Stock Market Declines and Liquidity*

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ABSTRACT

The evidence presented in this paper suggests that asset-side shock affecting the funding available to financial intermediaries contributes to significant time-variation in liquidity. Consistent with recent theoretical models where binding capital constraints lead to sudden liquidity dry-ups, we find that negative market returns decrease stock liquidity, especially for high volatility stocks and during times of tightness in the funding market. The asymmetric effect of changes in aggregate asset values on liquidity and commonality in liquidity cannot be fully explained by changes in demand for liquidity or volatility effects. We document inter-industry spill-over effects in liquidity, which are likely to arise from capital constraints in the market making sector. We also find economically significant returns to supplying liquidity following periods of large drop in market valuations.

1. Introduction

In recent theoretical research, the idea that market declines cause asset illiquidity has received much attention. Liquidity dry-ups occur either because market participants engage in panic selling (a demand effect) or financial intermediaries withdraw from providing liquidity (a supply effect) or both. Following these theories, we explore what happens to market liquidity after large market declines and ascertain whether supply effects exist in equity markets. However, it is difficult to establish the actual identity of financial intermediaries in these markets as they could be specialists, floor traders, limit order providers or others like hedge funds. Furthermore, the actual positions and balance sheet of these intermediaries are also unknown. Hence, in this paper, we take an encompassing approach by investigating the impact of market declines on various dimensions of liquidity, including: (a) time-series as well as cross-sectional variations in liquidity; (b) commonality in liquidity; and (c) cost of liquidity provision.

Theoretical models obtain illiquidity after market declines in a variety of ways. In Gromb and Vayanos (2002), Anshuman and Viswanathan (2005) and Brunnermeier and Pedersen (2007), market makers make market by absorbing temporary liquidity shocks. However, they also face funding constraints and obtain financing by posting margins and pledging the securities they hold as collateral. When stock prices decline considerably, the intermediaries hit their margin constraints and are forced to liquidate. In Brunnermeier and Pedersen (2007), a large market shock triggers the switch to a low-liquidity, high margin equilibrium, where markets are illiquid, resulting in larger margin requirements. This illiquidity spiral restricts dealers further from providing market liquidity. Anshuman and Viswanathan (2005), on the other hand, present a slightly different model where leveraged investors are asked to provide collateral when asset values fall and decide to endogenously default, leading to asset liquidation. At the same time, market makers face funding constraints as they are able to finance less in the repo market for the assets they own. Gromb and Vayanos (2002) emphasize that the reduction in supply of liquidity due to capital constraints has important welfare and regulatory implications. Partly motivated by the LTCM crises, the balance sheet of intermediaries matter in these collateral based models as they face financial constraints that are often binding precisely when it is most incumbent for them to provide liquidity.[1] The providers of liquidity in these models become demanders of liquidity after a large drop in asset prices causing both a demand effect (more liquidity is demanded) as well as a supply effect (less able to provide liquidity).

In limits to arbitrage based models such as Kyle and Xiong (2001) and Xiong (2001), shocks to noise traders make prices move away from fundamentals and arbitrageurs provide liquidity and take advantage of the arbitrage opportunity. However, these liquidity providers face decreasing absolute risk aversion. Following market declines, their demand for risky assets declines, and they become liquidity demanders as they liquidate their positions in risky assets. In the coordination failure models of Bernardo and Welch (2003) and Morris and Shin (2004), traders face differing trading limits that would cause them to sell. Since one trader hitting his limit may push down the price and make other traders' limits to be hit, early liquidation gives a better price than late liquidation. Here, traders rush to liquidate following negative shocks, and when prices fall enough, liquidity black holes emerge, analogous to a bank run model. Vayanos

[1] This spiral effect of a drop in collateral value is emphasized in a number of theoretical papers, starting with the foundational work in Kiyotaki and Moore (1997), where lending is based on the value of land as collateral. See also Allen and Gale (2005).

(2004) presents an asset pricing model where investors have to liquidate when asset prices fall below a lower bound, leading to liquidation risk being priced. Vayanos links the risk of needing to liquidate to volatility, especially for stocks with large exposure to market volatility. While the exact details of these theoretical models differ, they all predict that large market declines increase the demand for liquidity as agents liquidate their positions across many assets and reduce the supply of liquidity as liquidity providers hit their wealth or funding constraints.

Using proportional bid-ask spread (as a proportion of stock price) as one of our key variables measuring liquidity, we find that changes in spreads are negatively related to market returns. When weekly changes in spreads are regressed on lagged market returns, the regression coefficient increases significantly from -0.4 to -1.2 for negative market returns. In particular, large negative market returns have much stronger impact on individual firm spreads than positive returns, and the average spread increases by 2.8 (6.2) basis points after a (large) market decline. We also document that these changes in liquidity last for about two weeks, and reverse in the subsequent weeks. Moreover, we find that the impact of negative market returns on liquidity is stronger when financial intermediaries are more likely to face funding constraints. For example, negative market returns reduce liquidity more when there are also large declines in the aggregate balance sheets of financial intermediaries or in the market value of the investment banking sector.[2] This asymmetric relation between market returns and liquidity is robust to the inclusion of firm level control variables such as lagged own stock returns, turnover, and buy-sell order imbalance. Our results are also robust to effects of changes in

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[2] Adrian and Shin (2007) show that the changes in the balance sheets of financial intermediaries are linked to funding liquidity, through shifts in the market-wide risk appetite. In Eisfeldt(2004), liquidity is endogenously determined and is procyclical: assets are less liquid in bad times.

(market-wide and firm specific) volatilities suggested in Vayanos (2004). Brunnermeier and Pedersen (2007) suggest that a deterioration of dealer capital leads to greater cross-sectional differences in liquidity of high and low volatility stocks. Consistent with this flight to liquidity prediction, we find that the impact of market declines on liquidity is strongest for high volatility firms. These findings lend support to the hypothesis that the relation between liquidity and market declines are related to changes in supply of liquidity.

Next, we investigate the hypothesis suggested in Brunnermeier and Pedersen(2005) that huge market-wide decline in prices reduces the aggregate collateral of the market making sector which feeds back as higher comovement in market liquidity. 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 focus on the effect of stock market movements on commonality in liquidity. Two recent papers consider the effect of capital constraints on liquidity. Using daily data and specialist stock information, Coughenour and Saad (2004) ask whether changes in the market return affect stock liquidity commonality at a daily frequency. In an interesting paper on fixed income markets, Naik and Yadav (2003) show that Bank of England capital constraints affect price movements.[3] However, the extant empirical literature does not consider whether the comovement of liquidity increases

[3] Other related work include Pastor and Stambaugh (2003) who show that liquidity is a priced state variable; and Amihud and Mendelson (1986) who show that illiquid assets earn higher returns. In Acharya and Pedersen (2005), a fall in aggregate liquidity primarily affects illiquid assets. Sadka (2006) documents that the earnings momentum effect is partly due to higher liquidity risk.

dramatically after large market drops in a manner similar to the finding that stock return comovement goes up after large market drops (see Ang, Chen and Xing (2006) on downside risk and especially Ang and Chen (2002), for work on asymmetric correlations between portfolios).

We document that the commonality in liquidity (spreads) increases during periods of market declines. Using the coefficients from the market model regression of the stock spreads on the market average spreads, we find that the liquidity beta increases by 0.31 (0.39) during periods when the market has experienced a (large) drop in valuations. We also document that liquidity commonality is positively related to market volatility but unrelated to idiosyncratic volatility, indicating that inventory effects are not likely to be the main source. In a follow-up to our paper, Hendershott, Moulton and Seasholes (2006) provide confirmatory evidence that capital constraint, proxied by higher inventory holdings by NYSE specialists, lowers market liquidity and are binding after negative market returns.

We find that liquidity commonality also increases with buy-sell order imbalance, suggesting both demand and supply effects are present. We address the endogeneity issue of shifts in both demand and supply of liquidity by jointly estimating the commonality in buy and sell order imbalance, our proxy for commonality in demand for liquidity. Since outflows from the mutual fund industry generally lead to asset sales while inflows do not immediately lead to purchases, mutual fund outflows lead to selling pressures and order imbalances across all stocks. This observation leads to an instrumental variable, the aggregate flow of funds, which identifies the demand for liquidity equation and allows us to show that demand related variables do not fully explain the illiquidity conditional on large market declines.

Additional analyses reveal that large negative return shocks to industry and market indices increase comovement in liquidity. However, the market effect is bigger in magnitude than the industry effect. This suggests that spillover effects across all securities after negative market shocks are important and provides strong support for the idea of a contagion in illiquidity due to supply effects advocated in Brunnermeier and Pedersen (2005), Kyle and Xiong (2001) and others.

The argument that supply of liquidity drops in market downturns also predicts that the return to providing liquidity should be higher in the same market state. We use the short-term price reversals as our measure of the cost of supplying liquidity and examine if the cost varies with state of market returns. For example, in Campbell, Grossman and Wang (1993), risk-averse market makers require payment for accommodating heavy selling by liquidity traders. This cost of providing liquidity is reflected in the temporary decrease in price accompanying heavy sell volume and the subsequent increase as prices revert to fundamental values.[4] We use the returns to two return-reversal based trading strategies to empirically gauge the cost of supplying liquidity: contrarian investment strategy (Conrad, Hameed and Niden (1994) and Avramov, Chordia, Goyal (2005)); and limit-order trading strategy (Handa and Swartz (1996)).

A simple zero-cost contrarian investment strategy that captures the price reversals on heavy trading yields an economically significant return of 1.18 percent per week when conditioned on large negative market returns, and is much higher than the unconditional

[4] Similar sharp short-term price reversals due to liquidity shocks are predicted by other models, such as Morris and Shin (2003). Pastor and Stambaugh (2003) use a similar idea to show that liquidity risk is priced and liquidity events seem to occur often after large price declines (e.g. crash of 1987).

return of 0.58 percent. The stronger price reversals in large down markets lasts up to two weeks, is higher in periods of high liquidity commonality and cannot be explained by standard Fama-French risk factors. A limit order trading strategy of placing limit buy (sell) orders on price declines (increases) also captures the idea of return to liquidity provision. For example, a strategy that places a buy (sell) limit order at the beginning of each week after a 5 percent drop (rise) in stock prices, generates an unconditional buy-minus-sell portfolio weekly return of 0.71 percent. Again, the return to this strategy is most profitable after a large fall in the market, where the return increases dramatically to an economically significant 1.56 percent per week. Our cumulative evidence provides empirical support to the idea that supply of liquidity falls after large negative stock market returns and is consistent with the collateral based view of liquidity that has been espoused in recent theoretical papers.

The remainder of the paper is organized 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 are presented in Section 3, while Section 4 presents the same with respect to commonality in liquidity. The formulation and results from the investment strategy based on short-term price reversals are produced in Section 5. Section 6 concludes the paper.

2. Data

The transaction-level data are collected from the New York Stock Exchange Trades and Automated Quotations (TAQ) and the Institute for the Study of Securities Markets (ISSM). The daily and monthly return data are retrieved from the Center for Research in Security Prices (CRSP). The sample stocks are restricted to NYSE ordinary stocks from

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 must be within $3 and $999 each year. This filter is applied to avoid the influence of extreme price levels. The stock should also have at least 60 months of valid observations during the sample period. After all the filtering, the final database includes more than 800 million trades across about one thousand eight hundred stocks over sixteen years. The large sample enables us to conduct a comprehensive analysis on the relation among liquidity level, liquidity commonality, and market returns.

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%; (iv) Effective spread / Quoted spread > 4.0.

In this paper, we use bid-ask spread as the measure of liquidity. We compute the proportional quoted spread (QSPR) by dividing the difference between ask and bid quotes by the midquote. We repeat our empirical tests with the proportional effective spread, which is two times the difference between the trade execution price and the midquote scaled by the midquote, and find similar results (unreported). The individual stock daily spread is constructed by averaging the spread for all transactions for the stock on any given trading day. During the last decade, spreads have narrowed with the fall in tick size and growth in trading volume. Thus, to ascertain the extent to which the change of spread is caused by past returns, we adjust spreads for deterministic time-series variations such as changes in tick-size, time trend, and calendar effects. Following Chordia, Sarkar and Subrahmanyam (2005), we regress stock *i*'s QSPR on day *s* on a set of variables known to capture seasonal variation in liquidity:

$$\begin{aligned} QSPR_{i,s} = & \sum_{k=1}^{4} d_{i,k}\, DAY_{k,s} + \sum_{k=1}^{11} e_{i,k} MONTH_{k,s} + f_{1,i}\, HOLIDAY_s \\ & + f_{2,i}\, TICK1_s + f_{3,i}\, TICK2_s + f_{4,i}\, YEAR1_s + f_{5,i}\, YEAR2_s + ASPR_{i,s} \end{aligned} \quad (1)$$

In equation 1, the following variables are employed: (i) 4 day of the week dummies ($DAY_{k,s}$) for Monday through Thursday ; (ii) 11 month of the year dummies ($MONTH_{k,s}$) for February through December; (iii) a dummy for the trading days around holidays ($HOLIDAY_s$); (iv) two tick change dummies ($TICK1_s$ and $TICK2_s$) 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 $YEAR1_s$ ($YEAR2_s$) is equal to the difference between the current calendar year and 1988 (1997) or the first year when stock *i* started trading on NYSE, whichever is later. The regression residuals, including the intercept, provide us the adjusted proportional quoted spread (ASPR). The time series regression equation 1 is estimated for each stock in our sample. Unreported cross-sectional average of the estimated parameters show seasonal patterns in quoted spread: the bid-ask spreads are typically higher on Fridays and around holidays; spreads are lower from May to September relative to other months. 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 et al. (2005). After adjusting for the seasonality in spreads, we do not observe any significant time trend. In Table 1, the un-adjusted spread (QSPR) exhibits a clear time trend with the annual average spread decreasing from 1.26 percent in 1988 to 0.26 percent in 2003, but the trend is removed in the time series of the seasonally adjusted spread (ASPR) annual averages. We also plot the two series, QSPR and ASPR, in Figure 1, which comfortingly reveals that our adjustment process does a reasonable job in controlling for the deterministic time-series trend in stock spreads.

3. Liquidity and Past Returns

3.1 Time Series Analysis

In order to examine the impact of changes in aggregate asset valuations on liquidity, we first aggregate the daily adjusted spreads for each stock to obtain average weekly spreads. Denoting firm *i*'s adjusted proportional spread in week *t* as $ASPR_{i,t}$, we perform our analysis on changes in weekly spreads, ($ASPR_{i,t}$ minus $ASPR_{i,t-1}$) or $\Delta ASPR_{i,t}$.[5] Changes in weekly adjusted proportional spread for each firm i, $\Delta ASPR_{i,t}$, is regressed on the lagged market return ($R_{m,t-1}$), proxied by the CRSP value-weighted index. Focusing our analysis at weekly intervals provides us with a large number of time series observations while minimizing measurement problems associated with daily returns. Since the exact horizon over which declines in aggregate asset values affect liquidity is an empirical question, we examine the effect of up to four lags of weekly returns.[6] We test the key prediction of the underlying theoretical models that liquidity is affected by lagged market returns, particularly, negative returns. At the same time, it is possible that changes in liquidity are affected by lagged firm specific returns, since large changes in

[5] Estimates of the regression equations based on spread levels ($ASPR_{i,t}$) instead of changes in spreads ($\Delta ASPR_{i,t}$) produces qualitatively similar results at both monthly and weekly horizons. However, using changes in the variables has the advantage of reducing the econometric bias arising from highly autoregressive dependent and independent variables.

[6] We also consider the effect of up to eight weeks of lagged returns and these additional lags are in general insignificant and do not change our findings.

firm value may have similar wealth effects. Firm i's idiosyncratic returns ($R_{i,t}$) are defined as the difference between week t returns on stock i and the market index.[7]

We introduce a set of firm specific variables that may affect the intertemporal variation in liquidity. Market microstructure models in Demsetz (1968), Stoll (1978) and Ho and Stoll (1980) suggest that large trading volume and high turnover reduce inventory risk per trade and thus should lead to smaller spreads. We add weekly changes in turnover ($\Delta TURN_{it}$), measured by total trading volume divided by shares outstanding for firm i, into the regression to control for the spread changes arising from the market maker's inventory concern.

