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Abstract

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This paper explores liquidity spillovers in market-capitalization based portfolios of NYSE stocks. Return, volatility, and liquidity dynamics across the small and large cap sector are modeled by way of a vector autoregression model, using data that spans more than 3000 trading days. We find that volatility and liquidity innovations in either sector are informative in predicting liquidity shifts in the other. Impulse responses indicate the existence of persistent liquidity, return, and volatility spillovers across the large and small cap sectors. Lead and lag patterns across small and large cap stocks are stronger when spreads in the large cap sector are wider. Consistent with the notion that private informational trading in large cap stocks is transmitted to other stocks with a lag, order flows in large cap stocks decile significantly predict both transaction price-based and mid-quote returns of small cap deciles when large-cap spreads are high.

1 Introduction

Although many relations in finance rely on the ability of investors to trade any amount of a security without affecting the price, frictions, including those related to trading costs and short sale restrictions, do impact price formation. The role of a specific friction, namely, illiquidity, has recently attracted attention from traders, regulators, exchange officials as well as academics. Liquidity can be defined as the ability to quickly buy or sell large quantities of an asset at a low cost. Experiences of financial crises suggest that, at times, market conditions can be severe and liquidity can disappear,[1] which underscores the need to understand the dynamics of liquidity.

Whereas early studies on the determinants of liquidity focused principally on the cross-section (e.g., Benston and Hagerman, 1974, and Stoll, 1978), recent work has shifted its focus towards studying the time-series properties of liquidity. Hasbrouck and Seppi (2001), Huberman and Halka (2001), and Chordia, Roll and Subrahmanyam (2000, 2001) consider co-movements in trading activity and liquidity in the equity markets. Chordia, Sarkar, and Subrahmanyam (2005) study commonalities in daily aggregate spreads and depths in equity and U.S. Treasury Bond markets over an extended period.

In addition, liquidity has been shown to influence equilibrium asset prices in the cross-section. For instance, Amihud and Mendelson (1986) and Jacoby, Fowler, and Gottesman (2000) provide theoretical arguments to show how liquidity impacts financial market prices. Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan, Chordia and Subrahmanyam (1998), Jones (2001), and Amihud (2002) view liquidity as a determinant of expected returns in a transaction costs context, while Pástor and Stambaugh (2003) and Acharya and Pedersen (2004) relate liquidity risk to expected

[1] "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.

stock returns.[2]

As the above literature indicates, in recent years, there has been a resurgence of interest in the time-series dynamics of liquidity as well as the impact of the level of liquidity and liquidity risk on the cross-sectional determinants of expected returns and, in turn, the cost of capital. An important observation about liquidity is that it is a parameter endogenous to the environment. The interaction between investors' buying and selling decisions determines liquidity in equilibrium. Given the endogeneity of liquidity, it is of particular interest to explore the financial market determinants that cause time-series movements in liquidity, and how these determinants vary in the cross-section.

Motivated by these arguments, we study the joint dynamics of liquidity, returns and volatility for size-sorted decile portfolios of NYSE stocks using 15 years of daily data. While Chordia, Roll, and Subrahmanyam (2001) do clarify the crucial role of volatility and returns in causing dynamic shifts in liquidity, virtually all extant studies of dynamic movements in liquidity consider only market-wide aggregates. The issue of how the dynamics of liquidity vary in the cross-section is as yet unexplored. Also unexplored is whether there are liquidity "spillovers" across different sectors of the stock market. The existence of spillovers in liquidity would imply joint increases in cost of capital whenever liquidity dries up in a given sector.

Our study of the cross-dynamics of liquidity by market capitalization can be motivated in part by Lo and MacKinlay (1990) and Conrad, Gultekin, and Kaul (1991) who study volatility and cross-autocorrelations across small and large firms. The former study shows that there are differences in stock price dynamics across small and large firms, while the latter work demonstrates the existence of volatility spillovers across such firms. Our goal

[2]Two recent theoretical papers attempt to endogenize liquidity in asset-pricing settings. Eisfeldt (2004) relates liquidity to the real sector and finds that productivity, by affecting income, feeds into liquidity. Johnson (2004) models liquidity as arising from the price discounts demanded by risk averse agents to change their optimal portfolio holdings. He shows that such a measure may dynamically vary with market returns, and hence help provide a rationale for liquidity dynamics documented in the literature.

is to understand the dynamic interaction between trading frictions, returns and volatility across different market cap sectors. We use vector autoregression methodology to explore dynamic movements and co-movements in liquidity, returns, and volatility across large and small-cap stocks. The innovation over previous studies of liquidity dynamics is the analysis of the cross-sectional variation in the economic underpinnings of dynamic liquidity variations. Our empirical analysis sheds light on how the forecasting ability of potential attributes that cause dynamic shifts in liquidity, and the ability of liquidity to forecast these attributes, vary in the cross-section.

From a practical standpoint, our study is relevant because a number of practitioners have been attracted to small cap stocks owing to academic research (e.g., Keim, 1983, and, more recently, Fama and French, 1993) which provides evidence that expected returns of small cap stocks are systematically different from those of large cap stocks. The firm of Dimensional Fund Advisors is a prominent company that trades small cap stocks. To the extent that some of these investment companies are large, their activities may be particularly sensitive to liquidity in small cap stocks than in larger stocks which are capable of withstanding their trades at low cost. Our analysis is of potential relevance in this context, because our results can assist in forecasting and controlling trade execution costs in small as well as large firms.

The results suggest that there are spillovers across large and small cap stock liquidity, volatility, returns. Specifically, large-cap (small-cap) stock volatility Granger causes small-cap (large-cap) bid-ask spreads; also, large-cap bid-ask spreads Granger cause small-cap volatility. While there are similar cross effects from returns to volatilities, there are no cross effects from returns to bid-ask spreads. There is strong evidence that a predictive relationship exists between small firm and large firm liquidity, as measured by bid-ask spreads; lags of liquidity in one market Granger cause liquidity in the other.

We estimate impulse response functions to examine the dynamics of the cross-sectional relationships in liquidity, volatility and returns between small and large cap stocks. The impulse responses show that large-cap bid-ask spreads respond to orthogonalized shocks to spreads, volatility and returns in the small-cap sector, with the response to volatility and returns persisting for at least 10 days. In the reverse direction, shocks to large-cap spreads, volatility and returns have a persistent impact on small-cap spreads, with the response peaking after one or two days. Thus, there are spillovers in liquidity, volatility and returns across small and large stocks; moreover, the spillovers are often persistent, lasting days after the initial shock.

Our Granger-causality results indicate that, consistent with Lo and MacKinlay (1990), the returns of large stocks lead those of small stocks. One possible explanation for this phenomenon may be that the lead-lag relation between small and large cap returns is related to relative liquidity movements in the two sectors. Consistent with this idea, we show that these cross-autocorrelation patterns in returns are strongest when the large-cap bid-ask spreads are high. Further, order flows in the large cap sector play an important role in predicting small cap returns when large cap spreads widen. These results hold after using mid-quote returns for the post-1993 period, demonstrating that they are not due to stale prices or a particular sample period. An interpretation of these results is that market-wide information is first traded on in the large-cap sector, causing spreads there to widen, and subsequently incorporated into prices of small-cap stocks with a lag.

The rest of the paper is organized as follows. Section 2 describes how the liquidity data is generated, while Section 3 presents basic time-series properties of the data, and describes the adjustment process to stationarize the series. Section 4 provides an economic rationale for our vector autoregressions involving liquidity, returns, and volatility across large and small cap stocks, and presents the results from these regressions. Section 5 considers the role of liquidity in the lead-lag relation between large and small cap returns. Section 6 concludes.

2 Liquidity and Trading Activity Data

Stock liquidity data were obtained for the period January 1, 1988 to December 31, 2002 (the data extends the sample of Chordia, Roll, and Subrahmanyam, 2001, by four additional years). The data sources are the Institute for the Study of Securities Markets (ISSM) and the New York Stock Exchange TAQ (trades and automated quotations). The ISSM data cover 1988-1992, inclusive, while the TAQ data are for 1993-2002. We use only NYSE stocks to avoid any possibility of the results being influenced by differences in trading protocols between NYSE and Nasdaq.

This paper analyzes the potential drivers of stock liquidity measures that the previous literature has focused upon, viz., quoted spreads and market depth, for both large and small cap stocks. 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 imbalances bear a stronger relation to trading costs by representing aggregate pressure on the inventories of market makers. These imbalances are calculated by way of the Lee and Ready (1991) algorithm, and, as such, are estimates of the true imbalances. Since imbalances are intimately related to returns (see Chordia, Roll, and Subrahmanyam, 2002), the use of returns (in addition to imbalances) allows us to pick up any imbalance-related effects that may be attenuated by the use of an imperfect proxy for the imbalance variable.

We follow the filter rules and selection criteria in Chordia, Roll and Subrahmanyam (2001) to extract transaction based measures of liquidity and order imbalances from transactions data. The measures we extract are: (i) quoted spread (QSPR) measured as the difference between the inside bid and ask quote (ii) relative or proportional quoted spread (RQSPR) measured as the quoted spread divided by the midpoint of the bid-ask spread, and (iii) depth, (DEP) measured as the average of the posted bid and ask dollar amounts offered for trade.[3] The transactions based liquidity measures are averaged over the day to obtain daily liquidity measures for each stock. The daily order imbalance (OIB) is defined as the dollar value of shares bought less the dollar value of shares sold divided by the total dollar value of shares traded.

Once the individual stock liquidity data is assembled, in each calendar year, the stocks are divided into deciles by their market capitalization at the end of the previous year. Value-weighted daily averages of liquidity are then obtained for each decile, and daily time-series of liquidity are constructed for the entire sample period. The smallest firm group is called decile 0, while decile 9 denotes the largest firm group. Since any cross-sectional differences in liquidity dynamics would be most manifest in the extreme deciles, we mainly present results for deciles 9 and 0. This allows us to present our analysis parsimoniously. Where relevant, however, we also discuss results for other deciles.

3 Basic Properties of the Data

3.1 Summary Statistics

In Table 1, we present summary statistics associated with liquidity measures, together with information on the daily number of transactions for the two size deciles. Since previous studies such as Chordia, Sarkar, and Subrahmanyam (2005) suggest that the reduction in tick sizes likely had a major impact on bid-ask spreads, we provide separate statistics for the periods before and after the two changes to sixteenths and decimalization. We also present statistics on the absolute daily proportional change in quoted spreads and depth. These measures are of interest from a practical standpoint. For example, agents splitting their orders over time would presumably be interested in ascertaining the degree to which the spread moves from day to day.

