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Liquidity Spillovers and Cross-Autocorrelations

Tarun Chordia,[*] Asani Sarkar,[**] and Avanidhar Subrahmanyam[***]

[*]Goizueta Business School, Emory University.

[**]Federal Reserve Bank of New York.

[***]Anderson Graduate School of Management, University of California at Los Angeles.

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Abstract

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We investigate the persistence of liquidity spillovers and their interaction with return and volatility spillovers across market-capitalization-based stock portfolios. Liquidity innovations in either the large- or small-cap sector are informative in predicting liquidity shifts in the other. Moreover, the liquidity spillovers persist for at least 10 days. Granger-causality results indicate that return and volatility spillovers exist even after accounting for cross-sector liquidity shifts. Small cap volatility predicts large cap volatility more strongly when small cap stocks are more liquid, suggesting that retail investors create both volatility and liquidity in small caps, and their activity then spills over to large caps. Order flows in large-cap stocks significantly predict returns of small-cap stocks when large-cap spreads are high. This is consistent with the notion that trading on common information in large-cap stocks is transmitted to other stocks with a lag.

1 Introduction

Recent years have witnessed a surge of interest in financial market liquidity and its relation to asset prices. Since the seminal work of Amihud and Mendelson (1986), studies such as Brennan and Subrahmanyam (1996), Brennan, Chordia and Subrahmanyam (1998), Jacoby, Fowler, and Gottesman (2000), Jones (2001), and Amihud (2002) have documented the role of liquidity as a determinant of expected returns. Further, Pástor and Stambaugh (2003) and Acharya and Pedersen (2005) relate liquidity risk to expected stock returns.[1]

Since the literature suggests that stock returns and, hence, firms' cost of capital are influenced by levels of as well as fluctuations in liquidity, understanding its cross-sectional and time-series variation is of fundamental relevance, and much research has focused on this issue. While early studies of 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. Chordia, Roll and Subrahmanyam (2000, 2001), Hasbrouck and Seppi (2001) and Huberman and Halka (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 this paper, we consider two aspects of dynamics of liquidity that have not yet been addressed by the literature. The first issue is whether there are persistent liquidity "spillovers" across different sectors of the stock market. For example, does a shock to the liquidity of one sector in the stock market have a lasting effect on another?[2] The issue of whether such cross-effects exist is important for building a complete understanding of liquidity fluctuations, which, in turn, have been shown to affect asset prices. Economic

[1]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 (2005) 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.

[2]While the related paper by Chordia, Shivakumar, and Subrahmanyam (2004) does explore cross-sectional variation in the contemporaneous relation between liquidity and absolute returns, it does not consider persistent spillovers.

rationales for persistent liquidity spillovers are suggested by the previous literature. For example, liquidity shifts in one sector may lead to those in another because trades based on common information may be reflected in some stocks with a lag (Brennan, Jegadeesh, and Swaminathan, 1993). Since liquidity is intimately linked to price moves and volatility (Chordia, Roll, and Subrahmanyam, 2001), this observation leads us to the second issue that we investigate: How is liquidity dynamically related to return and volatility spillovers across different equity market sectors? This issue is important because understanding and predicting return and volatility movements is fundamental to asset allocation.

We attempt to answer the preceding questions by studying the joint dynamics of liquidity, returns, and volatility for common stocks using 15 years of daily data. To parsimoniously capture liquidity spillovers across stocks, we study size-sorted NYSE decile portfolios. We mostly present results for the extreme NYSE deciles but, for robustness, we also show results for the remaining NYSE deciles as well as for Nasdaq stocks. Why do we study stocks stratified by market capitalization? Our work can be motivated by that of 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.[3] Implicitly relying on the notion that the market-wide (e.g., macroeconomic) information shocks impact all stocks, Brennan, Jegadeesh and Swaminathan (1993) and Chordia and Swaminathan (2000) attribute the Lo and MacKinlay (1990) results to the differential adjustment speeds of large and small-cap stocks to such information. We shed new light on the economic causes of leads and lags in returns and volatility by investigating their linkages with liquidity.

Our impulse response functions 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

[3]It also is worth noting that 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.

spreads with the response peaking after one or two days. The persistence of spillovers in liquidity suggests that informational shocks which influence liquidity movements in one sector may have lasting impacts on another. This observation leads us to our subsequent analysis of the interaction between liquidity shocks and spillovers in returns as well as volatility.

Our vector autoregression results indicate that, consistent with Lo and MacKinlay (1990), the returns of large stocks lead those of small stocks. We find that such cross-autocorrelation patterns in returns are strongest when 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 transaction prices or a particular sample period. The results accord with our hypothesis that common information is first traded upon in the large-cap sector, causing spreads there to widen, and is subsequently incorporated into prices of small-cap stocks with a lag.

We also find that small-cap volatility is useful in forecasting large-cap volatility. We then provide evidence that volatility spillovers from small to large-cap stocks are stronger when spreads in small-cap stocks are lower. We suggest an explanation for this result by first observing that retail investors are likely to be dominant in small-cap stocks (e.g., Lee, Shleifer, and Thaler, 1991). Assuming these agents are uninformed, their differential reaction to public signals may increase liquidity as well as volatility. Subsequently, this volatility shift may spill over to the large-cap sector where retail investors are less dominant relative to institutions. Overall, our results indicate that at the daily horizon, price discovery appears to take place in large caps, but volatility discovery is more likely to happen in the small cap sector. This is consistent with the notions that price discovery is driven by the informational trades of sophisticated institutions who dominate the clientele in large caps, whereas a key driver of volatility is the trading activity of retail investors who are dominant in small caps.