In addition to turnover, liquidity is affected by 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 correlated with spread and conjecture that this could arise because of the specialist's difficulty in adjusting quotes during periods of large order imbalances. To control for this effect, we add changes in the relative order imbalance ($\Delta ROIB_{\text{it}}$), measured by the change in absolute value of the weekly difference in the dollar amount of buyer- and seller-initiated orders standardized by the dollar amount of trading volume over the same period.

It is well known that bid-ask spreads are positively affected by return volatility due to higher adverse selection and inventory risks (see, e.g. Stoll (1978)). In the volatility-return literature, a drop in stock prices increases the financial leverage, which makes the stock riskier and increases its subsequent volatility (see Black (1976) and Christie (1982)). This implies that negative returns may increase spreads through its impact on subsequent volatility. In Vayanos (2004), variation in demand for liquidity is driven by changes in market volatility and during volatile periods, increased risk aversion

[7] Our results are unchanged when idiosyncratic returns are computed as the excess returns from a market model specification: $(R_{it} - b_i R_{mt})$.

is associated with the flight to quality phenomenon. Vayanos also suggests that if transaction costs are higher during volatile times, the impact of volatility on liquidity (premia) would be stronger, emphasizing an important connection between changes in volatility of market returns and liquidity. These models illustrate both contemporaneous as well as lagged effects of volatility on liquidity. We account for the volatility effect by including contemporaneous and lagged changes in weekly volatility of market returns ($\Delta STD_{m,t}$) and weekly volatility of individual stock i returns ($\Delta STD_{i,t}$). Weekly volatility estimates are obtained from daily returns over the previous four weeks using the method described in French, Schwert and Stambaugh (1987). Finally, we incorporate lagged value of changes in spreads to account for any serial correlations in spread changes.

Weekly changes in adjusted spreads for each firm is regressed on weekly market and firm-specific returns over the previous four weeks and other control variables defined earlier:

$$\begin{aligned}\Delta ASPR_{i,t} = \alpha_i + \sum_{k=1}^{4} \beta_{i,k} R_{m,t-k} + \sum_{k=1}^{4} \gamma_{i,k} R_{i,t-k} + c_{1i}\Delta STD_{m,t} + c_{2i}\Delta STD_{i,t} + c_{3i}\Delta STD_{m,t-1} + c_{4i}\Delta STD_{i,t-1} \\ + c_{5i}\Delta TURN_{i,t-1} + c_{6,i}\Delta ROIB_{i,t-1} + \sum_{k=1}^{4} \phi_{i,k}\, \Delta ASPR_{i,t-k} + \varepsilon_{i,t}\end{aligned} \quad (2)$$

We run the time-series regression in equation (2) for each individual stock to estimate the coefficients, and then report the mean and median of the estimated regression coefficients across all firms in our sample, taking into account the cross-equation correlations in the estimated parameters in computing the standard errors.[8] Table 2 presents the equally-weighted average coefficients across all individual stock regressions. We also report the percentage of statistically significant coefficients at the 5 percent level (for a

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[8] The t-statistics associated with the mean coefficients in Table 2 have been adjusted for cross-equation correlations. We extend the correction in standard errors proposed in Chordia et al. (2000) by allowing the variance and pairwise covariances between coefficient estimates to vary across securities. The variance of each estimated coefficient β_i is obtained from stock i's liquidity-return regression in (2). The empirical correlation between the regression residuals for stocks i and j is used to estimate the pairwise correlation between the coefficients $\{\beta_i \text{ and } \beta_j\}$. Hence, the standard error of the mean estimated coefficient is provided by: $StdDev(\bar{\beta}) = StdDev(\frac{1}{N}\sum_{i=1}^{N}\beta_i) = \frac{1}{N}\sqrt{\sum_{i=1}^{N}Var(\beta_i) + \sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N}\rho_{i,j}\sqrt{Var(\beta_i)Var(\beta_j)}}$.

one-tail test). Consistent with the evidence in the previous literature, we find that an increase in turnover predicts lower spreads. Increases in the volatility of individual firm and market returns have significant, positive impact on spreads. The positive relation between change in spreads and volatility changes is significant for both lagged as well as contemporaneous volatility changes. The coefficient associated with changes in order imbalance ($\Delta ROIB_{it}$), on the other hand, has an expected positive value, but is statistically insignificant.

More importantly, we find that negative lagged market return (as well as negative idiosyncratic return) worsens stock liquidity, after controlling for the firm specific factors and market volatility effects. We find that the lagged market returns in each of the past four weeks affect current changes in spreads, with the effects declining rapidly as we move to longer lags. Additionally, lagged idiosyncratic returns have similar monotonically reducing, but significant relation with current changes in adjusted spreads. Consistent with the theoretical predictions in Kyle and Xiong (2001) and Brunnermeier and Pedersen (2005) and others, the wealth effect of a market-wide drop in asset prices is associated with a fall in liquidity. It should be noted that the sensitivity of changes in spreads to lagged market returns cannot be attributed to idiosyncratic shocks in stock prices or changes in volatility, which also affects spreads.[9]

The models that link changes in market prices and liquidity in fact pose a stronger prediction: the relation should be stronger for prior losses than gains. Hence, we modify equation (2) to allow spreads to react differentially to positive and negative lagged returns:

[9] To alleviate any concerns arising from the fact that the firm-specific control variables in equation (2) are correlated with spreads, we reestimate the equation without these controls. We continue to find that changes in spreads are (more) sensitive to (negative) market returns.

$$\Delta ASPR_{i,t} = \alpha_i + \sum_{k=1}^{4} \beta_{i,k} R_{m,t-k} + \sum_{k=1}^{4} \beta_{DOWN,i,k} R_{m,t-k} D_{DOWN,m,t-k} + \sum_{k=1}^{4} \gamma_{i,k} R_{i,t-k} + \sum_{k=1}^{4} \gamma_{DOWN,i,k} R_{i,t-k} D_{DOWN,i,t-k} + c_{1i} \Delta STD_{m,t} + c_{2i} \Delta STD_{i,t} + c_{3i} \Delta STD_{m,t-1} + c_{4i} \Delta STD_{i,t-1} + c_{5i} \Delta TURN_{i,t-1} + c_{6,i} \Delta ROIB_{i,t-1} + \sum_{k=1}^{4} \phi_{i,k} \Delta ASPR_{i,t-k} + \varepsilon_{i,t} \quad (3)$$

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

Panel B of Table 2 presents the empirical estimate of equation 3. We find a significantly greater effect of negative market returns on liquidity: the regression coefficient on lagged market returns in week t-1 amplifies significantly from -0.413 to -1.223 when the lagged market return is negative. There is also an asymmetric relation between changes in spreads and lagged idiosyncratic returns, although the magnitude of the change in coefficient is less dramatic, with the regression coefficient changing from -0.473 to -0.631 for negative idiosyncratic returns. The asymmetric effect of negative market returns is stronger, and does not persist beyond week t-2. Interestingly, the sharp increase in spreads in week t-1, due to negative market returns, reverses to its mean in week t-3 and t-4, indicating that the liquidity effects last for up to 2 weeks.

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

$$\Delta ASPR_{i,t} = \alpha_i + \sum_{k=1}^{4} \beta_{i,k} R_{m,t-k} + \sum_{k=1}^{4} \beta_{DOWN\ LARGE,i,k} R_{m,t-k} D_{DOWN\ LARGE,m,t-k} + \sum_{k=1}^{4} \beta_{UP\ LARGE,i,k} R_{m,t-k} D_{UP\ LARGE,m,t-k} + \sum_{k=1}^{4} \gamma_{i,k} R_{i,t-k} + \sum_{k=1}^{4} \gamma_{DOWN\ LARGE,i,k} R_{i,t-k} D_{DOWN\ LARGE,i,t-k} + \sum_{k=1}^{4} \gamma_{UP\ LARGE,i,k} R_{i,t-k} D_{UP\ LARGE,i,t-k} + c_{1i} \Delta STD_{m,t} + c_{2i} \Delta STD_{i,t} + c_{3i} \Delta STD_{m,t-1} + c_{4i} \Delta STD_{i,t-1} + c_{5i} \Delta TURN_{i,t-1} + c_{6,i} \Delta ROIB_{i,t-1} + \sum_{k=1}^{4} \phi_{i,k} \Delta ASPR_{i,t-k} + \varepsilon_{i,t} \quad (4)$$

where $D_{DOWN\ LARGE,m,t}$ ($D_{UP\ LARGE,m,t}$) is a dummy variable that is equal to one if and only if $R_{m,t}$ is greater than 1.5 standard deviation below (above) its unconditional mean return.

Similarly, $D_{DOWN\ LARGE,i,t}$ ($D_{UP\ LARGE,i,t}$) is a dummy variable that is equal to one if and only if $R_{i,t}$ is greater than 1.5 standard deviation below (above) its mean return.[10]

The results presented in Table 2, Panel C, show that large negative market shocks significantly widens the bid-ask spreads. On the other hand, large positive market returns have insignificant additional effect on spreads, reinforcing the striking asymmetric effect of market returns on liquidity. Our findings add to those in Chordia, Roll and Subrahmanyam (2000 and 2002) who show that at the aggregate level, daily spreads increase dramatically following days with negative market return but decrease only marginally on positive market daily returns. When we look at the effect of market returns at longer lags, large negative market returns in week t-3 and t-4 are positively associated with changes in spreads. Consistent with the results in Panel B, the increase in spreads following large negative market returns in week t-1 reverses at longer lags.

Although not reported in the tables (but available upon request from authors), additional analyses of the relation between changes in spreads and market returns provide more insights. First, we find an average change in adjusted spreads following a (large) negative market return in week *t-1* is economically and statistically significant at 2.8 (6.2) basis points, after controlling for other determinants of spreads in equation (2). Second, Deuskar (2007) presents a model where an increase in the investors perceived asset risk reduces current prices and makes the market more illiquid. In her model, higher forecasts of volatility affect investor sentiment and hence, realized volatility and liquidity. Specifically, her model predicts lowers liquidity when misperceived volatility, measured by the difference between implied volatility of S&P 100 index options (VIX) and realized index volatility, is higher. Consistent with Dueskar (2007), we find that changes in weekly adjusted spread is significantly and positively related to contemporaneous and lagged misperceived weekly volatility. However, the misperceived volatility effects do

[10] We have also considered other cut-offs of 2.0 and 1.0 standard deviations from the mean to identify large market return states and obtain similar results.

not displace the strong negative influence of lagged returns.[11] Moreover, adding more lags of volatility do not affect our results, indicating that the inter-temporal influence of volatility are different from the return effects. Third, we examine if changes in liquidity are related to other market wide factors, such as the size (SMB) and book-to-market (HML) factors introduced by Fama and French (1993). While we do not find any relation between liquidity changes and the HML factor, shocks to the SMB factor negatively affects individual firm spreads, suggesting a bigger impact of low returns on the small firm portfolio. Finally, we have considered several other empirical specifications such as including current and lagged average market spreads, contemporaneous individual stock and market returns, and find that our results are robust to estimation biases. Hence, a decrease in aggregate market value of securities leads to a drop in liquidity, consistent with the wealth effects proposed in recent collateral based models.

3.2 Evidence of Funding Constraint Effects

We interpret the relation between market declines and liquidity dry-ups, controlling for various other factors, as indicative of capital constraints in the marketplace. A direct test of this supply-side explanation for the inter-temporal changes in liquidity requires that we identify independent changes in funding liquidity at weekly frequencies. Although we do not have access to direct measures of aggregate supply shocks, we use indirect measures from the financial sector to investigate if the contraction in liquidity following aggregate market declines is consistent with liquidity providers becoming more

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[11] Recent behavioral models argue that a positive relation between past returns and firm liquidity could arise from an increase in supply of overconfident individual traders following price run-ups (Gervais and Odean (2001)), overreaction to sentiment shocks ((Baker and Stein (2004)) or disposition effects (Shefrin and Statman (1985)). We examine this possibility using the percentage of small trades, defined as trades below $5000, as a proxy for uninformed, behaviorally biased trades by individuals (see Lee (1992), Lee and Radhakrishna (2000), Barber, Odean and Zhu (2006)). While we find an increase in the percentage of small trades following positive returns, we do not find any evidence of decreases in small trades following negative returns. Hence, the asymmetric effect on market returns on liquidity cannot be explained by these behavioral biases. Detailed results are available form the authors.

capital constrained. With equation (3) as a starting point, we examine if the sensitivity of changes in spreads to negative market returns differs during periods when the suppliers of liquidity are likely to face capital tightness. The following regression model is estimated:

$$\begin{aligned}\Delta ASPR_{i,t} &= \alpha_i + \sum_{k=1}^{4}\beta_{i,k}R_{m,t-k} + \sum_{k=1}^{4}\beta_{DOWN,i,k}R_{m,t-k}D_{DOWN,m,t-k} \\ &+ \beta_{DOWN,CAP,i,k}R_{m,t-1}D_{DOWN,m,t-1}D_{CAP,t-1} + \sum_{k=1}^{4}\gamma_{i,k}R_{i,t-k} \\ &+ \sum_{k=1}^{4}\gamma_{DOWN,i,k}R_{i,t-k}D_{DOWN,i,t-k} + c_{1i}\Delta STD_{m,t} + c_{2i}\Delta STD_{i,t} + c_{3i}\Delta STD_{m,t-1} + \\ &c_{4i}\Delta STD_{i,t-1} + c_{5i}\Delta TURN_{i,t-1} + c_{6,i}\Delta ROIB_{i,t-1} + \sum_{k=1}^{4}\phi_{i,k}\,\Delta ASPR_{i,t-k} + \varepsilon_{i,t}\end{aligned} \tag{5}$$

where $D_{CAP,t}$ is a dummy variable that takes a value of one only if week t is associated with periods of higher capital constraints. Since we do not observe the balance sheet of financial intermediaries, we use three proxies of tightness of capital in the market. The first proxy is based on the (value-weighted) return on the portfolio of investment banks and securities brokers and dealers listed on NYSE, defined by SIC code 6211.[12] We compute the excess returns on the portfolio of stocks in the investment banking sector by the residuals from a one factor market model regression. A big fall in the market value of these large firms operating in investment banking and securities brokerage services is likely to reflect a weak aggregate balance sheet of the funding sector. Hence, when the excess returns on this portfolio of financial intermediaries is negative in week *t*, measured relative to the market portfolio, $D_{CAP,t}$ is set to be equal to 1.[13]

Adrian and Shin(2007) show that the financial intermediaries adjust their leverage in a procyclical manner and the margin of adjustment in the expansion and contraction of their balance sheets is through repos. For example, when financial intermediaries have weak balance sheets, their leverage is too high. The ensuing capital shortage forces the

[12] For example, in 1996, the 10 largest firms that belong to SIC code 6211 (Security Brokers, Dealers and Floatation Companies) are: Alex Brown, Bear Sterns, Dean Witter, A.G. Edwards, Lehmann Brothers, Merrill Lynch, Morgan Stanley, John Nuveen, Charles Schwab, and Travellers Group. The composition of firms is updated annually. Adrian and Shin (2007) use a similar portfolio of firms to examine the effect of changes in asset values on leverage of financial intermediaries.

