t$ is the number of days since the tick-size change to decimals (the introduction is staggered across stocks and ends January 30, 2001).

[Insert Figure 2 Here]

The residual from the regression in Equation (1) is $SPR_{j,t}$ and is our detrended volume-weighted average percentage effective spread for stock j on day t, which we then windsorize at the 1st and 99th percentiles. We calculate the daily market spread (illiquidity) measure, SPR_t, as the market-capitalization-weighted average of the windsorized detrended stock illiquidity measures ($SPR_{j,t}$) on day t, using each stock's market capitalization lagged six days.[12] Similarly, the daily specialist-firm-level spread, $SPR_{s,t}$, is the market-capitalization-weighted average of the windsorized $SPR_{j,t}$ for all of the stocks handled by specialist firm s on day t. These are the primary measures of liquidity used throughout the paper. Figure 2 depicts the undetrended and our windsorized detrended (il)liquidity measures.

[12] Market capitalization weighting of percentage spreads results in the spread measures being the sum across all stocks of the average daily dollar effective spread in each stock, times the shares outstanding in that stock, divided by the aggregate market capitalization across all stocks.

We use value weighting to avoid issues arising from changes in the number of stocks over the sample period (including the increase in listings in the late 1990s.) The paper's results hold if liquidity is calculated as above using dollar effective spreads instead of percentage effective spreads. The results also hold for various other liquidity measures such as quoted spreads (either time-weighted or trade-weighted). Results in this paper also hold for each of the tick-size sub-periods (eighths, sixteenths, and decimals) and if tick-size intercepts and time trends are used in place of detrending.

Our measure of market volatility is the daily closing Chicago Board Options Exchange (CBOE) volatility index (VIX), which is derived from the S&P 500 stock index options.[13] The index provides a forward looking measure of volatility, which theory and empirical evidence suggest is important for liquidity. VIX is interpreted as the expectation of the standard deviation of the return on the S&P 500 index over the next year, e.g., a VIX index price of 20 translates to an expectation that the standard deviation of the S&P 500's annualized returns will be 20%. Because liquidity and volatility should be correlated, and because we detrend liquidity, we also detrend VIX. We use the same methodology as in Equation (1) with the only difference that there is a single time series rather than data for each stock. Our resulting detrended volatility measure is VIX.

Table 1, Panel A provides summary statistics for the main variables used in this paper. Our market-level measure of spreads (illiquidity) has a mean of -0.141 and a standard deviation of 0.901 when expressed in basis points. The mean is negative due to the detrending procedure described above. The absolute value of market inventories has a mean of 2.015 and a standard deviation of 1.287 when expressed in units of \$100 millions. Market volatility, or VIX_{t-1}, has zero mean due to detrending and a standard deviation of 0.429 when expressed in percentage points divided by 10. Market returns (value-weighted CRSP market return, denoted R_{t-1}) have a mean of 0.048 and a standard deviation of 0.995 when expressed in percentage points.

[Insert Table 1 Here]

Panel B provides correlation statistics for market-wide spreads (SPR_t, and SPR_{t-1},), changes in our spread measure (ΔSPR_t,), absolute inventories $(|INV_{t-1}|)$, and market volatility (VIX_t and VIX_{t-1}). Spreads and volatility have a significant positive contemporaneous correlation coefficient of 0.59. Given the 0.96 autocorrelation in volatility, spreads are also significantly correlated with lagged volatility. Volatility is also positively correlated with absolute inventories. This stems from the fact that increases in volatility lead to lower price/returns.

[13] The paper's results continue to hold using other measures of volatility such as lagged absolute returns and expected volatility from the asymmetric GARCH(1,1) model of Glosten, Jagannathan, and Runkle (1993).

At the market level spreads are significantly autocorrelated with a 0.77 coefficient while the changes in spreads are significantly negatively autocorrelated with a -0.38 coefficient. These correlations suggest that differencing spreads may induce autocorrelation in a regression's computed residuals–see Hasbrouck and Seppi (2001). Throughout this paper, we focus on liquidity levels rather than changes in liquidity to avoid concerns about over-differencing. To control for autocorrelation in liquidity we include lags of the dependent variable in our regression analysis.

Consistent with limited risk-bearing capacity impacting liquidity, both spreads and changes in spreads are significantly positively correlated with the absolute value of the previous day's closing inventory (on day t-1) at the market level. The correlation coefficients are 0.13 and 0.04 respectively. Spreads are also positively correlated with day t-2's absolute inventory. Absolute inventories are positively autocorrelated with a 0.70 coefficient at the market level, suggesting that inventories are persistent (as found by Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993) for individual stocks). Persistence in inventories might imply that periods of low liquidity due to limited risk-bearing capacity might persist for extended periods of time.

Table 1, Panel C shows the market-level correlations between absolute inventories ($|INV_{t-1}|$), signed inventories (INV_{t-1}), contemporaneous market returns (R_{t-1}), and lagged market returns over days t-2 to t-5 ($R_{t-2:t-5}$). Because inventories are positive over 94 percent of the time, absolute and signed inventories are nearly identical and have a 0.97 correlation coefficient. Inventories and returns are significantly negatively correlated at both horizons—see the -0.56 and -0.34 coefficients.[14] Because an increase in volatility contemporaneously causes returns to fall and specialists' inventories increase with low returns, an increase in volatility is associated with an increase in inventories.

The results in Panel C demonstrate that specialists act as dealers and temporarily accommodate buying and selling pressure. While Hendershott and Seasholes (2006) show that specialists' inventories in individual stocks predict individual stock returns, aggregate inventories do not predict market returns. The correlation between R_{t-1} and INV_{t-2} is not significantly different from zero. There is also no autocorrelation in the market return, as the correlation between R_{t-1} and $R_{t-2:t-5}$ is -0.01 and not statistically different from zero.

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[14] At the transaction time horizon in individual stocks, the strong negative relationship between inventory innovations and return innovations should arise from exchange rules. NYSE rules 104.10(5) and 104.10(6) relate the destabilizing transactions of the specialist—buying on a plus or a zero plus tick (a positive transaction price change) and selling on a minus or a zero minus tick (a negative transaction price change)—with his inventory (see Panayides (2006) for detailed discussions of NYSE rules). In particular, for increasing or establishing an inventory position (either long or short), the specialist is not allowed to buy stocks on a direct plus tick or sell on a direct minus tick. However, the specialist is allowed to do so when decreasing or liquidating a position.

4. Market Liquidity and Inventories

To differentiate between traditional inventory models and models in which liquidity providers have limited risk-bearing capacity, we test the spread-inventory relationship. We begin our analysis with a regression of spreads on inventories and other variables shown to affect market liquidity. Chordia, Roll, and Subrahmanyam (2001) show that volatility and past returns are the only variables that significantly impact effective spreads. Therefore, we include volatility and past returns as explanatory variables in addition to inventories.

Panel A of Table 2 contains three regression specifications. The independent variable is SPR_t, the market effective spread expressed in basis points, as described in Section 3. To control for autocorrelation in effective spreads, we include, but do not report, ten lags of the left-hand-side variable (SPR_{t-1}, … , SPR_{t-10}) as explanatory variables. The lag length is chosen using the Bayes Information Criteria. Standard errors in all specifications control for heteroskedasticity as in White (1980).

