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Market-wide liquidity co-movements, volatility regimes and market cap sizes

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ABSTRACT

Liquidity co-movements are studied *within* three different market capitalization indices, each made up of 100 NYSE stocks. Long-run liquidity co-movements are quantified in each class and compared to short-run liquidity co-movements. To condition the analysis of systematic liquidity upon index volatility, three regimes of volatility are defined using the Markov-switching methodology. Our results show that the magnitude of liquidity co-movements is on average positively related to the market capitalization of the index. There are significant differences between short-run and long-run liquidity co-movements, and between spread-based measures and depth-based measures. Finally, the volatility regime bears on the liquidity co-movements relationships.

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I Introduction

In asset pricing theory, expected stock returns are sensitive to variations of some key 'state' variables. Market-wide liquidity has been shown to be such a priced state variable in both theoretical and empirical studies. For instance, Amihud and Mendelson (1986) and Jacoby, Fowler, and Gottesman (2000) provide theoretical arguments to show how liquidity impacts financial market prices. Using a wide variety of liquidity measures, a number of empirical studies have confirmed these theoretical findings (Amihud, 2002; Pastor and Stambaugh, 2003; Gibson and Mougeot, 2004). An important motive for considering a market-wide liquidity measure as a priced factor is evidence of the existence of co-movements of individual stock liquidity with market-wide liquidity. Both academics and practitioners have drawn particular attention to common liquidity fluctuations across stocks. This 'systematic liquidity', referred to as 'commonality in liquidity', is of interest for three main reasons. First, it may need to be accounted for in asset pricing models. If liquidity shocks are non-diversifiable and have a varying impact across individual securities, the more sensitive an asset's return is to such shocks, the greater must be its expected return. Whether and to what extent systematic liquidity has an important bearing on asset pricing is still debatable. Second, it may be a useful consideration for investors in forming their portfolios, as strong co-movements in liquidity among the assets within their portfolio may considerably influence the much sought-after diversification effect. The importance of the adverse effect of systematic liquidity on diversification has still to be correctly estimated. Finally, it may provide explanations about major market incidents as such events are traditionally accompanied by a large drop in market liquidity. However, the potential for commonality in liquidity to cause market collapse has not been rigorously explored in the literature yet.

The first seminal paper by Chordia, Roll, and Subrahmanyam (2000) shows that individual liquidity is positively and significantly influenced by market-wide variations in liquidity for around 55% of NYSE stocks (in 1992). Huberman and Halka (2001) obtain similar findings, showing that liquidity across stocks has some systematic component in a sample of daily NYSE data. Regarding the causes, Coughenour and Saad (2004) argue from a liquidity supply perspective that common market makers are one reason for liquidity commonality. As for markets without any designated liquidity supplier, Brockman and Chung (2002) and Bauer (2004) also document the existence of liquidity commonality in the purely order-driven settings of the Hong Kong Stock Exchange and the Swiss Stock Exchange, respectively.[1] Brockman and Chung (2006) shows that equity index inclusion is a significant source of commonality in liquidity for stocks traded on the Hong Kong stock exchange. In contrast to Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001) do not assign an a priori (explanatory) role to the market or to any other factor. They conduct a principal component analysis and canonical correlation analysis to investigate whether there are common factors in the order flow, return and liquidity. Although the liquidity of the Dow 30 stocks in 1994 exhibits a single common factor, the commonality in liquidity is not strong and is even weaker than the commonality in stock return and order flow.

With respect to this fast growing body of empirical literature, this paper sheds further light on liquidity co-movements in several ways. First, commonality in liquidity is studied *within* three market capitalization classes: small, mid, and large caps. More precisely, we examine whether, and to what extent, systematic liquidity risk is similar *within* each class of market capitalization. For instance, this approach allows us to compare liquidity co-movements *among* small caps to liquidity co-movements *among* large caps. This may be of importance for portfolio managers and investors who commonly deal with market capitalization indices (such as the S&P 100 or S&P 600 indices). Moreover, by using a different market liquidity index for each class, we avoid potential measurement biases that are introduced when, for example, a single value-weighted index is computed for all the stocks.[2]

Second, our analysis of systematic liquidity is conditioned on volatility regimes.[3] By defining three regimes of volatility (low, normal and high), we can investigate to what extent co-movements in liquidity are affected by volatility fluctuations. This is a key issue for the financial community as liquidity may co-move differently in volatile and quiet markets. First, practitioners and regulators have a dire need for better understanding of how co-movements in

[1]Contrary to Coughenour and Saad (2004), Brockman and Chung (2002) argue that order-driven markets are more prone to systematic liquidity due to the absence of market makers.

