Asymmetric Comovement in Liquidity*

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ABSTRACT

Recent theoretical work suggests that commonality in liquidity and variation in liquidity levels can be explained by supply side shocks affecting the funding available to financial intermediaries. Consistent with this prediction, we find that liquidity levels and commonality in liquidity respond asymmetrically to positive and negative market returns. Stock liquidity decreases while commonality in liquidity increases following large negative market returns because the collateral value of the aggregate market making sector falls. We show that a large drop in aggregate value of securities creates greater liquidity commonality due to inter-industry spillover effects of the capital constraints. We also show that the commonality is higher for high volatility stocks.

In recent theoretical research, the idea that market returns endogenously affect liquidity has received attention. A key paper is Brunnermeier and Pedersen (2004), where a drop in stock prices leads to drop in market liquidity when wealth constraints bind. Since market makers are likely to be long on securities, a decline in aggregate market value of securities reduces the capital available with market makers, leading to a sharp decrease in the bid price. Since this supply of liquidity effect - market makers face capital constraints because the value of their collateral (their long positions) fall - affects all securities, Brunnermeier and Pedersen predict greater commonality in liquidity following negative market performance.

Several other recent papers link changes in asset value to liquidity. Anshuman and Viswanathan (2005 in progress), present a slightly different model where investors are asked to provide collateral when asset values fall and decide to endogenously default, leading to liquidation of assets. Simultaneously, market makers are able to finance less in the repo market leading to higher spreads (and possibly greater commonality in liquidity). In Morris and Shin (2003), traders all sell when they hit price limits and liquidity black holes emerge when prices fall enough (the model in analogous to a bank run). In Kyle and Xiong (2002), a drop in stock prices leads to reduction in holdings of risky assets because investors have decreasing absolute risk aversion (see also Gromb and Vayonos (2002) for a model of capital constraints and limits to arbitrage). In Vayanos (2004), mutual fund managers sell when stock prices has hit an exogenously set level. Consequently, when mutual fund managers are close to the trigger price, they care about the volatility of the stock. Hence, these theoretical models show a demand for liquidity effect where more selling occurs when prices fall because of liquidation of assets.[1]

In this paper, we examine whether the empirical evidence supports the idea that stock market movements affect market liquidity and whether the hypothesis generated by the above theoretical research has any empirical support. Importantly, we focus on the idea that comovements in liquidity are higher when large negative market returns occur. While there is some research on comovements in market liquidity in stock and bond markets (Chordia, Roll, Subrahmanyam (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001) and others) and evidence that market making collapsed after the stock market crisis in 1987 (see the Brady commission report on the 1987 crisis), there is little empirical evidence that directly looks at the effect of stock market movements on liquidity of individual stocks and commonality in liquidity.

Chordia, Roll and Subrahmanyan (2001a, JoF) show that at an aggregate level, negative market returns lowers daily liquidity. Chordia, Roll and Subrahmanyan (2001b, JFE) show that at daily frequency, negative market return predicts higher market-wide daily spreads. Our paper takes this evidence much further. We ask how aggregate stock and industry returns affect individual stock liquidity at a monthly frequency (we also look at the liquidity in the first five days of the month to consider other frequency). We show that the effect of negative market returns is highest for large market returns in small stocks with high volatility. More importantly, we look at the comovement in liquidity across stocks conditional on market movements and show that the comovement increases

[1] The collateral effect is also emphasized in the classic work of Kiyotaki and Wright (1997) where lending is based on the value of land. The work of Eisfeldt (2004) suggests that assets could be more liquid during certain periods (good times) relative to others.

substantially following large negative market movements. Hence, while our work builds on the important work of Chordia, Roll and Subrahmanyam (2001a, 2001b), our work focus on the comovement of liquidity given prior market movements, a research topic that has not received attention in the prior literature.

Two recent papers also consider the effect of capital constraints on liqudity. Using daily data and specialist stock information, Coughenour and Saad (2004) ask whether changes in the market return affect stock liquidity at a daily frequency. As we will see below, our analysis of comovement is much more comprehensive and carefully attempts to test theoretical models. We also use a much longer data set. In an interesting paper on fixed income markets, Naik and Yadav (2003) show that Bank of England capital constraints affect price movements. However, they do not look at comovements in liquidity or attempt to test recent theories.

Other work that is related to our research includes Acharya and Pedersen (2005) who show that a fall in aggregate liquidity occurs primarily for illiquid assets. Pastor and Stambaugh (2003) show that liquidity is priced. Amihud and Mendelson (1986) show that illiquid assets earn a higher return. Sadka (2005) shows that the earnings momentum effect is partly due to higher liquidity risk.

As we have argued, the extant empirical literature does not consider whether the comovement of liquidity increases dramatically after large market drops in manner similar to the idea that the comovement of stock returns goes up after large market drops (see the work of Ang, Chen and Xing (2004) on downside risk and especially the work of Ang and Chen (2002) for work on asymmetric correlations between portfolios). Further the extant work does not attempt to test or relate its finding to theories of market making that focus on capital constraints. Finally this stream of work does not explore sufficiently the distinction between the effects due the demand for liquidity and effects due to the supply of liquidity.

Our empirical approach is as follows. We use as our key variable the proportional quoted spread (as a proportion of the stock price)[2]. Since spreads trend downward over time and there are regime changes corresponding to tick size changes, we adjust spreads using a regression that accounts for these effects and the day of the week, holiday and other effects, following Chordia, Sarkar and Subrahmanyam (2004). The adjusted proportional spread represents the key variable for our analysis.

First, we document that both the proportional quoted spread (as a proportion of the stock prices) are negatively related to lagged market returns and lagged own returns. These effects are robust to the inclusion of the lagged quoted spread, turnover, volatility, one over the price, and other control measures. Further, we document that lagged negative market returns and lagged negative own returns have much larger effects than positive returns. This is consistent with the idea that negative market returns lead to increases in the spread. Using the buy-sell imbalance to proxy for the demand effect, we show that the negative effect of market returns persists after inclusion of the buy-sell imbalance. We also show that the results are stronger when we use the returns in the first five days of the month, i.e, the time magnitude seems to be in weeks rather than months. We sort the portfolios by size and volatility and show that the effects are strongest with smaller firms and firms with high volatility – here the large negative return has the biggest punch. Again, these results are consistent with the implication of Vayanos (2002) and Brunnermeier and Pedersen (2005) and others.

[2] We repeat the analysis with effective proportional spreads and find similar results.

We pursue further the idea that large negative returns have a effect on the supply of market making by looking at the comovements in market liquidity. The idea that stocks may commove more after negative returns has received attention in the literature on asymmetric return correlations and betas (see Ang and Chen (2002) and Ang, Chen and Xing (2004)) but not in the literature on market liquidity. We first regress the individual stock spread on the equally weighted market spread. We find that the correlation (liquidity beta) is higher with negative returns. This is suggestive of the idea that large negative movements induce market illiquidity in all stocks.

The R^2 statistic from the market model regression of the stock liquidity on the market liquidity is used as our input in the comovement regressions. Since the seminal work of Roll (1988), a high R^2 in market model regressions have been used to measure synchronicity in returns. We use a similar idea here in context of liquidity. If aggregate market liquidity does not explain individual stock liquidity much, the comovement in liquidity is low and each stock's liquidity is determined by its individual characteristics. However, if the comovement in liquidity is high, the average R^2 from a regression of individual stock liquidity on aggregate liquidity will be high. Hence, the liquidity of all stocks tends to move together, individual characteristics tends to be less important.

We use the equally weighted R^2 from the individual stock regression as our measure of comovement. If the stocks liquidity measures are correlated, this will show up as a higher R^2 and will be picked up in our comovement measure. We thus follow the literature due to Roll (1988) and Morck, Yeung and Yu (2000) in using this measure. We regress this measure against market returns and find the large negative market returns dramatically increase the comovement. This is consistent with the idea that large negative market shocks increase market illiquidity across all stocks.

Furthermore, we consider whether the comovement is due to industry effects or market effects. An increase in comovement caused by a negative industry return could show up as a market wide effect. We show that when we include the industry return and the market return (without that particular industry), large negative shocks to both returns increase comovement in liquidity. However, the market effect is much bigger in magnitude than the industry effect. This suggest that spillover effects across securities are important after negative market shocks and provides strong support for the idea that market liquidity drops across all assets at the same time when market returns drop.

We also explore the possibility that our findings are induced by investors' behavioral biases. For example, Daniel, Hirshleifer and Subrahmanyam (1998) and Baker and Stein (2004) develop theoretical models where a group of irrational, overconfident investors are assumed to overreact to their private signals and underreact to the information in the order flow. The overreaction to private signals causes sentiment shocks, reduces adverse selction component of trading costs, and, hence, improves liquidity as spreads narrow. In the model by Gervais and Odean (2001), investor overconfidence increases with gains in market value. Higher investor overconfidence following price gains suggests that liquidity should improve following positive returns. While we find a slight improvement in liquidity following up markets, most of the effect of lagged returns is concentrated in periods of negative market and stock returns. In addition, while we find an increase in the percentage of small trades (a proxy for uninformed trades) following positive returns, we do not find evidence of a significant decrease in small trades following negative returns.

Together, these results suggest that the asymmetric effect of lagged returns on liquidity that we report in this paper cannot be fully explained by the existing behavioral models.

Our empirical work thus provides strong evidence for the idea that large negative market movements cause decreases in market liquidity, particularly for small stocks and stocks with large volatility. More importantly, we show that commonality in liquidity is much higher after large negative stock market returns and this commonality is very broad (they are not within industry effects). All this supports the idea that liquidity falls after large negative stock market movements and is consistent with the "collateral" based view of liquidity that has been espoused in recent theoretical papers.

The remainder of the paper is organised as follows. Section 2 provides a description of the data and key variables. The methodology and results pertaining to the relation between past returns and liquidity is presented in Section 3 while Section 4 presents the same with respect to commonality in liquidity. Section 5 concludes the paper.