Specification 1 includes simply a constant and the absolute value of inventories (in hundreds of millions of dollars) on the right-hand side (along with the lagged left-hand-side variables):

$$SPR_t = \alpha + \beta_1 \left| INV_{t-1} \right| + \sum_{i=1}^{10} \gamma_{t-i} SPR_{t-i} + \varepsilon_t \, . \qquad (2)$$

We find that larger inventories yesterday lead to higher spreads today. An additional \$100 million in inventory corresponds to an increase of 0.08 basis points in our spread measure, which is detrended.

[Insert Table 2 Here]

Specification 2 is similar to regressions run by Chordia, Roll, and Subrahmanyam (2001), Chordia, Sarkar, and Subrahmanyam (2005), and Hameed, Kang, and Viswanathan (2006).[15] Both volatility and returns are included as right-hand-side variables:

$$SPR_t = \alpha + \beta_1 VIX_{t-1} + \beta_2 Rm_{t-1} + \beta_3 Rm_{t-2:t-5} + \sum_{i=1}^{10} \gamma_{t-i} SPR_{t-i} + \varepsilon_t \, . \qquad (3)$$

VIX_{t-1} is the detrended closing volatility index from the CBOE on day t-1; while R_{t-1} and $R_{t-2:t-5}$ are the market returns on day t-1 and over the t-2 to t-5 interval. This specification yields results consistent with the aforementioned papers. Volatility and negative market returns at both horizons lead to higher spreads. The negative coefficient on market returns is consistent with capital constraints becoming more binding

[15] Given that past research shows that individual stocks' liquidity is sensitive to market liquidity (Chordia, Roll, and Subrahmanyam (2000) and others), inventories' predicting market liquidity links limited risk-bearing capacity with commonality in liquidity, as in Brunnermeier and Pedersen's (2006) model. Hameed, Kang, and Viswanathan (2006) provide a number of detailed tests for commonality in liquidity while focusing on the role of past market returns.

through the inventory channel (prices fall and market makers accumulate more inventory). Because inventories are seldom negative and market makers sell as prices rise, positive returns are associated with inventory positions moving closer to zero. Similarly, positive (negative) returns are associated with gains (losses) on market makers' average net long inventory positions.

Because inventories and returns are significantly negatively correlated, including both in a regression results in multicollinearity and the standard difficulties interpreting the coefficients. We take the view of Chordia, Sarkar, and Subrahmanyam (2005) that the price formation process begins with investors trading with market makers (i.e., information and endowment shocks affect prices through trading). Market maker inventories measure the sum of all past investor trading order flow. Therefore, our inventory variable captures the common component in both inventories and returns due to trading imbalances. The part of returns that is orthogonal to inventories may reflect wealth shocks to market makers who are on average long. The orthogonal part of returns may also result from specialists being only one source of liquidity provision while returns represent the aggregation of all investor trading.[16] We orthogonalize market returns to inventories by running an ancillary regression of returns on inventories: $R_{t-1} = a + b \cdot INV_{t-1} + R^{\perp}_{t-1}$. The residuals ($R^{\perp}_{t-1}$) represent the portion of returns that is orthogonal to inventories. We also run this ancillary regression with returns over the interval day t-2 to day t-5 on the left-hand side, which gives us $R^{\perp}_{t-2:t-5}$. In the first ancillary regression, a=0.86, b= -0.42, and the R^2=0.33.

Specification 3 regresses spreads on absolute inventories, volatility, and orthogonalized returns as explanatory variables. Absolute inventories have a significant positive coefficient estimate of 0.07, similar to the estimate of 0.08 in Specification 1 (without volatility and returns). The coefficient on volatility is positive and significant as in Specification 2. The orthogonalized return coefficients are similar to the non-orthogonalized coefficients in Specification 2.

The results in Panel A of Table 2 support the hypothesis that limited market maker risk-bearing capacity affects liquidity at the aggregate market level. This link between the common component of liquidity and inventories is the most economically significant way of demonstrating the importance of limited market maker risk-bearing capacity. In addition, if other liquidity suppliers' trading is correlated with market maker inventories (e.g., the NYSE traders categorized as individuals in Kaniel, Saar, and Titman (2006)), then tests at the aggregate market level may be the most powerful. However, demonstrating that limited risk-bearing capacity operates at the specialist-firm level provides more confidence that we are properly identifying a relationship between limited market maker risk-bearing capacity and liquidity.

[16] If market trading and price formation are viewed as the intersection of supply and demand curves, returns measure aggregate price and quantity effects of supply and demand. Specialist inventories, on the other hand, measure the quantity effect of only one market participant.

The simplest test of the inventory-spread relationship at the specialist-firm level is to run a regression analogous to Specification 1 in Panel A of Table 2:

$$SPR_{s,t} = \sum_{i=1}^{S} \alpha_i + \beta_1 \left| INV_{s,t-1} \right| + \sum_{i=1}^{10} \gamma_{t-i} SPR_{s,t-i} + \varepsilon_{s,t}. \tag{4}$$

To control for differences across the specialist firms, the regression includes fixed effects (α_i) for each specialist firm. To control for the autocorrelation in spreads we continue to include 10 lags of $SPR_{s,t}$. To control for contemporaneous correlation in the error terms, we calculate Rogers standard errors (see Petersen (2007) for a discussion of Rogers standard errors). Specification 1 in Panel B of Table 2 shows that the coefficient on absolute inventories (risk-bearing capacity committed by a specialist firm) is significantly positive with a *t*-statistic of 6.1. An additional 100 million dollars in inventory corresponds to an increase of 0.19 basis points in our detrended spread measure, which is more than double the coefficient on absolute inventories in the corresponding market level regression in Panel A of Table 2.

We also examine cross-sectional differences in specialist firms. Coughenour and Saad (2004) find that co-movement in liquidity is stronger for stocks traded by the same specialist firm and that the co-movement in liquidity is greater for smaller firms. We compute specialist-firm size ($MktCap_{s,t-6}$) as the market capitalizations of all stocks assigned to each specialist firm (lagged six days to avoid correlating this variable with stock returns). Interacting the market capitalization variable with the absolute inventory variable provides a parsimonious approach to allow for differential effects of inventory for smaller and larger specialist firms. Specification 2 in Panel B of Table 2 adds this interaction term to the regression. Specification 2 shows that the same amount of additional inventory has a greater impact on subsequent liquidity for stocks assigned to smaller specialist firms than for stocks assigned to larger specialist firms. This suggests that Coughenour and Saad's (2004) finding that co-movement in liquidity is greater for smaller firms is due to limited market maker risk-bearing capital. Specifications 3-5 show that adding returns and volatility do not change the results in Specifications 1 and 2. Inventories continue to cause commonality in the liquidity of stocks traded by the same specialist firm, and the impact of inventories on commonality in liquidity is greater for stock traded by smaller specialist firms.