[2]Large caps *automatically* display stronger commonalities in liquidity than small caps when a unique value-weighted index is employed.

[3]From an econometric point of view, the volatility regime states are determined by an endogenous classification rule based on Markov switching models (see Section III).

liquidity evolve in periods of stress. Second, academics have come up with conflicting results on the relationship between volatility and liquidity. At the individual stock level, both market microstructure theories and empirical studies point to a positive relation between illiquidity (e.g. spreads) and volatility (Tinic, 1972; Benston and Hagerman, 1974; Stoll, 1978a; Stoll, 1978b; Amihud and Mendelson, 1980; Ho and Stoll, 1981; Copeland and Galai, 1983; Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990; Stoll, 2003). However, empirical evidence at the aggregate level is mixed. For example, Pastor and Stambaugh (2003) show that the empirical correlation between aggregate illiquidity and market volatility is a positive 0.57, while Chordia et al. (2001) document a negative relation between aggregate volatility and illiquidity. As Domowitz, Glen, and Madhavan (2001) argue, an exogenous increase in volatility affects liquidity through its direct effect on transaction costs but also indirectly through its impact on turnover: higher volatility increases costs, which reduces trading, but may also lead to more turnover, so that the overall impact on liquidity of a shift on volatility is unclear. To the best of our knowledge, these two aspects of our work are new.[4]

Our results can be summarized as follows. First, the magnitude of liquidity co-movements is on average positively related to the market capitalization of the index: liquidity co-movements are least intense among small caps and most intense among large caps. Although we do not investigate index inclusion in this paper, these results seem to be in agreement with Brockman and Chung (2006) as large caps belong to many indexes routinely traded by portfolio managers. Compared to Chordia, Roll, and Subrahmanyam (2000), the magnitude of concurrent liquidity co-movements is smaller, but the proportion of individual stocks that is positively and significantly affected by concurrent class-wide liquidity shocks is larger. Second, long-run liquidity co-movements are found to be greater than short-run liquidity co-movements in all three market cap indices. Third, the magnitude of spread-based liquidity co-movements are greater in quiet markets for both large and mid caps. Spread adjustments by liquidity providers may therefore be more stock specific in stressful markets than in quiet markets. In contrast, liquidity co-movements measured by the number of shares displayed at the best bid and offer (BBO) are larger during stressful market times, implying that the size displayed at

[4] Closest to our study is perhaps Faff, Kalev, and Sujoto (2005) who investigate whether the liquidity beta is different in up and down markets. They rely upon an ad hoc procedure whereby cut-off points computed from excess market returns (EMR) are determined in such a way that the sample is evenly partitioned among up, down and neutral markets.

the BBO may be adjusted by liquidity providers in a more systematic manner in stressful than in quiet markets. We conjecture that, in stressful markets, liquidity providers fight against an increased risk of information asymmetry in a given stock by individually adjusting the spread rather than the size displayed at the BBO. Conversely, liquidity providers in quiet markets more often adjust the size than the spread on a stock-by-stock basis. Interestingly, a similar proportion of individual stocks within each market cap class rejects the null hypothesis of no difference in liquidity co-movements between the high and low volatility regimes.

The remainder of the paper is structured as follows. In Section II, we present the dataset and describe the liquidity measures used in this paper. We discuss the empirical results in Section III and conclude in Section IV.

II Data

Our dataset is built upon data extracted from the Trades and Quotes (TAQ) database provided by the New York Stock Exchange. These data are extracted in the form of two separate files, one for the trades and the other for the best bid and offer quotes. Trades are subsequently matched with quotes and the direction of a trade is defined according to the widely-used Lee and Ready (1991) algorithm. We follow the recommendation contained in *SEC Rule 11Ac1-5*, assuming trades were recorded 5 seconds later than their actual execution time. Our sample covers a five-year period starting on January 1, 1995 and ending on September 30, 1999, which represents 1,199 trading days.