2. Data

The transaction-level data is collected from the New York Stock Exchange Trades and Automated Quotations (TAQ) database, which includes both the trade prices and the bid and ask quotes. These data are merged with daily and monthly return data retrieved from Center for Research in Security Prices (CRSP). The sample stocks are restricted to NYSE ordinary stocks for the period January 1988 to December 2003. We exclude Nasdaq stocks because their trading protocols are different. ADRs, units, shares of beneficial interest, companies incorporated outside U.S., Americus Trust components, close-ended funds, preferred stocks, and REITs are also excluded. To be included in our sample, the stock's price within a calendar year must be within \$2 and \$999. This filter is applied to avoid the influence of extreme price levels. The final database includes more than 600 million trades over sixteen years. The large coverage enables us to conduct a comprehensive analysis on the relation between liquidity level, liquidity commonality, and returns for thousands of stocks.

For the transaction data, if the trades are out of sequence, recorded before the market open or after the market close, or with special settlement conditions, they are not used in the computation of the daily spread and other liquidity variables. Quotes posted before the market open or after the market close are also discarded. The sign of the trade is decided by the Lee and Ready (1991) algorithm, which matches a trading record to the most recent quote preceding this trade by at least five seconds. If a price is closer to the ask quote, it is classified as a buyer-initiated trade and if it is closer to the bid quote it is classified as a seller-initiated trade. If the trade is at the midpoint of the quote, we use a "tick-test" to classify it as buyer- (seller-) initiated trade if the price is higher (lower) than the price of the previous trade. The anomalous transaction records are deleted according to the following filtering rules: (i) Negative bid-ask spread; (ii) Quoted Spread > $5; (iii) Proportional Quoted Spread > 20%; (iii) Effective spread / Quoted Spread > 4.0.

Following recent work by Chordia, Roll and Subrahmanyam (2000) and others, we use the proportional quoted bid-ask spread (QSPR) as the measure of liquidity. The raw QSPR is obtained from the TAQ database by dividing the difference between the ask quote and the bid quote by the midquote. The individual stock daily spread is constructed by averaging the spread for all transactions for each individual stock on a given trading day. During the last decade the spread width shrinks sharply because of the decrease of the tick size and the growth in trading volume. Thus, in order to ascertain the extent to which the change of spread is caused by past returns, we need to adjust the spread for deterministic time-series variations such as tick change effect, time trend, and calendar effects. Following Chordia et al (2004), we regress QSPR on a set of variables known to capture the seasonal variation in liquidity:

$$
\begin{aligned}
QSPR_{j,t} \quad = \quad & a_j + \sum_{k=1}^{4} b_{j,k}\, DAY_{k,t} + \sum_{k=1}^{11} c_{j,k} MONTH_{k,t} + d_j\, HOLIDAY_t \\
& + e_j\, TICK1_t + f_j\, TICK2_t + g_t\, YEAR1_t + h_t\, YEAR2_t + ASPR_{j,t}
\end{aligned}
\qquad (1)
$$

In equation 1, the following variables are employed: (i) 4 day of the week dummies ($DAY_{k,t}$) for Monday through Thursday ; (ii) 11 month of the year dummies ($MONTH_{k,t}$) for February through December; (iii) a dummy for the trading days around holidays ($HOLIDAY_{,t}$); (iv) two tick change dummies ($TICK1_t$ and $TICK2_t$) to capture the tick change from 1/8 to 1/16 on 06/24/1997 and the change from 1/16 to decimal system on 01/29/2001 respectively; (v) a time trend variable $YEAR1_t$ ($YEAR2\ _t$) is equal to the difference between the current calendar year and the year 1988 (1997) or the first year when the stock is traded on NYSE, whichever is later. The regression residual provides us with the adjusted quoted percentage spread (ASPR), which is used in our subsequent analyses. The time series regression equation 1 is estimated for each stock in our sample. Although it is not reported in the tables, the cross-sectional average of the estimated parameters show significant seasonal patterns in quoted spread: the average bid-ask spreads are higher on Fridays and in January to April and October and around holidays. The tick-size change dummies also pick up significant drop in spreads after the change in tick rule on NYSE. Our results comports well with the seasonality in liquidity documented in Chordia, Sarkar and Subrahmanyam (2005). Interestingly, we do not observe a significant time trend after adjusting for this seasonality in spreads. This is confirmed by the yearly averages of the daily raw quoted spread (QSPR) presented in Table 1. QSPR has a clear time trend with average spreads decreasing from 1.28% in 1988 to 0.26% in 2003. However, the trend is significantly removed in the seasonally adjusted spread (ASPR) as shown in Table 1. We also plot the two series, QSPR and ASPR, in Figure 1. As revealed by Figure 1, it is comforting that our adjustment process does a reasonable job in controlling for the time series variation in individual stock spreads.

3. Liquidity Level and Past Returns

3.1 Liquidity and Past Returns : Time Series Analysis

In order to examine the impact of lagged returns on spreads, we first aggregate the daily adjusted spreads for each stock to obtain average monthly adjusted percentage quoted spreads. We chose to examine this relation at monthly intervals to minimize the market microstructure influences on spread. We maintain the same notation, ASPR, for expositional convenience. Next, we regress the monthly adjusted percentage quoted spread for each firm *i* ($ASPR_{i,t}$) on the previous monthly individual stock returns ($R_{i,t-1}$) and the lagged return on the CRPS value-weighted market index ($R_{m,t-1}$) We include lagged spread to account for autocorrelations in spread.

We also introduce a set of firm specific variables that may affect the intertemporal variation in liquidity, beyond past returns. Market microstructure models in Demsetz (1968), Stoll (1978) and Ho and Stoll (1980) suggest that inventory turnover rates affect the market maker's inventory risks. For example, if large trading volume or turnover in a stock reduces the inventory balances and risks per trade, more trading should lead to smaller spreads. We control for the changes in spread due to the market maker's inventory concern by adding turnover rate in the regression, although such inventory concerns are likely to be temporary and not dominant at monthly horizon. Monthly turnover rate for firm *i*, measured by total trading volume divided by shares outstanding, is denoted as $turn_{it.}$ In addition to turnover, liquidity may also be affected by large order imbalance. Heavy selling or buying may amplify the inventory problem, causing market makers to adjust their quotes to attract more trading on the other side of the market.. Chordia, Roll and Subrahmanyam (2002) report that order imbalances are contemporaneously correlated with spreads and conjecture that this could be due to specialists' difficulty in adjusting quotes on both sides of the market during periods of large imbalances. To control for this effect, we add $ROIB_{it}$, measured by the absolute value of the difference between dollar amount of buy and sell orders standardized by the dollar amount of trading volume over the same month, into the regression model.

It is well known that individual firm spreads are positively affected by the return volatility. Hence, we include the monthly volatility ($STD_{i,t}$) of returns on stock *i* using the method of French, Schwert and Stambaugh (1987). Finally, we add a price level control to ensure that the predictability in spread is not a manifestation of variations in the price level. Since the price level is used in the computation of proportional spread, we add the inverse of the stock price for firm *i* obtained in the month prior to *t* ($1/P_{t-2}$), and denote this variable as $PRC_{i,t-2}$.

We estimate the regression model for liquidity for each firm incorporating the above variables in our time series regression specification:

$$ASPR_{it} = a_i ASPR_{i.t-1} + b_i R_{i.t-1} + m_i R_{m.t-1} + c1_{i.} ROIB_{i.t-1} + c2_{i.} ROIB_{i.t} + d1_{i.} STD_{i.t-1} + d2_{i.} STD_{i.t} + f_{i.} PRC_{i.t-2} + v_{i.} TURN_{i.t} + \varepsilon_{i.t} \quad (2)$$

We run the OLS regression in equation (2) for each individual stock to estimate the coefficients. We report the mean and median of the estimated regression coefficients, together with the percentage of statistically significant ones (at 5% level), across all firms in our sample. To be included in the sample, the stock should be listed at NYSE and must have at least 60 valid monthly observations during the sample period 1988-2003. After this filtering, there are about one thousand five hundred stocks in our sample.

Table 2 presents the equally-weighted average coefficients across all individual stock regressions. We find that high order imbalances in the previous period increases the average firm level spread. Turnover is negatively related to spread, consistent with the exisiting literature that documents that a larger turnover is likely to lower spread. In addition, high contemporaneous stock price volatility increases the spread, consistent with Chordia, Sarkar and Subrahmanyam (2005). As expected the inverse of stock price is positively related to spread, suggesting that the time-series variation in proportional spread is affected by changes in price levels.

More importantly, we find that both the lagged individual stock return and the lagged market return have significant negative influence on spread width even after controlling for the above factors. The evidence presented in Table 2 shows that liquidity is positively affected by prior returns on the stock as well as the market. It would be interesting to examine if this relation is different for prior gains and losses. In particular, we want to examine whether a drop in the price of the individual stock (or the market index) leads to a significant increase in spreads. Hence, we modify equation (3) to allow liquidity to react differentially to positive and negative lagged returns:

$$\begin{aligned} ASPR_{it} &= a_i ASPR_{i.t-1} + b_{UP,i} R_{i.t-1} D_{UP,i,t-1} + b_{DOWN,i} R_{i.t-1} D_{DOWN,i,t-1} + m_{UP,i} R_{m.t-1} D_{UP,m,t-1} \\ &+ m_{DOWN,i} R_{m.t-1} D_{DOWN,m,t-1} + c1_{i.} ROIB_{i.t-1} + c2_{i.} ROIB_{i.t} + d1_{i.} STD_{i.t-1} \\ &+ d2_{i.} STD_{i.t} + f_{i.} PRC_{i.t-2} + v_{i.} TURN_{i.t} + \varepsilon_{i.t} \end{aligned} \qquad (3)$$

where $D_{UP,i,t}$ ($D_{DOWN,i,t}$) is a dummy variable that is equal to one if and only if $R_{i,t}$ is greater (less) than zero. $D_{UP,m,t}$ ($D_{DOWN,m,t}$) are similarly defined based on $R_{m,t.}$ The control variables are identical to those defined in equation (2).