5. The Dynamics of Liquidity, Inventories, Volatility, and Returns

The relation between market maker inventories and market liquidity—at the aggregate level and at the individual specialist-firm level—is supportive of models in which liquidity providers have limited risk-bearing capacity (Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2006)). We now test two additional predictions of these models: i) higher volatility predicts less available risk-bearing capacity; and ii) market makers are less willing to take on inventory when liquidity falls in order to avoid potential liquidity spirals due to capital constraints. These predictions require examining the dynamics of inventories, volatility, and liquidity. A more general study of these dynamics also serves a robustness check of the results in Table 2 by potentially better modeling changes in the trading environment. To do this we follow Chordia, Sarkar, and Subrahmanyam (2005) and estimate a four-variable vector autoregression (VAR) of the form:

$$y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \ldots + \Phi_p y_{t-P} + \varepsilon_t. \tag{5}$$

In Equation (5), y_t is a 4x1 vector of variables containing inventories, absolute value of returns, returns, and spreads: $y_t' = [\ |INV_t| \quad VIX_t \quad R_t \quad SPR_t\ ]$. These are the same four variables in Chordia, Sarkar, and Subrahmanyam (2005) with our inventory measure replacing their order imbalance measure. c is a 4×1 vector of constants. Φ_p is a 4×4 matrix of coefficients associated with lag-p variables. ε_t is a 4×1 vector with zero mean and covariance matrix Ω. We use OLS to obtain maximum likelihood estimates of c and Φ_p where $p = 1,\ldots,P$. The maximum lag length, P, is chosen using the Bayes Information Criteria.

Table 3, Panel A shows the correlation of the innovations (ε_t) from the VAR. The correlation between the innovations in inventories and spreads is 0.19, which is higher than the 0.13 correlation shown in Table 1. The correlation between the innovations in inventories and returns is -0.79, suggesting that after conditioning on past lags of all the variables, returns and inventories have much of the same information. The correlation between the innovations in volatility and returns is -0.78, showing that increases in volatility lead to lower price/returns. Given that the specialists' inventories increase with low returns, an increase in volatility contemporaneously causes returns to fall and inventories to increase, as seen in the correlation of the innovations in inventories and volatility of 0.63.

[Insert Table 3 Here]

Table 3, Panel B presents Granger causality tests. The null hypothesis is that the P lags of variable (y_2) do not Granger-cause another variable (y_1). The full VAR is estimated. We then perform an F-test that coefficients on all lags of the y_2 variable are jointly zero in the y_1 equation.[17] For example, the test of whether volatility Granger-causes spreads is the F-test that the coefficients on all lags of volatility in the spread equation are zero. The Chi-Squared statistic for that test is 25.1, which is significant at the 0.01

[17] Granger causality tests only for a direct relation between the variables. It does not test for indirect impacts one variable may have on another. For example, if volatility Granger causes spreads, but not inventories, and spreads Granger cause inventories, then volatility can impact inventories indirectly through spreads. The Granger test is not designed to detect this indirect relation. Impulse response functions, discussed below, capture both direct and indirect effects.

level. All combinations of pairs of variables are given in Table 3, Panel B with the causing variable given in the column heading and the caused variable in the row heading. For example, the test for volatility Granger-causing inventories is in the cell with volatility as the column heading and absolute inventory as the row heading and has a test statistic of 6.4, which is not significant at the 0.10 level.

Returns Granger-cause all other variables. Volatility Granger-causes spreads, but not inventories or returns. Spreads Granger-cause all other variables. Inventories Granger-cause returns, but do not directly cause volatility or spreads. This latter result is due to the high negative correlation between the innovations in returns and inventories. As in Chordia, Sarkar, and Subrahmanyam (2005), volatility and returns cause spreads at the 0.01 level.

To understand the dynamic relations between the variables and avoid reporting the 164 coefficients in Equation (5), we follow Hamilton (1994) and report impulse response functions (IRFs) up to a 10-day horizon. The IRFs measure the impact of a one standard deviation shock to each variable on the other variables. Because of the way we scale our variables—$|INV_t|$ is in hundreds of millions of dollars, VIX_t is divided by 10, R_t is in percentage points, and SPR_t is in basis points—unit shocks and standard deviation shocks are similar in magnitude.[18] We orthogonalize initial shocks to account for the correlations shown in Table 3, Panel B. The orthogonalized shocks, Λ, can be thought of as the lower triangular matrix of the "square root" of Ω: $\Omega = \Lambda\Lambda'$. The orthogonalization means a standard deviation shock to $|INV_t|$ is accompanied by simultaneous shocks to VIX_t, R_t, and SPR_t. The sign and magnitude of simultaneous shocks depends on the covariance matrix Ω. This makes the ordering of our variables in y_t important. We follow Chordia, Sarkar, and Subrahmanyam (2005) and microstructure theory more generally by viewing the price formation process beginning with trades through market makers. Prices and liquidity adjust through that trading process. Therefore, we place our measure of market maker trading (inventories) first. The ordering of volatility, returns, and spreads is less clear, but the IRF results are robust to changes in the ordering of these three variables.

[Insert Figure 3 Here]

Figure 3 presents the cumulative IRFs along with 95% confidence intervals for each of the 16 combinations of shocks and responses. Graphs in the same column correspond to a shock in the same variable (e.g., the first column of graphs are the IRFs corresponding to a shock in inventories). The variables are listed in the order that they appear in the VAR: inventories, volatility, returns, and spreads.

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[18] The initial shocks in each of our four variables $|INV_t|$, VIX_t, R_t, and SPR_t are 0.8603, 0.0960, 0.4869, and 0.4873 respectively. The initial shock to $|INV_t|$ is accompanied by simultaneous shocks to VIX_t, R_t, and SPR_t. The sizes of these simultaneous shocks are determined by the first column of Λ. The initial shock to VIX_t is accompanied by simultaneous shocks to R_t and SPR_t. The sizes of these simultaneous shocks are determined by the second column of Λ, and so forth.

In the top left graph, we see that $|INV_t|$ is persistent, as a one standard deviation shock at time zero leads to a change in $|INV_t|$ of 0.4 units (hundreds of millions of dollars) at day one with a decline to still statistically significant 0.13 at day 10. Our IRFs do not show the initial shock at time zero. In the graph immediately below, the same initial shock to $|INV_t|$ is followed by an increase in volatility. Inventories have a little effect on returns. A shock to inventories leads to spreads increasing by nearly 0.15 basis points on day one, almost double the 0.08 basis point increase in spreads in Table 2. In the bottom row of Figure 3, note the response of spreads to shocks in volatility and spreads is also positive. The response of spreads to a shock in returns is negative. These results are consistent with results in Chordia, Sarkar, and Subrahmanyam (2005).

Figure 3 shows that a positive shock to returns leads to lower spreads (as in Table 2). A shock to returns leads to an increase in inventories due to the returns causing spreads to decline, which in turn cause inventories to decline. A shock to volatility leads to a decline in inventories. Our finding that inventories fall in response to volatility and spreads is consistent with market makers' trying to avoid a liquidity spiral (Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2006)). Capital is more costly to commit when liquidity falls or volatility increases. Anticipating this possibility, market makers try to reduce their risk when volatility and/or spreads increase.

6. Flight to Quality and Inventories

The Brunnermeier and Pedersen (2006) model "implies that the liquidity differential between high-volatility and low-volatility securities increases as dealer capital deteriorates. … this happens because a reduction in [available] dealer capital induces traders to provide liquidity mostly in securities that do not use much capital (low volatility stocks)". They term this effect "flight to quality" because the liquidity of low-volatility (high quality) securities is relatively less sensitive when more risk-bearing capacity is available. Our inventory measure of limited risk-bearing capacity can be used to test predictions related to a flight to quality.