[3] We have also performed alternative analyses using effective spreads, defined as the twice the absolute difference between the transaction price and the mid-point of the prevailing quote. The results are largely unchanged from those for quoted spreads, hence, for brevity, we do not report these in the paper.

Interestingly, spreads for large and small stocks are very close to each other (18.6 and 19.1 cents, respectively), before the shift to sixteenths, but have diverged considerably since the shift. Indeed, the average spread for large stocks is half that of small stocks (5.0 versus 10.2 cents) in the period following decimalization. While we have verified that both these differences are statistically significant,[4] the point estimates indicate that decimalization has been accompanied by a substantial reduction in the spreads of large stocks, which is consistent with the prediction of Ball and Chordia (2001).

The difference in mean depths of large and small stocks has narrowed in recent times, though again, all differences are statistically distinguishable from zero. The depth of large stocks is on average double that of small ones in the pre-sixteenths period, but is about 50% higher than depth in the small-cap sector in the post-decimalization period. Depths have decreased after decimalization relative to the eighths regime, consistent with the prediction of Harris (1994), and an unreported t-test indicates that these decreases are also statistically significant for both small and large cap stocks.

In view of the recent interest in liquidity fluctuations (Pástor and Stambaugh, 2003, Acharya and Pedersen, 2004), it also is useful to note that the average absolute value of daily proportional changes in spreads, somewhat counterintuitively, is greater for larger firms than for smaller ones. For example, daily changes in depth were about 50% larger in large cap firms before the shift to sixteenths. While the differential has decreased in recent times, it is still substantive (about 25%).[5] We conjecture that significant fluctuations in order imbalances created by institutional demand within the large cap sector may cause greater fluctuations in liquidity.

The standard deviation of large cap spreads is double that of small cap spreads in the pre-sixteenth period, but the difference in dispersion across small- and large-cap spreads

[4]Unless otherwise stated, "significant" is construed as "significant at the 5% level or less" throughout the paper.

[5]Again, differences in liquidity fluctuation measures across small and large firms are all statistically significant in every subperiod.

reverses sign and is much smaller in the post-decimalization period. A similar narrowing in recent months is evident in the difference in the standard deviation of depths for the small- and large-cap sectors (however, all differences between large and small cap spread dispersions remain statistically significant).

It is worth observing that the average daily number of transactions has increased substantially in recent years, for both large and small cap stocks. For example, the average daily number of transactions increased from 580 in the first subperiod (before the shift to sixteenths) to 3,984 in the last subperiod (post decimalization), and this difference, not surprisingly, is statistically significant. Of course, large cap stocks are much more actively traded than small cap ones.

Figure 1, Panel A plots the time-series for quoted spreads for the largest and smallest deciles. The figure clearly documents the declines caused by two changes in the tick size and also demonstrates how large stock spreads have diverged away from those of small stocks towards the end of the sample period. In Panel B, we plot the proportional spreads for the large and small stocks. Spreads in small stocks tend to be much larger than those in the large cap stocks, though both series demonstrate a decrease over time, especially after the changes in the tick size. In the remainder of the paper, we focus primarily on spreads that are not scaled by price because we do not want to contaminate our inferences by attributing movements in stock prices to movements in liquidity. Our choice is justifiable because we do not examine the cross-section of liquidity at a point in time, but are interested in cross-sectional differences in the dynamics of liquidity within the largest and the smallest decile of stocks. We have ascertained, however, that our principal results are robust to using the proportional spread series as opposed to the one involving raw spreads.

3.2 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 the small and large cap sectors, at the daily horizon. Principally, we seek to ascertain the extent to which day-to-day movements in liquidity are caused by returns and return volatility. Return volatility (VOL) is obtained as the absolute value of the residual from the following regression for decile i on day t (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} (also the variable RET used below) represents the value-weighted average of individual stock CRSP returns for a particular decile.

Liquidity across stocks may be subject to deterministic movements such as time trends and calendar regularities. Since we do not wish to pick up such predictable effects in our time-series analysis, we adjust the raw data for deterministic time-series variations. All the series, returns, order imbalance, spreads, depths, and volatility are transformed by the method of Chordia, Sarkar, and Subrahmanyam (2005), who, in turn, adopt the procedure used by Gallant, Rossi, Tauchen (1992). Specifically, 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,

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

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

The adjustment variables used are as follows. First, to account for calendar regularities in liquidity, returns, and volatility, we use (i) four dummies for Monday through Thursday; (ii) 11 month of the year dummies for February through December, and (iii) a dummy for non-weekend holidays set such that if a holiday falls on a Friday then the preceding Thursday is set to 1, if the holiday is on a Monday then the following Tuesday is set to 1, if the holiday is on any other weekday then the day preceding and following the holiday is set to 1; this captures the fact that trading activity declines substantially around holidays. We also include (iv) a time trend and the square of the time trend to remove deterministic trends that we are not seeking to explain.

We further consider dummies for financial market events that could affect liquidity of both small and large-cap stocks. Specifically, we include (v) 3 crisis dummies, where the crises are: the Bond Market crisis (March 1 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),[6] (vi) dummies for the day of and the two days prior to macroeconomic announcements about GDP, employment and inflation; this intends to capture informed trading and portfolio balancing around public information releases, (vii) a dummy for the period between the shift to sixteenths and the shift to decimals, and another for the period after the shift to decimals, (viii) a dummy for the week after 9/11/01, where we expect liquidity to be unusually low, and (ix) a dummy for 9/16/91 where for some reason, most likely a recording error, only 248 firms were recorded as having been traded on the ISSM

[6] The dates for the bond market crisis are 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 from the Bank for International Settlements (see, "A Review of Financial Market Events in Autumn 1998", CGFS Reports No. 12, October 1999, available at http://www.bis.org/publ/cgfspubl.htm).

dataset whereas the number of NYSE-listed firms trading on a typical day in the sample is over 1,100.

Table 2 presents the regression coefficients for liquidity measures from the mean equation (2). For the sake of brevity, we do not present results for order imbalances, nor for the variance equation (3); however, these results are available upon request.

We are most interested in differences in the adjustment regression coefficients between the different size sectors. A readily noticeable finding is that the nature of calendar regularities in liquidity is different across large and small stocks. For example, January spreads are higher for large stocks than spreads in other months (all dummy coefficients from February to December are negative and significant for large cap stocks). This regularity is much less apparent for small cap stocks since only the November and December coefficients are negative and significant in the regressions. To confirm a January effect in large cap spreads, we compare the mean difference in January spreads across the two sectors and find that large cap spreads are significantly higher than small cap spreads at the 5% level. In addition, omitting all of the monthly dummy coefficients and including only the January dummy, we find that this dummy is not significant for small cap stocks. It is, however, significant with a t statistic of 12.17 for large cap stocks. Thus, overall the evidence indicates that large cap spreads are significantly higher in January, but the same is not true for small cap stocks.[7]

We also note that Monday spreads are low for large stocks but high for small stocks relative to Friday; however, depths are lower on Mondays for both sectors. The January behavior may be due to the fact that portfolio managers shift out of the large-cap sector following window-dressing in December. The differential Monday effect is a puzzle and we discuss it further after we present the return adjustment results. We observe that large cap spreads are higher during all three crisis periods, and small cap spreads are

[7]Clark, McConnell, and Singh (1992) document a decline in spreads from end of December through end of January, but do not compare seasonals for large and small cap stocks explicitly.

higher in two of the three crises. These results are generally consistent with the notion that financial crises result in a loss of market liquidity.[8] As expected, we see that spreads are higher in the week following 9/11/2001. In addition, there has been a strong negative trend in spreads since decimalization for both small and large companies. The results for stock depths (also in Panel A of Table 2) are generally consistent with those for spreads.

Next, we briefly discuss the results for returns and volatility, presented in Table 3. Since day-of-the-week effects are incorporated when computing volatility in equation (3), these effects are omitted from the adjustment regressions. It can be seen that large-cap stock returns display little systematic time-series variation. However, small cap returns are high on Fridays relative to the rest of the week and in January relative to other months; these results are consistent with early studies on return regularities such as Gibbons and Hess (1981) and Keim (1983). Stock volatility is high from October to January for small-cap stocks and in October and January for both large-cap stocks, relative to other months.

The higher spreads on Monday for small cap stocks are to be understood in conjunction with the day of the week effect in returns. In unreported results, we find that order flow is tilted significantly to the sell-side for small stocks on Mondays relative to Fridays. Thus, agents appear to be trading in order to countervail the buying pressure on Fridays. This "rebound" selling on Mondays following high returns towards the end of the week can contribute to increased spreads, as market makers struggle to offload the increased inventory.[9]

To formally test for stationarity, we perform augmented Dickey-Fuller and Phillips-Perron tests on the adjusted series. We allow for an intercept under the alternative

[8]Recent studies (Davis, 1999, Emmons and Schmid, 2000, Muller and Verschoor, 2004) suggest that financial crises resulted in increased uncertainty about firms' prospects; such uncertainty can contribute to decreased liquidity during crises (viz., Stoll, 1978).

[9]See Chordia, Roll, and Subrahmanyam (2001, 2002) that down markets and high order imbalances are accompanied by decreased liquidity.

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 values less than 0.01. Thus, the evidence indicates that all of the adjusted series are stationary. For the remainder of the paper, we analyze these adjusted series, and all references to the original variables refer to the adjusted time-series of the variables.

4 Vector Autoregresssion

4.1 Economic Motivation for the VAR

Our goal is to explore intertemporal associations between market liquidity, returns, volatility, and order imbalances. In earlier literature such as Benston and Hagerman (1974), and Branch and Freed (1977), the latter three variables have been treated as determinants of liquidity (i.e., as independent variables). However, bi-directional causality between liquidity and the other variables is a distinct possibility because of economic rationales provided in earlier literature. For example, liquidity may impact returns through a premium for greater trading costs (Amihud and Mendelson, 1986). However, returns may also influence future trading behavior, which may, in turn, affect liquidity. In particular, both standard portfolio rebalancing arguments (Merton, 1973) as well as loss aversion (Odean, 1988) imply return-dependent investing behavior which, by creating an order imbalance, may affect liquidity.

Next, volatility impacts liquidity because of its effect on inventory risk (Stoll, 1978). In the reverse direction, decreased liquidity could increase asset price fluctuations (see, e.g., Longin, 1997, or Subrahmanyam, 1994). Further, Chordia, Roll, and Subrahmanyam (2002) find that days with high net order flow are followed by days of low liquidity, presumably because of strained market maker inventories.[10] If increased liquidity decreases

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

the reservation price of the asset for investors, then it may spark buying activity and thus affect order imbalances.