[13] We also considered additional lags to $D_{CAP,t}$, but found them to be insignificant in all cases and hence do not report them.

intermediaries to contract their balance sheets.[14] Adrian and Shin show that these changes in aggregate intermediary balance sheets are linked to funding liquidity through shifts in market-wide risk appetite. We, therefore, use the weekly changes in aggregate repos used in Adrian and Shin (2007) as our second measure of constraints in the funding market and set $D_{CAP,t}$ to be 1 when there is a decline in aggregate repos in week t.[15]

Our third measure of changes aggregate funding liquidity relies on the weekly spread in commercial papers (CP), measured as the difference in the weekly returns on the three-month commercial papers rate and three-month Treasury Bills rate.[16] It is well known that the CP market is very illiquid. As Krishnamurthy (2002) shows, the difference in the return on CP and T-Bills (or the CP spread) reflects a liquidity premium demanded by the large investors in CP such as money market mutual funds and other financial corporations. Getav and Strahan (2006) use CP spread to measure liquidity supply and show that the spread widens during liquidity events. Since changes in CP spreads are related to the willingness of these intermediaries to provide liquidity, we argue that an increase in the weekly CP spread is likely to be associated with a period when the funding market is capital constrained. Hence, $D_{CAP,t}$ is equal to 1 when there is an increase in CP spread in week t.

The empirical estimate of equation (5) for all three proxies of capital tightness is presented in Table 3. Panel A of Table 3 shows that a decline in aggregate market valuations leads to a significantly greater increase in bid-ask spreads when there is also an underperformance in the investment banking and brokerage sector.[17] As shown in Panel B, a contraction in the balance sheet of the financial intermediaries, measured by a decrease in repos, has a similar effect. To be precise, a negative return on the market

[14] Adrian and Shin argue that there is also a potential feedback effect: weaker balance sheets lead to greater sale of assets, which puts downward pressure on asset prices and lead to even weaker balance sheets.

[15] We thank Tobias Adrian for generously sharing the weekly data on the primary dealer repo positions compiled by the Federal Reserve Bank of New York.

[16] The weekly data is downloaded from the Federal Reserve website at www.federalreserve.gov.

[17] For ease of exposition, we report the coefficients for the combined market (and portfolio) returns in weeks t-3 and t-4.

index in week t-1 increases the regression coefficient for market returns from -0.43 to -0.95. However, the coefficient increases significantly higher to -1.63 when there is also a decrease in aggregate repos in the capital markets. Finally, our findings are reinforced by the significant increase in the regression coefficient when CP spreads are higher. Together, the evidence in Table 3 is strongly supportive of our interpretation that liquidity dry-ups following market declines are related of tightness in funding liquidity.

3.3 Cross-sectional Evidence

The theoretical models of liquidity supply under capital constraints in Gromb and Vayanos (2002) and Brunnermeier and Pederson (2007) 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 (margin requirements) when funding constraints bind. Brunnermeier and Pedersen (2007) also predict that a drop in funding capital (large negative market return shock) increases the differential liquidity between high and low volatility securities as market makers reduce (increase) provision of liquidity for securities that require more (less) capital. The latter effect is synonymous with the flight to liquidity phenomenon documented in Achraya and Pedersen (2005).

In this sub-section, we examine the cross-sectional differences in the relation between lagged returns and spreads among stocks that differ in volatility, controlling for firm size. Firms are sorted into nine size-volatility portfolios based on two-way dependent sorts on each firm's beginning of year market capitalization and its return volatility in the previous year, rebalancing the portfolio composition each year. In each week t, we average the adjusted spreads on each firm to produce nine portfolio level spreads, $ASPR_{p,t}$. Similar to the firm-specific variables defined in equation (3), for each week t, we average relative order imbalance across all firms in each portfolio, denoted as $ROIB_{p,t}$;

and calculate portfolio turnover, $TURN_{p,t}$; portfolio specific returns ($R_{p,t}$) and volatility, $STD_{p,t}$. We regress the change in spreads at portfolio level on changes in the control variables as well as portfolio and market return, parallel to equation (3), but for portfolio p, where p=1,2,…,9:

$$\Delta ASPR_{p,t} = \alpha_i + \sum_{k=1}^{4}\beta_{p,k}R_{m,t-k} + \sum_{k=1}^{4}\beta_{DOWN,p,k}R_{m,t-k}D_{DOWN,m,t-k} + \sum_{k=1}^{4}\gamma_{p,k}R_{p,t-k}$$
$$+ \sum_{k=1}^{4}\gamma_{DOWN,p,k}R_{p,t-k}D_{DOWN,p,t-k} + c_{1p}\Delta STD_{m,t} + c_{2p}\Delta STD_{p,t} + c_{3p}\Delta STD_{m,t-1} + \tag{6}$$
$$c_{4p}\Delta STD_{p,t-1} + c_{5p}\Delta TURN_{p,t-1} + c_{6,p}\Delta ROIB_{p,t-1} + \sum_{k=1}^{4}\phi_{p,k}\Delta ASPR_{p,t-k} + \varepsilon_{p,t}$$

The system of equations in (6) is estimated using the seemingly unrelated regression (SUR) method, allowing for cross-equation correlations. Consistent with the results in Table 2, Table 4 shows that changes in portfolio level adjusted spreads are negatively related to market returns, controlling for portfolio specific returns and other factors. The sensitivity of changes in spreads to market and portfolio returns is higher for the small stock portfolio and high volatility portfolios. Statistical tests of the difference in the coefficients corresponding to the regression of changes in spreads on negative market returns in week *t-1* indicate that high volatility firms experience a significantly larger increase in spreads during market downturns. These sharp increases in spreads do appear to reverse in the subsequent weeks indicating the short-run nature of the phenomenon. Our results are not a manifestation of size related effects since we find analogous results within each of the size thirtiles. On the other hand, the reaction of spreads to own portfolio negative returns are, generally, less dramatic. Hence, these results indicate that less liquidity is available for high volatility stocks when the liquidation of these assets (collateral) becomes more costly, consistent with the predictions of a flight to liquidity.

It is interesting to note that the impact of negative market returns on liquidity takes the same direction for each of the nine size-volatility portfolios, suggesting a high commonality in liquidity, an issue that we investigate deeper in the next section.

4 Comovement in Liquidity

4.1. Comovement in Liquidity and Market Returns

When market makers and other intermediaries are constrained by their capital base, a large negative return reduces the pool of capital that is tied to marketable securities and, hence, reduces the supply of liquidity. In particular, the theoretical models in Brunnermeier and Pedersen (2005) and Kyle and Xiong (2001) predict that the funding liquidity constraints in down market states increase the commonality in liquidity across securities and its comovement with market liquidity. In this section, we pursue this idea further and investigate whether the commonality in liquidity increases when there is a negative market return, especially a large negative market shock.

We start with an investigation of the impact of market returns on a firm's liquidity beta, using the regression framework in (3). We do this by introducing a measure of weekly market level spreads, $ASPR_{m,t}$, where $ASPR_{m,t}$ is obtained by equally-weighting across all firms, the adjusted spreads for firm *i* in week *t*, $ASPR_{i,t}$. The weekly change in market spreads, ($ASPR_{m,t}$-$ASPR_{m,t-1}$) is denoted as $\Delta ASPR_{m,t}$. Equation (3) is modified by adding $\Delta ASPR_{m,t}$ to the regression and the sensitivity of firm *i*'s spread to $\Delta ASPR_{m,t}$ is its liquidity beta, $b_{LIQ,i}$.

$$\begin{aligned}\Delta ASPR_{i,t} &= \alpha_i + b_{LIQ,i}\Delta ASPR_{m,t} + b_{LIQ,DOWN,i}\Delta ASPR_{m,t} D_{DOWN,m,t} \\ &+ \sum_{k=1}^{4}\beta_{i,k} R_{m,t-k} + \sum_{k=1}^{4}\beta_{DOWN,i,k} R_{m,t-k} D_{DOWN,m,t-k} + \sum_{k=1}^{4}\gamma_{i,k} R_{i,t-k} \\ &+ \sum_{k=1}^{4}\gamma_{DOWN,i,k} R_{i,t-k} D_{DOWN,i,t-k} + c_{1i}\Delta STD_{m,t} + c_{2i}\Delta STD_{i,t} + c_{3i}\Delta STD_{m,t-1} + \\ & c_{4i}\Delta STD_{i,t-1} + c_{5i}\Delta TURN_{i,t-1} + c_{6,i}\Delta ROIB_{i,t-1} + \sum_{k=1}^{4}\phi_{i,k}\Delta ASPR_{i,t-k} + \varepsilon_{i,t}\end{aligned} \tag{7}$$

$$\begin{aligned}\Delta ASPR_{i,t} &= \alpha_i + b_{LIQ,i}\Delta ASPR_{m,t} + b_{LIQ,DOWN\ SMALL,i}\Delta ASPR_{m,t} D_{DOWN\ SMALL,m,t} \\ &+ b_{LIQ,DOWN\ LARGE,i}\Delta ASPR_{m,t} D_{DOWN\ LARGE,m,t} \\ &+ \sum_{k=1}^{4}\beta_{i,k} R_{m,t-k} + \sum_{k=1}^{4}\beta_{DOWN,i,k} R_{m,t-k} D_{DOWN,m,t-k} + \sum_{k=1}^{4}\gamma_{i,k} R_{i,t-k} \\ &+ \sum_{k=1}^{4}\gamma_{DOWN,i,k} R_{i,t-k} D_{DOWN,i,t-k} + c_{1i}\Delta STD_{m,t} + c_{2i}\Delta STD_{i,t} + c_{3i}\Delta STD_{m,t-1} + \\ & c_{4i}\Delta STD_{i,t-1} + c_{5i}\Delta TURN_{i,t-1} + c_{6,i}\Delta ROIB_{i,t-1} + \sum_{k=1}^{4}\phi_{i,k}\Delta ASPR_{i,t-k} + \varepsilon_{i,t}\end{aligned} \tag{8}$$

It should be noted that we exclude firm *i* in the computation of average spreads as the independent variable. Although changes in liquidity levels are different from liquidity commonality, it is possible that they are correlated. For example, if low market returns predict low liquidity for all stocks, then liquidity covariance with aggregate liquidity may increase following low market returns. Hence, we test for both liquidity level and commonality effects in equation (7). Specifically, we check if $b_{LIQ,i}$ changes during periods of negative market returns, described by the dummy variable $D_{DOWN,m,t}$, after accounting for the effect of changes in liquidity. We also check in equation (8) if $b_{LIQ,i}$ changes when market returns are negative and small ($D_{DOWN\ SMALL,m,t}$) or negative and large ($D_{DOWN\ LARGE,m,t}$), where small (large) is defined as negative market returns that is less (greater) than 1.5 standard deviation below the unconditional mean market returns.

The empirical estimate of equations (7) and (8) are produced in Table 5. Consistent with the theoretical predictions, Panel A shows that $b_{LIQ,i}$ increase significantly from 0.56 to 0.87 in down market states. The increase in liquidity commonality is present for both small as well as large negative market returns as shown in Panel B. While $b_{LIQ,i}$ increases to 0.83 for small negative drop in market valuations, the largest increase in commonality in liquidity happens during large market downturns, when $b_{LIQ,i}$ increases to 0.95. Moreover, Table 5 also shows that the asymmetric effect of market returns on spreads documented in Section 3.2 continues to persist, after accounting for changes in liquidity commonality. Hence, the results in Table 5 emphasize two separate effects: an increase in illiquidity levels as well as commonality in illiquidity in response to market downturns.

We also investigate the effect of market returns on commonality in liquidity using an alternate metric that captures comovement. 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 (in returns) is due to common, market-wide movements. We apply the same concept by using a single-factor market model to compute the commonality in liquidity.

Changes in daily adjusted proportional spreads for firm *i* on day *s* ($\Delta ASPR_{i,s}$) are regressed on changes in daily market-wide average adjusted spreads ($\Delta ASPR_{m,s}$). Following Chordia, Roll and Subrahmanyam (2001), we estimate the linear regression:

$$\Delta ASPR_{i,s} = a_i + b_{LIQ,i} \Delta ASPR_{m,s} + \varepsilon_{i,s} \qquad (9)$$

For each stock *i* with at least 15 valid daily observations in month *t*, the market model regression yields a regression r-square denoted as $R^2_{i,t}$. A high $R^2_{i,t}$ suggests that a large portion of the daily variations in liquidity for stock *i* in month *t* are due to market-wide liquidity variations. For each month *t*, the strength of liquidity comovement is given by an equally-weighted average of $R^2_{i,t}$, denoted as R^2_t.

Figure 2 plots the time series variation in liquidity commonality, R^2_t, over the sample period 1988 to 2003. Commonality in liquidity in Figure 2 exhibits significant variation over time and spikes in the level of commonality are associated with periods of liquidity crisis. For example, the highest levels of commonality in liquidity in Figure 2 coincide with liquidity dry-ups during the Asian financial crisis (1997), LTCM crisis (1998) and September 11, 2001 terrorist attacks. These periods are also accompanied by large negative market returns, denoting the episodic nature of illiquidity. The average liquidity R^2 increases to 8.0 (10.1) percent in negative (large negative) market returns states compared to 7.4 percent R^2 when market returns are positive. In addition, commonality in liquidity has a significant correlation with market returns, but only in down markets. The correlation between commonality in liquidity and absolute market returns is 0.48 (0.002) in down (up) markets. Hence, commonality in liquidity increases dramatically when there are large declines in aggregate market valuations.

As a robustness check, we also analyse the conditional correlations in liquidity across size-sorted portfolios, following the dynamic conditional correlations (DCC) methodology introduced by Engle (2002), and relegate the results to Appendix I. Starting with the average (equally-weighted) daily adjusted spreads (ASPR) for each portfolio, we fit a GARCH(1,1) model for the liquidity variable. The conditional correlations between the GARCH residuals for each pair of portfolios are allowed to vary over time. We sort firms into thirtiles based on their beginning of year market capitalization. We find that the average conditional correlation between the liquidity of the small and large size portfolios monotonically increase from 0.226 following large up market states to 0.307 after large market declines. The conditional correlations in liquidity are significantly higher following large market declines, across all pairs of size portfolios.

The common variation in liquidity could also arise from correlated demand for liquidity by index-linked funds or index arbitrageurs. For example, Harford and Kaul (2005) find that indexing leads to common effects in the intra-day (fifteen minute) order flow and (to a lesser extent) trading costs for S&P 500 constituent stocks, the most widely followed index. We repeat the DCC analysis using two portfolios of stocks, constructed based on whether the stock is an S&P 500 index stock or not. Data on S&P membership is obtained from Standard and Poor's records and the membership information is updated annually. We find similar increase in conditional correlations in illiquidity between these two portfolios, suggesting that indexing effects alone cannot explain our results. These results underscore the main idea that illiquidity becomes more correlated across all assets following market declines.

The inter-temporal variation in liquidity commonality may also be affected by other factors. Vayanos (2004) specifies stochastic market volatility as a key state variable that affects liquidity in the economy. In his model, investors become more risk averse and their preference for liquidity increases in volatile times. Consequently, a jump in market volatility is associated with higher demand for liquidity (also termed as flight to liquidity) and, conceivably increases liquidity commonality. On the other hand, if liquidity is not a systematic factor and is primarily determined by firm specific effects, then changes in liquidity should be related to variation in idiosyncratic volatility. Hence, we examine if changes in liquidity commonality are related to market or firm-specific volatility.[18]

Large differences between buy and sell orders for a particular security have the effect of reducing liquidity. Extreme aggregate order imbalance is likely to increase the demand on the liquidity provision by market makers and also increase the inventory concern faced by maker makers as shown by Chordia, Roll and Subrahmnayam (2002). If high levels of aggregate order imbalance impose similar pressure on the demand for liquidity across securities, we expect to see a positive relation between order imbalance and commonality in spreads. In addition, if the effect of order imbalance on aggregate stock liquidity is due to correlated shifts in demand by buyer or seller initiated trades, commonality in liquidity may be attributed to the commonality in order imbalance. Hence, we explore the impact of both the level and commonality in order imbalance on liquidity comovement. Since we are interested in the magnitude of order imbalance, we use the cross-sectional mean relative order imbalance *(ROIB*) defined in Section 3.1 as our measure of level of order imbalance. To measure commonality in order imbalances, we estimate the R^2 from a single-factor regression model of individual firm order imbalance on market (equally-weighted average) order imbalance, similar in spirit to the liquidity commonality measure using proportional spreads in equation (9).