Because fundamental volatility is unobservable, we sort stocks into quartiles using their realized volatility. Each day we calculate each stock's rolling 60-day return volatility, lagged 10 days (i.e., using returns from days t-11 to t-70). We then sort the stocks based on this rolling volatility. For the lowest and highest quartiles, we calculate an aggregate spread measure for day t using the same detrending and aggregation methodology described in Section 3. The new measures are $SPR_t^{Lo\sigma}$ and $SPR_t^{Hi\sigma}$.

The simplest test of limited risk-bearing capacity causing a flight to quality is to regress the difference between the spreads of the lowest and highest volatility quartiles on absolute inventories:

$$SPR_t^{Lo\,\sigma} - SPR_t^{Hi\,\sigma} = \alpha + \beta_1 \left| INV_{t-1} \right| + \sum_{i=1}^{10} \gamma_{t-i} \left(SPR_{t-i}^{Lo\,\sigma} - SPR_{t-i}^{Hi\,\sigma} \right) + \varepsilon_t \,. \tag{6}$$

The lags of the left-hand-side variable are included to control for the autocorrelation in the spreads, but, as is true throughout the paper, the inventory coefficient is not sensitive to their omission. Estimating the regression shown in Equation (6) yields a coefficient on absolute inventories of -0.19 with a -5.02 t-statistic. In other words, as $|INV_{t\text{-}1}|$ increases, less risk-bearing capacity is available and spreads on high volatility stocks go up more than spreads on low volatility stocks.

While the regression results from Equation (6) confirm the flight-to-quality prediction, Table 4 presents more general results. We estimate the impacts of inventories on low-volatility stocks and high-volatility stocks and then test for differences in these impacts. Omitting the volatility and return variables, our main estimation equation is:

$$\begin{aligned} SPR_t^{Lo\,\sigma} &= \alpha^{Lo\,\sigma} + \beta^{Lo\,\sigma} \left| INV_{t-1} \right| + \sum_{i=1}^{10} \gamma_{t-i}^{Lo\,\sigma} SPR_{t-i}^{Lo\,\sigma} + \varepsilon_t^{Lo\,\sigma} \\ SPR_t^{Hi\,\sigma} &= \alpha^{Hi\,\sigma} + \beta^{Hi\,\sigma} \left| INV_{t-1} \right| + \sum_{i=1}^{10} \gamma_{t-i}^{Hi\,\sigma} SPR_{t-i}^{Hi\,\sigma} + \varepsilon_t^{Hi\,\sigma} \end{aligned} , \tag{7}$$

The equations are simultaneously estimated as seemingly unrelated regressions (SUR). Equation (7) is similar to the basic regression of liquidity on inventories in Table 2, but now performed for two portfolios of stocks.

[Insert Table 4 Here]

Panel A of Table 4 shows the β estimates and α estimates from Equation (7) along with the coefficient estimates on volatility and past returns. At the market level, β coefficients are positive and significant for both low- and high-volatility stocks, with the coefficient for high-volatility stocks (0.26) significantly larger than the coefficient for low-volatility stocks (0.06) in Specification 1. In Specification 3, the impact of inventories on low-volatility stocks and high-volatility stocks is robust to the inclusion of volatility and orthogonalized returns.[19] Market volatility ($VIX_{t\text{-}1}$) is a significant predictor of spreads for both low-volatility (0.05) and high-volatility stocks (0.57). Limited risk-bearing capacity has a significantly larger impact on the liquidity of high-volatility stocks than low-volatility stocks.

[19] Hameed, Kang, and Viswanathan (2006) provide a number of detailed tests for the differential impact of past returns across firm size and firm volatility.

To even more closely identify limited risk-bearing capacity with flight to quality we perform similar analysis at the specialist-firm level. The simplest test of this is to modify Equation (6) to regress the difference between the spreads of the lowest and highest volatility quartiles on absolute inventories at the specialist-firm level:

$$SPR_{s,t}^{Lo\,\sigma} - SPR_{s,t}^{Hi\,\sigma} = \sum_{i=1}^{S}\alpha_i + \beta_1\left|INV_{s,t-1}\right| + \sum_{i=1}^{10}\gamma_{t-i}\left(SPR_{s,t-i}^{Lo\,\sigma} - SPR_{s,t-i}^{Hi\,\sigma}\right) + \varepsilon_{s,t}. \tag{8}$$

Estimating the regression in Equation (8) yields a β_1 coefficient of -0.30 with a -4.38 *t*-statistic, demonstrating that larger inventories at the specialist-firm level also cause a flight to quality.

Panel B of Table 4 extends the seemingly unrelated regressions from Panel A to the specialist-firm level:

$$\begin{aligned} SPR_{s,t}^{Lo\,\sigma} &= \sum_{i=1}^{S}\alpha_i^{Lo\,\sigma} + \beta^{Lo\,\sigma}\left|INV_{s,t-1}\right| + \sum_{i=1}^{10}\gamma_{t-i}^{Lo\,\sigma} SPR_{s,t-i}^{Lo\,\sigma} + \varepsilon_{s,t}^{Lo\,\sigma} \\ SPR_{s,t}^{Hi\,\sigma} &= \sum_{i=1}^{S}\alpha_i^{Hi\,\sigma} + \beta^{Hi\,\sigma}\left|INV_{s,t-1}\right| + \sum_{i=1}^{10}\gamma_{t-i}^{Hi\,\sigma} SPR_{s,t-i}^{Hi\,\sigma} + \varepsilon_{s,t}^{Hi\,\sigma} \end{aligned}. \tag{9}$$

Each specialist firm's daily high-volatility and low-volatility stock quartiles are formed with a procedure analogous to the one used at the market level. We use the same controls and statistics: fixed effects (α_i) for each specialist firm's high- and low-volatility stocks; 10 lags of left-hand side variable, and Rogers standard errors. As in Table 2, Specifications 2 and 3 include combinations of volatility and returns as independent variables added to Equation (9).

As with the aggregate liquidity regressions in Table 2, the coefficient estimates on inventories for both low- and high-volatility stocks are greater at the specialist-firm level (Panel B of Table 4) than at the market level (Panel A of Table 4). The difference between the coefficient estimates for low-volatility stocks and high-volatility stocks is statistically significant in Specification 1. Volatility and orthogonalized returns also significantly impact liquidity, with the impact being greater for high-volatility stocks than low-volatility stocks.

7. Inventory and the Cost of Buying versus Selling

We next test a common prediction of market microstructure models with and without limited risk-bearing capacity. As described above, due to the market maker's desire to adjust his inventory, the bid-ask spread is no longer centered around the security's true value. Adjusting quotes in this way changes the relative profitability of buying and selling from the market maker's perspective. On days when a market maker is trying to induce other traders to buy rather than sell, the cost of buying should be cheaper than the cost of selling.