A Filters

Following Chakravarty, Van Ness, and Van Ness (2005) and Chordia, Roll, and Subrahmanyam (2000), we only retain class A stocks and remove preferred stocks or shares, warrants, rights, derivatives, trusts, closed-end investment companies, American depositary receipts, units, shares of beneficial interest, holdings and realty trusts. We restrict our selection to stocks whose price was higher than \$5 and lower than \$999. The remaining stocks are then selected on the basis of market capitalization, leading to the creation of three portfolios: large, mid, and small. We use Standard and Poor's criteria that set the market capitalization of large, mid and small caps to be respectively above \$4B, between \$1B and \$4B, and between \$300M and \$1B. Each of these three portfolios is made up of the first hundred stocks in each category at the beginning of each year.

Applying traditional filtering procedures (Chordia, Roll, and Subrahmanyam, 2001; Huang and Stoll, 1996), we reject quotes exhibiting (a) price (at the bid or at the ask) lower than or equal to 0; (b) size (at the bid or at the ask) lower than or equal to 0; (c) price at the bid higher than price at the ask; (d) bid-ask spread greater than \$4; (e) proportional bid-ask spread greater than 40%. Trades are excluded if they satisfy at least one of the following conditions: (a) trade price is lower than or equal to 0; (b) trade size is lower than or equal to 0; (c) trade is not "regular", i.e. it is subsequently corrected or canceled. We additionally remove any trade or quote time-stamped outside regular trading hours on the NYSE, that is, before 9:30 AM and after 4:00 PM (or 1:00 PM on the days the exchange closed early). Also, an absolute change greater than 10% (in the trade price, the ask quote, or the bid quote) leads to the deletion of the record. Finally, following Chordia, Roll, and Subrahmanyam (2001), we exclude records for which the (proportional) effective spread was greater than four times the (proportional) quoted spread. On average, those filters lead to the rejection of around 0.4% of the original trade records and 0.06% of the original quotes.

B Transactional liquidity measures

Working on filtered records, we first measure liquidity at the transaction level and compute the (proportional) quoted spread, and quoted depth. We also compute the (proportional) effective spread, applying *SEC Rule 11Ac1-5* in the definition of the time difference between the recording of trades and quotes. According to this rule, trades are assumed to be recorded, on average, 5 seconds later than their actual execution time. Trades are signed according to the methodology proposed by Lee and Ready (1991). We additionally report the number of shares traded. Finally, we include some of the bidimensional liquidity measures introduced by Hasbrouck and Seppi (2001), allowing liquidity to be a function of both spreads and depth.

Quote slopes and log quote slopes therefore complete the set of our measures of liquidity. Table I gives a brief description of these liquidity measures.

C Aggregated liquidity measures

We then aggregate these transactional liquidity measures over three intraday intervals: (1) the morning interval, running from 9:30 AM until 12:00 AM, (2) the midday interval, from 12:00 AM until 2:00 PM, and (3) the afternoon interval, starting at 2:00 PM and ending at 4:00 PM.

Three aggregation techniques are applied. First, we compute EWL_i, which is the equally-weighted average of a liquidity measure, denoted by L_t. This technique puts equal weight on every data point inside the interval. It is defined as follows:

$$EWL_i = \frac{1}{T} \sum_{t=1}^{T} L_t, \tag{1}$$

where t=1,...,T is the t^{th} L in interval i.

Following this technique, we compute the equally-weighted average of quoted spreads (EWQS), proportional quoted spreads (EWPQS), effective spreads (EWES), quote slopes (EWQSl) and log quote slopes (EWLQSl). Adding to our battery of liquidity measures, we also compute the equally-weighted traded spread (EWTS) by combining the average effective spreads of buy and sell orders over interval i (as in Stoll, 2003).

Second, we consider SWL_i, the size-weighted (SW) average of a liquidity measure L_t. This technique allows the weight of each data point to vary within the interval. It is defined as follows:

$$SWL_i = \frac{\sum_{t=1}^{T} L_t * Size\_L_t}{\sum_{t=1}^{T} Size\_L_t}, \tag{2}$$

where t=1,...,T is the t^{th} L in interval i. Size-weighted proportional quoted spread (SWPQS) are weighted by the depth available at the prevailing quotes while both size-weighted proportional effective spreads (SWPES) and traded spreads (SWPTS) are weighted by the number of traded shares.