Our analysis also reports some hitherto undocumented cross-sectional heterogeneities in calendar regularities. For example, the January effect in small firm returns (e.g., Rozeff and Kinney, 1976, Keim, 1983) has been attributed partially to window-dressing by portfolio managers at the turn of the year (Haugen and Lakonishok, 1987). There is a statistically significant increase in large-cap spreads in January that is not strongly evident for small firms. This increase is consistent with the notion that portfolio managers' withdrawal from the large-cap sector after end-of-the-year window dressing affects large-cap liquidity at the beginning of the year. We also shed light on the relation between liquidity and the day-of-the-week effect in stock returns (French, 1980, Gibbons and Hess, 1981). Specifically, 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. Further, small-cap order imbalances are tilted towards the sell side at the beginning of the week. Coupled with the finding that there is upward pressure on small-cap returns at the end 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 to reverse the end-of-the week upward pressure on small-cap returns.

We conduct a robustness check using a comprehensive sample of the relatively smaller Nasdaq stocks, whose liquidity indicators are obtained by using closing bid and ask quotes available from CRSP data.[4] This analysis indicates that the broad thrust of our spillover results obtains for Nasdaq stocks as well. Notably, bid-ask spreads of NYSE large-cap stocks are informative in forecasting Nasdaq spreads, and large-cap order flows predict Nasdaq returns when large-cap spreads are high.

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 presents the vector autoregressions involving liquidity, returns, and volatility across large and small-cap stocks. Section 5 considers the role of liquidity in the lead-lag relation between large and small-cap returns. Section 6 discusses robustness checks using a holdout sample of Nasdaq stocks and section 7 concludes.

[4]Closing bid and ask quotes are not available on CRSP for NYSE stocks, so we use intradaily averages. Since the spread computation procedure is different across NYSE and Nasdaq stocks, we do not use Nasdaq stocks in the main analysis from the outset.

2 Liquidity and Trading Activity Data for NYSE Stocks

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.

This paper considers stock liquidity indicators that the previous literature has focused upon (viz., quoted spreads and market depth for both large and small-cap stocks). Motivated by earlier research (e.g., Benston and Hagerman, 1974) on the determinants of liquidity, we analyze the persistence of return, volatility, and liquidity spillovers after accounting for the effects of trading activity. We use order imbalances, rather than volume, as measures of trading activity because imbalances bear a stronger relation to trading costs by representing the aggregate pressure on the inventories of market makers. These imbalances are calculated using 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.[5] 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 at the inside quotes.[6] The transactions based liquidity

[5]The following securities were not included in the sample since their trading characteristics might differ from ordinary equities: ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks and REITs.

[6]We have also performed alternative analyses using effective spreads, defined as 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 and so, for brevity, we do not report them in the paper.

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 on the last trading day of the previous year (obtained from CRSP). 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 largest firm group is denoted decile 9, while decile 0 denotes the smallest firm group. The average market capitalizations across the deciles ranges from about $26 billion for the largest decile to about $47 million for the smallest one.[7] As we mentioned in the introduction, 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, allowing us to present our analysis parsimoniously. When relevant, however, we also discuss results for other deciles.

3 Basic Properties of the Data: NYSE stocks

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, Roll, and Subrahmanyam (2001) 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.[8] We find that 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 they diverge considerably after 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

[7]For the middle eight deciles, the average market capitalizations (in billions of dollars) are 5.05, 2.56, 1.48, 0.94, 0.61, 0.39, 0.24, and 0.13.

[8]Chordia, Shivakumar, and Subrahmanyam (2004) provide similar statistics for size-based quartiles, but they do not present statistics for the post-decimalization period, since their sample ends in 1998.

both of these differences are statistically significant,[9] 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 use of exchange-traded funds (ETFs), rising fast in popularity, would likely result in still lower spreads for broad portfolios (Subrahmanyam, 1991).

The difference in mean inside depths of large and small stocks has narrowed in recent times, and the 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 it 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. This is 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, 2005), we also present statistics on the absolute daily proportional change in quoted spreads and depth. This measure is also of practical significance since agents splitting their orders over time would presumably be interested in ascertaining the degree to which the spread moves from day to day. We find 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%).[10] 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 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. The average daily number of transactions has increased

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

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

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.

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 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. Proportional 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 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. 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. Following Schwert, 1990, Jones, Kaul, and Lipson, 1994, Chan and Fong, 2000, and Chordia, Sarkar, and Subrahmanyam (2005), return volatility (VOL) is obtained as the absolute value of the residual from the following regression for decile i on day t :

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

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, and Tauchen (1992). Details of the adjustment process are available in the appendix.

Table 2 presents selected regression coefficients for liquidity measures from the adjusted series. For the sake of brevity, we only present the coefficients for the calendar regularities. We do not present results for order imbalances, nor for the variance equation (3). These results are available upon request.

We are 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. However, it is 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.[11]

We also note that, relative to Friday, Monday spreads are low for large stocks but high for small stocks; 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 that

[11] 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.

we discuss further after we present the return adjustment results. 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 of return regularities such as Gibbons and Hess (1981) and Keim (1983). Relative to other months, stock volatility is high from October to January for small-cap stocks and in October and January for large-cap stocks; this result deserves further analysis in follow-up research.

The higher spreads on Mondays 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 trade 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.[12]

To examine the presence of unit roots in the adjusted series, we conduct augmented Dickey-Fuller and Phillips-Perron tests. We allow for an intercept under the alternative hypothesis, and we 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. 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.

[12]Chordia, Roll, and Subrahmanyam (2001, 2002) show that down markets and high levels of absolute order imbalances are accompanied by decreased liquidity.

4 Vector Autoregresssion: NYSE Stocks

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, as Hasbrouck (1991) and Chordia, Sarkar, and Subrahmanyam (2005) point out, bi-directional causalities across these variables are economically plausible. In particular, liquidity can affect volatility by attracting more trading, and can affect prices through the traditional channel of 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 that, by creating an order imbalance, may affect liquidity. In addition, volatility may affect liquidity by affecting the inventory risk borne by market makers.