Panel A of Table 3 presents the empirical estimate of equation 3 for monthly adjusted spreads averaged from all the trading days in that month. We find a significantly greater effect of negative lagged returns on liquidity. Although both negative and positive stock returns affect liquidity, the regression coefficient for negative lagged individual stock return (market return) is -0.417 (-0.246), which is more than the coefficient of -0.175 (-0.149) for lagged positive individual stock return (market return). In order words, a drop in stock price over the past month leads to a bigger decline in the stock's liquidity when compared to the liquidity improvement following a rise in stock price. We have considered additional lagged returns (not reported here) and we obtain similar. While the effect of lagged returns declines as we move to longer lags, the asymmetric effect of positive and negative returns remains prominent. We also consider the effect of lagged returns on liquidity over a shorter frequency based on the first five days of the month. Panel B of Table 3 shows that the relation between lagged returns and subsequent liquidity is stronger in the first five days, indicating that the phenomenon is more pronounced at the higher time frequency, i.e. weekly horizon.

As the next step, we examine whether the magnitude of lagged returns have differential impact on the firm's liquidity level. Thus, we run the regression as follows

$$\begin{aligned} ASPR_{it} &= a_i ASPR_{i.t-1} + b_{UP,SMALL,i} R_{i.t-1} D_{UP,SMALL,i,t-1} + b_{UP,LARGE,i} R_{i.t-1} D_{UP,LARGE,i,t-1} \\ &+ b_{DOWN,SMALL,i} R_{i.t-1} D_{DOWN,SMALL,i,t-1} + b_{DOWN,LARGE,i} R_{i.t-1} D_{DOWN,LARGE,i,t-1} \\ &+ m_{UP,SMALL,i} R_{m.t-1} D_{UP,SMALL,m,t-1} + m_{UP,LARGE,i} R_{m.t-1} D_{UP,LARGE,m,t-1} \\ &+ m_{DOWN,SMALL,i} R_{m.t-1} D_{DOWN,SMALL,m,t-1} + m_{DOWN,LARGE,i} R_{m.t-1} D_{DOWN,LARGE,m,t-1} \\ &+ c1_{i.} ROIB_{i.t-1} + c2_{i.} ROIB_{i.t} + d1_{i.} STD_{i.t-1} \\ &+ d2_{i.} STD_{i.t} + f_{i.} PRC_{i.t-2} + v_{i.} TURN_{i.t} + \varepsilon_{i.t} \end{aligned} \qquad (4)$$

where $D_{UP,,SMALL,,i,,t}$ ($D_{DOWN,,SMALL,,i,,t}$) is a dummy variable that is equal to one if and only if $R_{i,t}$ is between zero and 1.5 standard deviation above (below) the mean return for stock i. $D_{UP,,LARGE,,i,,t}$ ($D_{DOWN,,LARGE,,,i,,t}$) is a dummy variable that is equal to one if and only if $R_{i,t}$ is greater (less) than 1.5 standard deviation above (below) the mean return for stock i. $D_{UP,,SMALL,,m,,t}$ ($D_{DOWN,,SMALL,,m,,t}$) and $D_{UP,,LARGE,,m,,t}$ ($D_{DOWN,,LARGE,,m,,t}$) are similarly defined based on $R_{m,t}$.

The results presented in Table 3 Panels C (based on monthly adjusted spreads) and D (based on the spreads in the first five trading days of the month) highlights the distinct asymmetric effects of large negative returns on both the individual stock as well as the market. As shown in Panels C and D, a large negative return leads to a bigger widening of the spreads when compared to the effect of small negative returns. On the other hand, spreads are not differentially affected by large and small positive returns on individual and market returns. Hence, we show that large negative returns, particularly on the market index, exerts stronger influence of liquidity. This result is consistent with the funding constraint argument proposed in the recent theoretical models (Brunnermeier and Pedersen (2005)).

3.2 Liquidity and Past Returns: Cross-sectional Evidence

The theoretical models (e.g. Brunnermeier and Pederson (2005) and Vayanos (2002)) on the effect of funding constraints on liquidity suggest that the reduction in liquidity following a down market would be dominant in high volatility stocks. This is based on the idea that high volatility stocks require greater use of capital as they are more likely to suffer higher haircuts (and margin requirements) when funding constraints bind. We go on to examine the cross-sectional differences in the relation between lagged returns and spreads among stocks that differ in historical volatility, controlling for firm size. To do this, the parameter estimates from equation (3) are grouped into nine portfolios formed by a two-way dependent sorts based on firm size and historical stock return volatility. We first sort the sample stocks according to their average market value during the year 1996, 1997, and 1998 (in the middle of the sample period) and form three size-portfolios (small, medium and large size). Within each size portfolio, we sort the stocks by their average monthly volatility during the year 1996, 1997, and 1998 and form three volatility-portfolios (high, medium and low volatility). The mean and median individual stock's coefficient estimates from the regression of equation (4) are reported for each size-volatility portfolio.

As shown in Table 4, the effect of lagged returns on spreads are higher for small firms and firms with highly volatile returns. The cross-sectional result confirms our previous conclusion that lagged negative returns, on both the individual stock and the market, have stronger impact on stock's liquidity. Furthermore, we find that the negative return on the stock in the past month predicts a significantly greater reduction in liquidity for high volatility stocks, controlling for firm size. Similarly, a down market state is followed by significantly larger stock spreads. The asymmetric effects of the lagged large negative monthly returns on liquidity occur primarily for the smallest, most volatile firms. Hence, our findings support the hypothesis in Brunnermeier and Pedersen (2005) and others that a stock's market liquidity is affected by the traders' funding liquidity.

The above findings on the asymmetric effect of negative and positive returns are also consistent with those reported in recent empirical work. Chordia, Roll and Subrahmanyam (2001, 2002) show that at an aggregate level, daily spreads increase dramatically on days with negative daily market return but decrease only marginally on positive market returns. They interpret this to indicate that inventory accumulation concerns (high specialist inventory levels) are more binding in down markets.

In this section we contribute to the existent literature in the following ways. First, we show that individual stock returns, as well as market returns, have significant prediction power for the firm-level liquidity in next month. At the monthly frequency, the market maker's direct inventory concern is likely to be alleviated since he or she has more time to adjust his or her inventory. Thus, our results are more likely to be driven by the funding constraint story. Second, we document the asymmetric response of liquidity to positive and negative returns, that is, negative returns have stronger impact on liquidity. Third, we find that the magnitude of returns matters and the effect of lagged returns are strongest in states of the world when the negative returns are large. Finally, we find that the relation between (large) negative lagged returns and liquidity level are most prominent for small, volatile stocks. Overall, our findings in this section provide empirical support to the recent theoretical predictions on market liquidity from the funding constraint models.

3.3 Liquidity and Past Returns: Alternative Explanations

Recent behavioral models provide a potentially different interpretation of our results. Barber and Odean (2001, 2002) and Glaser and Weber (2004) report that high past market returns and past portfolio returns lead to more subsequent trading volume by (overconfident) individual investors. Although these papers consider the impact of past returns on trading volume, they do not explore whether past returns have an impact on a stock's liquidity. By increasing supply of (overconfident) buyers and sellers following price run-ups, the behavioral model in Baker and Stein (2004) predict a positive relation between lagged returns and firm level liquidity when sentiment traders may be kept out of the market when the market return is negative because of prohibitive short-sale constraints. Hence, the liquidity effect of lagged returns may also be related to behavioral factors, which we explore in this sub-section.

We use trade-size to distinguish between the sophisticated and less sophisticated traders and examine the trading behavior of different trade-size groups, focusing on the small, less sophisticated, heuristics based traders. Recent studies, such as Lee (1992), Lee and Radhakrishna (2000), Bhattacharya (2001), Hvidkjaer(2003), and Shantikumar (2004), show that small trades are more likely to be affected by behavioral biases. For example, Shantikumar (2004) shows that the reaction of small traders to sequences of positive and negative earnings surprise are most consistent with the predictions of behavioral models in Daniel, Hirshleifer and Subrahmanyam (1998) and others. We explore if the inter-temporal variation in the liquidity is better explained by the entry and exit of the less sophisticated (small) traders in reaction to past returns. In our work, small traders are measured by proportion of small trades (i.e. number of small trades divided by total number of trades) denoted as, SmallTrade%. Following previous papers (Chan and Fong (2000)), we classify trades below 500 shares as those by small traders. We estimate the following regression equation:

$$SmallTrade\%_{i.t} = \alpha_i SmallTrade\%_{i.t-1} + \beta_i^{+} PosR_{i.t-1} + m_{i.} R_{m.t} + \beta_i^{-} NegR_{i.t-1} + \varepsilon_{i.t} \quad (5)$$

The empirical estimate of equation 5 in Table 5 reveals that small trades are positively dependent on lagged returns on both the individual stock as well as the market, consistent with the behavioral predictions. Also reported in Table 5 is the relation between small trades and lagged positive and negative returns. Unlike the stronger relation between lagged negative returns and spreads we document in this paper, we find that small trades have a significant relation with lagged positive returns only. The differential effect of positive and negative returns on liquidity and small trades suggests that the overconfidence models do not fully explain the directional asymmetry we observe between lagged returns and liquidity.

4 Comovement in Liquidity

4.1. Comovement in Liquidity and Market Returns

The models in Brunnermeier and Pedersen (2005) suggest that large negative return reduce the pool of capital and the supply of market making and hence reduces the market liquidity. In particular, their model predicts that the funding liquidity constraints following down market states increases the commonality in liquidity across securities and its comovement with the market. In this section, we pursue this idea further and examine the relation between commonality in liquidity and market returns. Specifically, we investigate whether the commonality in liquidity increases when there is a negative market return, especially large negative market return.