We introduce these additional variables that affect liquidity commonality using a regression framework in Table 6. Since the R^2_t values are constrained to be between zero and one by construction, we define liquidity comovement as the logit transformation of R^2_t, $LIQCOM_t = \ln[R^2_t /(1-R^2_t)]$. We regress our comovement measure on market returns (R_{mt}) , taking into account the sign and magnitude of market returns:

[18] Monthly idiosyncratic volatility for each firm is obtained by taking the standard deviation of the daily residuals from a one-factor market model regression. The firm-specific residual volatility is averaged across all stocks to generate our idiosyncratic volatility measure.

$$LIQCOM_t = a + \beta R_{m,t} + \beta_{DOWN\ LARGE} R_{m,t} D_{DOWN\ LARGE,t} + \beta_{UP\ LARGE} R_{m,t} D_{UP\ LARGE,t} + controls + \varepsilon_t \quad (10)$$

where, the return and dummy variables are defined in equation (4), Section 3.1.

As shown in the first column of estimates in Table 6, liquidity comovement is strongest when there is a large drop in market prices. The correlation between market returns and commonality in liquidity is significantly larger only when market returns are large and negative. Shifts in the order imbalance co-movement, which we interpret as a measure of correlation in demand for liquidity, are positively associated with liquidity commonality. In other words, periods of large systematic movement in liquidity is associated with periods of high systematic movement in imbalance in buy and sell orders.

In the next columns in Table 6, we report a significant positive relation between market volatility and liquidity commonality, separate from the effect of market returns. On the other hand, changes in the level of idiosyncratic volatility do not affect the degree of comovement in liquidity among stocks. These results are consistent with the prediction in Vayonas (2004) that uncertainty in the market increases investor demand for liquidity and subsequently increasing liquidity commonality. Extreme shifts in the aggregate order imbalance (*ROIB*), in addition to market volatility, have positive effects on liquidity commonality. Nevertheless, adding these demand measures does not eliminate the significant asymmetric effect of market returns on liquidity commonality.

To the extent that comovement in order imbalance across securities picks up correlation in demand for liquidity, it would be interesting to document the sources that drive the common variations in order flow. In addition to the control variables introduced above, we also consider another factor that may affect the time variation in commonality in liquidity demand. Flow of cash into and out of equity mutual funds can create correlated imbalances in order flows. For example, when there is a large withdrawal of funds by mutual fund owners in aggregate, fund managers are less willing and able to hold (particularly illiquid) assets, creating correlated demand for liquidity across stocks.

New flow of funds into the mutual fund companies, on the other hand, does not create an immediate buy pressure and hence, may not affect the correlation in liquidity demand. We obtain data on monthly net flow of funds into U.S. equity mutual funds for our sample period from 1984 to 2004 from Investment Company Institute. We divide the net fund flow by the total assets under management by U.S. equity funds to generate our monthly time series of net mutual fund flow.

We report the determinants of order imbalance commonality in column (4) of Table 6. We find that order imbalance comovement increases with market volatility and is negatively related to net mutual fund flows, corresponding to changes in demand for liquidity. However, order imbalances across stocks decreases after a large drop in market valuations, unlike the evidence on liquidity commonality. The latter result is not surprising since market returns and constraints on aggregate capital are not expected to affect liquidity demand in the same way. We also find greater persistence in order imbalance comovement, as reflected by the significant coefficient for its own lagged value. Moreover, correlations in order flow are positively associated with liquidity commonality.

There appears to be a significant association between the two comovement measures, and that both variables may affect each other simultaneously. In this case, the endogeneity problem is likely to cause the parameter estimates to be biased and inconsistent. We therefore estimate the coefficients based on two-stage least squares (2SLS) estimation, using net mutual fund flow and lagged order imbalance comovement to identify the demand (commonality in order imbalance) equation. As shown in the last two columns of Table 6, our finding that liquidity commonality increases only in large, down market states remains robust.

Overall, the results presented so far show that while liquidity commonality is driven by changes in supply as well as demand for liquidity, the demand factors cannot explain the asymmetric effect of market returns on liquidity. On the other hand, the increase in liquidity commonality in down market states is consistent with the adverse effects of a fall in the supply of liquidity.

4.2 Commonality in Liquidity: Industry Spillover Effects

Virtually all the theoretical models, including Kyle and Xiong (2001), Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2005), suggest a contagion in illiquidity. Coughenour and Saad (2004) provide empirical evidence of covariation in liquidity arising from specialist firms providing liquidity for a group of firms and sharing a common pool of capital, inventory and profit information. We broaden the investigation by addressing 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. If the common effects of market returns on liquidity commonality are due to correlated industry events, then, stocks in the same industry will exhibit common reaction to industry-wide information flow. If commonality in liquidity, on the other hand, is driven by capital constraints faced by the market making sector in supplying liquidity, we ought to observe correlated illiquidity within an industry to increase with a fall in market values of securities in other industries.

We begin by estimating the following industry-factor model for daily change in liquidity for security *i* ($\Delta ASPR_{i,s}$), within each month:

$$\Delta ASPR_{i,s} = a_i + b_{LIQ,i}\Delta ASPR_{INDj,s} + \varepsilon_{i,s} \qquad (11)$$

where the industry-liquidity factor ($\Delta ASPR_{INDj,s}$) is the daily change in the equally-weighted average of adjusted spreads across all stocks in *industry j* on day *s*. Similar to our approach in estimating market-wide liquidity commonality in equation (9), we aggregate the regression R^2 from equation (11) for each month *t*, across all firms in industry *j*. To obtain an industry-wide measure of commonality in liquidity for each month, we perform a logit transformation of the industry average $R_{INDj,t}^2$, denoted as

$LIQCOM_{INDj,t}$. We form 17 industry-wide comovement measures using the SIC classification derived by Fama-French.[19] $LIQCOM_{INDj,t}$, is regressed on the monthly returns on the industry portfolio j ($R_{INDj,t}$) and the returns on the market portfolio, excluding portfolio j ($R_{MKTj,t}$), taking into account the effect of positive and negative industry and market returns on liquidity comovement, as well as the effect of the magnitude of these returns:

$$\begin{aligned} LIQCOM_{INDj,t} &= a + \delta R_{INDj,t} + \delta_{DOWN} R_{INDj,t} D_{DOWN,INDj,t} \\ &+ \beta R_{MKTj,t} + \beta_{DOWN} R_{MKTj,t} D_{DOWN,MKTj,t} + \varepsilon_t \end{aligned} \qquad (12)$$

$$\begin{aligned} LIQCOM_{INDj,t} &= a + \delta R_{INDj,t} + \delta_{DOWN\,LARGE} R_{INDj,t} D_{DOWN\,LARGE,INDj,t} + \delta_{UP\,LARGE} R_{INDj,t} D_{UP\,LARGE,INDj,t} \\ &+ \beta R_{MKTj,t} + \beta_{DOWN\,LARGE} R_{MKTj,t} D_{DOWN\,LARGE,MKTj,t} + \beta_{UP\,LARGE} R_{MKTj,t} D_{UP\,LARGE,MKTj,t} + \varepsilon_t \end{aligned} \qquad (13)$$

where the dummy variables are defined in the same way as in equations (3) and (4). The regression coefficient associated with the independent variable $R_{MKTj,t}$ measures liquidity spillover effects. We also consider using the liquidity betas, $b_{LIQ,t}$, in equation (11) as an alternative measure of commonality in liquidity.

The estimates of equations (12) and (13) are reported in Table 7. We find that industry portfolio returns, especially large, negative returns, have a significant effect on commonality in liquidity while positive industry returns do not affect liquidity comovement. More interestingly, we find that the returns on a portfolio securities in other industries (excluding own industry returns) exert a strong influence on comovement in industry-wide liquidity, especially when the returns are negative. In fact, the market portfolio returns dominate the industry returns in terms of its effect of industry-wide liquidity movements. The regression coefficient estimate for negative market returns is a significant -1.995 while the coefficient for negative industry returns is smaller at -0.986. When we separate the returns according to their magnitude, large negative market returns turn out to have the biggest impact on industry level liquidity movements. On the other

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

hand, the marginal effect of large, positive industry and market returns are insignificant. As shown in Table 7, we obtain similar spillover effects of market-wide returns on within industry liquidity commonality when we replace *LIQCOM* with the industry average liquidity betas, $b_{LIQ,t}$. These results strongly support the idea that when large negative market returns occur, spillovers due to capital constraints broaden across industries, increasing the commonality in liquidity.

5 Liquidity and Short-term Price Reversals

The collateral based models imply that the cost to supplying liquidity increases when the capital constraint binds. In this section, we examine two investment trading strategies that capture the return to providing liquidity. In Campbell, Grossman, and Wang (1993), for example, risk-averse, utility maximising market makers require compensation for supplying liquidity to meet fluctuations in aggregate demand for liquidity. In their model, heavy volume is accompanied by large price decreases as market makers require higher expected returns to accommodate the heavy liquidity (selling) pressure. Their model implies that these stock prices will experience a subsequent reversal, as prices go back to their fundamental value.[20] Conrad, Hameed, and Niden (1994), Avramov, Chordia, and Goyal (2005) and Kaniel, Saar and Titman (2006) provide empirical support to the relation between short-term price reversals and illiquidity and show that high-volume stocks exhibit significant weekly return reversals. If there are liquidity supply effects in equity markets, we expect these returns to be higher following market declines.

We examine the extent of price reversals in different market states using two empirical trading strategies: contrarian and limit-order trading strategies. The first trading strategy relies on the weekly contrarian investment strategy formulation in Avramov, Chordia, and Goyal (2005). We construct Wednesday to Tuesday weekly returns for all

[20] Pastor and Stambaugh (2003) use a parallel motivation to develop a liquidity risk factor for empirical asset pricing models.

NYSE stocks in our sample for the period 1988 to 2003. Skipping one day between two consecutive weeks avoids the potential negative serial correlation caused by the bid-ask bounce and other microstructure influences. Next, we sort the stocks in week t into positive and negative return portfolios. For each week t, return on stock i (R_{it}) which is higher (lower) than the median return in the positive (negative) return portfolio is classified as a winner (loser) securities. We focus our analysis on the behavior of weekly returns for securities in these extreme winner and loser portfolios. We use stock i's turnover in week t ($Turn_{it}$), which is the ratio of weekly trading volume and the number of shares outstanding, to measure the amount of trading.

The contrarian portfolio weight of stock i in week $t+1$ within the winner and loser portfolios is given by: $w_{i,p,t+1} = -R_{i,t}Turn_{i,t} / \sum_{i=1}^{Npt} R_{i,t}Turn_{i,t}$, where Npt denotes the number of securities in the loser or winner portfolios in week t. The contrarian investment strategy is long on the loser securities and short on the winner securities, with weights depending positively on the magnitude of returns and turnover. The sum of weights for each portfolio is 1.0 by construction. The contrarian profit for the loser and winner portfolio for week $t+k$ is: $\pi_{p,t+k} = \sum_{i=1}^{Np} w_{it+1} R_{i,t+k}$, which can be interpreted as the return to a \$1 investment in each portfolio. The combined zero-investment profits are obtained by taking the difference in profits from the loser and winner portfolios.

To the extent that the contrarian profits reflect the cost of supplying liquidity, we expect the price reversals on heavy volume to be negatively related to changes in aggregate market valuations. We investigate the effect of lagged market returns on the above contrarian profits by conditioning the profits on cumulative market returns over the previous four weeks. Specifically, we examine contrarian profits over four market states: large up (down) market is defined as market return being 1.5 standard deviation above (below) mean returns; and small up and down market refers to market return being between zero and 1.5 standard deviations around the mean returns.

In the second trading strategy, we follow Handa and Schwartz (1996) in devising a simple limit-order trading rule to measure the profits to supplying liquidity.[21] When a limit buy order is submitted below the prevailing bid price, the limit order trader provides liquidity to the market. If price variations are due to short-term selling pressure, the limit buy order will be executed and we should observe subsequent price reversals, reflecting compensation for liquidity provision. At the same time, the limit order trader expects to lose from the trade upon arrival of informed traders, in which case the price drop would be permanent (ie. limit buy order imbeds a free put option). Our maintained hypothesis that funding constraint takes effect after a dive in aggregate market values implies that the expected return to supplying liquidity via limit orders is highest following large down markets.

The limit-order strategy is implemented as follows. At the beginning of each week *t*, a limit buy order is placed at *x%* below the opening price(P_o). We consider three values of *x*, i.e. 3%, 5%, and 7%. If the transaction price falls to or below P_o (1- *x%*) within week *t* (week *t* is the trading window), the limit order is executed and the investment is held for a period of *k* weeks (*k* = 1 and 2 weeks). If the limit order is not executed in week *t,* we assume that the order is withdrawn. A similar strategy is employed to execute limit sell orders if prices reach or exceed P_o (1+ *x%*). The above procedure is applied to each stock in our sample to generate buy and sell limit-order weekly returns. For each week *t+1*, we construct the cross-sectional average weekly returns (for buy and sell orders), weighting each stock *i* by its turnover in week *t* $w_{i,t+1} = Turn_{i,t} / \sum_{i=1}^{Npt} Turn_{i,t}$. Again, we investigate if the payoff to the limit order trading strategy is dependent on market states.

Table 7 and 8 report the results for the contrarian and limit-order trading strategies respectively. Table 7, Panel A reports significant contrarian profit of 0.58 percent in week

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[21] We thank Joel Hasbrouck for suggesting this alternative trading strategy.

t+1 (*t*-statistics is 5.38) for the full sample period. A large portion of the profits comes from the loser portfolio with a return of 0.75 percent, suggesting that price reversals on heavy volume are stronger after an initial price decline. The contrarian profit declines rapidly and becomes insignificant as we move to longer lags. Since the contrarian profits and price reversals appear to lasts for at most two weeks, we limit our subsequent analyses to the first two weeks after portfolio formation.

As shown in Panel B of Table 7, lagged market returns significantly affect the magnitude of contrarian profits, with largest profit registered in the period following large decline in market prices. Week t+1 profit in the large down market increases noticeably to 1.18 percent compared to profits of between 0.52 and 0.64 percent in the other three market states. We find similar profit pattern in week t+2, although the magnitude falls quickly. It is noteworthy that the loser portfolio shows the largest profit (above 1.0 percent per week) following large negative market returns.

To ascertain if the difference in loser and winner portfolio returns can be explained by loadings on risk factors, we estimate the alphas from a Fama-French three factor model. We regress the contrarian profits on the three factors representing the market (return on the value-weighted market index), size (difference in returns on small and large market capitalization portfolios) and book-to-market (difference in returns on value and growth portfolios).[22] As shown in Panel B, the risk-adjusted profits in large down markets remain economically large at 1.16 percent per week, indicating that these risk factors cannot explain the price reversals.

The observed relation between contrarian profits and market states is consistent with the hypothesis that funding constraints arising from a large market decline increases the expected compensation for liquidity provision. In unreported results, we find that the contrarian profits jumps to 1.73 percent following periods of high liquidity commonality

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[22] The weekly returns on the three Fama-French factors are constructed using daily portfolio returns downloaded from Ken French's data library.

(as defined in Section 4.1) as well as large decline in market valuations. We also consider the effects of order imbalance by implementing the contrarian strategy separately on stocks with net buyer initiated and net seller initiated orders. The augmented strategy yields higher profits of 1.64 percent in large down markets when we long loser, sell pressure portfolio and short the winner, buy pressure portfolio. In particular, the biggest price rebound occurs for loser stocks with high sell pressure. This is consistent with our contention that liquidity suppliers require highest compensation (to accommodate selling pressure) following large market declines when funding constraints are binding. Hence, in addition to demand effects (selling pressure), we also observe significant supply effects in liquidity provision.