Evidence also suggests that cross-stock effects may be significant. Return and volatility predictability and spillovers at short horizons are documented by Lehmann (1988), Lo and MacKinlay (1990), and Conrad, Gultekin, and Kaul (1991). Since imbalances are intimately linked to returns (Chan and Fong, 2000, Chordia, Roll, and Subrahmanyam, 2002), spillovers may exist in this variable as well. Furthermore, if there are leads and lags in trading activity in response to systematic wealth or informational shocks between liquid and 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, in the spirit of Hasbrouck (1991) and Chordia, Sarkar, and Subrahmanyam (2005) we adopt an eight-equation vector autoregression (VAR) that incorporates eight variables, (four each - i.e., measures of liquidity, returns, volatility, and order flows - from large and small-cap stocks). We choose the number of lags in the VAR on the basis of the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC).[13] We now provide estimates from this VAR mode.

4.2 VAR Estimation Results

The VAR includes the endogenous variables OIB0, OIB9, VOL0, VOL9, RET0, RET9, QSPR0, and QSPR9, whose suffixes 0 and 9 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. Since the key contribution of our study is to examine persistent spillovers across different stock market sectors, we first present Chi-square statistics for the null hypothesis that variable i does not Granger-cause variable j. Specifically, in Table 4 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 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, that tend to be owned more often 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 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

[13]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.

the reverse is not true; thus, large-cap returns lead small-cap returns. Also, small-cap volatility Granger-causes large-cap returns but large-cap volatility does not predict large-cap returns. Section 5 further explores these findings.

For completeness, we also examine the cross-correlations of innovations obtained from the VAR estimation in Table 5. Cross-sector liquidities and volatilities are positively and significantly correlated. Also, 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).[14] Overall, these results point to the importance of the large-cap sector in the determination of liquidity and volatility in the small-cap sector.

We now estimate the impulse response functions (IRFs) in order to examine the joint dynamics of liquidity, volatility and returns implied by the full VAR system. 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.[15] Since prices are formed after observing order flow, we place imbalance first in our ordering. Thus, in our base IRFs, 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

[14]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 argument.

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

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. Period 1 in the impulse response functions represents the contemporaneous response, and the units on the vertical axis are in actual units of the response variable (e.g., dollars in the case of spreads). Consider 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 models of microstructure which argue that increased volatility, by increasing inventory risk, tends to decrease liquidity. Volatility spillovers persist even after accounting for liquidity. There is clear evidence that shocks to small-cap volatility are useful in forecasting large-cap volatility.

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 to 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 with the interpretation that informational events are first incorporated into the large-cap sector and then are transmitted to the small-cap sector with a lag. We will provide additional evidence in support of this hypothesis in section 5.

In unreported own-sector impulse response functions, we find that volatility shocks in a sector result in a persistent decline in liquidity in that sector, as in Stoll (1978). Furthermore, liquidity decreases for several days in response to a negative return shock in either sector, likely because during periods of declining prices 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 qualitatively 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 magnitude of the highest response (one day after the shock) of small-cap spreads to large-cap volatility, is about 0.002 (from Figure 2, Panel B). A one-standard deviation shock to large-cap volatility forecasts an increased annual trading cost of \$50,000 on a 100,000 share round-trip trade per day, assuming 100 such trading days per year. The forecasting impact of large-cap spreads on small-cap spreads is about half this amount.

Importantly, unreported analyses indicate that spillovers from large-cap stocks to deciles higher than 0 have greater economic significance. For example, responses of decile 8 spreads to decile 9 spreads die out slowly and are significant even after twenty days. Using a 30 day accumulated response, and about eight (i.e., about 250/30) shocks in an year, the total impact of a one-standard deviation shock to large-cap (decile 9) spreads upon decile 8 spreads is about \$1.75 per share. For a \$100,000 share trade, this works out to about \$175,000, which is substantive. The numbers for decile 7 spreads are quite similar. Thus, the economic significance of liquidity spillovers is material across the relatively larger capitalization shocks.

5 The Effect of Liquidity on Return and Volatility Spillovers

The persistence of return and volatility spillovers documented in the previous section raises the issue of how liquidity interacts with these spillovers. Economic arguments suggest that we should expect such interactions. For example, informational shocks impact liquidity, and if these also influence return spillovers, then we would expect the strength of spillovers to time-vary with liquidity. Similarly, trading activity influences liquidity but also has an impact on volatility, so again, we might see a link between the strength of volatility spillovers and liquidity. We discuss return spillovers in Subsections 5.1 and 5.2 and consider volatility spillovers in Subsection 5.3.

5.1 Impact of Liquidity on Return Cross-Autocorrelations

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, Avramov, Chordia, and Goyal, 2004, Sadka and Scherbina, 2004, Hou and Moskowitz, 2005, and Chordia, Roll and Subrahmanyam, 2006). We first 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. 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. We follow Brennan, Jegadeesh and Swaminathan (1993) in conducting the lead-lag analysis at the daily frequency.[16]

Why specifically 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 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

[16]In an exploratory investigation, we considered 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-lag relation 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.

of systematic public signals would result in a near-simultaneous updating of quotes by market makers in all stocks, and thus would not likely cause a significant lead-lag effect. On the other hand, Brennan, Jegadeesh, and Swaminathan (1993) suggest that lead and lag effects are caused by differential speeds of adjustment of large and small stocks to common private information. If agents with 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). This argument suggests that during periods when agents receive privileged information about common factors, lead and lag effects are much more likely.

Since the informed trading that causes the lead-lag in the above line of argument is expected to reduce liquidity temporarily 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 is 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 lagged large-cap spreads 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 to 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 exogenous 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 coefficient 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 including 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, 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.

5.2 Is the Lead-Lag Effect due to Informed Trades?

In this section, we further test the notion that information gets transmitted to prices in either sector by way of informed order flows. We interact order imbalance (OIB) with spreads in the large-cap market and include the interaction variable in the regression.[17] The results, shown in the third column of Table 6, 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 OIB. 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

[17] Small cap order flow is not significantly related to future large or small cap returns, consistent with the notion that informational events first occur in large cap stocks and then spillover to small cap stocks, and not vice versa.

between large-cap and small-cap firms.