Evidence also suggests that cross-stock effects may be significant. For example, not only is volatility persistent but there are volatility spillovers across small and large stocks. Conrad, Gultekin, and Kaul (1991) attribute the latter phenomenon to volatility information being incorporated with a lag in smaller firms. Return predictability and spillovers at short horizons are documented by Lehmann (1988) and Lo and MacKinlay (1990). Insofar as our final variable, imbalance, is intimately linked to returns (Chan and Fong, 2000, Chordia, Roll, and Subrahmanyam, 2002), spillovers cannot be ruled out in this variable either. Furthermore, if there are leads in trading activity in response to systematic wealth or informational shocks from liquid to illiquid sectors, then liquidity in the large cap sector may predict trading activity, and, in turn, liquidity in the small cap sector. Moreover, if any of the above variables in one sector forecast liquidity in the other, the arguments in the previous two paragraphs carry over to cross-market effects on liquidity.

Given that there are reasons to expect cross-sector effects and bi-directional causalities, we adopt an eight-equation vector autoregression that incorporates eight variables, four each (i.e., measures of liquidity, returns, volatility, and order flows) from large and small cap stocks.[11] 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 the adjusted series of liquidity, returns, volatility,

By using signed order flow, essentially we are allowing for asymmetric effects of buy and sell imbalances on spreads.

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

and imbalance in the large (small) cap stock deciles. We choose the number of lags in equations (5) and (6) on the basis of the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC).[12] We now provide estimates from the VAR model that captures time-series movements in stock liquidity. We are also interested in examining whether unexpected liquidity shocks are systemic in nature; an examination of the VAR disturbances allows us to address this issue. For convenience, we use the same variable names for the adjusted series as for the unadjusted ones.

4.2 VAR Estimation Results

We present results from a VAR with endogenous variables OIB9, OIB0, VOL9, VOL0, RET9, RET0, QSPR9, and QSPR0, where the 0 and 9 suffixes denote the size deciles, with 0 representing the smallest size decile and 9 the largest. The VAR is estimated with two lags and a constant term, and uses 3782 observations. We first examine the cross-correlations of innovations obtained from the VAR estimation. This exercise helps us understand if there is a joint dynamic structure to liquidity across small and large cap stocks. The practical implication is that if liquidity innovations are positively correlated across sectors, then investors should attempt contemporaneous execution of orders in both sectors on unusually high liquidity days in any one sector. We omit results for depth from the analysis because these are qualitatively similar to those for spreads.

Table 4 reports the correlation matrix of the VAR innovations. We find that shocks to spreads are negatively associated with returns in either sector. This accords with Chordia, Roll, and Subrahmanyam (2001), who show that positive market returns are accompanied by decreased spreads and vice versa. The result is generally consistent with the liquidity premium theory (Amihud and Mendelson, 1986), wherein shocks that decrease liquidity have a downward effect on contemporaneous asset prices. The magnitude of the own-

[12]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.

sector correlation is about three times larger for the large cap sector relative to the small cap sector (in an unreported z-test, the difference is also statistically significant at the 5% level).

We also find that cross-sector liquidities and volatilities are positively and significantly correlated. Innovations in small cap and large cap spreads have a correlation of 0.133, while that between volatility innovations is 0.264; these numbers are statistically different from zero. Thus, there is evidence of common dynamics between large and small cap spreads as well as volatilities. Also, note that small cap volatility innovations bear strong correlations with large cap volatility as well as spread innovations. Interestingly, the latter correlation is much larger than the own-sector correlation between small cap spreads and volatility (again, the difference is significantly different from zero).[13] Overall, these results point to the importance of the large-cap sector in the determination of liquidity and volatility in the small-cap sector. To investigate predictability we now turn to Granger-causality results.

In Table 5, we present Chi-square statistics for the null hypothesis that variable i does not Granger-cause variable j. Specifically, we test whether the lag coefficients of i are jointly zero when j is the dependent variable in the VAR. The cell associated with the i^{th} row variable and the j^{th} column variable shows the statistic associated with this test.

Within each market, there is two-way Granger causation between quoted spreads and volatility. Spreads and volatility also Granger-cause each other across markets, except that small cap spreads do not Granger-cause large cap volatility. Spreads do not

[13]The greater correlation of small cap volatility with large cap spreads than with small cap spreads can be interpreted in the context of the price experimentation literature (viz. Glosten, 1989, and Leach and Madhavan, 1993). These authors suggest that a specialist with greater monopoly power will smooth out liquidity across periods of high and low adverse selection, thus reducing the sensitivity of liquidity to the extent of information asymmetry. Under the plausible premise that volatility partially proxies for the degree of information asymmetry (Kyle, 1985), and that specialists in large stocks face more competition from the trading floor, we would expect a smaller correlation between liquidity and volatility in large stocks relative to small ones; the result in Table 4 is consistent with this economic argument.

Granger-cause returns. While large cap returns do Granger-cause large cap spreads, small cap spreads are not Granger-caused by either large or small cap returns. An economic interpretation is that order flow shocks have larger magnitudes in the large cap sector than in the small cap sector, possibly because of more herding (and thus more extreme imbalances) in large cap stocks, which are owned relatively more by institutions (Sias and Starks, 1997, Dennis and Strickland, 2003). Hence price movements induced by inventory imbalances may have a greater persistent effect on large cap liquidity than on small cap liquidity.

Overall, there is compelling evidence that liquidities in the large cap and small cap sectors are not just contemporaneously correlated, but further, lags in liquidity in one market help predict liquidity in the other. Both own- and cross-volatilities are relevant in forecasting liquidity in a given sector so that volatility shifts in either sector play a key role in liquidity dynamics in both sectors. Among other results not involving spreads, it is particularly interesting that large-cap returns cause small-cap returns but the reverse is not true; thus, large-cap returns lead small-cap returns. Section 5 further explores this finding. Also, small-cap volatility Granger-causes large-cap returns but large-cap volatility does not predict large-cap returns.

Having performed Granger causality tests, which are based on analyses of coefficients from a single equation, to assess cross-sectional predictability, we now turn to examining the joint dynamics of liquidity, volatility and returns implied by the full VAR system. To this end, we estimate impulse response functions (IRFs). An IRF traces the impact of a one standard deviation innovation to a specific variable on the current and future values of the chosen endogenous variable. Since the innovations are correlated (as shown in Table 4), we use the inverse of the Cholesky decomposition of the residual covariance matrix to orthogonalize the impulses. Results from the IRFs are generally sensitive to the specific ordering of the endogenous variables.[14] We arrange the variables according

[14]However, the VAR coefficient estimates (and, hence, the Granger causality tests) are unaffected by

to the order in which they influence the other variables.

We note that the price formation process starts with market makers observing an order, which represents an information or an endowment shock. These shocks then affect prices and liquidity through trading. This suggests an argument for order imbalance to be placed first in the ordering. Given these considerations, we fix the ordering for endogenous variables as follows: OIB0, OIB9, VOL0, VOL9, RET0, RET9, QSPR0 and QSPR9. While the rationale for the relative ordering of returns, volatility and liquidity is ambiguous, we find that the impulse response results are robust to the ordering of these three variables. Also, our qualitative results remain mostly unchanged if we reverse the ordering of small and large cap stocks; we note instances when this is not the case. 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 2 (Panel A) illustrates the response of endogenous variables in the large cap sector to a unit standard deviation orthogonalized shock in the endogenous variables within the small cap sector for a period of 10 days. Monte Carlo two-standard-error bands are provided to gauge the statistical significance of the responses. We focus on the response of the quoted bid-ask spread of large cap stocks to the small-cap market. The large cap spread responds negatively to an innovation in small cap stock returns and positively to a shock to small cap volatility. In both cases, the response persists for at least 10 days, illustrating the strength of the cross-market effects. These results are consistent with those of Chordia, Roll, and Subrahmanyam (2001) who show that up-market moves positively affect the spread and vice versa, and with models of microstructure which argue that increased volatility, by increasing inventory risk, tends to decrease liquidity. Large-cap bid-ask spreads respond positively to innovations in small cap spreads contemporaneously.

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the ordering of variables.

Panel B of Figure 2 shows the response of the small cap sector to unit shocks in the large cap sector. First, while large cap returns respond to small cap returns only contemporaneously, small cap returns respond to large cap stock return shocks after a lag of one day (this finding is explored further in Section 5). There is reliable evidence that small cap spreads respond to large cap spreads, as well as large cap volatility and returns. It can also be seen that small cap volatility responds to large cap spreads. In all cases, there is evidence that the response persists and is strongest after the event day.

Are these results robust to the relative ordering of the small and large cap sectors? We reestimate the IRFs after reversing the VAR ordering as follows: OIB9, OIB0, VOL9, VOL0, RET9, RET0, QSPR9 and QSPR0. The results are unchanged except that the response of large-cap spreads to small-cap spreads persists beyond the contemporary period and the response of small cap returns to large cap returns persists for at least 10 days. Overall, cross-market IRFs show that the biggest response of the large cap sector to shocks in the small cap market tends to be contemporaneous; whereas the small cap market appears to have a more delayed response to the large cap sector. These results are consistent the interpretation that informational events are first incorporated into the stock market via large cap trades and then transmitted to the small cap sector with a lag. We will provide additional evidence in support of this hypothesis in section 5.

Panels C and D report the own-sector impulse response functions. These plots confirm the notion that liquidity shocks are persistent, and that volatility shocks in a sector result in a persistent decline in liquidity in that sector, which is consistent with Stoll (1978). Furthermore, liquidity decreases for several days in response to a negative return shock in either sector, likely because during periods of price declines market makers require more time to recover from strained inventories.

For robustness, in unreported analysis, we also examine the impulse responses of large cap or decile 9 stocks to other deciles (e.g. decile 5), and find that the results are materially similar to the previously reported responses of large cap stocks to decile 0 stocks

4.3 Summary of VAR Results

Volatility and return shifts in both large and small cap sectors are informative in forecasting liquidity shifts in the other sector. This evidence is consistent with the notion that volatility and return spillovers, by affecting the risk of carrying inventory as well as order imbalances, affect liquidity in either sector. In addition, liquidity shocks in one market predict liquidity changes in the other market, demonstrating that liquidity shocks transmit directly across sectors, in addition to their indirect transmission via volatility and returns movements.

The transmission of financial market shocks between sectors is in some cases asymmetric, moving from large to small cap stocks but not in the reverse direction. In particular, liquidity and returns in the large cap sector predict volatility and returns, respectively, in the small cap sector but the reverse is not true. This asymmetry suggests a relatively more active role of the large cap sector in propagating market-wide shocks. In addition to these cross-influences, own-sector volatility and returns help forecast own-sector liquidity.