Finally, we compute a weighted average determined by the duration of the quote, i.e. the number of seconds the quote prevails on the market. Time-weighted proportional quoted spreads are computed in two steps: (1) we define ξ_t, the number of seconds the quotes remained unchanged on the market (i.e. neither the price nor the size was changed); (2) we define the time-weighted proportional quoted spread over interval i as:

$$TWPQS_i = \frac{\sum_{t=1}^{T}(\xi_t * QS_t)}{\sum_{t=1}^{T}\xi_t}, \tag{3}$$

where t=1,...T is the t^{th} quote in interval i.

Table II gives some cross-sectional statistics of (time series) means for each of the 12 measures of liquidity defined above. All measures point to higher liquidity costs for small caps than for large caps. Interestingly, the two bidimensional liquidity measures show that differences in liquidity costs between small caps and large caps are stronger when liquidity is defined as a function of both spreads and depth. Consistent with previous studies, there is some right skewness, i.e. sample means exceeding medians. Right skewness seems to be more pronounced for small caps than for large caps. As expected, the effective and traded spreads are smaller than the equally-weighted (log) quoted spreads, for all three market cap categories. Taking into account the cross-sectional average of mean price levels, liquidity cost measures are more than three times higher for small caps than for large caps. This is a much larger increase than in the case of non-proportional liquidity measures.

Size-weighted proportional quoted spreads are systematically larger than equally-weighted proportional quoted spreads, meaning that larger spreads are posted for larger quoted sizes. However, proportional quoted spreads are smallest when they are weighted by the number of seconds they remain unchanged, implying tighter spreads are posted on average for longer periods of time. These observations hold for all market cap categories. All in all, tighter spreads are posted for smaller sizes over a longer time period, and larger spreads are posted for larger sizes over a shorter time period. Also, size-weighted proportional traded spreads are larger than corresponding effective spreads, in each of the three market cap categories. Interestingly, depth and share volume point to the sharpest differences in liquidity between large and small caps since both of them are more than 10 times lower for small caps than for large caps. As expected, coefficients of variation are higher for small caps than for large caps. Finally, liquidity measures for large caps exhibit stronger first-order autocorrelation than either mid and small caps.

D Standardization

The final step consists in removing the influence of intraday seasonality by standardizing the data. The liquidity variables are standardized following Hasbrouck and Seppi's (2001) two-step procedure. First, we compute the equally-weighted average and the standard deviation over the sample period within each of the three intraday intervals and for each aggregate liquidity measure. Second, we obtain the standardized liquidity measure by subtracting the equally-weighted mean from the aggregate liquidity measure and dividing by the standard deviation.

To smooth out intraday peculiarities and to take into account volatility regimes, Table III reports descriptive statistics on standardized liquidity measures in both the high and low volatility regimes.[5]. Looking at the low volatility regime, all spread-based measures of liquidity display standard deviations lower than 1, and have negative means and medians, consistent with the fact that liquidity costs tends to fall in quiet markets. Interestingly, depth displays negative means for mid and small caps and negative medians for all types of stock. In quiet markets, displaying higher sizes at the best bid-offer (BBO) does not seem to be a systematic behavior of liquidity providers. Besides, the standardized average number of shares traded is lower than in normal markets.

In the high volatility regime, the means of nearly all spread-based standardized liquidity measures are above 0, suggesting that illiquidity is positively correlated to volatility (as found in e.g. Pastor and Stambaugh, 2003). In each market cap class, the EWLQSl bidimensional liquidity measure exhibits the highest standardized mean and median, suggesting that depth (as well as spread) depends upon volatility regimes. Indeed, depth exhibits negative standardized means and medians in each market cap class, with standard deviations below one. This also

[5] The econometric methodology used to define the three regimes of volatility (low, normal, high) is explained in Section III

points to a positive correlation between illiquidity and volatility. While the average number of shares displayed at the BBO shrinks in volatile markets, the standardized average number of shares traded in the high volatility regime is higher than the unconditional standardized average (equal to 0). Interestingly, the median values of EWES and EWTS for small caps are negative, indicating that there are more (but smaller) price improvements during volatile market times than during normal market times.