In order to provide additional insight regarding 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 correlations when the large-cap order imbalance is used in place of returns 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 lagged 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 computing additional correlations. First, we find that the correlation between OIB0 on day t and OIB9 on day $t-1$ is 0.14 ($p < 0.01$) 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 when the small-cap spread is one standard deviation above and below its sample mean. 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.[18] When the order imbalance replaces returns, the corresponding

[18]To clarify, these correlations document a link between cross-autocorrelations and small cap spreads at time t. As Table 6 demonstrates, there is no significant link between small cap return predictability from large caps and small cap spreads at time $t-1$. As we discuss, this is consistent with information events widening spreads first in large caps at time $t-1$, and then in small caps at time t.

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. We 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 for only 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 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 that 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 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, for instance, then the transaction price would not incorporate information shocks that occur later in the day.

To address the above issue, we perform an alternative analysis by computing midquote 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 paper's authors. One benefit of using the post-1993 sample is that it 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.[19] 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 liquidity can reduce trading activity in small-cap stocks and this reduction 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.[20]

5.3 Volatility Spillovers

Recall that the VAR results in Table 4 indicate that small-cap volatility Granger-causes large-cap volatility, and the impulse responses in Figure 3 also indicate a similar spillover. To analyze the interaction of this spillover with liquidity, in Table 9 we include interactions of small-cap volatility with large-cap and small-cap spreads as exogenous vari-

[19] 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 less than 0.05.

[20] 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 we find that large-cap spreads are most relevant to the lead from large to small stock returns.

ables in the equation for large-cap volatility within the VAR (in addition to the return interaction variables). Specifically, the volatility interaction variables are defined as QVOL90=QSPR9*VOL0 and QVOL00=QSPR0*VOL0. The reported coefficients indicate that while the return interaction results are not altered by this inclusion, there is some evidence that the spillover from small-cap to large-cap volatility is stronger when small-cap spreads are smaller.[21] This result is counter-intuitive, and deserves further analysis. We suspect it occurs because retail investors dominate small-cap stocks (Lee, Shleifer, and Thaler, 1991, Kumar and Lee, 2005). In this situation, the response of retail investors to public information or systematic liquidity shocks may occur first in small-cap stocks. This response would increase liquidity under the assumption that retail investors generally do not have private information. However, it would also increase volatility (Subrahmanyam, 1994). Subsequently, this response may spill over with a lag to large-cap stocks, in which proportional holdings of retail investors are smaller than for small-cap stocks.

Overall, our results indicate that the spillovers in signed price movements run from large to small caps whereas the reverse is true for volatility shifts. As we discuss, these results can be explained by observing that the directional price impact due to informational trades of sophisticated institutions is expressed first in the large cap sector, but unsigned trading activity from retail investors because of their differential response to public information (which drives volatility) is expressed first in the small cap sector.

The economic significance of our results is material, though it does not suggest a gross violation of market efficiency. For example, the standard deviation of the return and spread-based interaction variable in Table 6 is about 0.002. Based on the relevant coefficient (0.368) in Table 6, we find that a one standard deviation move in the interaction variable changes small-cap returns by 0.073%. However, assuming 83 such events in an year (i.e., on about 33% of days forming a typical 250 trading-day year), this works out to 6.08% on an annual basis. Based on the coefficient of 0.054 (for the smallest firm decile) in Table 8, a one standard deviation move (equaling about 0.015) in the order-flow based interaction variable has a daily effect of 0.068%, aggregating to about 6.52%

[21] For brevity, we do not present the analogs of Table 9 for the other deciles. Unreported analyses indicate that the volatility spillover from the smaller deciles to the larger ones is confined to deciles 0 and 1.

across 83 events. Frictions such as brokerage commissions, however, could nullify the profitability of such strategies to individual investors, though the same may not be true for floor traders and large institutions.

6 Nasdaq Stocks: A Robustness Check

As a robustness check on our basic results, we now consider spillovers between the liquidity of NYSE stocks and a holdout sample of the relatively smaller Nasdaq stocks.[22] Our analysis also allows us to consider the potential effects of the different market structures across NYSE and Nasdaq on liquidity spillovers.

We use daily Nasdaq closing bid and ask prices on the CRSP database in order to compute daily bid-ask spreads for Nasdaq. The Nasdaq spread index is constructed by using the value-weighted average of the spread in a manner similar to that used for the NYSE indices described in Section 2; return and volatility measures are also constructed in the corresponding manner. Due to the potentially more severe problem of stale prices among the relatively smaller Nasdaq stocks, however, we report results using quote mid-point return series to compute returns and volatility (though results are substantively similar for transaction return series).

As before, we adjust the Nasdaq series of spreads, returns, and volatility to account for regularities as in Tables 2 and 3.[23] These adjustment regressions are not presented, but it is worth mentioning that we find Nasdaq spreads to be statistically higher (at the 5% level) on Mondays and lower in the latter part of the year. These results are similar to those obtained in the case of NYSE small-cap stocks (viz. Table 2).

We estimate a VAR for which the endogenous variables are returns, volatilities, and

[22] The average market capitalization of Nasdaq stocks is \$0.93 billion, which is comparable to the average market capitalization of stocks in NYSE decile 5 (about \$0.94 billion).