We adopt a measure that is commonly used to analyse stock price comovement to analyze the synchronicity in liquidity. The R^2 statistic from the market model regression has been extensively used to measure comovement in stock prices (e.g. Roll (1988), Morck, Yueng and Yu (2000)). A high R^2 indicates that a large portion of the variation is due to common, market-wide movements. As the first step, we use a single-factor market model to compute the commonality in daily liquidity for each stock in each month. Following Chordia, Roll and Subrahmanyam (2001), the daily percentage change in quoted bid-ask spread for an individual stock (averaged using intra-day transactions) is regressed on the cross-sectional average of daily percentage change in spread within each month. We estimate the linear regression:

$$DL_{i,s} = a_i + \beta_i DL_{m.s} + \varepsilon_{i.s} \qquad (6)$$

where $DL_{i,s} = (ASPR_{i.s} - ASPR_{i.,s-1}) / ASPR_{i.s-1}$ is the percentage change in adjusted daily proportional quoted spread for stock *i* from day *s-1* to *s*, and $DL_{m.s} = (ASPR_{m.s} - ASPR_{m.s-1}) / ASPR_{m.s-1})$ is the daily percentage change in spreads for the market portfolio (measured by the cross-sectional (equally-weighted) average of adjusted spreads across all stocks in the sample) in day *s*. Thus, for each stock *i* in each month *t*, the above "market model" regression yields an $R^2_{i,t}$ which is used as a proxy for the comovement of the individual stock liquidity with the market average liquidity. A high $R^2_{i,t}$ suggests that a large portion of the daily variations in liquidity for stock i in month t can be explained by changes in market-wide liquidity. Table 6 reports that the average beta coefficient across all stocks is 1.092, with higher average coefficients when the market index returns are negative. Hence, negative market returns increases the illiquidity of all stocks in the market.

Next, we compute the cross-sectional (equally-weighted) average of $R^2_{i,t}$ for each month *t*, denoted as R_t^2, which measures the degree of commonality in liquidity movements in month t. A high value of R_t^2 reflects a strong common component in liquidity changes, and hence, high comovement in liquidity. Since the R_t^2 values are constrained to be between zero and one by construction, comovement is defined by the logit transformation of R_t^2, $COMOVE_t = \ln[R_t^2/(1-R_t^2)]$. A high $COMOVE_t$ indicates that liquidity changes for stocks traded in the market in month t is primarily driven by the market liquidity. In order to examine the effect of returns on commonality in liquidity, we regress our comovement measure on market returns (R_{mt}):

$$COMOVE_t = a + \gamma R_{m,t} + \varepsilon_t \qquad (7)$$
$$COMOVE_t = a + b R_{m,t} D_{UP,t} + c R_{m,t} D_{DOWN,t} + \varepsilon_t \quad (8)$$
$$COMOVE_t = a + g R_{m,t} D_{DOWN,LARGE,t} + e R_{m,t} D_{UP,LARGE,t} + h R_{m,t} D_{SMALL,t} + \varepsilon_t \quad (9)$$

where, $D_{UP,t}$ ($D_{DOWN,t}$) is the dummy variable that captures the positive and negative returns, and $D_{UP,LARGE,t}$ ($D_{DOWN,LARGE,t}$) is the dummy variable that is equal to one when the positive (negative) return is large, defined as z standard deviations from its mean. We consider three values of z: 2.0 or 1.5 or 1.0 standard deviations from the mean. Equation (7) is a time-series regression of liquidity comovement on market returns at monthly frequency. Equations (8) allows us to examine the separate effects of positive and negative market return states while equation (8) incorporates the sign as well as the magnitude of market returns.

Table 7 presents the empirical estimates of the relation between comovement and market returns. As shown in the first column in Panel A of Table 7, which reports the coefficient estimates of Equation (7), the comovement in liquidity is significantly negatively related to market returns. More importantly, when we use Equation (8) as the regression specification, the result suggests that liquidity comovement is significantly higher in down markets but its change is insignificant in up markets. Consistent with the theoretical predictions, when the market prices decline, the capital constraint faced by the market making sector becomes more binding and market liquidity declines.

Equation (9) allows the commonality estimates to vary with the magnitude of market returns. Assuming that the market makers hold long positions on the market, the capital constraint on the providers of liquidity is most binding when there is a huge decline in market prices, i.e., the crisis period. To be consistent with the hypothesis, we should observe that large declines in market prices induce a huge, more than proportional, impact on the liquidity of all stocks in the market. The evidence supports this prediction: there is a much stronger comovement in liquidity when there is a huge decline in market prices. From the third to the fifth column in Panel A of Table 7, we test one standard deviation, one and half standard deviation, and two standard deviation drop in market valuation level, and find all these different specifications of large negative market returns produce much greater commonality in liquidity. On the other hand, periods of rising market valuations of similar magnitudes do not affect commonality in liquidity significantly.

When the aggregate liquidity R_t^2 indicates a high proportion of market-wide information, it might have more market-wide volatility or less firm-specific volatility. To examine whether our results are due to smaller firm-specific volatility in down markets, we estimate another set of regressions similar to equations (7) to (9), but replacing the comovement measure $COMOVE_t$ with the volatility of the residual liquidity ($log(SSR_t)$) as the dependent variable. The results, presented in Panel B of Table 7, show that the residual volatility is unaffected by the state of the market, across all specifications. This suggests that the increase in liquidity comovement in down market states documented in our paper is due to an increase in market-wide comovement rather than a decline in firm-level liquidity variations.

4.2 Commonality in Liquidity: Industry Spillover Effects

Our findings on liquidity commonality comport with those in Coughenour and Saad (2004). Coughenour and Saad (2004) provide evidence of covariation in liquidity arising because specialist firm provide liquidity for a group of firms and share common pool of capital, inventory and profit information. An important issue that remains unexplored is whether there are any spillover effects of the supply side constraints on the liquidity of other stocks in the market. Specifically, we examine if industry-wide comovement in liquidity is affected by a decrease in the valuation of stocks from other industries, over and above the effect of its own industry portfolio returns. We estimate the following factor model for daily change in liquidity for security i ($DL_{i,s}$), within each month :

$$DL_{i,s} = a_i + \beta_i DL_{INDj,.s} + \varepsilon_{i.s} \qquad (10)$$

where the industry-liquidity factor $DL_{INDj.s} = (ASPR_{INDj.s} - ASPR_{INDj,s-1}) / ASPR_{INDj,s-1}$ is the daily percentage change in the equally-weighted average of adjusted spreads across all stocks in *industry j* in day *s*, using the 17 industry classification by Fama-French.[3] The regression r-square obtained from equation (10) is averaged across all stocks within the same industry to measure commonality in liquidity at the industry level. The logit transformation of the industry level average R_t^2 ($COMOVE_{INDj,t}$) is regressed on the monthly returns on two portfolios: the returns on industry portfolio j ($R_{INDj,t}$) and the returns on the market portfolio, excluding industry portfolio j ($R_{MKTj,t}$).

$$COMOVE_{INDj,t} = a + b_{IND} R_{INDj,t} + b_{MKT} R_{MKTj,t} + \varepsilon_t \qquad (11)$$

We also investigate the asymmetric effect of positive and negative industry and market returns on liquidity comovement as well as the effect of large and small industry and market returns:

$$\begin{aligned} COMOVE_{INDj,t} = {} & a + b_{IND} R_{INDj,t} D_{UP,INDj,t} + c_{IND} R_{INDj,t} D_{DOWN,INDj,t} \\ & + b_{MKT} R_{MKTj,t} D_{UP,MKTj,t} + c_{MKT} R_{MKTj,t} D_{DOWN,MKT,t} + \varepsilon_t \qquad (12) \end{aligned}$$

$$COMOVE_{INDj,t} = a + f_{IND} R_{INDj,t} D_{UP,LARGE,INDj,t} + g_{IND} R_{INDj,t} D_{DOWN,LARGE,INDj,t}$$

[3] The industry classifications are obtained from K. French's website at
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

$$+ h_{IND} \; R_{INDj,t} D_{SMALL,INDj,t} + f_{MKT} R_{MKTj,t} D_{UP,LARGE,MKTj,t} + g_{MKT} \; R_{MKTj,t} D_{DOWN,LARGE,MKTj,t}$$
$$+ h_{MKT} \; R_{MKTj,t} D_{SMALL,MKTj,t} + \varepsilon_t \qquad (13)$$

where the dummy variables are defined in the same way as in equations (8) and (9). The regression coefficient associated with the independent variable $R_{MKTj,t}$ provides a measure liquidity spillover effects.

The results are reported in Table 8, Panel A. We find that industry portfolio returns, especially large, negative returns, have a significant effect on liquidity commonality while positive industry returns do not affect liquidity comovement. More interestingly, we find that the return on the market portfolio (excluding own industry returns) exert a strong influence on liquidity comovement on industry liquidity. In the basic formulation (Model A), the market portfolio returns dominate the industry returns in terms of its effect of industry-wide liquidity movements. The regression coefficient estimate for $R_{MKTj,t}$ is a significant -0.609 while the coefficient for $R_{INDj,t}$ is -0.191 and statistically insignificant at conventional levels. When we separate the returns according to their magnitude, large negative market returns turn out to have the biggest impact on liquidity movements. For example, large negative industry portfolio return (Model C3) is associated with an increase in the industry liquidity comovement by 0.727 while a large negative market return deepens the industry-wide comovement by more than twice the magnitude at 1.523. These results strongly support the idea that when negative market returns occur, spillovers due to capital constraints occur across industries, increasing the comovement in liquidity.

To check for the robustness of our results, we also consider a two-factor (market and industry) version of equation (10):

$$DL_{i,s} = a_i + \beta_{MKT,i} DL_{MKTj,.s} + \beta_{IND,i} DL_{INDj,.s} + \varepsilon_{i.s} \qquad (14)$$

where we add an additional market factor, $DL_{MKT.s} = (ASPR_{MKT,s} - ASPR_{MKT,s-1}) / ASPR_{MKT,s-1}$, which is the daily percentage change of the cross-sectional average of adjusted spreads across all stocks in the sample in day *s*. We repeat our regression analysis in equations (11) to (13) using the two factor model in equation (14) and report the results in Panel B, Table 8. We obtain results similar to that using a single factor model, and hence, our results are robust to alternative specifications of the factor model for liquidity. Overall, we show that liquidity of stocks within an industry show the greatest commonality when the aggregate market experience a huge decline in market valuations, emphasizing the importance of the spillover effect across industries and consistent with the funding constraint faced by the market making sector.