Table 8, Panel A shows that our limit order trading strategy generates significant profits for all three values filter rules of 3, 5 and 7 percent, with weekly buy-minus-sell portfolio expected returns ranging from 0.37 percent to 0.97 percent in the first week. These returns become economically small in magnitude beyond one week. For example, a limit order strategy of buying (selling) when prices fall (rise) by 5 percent in week t gives a significant average return of 0.71 percent in week t+1, which decreases to 0.10 percent in week t+2. In Panel B, we examine if these returns are different across market states. The buy-minus-sell portfolio returns are similar in all the market states, except for large down states. For example, the 5 percent limit order trading rule generates a buy-minus-sell returns of between 0.63 to 0.68 percent per week in almost all market states, close to the unconditional returns. The striking exception is in the large down markets, where the buy-minus-sell portfolio weekly return more than doubles to 1.56 percent. Hence, the evidence on limit order investment portfolio returns provides corroborative evidence that the compensation for supplying liquidity increases in large down markets, when capital constraints are tightest, indicative of supply effects in equity markets.

6. Conclusion

This paper documents that liquidity responds asymmetrically to changes in asset market values. Consistent with the models emphasizing capital constraints affecting the supply of liquidity, negative market returns decrease liquidity much more than positive returns increase liquidity, with the effect being strongest for high volatility firms and during times when the funding sector is likely to face capital tightness. We show a drastic increase in commonality in liquidity after large negative market returns and peaks in the commonality measure coincide with periods often associated with liquidity crisis. Hence, market declines affect both liquidity and liquidity commonality. We also document spillover effects of liquidity commonality across industries. Liquidity commonality within an industry increases significantly when the returns on other industries (excluding the specific industry) are large and negative, suggesting contagion in illiquidity: illiquidity in one industry spills over to other industries.

The contagion in illiquidity and increase in commonality in liquidity as aggregate asset value declines provide indirect evidence of a drop in supply of liquidity affecting all securities. We argue that demand effects, measured by buy-sell order imbalances and flow of funds out of the equity mutual funds, cannot fully explain our results. Hence, our results indicate that there is a supply effect. Finally, we use the idea that short-term stock price reversals following heavy trading reflect compensation for supplying liquidity and examine if cost of liquidity provision varies with large changes in aggregate asset values. Indeed, we find that the cost of providing liquidity is highest in periods with large market declines and high commonality in liquidity. Long-short investment trading strategies aimed at generating returns from supplying liquidity produce economically significant returns (between 1.18 percent and 1.56 percent per week) after a large fall in aggregate market prices. Taken together, our results are suggestive of a supply effect on liquidity advocated in Brunnermeier and Pedersen (2005), Anshuman and Viswanathan (2005), Kyle and Xiong (2001), and Gromb and Vayanos (2002). We also show that the illiquidity effect in the equity market lasts between one to two weeks, on average. We interpret our results as indicative of the presence of supply effects even in liquid markets like U.S. equities, and that capital does flow into the market fairly quickly.

Overall, our paper presents evidence supportive of the collateral view of market liquidity: market liquidity falls after large negative market returns because aggregate collateral of financial intermediaries fall and many asset holders are forced to liquidate, making it difficult to provide liquidity precisely when the market demands it. While our evidence is indirect, a fruitful avenue for future research would be to investigate the effect of funding constraints using high frequency data on the balance-sheet positions held by intermediaries.

References

Acharya, Viral V., and Lasse Heje Pedersen, 2005, Asset Pricing with Liquidity Risk, *Journal of Financial Economics* 77, 375-410.

Adrian, Tobias and Hyun Song Shin , 2007, Liquidity and Financial Circles, Working paper, Princeton University

Allen, Franklin and Douglas Gale, 2005, From Cash-in-the-Market Pricing to Financial Fragility, *Journal of European Economic Association*, 535-546.

Amihud, Yakov and Haim Mendelson, 1986, Asset Pricing and the Bid-Ask Spread, *Journal of Financial Economics* 17, 223-249.

Ang, Andrew, and Joe Chen, 2002, Asymmetric correlations in Equity Portfolios, *Journal of Financial Economics* 63, 443-494.

Ang, Andrew, Joe Chen, and Yuhang Xing, 2006, Downside Risk, *Review of Financial Studies*, 19, 1191-1239..

Anshuman, Ravi and S. Viswanathan, 2005, Market Liquidity, Working Paper, Duke University.

Avramov, Doron, Tarun Chordia, and Amit Goyal, 2006, Liquidity and Autocorrelation of Individual Stock Returns, *Journal of Finance*, 2365-2394.

Baker, Malcolm and Jeremy C. Stein, 2004, Market Liquidity as a Sentiment Indicator, *Journal of Financial Markets*, Volume 7, Issue 3 , June 2004, 271-299

Barber, Brad, Terrance Odean, and Ning Zhu, 2006, Do Noise Traders Move Markets?, Working Paper, University of California, Berkeley.

Bernado, Antonio, and Ivo Welch, 2003, Liquidity and Financial Market Runs, *Quarterly Journal of Economics*, 119, 135-158.

Black, F., 1976, Studies of Stock Price Volatility Changes, Proceedings of the 1976 Meetings of the Business and Economics Statistics Section, American Statistical Association, 177-181

Brennan, Michael J., and Avanidhar Subrahmanyam, 1995, Investment analysis and price formation in securities markets, *Journal of Financial Economics* 38, 361-381.

Brunnermeier, Markus and Lasse Pedersen, 2007, Market Liquidity and Funding Liquidity, *Review of Financial Studi*es, forthcoming.

Cappiello Lorenzo, Robert Engle, and Kevin Sheppard, 2003, Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns, Working Paper, European Central Bank.

Campbell, John Y., Sanford J. Grossman and Jiang Wang, 1993, Trading Volume and Serial Correlation in Stock Returns, *The Quarterly Journal of Economics*, Vol. 108(4), 905-939.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2000, Commonality in liquidity, *Journal of Financial Economics* 56, 3-28.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2001, Market liquidity and trading activity, *Journal of Finance* 56, 501-530.

Chordia, Tarun, Richard Roll and Avanidhar Subrahmanyam, 2002, Order imbalance, liquidity and market returns, *Journal of Financial Economics* 65, 111-130.

Chordia, Tarun, Asani Sarkar, and Avanidhar Subrahmanyam, 2005, An Empirical Analysis of Stock and Bond Market Liquidity, *Review of Financial Studies* 18, 85-129.

Christie, A. A., 1982, The Stochastic Behavior of Common Stock Variances: Value, Leverage and Interest Rate Effect, *Journal of Financial Economics* 10, 4, 407-432

Conrad, Jennifer, Allaudeen Hameed, and Cathy Niden, 1994, Volume and Autocovariances in Short-Horizon Individual Security Returns, *Journal of Finance*, 49, 1305-1329.

Coughenour, Jay and Mohsen Saad, 2004, Common market makers and commonality in liquidity, *Journal of Financial Economics*, 37-69.

Demsetz, Harold, 1968, The Cost of Transaction, *Quarterly Journal of Economics* 82, 33-53.

Dueskar, Prachi, 2007, Extrapolative Expectations: Implications for Volatility and Liquidity, Working paper, University of Illinois at Urbana-Champaign

Eisfeldt, Andrea, 2004, Endogenous Liquidity in Asset Markets, *Journal of Finance* 59, 1-30.

Engle, Robert, 2002, Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models, *Journal of Business & Economic Statistics* 20, 339-350.

Fama, E. F. and K. R. French, 1993, Common Risk Factors in the Return on Stocks and Bonds, Journal of Financial Economics 33, 3-56.

French, Kenneth, G. William Schwert, and Robert Stambaugh, 1987, Expected Stock Returns and Volatility, *Journal of Financial Economics* 19, 3-29.

Gervais, Simon, and Terrance Odean, 2001, Learning to be Overconfident, *Review of Financial Studies* 14, 1-27.

Gatev, Evan, and Philip E. Strahan, 2006, Banks Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market, *Journal of Finance* 61, 2, 867-892

Gromb, Denis, and Dimitri Vayanos, 2002, Equilibrium and Welfare in Markets with Financially Constrint Arbitrageurs, *Journal of Financial Economics*, 66, 361-407.

Handa, Puneet, and Robert A. Schwartz, 1996, Limit Order Trading, *Journal of Finance* 51, 1835-1861.

Harford, Jarrad, and Aditya Kaul, 2005, Correlated Order Flow: Persvasiveness, Sources and Pricing Effects, *Journal of Financial and Quantitative Analysis*, 40, 29-55.

Hasbrouck, Joel, and Duane J. Seppi, 2001, Common factors in prices, order flows, and liquidity, *Journal of Financial Economics* 59, 383-411.

Hendershott, Terence, Pamela Moulton and Mark Seasholes, 2006, Capital Constraints and Stock Market Liquidity, Working Paper, UC-Berkeley.

Ho, Thomas, and Hans H. Stoll, 1980, On dealer markets under competition, *Journal of Finance* 35, 259-267.

Huberman, Gur, and Dominika Halka, 2001, Systematic liquidity, *Journal of Financial Research* 24, 161-178.

Kaniel, Ron, Gideon Saar, and Sheridan Titman, 2006, "Individual Investor Sentiment and Stock Returns" Working Paper, Duke University.

Kiyotaki, Nobuhiro, and John Moore, 1997, Credit Cycles, *Journal of Political Economy*, 105, (1997), 211-248.

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

Kyle, Pete, and Wei Xiong, 2001, Contagion as a wealth Effect, Journal of Finance, 4, 1401-1440.

Lee, Charles M.C. 1992. Earnings news and small traders: An intraday analysis. *Journal of Accounting and Economics* 15: 265-302.

Lee, Charles M. C., and Balakrishna Radhakrishna, 2000, Inferring investor behavior: Evidence from TORQ data, *Journal of Financial Markets* 3, 83-111.

Lee, Charles M. C., and Mark J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733-746.

Morck, Randall, Bernard Yeung, and Wayne Yu, 2000, the Information Content of Stock Markets: Why Do Emerging Markets Have Synchronous Stock Price Movements?, *Journal of Financial Economics* 59, 215-260.

Morris, Stephen, and Hyun Song Shin, 2004, Liquidity Black Holes, *Review of Finance* 8, 1-18.

Naik, Narayan, and Pradeep Yadav, 2003, Risk Management with Derivatives by Dealers and Market Quality in Government Bond Markets, *Journal of Finance* 5, 1873-1904.

Roll, Richard, 1988, R^2, *Journal of Finance* 42, 541-566.

Pastor, Lubos, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642-685.

Sadka, Ronnie, 2006, Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk, *Journal of Financial Economics*, 80, 309-349.

Shefrin, Hersh, and Meir Statman, 1985, The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence, *Journal of Finance* 40, 777-790

Stoll, Hans R., 1978, The supply of dealer services in securities markets, *Journal of Finance* 33, 1133-1152.

Vayanos, Dimitri, 2004, Flight To Quality, Flight to Liquidity and the Pricing of Risk, NBER working paper.

Xiong, Wei, 2001, Convergence Trading with Wealth Effects: An Amplification Mechanism in Financial Markets, *Journal of Financial Economics*, 62, 247-292.

Appendix I: Dynamic Conditional Correlation of Spreads and Market Returns

In this appendix, we examine the relationship between market returns and the conditional correlations in stock liquidity, measured by the dynamic conditional correlation (DCC) method proposed by Engle (2002) and Cappiello, Engle and Sheppard (2003) . The DCC model relies on the parsimonious univariate GARCH estimates of liquidity for each asset and has the computational advantage over the multivariate GARCH model. The estimation starts with first obtaining a series of liquidity shocks from univariate GARCH specification of the liquidity variable and, in the second stage, we estimate the conditional correlation between asset liquidity shocks. We follow Engle (2002) and Cappiello et al. (2003), who use a similar methodology to estimate the time-varying correlation between the stock and the bond market returns.

We use the DCC methodology to model the liquidity movements between a pair of portfolios. We consider pairs of size sorted portfolios (small, medium and large size portfolios) and also the correlation in liquidity between S&P and non-S&P constituent stocks. We sort the stocks in our sample into three size portfolios (or S&P and non-S&P portfolios) and take the equally-weighted average daily adjusted spread as the portfolio daily spread. As spreads tend to be highly autocorrelated, we fit an AR(1) model for average spreads and use the residuals as our liquidity variable. We obtain weekly dynamic correlation estimates between a pair of portfolio liquidity shocks by taking the average of all the daily DCC estimates in a week. Finally, we report the weekly dynamic correlations for each market state based on the magnitude and sign of market returns, as defined in the text in Section 3.

Table A1 presents the conditional correlations in liquidity between size portfolios for each market state. The average DCC estimate of the correlation in spreads between large and small stock portfolios increases from 0.25 to 0.31 after a large negative market return. A large drop in market prices has a similar effect on conditional correlations between other pairs of size portfolios. The conditional correlation between liquidity of S&P and non-S&P constituent stocks exhibit a parallel behavior: the conditional correlation between these two portfolio spreads increases after a large negative market returns from 0.38 to 0.44. The DCC confirms that the sharp increase in commonality in spreads following large market declines.

Table A1: DCC Estimates Conditional on Market Returns

The sample stocks are sorted into three size portfolios (or the S&P and non-S&P constituent portfolios). The portfolio daily spread is equally-weighted average of the stock daily adjusted spread in the portfolio. We obtain the residual of the first-order auto-regression on the portfolio spreads and apply the DCC with mean-reverting model on various pairs of the portfolio spread residuals. The daily DCC estimates are averaged into the weekly dynamic correlation estimates. The weekly dynamic correlation conditional on market states is reported below. Market states are defined based on the cumulative CRSP value-weighted return from week t-4 to week t-1. Large Up (Large Down) refers to cumulative market returns being 1.5 standard deviation above (below) the mean. Small Up (Small Down) market refers to cumulative market returns between zero and 1.5 (-1.5) standard deviation. The DCC differences that are significant at 99%, 95%, and 90% confidence level are labelled with ***, **, and * respectively.

DCC Estimates	Past Market Return					
	(a): Large Up	(b): Small Up	(c): Small Down	(d): Large Down	(e): Average excluding (d)	(d) - (e)
DCC between small and large size portfolios	0.226	0.243	0.260	0.307	0.248	0.060***
DCC between small and medium size portfolios	0.394	0.399	0.405	0.451	0.401	0.051***
DCC between medium and large size portfolios	0.423	0.467	0.497	0.537	0.474	0.063***
DCC between S&P and non-S&P portfolios	0.362	0.372	0.393	0.442	0.378	0.063***

Table 1: Descriptive Statistics: Raw and Adjusted Spreads

The proportional quoted bid-ask spread for firm *i*, $QSPR_i$, is defined as (ask quote – bid quote) / [(ask quote + bid quote)/2]. Daily $QSPR_{i,s}$ is generated by averaging the spread of all the transactions within a day. The daily quoted spreads are adjusted for seasonality to obtain the adjusted spreads, $ASPR_{i,s}$, using the following regression model:

$$QSPR_{j,s} = \sum_{k=1}^{4} d_{j,k}\, DAY_{k,s} + \sum_{k=1}^{11} e_{j,k} MONTH_{k,s} + f_{1,j}\, HOLIDAY_s + f_{2,j}\, TICK1_s + f_{3,j}\, TICK2_s + f_{4,j}\, YEAR1_s + f_{5,j}\, YEAR2_s + ASPR_{j,s}$$

where we employ (i) 4 day of the week dummies ($DAY_{k,s}$) for Monday through Thursday ; (ii) 11 month of the year dummies ($MONTH_{k,s}$) for February through December; (iii) a dummy for the trading days around holidays ($HOLIDAY_s$); (iv) two tick change dummies ($TICK1_s$ and $TICK2_s$) 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 $YEAR1_s$ ($YEAR2_s$) 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 below.