[23] For Nasdaq stocks, the dummy variable for the change to sixteenths equals 1 for the period June 12, 1997 to March 11, 2001. Further, there are 3 decimalization dummies to reflect the gradual introduction of decimalization for various subsets of stocks over the following periods: March 12, 2001 to March 25, 2001; March 26, 2001 to April 8, 2001; and from April 9, 2001 to December 31, 2002 (see, for example, Chung and Chuwonganant, 2003). Consistent with Bessembinder (2003), the value-weighted average spread on Nasdaq of 44.2 cents in our sample period prior to June 12,1997 drops to 12.5 cents in the period June 12, 1997 to March 24, 2001, and remains at just 3.6 cents for the remainder of our sample period. The high spread in the pre-sixteenth period relative to that of NYSE stocks is consistent with Huang and Stoll (1996).

quoted spreads for Nasdaq stocks and NYSE decile 9 stocks. The VAR includes 3 lags and a constant term. The Granger causality results and correlations in VAR innovations across large-cap NYSE stocks and Nasdaq stocks are presented, respectively, in Panels A and B of Table 10. Although the correlation between liquidity innovations in Nasdaq and NYSE stock spreads is small, spreads of large-cap NYSE stocks Granger-cause Nasdaq spreads, and the reverse is not true. Thus, there is evidence of a liquidity spillover from NYSE to Nasdaq, but not from Nasdaq to NYSE stocks. Recall that in Table 5, there is evidence of bivariate causality from large-cap to small-cap stocks and vice-versa. The Granger causality results indicate that liquidity discovery may take place in the larger exchange market.

In Figure 3, we present the impulse response functions that document the responses of the Nasdaq market to NYSE large-cap stocks.[24] We find that shocks to large-cap spreads significantly affect Nasdaq spreads on the day following the shock; moreover, the response remains strong and statistically significant even after 10 days. In addition, Nasdaq volatility is forecasted by large-cap spreads. By and large, the impulse response functions reveal that the spillover effects documented in the previous section are not an artifact of the market structure of the NYSE since they are preserved for Nasdaq stocks as well.

In Table 11, we present the analog of the lead-lag regression in Table 6. Specifically, we examine the response of Nasdaq stock returns to lagged returns of NYSE decile 9 stocks, to the interaction of decile 9 returns with Nasdaq and decile 9 spreads, and to the interaction of decile 9 order flow with decile 9 spreads. As before, the interaction terms are treated as exogenous variables in the VAR. It is noteworthy that while there is no evidence of daily return leads from NYSE to Nasdaq, the large-cap imbalance interacted with large-cap spreads is significant, and that its magnitude is greater than the corresponding coefficient magnitude in Table 6.[25] Overall, these results confirm the role of large-cap order flows and liquidity in predicting returns in both small-cap NYSE

[24]We follow the same VAR ordering as before in computing the impulse responses, with the Nasdaq portfolio replacing the small-cap NYSE deciles. Thus, the ordering is VARN, VAR9, RETN, RET9, QSPRN, QSPR9 where the suffixes "9" and "N" indicate NYSE decile 9 and the Nasdaq portfolios, respectively.

[25]Since we find the role of liquidity in causing Nasdaq volatility spillovers not to be significant, we do not present the equivalent of Table 9 for Nasdaq stocks.

firms as well as Nasdaq firms. Thus, our key results continue to obtain even after inclusion of Nasdaq stocks in our analysis.

7 Concluding Remarks

Our principal aims in this paper are to examine whether there are persistent liquidity spillovers across different stock market sectors, and to investigate the link between liquidity and spillovers in return and volatility. The topic is particularly important given that price moves and volatility are fundamental inputs to asset allocation, and that liquidity levels, as well as the risk arising from dynamic liquidity movements, have been shown to impact firms' cost of capital. In our analysis, we use vector autoregressions to examine the joint time-series of liquidity, returns, and volatility for NYSE size decile portfolios and the value-weighted Nasdaq portfolio over the period 1988 through 2002. Our analysis of size-based portfolios is motivated by research (Lo and MacKinlay, 1988, Conrad, Gultekin, and Kaul, 1991) that documents spillovers in returns and volatility, both of which have been strongly linked to liquidity in earlier literature (Chordia, Roll, and Subrahmanyam, 2001).

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. First, liquidity innovations in either the large- or small-cap sector are informative in predicting liquidity shifts in the other, with spillovers persisting for at least 10 days. Further, the impulse responses indicate that the small-cap market appears to have a more delayed response to shocks originating in the large-cap sector than vice-versa, indicating that the liquidity-shifting events that cause persistent shifts in future 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, inform the forecasting of liquidity shifts in either sector. Own-sector returns and volatility are also informative in forecasting dynamic liquidity movements. Finally, liquidity shifts in the large-cap sector forecast liquidity shifts in Nasdaq stocks.

Our results also show that order flows in the large-cap sector predict small-cap returns when large-cap spreads are high. This result holds for both transaction returns as well as mid-quote returns, demonstrating that the finding is not due to stale prices. This finding is consistent with our hypothesis that informational events impact the large-cap sector first, causing large-cap spreads to widen, and are subsequently incorporated with a lag into the prices of small-cap stocks. In addition, we show that volatility spillovers from small to large-cap stocks are stronger when spreads in small-cap stocks are lower. We suggest an interpretation of this result by noting that retail investors are likely to dominate small-cap stocks (Lee, Shleifer, and Thaler, 1991). Their largely uninformed trading activity in small-caps in response to noisy public signals or endowment shocks could increase liquidity as well as volatility in the small-cap sector, and this could then spill over to the large-cap sector, where such investors are less active relative to institutions. Overall, large cap stocks appear to lead small caps in directional price moves, but small caps lead large caps in the discovery of volatility. These seemingly disparate pieces of evidence can be reconciled by the notion that informational trades of sophisticated institutions (who dominate the large cap clientele) are expressed first in the large cap sector, but unsigned trading activity from retail investors because of their differential response to public information (which drives volatility) is expressed first in the small cap sector.

As a by-product of our analysis, we document some interesting differences in calendar regularities across market cap-based deciles. For instance, within our sample period, there is a distinct upward pressure on large-cap NYSE 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. 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.

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 its 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 as well as to understand its indirect impact by way of its effect on liquidity.