One standard approach of estimating the *ex post* profitability of a market maker's trade is to calculate the realized spread. The percentage realized spread for a trade in stock j at time k on day t is defined as:

$$\begin{aligned} RSpread_{j,k,t} &= \text{Percentage Realized Spread for stock } j \text{ at time } k \text{ on day } t \\ &= 2\, I_{j,k,t}\, (P_{j,k,t} - M_{j,k+5,t}) \,/\, M_{j,k,t}\ , \end{aligned}$$

where $I_{j,k,t}$ is an indicator variable that equals one for buyer-initiated trades and negative one for seller-initiated trades, $P_{j,k,t}$ is the trade price, $M_{j,k+5,t}$ is the quote midpoint of the bid and ask prices five minutes after the trade, and $M_{j,k,t}$ is the quote midpoint at the time of the trade. As with the effective spreads in Section 3, we follow the trade-signing approach of Lee and Ready (1991) for data up through 1998 and contemporaneous quotes to sign trades after 1998.

We compute the volume-weighted average realized spread separately for buyer-initiated trades and for seller-initiated trades for each stock on each day. We then calculate the market-capitalization weighted realized spreads for buyer-initiated trades and for seller-initiated trades across all stocks on each day and across the group of stocks handled by each specialist firm on each day. Because we are interested in the relative costs of buying and selling, rather than the cost of just buying and just selling, it is not necessary to detrend the realized spreads.

We test the impact of inventories on the relative costs/profitability of buying versus selling. Our simple formulation is similar to Equation (8) in Section 6:

$$RSpread_t^B - RSpread_t^S = \alpha + \beta_1 INV_{t-1} + \sum_{i=1}^{10} \gamma_{t-i} \left(RSpread_{t-i}^B - RSpread_{t-i}^S \right) + \varepsilon_t\ , \tag{10}$$

where the superscripts B and S on $RSpread_t$ denote the realized spread for buyer-initiated and seller-initiated trades, respectively. Because we are testing the impact of inventories, not limited risk-bearing capacity, signed inventories are used instead of absolute inventories on the right-hand side.

[Insert Table 5 Here]

Specification 1 in Panel A of Table 5 shows the estimated coefficients from Equation (10) at the market level. The coefficient on inventories has the predicted negative sign and is significant. The negative coefficient on lagged inventories shows that when market makers are long, they make relatively less profit when selling shares than they make when buying shares. In other words, other investors are able to buy relatively more cheaply than they are able to sell. Similarly, when market makers are short, they make relatively less profit when buying shares then they make when selling shares. Again, this translates to other investors being able to buy relatively more cheaply than they are able to sell.

Specifications 2 and 3 add market returns to the regression. Inventories are replaced by returns in Specification 2, and inventories are supplemented with orthogonalized returns in Specification 3. Volatility is omitted because there is no theoretical link between it and the relative costs of buying versus selling. In Specification 2, lagged returns have a significantly positive coefficient, consistent with returns proxying for market maker inventory positions. Positive returns are associated with market maker inventories moving below target levels. Therefore, selling to a market maker the next day should be cheaper than buying from a market maker. In Specification 3, both inventories and orthogonalized returns are significant.

To test the relation between inventory and the relative costs of buying and selling at the specialist-firm level, we run panel a regression:

$$RSpread_{s,t}^{B} - RSpread_{s,t}^{S} = \sum_{i=1}^{S} \alpha_i + \beta_1 INV_{s,t-1} + \sum_{i=1}^{10} \gamma_{t-i} \left(RSpread_{s,t-i}^{B} - RSpread_{s,t-i}^{S} \right) + \varepsilon_{s,t}, \quad (11)$$

with fixed effects (α_i) for each specialist firm, 10 lags of the left-hand-side variable, and Rogers standard errors. Specification 1 in Panel B of Table 5 shows that the coefficient on inventories is the predicted sign and same magnitude as in the market-level regression, but it is not significant at the noisier specialist-firm level. Lagged returns have significantly positive coefficients at the specialist-firm level, as they do at the market level. In Specification 3, the coefficient on inventories emerges as positive and significant with the inclusion of orthogonalized returns in the regression equation.

This section’s results on the relative costs of buying and selling confirm the non-centered bid-ask quote prediction of market microstructure models. At the market level, we show that buying is cheaper (more expensive) than selling when market makers are long (short) in aggregate. Results are echoed at the specialist-firm level. Our results complement the interdealer trading results from the London Stock Exchange in Hansch, Naik, and Viswanathan, (1998) and Reiss and Werner (1998). If inventories across dealers become different enough (in a multi-dealer market like the LSE, one dealer might be very long and another dealer short), then the dealers adjust their quotes sufficiently that they trade directly with each other in order to adjust their inventory positions toward their target levels.

8. Conclusion

Traditional microstructure models do not predict a link between liquidity and the level of market makers' positions (level of their inventories). Recent theoretical work incorporating limited risk-bearing capacity predicts that market makers' positions impact overall liquidity—the common component of liquidity in all stocks. While all stocks exhibit this commonality, limited risk-bearing capacity implies that the inventory-liquidity effects are greater for more volatile securities—flight to quality.

In this paper, we use 11 years of NYSE specialists' inventory data to identify times when there is less available risk-bearing capacity: When inventories are high, market maker capital is committed, and there is less available risk-bearing capacity. Larger inventory positions lead to lower liquidity, consistent with the hypothesis that limited risk-bearing capacity impacts market liquidity. This is true both at the market level and at the individual specialist-firm level. The impact of inventories on liquidity is larger for smaller specialist firms. The liquidity of both high- and low-volatility stocks is reduced when inventories are high, with inventories having a greater impact on the liquidity of more volatile stocks.

Both traditional microstructure models and models with limited risk-bearing capacity predict that inventories shift the relative distance of market makers' bid and ask prices from the true asset value. To reduce inventory risk, the more positive an inventory position, the closer the ask price is to the true value and the farther the bid price is from the true value. We find support for this prediction in that larger positive inventories make buying cheaper than selling, while inventories closer to zero make selling cheaper than buying.

Because liquidity is a public good with positive externalities for all traders, limited market maker risk-bearing capacity can lead to an undersupply of liquidity. Therefore, the impact of limited market maker risk-bearing capacity also has public policy and regulatory implications. If too little capital is available/supplied for market making there are a several possible solutions. First, regulators could raise capital requirements for liquidity suppliers such as specialists. This may be beneficial in avoiding liquidity meltdowns, but could also raises the costs of liquidity suppliers' day-to-day operations due to potential opportunity costs of underutilized capital. Thus, higher capital requirements make supplying liquidity less attractive, potentially driving out existing market makers and/or reducing new entry. We are currently investigating how specialist firm consolidation over the past decade affected risk-bearing capacity and market liquidity. Second, there could be subsidies for liquidity suppliers through reduced trading fees, direct payment for trading, e.g., liquidity rebates for non-marketable limit orders, or an advantageous position in the trading environment. Special privileges for market makers have been the traditional mechanism to encourage liquidity provision, but such advantages are open to abuse as seen by the odd eighths and specialist scandals on Nasdaq and the NYSE. Third, predation of liquidity suppliers should be discouraged, especially when liquidity suppliers have taken large capital positions. Measuring and defining predation would undoubtedly prove challenging, intrusive, and contentious. Finally, a liquidity supplier of last resort may be valuable when existing liquidity suppliers have committed most of their capital. For example, the Fed's actions to provide liquidity in 1987 may have prevented a crisis (SEC (1988)). However, having a liquidity supplier of last resort can cause moral hazard problems in the form of excess risk-taking. To prevent this, regulators could designate liquidity suppliers and track their positions and trading closely. In exchange for being monitored, market makers could receive more favorable lending terms from the Fed (especially during times of low liquidity). The data gathered through such arrangements could facilitate a better understanding of who supplies liquidity and when. Such improved understanding could help identify potential liquidity meltdowns and facilitate early action.