Year	Number of Securities	QSPR (Unadjusted Proportional Quoted Spread)			ASPR (Adjusted Proportional Quoted Spread)		
		Mean	Median	Coefficient of Variation	Mean	Median	Coefficient of Variation
1988	1027	1.26%	1.04%	0.618	1.33%	1.08%	0.641
1989	1083	1.13%	0.91%	0.671	1.24%	0.98%	0.708
1990	1146	1.41%	1.09%	0.720	1.56%	1.23%	0.748
1991	1224	1.32%	1.02%	0.712	1.50%	1.16%	0.723
1992	1320	1.25%	0.98%	0.714	1.47%	1.17%	0.703
1993	1430	1.18%	0.92%	0.736	1.45%	1.17%	0.692
1994	1497	1.14%	0.90%	0.717	1.47%	1.20%	0.657
1995	1562	1.06%	0.82%	0.741	1.43%	1.17%	0.657
1996	1641	0.97%	0.74%	0.769	1.38%	1.15%	0.649
1997	1709	0.77%	0.59%	0.812	1.31%	1.07%	0.670
1998	1709	0.78%	0.57%	0.834	1.32%	1.07%	0.692
1999	1607	0.85%	0.62%	0.822	1.34%	1.11%	0.679
2000	1482	0.93%	0.62%	0.930	1.38%	1.15%	0.666
2001	1328	0.55%	0.32%	1.213	1.38%	1.15%	0.648
2002	1243	0.39%	0.21%	1.266	1.26%	1.06%	0.657
2003	1200	0.26%	0.13%	1.251	1.13%	0.95%	0.692

Table 2: Relation Between Spread and Lagged Market Returns

Weekly changes in adjusted spreads for each security is regressed on lagged market returns and idiosyncratic stock returns.

Panel A uses the following regression specification:

$$\Delta ASPR_{i,t} = \alpha_i + \sum_{k=1}^{4} \beta_{i,k} R_{m,t-k} + \sum_{k=1}^{4} \gamma_{i,k} R_{i,t-k} + c_{1i}\Delta STD_{m,t} + c_{2i}\Delta STD_{i,t} + c_{3i}\Delta STD_{m,t-1} + c_{4i}\Delta STD_{i,t-1}$$
$$+ c_{5i}\Delta TURN_{i,t-1} + c_{6,i}\Delta ROIB_{i,t-1} + \sum_{k=1}^{4} \phi_{i,k}\, \Delta ASPR_{i,t-k} + \varepsilon_{i,t}$$

where $ASPR_{i,t}$ refers to stock *i*'s seasonally adjusted, daily proportional spread averaged across all trading days in week t; $R_{m,t}$ is the week *t* return on the CRSP value-weighted index; $R_{i,t}$ is the idiosyncratic return on stock *i* in week t, where idiosyncratic stock returns are calculated as individual stock returns minus market returns; $TURN_{i,t}$ refers to the number of shares traded each week divided by the total shares outstanding; $ROIB_{i,t}$ is the absolute value of the weekly difference in the dollar value of buyer- and seller-initiated transactions (standardized by weekly dollar trading volume); $STD_{m,t}$ is the volatility of market return in week *t*, and $STD_{i,t}$ is the volatility of stock *i*'s idiosyncratic returns in week *t*. The Δ operator represents the first-order difference of the corresponding variables.

Panel B is based on the regression:

$$\Delta ASPR_{i,t} = \alpha_i + \sum_{k=1}^{4} \beta_{i,k} R_{m,t-k} + \sum_{k=1}^{4} \beta_{DOWN,i,k} R_{m,t-k} D_{DOWN,m,t-k} + \sum_{k=1}^{4} \gamma_{i,k} R_{i,t-k}$$
$$+ \sum_{k=1}^{4} \gamma_{DOWN,i,k} R_{i,t-k} D_{DOWN,i,t-k} + c_{1i}\Delta STD_{m,t} + c_{2i}\Delta STD_{i,t} + c_{3i}\Delta STD_{m,t-1} +$$
$$c_{4i}\Delta STD_{i,t-1} + c_{5i}\Delta TURN_{i,t-1} + c_{6,i}\Delta ROIB_{i,t-1} + \sum_{k=1}^{4} \phi_{i,k}\, \Delta ASPR_{i,t-k} + \varepsilon_{i,t}$$

where $D_{DOWN,m,t}$ ($D_{DOWN,i,t}$) is a dummy variable that is equal to one if and only if $R_{m,t}$ ($R_{i,t}$) is less than zero.

Panel C uses the following specification:

$$\Delta ASPR_{i,t} = \alpha_i + \sum_{k=1}^{4} \beta_{i,k} R_{m,t-k} + \sum_{k=1}^{4} \beta_{DOWN\ LARGE,i,k} R_{m,t-k} D_{DOWN\ LARGE,m,t-k}$$
$$+ \sum_{k=1}^{4} \beta_{UP\ LARGE,i,k} R_{m,t-k} D_{UP\ LARGE,m,t-k} + \sum_{k=1}^{4} \gamma_{i,k} R_{i,t-k}$$
$$+ \sum_{k=1}^{4} \gamma_{DOWN\ LARGE,i,k} R_{i,t-k} D_{DOWN\ LARGE,i,t-k} + \sum_{k=1}^{4} \gamma_{UP\ LARGE,i,k} R_{i,t-k} D_{UP\ LARGE,i,t-k}$$
$$+ c_{1i}\Delta STD_{m,t} + c_{2i}\Delta STD_{i,t} + c_{3i}\Delta STD_{m,t-1} +$$
$$c_{4i}\Delta STD_{i,t-1} + c_{5i}\Delta TURN_{i,t-1} + c_{6,i}\Delta ROIB_{i,t-1} + \sum_{k=1}^{4} \phi_{i,k}\, \Delta ASPR_{i,t-k} + \varepsilon_{i,t}$$

where $D_{DOWN\ LARGE,m,t}$ ($D_{UP\ LARGE,m,t}$) is a dummy variable that is equal to one if and only if $R_{m,t}$ is greater than 1.5 standard deviation below (above) its unconditional mean return. $D_{DOWN\ LARGE,i,t}$ and $D_{UP\ LARGE,i,t}$ are similarly defined based on idiosyncratic returns, $R_{i,t}$.

Cross-sectional mean and median of the coefficient estimates are reported in the row labelled as "Mean" and "Median". The t-statistics of the mean are reported in the parenthesis below the mean. "% 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).

Panel A: Relation between Spreads and Lagged Returns

Estimate Statistics	$R_{m,t-1}$	$R_{m,t-2}$	$R_{m,t-3}$	$R_{m,t-4}$	$R_{i,t-1}$	$R_{i,t-2}$	$R_{i,t-3}$	$R_{i,t-4}$
Mean	-0.830	-0.397	-0.216	-0.052	-0.549	-0.282	-0.177	-0.089
(t-statistics)	*(-17.19)*	*(-8.15)*	*(-4.48)*	*(-1.09)*	*(-27.26)*	*(-13.92)*	*(-8.73)*	*(-4.43)*
Median	-0.528	-0.234	-0.101	-0.003	-0.423	-0.200	-0.117	-0.051
% positive (negative)	(98.4%)	(86.8%)	(71.6%)	(50.5%)	(98.9%)	(94.1%)	(86.2%)	(72.2%)
% positive (negative) significant	(78.2%)	(35.4%)	(13.9%)	(6.0%)	(92.7%)	(63.5%)	(38.0%)	(15.9%)

Estimate Statistics	$\Delta STD_{m,t-1}$	$\Delta STD_{i,t-1}$	$\Delta Turn_{i,t-1}$	$\Delta OIB_{i,t-1}$	$\Delta STD_{m,t}$	$\Delta STD_{i,t}$
Mean	0.221	0.233	-0.019	0.008	0.311	0.213
(t-statistics)	*(1.71)*	*(5.90)*	*(-4.01)*	*(0.68)*	*(4.35)*	*(8.78)*
Median	0.147	0.162	-0.010	0.006	0.159	0.169
% positive (negative)	63.2%	78.5%	(76.7%)	54.7%	73.3%	85.0%
% positive (negative) significant	11.4%	27.6%	(20.7%)	9.4%	20.4%	45.8%

Estimate Statistics	$\Delta ASPR_{i,t-1}$	$\Delta ASPR_{i,t-2}$	$\Delta ASPR_{i,t-3}$	$\Delta ASPR_{i,t-4}$
Mean	-0.523	-0.353	-0.226	-0.119
(t-statistics)	*(-66.43)*	*(-40.70)*	*(-26.22)*	*(-15.39)*
Median	-0.536	-0.361	-0.233	-0.122
% positive (negative)	(100.0%)	(100.0%)	(98.9%)	(94.4%)
% positive (negative) significant	(99.5%)	(98.4%)	(93.6%)	(76.3%)

Panel B: Relation between Spread and Signed Lagged Returns

Estimate Statistics	$R_{m,t-1}$	$R_{m,t-2}$	$R_{m,t-3}$	$R_{m,t-4}$	$R_{i,t-1}$	$R_{i,t-2}$	$R_{i,t-3}$	$R_{i,t-4}$
Mean	-0.413	-0.321	-0.307	-0.163	-0.473	-0.298	-0.204	-0.126
(t-statistics)	*(-4.10)*	*(-3.55)*	*(-3.47)*	*(-1.89)*	*(-12.61)*	*(-9.20)*	*(-6.34)*	*(-3.93)*
Median	-0.221	-0.195	-0.175	-0.051	-0.334	-0.209	-0.134	-0.073
% positive (negative)	(73.9%)	(73.3%)	(71.4%)	(58.0%)	(91.3%)	(89.4%)	(80.4%)	(69.9%)
% positive (negative) significant	(15.4%)	(14.5%)	(12.1%)	(6.7%)	(56.5%)	(42.2%)	(24.8%)	(14.9%)
Estimate Statistics	$R_{m,t-1} \times D_{Down,m,t-1}$	$R_{m,t-2} \times D_{Down,m,t-2}$	$R_{m,t-3} \times D_{Down,m,t-3}$	$R_{m,t-4} \times D_{Down,m,t-4}$	$R_{i,t-1} \times D_{Down,i,t-1}$	$R_{i,t-2} \times D_{Down,i,t-2}$	$R_{i,t-3} \times D_{Down,i,t-3}$	$R_{i,t-4} \times D_{Down,i,t-4}$
Mean	-0.810	-0.038	0.257	0.208	-0.158	0.048	0.073	0.094
(t-statistics)	*(-4.79)*	*(-0.25)*	*(1.83)*	*(1.42)*	*(-2.33)*	*(0.83)*	*(1.28)*	*(1.65)*
Median	-0.443	0.028	0.155	0.086	-0.117	0.036	0.040	0.057
% positive (negative)	(76.7%)	(48.0%)	62.3%	57.9%	(63.1%)	56.3%	56.5%	59.1%
% positive (negative) significant	(17.2%)	(4.6%)	8.9%	6.0%	(15.1%)	7.9%	7.9%	9.1%

Panel C: Relation between Spread and the Magnitude of Lagged Returns

Estimate Statistics	$R_{m,t-1}$	$R_{m,t-2}$	$R_{m,t-3}$	$R_{m,t-4}$	$R_{m,t-1} \times D_{DownLarge,m,t-1}$	$R_{m,t-2} \times D_{DownLarge,m,t-2}$	$R_{m,t-3} \times D_{DownLarge,m,t-3}$	$R_{m,t-4} \times D_{DownLarge,m,t-4}$
Mean	-0.715	-0.308	-0.203	-0.153	-0.430	-0.063	0.121	0.234
(t-statistics)	*(-10.00)*	*(-4.30)*	*(-2.84)*	*(-2.15)*	*(-3.56)*	*(-0.55)*	*(1.03)*	*(2.01)*
Median	-0.459	-0.192	-0.097	-0.042	-0.196	0.024	0.088	0.094
% positive (negative)	(92.2%)	(74.4%)	(64.6%)	(57.1%)	(68.1%)	(47.0%)	58.6%	60.1%
% positive (negative) significant	(46.6%)	(19.9%)	(10.3%)	(8.2%)	(13.4%)	(5.1%)	7.0%	7.9%

Estimate Statistics	$R_{m,t-1} \times D_{UpLarge,m,t-1}$	$R_{m,t-2} \times D_{UpLarge,m,t-2}$	$R_{m,t-3} \times D_{UpLarge,m,t-3}$	$R_{m,t-4} \times D_{UpLarge,m,t-4}$				
Mean	0.161	-0.222	-0.209	0.065				
(t-statistics)	*(1.30)*	*(-1.55)*	*(-1.51)*	*(0.54)*				
Median	0.113	-0.066	-0.094	0.001				
% positive (negative)	60.8%	(57.6%)	(59.3%)	50.2%				
% positive (negative) significant	6.6%	(7.1%)	(7.6%)	5.4%				

Table 3: Relation between Spread and Lagged Market Returns – Interacted with Funding Market Data

Weekly changes in the adjusted spreads of each security is regressed on signed lagged market returns with an interaction dummy variable, $D_{CAP,t}$ which is equal to 1 when the funding market is likely to face capital contraints in week t:

$$\Delta ASPR_{i,t} = \alpha_i + \sum_{k=1}^{4} \beta_{i,k} R_{m,t-k} + \sum_{k=1}^{4} \beta_{DOWN,i,k} R_{m,t-k} D_{DOWN,m,t-k}$$
$$+ \beta_{DOWN,CAP,i,k} R_{m,t-1} D_{DOWN,m,t-1} D_{CAP,t-1} + \sum_{k=1}^{4} \gamma_{i,k} R_{i,t-k}$$
$$+ \sum_{k=1}^{4} \gamma_{DOWN,i,k} R_{i,t-k} D_{DOWN,i,t-k} + c_{1i} \Delta STD_{m,t} + c_{2i} \Delta STD_{i,t} + c_{3i} \Delta STD_{m,t-1} +$$
$$c_{4i} \Delta STD_{i,t-1} + c_{5i} \Delta TURN_{i,t-1} + c_{6,i} \Delta ROIB_{i,t-1} + \sum_{k=1}^{4} \phi_{i,k} \Delta ASPR_{i,t-k} + \varepsilon_{i,t}$$

The other variables are: $ASPR_{i,t}$ refers to stock *i*'s seasonally adjusted, daily proportional spread averaged across all trading days in week t; $R_{m,t}$ is the week *t* return on the CRSP value-weighted index; $R_{i,t}$ is the idiosyncratic return on stock *i* in week t, where idiosyncratic stock returns are calculated as individual stock returns minus market returns; $TURN_{i,t}$ refers to the number of shares traded each week divided by the total shares outstanding; $ROIB_{i,t}$ is the absolute value of the weekly difference in the dollar value of buyer- and seller-initiated transactions (standardized by weekly dollar trading volume); $STD_{m,t}$ is the volatility of market return in week *t*, and $STD_{i,t}$ is the volatility of stock *i*'s idiosyncratic returns in week *t;* $D_{DOWN,m,t}$ ($D_{DOWN,i,t}$) is a dummy variable that is equal to one if and only if $R_{m,t}$ ($R_{i,t}$) is less than zero. The Δ operator represents the first-order difference of the corresponding variables.

In Panel A, $D_{CAP,t}$ is equal to 1 when the excess return on a portfolio of investment banks in week t is negative. $D_{CAP,t}$, in Panel B, is equal to 1 when there is a decrease in the aggregate repos in week t. Finally, when there is a decrease in the commercial paper spread, we assign a value of 1 to $D_{CAP,t}$ in Panel C.