The cross-sectional means of the correlations between the standardized liquidity measures in both high and low volatility regimes are reported in Tables IV to VI. All measures of spread are positively correlated to each other across time and negatively correlated with depth. Although spread-based liquidity measures in the high volatility regime are positively (albeit only slightly) correlated with the number of traded shares (SVOLU), the picture is somewhat different in the low volatility regime, with the equally-weighted effective and traded spreads displaying a negative correlation. The two bidimensional liquidity measures (EWQSl and EWLQSl) are negatively correlated with depth, and also with the number of traded shares (in 11 out of 12 cases). Finally, depth and the number of shares traded are positively correlated. Although correlations between liquidity measures are higher overall (in absolute value) in the high volatility regime than in the low one, the differences are not large. Finally, levels of correlation are very similar across market capitalization classes.

III Empirical Analysis

The empirical analysis is carried out in three steps. First, co-movements within each market capitalization class are assessed using 'market model' time series regressions à la Chordia, Roll, and Subrahmanyam (2000). Second, a comparison is provided with Cartwright and Lee's (1987) approach that allows for the measurement of liquidity co-movements in the long-run. Finally, the Markov-switching methodology is used to define three regimes of volatility which the analysis of liquidity co-movements is conditioned upon.

A Liquidity co-movements in market cap indices

To assess liquidity co-movements within each of the three market capitalization classes (small, mid, and large), we first follow Chordia, Roll, and Subrahmanyam's (2000) methodology. We run simple 'market model' time series regressions, in which the liquidity proxy of an individual stock is regressed on the market wide liquidity proxy. The market wide liquidity proxy is the value-weighted average of individual liquidity measures of all stocks belonging to the same market capitalization class (excluding the dependent variable stock). However, the Chordia, Roll, and Subrahmanyam methodology differs from ours in the sense that we follow Hasbrouck and Seppi (2001) in taking spread-based measures of liquidity in levels, whereas Chordia, Roll, and Subrahmanyam (2000) work with changes. Generally, variables are differenced when it is suspected that they may contain unit-root (i.e., random-walk) components. Spreads and other liquidity variables are usually not characterized as such. Overdifferencing (i.e., differencing series that are already stationary) induces autocorrelation in computed residuals. For these reasons, Hasbrouck and Seppi (2001) believe that analysis of levels is more economically meaningful and statistically appropriate.

Tables VII and VIII report the cross-sectional results of estimating the following equation for each individual stock j included in the large, mid or small market cap index:

$$L_{j,t} = \alpha_j + \beta_{1,j} L_{M,t} + \beta_{2,j} L_{M,t-1} + \beta_{3,j} L_{M,t+1} + \gamma_j V_{j,t} + \sum_{i=-1}^{+1} \delta_{i,j} R_{M,t+i} + \varepsilon_{j,t}, \qquad (4)$$

where $L_{j,t}$ is the liquidity proxy in level form for stock j and time interval t; $L_{M,t}$ is the value-weighted average liquidity in time interval t for all stocks (excluding stock j) that belong to the same market capitalization class as stock j;[6] $L_{M,t+1}$ and $L_{M,t-1}$ are one lead and one lag of $L_{M,t}$ to capture any non-contemporaneous adjustment in liquidity commonality; $V_{j,t}$ is the contemporaneous change in intradaily squared returns for stock j (acting as a proxy for volatility); R_M are market returns, of which the concurrent, lead, and lag values are included to mitigate any bias caused by the association between liquidity measures and market returns.

[6]This is not a prerequisite in Chordia, Roll, and Subrahmanyam's (2000) study.

Tables VII and VIII show evidence of liquidity co-movements within market cap indices.[7] For example, the equally-weighted quoted spread (EWQS) of large caps displays an average value of 0.291 for β_1.[8] The cross-sectional t-statistic for the average β_1 exceeds the 5% one-tailed critical value of 1.645. Moreover, 94% of the individual $\beta_{1,j}$'s are positive and statistically greater than zero at the 5% level. However, the 0.291 value for β_1 is much lower than the 0.69 value obtained by Chordia, Roll, and Subrahmanyam (2000) in 1992 for 1,169 stocks (mixing large, mid and small caps). Moreover, 0.291 is the highest average value that we obtain throughout the different liquidity measures. All in all, we obtain smaller concurrent co-movements of liquidity, but the liquidity of a larger proportion of individual stocks are positively and significantly affected by concurrent class-wide liquidity shocks.