Appendix

In this appendix, we provide details about the adjustment process for the different time series. 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 do not seek to explain.

We further consider dummies for financial market events that could affect the 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);[26] (vi) dummies for the day of and the two days prior to macroeconomic

[26]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).

announcements about GDP, employment and inflation (intended 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, when 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 dataset whereas the number of NYSE-listed firms trading on a typical day in the sample is over 1,100.

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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. 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**
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

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. 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**
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**

Table 4: Granger causality results.

The table presents causality results from a VAR with endogenous variables OIB0, OIB9, VOL0, VOL9, RET0, RET9, QSPR0, QSPR9, with the smallest decile being “0” and the largest being “9”. The VAR is estimated with two lags, includes a constant term, and uses 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 , VOL is the return volatility, and OIB is the buy dollar volume less sell dollar volume normalized by the total dollar volume. 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 5: Contemporaneous Correlation between VAR Innovations.

The table presents the correlation matrix of innovations from a VAR with endogenous variables OIB0, OIB9, VOL0, VOL9, RET0, RET9, QSPR0, QSPR9, with the smallest decile being “0” and the largest being “9”. The VAR is estimated with two lags, includes a constant term, and uses 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, VOL is the return volatility, and OIB is the buy dollar volume less sell dollar volume normalized by the total dollar volume. 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 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 decile.

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, MVOLN, MVOL9, 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, and include a constant term. 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. ** 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

Table 9: VAR Results With Interaction Terms for Volatility and Returns, for the Smallest Decile. The table presents results from VARs with endogenous variables MRET0, MRET9, MVOL0, MVOL9, QSPR0, QSPR9, MRET denotes the mid-quote return, MVOL the return volatility, and QSPR the quoted spread, with the smallest decile being “0” and the largest being “9”. In addition, one lag of the exogenous variables QMRET09, QMRET99, and QOIB99 are included in the equation for MRET0, and QMRET09= QSPR0*MRET9, QMRET99= QSPR9*MRET9, and QOIB99= QSPR9*OIB9. Further, one lag of the exogenous variables QMVOL90=QSPR9*MVOL0 and QMVOL00=QSPR0*MVOL0 are included in the equation for VOL9. 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. 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, 1993 to December 31, 2002. ** denotes significance at the 1% level and * denotes significance at the 5% level.

	Estimate	t-statistic
Endogenous variable: MRET0		
MRET9(-1)	0.041	0.797
QMRET09(-1)	0.082	0.262
QMRET99(-1)	-0.142	-0.765
QOIB99(-1)	0.054**	3.002
Endogenous variable: MVOL9		
MVOL0(-1)	0.301**	2.872
QMVOL90(-1)	0.089	0.258
QMVOL00(-1)	-1.499*	-2.349
Wald Test		
Chi-square	15.447	
Probability	0.009	

Table 10: VARs Including Nasdaq Stocks

Panel A of the table presents the correlation matrix of innovations from a VAR with endogenous variables VOL0, VOL9, VOLN, RET0, RET9, RETN, QSPR0, QSPR9, QSPRN with the smallest NYSE decile being "0" and the largest being "9"; the subscript "N" represents Nasdaq stocks. The VAR uses 3782 observations. QSPR stands for quoted spread. RET is the decile return, VOL is the return volatility, and OIB is the buy dollar volume less sell dollar volume normalized by the total dollar volume. Panel B of the table presents causality results from the VAR. 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. 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.

Panel A: Granger Causality Results

	VOLN	VOL9	RETN	RET9	QSPRN	QSPR9
VOLN		**18.951****	3.296	2.407	**11.291***	4.513
VOL9	4.720		7.719	**8.504***	0.310	**96.061****
RETN	**19.960****	6.282		2.863	5.109	0.912
RET9	2.079	**13.014****	0.321		7.173	**11.824****
QSPRN	**23.513****	**10.091***	5.416	2.248		5.479
QSPR9	**37.964****	**55.411****	3.833	0.499	**18.562****	

Panel B: Contemporaneous Correlations between VAR Innovations

	VOLN	VOL9	RETN	RET9	QSPRN	QSPR9
VOLN	1.000					
VOL9	**0.529****	1.000				
RETN	**-0.064****	**-0.055****	1.000			
RET9	**-0.057****	**-0.042****	**0.729****	1.000		
QSPRN	**-0.045****	**-0.055****	**-0.034***	-0.030	1.000	
QSPR9	**0.210****	**0.318****	**-0.151****	**-0.183****	**0.039***	1.000

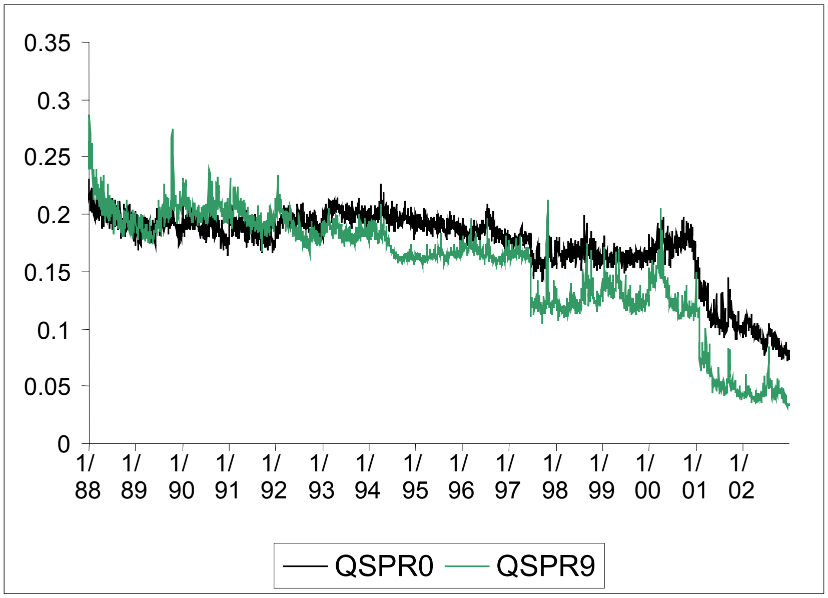
Table 11: VAR Results With Interaction Terms, including Nasdaq Stocks