4.3 Comovement in Liquidity: Cross-sectional analysis

Brunnermeier and Pedersen (2005) suggest that the funding liquidity constraint has greater impact on the liquidity level of high volatility stocks than low volatility stocks. This prediction is supported by our empirical result in Table 4. A natural question is whether the impact of funding liquidity constraint on the liquidity commonality is also greater for high volatility stocks. To answer this question, we sort the sample stocks into nine (three by three) size-volatility portfolios by the two-way dependent sorting method as described in Section 3. We run the regression of equation (6) and take the average of R2i,t within each of the nine size-volatility portfolios and regress them on the contemporaneous market returns using equation (9).

The estimates of liquidity comovement for size-volatility sorted groups reported in Table 9 reveal several patterns. First, significant liquidity commonality across all size-volatility portfolios is exclusive to down market states with large negative returns. This evidence corroborates well with our earlier results on the drop in liquidity in (large) down market states. Second, within each size category, the sensitivity of liquidity commonality to large negative market returns increases with stock return volatility. A large drop in market prices increases the funding constraints of the liquidity providers, and this effect is most prominent for stocks which are exposed to tight margin requirements. Consequently, comovement in liquidity increases the most for the high volatility stocks. Finally, commonality in liquidity among large stocks is more sensitive to large negative return shocks than that for small stocks. We conjecture that when investors face a large liquidity constraint, they are more likely to unwind their position in liquid (large) stocks first, due to their relatively low transaction costs in down market state. In addition, index funds are more likely to sell the stocks in their index when market goes down, and the most popular index is composed mainly of large stocks such as the S&P 500 index.

5. Conclusion

This paper shows that liquidity responds asymmetrically to changes in asset market values. Large negative returns decrease liquidity much more than positive returns increase liquidity. Further these effects of returns on liquidity are strongest for high volatility firms, consistent with the theoretical literature due Kyle and Xiong (2000), Vayanos (2004) and Brunnermeier and Pedersen (2005). We explore the commonality in liquidity and show a drastic increase in commonality after large negative market returns. This relation between market returns and commonality in liquidity is highest for high volatility stocks. We also document a spillover effect of liquidity commonality across industries. Liquidity commonality within an industry increases significantly when the market returns (excluding the specific industry) are large and negative. These are strong evidence of a supply effect considered in Brunnermeier and Pedersen (2004) and Anshuman and Viswanathan (2005).

Overall, we believe that our paper presents strong evidence of the collateral view of market liquidity, the idea that market liquidity falls after large negative market returns because many holders of assets are forced to liquidate and because collateral value of the assets of financial intermediaries falls, making it difficult for them to provide liquidity precisely when the market demands it.

*** Note: This is a preliminary version of the paper, subsequent versions will look at distinguishing between demand (inventory) effects and supply effects more carefully. ***

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Table 1: Descriptive Statistics: Raw and Adjusted Spreads

The proportional quoted bid-ask spread for firm j, $QSPR_j$, is defined as (ask quote–bid quote) / [(ask quote + bid quote)/2]. Daily $QSPR_j$ is generated by averaging the spread of all the transactions within a day. The daily quoted spreads are adjusted for seasonality to obtain the seasonally adjusted spreads, $ASPR_j$, using the following regression model:

$$QSPR_{j,t} = a_j + \sum_{k=1}^{4} b_{j,k}\, DAY_{k,t} + \sum_{k=1}^{11} c_{j,k} MONTH_{k,t} + d_j\, HOLIDAY_t$$
$$+ e_j\, TICK1_t + f_j\, TICK2_t + g_t\, YEAR1_t + h_t\, YEAR2_t + ASPR_{j,t}$$

where we employ (i) 4 day of the week dummies ($DAY_{k,t}$) for Monday through Thursday ; (ii) 11 month of the year dummies ($MONTH_{k,t}$) for February through December; (iii) a dummy for the trading days around holidays ($HOLIDAY_{,t}$); (iv) two tick change dummies ($TICK1_t$ and $TICK2_t$) to capture the tick change from 1/8 to 1/16 on 06/24/1997 and the change from 1/16 to decimal system on 01/29/2001 respectively; (v) a time trend variable $YEAR1_t$ ($YEAR2_t$) is equal to the difference between the current calendar year and the year 1988 (1997) or the first year when the stock is traded on NYSE, whichever is later.
The summary statistics of the annual average of the daily quoted spread (QSPR) and adjusted spread (ASPR) for the sample period January 1988 to December 2003 are reported in the panel below.

Year	Number of Securities	QSPR (Unadjusted Proportional Quoted Spread)			ASPR (Adjusted Proportional Quoted Spread)		
		Mean	Median	Coefficient of Variation	ASPR EW-Average	ASPR Median	Coefficient of Variation of ASPR
1988	1040	1.28%	1.04%	0.636	1.37%	1.10%	0.661
1989	1098	1.14%	0.91%	0.694	1.27%	1.00%	0.729
1990	1149	1.42%	1.09%	0.728	1.59%	1.24%	0.748
1991	1228	1.32%	1.02%	0.710	1.52%	1.17%	0.722
1992	1319	1.25%	0.98%	0.715	1.49%	1.18%	0.705
1993	1445	1.21%	0.92%	0.808	1.50%	1.19%	0.710
1994	1504	1.16%	0.90%	0.731	1.51%	1.23%	0.664
1995	1567	1.06%	0.82%	0.758	1.47%	1.19%	0.669
1996	1643	0.98%	0.74%	0.818	1.42%	1.18%	0.662
1997	1707	0.77%	0.59%	0.814	1.35%	1.09%	0.694
1998	1698	0.78%	0.57%	0.844	1.38%	1.10%	0.712
1999	1577	0.85%	0.61%	0.840	1.39%	1.13%	0.692
2000	1452	0.93%	0.61%	0.949	1.42%	1.17%	0.682
2001	1308	0.54%	0.31%	1.217	1.41%	1.17%	0.650
2002	1226	0.40%	0.21%	1.290	1.30%	1.07%	0.672
2003	1190	0.26%	0.13%	1.262	1.16%	0.96%	0.707

Table 2: Relation Between Spread and Lagged Returns

Monthly average adjusted spreads for each security is regressed on lagged individual stock and market returns.

$$ASPR_{it} = a_i ASPR_{i.t-1} + b_i R_{i.t-1} + m_i R_{m.t-1} + c1_{i.} ROIB_{i.t-1} + c2_{i.} ROIB_{i.t} + d1_{i.} STD_{i.t-1}$$
$$+ d2_{i.} STD_{i.t} + f_{i.} PRC_{i.t-2} + v_{i.} TURN_{i.t} + \varepsilon_{i.t}$$

where $ASPR_{i,t}$ refers to stock i's seasonally adjusted proportional spread, $R_{i,t}$ is the return on stock i in month t, $R_{m,t}$ is the month t return on the CRSP value-weighted index, $ROIB_{i,t}$ is the absolute value of the monthly difference in the dollar value of buyer- and seller-initiated transactions (standardized by monthly dollar trading volume); $TURN_{i,t}$ refers to the number of shares traded each month divided by the total shares outstanding; $PRC_{i,t-2} = (1/P_{i,t-2})$, where $P_{i,t-2}$ is the stock price at the beginning of month t-2.; $STD_{i,t}$ is the volatility of stock i's returns in month t. $ASPR_{i,t}$ is the average daily spreads across all trading days in month t. Cross-sectional averages and medians of coefficient estimates are reported in the row labeled as "Mean" and "Median". The averages that are significant at 99%, 95%, and 90% confidence level are labeled with ***, **, and * correspondingly. "% of positive (negative)" and "% of positive (negative) significant" refer to the percentage of the positive (negative) coefficient estimates and the percentage of the coefficient estimates with t-statistics greater than +1.645 (-1.645) as the 5% critical level in a one-tailed test.

Estimate Statistics	Intercept	$R_{i.t-1}$	$R_{m.t-1}$	$ROIB_{i.t-1}$	$ROIB_{i.t}$	$STD_{i.t-1}$	$STD_{i.t}$	$PRC_{i.t-2}$	$TURN_{i.t}$	$ASPR_{i.t-1}$
Mean	0.344***	-0.297***	-0.208***	0.020**	-0.017**	-0.003	0.409***	1.202***	-0.021***	0.695***
Median	0.261	-0.218	-0.093	0.013	-0.025	-0.015	0.299	0.803	-0.003	0.713
% of negative		97.3%	69.6%		59.7%	53.3%			73.5%	
% of positive	97.7%			57.1%			87.7%	81.4%		100.0%
% of significant	89.8%	71.1%	14.8%	10.7%	5.7%	7.8%	53.0%	36.2%	31.1%	69.5%

Table 3: Relation Between Spread and the Sign and Magnitude Lagged Returns

Monthly average adjusted spreads for each security is regressed on lagged individual stock and market returns.

Specification 1: The Signed Lagged Return Regression

$$ASPR_{it} = a_i ASPR_{i.t-1} + b_{UP,i} R_{i.t-1} D_{UP,i,t-1} + b_{DOWN,i} R_{i.t-1} D_{DOWN,i,t-1} + m_{UP,i} R_{m.t-1} D_{UP,m,t-1}$$
$$+ m_{DOWN,i} R_{m.t-1} D_{DOWN,m,t-1} + c1_{i.} ROIB_{i.t-1} + c2_{i.} ROIB_{i.t} + d1_{i.} STD_{i.t-1}$$
$$+ d2_{i.} STD_{i.t} + f_{i.} PRC_{i.t-2} + v_{i.} TURN_{i.t} + \varepsilon_{i.t}$$

where $ASPR_{i,t}$ refers to stock i's seasonally adjusted proportional spread, $R_{i,t}$ is the return on stock i in month t, $R_{m,t}$ is the month t return on the CRSP value-weighted index, $D_{UP,i,,t}$ ($D_{DOWN,,i,,t}$) is a dummy variable that is equal to one if and only if $R_{i,t}$ is greater (less) than zero. $D_{UP,m,,t}$ ($D_{DOWN,,m,,t}$) are similarly defined based on $R_{m,t}$. In Panel A (B), $ASPR_{i,t}$ is the average daily spreads across all (first five) trading days in month t.