Panel A: Investment Bank & Broker Sector Returns

Estimate Statistics	$R_{m,t-1}$	$R_{m,t-2}$	$R_{m,t-3\sim t-4}$	$R_{m,t-1} \times D_{Down,m,t-1}$	$R_{m,t-2} \times D_{Down,m,t-2}$	$R_{m,t-3\sim t-4} \times D_{Down,m,t-3\sim t-4}$	$R_{m,t-1} \times D_{Down,m,t-1} \times D_{CAP,t-1}$
Mean	-0.413	-0.333	-0.230	-0.673	-0.026	0.216	-0.297
(t-statistics)	*(-4.13)*	*(-3.72)*	*(-3.69)*	*(-3.82)*	*(-0.18)*	*(1.97)*	*(-2.20)*
Median	-0.210	-0.196	-0.118	-0.353	0.035	0.136	-0.155
% positive (negative)	(74.0%)	(73.9%)	(71.1%)	(72.7%)	(46.9%)	65.8%	(61.8%)
% positive (negative) significant	(14.4%)	(15.6%)	(11.7%)	(14.7%)	(4.4%)	9.0%	(10.6%)

Panel B: Change in Repos

Estimate Statistics	$R_{m,t-1}$	$R_{m,t-2}$	$R_{m,t-3\sim t-4}$	$R_{m,t-1} \times D_{Down,m,t-1}$	$R_{m,t-2} \times D_{Down,m,t-2}$	$R_{m,t-3\sim t-4} \times D_{Down,m,t-3\sim t-4}$	$R_{m,t-1} \times D_{Down,m,t-1} \times D_{CAP,t-1}$
Mean	-0.426	-0.334	-0.210	-0.528	-0.044	0.207	-0.672
(t-statistics)	*(-4.37)*	*(-3.83)*	*(-3.45)*	*(-3.06)*	*(-0.30)*	*(1.93)*	*(-4.98)*
Median	-0.230	-0.197	-0.110	-0.264	0.030	0.139	-0.372
% positive (negative)	(75.4%)	(74.0%)	(69.2%)	(68.3%)	(47.9%)	65.8%	(75.4%)
% positive (negative) significant	(15.6%)	(15.4%)	(10.6%)	(10.7%)	(4.7%)	9.0%	(20.3%)

Panel C: Commercial Paper Spread

Estimate Statistics	$R_{m,t-1}$	$R_{m,t-2}$	$R_{m,t-3\sim t-4}$	$R_{m,t-1} \times D_{Down,m,t-1}$	$R_{m,t-2} \times D_{Down,m,t-2}$	$R_{m,t-3\sim t-4} \times D_{Down,m,t-3\sim t-4}$	$R_{m,t-1} \times D_{Down,m,t-1} \times D_{CAP,t-1}$
Mean	-0.433	-0.320	-0.218	-0.492	-0.042	0.202	-0.453
(t-statistics)	*(-4.36)*	*(-3.59)*	*(-3.53)*	*(-2.57)*	*(-0.28)*	*(1.85)*	*(-3.34)*
Median	-0.230	-0.187	-0.114	-0.248	0.015	0.132	-0.267
%positive(negative)	(75.0%)	(72.8%)	(70.0%)	(65.3%)	(48.8%)	65.4%	(71.9%)
%positive(negative) significant	(15.6%)	(14.5%)	(11.1%)	(8.6%)	(4.6%)	8.9%	(14.1%)

Table 4: Relation between Spread and Lagged Returns: Cross-Sectional Estimates

Stocks are sorted into nine size-volatility portfolios using two-way dependent sorts on market capitalization and return volatility. Weekly changes in portfolios average spreads ($ASPR_{p,t}$) are regressed on lagged market returns ($R_{m,t}$) and portfolio specific returns ($R_{p,t}$) using the SUR method:

$$\Delta ASPR_{p,t} = \alpha_i + \sum_{k=1}^{4} \beta_{p,k} R_{m,t-k} + \sum_{k=1}^{4} \beta_{DOWN,p,k} R_{m,t-k} D_{DOWN,m,t-k} + \sum_{k=1}^{4} \gamma_{p,k} R_{p,t-k}$$

$$+ \sum_{k=1}^{4} \gamma_{DOWN,p,k} R_{p,t-k} D_{DOWN,p,t-k} + c_{1p} \Delta STD_{m,t} + c_{2p} \Delta STD_{p,t} + c_{3p} \Delta STD_{m,t-1} +$$

$$c_{4p} \Delta STD_{p,t-1} + c_{5p} \Delta TURN_{p,t-1} + c_{6,p} \Delta ROIB_{p,t-1} + \sum_{k=1}^{4} \phi_{p,k} \Delta ASPR_{p,t-k} + \varepsilon_{p,t}$$

Where the control variables include $TURN_{p,t}$, the average portfolio turnover in week *t*; $ROIB_{p,t}$ is the portfolio average of the absolute value of the weekly difference in the dollar value of buyer- and seller-initiated transactions (standardized by weekly dollar volume); $STD_{m,t}$ is the volatility of market return in week *t*, and $STD_{p,t}$ is the volatility of stock portfolio *p*'s idiosyncratic returns in week *t*. $D_{DOWN,m,t}$ is a dummy variable that is equal to one if and only if $R_{m,t}$ is less than zero; $D_{DOWN,p,t}$ is similarly defined based on $R_{p,t}$ .The Δ operation represents the first-order difference of the corresponding variables. The t-statistics are reported below the coefficients. High-Low column shows the t-statistics for the test of the null hypothesis that the coefficients corresponding to the High and Low Volatility portfolios are equal.

	Small-Size				Medium-Size				Large-Size			
	High Volatility	Medium Volatility	Low Volatility	High - Low	High Volatility	Medium Volatility	Low Volatility	High - Low	High Volatility	Medium Volatility	Low Volatility	High - Low
$R_{m,t-1}$	-1.23	-0.47	-0.38	-0.85***	-0.27	-0.21	-0.24	-0.04	-0.13	-0.10	-0.08	-0.05
	-4.34	*-2.69*	*-3.04*		*-2.76*	*-2.50*	*-3.59*		*-2.33*	*-2.26*	*-2.25*	
$R_{m,t-2}$	-0.57	-0.61	-0.25	-0.31	-0.24	-0.21	-0.18	-0.06	-0.13	-0.10	-0.10	-0.03
	-2.14	*-3.81*	*-2.22*		*-2.68*	*-2.78*	*-2.95*		*-2.58*	*-2.27*	*-2.88*	
$R_{m,t-3\sim t-4}$	-0.39	-0.37	-0.33	-0.06	-0.16	-0.15	-0.08	-0.08	-0.05	-0.02	-0.02	-0.03
	-2.13	*-3.30*	*-4.06*		*-2.45*	*-2.81*	*-1.88*		*-1.25*	*-0.80*	*-0.69*	
$R_{m,t-1}\times D_{Down,m,t-1}$	-1.74	-1.26	-0.71	-1.03***	-0.67	-0.57	-0.40	-0.28***	-0.34	-0.29	-0.21	-0.13**
	-3.85	*-4.40*	*-3.44*		*-4.11*	*-4.10*	*-3.57*		*-3.65*	*-3.75*	*-3.43*	
$R_{m,t-2}\times D_{Down,m,t-2}$	0.24	0.32	0.03	0.21	0.10	0.09	0.07	0.03	0.12	0.10	0.15	-0.03
	0.58	*1.24*	*0.14*		*0.67*	*0.75*	*0.66*		*1.45*	*1.43*	*2.62*	
$R_{m,t-3\sim t-4}\times D_{Down,m,t-3\sim t-4}$	0.63	0.51	0.50	0.13	0.28	0.27	0.14	0.14	0.14	0.09	0.08	0.06
	2.17	*2.71*	*3.67*		*2.53*	*2.89*	*1.86*		*2.20*	*1.77*	*1.84*	
$R_{p,t-1}$	-1.92	-0.98	-0.61	-1.30***	-0.55	-0.43	-0.39	-0.16*	-0.25	-0.19	-0.16	-0.10*
	-8.17	*-6.19*	*-4.84*		*-5.24*	*-4.63*	*-5.01*		*-4.53*	*-4.40*	*-3.33*	
$R_{p,t-2}$	-0.28	-0.13	-0.22	-0.06	-0.11	-0.13	-0.19	0.08	-0.15	-0.13	-0.02	-0.12
	-1.23	*-0.87*	*-1.82*		*-1.07*	*-1.45*	*-2.54*		*-2.76*	*-3.19*	*-0.53*	
$R_{p,t-3\sim t-4}$	-0.24	-0.18	-0.05	-0.19	-0.03	-0.03	-0.06	0.03	-0.01	-0.03	-0.05	0.04
	-1.63	*-1.79*	*-0.54*		*-0.46*	*-0.54*	*-1.06*		*-0.31*	*-1.00*	*-1.65*	
$R_{p,t-1}\times D_{Down,p,t-1}$	0.78	0.37	-0.03	0.80**	0.07	0.03	0.02	0.05	-0.08	-0.10	-0.08	0.00
	1.87	*1.40*	*-0.12*		*0.40*	*0.21*	*0.15*		*-0.82*	*-1.31*	*-0.90*	
$R_{p,t-2}\times D_{Down,p,t-2}$	-0.06	-0.35	-0.07	0.01	-0.24	-0.20	-0.03	-0.21	0.18	0.18	0.01	0.18
	-0.15	*-1.38*	*-0.31*		*-1.38*	*-1.28*	*-0.24*		*1.96*	*2.48*	*0.09*	
$R_{p,t-3\sim t-4}\times D_{own,p,t-3\sim t-4}$	0.18	-0.02	-0.22	0.39	-0.13	-0.10	-0.01	-0.11	-0.06	-0.03	0.09	-0.15
	0.66	*-0.08*	*-1.46*		*-1.01*	*-0.95*	*-0.15*		*-0.86*	*-0.62*	*1.49*	

Table 5: Liquidity Betas and Market Returns

Weekly adjusted spreads for each security i ($ASPR_{i,t}$) is regressed on lagged market returns ($R_{m,t}$), idiosyncratic stock returns ($R_{i,t}$) and market average spreads, $ASPR_{m,t}$.

$$\Delta ASPR_{i,t} = \alpha_i + b_{LIQ,i}\Delta ASPR_{m,t} + b_{LIQ,DOWN,i}\Delta ASPR_{m,t} D_{DOWN,m,t}$$
$$+ \sum_{k=1}^{4} \beta_{i,k} R_{m,t-k} + \sum_{k=1}^{4} \beta_{DOWN,i,k} R_{m,t-k} D_{DOWN,m,t-k} + \sum_{k=1}^{4} \gamma_{i,k} R_{i,t-k}$$
$$+ \sum_{k=1}^{4} \gamma_{DOWN,i,k} R_{i,t-k} D_{DOWN,i,t-k} + c_{1i}\Delta STD_{m,t} + c_{2i}\Delta STD_{i,t} + c_{3i}\Delta STD_{m,t-1} +$$
$$c_{4i}\Delta STD_{i,t-1} + c_{5i}\Delta TURN_{i,t-1} + c_{6,i}\Delta ROIB_{i,t-1} + \sum_{k=1}^{4} \phi_{i,k}\Delta ASPR_{i,t-k} + \varepsilon_{i,t}$$

$$\Delta ASPR_{i,t} = \alpha_i + b_{LIQ,i}\Delta ASPR_{m,t} + b_{LIQ,DOWN\ SMALL,i}\Delta ASPR_{m,t} D_{DOWN\ SMALL,m,t}$$
$$+ b_{LIQ,DOWN\ LARGE,i}\Delta ASPR_{m,t} D_{DOWN\ LARGE,m,t}$$
$$+ \sum_{k=1}^{4} \beta_{i,k} R_{m,t-k} + \sum_{k=1}^{4} \beta_{DOWN,i,k} R_{m,t-k} D_{DOWN,m,t-k} + \sum_{k=1}^{4} \gamma_{i,k} R_{i,t-k}$$
$$+ \sum_{k=1}^{4} \gamma_{DOWN,i,k} R_{i,t-k} D_{DOWN,i,t-k} + c_{1i}\Delta STD_{m,t} + c_{2i}\Delta STD_{i,t} + c_{3i}\Delta STD_{m,t-1} +$$
$$c_{4i}\Delta STD_{i,t-1} + c_{5i}\Delta TURN_{i,t-1} + c_{6,i}\Delta ROIB_{i,t-1} + \sum_{k=1}^{4} \phi_{i,k}\Delta ASPR_{i,t-k} + \varepsilon_{i,t}$$

The control variables are as follows: $TURN_{i,t}$ refers to the number of shares traded each week divided by the total shares outstanding; $ROIB_{i,t}$ is the absolute value of the weekly difference in the dollar value of buyer- and seller-initiated transactions (standardized by weekly dollar trading volume); $STD_{m,t}$ is the volatility of market return in week *t*, and $STD_{i,t}$ is the volatility of stock *i*'s idiosyncratic returns in week *t*. $D_{DOWN,m,t}$ is a dummy variable that is equal to one if and only if $R_{m,t}$ ($R_{i,t}$) is less than zero. $D_{DOWN\ LARGE,m,t}$ ($D_{DOWN\ SMALL,m,t}$) is a dummy variable that is equal to one if and only if $R_{m,t}$ is negative and greater (less) than 1.5 standard deviation below its unconditional mean return. The Δ operator represents the first-order difference of the corresponding variables.

Panel A

Estimate Statistics	$R_{m,t-1}$	$R_{m,t-2}$	$R_{m,t-3\sim t-4}$	$R_{m,t-1} \times D_{Down,m,t-1}$	$R_{m,t-2} \times D_{Down,m,t-2}$	$R_{m,t-3\sim t-4} \times D_{Down,m,t-3\sim t-4}$	$\Delta ASPR_{m,t}$	$\Delta ASPR_{m,t} \times D_{Down,m,t}$
Mean	-0.419	-0.227	-0.161	-0.293	-0.281	0.091	0.562	0.310
(t-statistics)	*(-21.62)*	*(-12.50)*	*(-12.36)*	*(-9.83)*	*(-9.90)*	*(4.32)*	*(46.34)*	*(19.76)*
Median	-0.211	-0.125	-0.074	-0.125	-0.136	0.061	0.381	0.208
%positive(negative)	(74.7%)	(65.3%)	(63.0%)	(58.7%)	(60.9%)	56.8%	91.5%	73.7%
%positive(negative) significant	(15.5%)	(10.0%)	(8.5%)	(7.0%)	(8.2%)	5.6%	57.0%	27.8%

Panel B

Estimate Statistics	$R_{m,t-1}$	$R_{m,t-2}$	$R_{m,t-3\sim t-4}$	$R_{m,t-1} \times D_{Down,m,t-1}$	$R_{m,t-2} \times D_{Down,m,t-2}$	$R_{m,t-3\sim t-4} \times D_{Down,m,t-3\sim t-4}$	$\Delta ASPR_{m,t}$	$\Delta ASPR_{m,t} \times D_{DownSmall,m,t}$	$\Delta ASPR_{m,t} \times D_{DownLarge,m,t}$
Mean	-0.424	-0.227	-0.163	-0.294	-0.277	0.097	0.561	0.268	0.387
(t-statistics)	*(-19.33)*	*(-11.14)*	*(-11.33)*	*(-8.48)*	*(-8.59)*	*(4.06)*	*(43.09)*	*(13.13)*	*(23.07)*
Median	-0.212	-0.125	-0.077	-0.124	-0.140	0.067	0.381	0.173	0.252
%positive(negative)	(74.5%)	(65.8%)	(63.6%)	(59.0%)	(60.5%)	57.7%	91.5%	67.0%	73.0%
%positive(negative) significant	(15.7%)	(10.0%)	(8.7%)	(6.8%)	(8.0%)	6.3%	57.0%	22.4%	27.3%

Table 6: Commonality in Liquidity and Market Returns

Daily changes in adjusted spreads for each stock is regressed on changes in market average spreads within each month *t* to generate monthly r-square values. Commonality in liquidity in month *t* ($LIQCOM_t$) is defined as the logit transformation of the cross-section average r-square. Commonality in order imbalance in month *t* ($ROIBCOM_t$) is obtained from within month regressions of daily individual firm relative order imbalance on the market average, similar to $LIQCOM_t$. We estimate the following regression equations:

$$LIQCOM_t = a + \beta R_{m,t} + \beta_{DOWN\ LARGE} R_{m,t} D_{DOWN\ LARGE,t}$$
$$+ \beta_{UP\ LARGE} R_{m,t} D_{UP\ LARGE,t} + controls + \varepsilon_t$$
$$ROIBCOM_t = a + \beta R_{m,t} + \beta_{DOWN\ LARGE} R_{m,t} D_{DOWN\ LARGE,t}$$
$$+ \beta_{UP\ LARGE} R_{m,t} D_{UP\ LARGE,t} + controls + \varepsilon_t$$

where the dummy variables $D_{DownLarge,m,t}$ ($D_{UpLarge,m,t}$) is equal to one if the market return in month t ($R_{m,t}$) is lesser (greater) than *1.5* standard deviation below (above) its unconditional mean. The control variables include (a) ROIB, the cross-sectional average relative order imbalance level; (b) equity mutual fund flows as a proportion of total mutual fund investment; (d) market-wide volatility; and (e) average idiosyncratic volatility. The first four columns present OLS estimates while the last two columns present estimates from a two-stage least squares (2SLS). The White's corrected t-statistics are reported in italic.