The impulse responses show that the response of one market to shocks in the other is statistically significant and often persists for days. The impulse responses also appear to be economically significant. For example, considering the magnitude of the highest response (one day after the shock), a one-standard deviation shock to large cap volatility results forecasts an increased annual trading cost of $500,000 on a one million share round-trip trade per day (assuming 250 trading days per year). The forecasting impact of large cap spreads on small cap spreads is about half this amount.

5 Liquidity and Market Efficiency in the Small Cap Sector

Of late, there has been interest in the notion that market frictions are related to the efficiency with which financial markets incorporate information (see, for example, Mitchell, Pulvino, and Stafford, 2002, Hou and Moskowitz, 2004, Avramov, Chordia, and Goyal, 2004, and Sadka and Scherbina, 2004). In this section, we consider whether market efficiency in the small cap sector is influenced by liquidity shifts.

The Granger-causality results of Section 4 indicate that large cap returns are informative in predicting small cap returns. This is consistent with the analysis of Lo and MacKinlay (1990), who document that large cap returns lead small cap returns at short horizons.[15] Chordia and Swaminathan (2000) suggest that leads and lags may be caused by differences in the speed of adjustment to common information. We examine whether liquidity dynamics are related to the strength of the lead from large firm returns to small firm returns.

Why might movements in liquidity be related to the strength of the lead-lag effect? There are two possible reasons. First, arbitrageurs may choose to trade in small cap stocks in order to profit from common information shocks that have already been incorporated into the prices of large firms. An exogenous widening of small cap spreads can possibly create greater frictions for arbitrageurs that seek to close the pricing gap between large and small firms. This simple argument suggests that the lead and lag effect would increase

[15] In an exploratory investigation, we consider a weekly horizon similar to that used by Lo and MacKinlay (1990) (and subsequently in studies by Mech, 1993, Badrinath, Kale, and Noe, 1995, McQueen, Pinegar, and Thorley, 1996, and Sias and Starks, 1997). We find that the lead from large to small stocks has weakened in recent years. Indeed, a quick check using the CRSP size decile returns indicates that from July 1962 to December 1988 (defining a week as starting Wednesday and ending Tuesday), the correlation between weekly small cap returns and one lag of the weekly large cap return is as high as 0.210, whereas from 1988 to 2002, this correlation drops to 0.085. This is perhaps not surprising; we would expect technological improvements in trading to contribute to greater market efficiency. Since the baseline lead-lag effect is weak over the weekly horizon within our sample period, we desist from an analysis of weekly returns and liquidity in this paper.

when small cap spreads are high. The reasoning offers little role for large cap spreads, since arbitrageurs' activity is initiated in the small firms, whose returns lag those of the large firms.

Arbitrage, however, is not necessary for closing the lead-lag gap because market makers in the small cap sector may directly use price quotes from the large cap sector to update their own quotes. This leads us to our second line of argument, which indicates that *large cap* spreads may play a role in determining leads and lags by signaling the occurrence of informational events.

To understand this second argument, note that price moves occur due to public signals as well as private information conveyed to the market by way of order flows. Revelation of systematic public signals would result in a near-simultaneous updating of quotes by market makers in all stocks, and thus would likely not cause a significant lead-lag effect. On the other hand, if agents with *private* information about common factors choose to exploit their informational advantage in the large-cap sector (which has a higher baseline level of liquidity than the small-cap sector), then lagged quote updating by small cap market makers may cause small stock returns to lag those of large stocks (viz. Chan, 1993, Chowdhry and Nanda, 1991, Gorton and Pennacchi, 1993, and Kumar and Seppi, 1994). Thus, during periods where agents receive privileged information about common factors, lead and lag effects are much more likely (viz., Brennan, Jegadeesh, and Swaminathan, 1993).

Since the informed trading which causes the lead-lag in the above line of argument is expected to temporarily reduce liquidity in the large-cap sector (Glosten and Milgrom, 1985), spread increases in the large cap sector may portend an increased lag of small firm returns to large firm returns. Also, if it is the case that the content of private information-based trades gets reflected first in the large-cap sector, we would expect both large-cap order flows and large-cap returns to play important roles in predicting small cap returns.

In the first line of argument, lagged small cap spreads play a crucial role in determining the extent of the lead-lag relationship, whereas in the second, it is lagged large cap spreads that are relevant. Furthermore, the two arguments are not mutually exclusive. In order to distinguish which of the above lines of argument, if any, is more germane to the lead and lag relationship, we analyze the link between the extent of the lead-lag relationship and the levels of large and small cap spreads.

We capture the influence of liquidity levels and order-flow dynamics on the lead-lag relationship between small and large cap stocks by adding a number of interaction variables in the equation for RET0 within the VAR framework. These interaction variables include the first lags of QRET09, QRET99, and QOIB99, where QRET09=QSPR0*RET9, QRET99=QSPR9*RET9, and QOIB99= QSPR9*OIB9. Consistent with the discussion above, wherein information events are assumed to occur exogenously, the interaction variables are treated as extraneous to the VAR system. With the addition of these interaction terms, the VAR no longer conforms to the standard form and so the OLS method is no longer efficient. Thus, we use the Seemingly Unrelated Regression (SUR) method to estimate the system of equations.

In Table 6 we present the results of these regressions. We first consider the coefficient of lagged return alone (which already is part of the main VAR). This is statistically significant and positive, supporting the analysis of Lo and MacKinlay (1990). The second column interacts the spread in large and small cap stocks with the lagged large cap return. The coefficient of the lagged return is considerably reduced and the lagged large cap return becomes insignificant after inclusion of the interaction variables. The coefficient on QRET99 (large cap spread interacted with returns) is positive and significant suggesting that the lead-lag relation between lagged returns of large cap stocks and the current returns of small cap stocks is strongest when the large cap sector is illiquid. Thus, the evidence is consistent with our second line of argument provided above, i.e., with the notion that a widening of large cap spreads signals an information event that is transmitted to small cap stocks with a lag.

To consider the notion that information gets transmitted to prices in either sector by way of order flows, we interact order imbalance (OIB) with spreads in the large cap market and include the interaction variable in the regression. The results indicate that large cap order flow interacted with large cap spreads is strongly predictive of small cap returns, whereas the return interaction variable becomes insignificant and its magnitude diminishes in the presence of the imbalance variable. We also present the chi-square statistics and p-values associated with the Wald test for the null hypothesis that the coefficients of all exogenous variables are jointly zero. We reject the null hypothesis that the coefficients of the imbalance interaction term OIB99 and the spread-return interaction terms QRET09 and QRET99 are jointly zero at a p-value below 0.001. Overall, the evidence supports the reasoning that large cap order flows induced by informational events drive the lead and lag relationship between large cap and small cap firms.

In order to provide additional insight on the results in Table 6, we calculate cross-autocorrelations between small cap returns on day t and large cap returns on day $t-1$ for days $t-1$ where the quoted large cap spread is one standard deviation above and below its sample mean. The estimates obtained for the two cases are 0.20 ($p = 0.00$) and 0.05 ($p = 0.10$). The corresponding correlation when the large cap order imbalance is used in place of return are 0.15 ($p = 0.00$) and 0.08 ($p = 0.06$). These correlations clearly confirm our basic result that the lead from large cap returns to small cap returns is strongest when large cap spreads are high.

Of course, the information-based trading that causes large cap spreads to widen may spill over to small cap stocks, for two reasons. First, some investors may receive information later than others (Hirshleifer, Subrahmanyam, and Titman, 1994). Second, small cap market makers may not be able to update their quotes to fully reflect the information content of large cap trades, owing to camouflage provided by liquidity trades

(Kyle, 1985). This would leave some profit potential for late informed traders in small cap stocks. If large cap informed trading does indeed spill over to small cap stocks with a lag, we expect small cap order flows to exhibit an increased correlation with large cap order flows when large cap spreads are high. Additionally, a greater small cap spread on day t should be associated with a greater cross auto-correlation between small cap returns at time t and large cap returns at time $t-1$.

We investigate the above issue by computation of additional correlations. First, we find that the correlation between OIB0 on day t and OIB9 on day $t-1$ is 0.14 ($p = 0.00$) when QSPR9 on day $t-1$ is one standard deviation above its mean and 0.09 ($p = 0.05$) otherwise. Second, we sort the sample by days t where the small cap spread is one standard deviation above and below its sample mean. In this case, the correlation between day t small cap returns and day $t-1$ large cap returns is 0.15 (0.05) when the small cap spread is above (below) its sample mean on day t. Only the correlation of 0.15 is significantly different from zero at the 5% level. When the order imbalance replaces returns, the corresponding correlations are 0.09, and 0.07, respectively; again, only the first correlation is significantly different from zero at the 5% level. Thus, the evidence is consistent with leads and lags being caused by liquidity-straining private informational trading that occurs first in the large cap sector, and then in the small cap sector.

Since we consider the above finding on small cap return predictability to be quite intriguing, we conduct a robustness check and report results for all other deciles in Table 7. We use the same interaction variables as above, except that we replace QRET09 with QRETN9=QRETN*RET9, where N represents the size decile; and make a similar replacement for the OIB variable. We find that the large cap order flow variable interacted with large cap spreads is informative in predicting returns in every size decile, though large cap returns themselves are useful in predicting returns of a particular decile only for the relatively smaller firms. With the exception of decile 1, the coefficient magnitudes on the order flow variable generally decline with size decile, and the magnitudes for the four largest firm deciles is about 40% smaller than for the four smallest firm ones. Note also that the p-values associated with the Wald test are below 0.05 in the case of every decile for the regression results reported in the last two columns of Table 7, which includes the order flow variables.

Our information-based rationale for leads and lags is based on the notion that transactions in response to informational events occur first in large stocks, and then spill over to small stocks partially in the form of lagged transactions in the small cap sector and partially in the form of lagged quote updates by small cap market makers. Our return computations are based on transaction prices, and account for transaction-induced lags. However, small stocks often do not trade for several hours within a day. Thus, if the last transaction in a stock is at 10:00 am (say), then the transaction price would not incorporate information shocks that occur later in the day.

To fully address the above issue, we perform an alternative analysis by computing mid-quote returns using the last available quote for each firm on a given day. We do this for the 1993-2002 period because access to ISSM for the 1988-1992 period was not available to any of the project's authors. One benefit of using the post-1993 sample is that this allows us to assess whether the lead-lag relation between small and large firm returns is particular to the earlier part of our sample. The results appear in Table 8. As can be seen, the coefficients of the imbalance interaction variables are positive in every case and significant at the 5% level in all but one case.[16] The coefficient magnitudes are comparable to those in Table 7. Thus, our transaction price-based results on predictability extend to mid-quote returns as well; and our earlier results continue to hold for the post-1993 sample.