$ROIB_{i,t}$ is the absolute value of the monthly difference in the dollar value of buyer and seller-initiated transactions (standardized by monthly dollar trading volume); $TURN_{i,t}$ refers to the number of shares traded each month divided by the total shares outstanding; $PRC_{i,t-2} = (1/P_{i,t-2})$, where $P_{i,t-2}$ is the stock price at the beginning of month t-2.; $STD_{i,t}$ is the volatility of stock i's returns in month t.

Cross-sectional averages and medians of coefficient estimates are reported in the row labeled as "Mean" and "Median". The averages that are significant at 99%, 95%, and 90% confidence level are labeled with ***, **, and * correspondingly. "% of positive (negative)" and "% of positive (negative) significant" refer to the percentage of the positive (negative) coefficient estimates and the percentage of the coefficient estimates with t-statistics greater than +1.645 (-1.645) as the 5% critical level in a one-tailed test. The estimates of the regression coefficients for the control variables are not reported here.

Specification 2: The Signed Lagged Return Magnitude Regression

$$ASPR_{it} = a_i ASPR_{i.t-1} + b_{UP,SMALL,i} R_{i.t-1} D_{UP,SMALL,i,t-1} + b_{UP,LARGE,i} R_{i.t-1} D_{UP,LARGE,i,t-1}$$
$$+ b_{DOWN,SMALL,i} R_{i.t-1} D_{DOWN,SMALL,i,t-1} + b_{DOWN,LARGE,i} R_{i.t-1} D_{DOWN,LARGE,i,t-1}$$
$$+ m_{UP,SMALL,i} R_{m.t-1} D_{UP,SMALL,m,t-1} + m_{UP,LARGE,i} R_{m.t-1} D_{UP,LARGE,m,t-1}$$
$$+ m_{DOWN,SMALL,i} R_{m.t-1} D_{DOWN,SMALL,m,t-1} + m_{DOWN,LARGE,i} R_{m.t-1} D_{DOWN,LARGE,m,t-1}$$
$$+ c1_{i.} ROIB_{i.t-1} + c2_{i.} ROIB_{i.t} + d1_{i.} STD_{i.t-1}$$
$$+ d2_{i.} STD_{i.t} + f_{i.} PRC_{i.t-2} + v_{i.} TURN_{i.t} + \varepsilon_{i.t}$$

where $ASPR_{i,t}$ refers to stock i's seasonally adjusted proportional spread, $R_{i,t}$ is the return on stock i in month t, $R_{m,t}$ is the month t return on the CRSP value-weighted index, $D_{UP,,SMALL,,i,,t}$ ($D_{DOWN,,SMALL,,i,,t}$) is a dummy variable that is equal to one if and only if $R_{i,t}$ is between zero and 1.5 standard deviation above (below) the mean return for stock i. $D_{UP,,LARGE,,i,,t}$ ($D_{DOWN,,LARGE,,,i,,t}$) is a dummy variable that is equal to one if and only if $R_{i,t}$ is greater (less) than 1.5 standard deviation above (below) the mean return for stock i. $D_{UP,,SMALL,,m,,t}$ ($D_{DOWN,,SMALL,,m,,t}$) and $D_{UP,,LARGE,,m,,t}$ ($D_{DOWN,,LARGE,,m,,t}$) are similarly defined based on $R_{m,t}$. The definition of the control variables are the same as above. In Panel C (D), $ASPR_{i,t}$ is the average daily spreads across all (first five) trading days in month t. The estimates of the regression coefficients for the control variables are not reported here.

Panel A: The dependent variable ASPR(t), which is the average spread across all the trading days in month t, is regressed on lag positive/negative individual and market returns.

Estimate Statistics	$R_{i.t-1}D_{UP,i,t-1}$	$R_{i.t-1}D_{DOWN,i,t-1}$	$R_{m.t-1}D_{UP,m,t-1}$	$R_{m.t-1}D_{DOWN,m,t-1}$
Mean	-0.175***	-0.417***	-0.149***	-0.246***
Median	-0.126	-0.281	-0.074	-0.076
% of negative	79.0%	89.6%	60.4%	58.5%
% of positive				
% of significant	24.8%	44.7%	8.0%	10.2%

Panel B: The dependent variable ASPR(t), which is the average spread across the first five trading days in month t, is regressed on lag positive/negative individual and market returns.

Estimate Statistics	$R_{i.t-1}D_{UP,i,t-1}$	$R_{i.t-1}D_{DOWN,i,t-1}$	$R_{m.t-1}D_{UP,m,t-1}$	$R_{m.t-1}D_{DOWN,m,t-1}$
Mean	-0.441***	-0.671***	0.028	-0.409***
Median	-0.307	-0.461	0.004	-0.176
% of negative	89.1%	93.4%		63.7%
% of positive			50.3%	
% of significant	46.2%	53.4%	4.9%	12.5%

Panel C: The dependent variable ASPR(t), which is the average spread across all the trading days in month t, is regressed on lag positive/negative and large/small individual and market returns.

Estimate Statistics	$R_{i.t-1}D_{UP,SMALL,i,t-1}$	$R_{i.t-1}D_{DOWN,SMALL,i,t-1}$	$R_{i.t-1}D_{UP,LARGE,i,t-1}$	$R_{i.t-1}D_{DOWN,LARGE,i,t-1}$
Mean	-0.176***	-0.384***	-0.181***	-0.430***
Median	-0.134	-0.250	-0.124	-0.279
% of negative	72.6%	80.1%	75.6%	85.9%
% of positive				
% of significant	17.0%	27.6%	22.3%	38.3%
Estimate Statistics	$R_{m.t-1}D_{UP,SMALL,i,t-1}$	$R_{m.t-1}D_{DOWN,SMALL,i,t-1}$	$R_{m.t-1}D_{UP,LARGE,i,t-1}$	$R_{m.t-1}D_{DOWN,LARGE,i,t-1}$
Mean	-0.191***	-0.003	-0.213***	-0.290***
Median	-0.081	0.041	-0.101	-0.090
% of negative	59.0%	46.8%	61.1%	59.9%
% of positive				
% of significant	7.2%	3.9%	7.9%	11.0%

Panel D: The dependent variable ASPR(t), which is the average spread across the first five trading days in month t, is regressed on lag positive/negative and large/small individual and market returns.

Estimate Statistics	$R_{i.t-1}D_{UP,SMALL,i,t-1}$	$R_{i.t-1}D_{DOWN,SMALL,i,t-1}$	$R_{i.t-1}D_{UP,LARGE,i,t-1}$	$R_{i.t-1}D_{DOWN,LARGE,i,t-1}$
Mean	-0.437***	-0.623***	-0.454***	-0.694***
Median	-0.324	-0.420	-0.310	-0.451
% of negative	83.2%	85.1%	86.3%	89.0%
% of positive				
% of significant	31.1%	34.1%	41.5%	47.9%
Estimate Statistics	$R_{m.t-1}D_{UP,SMALL,i,t-1}$	$R_{m.t-1}D_{DOWN,SMALL,i,t-1}$	$R_{m.t-1}D_{UP,LARGE,i,t-1}$	$R_{m.t-1}D_{DOWN,LARGE,i,t-1}$
Mean	-0.054	-0.199***	0.012	-0.373***
Median	-0.021	-0.090	0.005	-0.137
% of negative	51.7%	55.4%		60.6%
% of positive			50.3%	
% of significant	5.0%	5.9%	4.7%	11.8%

Table 4: Relation Between Spread and Magnitude of Lagged Returns : Two-way dependent sorts based on Size and Volatility

The regression model and the definition of variables are identical to the Specification 2 in Table 5, except that the estimates are reported separately for nine portfolios that is formed by the two-way dependent sorts based on size and volatility. The dependent variable $ASPR_{i,t}$ is the average daily spreads across all the trading days in month t.

$R_{i.t-1}D_{UP,i,t-1}$	Estimate Statistics	High Volatility	Medium Volatility	Low Volatility	High Volatility-Low Volatility
Small Size	Mean	-0.297***	-0.380***	-0.168***	-0.129*
	Median	-0.264	-0.302	-0.156	-0.108
	% of negative	73.6%	82.3%	66.1%	
	% of positive				
	% of significant	22.6%	29.2%	17.0%	
Medium Size	Mean	-0.191***	-0.184***	-0.174***	-0.017
	Median	-0.191	-0.189	-0.177	-0.015
	% of negative	81.4%	86.7%	83.0%	
	% of positive				
	% of significant	30.1%	28.3%	30.4%	
Large Size	Mean	-0.115***	-0.095***	-0.109***	-0.006
	Median	-0.115	-0.079	-0.087	-0.028
	% of negative	86.6%	85.0%	87.5%	
	% of positive				
	% of significant	34.8%	27.4%	32.1%	

$R_{i.t-1}D_{DOWN,i,t-1}$	Estimate Statistics	High Volatility	Medium Volatility	Low Volatility	High Volatility-Low Volatility
Small Size	Mean	-0.976***	-0.703***	-0.625***	-0.351***
	Median	-0.827	-0.679	-0.516	-0.311
	% of negative	93.4%	92.0%	86.6%	
	% of positive				
	% of significant	51.9%	46.0%	38.4%	
Medium Size	Mean	-0.484***	-0.322***	-0.282***	-0.202***
	Median	-0.395	-0.269	-0.233	-0.161
	% of negative	95.6%	92.0%	82.1%	
	% of positive				
	% of significant	61.9%	38.1%	33.9%	
Large Size	Mean	-0.291***	-0.176***	-0.169***	-0.122***
	Median	-0.253	-0.155	-0.149	-0.104
	% of negative	96.4%	92.0%	87.5%	
	% of positive				
	% of significant	64.3%	46.9%	43.8%	