Dependent Variables	**OLS**				**2SLS**	
	Liquidity Commonality			**ROIB Commonality**	Liquidity Commonality	ROIB Commonality
Intercept	-2.102 *-9.91*	-2.005 *-7.19*	-1.994 *-5.29*	-0.647 *-2.70*	-2.432 *-7.47*	-0.649 *-1.07*
$R_{m,t}$	0.233 *0.35*	-0.040 *-0.06*	0.023 *0.03*	-1.650 *-4.32*	-0.409 *-0.62*	-1.650 *-4.11*
$R_{m,t}$ * $D_{DownLarge,m,t}$	-3.715 *-3.06*	-2.392 *-1.80*	-2.967 *-2.25*	1.919 *2.61*	-2.116 *-1.87*	1.916 *2.11*
$R_{m,t}$ * $D_{UpLarge,m,t}$	-0.696 *-0.97*	-1.247 *-1.65*	-1.018 *-1.37*	0.632 *0.85*	-1.180 *-1.08*	0.631 *0.88*
Market Volatility $_t$		0.115 *2.40*		0.079 *2.71*	0.135 *2.86*	0.079 *2.09*
Idiosyncratic Volatility $_t$			0.099 *1.03*			
ROIB Level $_t$		1.316 *1.78*	1.363 *1.85*		1.730 *2.61*	
ROIB Commonality $_t$	0.182 *2.14*	0.082 *0.90*	0.147 *1.52*		-0.119 *-0.88*	
Liquidity Commonality $_t$				0.096 *1.81*		0.095 *0.41*
ROIB Commonality$_{t-1}$				0.499 *7.91*		0.499 *7.50*
Mutual Fund Flow $_t$				-0.652 *-2.88*		-0.653 *-2.42*

Table 7: Commonality in Liquidity, Market and Industry Returns

Daily changes in adjusted spreads for each stock is regressed on changes in industry average spreads within each month *t* to generate monthly r-square values and liquidity betas ($b_{LIQ,t}$). Commonality in liquidity ($LIQCOM_t$) is defined as the logit transformation of the cross-section average r-square for all stocks within the same industry in month *t*. We estimate the following regressions:

$$LIQCOM_{INDj,t} = a + \delta R_{INDj,t} + \delta_{DOWN} R_{INDj,t} D_{DOWN,INDj,t}$$
$$+ \beta R_{MKTj,t} + \beta_{DOWN} R_{MKTj,t} D_{DOWN,MKTj,t} + \varepsilon_t$$
$$LIQCOM_{INDj,t} = a + \delta R_{INDj,t} + \delta_{DOWN\ LARGE} R_{INDj,t} D_{DOWN\ LARGE,INDj,t}$$
$$+ \beta R_{MKTj,t} + \beta_{DOWN\ LARGE} R_{MKTj,t} D_{DOWN\ LARGE,MKTj,t} + \varepsilon_t$$

where $R_{INDj,t}$ and $R_{MKTj,t}$ denote the month *t* return on the value-weighted returns on industry *j* and the market (excluding industry *j*). The dummy variable $D_{Down,INDj,t}$ ($D_{DownLarge,INDj,t}$) is equal to one if $R_{INDj,t}$ is less than zero (below 1.5 standard deviation from its mean return). $D_{Down,MKTj,t}$ ($D_{DownLarge,MKTj,t}$) are similarly defiend based on $R_{MKTj,t}$. In the last two columns, we replace LIQCOM with liquidity betas ($b_{LIQ,t}$) as the dependent variable. White's heteroskedasticity consistent t-statistics are reported in brackets.

Dependent Variable	***LIQCOM***		**Liquidity Betas**	
Intercept	-2.438 *-271.1*	-2.405 *-401.05*	0.668 *60.41*	0.711 *97.69*
$R_{INDj,t}$	0.192 *1.15*	-0.023 *-0.15*	0.159 *0.72*	-0.178 *-0.88*
$R_{MKTJ,t}$	0.327 *1.35*	-0.206 *-1.02*	1.074 *3.46*	0.327 *1.29*
$R_{INDj,t}$ * $D_{Down,INDj,t}$	-0.986 *-3.01*		-0.999 *-2.69*	
$R_{MKTj,t}$ * $D_{Down,MKTj,t}$	-1.995 *-4.39*		-2.122 *-4.06*	
$R_{INDj,t}$ * $D_{DownLarge,INDj,t}$		-0.875 *-3.1*		-0.701 *-2.25*
$R_{INDj,t}$ * $D_{UpLarge,IND,t}$		0.098 *0.48*		0.292 *1.01*
$R_{MKTj,t}$ * $D_{DownLarge,MKTj,t}$		-1.359 *-3.86*		-0.726 *-1.77*
$R_{MKTj,t}$ * $D_{UpLarge,MKTj,t}$		0.210 *0.72*		-0.039 *-0.1*

Table 8: Contrarian Profits and Market Returns

Weekly stock returns are sorted into winner (loser) portfolios if the returns are above (below) the median of all positive (negative) returns in week t. Contrarian portfolio weight on stock *i* in week *t* is given by:

$$w_{p,i,t} = \frac{R_{i,t-1}Turn_{i,t-1}}{\sum_{i=1}^{Np} R_{i,t-1}Turn_{i,t-1}}$$

where $R_{i,t}$ and $Turn_{i,t}$ is stock *i*'s return and turnover in week *t*. Post-formation contrarian profits for week t+k, for k=1,2,3 and 4 are reported in Panel A. Panel B reports contrarian profits conditional on market returns. Large Up (Large Down) refers to cumulative market returns from week t-4 to t-1 being 1.5 standard deviation above (below) the mean. Small Up (Small Down) market refers to cumulative market returns between zero and 1.5 (-1.5) standard deviation. Factor-adjusted returns represent the alphas from regressing the returns on Fama-French 3 factors: i.e. market, size and book-to-market factors. Newey-West autocorrelation corrected t-statistics are given in brackets.

Panel A: Unconditional Contrarian Profits

	Week			
Portfolio	t+1	t+2	t+3	t+4
Loser	0.75%	0.43%	0.39%	0.37%
Winner	0.17%	0.29%	0.37%	0.41%
Loser minus Winner	0.58%	0.14%	0.03%	-0.04%
(t-statistics)	(5.38)	(1.69)	(0.38)	(-0.52)

Panel B: Contrarian Profits Conditional on Market Returns

Week t+1				
Portfolio	Past Market Return			
	Large Up	Small Up	Small Down	Large Down
Loser	0.54%	0.83%	0.48%	1.37%
Winner	-0.10%	0.29%	-0.04%	0.19%
Loser minus Winner	0.64%	0.54%	0.52%	1.18%
(t-statistics)	(0.93)	(4.07)	(2.51)	(3.01)
Loser minus Winner (adjusted for French-French factors)	0.57%	0.48%	0.50%	1.16%
(t-statistics)	(0.83)	(3.83)	(2.41)	(2.90)

Week t+2				
Portfolio	Past Market Return			
	Large Up	Small Up	Small Down	Large Down
Loser	0.86%	0.44%	0.21%	0.97%
Winner	0.43%	0.40%	0.09%	0.07%
Loser minus Winner	0.43%	0.03%	0.12%	0.90%
(t-statistics)	(1.21)	(0.33)	(0.88)	(1.93)
Loser minus Winner (adjusted for Fama-French factors)	0.34%	-0.01%	0.12%	0.84%
(t-statistics)	(0.88)	(-0.09)	(0.87)	(1.88)

Table 9: Limit Order Trading Profits

At the beginning of each week, stocks are sorted into the sell (buy) portfolios if its price hit x% above (below) its opening price. If the stock price hits the limit, the stock is added to the buy or sell portfolios, with stocks weights proportional to its turnover in ranking week, i.e. weight for firm i in week t is $Turn_{i,t}$ / $\sum_{i=1}^{Np} Turn_{i,t-1}$, where $Turn_{i,t}$ is stock *i*'s turnover in week *t*. We consider x equal to 3, 5, and 7 percent and holding periods of one (t+1) and two (t+2) weeks. Post-formation contrarian profits for week t+1 and t+2 are reported in Panel A. Panel B reports contrarian profits conditional on market returns. Large Up (Large Down) refers to cumulative market returns from week t-4 to t-1 being 1.5 standard deviation above (below) the mean returns. Small Up (Small Down) market refers to cumulative market returns between zero and 1.5 (-1.5) standard deviation. Newey-West autocorrelation corrected t-statistics are given in brackets.

Panel A: The Unconditional Profits of Limit Order Contrarian Strategy

	Open Price +/- 3%		Open Price +/- 5%		Open Price +/- 7%	
Portfolio	Week		Week		Week	
	t+1	t+2	t+1	t+2	t+1	t+2
Limit Buy	0.70%	0.40%	0.93%	0.39%	1.07%	0.39%
Limit Sell	0.33%	0.30%	0.21%	0.29%	0.10%	0.29%
Buy-minus-Sell	0.37%	0.10%	0.71%	0.10%	0.97%	0.09%
(t-statistics)	(7.69)	(2.59)	(10.47)	(1.64)	(9.65)	(1.02)

Panel B: The Profits of Limit Order Contrarian Strategy Conditional on Market Returns

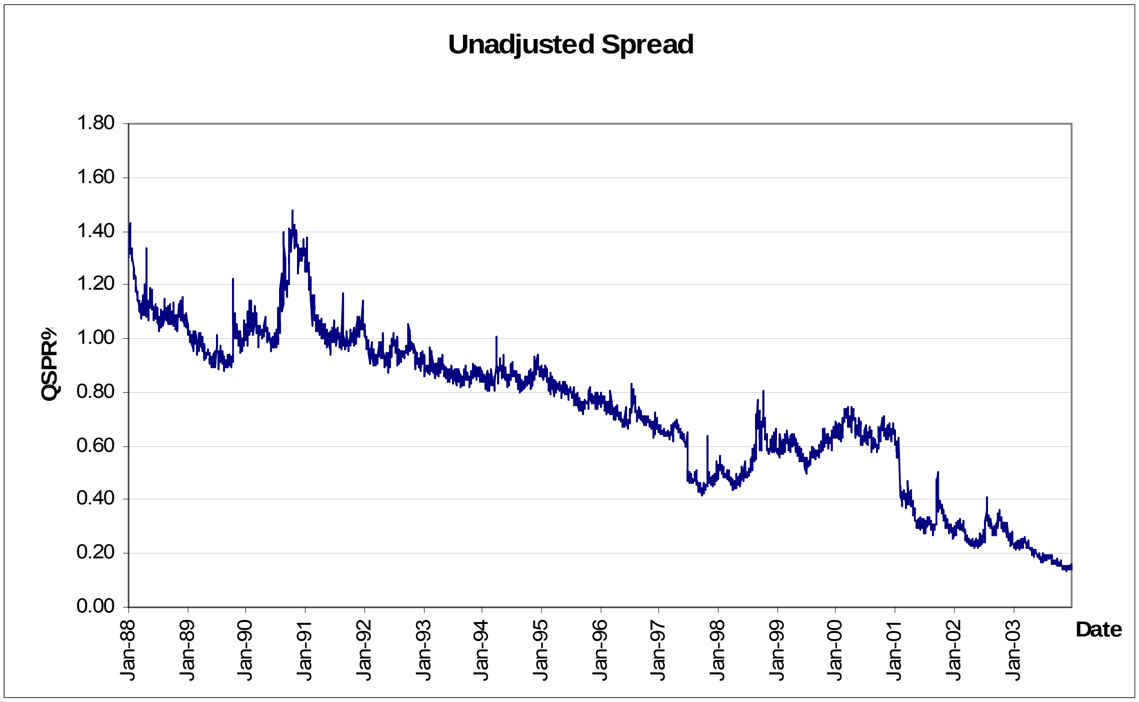
Criteria = Open Price +/- 3%				
	Week t+1			
Portfolio	Past Market Return			
	Large Up	Small Up	Small Down	Large Down
Limit Buy	0.58%	0.72%	0.62%	0.90%
Limit Sell	0.24%	0.41%	0.29%	-0.06%
Buy-minus-Sell	0.33%	0.31%	0.34%	0.96%
(t-statistics)	(1.51)	(5.70)	(4.05)	(4.16)

Criteria = Open Price +/- 5%				
	Week t+1			
Portfolio	Past Market Return			
	Large Up	Small Up	Small Down	Large Down
Limit Buy	0.68%	0.96%	0.79%	1.36%
Limit Sell	0.04%	0.33%	0.12%	-0.21%
Buy-minus-Sell	0.64%	0.63%	0.68%	1.56%
(t-statistics)	(1.81)	(7.52)	(5.52)	(5.17)

Criteria = Open Price +/- 7%				
	Week t+1			
Portfolio	Past Market Return			
	Large Up	Small Up	Small Down	Large Down
Limit Buy	0.76%	1.12%	0.86%	1.73%
Limit Sell	-0.10%	0.24%	-0.01%	-0.40%
Buy-minus-Sell	0.86%	0.88%	0.87%	2.13%
(t-statistics)	(1.75)	(6.72)	(5.36)	(4.89)

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 constant sample of stocks that have valid observations throughout the full sample period.



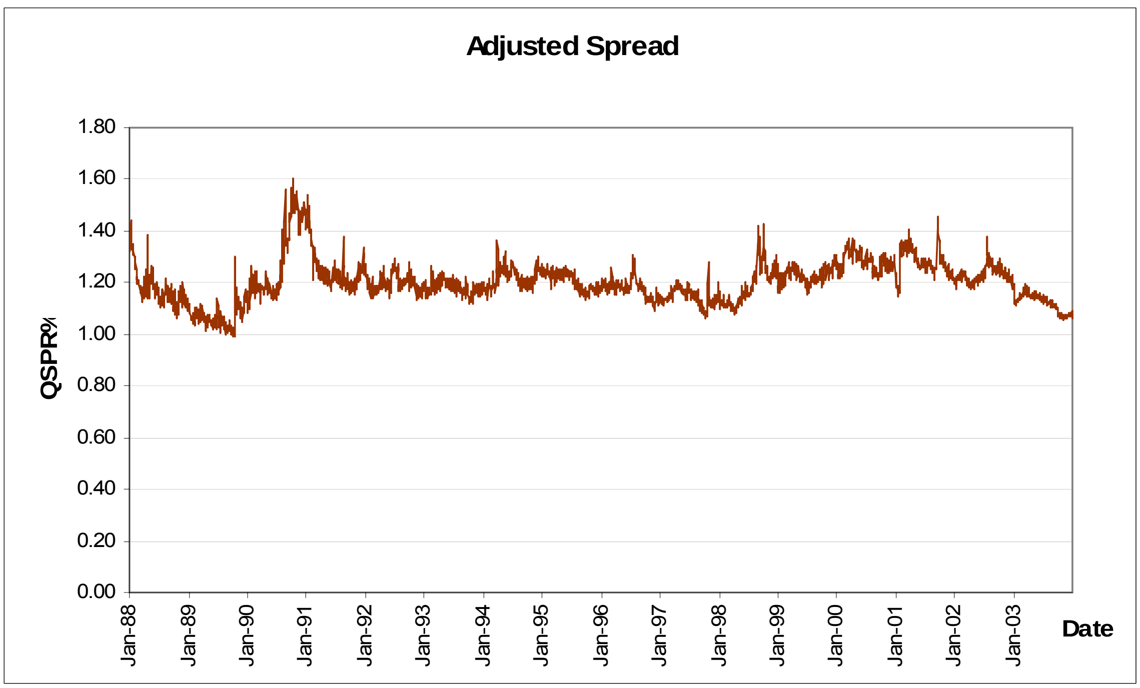


Figure 2: The Time-Series Variation in Liquidity Comovement