This table presents results from a VAR with endogenous variables VOL0, VOL9, VOLN, RET0, RET9, RETN, QSPR0, QSPR9, QSPRN with the smallest NYSE decile being "0" and the largest being "9"; the subscript "N" in this table represents Nasdaq stocks. RET denotes the 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, and QRETN9= QSPRN*RET9, QRET99= 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. The Seemingly Unrelated Regression (SUR) method is used to estimate the system of equations. 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: RETN						
RET9(-1)	-0.019	-0.526	0.008	0.189	-0.066	-1.326
QRETN9(-1)	---	---	0.167	1.013	0.162	0.984
QRET99(-1)	---	---	-0.103	-0.304	-0.074	-0.217
QOIB99(-1)	---	---	---	---	0.077**	2.799
Wald Test						
Chi-square	---	---	2.969		10.815	
Probability	---	---	0.227		0.013	

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

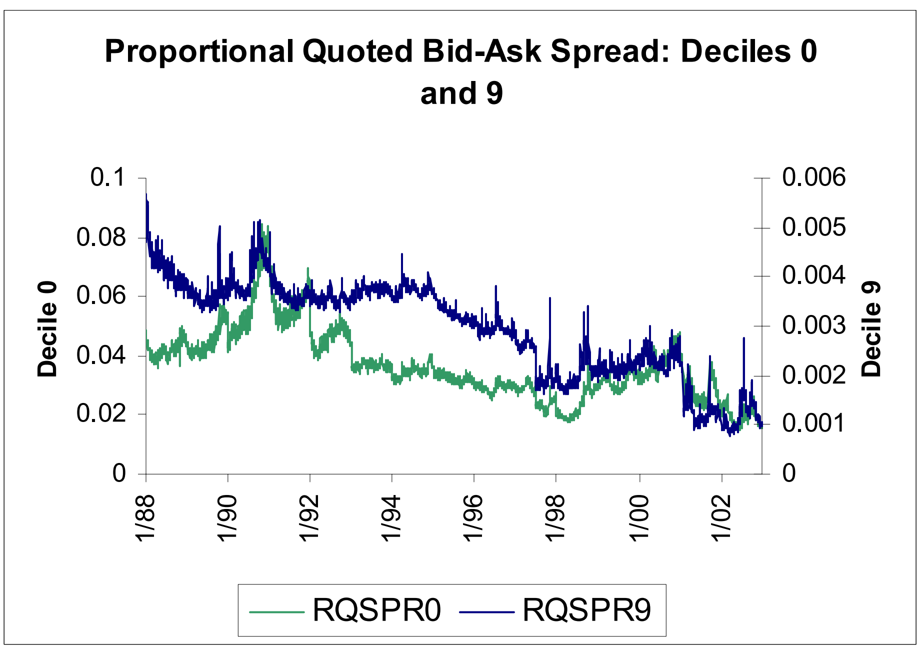


Figure 2. Impulse Response Functions
The figure presents impulse response functions from the VARs with endogenous variables representing order imbalance (OIB), volatility (VOL), returns (RET) and quoted bid-ask spreads (QSPR). The ordering is OIB0, OIB9, VOL0, VOL9, RET0, RET9, QSPR0, QSPR9, with the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