$R_{m.t-1}D_{UP,m,t-1}$	Estimate Statistics	High Volatility	Medium Volatility	Low Volatility	High Volatility-Low Volatility
Small Size	Mean	-0.436**	-0.204*	-0.162*	-0.274
	Median	-0.237	-0.288	-0.176	-0.060
	% of negative	57.5%	62.8%	61.6%	
	% of positive				
	% of significant	12.3%	9.7%	4.5%	
Medium Size	Mean	-0.166*	-0.169**	-0.019	-0.147*
	Median	-0.101	-0.144	-0.042	-0.059
	% of negative	58.4%	71.7%	53.6%	
	% of positive				
	% of significant	4.4%	6.2%	7.1%	
Large Size	Mean	-0.132**	-0.092**	-0.036*	-0.096**
	Median	-0.070	-0.058	-0.039	-0.030
	% of negative	68.8%	69.9%	63.4%	
	% of positive				
	% of significant	8.9%	11.5%	6.3%	

$R_{m.t-1}D_{DOWN,m,t-1}$	Estimate Statistics	High Volatility	Medium Volatility	Low Volatility	High Volatility-Low Volatility
Small Size	Mean	-0.725***	-0.498***	-0.404***	-0.321*
	Median	-0.486	-0.173	-0.353	-0.133
	% of negative	60.4%	57.5%	74.1%	
	% of positive				
	% of significant	16.0%	13.3%	16.1%	
Medium Size	Mean	-0.393***	-0.243***	-0.098**	-0.295**
	Median	-0.228	-0.158	-0.064	-0.164
	% of negative	61.9%	65.5%	57.1%	
	% of positive				
	% of significant	13.3%	14.2%	7.1%	
Large Size	Mean	0.037	-0.042	-0.023	0.060
	Median	0.007	0.002	0.021	-0.014
	% of negative	47.3%	49.6%	45.5%	
	% of positive				
	% of significant	2.7%	7.1%	5.4%	

Table 5: Small Trade% and Past Return

The Small Trade% is the number of small trade divided by the total trade number expressed in percentage points. It is regressed on its own lag value, the stock's return in previous month t-1 and current month t, the market return in previous month t-1, and other independent variables. Cross-sectional averages and medians of coefficient estimates are reported in the row labeled as "Mean" and "Median". The averages that are significant at 99%, 95%, and 90% confidence level are labeled with ***, **, and * correspondingly. "% of positive (negative)" and "% of positive (negative) significant" refer to the percentage of the positive (negative) coefficient estimates and the percentage of the coefficient estimates with t-statistics greater than +1.645 (-1.645) as the 5% critical level in a one-tailed test. $R_{i.t-1}$ stands for the individual stock i's return in month t-1. $R_{m.t-1}$ is the market return measured by the CRSP value-weighted return in month t-1. $PosR = 1\{R > 0\} \times R$ and $NegR = 1\{R \le 0\} \times R$.

The regression models are as follows.

Model: $SmallTrade\%_{i.t} = \alpha_i SmallTrade\%_{i.t-1} + \beta_i^+ PosR_{i.t-1} + m_{i.} R_{m.t} + \beta_i^- NegR_{i.t-1} + \varepsilon_{i.t}$

	Estimate Statistics	Model 1	Model 2
R^i_{t-1}	Mean	3.341***	
	Median	2.652	
	% of positive	70.5%	
	% positive significant	20.6%	
$PosR^i_{t-1}$	Mean		5.633***
	Median		4.417
	% of positive		71.2%
	% positive significant		22.5%
$NegR^i_{t-1}$	Mean		0.651*
	Median		0.000
	% of positive		49.6%
	% positive significant		7.8%
R^m_{t-1}	Mean	-0.058	
	Median	0.000	
	% of positive	48.4%	
	% positive significant	6.3%	
$Small\ Trade\%^i_{t-1}$	Mean	0.690***	0.690***
	Median	0.796	0.797
	% of positive	90.4%	90.4%
	% positive significant	69.0%	69.0%

Table 6: Liquidity Betas and Market Returns

The percentage change in adjusted daily proportional spread for each stock *i* is regressed on the percentage change in the aggregate market spreads.

Model A: $DL_{i.t} = a_i + \beta_i DL_{m.t} + \varepsilon_{i.t}$

Model B: $DL_{i.t} = a_i + b_i DL_{m.t} D_{UP,m,t} + c_i DL_{m.t} D_{DOWN,m,t} + \varepsilon_{i.t}$

where $DL_{i.t} = (ASPR_{i.t} - ASPR_{i.t-1}) / ASPR_{i.t-1}$, the percentage change in adjusted daily proportional spread for stock *I*; $DL_{m.t} = (ASPR_{m.t} - ASPR_{m.t-1}) / ASPR_{m.t-1}$) and $ASPR_{m,t}$ is the cross-sectional (equally-weighted) average of daily spreads across all stocks in the sample. The dummy variable $D_{UP,m,t}$ ($D_{,DOWN,m,t}$) is equal to one if and only if the return on the NYSE value-weighted market index in month *t* is positive (negative).

Estimate Statistics	Intercept	$DL_{m.t}$	$DL_{m.t} D_{UP,m,t}$	$DL_{m.t} D_{DOWN,m,t}$
Mean	0.030***	1.092***		
Median	0.014	0.822		
% of negative				
% of positive	100.0%	99.0%		
% of significant	98.9%	92.4%		
Mean	0.030***		1.059***	1.133***
Median	0.014		0.771	0.849
% of negative				
% of positive	100.0%		97.8%	97.5%
% of significant	98.8%		83.6%	80.7%

Table 7: Commonality in Liquidity and Market Returns

Commonality in liquidity is measured by the r-square ($R^2_{i,t}$) from the following regression for stock i within each month t based on daily change in spreads:

$$DL_{i,s} = a_i + \beta_i DL_{m.s} + \varepsilon_{i.s}$$

where $DL_{i,s} = (ASPR_{i.s} - ASPR_{i.,s-1}) / ASPR_{i.s-1}$, the percentage change in adjusted daily proportional spread for stock *i* from day *s-1* to *s*; $DL_{m.s} = (ASPR_{m.s} - ASPR_{m.s-1}))$ $/ ASPR_{m.s-1}$ and $ASPR_{m,s}$ is the cross-sectional (equally-weighted) average of spreads across all stocks in the sample in day *s*. For each stock *i* , the above regression equation generates an $R^2_{i,t}$, for each month *t*. The cross-sectional (equal-weighted) average of $R^2_{i,t}$ for each month *t* is denoted as R_t^2, which is then used in the second stage time-series monthly regression in Panel A :

Model A: $COMOVE_t = a + \gamma\ R_{m,t} + \varepsilon_t$
Model B: $COMOVE_t = a + b\ R_{m,t} D_{UP,t} + c\ R_{m,t} D_{DOWN,t} + \varepsilon_t$
Model C: $COMOVE_t = a + g\ R_{m,t} D_{DOWN,LARGE,t} + e\ R_{m,t} D_{UP,LARGE,t}$
$+ hR_{m,t} D_{SMALL,t} + \varepsilon_t$

where $COMOVE_t$ is defined as $\ln[R_t^2 / (1 - R_t^2)]$. The dummy variable $D_{UP,t}$ ($D_{DOWN,t}$) is equal to one if and only if the return on the CRSP value-weighted market index in month *t* ($R_{m,t}$) is positive (negative). $D_{UP,LARGE,t}$ ($D_{DOWN,LARGE,t}$) is a dummy variable that is equal to one if and only if $R_{m,t}$ is greater (less) than *z* standard deviation above (below) its mean return. $D_{SMALL,t}$ is a dummy variable that is equal to one if and only if $R_{m,t}$ is within *z* standard deviation around its mean. We consider three values of z: 2.0, 1.5 and 1.0 under models C1, C2, C3. In Panel B, we repeat the same analysis but use the Sum of Squared Residuals (SSR) (or idiosyncratic volatility) as the dependent variable. The t-statistics is reported in italic form under the coefficient estimate.

Panel A: Dependent Variable is COMOVE={Ln(R^2/(1-R^2))}

Model	A	B	C1	C2	C3
Intercept	-2.481 *-104.34*	-2.564 *-65.49*	-2.500 *-99.58*	-2.513 *-94.39*	-2.533 *-84.59*
$R_{m.t}$	-1.113 *-2.06*				
$R_{m.t} D_{DOWN,m,t}$		-3.518 *-3.33*			
$R_{m.t} D_{UP,m,t}$		1.166 *1.15*			
$R_{m.t} D_{DOWN,LARGE,m,t}$			-3.312 *-2.87*	-3.298 *-3.26*	-3.365 *-3.52*
$R_{m.t} D_{UP,LARGE,m,t}$			-2.868 *-0.96*	-0.149 *-0.12*	0.760 *0.81*
$R_{m.t} D_{SMALL,m,t}$			-0.291 *-0.45*	0.067 *0.09*	0.226 *0.2*

Panel B: Dependent Variable is Ln(SSR)

Model	A	B	D1	D2	D3
Intercept	0.300 *14.9*	0.249 *7.45*	0.300 *13.94*	0.303 *13.24*	0.291 *11.29*
$R_{m.t}$	0.190 *0.41*				
$R_{m.t} D_{DOWN,m,t}$		-1.282 *-1.42*			
$R_{m.t} D_{UP,m,t}$		1.584 *1.83*			
$R_{m.t} D_{DOWN,LARGE,m,t}$			0.262 *0.26*	0.427 *0.49*	-0.301 *-0.37*
$R_{m.t} D_{UP,LARGE,m,t}$			-0.067 *-0.03*	0.135 *0.13*	1.109 *1.38*
$R_{m.t} D_{SMALL,m,t}$			0.176 *0.32*	0.044 *0.07*	-0.281 *-0.29*

Table 8: Commonality in Liquidity and Returns for Industry Portfolios

In Panel A, commonality in *industry-wide* liquidity is measured by the r-square ($R^2_{i,t}$) from the following regression for stock i in each month t based on daily change in spreads:

$$DL_{i,s} = a_i + \beta_i DL_{INDj,.s} + \varepsilon_{i.s} \qquad (1)$$

where $DL_{i,s} = (ASPR_{i.s} - ASPR_{i.,s-1}) / ASPR_{i.s-1}$, the percentage change in adjusted daily proportional spread for stock *i* from day *s-1* to *s*; $DL_{INDj.s} = (ASPR_{INDj.s} - ASPR_{INDj,s-1}) / ASPR_{INDj,s-1}$) and $ASPR_{INDj,s}$ is the cross-sectional (equally-weighted) average of spreads across all stocks in the *industry j* in day *s*. For each stock *i* , the above regression equation generates an $R^2_{i,t}$, for each month *t*. The cross-sectional (equal-weighted) average of $R^2_{i,t}$ of all stocks within industry *j* for each month *t* is denoted as $R_{INDj,t}^2$, which is then used in the second stage time-series monthly regression :