The results in Table 8 shed additional light on the economic causes of the lead and lag effect. Specifically, one possible interpretation of Table 7 is that secular decreases in

[16]The Wald test is not presented for brevity, but, as before all p values except the one for decile 7 (where none of the variables are significant) are below 0.05.

liquidity can reduce trading activity in small cap stocks and this can affect leads and lags. Our results point to the notion that this effect is not the predominant driver of lead-lag between the large and small cap sectors. To see this, observe that the mid-quote series in Table 8 only captures the quote updating activity of market makers. The frequency of *quote updating* is not likely to be affected directly by liquidity, because specialists can continuously update quotes even in the absence of trading. Since our results are robust to both transaction returns as well as mid-quote returns, they are consistent with the view that market makers' opportunity costs of continuously monitoring order flow in other markets play a pivotal role in the lead and lag relationship across small and large cap stocks.

Overall, our findings underscore the role of order flow in the lead-lag relationship between the large cap sector and other stocks.[17] From the perspective of economic significance, we find that a spread increase of two cents and a daily transaction price-based return innovation of 0.5% in large cap stocks increases daily small cap returns by 0.0037%. On an annualized basis (over 250 trading days), this works out to 92 basis points per year. An order flow innovation of 50%, together with the same percentage spread increase has an annualized effect of 12.5 basis points on small cap returns. These effects are material, especially for professional investors with low trading costs. Frictions such as brokerage commissions, however, could nullify the profitability of such strategies to individual investors.

[17]Mech (1993) tests the hypothesis that the lead from large to small stock returns is greater when the small-cap spread is high relative to the profit potential (proxied by the absolute return). He does not find support for this hypothesis. From a conceptual standpoint, in contrast to Mech (1993), we do not view the spread as an inverse measure of profit potential, but as an indicator that private information traders are active in large-cap stocks. There are two other differences between our study and that of Mech (1993). First, we consider daily intervals, as opposed to the weekly ones considered by Mech (1993). Second, unlike Mech (1993), we consider the role of large-cap spreads in addition to small-cap spreads in determining the extent of the lead-lag relationship and find that it is large-cap spreads that are most relevant to the lead from large to small stock returns.

6 Concluding Remarks

We use vector autoregressions to examine the joint time-series of liquidity, returns, and volatility across the small and large cap stock sectors over the period 1988 through 2002. Analyzing the time-series relation between liquidity and stock price movements for both sectors helps us gain a better economic understanding of the cross-section of liquidity dynamics, an issue that is particularly important given that liquidity levels as well as the risk arising from dynamic liquidity movements have been shown to impact firms' cost of capital.

A number of hitherto unknown findings from our analysis indicate that there are differences as well as similarities in the dynamics of liquidity, returns, and volatility across big and small firms. For example, the impulse responses indicate that the biggest response of the large cap sector to shocks originating in the small cap market tends to be contemporaneous; on the other hand, the small cap market appears to have a more delayed response to shocks originating in the large cap sector. These results all indicate that liquidity-shifting events that cause persistent shifts in future volatility and liquidity frequently originate in the large cap sector.

We also find that shocks to returns and volatility in either sector are informative in predicting liquidity in the other sector. Thus, the evidence is consistent with the notion that cross-effects in volatility and return, by affecting the risk of carrying inventory as well as order imbalances, influence liquidity in either sector. Own-sector returns and volatility are also informative in forecasting dynamic liquidity movements.

As a by-product of our analysis, we document some interesting differences in calendar regularities across market cap-based deciles, which are worthy of further analysis. For instance, within our sample period, there is a distinct upward pressure on large cap spreads in January relative to other months, that is not as strongly evident in small cap stocks. This finding is consistent with portfolio managers withdrawing from the large cap sector following window-dressing at the turn of the year. We also find that spreads of large cap stocks are lowest at the beginning of the week but those of small cap stocks appear to be highest at this time, and small cap order imbalances are tilted towards the sell side at the beginning of the week. This pattern accords with the notion that arbitrageurs indulge in net selling activity in small cap stocks at the beginning of the week following the upward pressure on small cap returns at the end of the week. Further, small and large cap spreads were comparable in magnitude prior to changes in the tick size, but large cap spread levels following decimalization have remained at about half the levels of small cap spreads; this result sheds light on the extent to which the tick size was binding for large cap spreads.

Overall, the analysis presents a compelling picture which not only indicates that liquidity across different sectors is jointly determined in a contemporaneous sense, but also is consistent with the notion that cross-effects of returns and volatility on liquidity are persistent. Intriguingly, we also find that spreads convey information about the strength of the lead-lag relationship in returns across small and large cap stocks. In particular, daily leads from large cap stocks to small cap ones are strongest when large cap spreads are high, suggesting that large cap spreads signal the occurrence of market-wide informational events whose pricing implications are transmitted to the small cap sector with a lag. This result is robust to mid-quote returns, indicating that it is does not arise principally from stale transaction prices in the small cap sector, but is at least in part due to opportunity costs faced by market makers in continually updating bid and ask quotes.

Our results have clear implications for the prediction and control of execution costs, particularly for large investment companies that regularly trade the small cap sector and whose relatively big trades may be sensitive to liquidity in the relatively illiquid small cap sector. From the standpoint of asset pricing, our results indicate that the liquidity of a stock is not an exogenous attribute, but its dynamics are sensitive to movements in financial market variables, such as returns and volatility, in both own and other markets. Developing a general equilibrium model that prices liquidity while recognizing this endogeneity is a challenging task, but is worthy of future investigation. In particular, it would be important to tease out the direct impact of volatility on expected returns through the traditional risk-reward channel, and its indirect impact by way of its effect on liquidity.

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Table 1: Levels of stock market liquidity

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, NTRADE for the number of shares traded, and DEP for depth measured as the average of the posted bid and ask dollar amounts offered for trade. DQSPR is the absolute value of the daily proportional change in the quoted spread QSPR. DDEP is the absolute value of the daily percent change in DEP, measured as the average of the posted bid and ask dollar amounts offered for trade. The suffixes "0" and "9" represent the smallest and largest size deciles, respectively. The stock data series excludes September 4, 1991, on which no trades were reported in the transactions database. The mean, median, and standard deviation (S.D.) is reported for each measure. The sample spans the period January 4, 1988 to December 31, 2002; the number of observations is 3782 for all deciles.

	1/4/1988-6/23/1997			6/24/1997-1/28/2001			1/29/2001-12/31/2002		
	Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median	S.D.
QSPR0	0.191	0.191	0.009	0.167	0.166	0.009	0.102	0.101	0.016
DQSPR0	0.125	0.101	0.107	0.140	0.108	0.132	0.116	0.093	0.097
DEP0	6.373	6.277	1.036	4.378	4.387	1.206	2.169	2.211	0.502
DDEP0	0.194	0.140	0.377	0.206	0.146	0.281	0.244	0.184	0.214
NTRADE0	13.168	12.488	4.269	31.866	28.162	13.985	47.052	43.558	16.324
QSPR9	0.186	0.185	0.019	0.127	0.124	0.013	0.050	0.047	0.012
DQSPR9	0.163	0.122	0.207	0.179	0.137	0.175	0.182	0.126	0.224
DEP9	13.215	12.865	3.515	7.524	7.081	1.788	3.420	3.278	0.633
DDEP9	0.317	0.168	2.555	0.647	0.308	2.747	0.306	0.198	0.570
NTRADE9	579.7	551.2	222.3	2401.1	2295.4	982.1	3984.3	3836.6	1002.5

Table 2: Adjustment regressions for liquidity

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, and DEP for depth measured as the average of the posted bid and ask dollar amounts offered for trade. The sample spans the period January 4, 1988 to December 31, 2002; the number of observations is 3782 for all deciles. The stock data series excludes September 4, 1991, on which no trades were reported in the transactions database. The suffixes "0" and "9" represent the smallest and largest size deciles, respectively. 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 zero otherwise. Monday-Thursday: equals one if the trading day is Monday, Tuesday, Wednesday, or Thursday, and zero otherwise. February-December: equals one if the trading day is in one of these months, and zero otherwise. The tick size change dummy equals 1 for the period June 24 1997 to January 28 2001. The decimalization dummy equals 1 for the period January 29 2001 till December 31 2002. PPI: dummy variable that equals one on the day of the PPI announcement and zero otherwise. PPI 12: dummy variable that equals one on two days prior to the PPI announcement and zero otherwise. Emp, Emp12, CPI, CPI12: dummy variables for employment and CPI announcements respectively. The definition of the dummy variables is the same as for PPI announcements. Estimation is done using the Ordinary Least Squares (OLS). All coefficients are multiplied by a factor of 100. Estimates marked **(*) are significant at the one (five) percent level or better.

Table 2, continued

	QSPR0	QSPR9	DEP0	DEP9
Intercept	19.218**	21.797**	685.180**	722.286**
Day of the week				
Monday	0.198**	-0.160**	-18.537**	-29.669**
Tuesday	-0.017	-0.133*	-3.274	3.468
Wednesday	-0.060	-0.032	5.957	11.397
Thursday	-0.033	-0.018	5.227	6.890
Holiday	0.014	-0.002	-2.548	-82.535**
Month				
February	0.170*	-0.172*	6.997	11.328
March	0.231**	-0.406**	17.976*	49.737**
April	0.281**	-0.285**	-17.945*	50.291**
May	-0.031	-0.844**	-7.374	76.167**
June	-0.066	-0.993**	1.332	109.950**
July	0.072	-0.967**	-19.058**	125.763**
August	0.067	-1.023**	-23.136**	128.828**
September	0.016	-1.292**	-7.407	187.114**
October	0.089	-0.722**	-14.146*	101.307**
November	-0.196**	-1.147**	-2.573	103.219**
December	-0.605**	-1.042**	60.077**	77.545**
Crisis				
Russian crisis 07/06/98-12/31/98	0.458**	0.558**	-94.269**	-89.695**
Asian crisis 07/02/97-12/31/97	-0.357*	1.804**	166.484**	-102.150**
Bond crisis 03/01/94-05/31/94	1.108**	0.315*	-111.125**	-9.965
Tick size change dummy	-2.749**	-10.951**	-429.364**	29.142
Decimalization dummy	-6.598**	-13.879**	-423.927**	-402.167**
Trend, pre-tick size change				
Time	0.000**	-0.002**	-0.138**	0.574**
$Time^2$	0.0000**	0.0000**	0.0001**	0.000**
Trend, pre-decimalization				
Time	-0.0014*	0.0120**	0.6109**	-1.086**
$Time^2$	0.003**	0.0000**	-0.0004**	0.002**
Trend, post-decimalization				
Time	-0.0128**	-0.018**	0.0640	-0.384
$Time^2$	0.000**	0.000**	-0.001**	0.000
Week after 9/11/2001 dummy	2.316**	2.616**	-0.476	7.356
Sep 16 1991 dummy	-0.478	-1.882	-92.387	631.020**
Macroeconomic announcements				
PPI	-0.079	0.091	1.585	-1.532
PPI12	-0.073	-0.084	-5.456	-1.319
EMP	0.074	0.219*	-13.2114	-25.181
EMP12	0.068	0.002	-13.397*	11.772
CPI	-0.019	-0.030	-0.044	16.476
CPI12	-0.021	-0.069	-0.508	16.710