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Table 1: Descriptive Statistics and Correlations

The table presents summary statistics of the variables used in this paper. Panel A shows descriptive statistics for each variable at the market level. Panels B and C show correlations at the market level. SPR is our measure of spreads, as defined in Section 3 of the text, expressed in basis points. INV is the sum of specialist inventories across stocks. VIX is the detrended value of the closing price of the VIX Index and is our measure of volatility. R is the market capitalization-weighted stock return. We consider variables at time t, at time t-1, and over the interval t-2:t-5. The notation "| |" indicates absolute value, and the symbol "Δ" indicates daily change. Data are from CRSP, CBOE, TAQ, and the NYSE SPETS file for the period 1994 to 2004. Correlation coefficients are marked ***, **, and * to indicate significance at the 1%, 5%, and 10% significance levels, respectively.

Panel A: Summary Statistics

	Units	Mean	Stdev	Skew	Kurt
$\mathbf{SPR_t}$	Basis Points	-0.141	0.901	1.718	10.665
$\mathbf{\lvert INV_{t-1} \rvert}$	\$100 million	2.015	1.287	1.069	5.096
$\mathbf{VIX_{t-1}}$	/ 10	0.000	0.429	1.183	5.274
$\mathbf{R_{t-1}}$	%	0.048	0.995	-0.129	6.705
$\mathbf{R_{t-2:t-5}}$	%	0.191	2.003	-0.201	6.343

Panel B: Correlations of Spreads, Spread Changes, Absolute Inventories, and Volatility

	SPR_t	SPR_{t-1}	ΔSPR_t	ΔSPR_{t-1}	$\lvert INV_{t-1} \rvert$	$\lvert INV_{t-2} \rvert$	VIX_t	VIX_{t-1}
SPR_t	1.00							
SPR_{t-1}	0.77 ***	1.00						
ΔSPR_t	0.34 ***	-0.34 ***	1.00					
ΔSPR_{t-1}	0.08 ***	0.34 ***	-0.38 ***	1.00				
$\lvert INV_{t-1} \rvert$	0.13 ***	0.10 ***	0.04 **	0.13 ***	1.00			
$\lvert INV_{t-2} \rvert$	0.13 ***	0.13 ***	-0.01	0.04 **	0.70 ***	1.00		
VIX_t	0.59 ***	0.56 ***	0.05 ***	0.04 *	0.20 ***	0.18 ***	1.00	
VIX_{t-1}	0.57 ***	0.59 ***	-0.02	0.05 ***	0.21 ***	0.20 ***	0.96 ***	1.00

Panel C: Correlations of Absolute Inventories, Inventories, and Returns

	$\lvert INV_{t-1} \rvert$	$\lvert INV_{t-2} \rvert$	INV_{t-1}	INV_{t-2}	R_{t-1}	$R_{t-2:t-5}$
$\lvert INV_{t-1} \rvert$	1.00					
$\lvert INV_{t-2} \rvert$	0.70 ***	1.00				
INV_{t-1}	0.97 ***	0.69 ***	1.00			
INV_{t-2}	0.69 ***	0.97 ***	0.70 ***	1.00		
R_{t-1}	-0.56 ***	-0.03 *	-0.58 ***	-0.02	1.00	
$R_{t-2:t-5}$	-0.34 ***	-0.56 ***	-0.34 ***	-0.57 ***	-0.01	1.00

Table 2: Liquidity Regressions

The table presents results from regressions of spreads on inventories and returns. Panel A is at the market level, and Panel B is at the specialist-firm level (denoted by subscript "s"). The dependent variable is SPR_t, our measure of spreads on day t, as defined in Section 3 of the text, expressed in basis points. $|INV_{t-1}|$ is the absolute value of the sum of specialist inventories across stocks at the close on day t-1. $MktCap_{s,t-6}$ is the market capitalization of the stocks assigned to specialist firm "s" lagged six days. VIX_{t-1} is the closing price of the VIX index on day t-1; R_{t-1} and $R_{t-2:t-5}$ are the market-capitalization-weighted returns on day t-1 and over the period from day t-2 to day t-5. $R^{\perp}_{t-1}$ and $R^{\perp}_{t-2:t-5}$ capture the part of returns on day t-1 and over the period from day t-2 to day t-5 that is orthogonal to inventories. Ten lags of the dependent variable are included in the regression, but coefficients are not reported. Data are from CRSP, CBOE, TAQ, and the NYSE SPETS file for the period 1994 to 2004. T-statistics, shown below coefficient estimates, are based on standard errors that control for heteroskedasticity and clustering of contemporaneous observations.

Panel A: Market Level

	Reg. 1	**Reg. 2**	**Reg. 3**
$\|INV_{t-1}\|$	0.08		0.07
	(5.9)		*(5.8)*
VIX_{t-1}		0.11	0.11
		(3.0)	*(2.9)*
R_{t-1}		-0.11	
		(-5.5)	
$R_{t-2:t-5}$		-0.04	
		(-5.1)	
$R^{\perp}_{t-1}$			-0.12
			(-5.8)
$R^{\perp}_{t-2:t-5}$			-0.04
			(-5.1)
Const.	-0.16	0.00	-0.17
	(-6.8)	*(-0.3)*	*(-6.9)*

Panel B: Specialist-Firm Level					
	Reg. 1	**Reg. 2**	**Reg. 3**	**Reg. 4**	**Reg. 5**
$\lvert INV_{s,t-1} \rvert$	0.19	0.38		0.15	0.29
	(6.1)	*(3.9)*		*(5.9)*	*(4.2)*
$\lvert INV_{s,t-1} \rvert$ * $MktCap_{s,t-6}$		-0.01			-0.01
		(-2.4)			*(-2.4)*
VIX_{t-1}			0.22	0.24	0.24
			(5.6)	*(6.2)*	*(6.1)*
$R_{s,t-1}$			-0.12		
			(-9.5)		
$R_{s,t-2:t-5}$			-0.06		
			(-10.7)		
$R^{\perp}_{s,t-1}$				-0.12	-0.12
				(-9.3)	*(-9.3)*
$R^{\perp}_{s,t-2:t-5}$				-0.06	-0.06
				(-10.6)	*(-10.6)*
Const.	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects

Table 3: Vector Autoregression

The table presents results from market-level vector autoregression analysis of inventories, volatilites, returns, and spreads. Panel A shows the correlation of residuals. Panel B shows the results of Granger causality tests using the chi-squared test statistic. $|INV_t|$ is the absolute value of the sum of specialist inventories across all stocks at the close on day t. VIX_t is the detrended closing price of the VIX index on day t and our measure of volatility. R_t is the market-capitalization-weighted return on day t. SPR_t is our measure of market-wide spreads on day t, as defined in Section 3 of the text. Data are from CRSP, CBOE, TAQ, and the NYSE SPETS file for the period 1994 to 2004. Each row in Panel B represents one VAR equation, with the left-side variable in the first column and the right-side variables in the remaining columns. Coefficients are marked ***, **, and * to indicate significance at the 1%, 5%, and 10% significance levels, respectively.