Model A:

$$COMOVE_{INDj,t} = a + b_{IND} R_{INDj,t} + b_{MKT} R_{MKTj,t} + \varepsilon_t$$

Model B:

$$COMOVE_{INDj,t} = a + b_{IND} R_{INDj,t} D_{UP,INDj,t} + c_{IND} R_{INDj,t} D_{DOWN,INDj,t} + b_{MKT} R_{MKTj,t} D_{UP,MKTj,t} + c_{MKT} R_{MKTj,t} D_{DOWN,MKT,t} + \varepsilon_t$$

Model C:

$$COMOVE_{INDj,t} = a + f_{IND} R_{INDj,t} D_{UP,LARGE,INDj,t} + g_{IND} R_{INDj,t} D_{DOWN,LARGE,INDj,t} + h_{IND} R_{INDj,t} D_{SMALL,INDj,t} + f_{MKT} R_{MKTj,t} D_{UP,LARGE,MKTj,t} + g_{MKT} R_{MKTj,t} D_{DOWN,LARGE,MKTj,t} + h_{MKT} R_{MKTj,t} D_{SMALL,MKTj,t} + \varepsilon_t$$

where $COMOVE_{INDj,t}$ is defined as $\ln[R^2_{INDj,t} / (1 - R^2_{INDj,t})]$. The dummy variable $D_{UP,INDj,t}$ ($D_{DOWN,INDj,t}$) is equal to one if and only if the return on value-weighted portfolio for *industry j* in month *t* ($R_{INDj,t}$) is positive (negative). $D_{UP,LARGE,INDj,t}$ ($D_{DOWN,LARGE,INDj,t}$) is a dummy variable that is equal to one if and only if $R_{INDj,,t}$ is greater (less) than *z* standard deviation above (below) its mean return. $D_{SMALL,INDjt}$ is a dummy variable that is equal to one if and only if $R_{INDj,t}$ is within *z* standard deviation around its mean return. $R_{MKTj,t}$ denotes the return on the market portfolio, excluding the return on industry *j* portfolio. The corresponding dummy variables are similarly defined. We consider three values of *z*: 2.0, 1.5 and 1.0 under models C1, C2, C3.

In Panel B, we replace equation (1) with a two-factor model:

$$DL_{i,s} = a_i + \beta_i DL_{INDj,s} + \gamma \, DL_{MKT,s} + \varepsilon_{i.s} \qquad (2)$$

where the second factor $DL_{MKT.s} = (ASPR_{MKT,s} - ASPR_{MKT,s-1}) / ASPR_{MKT,s-1}$ and $ASPR_{MKTj,s}$ is the cross-sectional (equally-weighted) average of spreads across all stocks in the market. The t-statistics is reported in italic form under the coefficient estimate.

Panel A: Single Factor Industry Liquidity Co-movement and market returns

Model	A	B	C1	C2	C3
Intercept	-2.361 *-409.51*	-2.416 *-238.36*	-2.374 *-384.76*	-2.385 *-358.84*	-2.395 *-313.73*
$R_{IND.t}$	-0.191 *-1.46*				
$R_{IND.t}D_{DOWN,IND,t}$		-0.844 *-3.53*			
$R_{IND.t}D_{UP,IND,t}$		0.291 *1.49*			
$R_{MKT.t}$	-0.609 *-3.58*				
$R_{MKT.t}D_{DOWN,MKT,t}$		-1.472 *-4.69*			
$R_{MKT.t}D_{UP,MKT,t}$		0.296 *1.06*			
$R_{IND.t}D_{DOWN,LARGE,IND,t}$			-0.651 *-2.22*	-0.765 *-3.19*	-0.727 *-3.26*
$R_{IND.t}D_{UP,LARGE,IND,t}$			0.157 *0.63*	0.074 *0.37*	0.164 *0.91*
$R_{IND.t}D_{SMALL,IND,t}$			-0.149 *-0.97*	-0.008 *-0.05*	-0.074 *-0.3*
$R_{MKT.t}D_{DOWN,LARGE,MKT,t}$			-1.637 *-4.68*	-1.663 *-5.64*	-1.523 *-5.38*
$R_{MKT.t}D_{UP,LARGE,MKT,t}$			-1.395 *-1.98*	0.379 *1.18*	0.197 *0.78*
$R_{MKT.t}D_{SMALL,MKT,t}$			-0.181 *-0.94*	-0.152 *-0.67*	0.065 *0.21*

Panel B: Two-Factor Industry Liquidity Co-movement and market returns

Model	A	B	C1	C2	C3
Intercept	-1.690 *-358.42*	-1.741 *-210.4*	-1.702 *-338.22*	-1.714 *-316.32*	-1.722 *-276.33*
$R_{IND.t}$	-0.143 *-1.34*				
$R_{IND.t} D_{DOWN,IND,t}$		-0.616 *-3.16*			
$R_{IND.t} D_{UP,IND,t}$		0.207 *1.29*			
$R_{MKT.t}$	-0.569 *-4.09*				
$R_{MKT.t} D_{DOWN,MKT,t}$		-1.525 *-5.96*			
$R_{MKT.t} D_{UP,MKT,t}$		0.387 *1.69*			
$R_{IND.t} D_{DOWN,LARGE,IND,t}$			-0.752 *-3.15*	-0.575 *-2.94*	-0.520 *-2.86*
$R_{IND.t} D_{UP,LARGE,IND,t}$			0.052 *0.26*	0.010 *0.06*	0.087 *0.59*
$R_{IND.t} D_{SMALL,IND,t}$			-0.014 *-0.11*	0.010 *0.07*	-0.019 *-0.09*
$R_{MKT.t} D_{DOWN,LARGE,MKT,t}$			-1.410 *-4.94*	-1.750 *-7.29*	-1.553 *-6.72*
$R_{MKT.t} D_{UP,LARGE,MKT,t}$			-1.822 *-3.17*	-0.034 *-0.13*	0.259 *1.25*
$R_{MKT.t} D_{SMALL,MKT,t}$			-0.191 *-1.22*	0.122 *0.66*	0.101 *0.4*

Table 9: Commonality in Liquidity and Market Returns
-- Two-way dependent sorts based on Size and Volatility

Commonality in liquidity is measured by the r-square ($R^2_{i,t}$) from the following regression for stock i within each month t based on daily change in spreads:

$$DL_{i,s} = a_i + \beta_i DL_{m.s} + \varepsilon_{i.s}$$

where $DL_{i,s} = (ASPR_{i.s} - ASPR_{i.,s-1}) / ASPR_{i.s-1}$, the percentage change in adjusted daily proportional spread for stock *i* from day *s-1* to *s*; $DL_{m.s} = (ASPR_{m.s} - ASPR_{m.s-1}))$ $/ ASPR_{m.s-1}$ and $ASPR_{m,s}$ is the cross-sectional (equally-weighted) average of spreads across all stocks in the sample in day *s*. For each stock *i* , the above regression equation generates an $R^2_{i,t}$, for each stock *i* in each month *t*.

The equal-weighted average of $R^2_{i,t}$ of each of the nine portfolios, which are formed by the *two-way dependent sorts* based on size and volatility, for each month *t* is denoted as R_t^2. R_t^2 is then used in the second stage time-series monthly regression:

$$COMOVE_t = a + g\ R_{m,t} D_{DOWN,LARGE,t} + e\ R_{m,t} D_{UP,LARGE,t} + hR_{m,t} D_{SMALL,t} + \varepsilon_t$$

where $COMOVE_t$ is defined as $\ln[R_t^2 / (1 - R_t^2)]$. The dummy variable $D_{UP,t}$ ($D_{DOWN,t}$) is equal to one if and only if the return on the CRSP value-weighted market index in month *t* ($R_{m,t}$) is positive (negative). $D_{UP,LARGE,t}$ ($D_{DOWN,LARGE,t}$) is a dummy variable that is equal to one if and only if $R_{m,t}$ is greater (less) than *z* standard deviation above (below) its mean return. $D_{SMALL,t}$ is a dummy variable that is equal to one if and only if $R_{m,t}$ is within *z* standard deviation around its mean return. In the reported results, we set the value of z equal to 1.5. The t-statistics is reported in italic form under the coefficient estimate.

$R_{m.t} D_{DOWN,LARGE,m,t}$	High Volatility	Medium Volatility	Low Volatility
Small Size	-1.611 *-1.50*	-1.339 *-1.41*	-0.280 *-0.30*
Medium Size	-3.452 *-2.82*	-2.743 *-2.57*	-2.102 *-1.96*
Large Size	-6.111 *-4.32*	-4.768 *-3.42*	-4.129 *-3.27*

$R_{m.t} D_{UP,LARGE,t}$	High Volatility	Medium Volatility	Low Volatility
Small Size	0.577 *0.44*	0.101 *0.09*	-0.742 *-0.64*
Medium Size	0.496 *0.33*	-1.139 *-0.87*	0.015 *0.01*
Large Size	-0.432 *-0.25*	0.397 *0.23*	0.798 *0.52*

$R_{m.t} D_{SMALL,t}$	High Volatility	Medium Volatility	Low Volatility
Small Size	-0.068 *-0.08*	0.701 *0.95*	1.01 *1.38*
Medium Size	0.473 *0.50*	0.530 *0.64*	-0.114 *-0.14*
Large Size	-0.400 *-0.36*	-0.556 *-0.51*	-0.234 *-0.24*

Figure 1: A time series plot of the average raw and adjusted quoted spreads

The figures below show the cross-sectional mean of the raw and adjusted proportional quoted spreads for a constatnt sample of securities that have valid observations throughout the full sample period (1988 to 2003).