Panel A. Response of Decile 9 to Decile 0

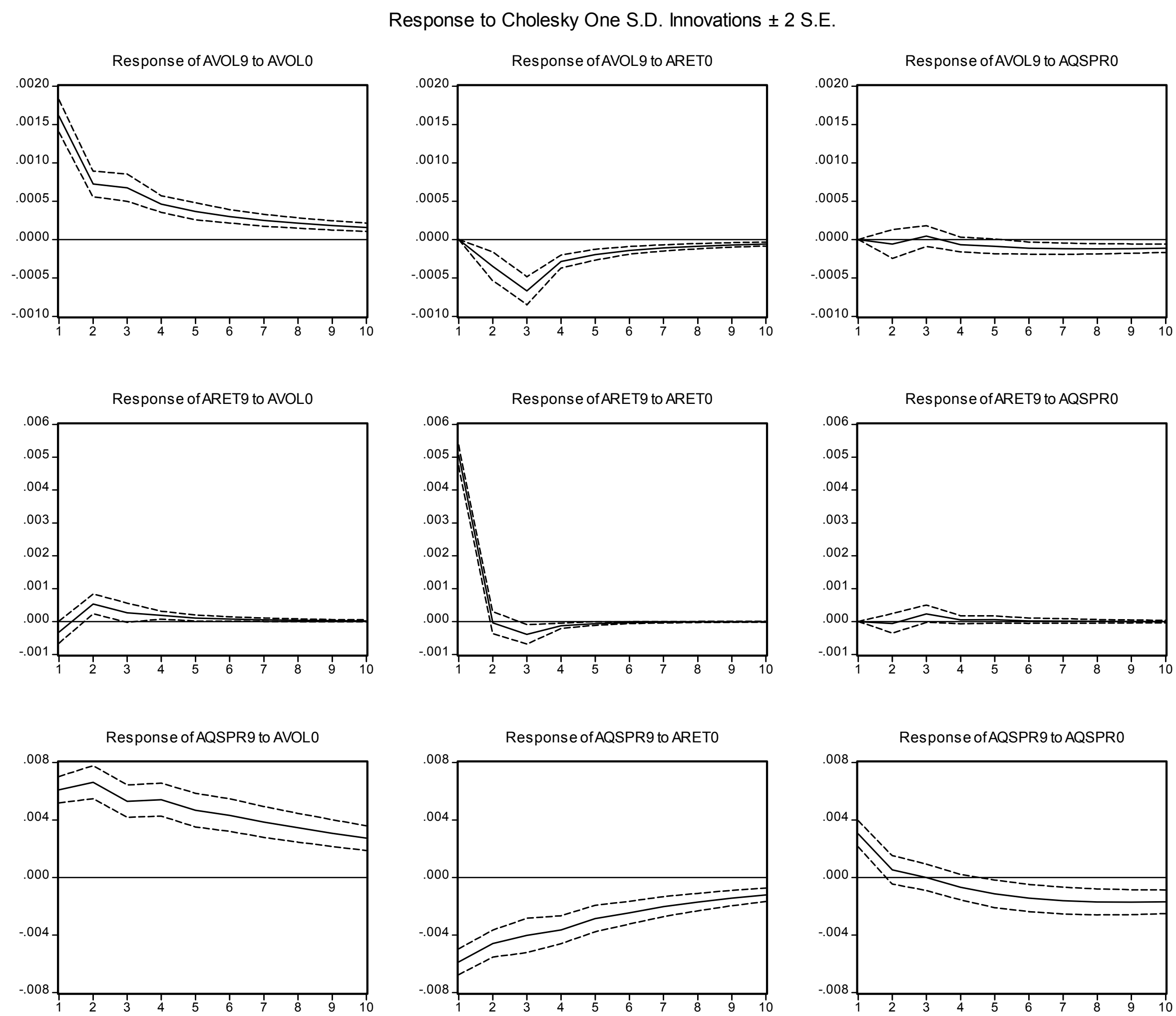


Figure 2, continued

Panel B. Response of Decile 0 to Decile 9

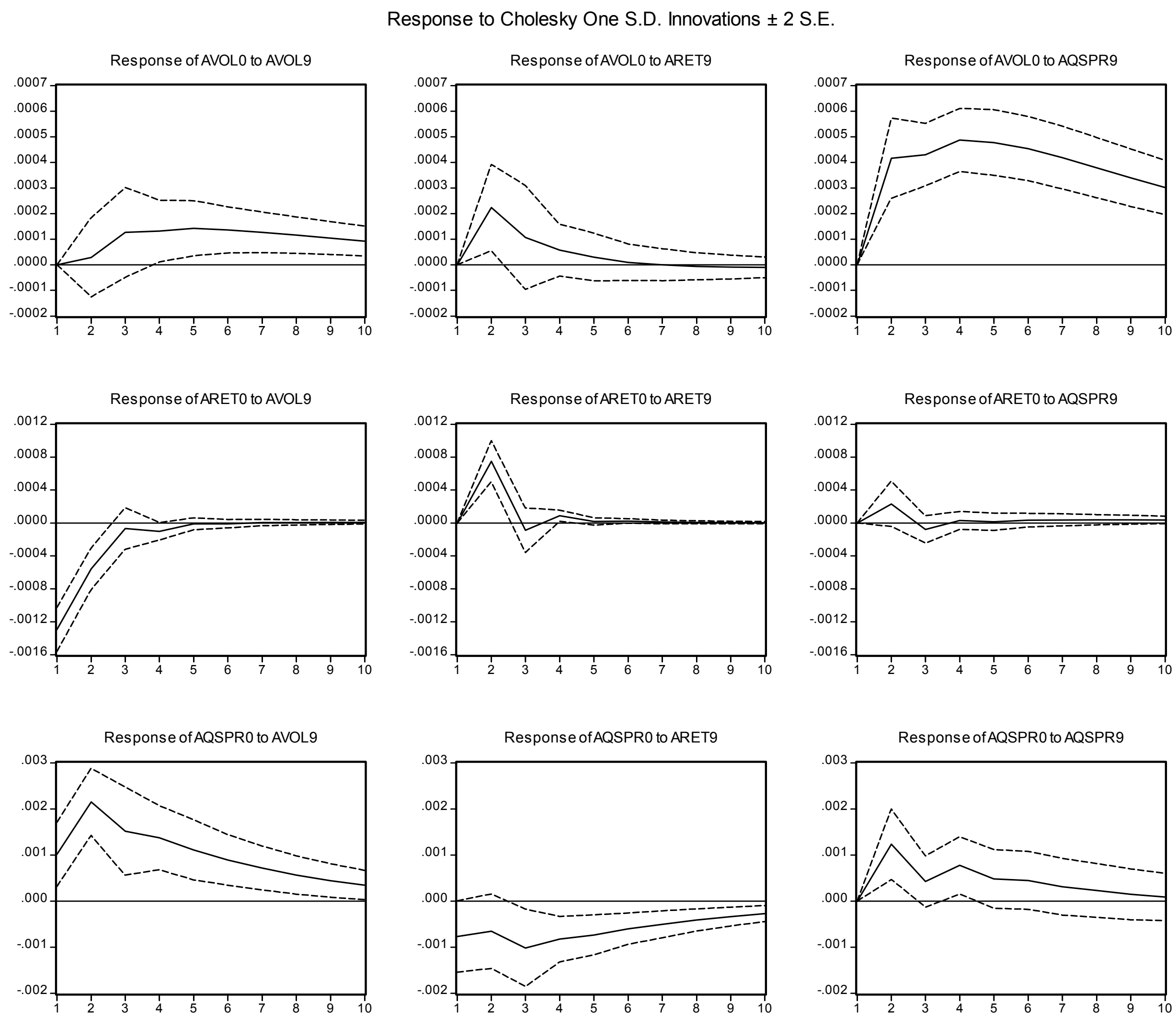


Figure 3. Impulse Response Functions for Nasdaq stocks to Large NYSE Stocks
The figure presents impulse response functions from the VARs with endogenous variables representing volatility (VOL), returns (RET) and quoted bid-ask spreads (QSPR), for small and large NYSE firm deciles, and Nasdaq stocks. The largest firm NYSE deciles is denoted "9"; "N" represents Nasdaq stocks.