Table 3: Adjustment regressions for returns and volatility

The sample spans the period January 4, 1988 to December 31, 2002; the number of observations is 3782 for all deciles. RET is the decile return and VOL is the return volatility. The suffixes “0” and “9“ represent the smallest and largest size deciles, respectively. 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 zero otherwise. Monday-Thursday: equals one if the trading day is Monday, Tuesday, Wednesday, or Thursday, and zero otherwise. February-December: equals one if the trading day is in one of these months, and zero otherwise. The tick size change dummy equals 1 for the period June 24 1997 to January 28 2001. The decimalization dummy equals 1 for the period January 29 2001 till December 31 2002. PPI: dummy variable that equals one on the day of the PPI announcement and zero otherwise. PPI 12: dummy variable that equals one on two days prior to the PPI announcement and zero otherwise. Emp, Emp12, CPI, CPI12: dummy variables for employment and CPI announcements respectively. The definition of the dummy variables is the same as for PPI announcements. Estimation is done using the Ordinary Least Squares (OLS). All coefficients are multiplied by a factor of 100. Estimates marked **(*) are significant at the one (five) percent level or better.

Table 3, continued

	RET0	RET9	VOL0	VOL9
Intercept	0.490**	0.053	2.784**	1.313**
Day of the week				
Monday	-0.365**	0.141*	---	---
Tuesday	-0.287**	0.096	---	---
Wednesday	-0.233**	0.103	---	---
Thursday	-0.189**	0.020	---	---
Holiday	0.315**	-0.103	0.089	-0.045
Month				
February	-0.185**	-0.044	-0.131**	-0.127**
March	-0.196**	-0.015	-0.185**	-0.123**
April	-0.248**	0.012	-0.136**	-0.023
May	-0.224**	0.050	-0.271**	-0.230**
June	-0.344**	-0.062	-0.325**	-0.221**
July	-0.335**	-0.003	-0.271**	-0.171**
August	-0.382**	-0.118	-0.264**	-0.249**
September	-0.372**	-0.038	-0.238**	-0.209**
October	-0.421**	0.069	0.074	0.011
November	-0.271**	0.062	0.013	-0.265**
December	-0.216**	0.039	0.102*	-0.317**
Crisis				
Russian crisis 07/06/98-12/31/98	-0.093	-0.030	0.280**	0.408**
Asian crisis 07/02/97-12/31/97	0.051	-0.111	0.295**	0.342**
Bond crisis 03/01/94-05/31/94	-0.191	-0.084	-0.342**	0.055
Tick size change dummy	0.132	0.117	-1.021**	-0.129
Decimalization dummy	-0.021	-0.146	0.275**	0.801**
Trend, pre-tick size change				
Time	0.000	0.000	0.001**	0.000**
$Time^2$	0.000	0.000	0.000**	0.000**
Trend, pre-decimalization				
Time	-0.001	0.000	0.002**	0.002**
$Time^2$	0.000	0.000	0.000	0.000
Trend, post-decimalization				
Time	0.001	0.000	-0.002**	-0.004**
$Time^2$	0.000	0.000	0.000**	0.000**
Week after 9/11/2001 dummy	-2.873**	-2.147**	1.992**	1.761**
Sep 16 1991 dummy	0.444	0.764	1.932**	0.115
Macroeconomic announcements				
PPI	-0.059	0.155	-0.051	0.056
PPI12	-0.082	-0.108	-0.083**	0.001
EMP	-0.150*	0.125	-0.085*	0.076
EMP12	0.080	-0.073	0.016	-0.032
CPI	-0.134*	-0.027	-0.065	0.034
CPI12	-0.006	-0.047	0.014	-0.012

Table 4: Contemporaneous Correlation between VAR Innovations.

The table presents the correlation matrix of innovations from the VARs with endogenous variables OIB0, OIB9, VOL0, VOL9, RET0, RET9, QSPR0, QSPR9, with the smallest decile being “0” and the largest being “9”. All VARs are estimated with two lags, include a constant term, and use 3782 observations. QSPR stands for quoted spread. 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. RET is the decile return and VOL is the return volatility. The sample spans the period January 4, 1988 to December 31, 2002. ** denotes significance at the 1% level and * denotes significance at the 5% level.

	VOL0	VOL9	RET0	RET9	QSPR0	QSPR9
VOL0	1.000					
VOL9	**0.264****	1.000				
RET0	**0.059****	**-0.143****	1.000			
RET9	-0.032	**-0.045****	**0.495****	1.000		
QSPR0	**0.053****	**0.056****	**-0.063****	**-0.061****	1.000	
QSPR9	**0.196****	**0.318****	**-0.219****	**-0.182****	**0.133****	1.000

Table 5: Granger causality results.

The table presents causality results from the VARs with endogenous variables OIB0, OIB9, VOL0, VOL9, RET0, RET9, QSPR0, QSPR9, with the smallest decile being "0" and the largest being "9". All VARs are estimated with two lags, include a constant term, and use 3782 observations. Cell *ij* shows chi-square statistics and p-values of pairwise Granger Causality tests between the i^{th} row variable and the j^{th} column variable. The null hypothesis is that all lag coefficients of the i^{th} row variable are jointly zero when j is the dependent variable in the VAR. QSPR stands for quoted spread. 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. RET is the decile return and VOL is the return volatility. The sample spans the period January 4, 1988 to December 31, 2002. ** denotes significance at the 1% level and * denotes significance at the 5% level.

	VOL0	VOL9	RET0	RET9	QSPR0	QSPR9
VOL0		**38.808****	**38.119****	**10.213****	**32.659****	**19.282****
VOL9	2.123		**12.439****	5.537	**8.868***	**101.944****
RET0	**13.296****	**8.721***		2.891	4.505	2.540
RET9	**9.552****	**18.792****	**39.728****		1.035	**12.910****
QSPR0	**96.854****	0.953	0.314	4.959		**10.568****
QSPR9	**68.278****	**60.968****	4.859	2.176	**11.146****	

Table 6: VAR Results With Interaction Terms, for the Smallest Decile.
The table presents results from VARs with endogenous variables VOL0, VOL9, RET0, RET9, QSPR0, QSPR9, where N=0 and 9 refer to size deciles. The deciles are numbered in order of increasing size, with the smallest decile being "0" and the largest being "9". In addition, one lag of the exogenous variables QRET09, QRET99, and QOIB99 are included in the equation for RET0, where QRET09= QSPR0*RET9, QRET99= QSPR9*RET9, and QOIB99= QSPR9*OIB9. The VAR is estimated with two lags, include a constant term, and uses 3782 observations. The Seemingly Unrelated Regression (SUR) method is used to estimate the system of equations. QSPR stands for quoted spread. 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. RET is the decile return and VOL is the return volatility. OIB is measured as the dollar value of shares bought minus the dollar value of shares sold, divided by the total dollar value of trades. The sample spans the period January 4, 1988 to December 31, 2002. The Wald test reports the chi-square statistics for the null hypothesis that the coefficients of all exogenous variables are jointly zero. ** denotes significance at the 1% level and * denotes significance at the 5% level.

	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
Endogenous variable: RET0						
RET9(-1)	0.088**	6.028	0.059	1.024	0.015	0.255
QRET09(-1)	---	---	-0.214	-0.689	-0.179	-0.578
QRET99(-1)	---	---	0.368*	2.226	0.313	1.892
QOIB99(-1)	---	---	---	---	0.047**	4.317
Wald Test						
Chi-square	---	---	4.994		23.727	
Probability	---	---	0.082		0.000	

Table 7: VAR Results With Interaction Terms, for all deciles excluding the smallest and largest deciles.

The table presents results from VARs with endogenous variables VOLN, VOL9, RETN, RET9, QSPRN, QSPR9, where N=1 through 8 refers to size deciles. RET denotes the decile return, VOL the return volatility, and QSPR the quoted spread. The deciles are numbered in order of increasing size, with the smallest decile being "0" and the largest being "9". In addition, one lag of the exogenous variables QRETN9, QRET99, and QOIB99 are included in the equation for RETN, where N=1 through 8, and QRETN9= QSPRN*RET9, QRET99= QSPR9*RET9, and QOIB99= QSPR9*OIB9. OIB is the order imbalance, measured as the dollar value of shares bought minus the dollar value of shares sold, divided by the total dollar value of trades. All VARs are estimated with two lags, include a constant term, and use 3782 observations. The Seemingly Unrelated Regression (SUR) method is used to estimate the system of equations. 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 January 4, 1988 to December 31, 2002. The last two rows of each decile group report the Wald test chi-square statistics and p-values for the null hypothesis that the coefficients of all exogenous variables are jointly zero. ** denotes significance at the 1% level and * denotes significance at the 5% level.