Panel A: Correlation of Residuals

VAR Eq.	$\mid INV_t \mid$	VIX_t	R_t	SPR_t
$\mid INV_t \mid$	1.00			
VIX_t	0.63 ***	1.00		
R_t	-0.79 ***	-0.78 ***	1.00	
SPR_t	0.19 ***	0.28 ***	-0.22 ***	1.00

Panel B: Granger Causality Tests (Chi-Sq)

VAR Eq.	$\mid INV_t \mid$	VIX_t	R_t	SPR_t
$\mid INV_t \mid$		6.4	43.4 ***	28.9 ***
VIX_t	8.3		11.9 *	10.6 *
R_t	18.6 ***	4.9		23.2 ***
SPR_t	5.5	25.3 ***	66.4 ***	

Table 4: Flight to Quality Regressions

The table presents results from seemingly unrelated regressions (SUR) of spreads on inventories and returns. Results are presented for two stock quartiles: those with the lowest volatility (Low) and those with the highest volatility (High). Panel A is at the market level, and Panel B is at the specialist-firm level (denoted by subscript "s"). The dependent variable is $SPR_t^{Lo\sigma}$ or $SPR_t^{Hi\sigma}$, our measure of spreads by quartile on day t, as defined in Section 6 of the text, expressed in basis points. $|INV_{t-1}|$ is the absolute value of the sum of specialist inventories across stocks at the close on day t-1. VIX_{t-1} is the closing price of the VIX index on day t-1; R_{t-1} and $R_{t-2:t-5}$ are the market-capitalization-weighted returns on day t-1 and over the period from day t-2 to day t-5. $R^{\perp}_{t-1}$ and $R^{\perp}_{t-2:t-5}$ capture the part of returns on day t-1 and over the period from day t-2 to day t-5 that is orthogonal to inventories. Ten lags of the dependent variable are included in the regression, but coefficients are not reported. Data are from CRSP, CBOE, TAQ, and the NYSE SPETS file for the period 1994 to 2004. T-statistics, shown below coefficient estimates, are based on standard errors that control for heteroskedasticity and clustering of contemporaneous observations.

Panel A: Market Level

	Reg. 1 Stock Volatility		**Reg. 2 Stock Volatility**		**Reg. 3 Stock Volatility**	
	Low	**High**	**Low**	**High**	**Low**	**High**
$\|INV_{t-1}\|$	0.06	0.26			0.06	0.23
	(9.0)	*(9.3)*			*(8.8)*	*(7.6)*
VIX_{t-1}			0.05	0.60	0.05	0.57
			(2.3)	*(5.2)*	*(2.1)*	*(4.9)*
R_{t-1}			-0.08	-0.26		
			(-9.5)	*(-6.9)*		
$R_{t-2:t-5}$			-0.03	-0.15		
			(-6.6)	*(-7.3)*		
$R^{\perp}_{t-1}$					-0.08	-0.24
					(-7.6)	*(-5.3)*
$R^{\perp}_{t-2:t-5}$					-0.03	-0.14
					(-6.2)	*(-6.7)*
Const.	-0.14	-0.56	-0.01	-0.01	-0.14	-0.51
	(-8.8)	*(-8.4)*	*(-1.2)*	*(-0.4)*	*(-8.9)*	*(-7.5)*

Panel B: Specialist-Firm Level						
	Reg. 1 Stock Volatility		Reg. 2 Stock Volatility		Reg. 3 Stock Volatility	
	Low	High	Low	High	Low	High
| $INV_{s,t-1}$ |	0.16	0.43			0.11	0.31
	(2.5)	*(3.0)*			*(1.7)*	*(2.1)*
VIX_{t-1}			0.29	0.69	0.30	0.74
			(9.7)	*(10.0)*	*(10.2)*	*(10.7)*
$R_{s,t-1}$			-0.07	-0.27		
			(-7.7)	*(-12.6)*		
$R_{s,t-2:t-5}$			-0.03	-0.10		
			(-6.5)	*(-9.1)*		
$R^{\perp}_{s,t-1}$					-0.07	-0.27
					(-7.2)	*(-12.0)*
$R^{\perp}_{s,t-2:t-5}$					-0.03	-0.10
					(-6.1)	*(-8.8)*
Const.	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects

Table 5: Realized Spread Regressions

The table presents results from regressions of realized spread differences on inventories and returns. Panel A is at the market level, and Panel B is at the specialist-firm level (denoted by subscript "s"). $RSpread_t^B$ and $RSpread_t^S$ are our measures of realized spreads for buys and sells, respectively, as defined in Section 7 of the text. The dependent variable is the difference between $RSpread_t^B$ and $RSpread_t^S$, expressed in basis points. INV_{t-1} is the sum of specialist inventories across stocks at the close on day t-1. R_{t-1} and $R_{t-2:t-5}$ are the market-capitalization-weighted returns on day t-1 and over the period from day t-2 to day t-5. $R^{\perp}_{t-1}$ and $R^{\perp}_{t-2:t-5}$ capture the part of market returns on day t-1 and over the period from day t-2 to day t-5 that is orthogonal to inventories. Ten lags of the dependent variable are included in the regression equation, but coefficients are not reported. Data are from CRSP, TAQ, and the NYSE SPETS file for the period 1994 to 2004. T-statistics, shown below coefficient estimates, are based on standard errors that control for heteroskedasticity and clustering of contemporaneous observations.

Panel A: Market Level

	Reg. 1	**Reg. 2**	**Reg. 3**
$\mathbf{INV_{t-1}}$	-0.15		-0.19
	(-3.6)		*(-4.2)*
$\mathbf{R_{t-1}}$		0.22	
		(2.8)	
$\mathbf{R_{t-2:t-5}}$		0.17	
		(4.3)	
$\mathbf{R^{\perp}_{t-1}}$			0.18
			(2.1)
$\mathbf{R^{\perp}_{t-2:t-5}}$			0.16
			(3.8)
Constant	-0.35	-0.55	-0.13
	(-3.4)	*(-7.6)*	*(-1.1)*

Panel B: Specialist-Firm Level			
	Reg. 1	**Reg. 2**	**Reg. 3**
$INV_{s,t-1}$	-0.15 *(-1.5)*		-0.23 *(-2.2)*
$R_{s,t-1}$		0.27 *(5.8)*	
$R_{s,t-2:t-5}$		0.12 *(5.7)*	
$R_s{}^{\perp}{}_{t-1}$			0.27 *(5.7)*
$R_m{}^{\perp}{}_{t-2:t-5}$			0.12 *(5.7)*
Constant	Fixed Effects	Fixed Effects	Fixed Effects

Figure 1: Specialist Daily Closing Inventory

The chart presents the sum of specialist inventories across all stocks, in millions of dollars. Data are from the NYSE SPETS file for the period 1994 to 2004.