Table 7, continued

Endogenous variable: RET1	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
RET9(-1)	0.064**	4.057	0.037	0.783	0.001	0.018
QRET09(-1)	---	---	-0.167	-0.721	-0.096	-0.413
QRET99(-1)	---	---	0.340*	2.127	0.290	1.802
QOIB99(-1)	---	---	---	---	0.030**	2.932
Chi-square	---	---	4.529		13.162	
Probability	---	---	0.104		0.004	
Endogenous variable: RET2						
RET9(-1)	0.053**	3.027	0.035	0.851	-0.015	-0.341
QRET29(-1)	---	---	-0.248	-1.340	-0.143	-0.768
QRET99(-1)	---	---	0.391*	2.453	0.310	1.930
QOIB99(-1)	---	---	---	---	0.042**	4.257
Chi-square	---	---	6.168		24.383	
Probability	---	---	0.046		0.000	
Endogenous variable: RET3						
RET9(-1)	0.062**	3.352	0.056	1.500	0.011	0.293
QRET39(-1)	---	---	-0.185	-1.131	-0.117	-0.711
QRET99(-1)	---	---	0.247	1.524	0.165	1.017
QOIB99(-1)	---	---	---	---	0.045**	4.582
Chi-square	---	---	2.560		23.609	
Probability	---	---	0.278		0.000	
Endogenous variable: RET4						
RET9(-1)	0.045*	2.230	0.050	1.413	0.005	0.123
QRET49(-1)	---	---	-0.302*	-1.983	-0.245	-1.615
QRET99(-1)	---	---	0.321*	2.002	0.234	1.454
QOIB99(-1)	---	---	---	---	0.049**	5.228
Chi-square	---	---	5.263		32.687	
Probability	---	---	0.072		0.000	
Endogenous variable: RET5						
RET9(-1)	0.025	1.141	0.018	0.496	-0.025	-0.674
QRET09(-1)	---	---	-0.051	-0.318	0.026	0.164
QRET99(-1)	---	---	0.097	0.653	0.012	0.082
QOIB99(-1)	---	---	---	---	0.041**	4.840
Chi-square	---	---	0.428		23.881	
Endogenous variable: RET6						
RET9(-1)	0.034	1.415	0.059	1.801	0.030	0.895
QRET69(-1)	---	---	-0.201	-1.216	-0.164	-0.991
QRET99(-1)	---	---	0.079	0.442	0.009	0.049
QOIB99(-1)	---	---	---	---	0.034**	4.213
Chi-square	---	---	1.981		19.736	
Probability	---	---	0.372		0.000	
Endogenous variable: RET7						
RET9(-1)	0.018	0.661	0.019	0.534	0.000	-0.002
QRET79(-1)	---	---	0.154	0.890	0.177	1.022
QRET99(-1)	---	---	-0.176	-1.008	-0.220	-1.255
QOIB99(-1)	---	---	---	---	0.022**	2.900
Chi-square	---	---	1.045		9.456	
Probability	---	---	0.593		0.024	
Endogenous variable: RET8						
RET9(-1)	-0.040	-1.141	-0.030	-0.794	-0.048	-1.241
QRET89(-1)	---	---	-0.023	-0.149	-0.013	-0.081
QRET99(-1)	---	---	-0.027	-0.148	-0.061	-0.335
QOIB99(-1)	---	---	---	---	0.020**	3.245
Chi-square	---	---	0.327		10.863	
Probability	---	---	0.849		0.013	

Table 8: VAR Results With Interaction Terms, for all Deciles, Using Mid-quote Returns.

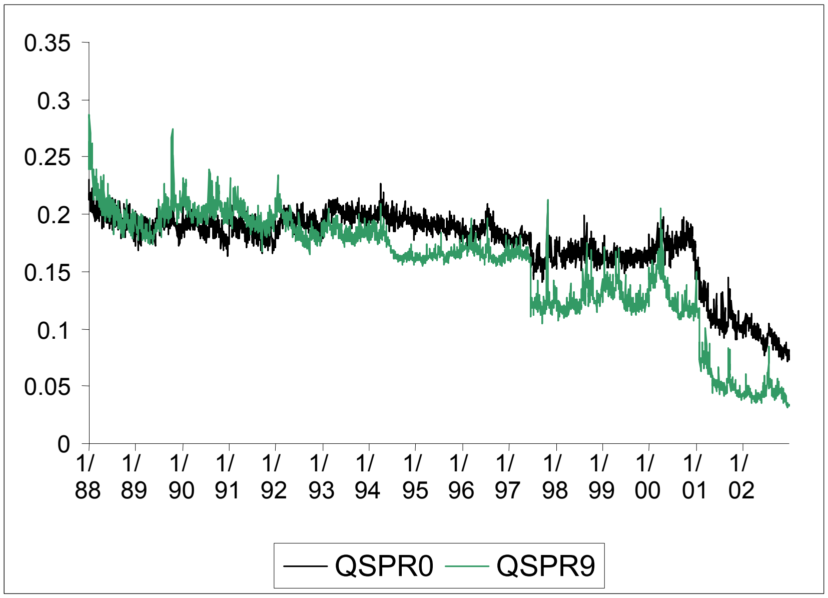
The table presents results from VARs with endogenous variables MRETN, MRET9, VOLN, VOL9, QSPRN, QSPR9, where N=0 through 8 refers to size deciles. MRET denotes the mid-quote return, MVOL the return volatility, and QSPR the quoted spread. The deciles are numbered in order of increasing size, with the smallest decile being "0" and the largest being "9". In addition, one lag of the exogenous variables QMRETN9, QMRET99, and QOIB99 are included in the equation for MRETN, and QMRETN9= QSPRN*MRET9, QMRET99= QSPR9*MRET9, and QOIB99= QSPR9*OIB9. OIB is the order imbalance, measured as the dollar value of shares bought minus the dollar value of shares sold, divided by the total dollar value of trades. All VARs are estimated with two lags, include a constant term, and use 3782 observations. The Seemingly Unrelated Regression (SUR) method is used to estimate the system of equations. 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 January 4, 1988 to December 31, 2002. The Wald test reports the chi-square statistics for the null hypothesis that the coefficients of all exogenous variables are jointly zero. ** denotes significance at the 1% level and * denotes significance at the 5% level.

Table 8, continued

	Estimate	t-statistic
Endogenous variable: MRET0		
MRET9(-1)	0.040	0.772
QMRET09(-1)	0.093	0.296
QMRET99(-1)	-0.147	-0.795
QOIB99(-1)	0.054**	3.024
Endogenous variable: MRET1		
MRET9(-1)	0.065	1.347
QMRET19(-1)	-0.028	-0.107
QMRET99(-1)	-0.149	-0.759
QOIB99(-1)	0.116**	8.196
Endogenous variable: MRET2		
MRET9(-1)	0.054	1.176
QMRET29(-1)	-0.271	-1.233
QMRET99(-1)	-0.037	-0.189
QOIB99(-1)	0.061**	3.119
Endogenous variable: MRET3		
MRET9(-1)	0.023	0.524
QMRET39(-1)	0.145	0.656
QMRET99(-1)	-0.257	-1.223
QOIB99(-1)	0.061**	3.028
Endogenous variable: MRET4		
MRET9(-1)	0.063	1.541
QMRET49(-1)	-0.290	-1.438
QMRET99(-1)	-0.099	-0.462
QOIB99(-1)	0.056**	2.837
Endogenous variable: MRET5		
MRET9(-1)	0.005	0.109
QMRET59(-1)	-0.051	-0.253
QMRET99(-1)	-0.324	-1.587
QOIB99(-1)	0.080**	4.232
Endogenous variable: MRET6		
MRET9(-1)	0.046	1.213
QMRET69(-1)	0.018	0.079
QMRET99(-1)	-0.511*	-2.109
QOIB99(-1)	0.055**	3.127
Endogenous variable: MRET7		
MRET9(-1)	0.036	0.895
QMRET79(-1)	0.004	0.015
QMRET99(-1)	-0.284	-1.104
QOIB99(-1)	0.025	1.497
Endogenous variable: MRET8		
MRET9(-1)	-0.025	-0.601
QMRET89(-1)	-0.286	-1.120
QMRET99(-1)	-0.119	-0.439
QOIB99(-1)	0.047**	3.441

Figure 1

Panel A: Quoted Bid-Ask Spread for small and large cap stocks



Panel B: Proportional Quoted Bid-Ask Spread for small and large cap stocks

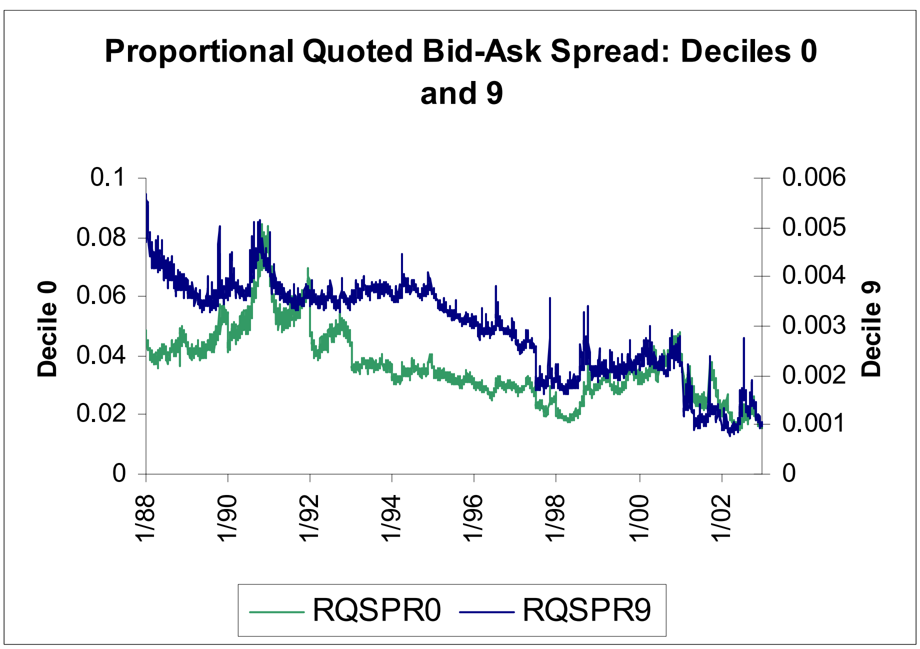


Figure 2. Impulse Response Functions
The figure presents impulse response functions from the VARs with endogenous variables representing order imbalance (OIB), volatility (VOL), returns (RET) and quoted bid-ask spreads (QSPR). The ordering is OIB0, OIB9, VOL0, VOL9, RET0, RET9, QSPR0, QSPR9, with the smallest decile being "0" and the largest being "9".