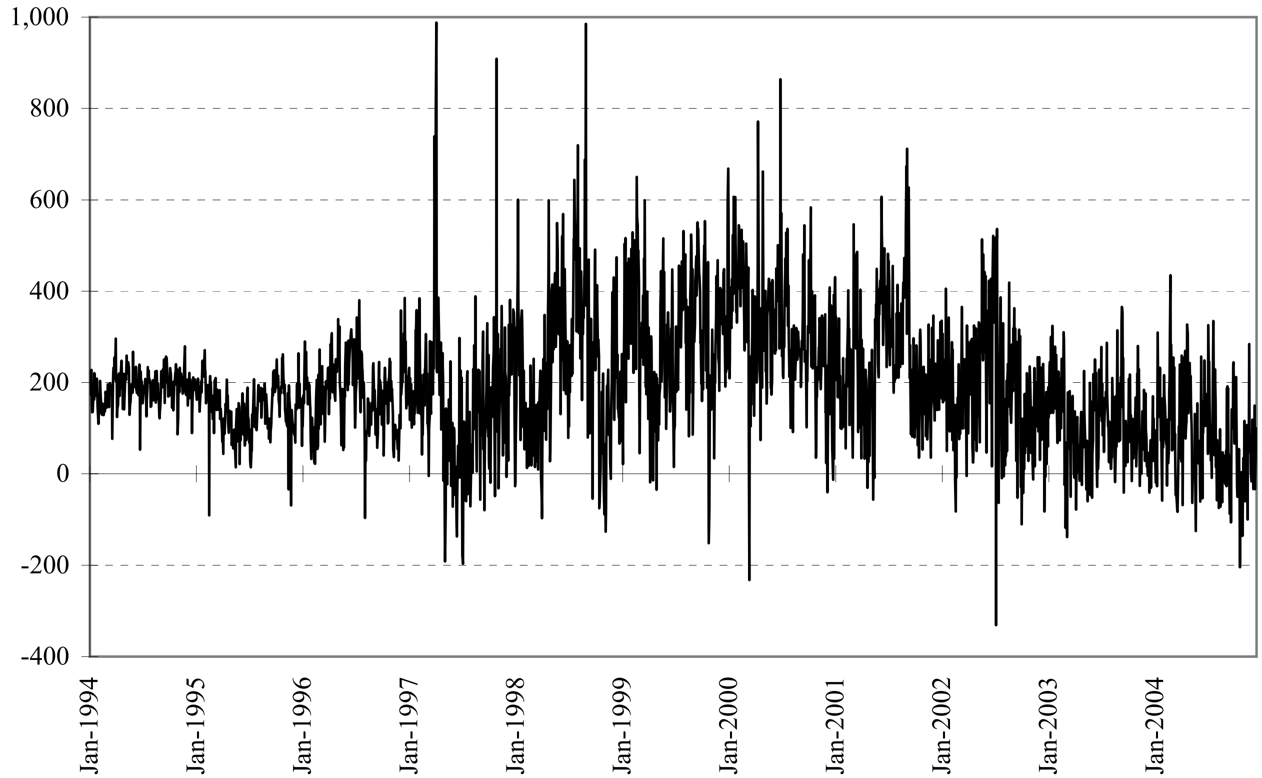

Figure 2: Daily Average Spreads

The chart presents market-wide raw spreads and our measure of market-wide windsorized detrended spreads in basis points, as defined in Section 3 of the text. Data are from TAQ for the period 1994 to 2004.

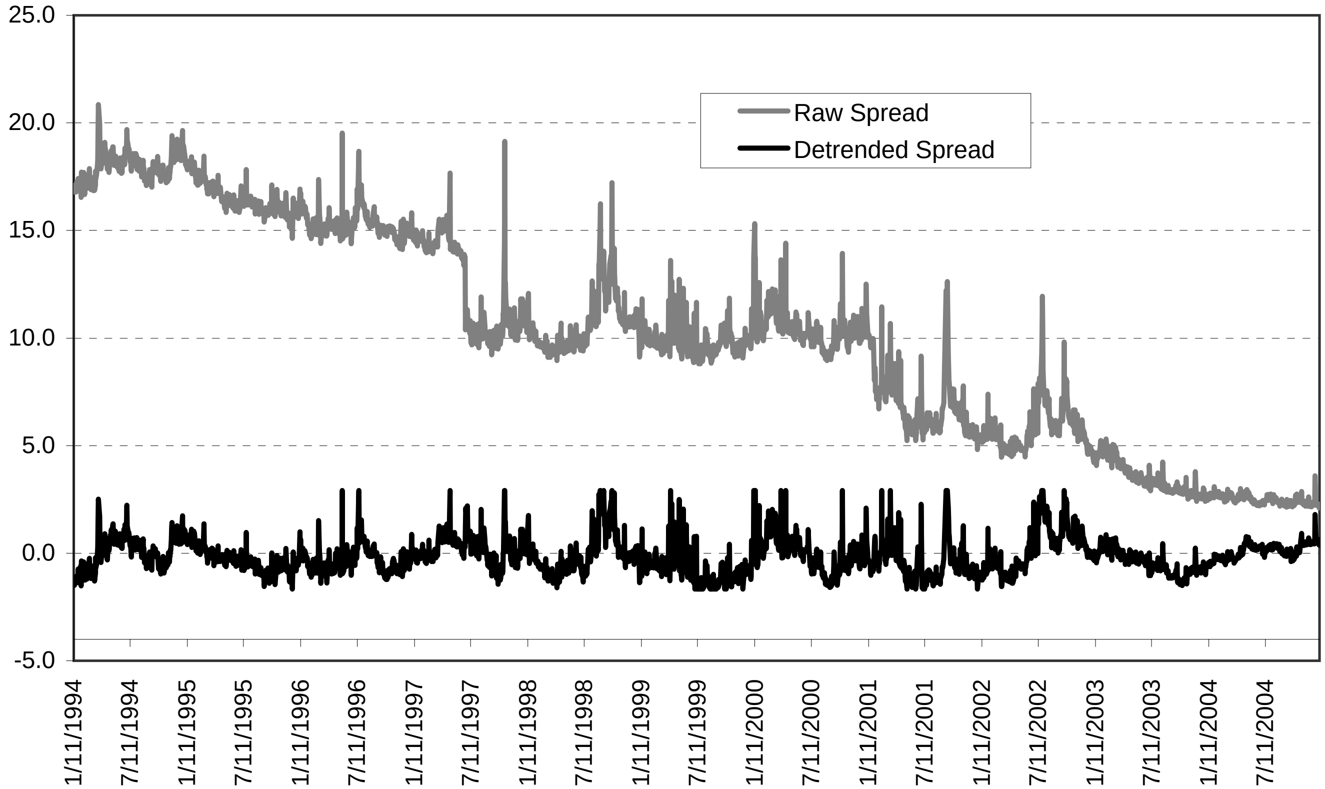

Figure 3: Vector Autoregression Impulse Response Functions

The charts present the impulse response functions from the vector autoregression analysis. | INV | is the absolute value of the sum of specialist inventories across all stocks. VIX is the closing price of the VIX index and our measure of volatility. R is the market-capitalization-weightedreturn. SPR is our measure of market-wide spreads, as defined in Section 3 of the text. The impulse response function is the center (blue or darker) line in each chart; 95% confidence intervals are the outer (red or lighter) two lines in each chart. Data are from CRSP, CBOE, TAQ, and the NYSE SPETS file for the period 1994 to 2004.