Panel A. Response of Decile 9 to Decile 0

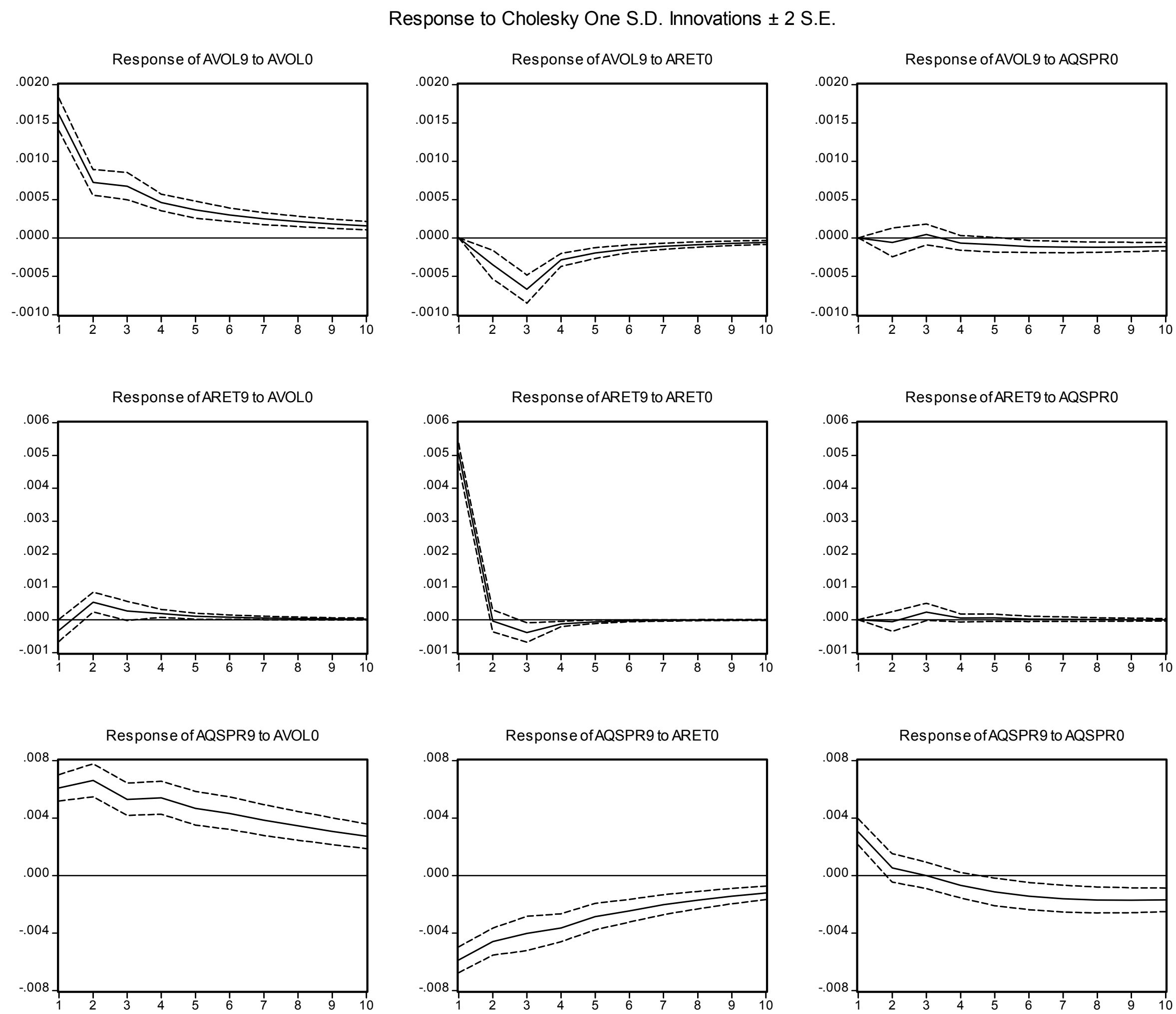


Figure 2, continued

Panel B. Response of Decile 0 to Decile 9

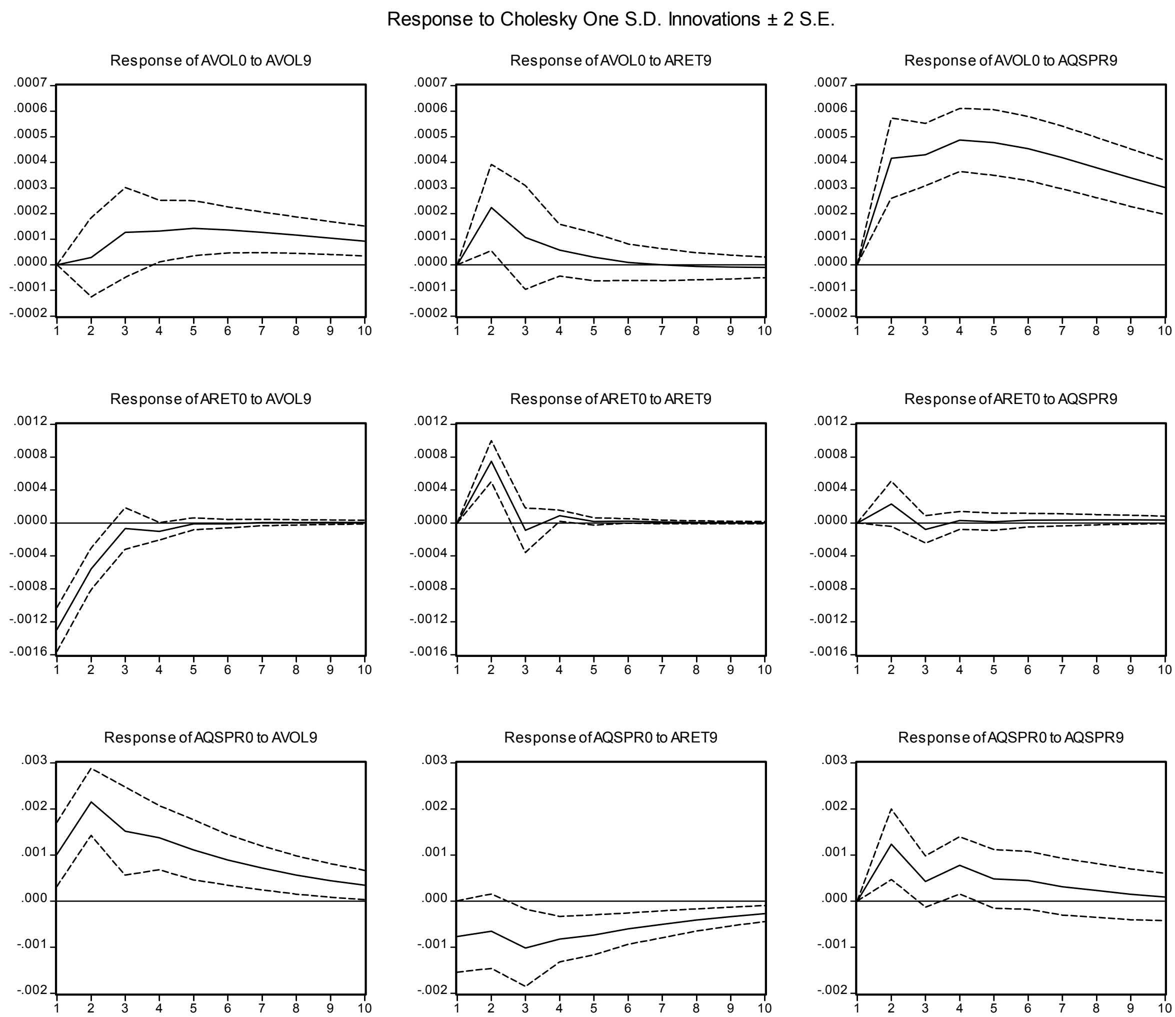


Figure 2, continued

Panel C. Response of Decile 0 to Decile 0

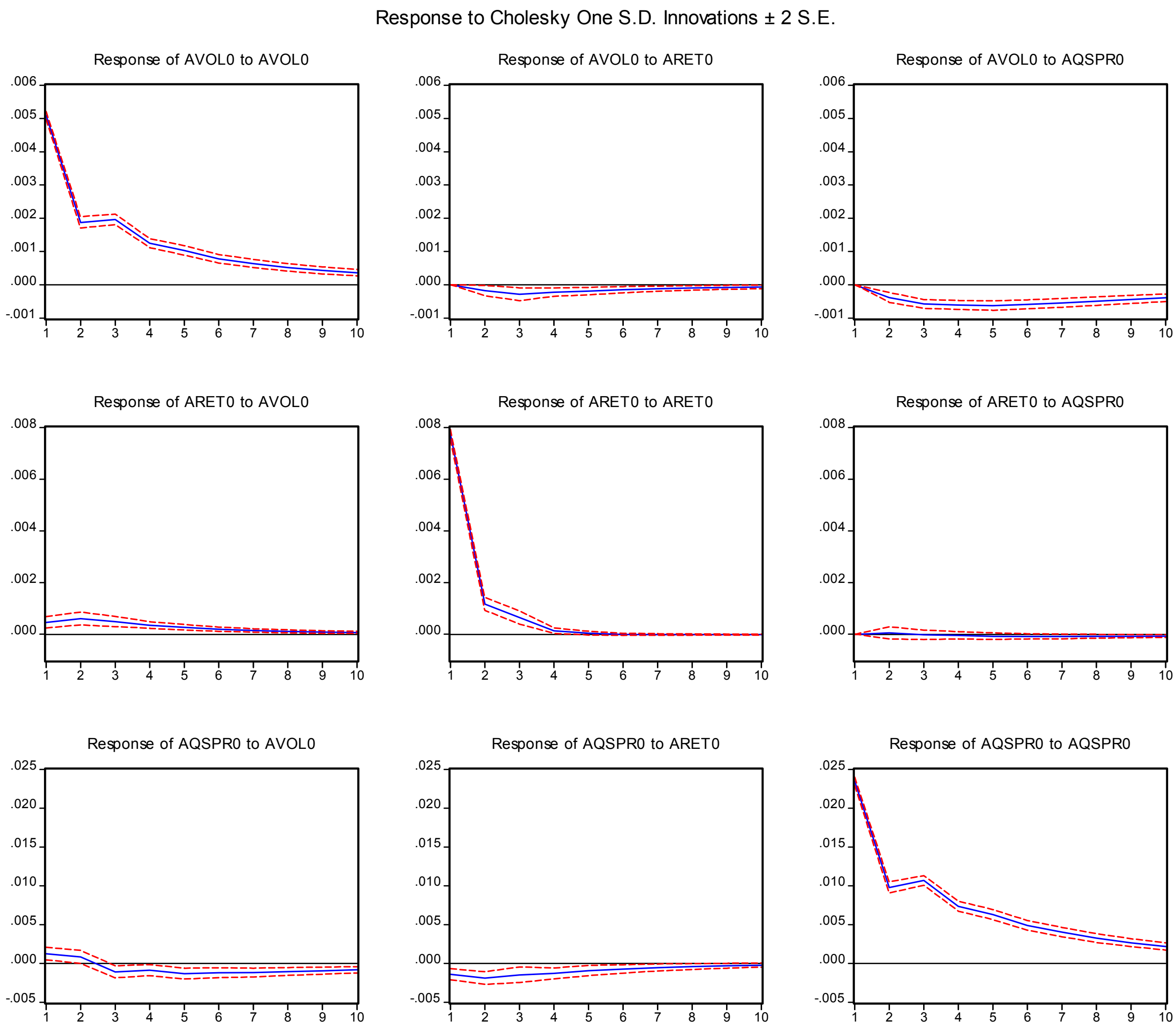


Figure 2, continued

Panel D. Response of Decile 9 to Decile 9