The value and t-statistic of the combined coefficient (labeled 'Sum') confirms the findings that liquidity co-movements are smaller in magnitude but statistically significant. Compared to previous studies, the average R^2 that we obtain is much higher, reaching 0.42 in the EWPQS equation for large caps. On average, we find no statistical evidence of lagged or lead adjustment in liquidity commonality within market cap categories. At the individual stock level, evidence of non-contemporaneous adjustment in liquidity commonality is somewhat stronger as the leading and/or lagged terms are positive and significant for a larger proportion of individual stocks than in Chordia, Roll, and Subrahmanyam (2000). Comparing liquidity measures among them, the strongest evidence of liquidity co-movements is displayed by spread-based measures that rely exclusively on quotes (i.e. EWQS, EWPQS, SWPQS, and TWPQS). Then, come non-proportional spread-based measures that rely upon quotes and trades (i.e. EWES and EWTS), and bidimensional liquidity measures that rely upon both quotes and sizes (i.e. EWQSl and EWLQSl). Consistent with Chordia, Roll, and Subrahmanyam (2000), SWPES, SWPTS, DEPTH and SVOLU show the weakest sign of liquidity co-movements.[9]

Comparing market cap classes, liquidity co-movements are most (least) intense among large (small) caps. Liquidity co-movements among mid caps are in-between, but closer in

[7] Because the tables are already voluminous, we do not report coefficients for the nuisance variables: the market return and squared stock return. As there was a tick size reduction (from 1/8th to 1/16th) on the 24th of June 1997, we apply a Wald test for structural break. We find weak statistical evidence of such a break. All these results are available upon request.

[8] β_1 measures the average sensitivity of individual stock liquidity to contemporaneous market wide liquidity.

[9] The main difference between DEPTH and SVOLU, on the one hand, and SWPES and SWPTS, on the other, is that the latter always have t-statistics higher than 1.645 for the combined coefficients (labeled 'Sum').

magnitude to liquidity co-movements among small caps. Evidence of liquidity co-movements among small caps is rather mixed. On the one hand, t-statistics for the combined coefficients ('Sum') are higher than the 5% one-tailed critical value in 9 out of 12 liquidity measure equations. On the other hand, the cross-sectional t-statistic for the average β_1 exceeds the 5% one-tailed critical value in only 4 cases (out of 12), all related to the quoted spread. A recent paper by Brockman and Chung (2006) links liquidity commonality to index inclusion. While we do not tackle this issue here, it is well known that large cap stocks are, by definition, much more traded by institutional investors and hence are the main constituents of actively traded indexes. In light of these recent research developments, our results regarding large and small caps are therefore not surprising.

Table IX reports the results of three tests. First, we apply a Wald test on a stock by stock basis. The null hypothesis is defined as $H0 : \beta_{1,j} + \beta_{2,j} + \beta_{3,j} = 0$. We report the percentage of stocks which significantly reject the null at the 5% level. While the magnitude of liquidity co-movements is measured by the β and SUM coefficients reported in Tables VII and VIII, the Wald test gives information on the pervasiveness of liquidity co-movements within market cap classes. Looking at proportional measures of liquidity, Table IX shows that the null hypothesis is rejected equally often in all three market cap classes. Pervasiveness of liquidity co-movements is therefore shown to be equivalent in all three categories, although the cross-sectional β and SUM coefficients in Tables VII and VIII point to liquidity co-movements of greater magnitude for large caps. This observation holds true for proportional quoted-spread measures of liquidity for which evidence of liquidity co-movements based on cross-sectional t-statistics was reported to be the strongest. Regarding non-proportional measures of liquidity, co-movements in liquidity seem most pervasive for large caps and equally pervasive for small and mid caps. We apply a second Wald test with the null hypothesis defined as $H0 : \gamma_j = \delta_{-1,j} = \delta_{0,j} = \delta_{1,j} = 0$. We also report the percentage of stocks which significantly reject the null at the 5% level. This test gives stock-by-stock information on the influence of variables unrelated to market liquidity. Such influence is shown to be equivalent across all three market cap indices and even more pervasive than the influence of liquidity co-movements. Finally, we apply a simple F-test and report the percentage of stocks, which significantly reject the null at the 1% level. Except for the DEPTH variable, the null is always rejected by more than 80% of the stocks.

B Long-run versus short-run liquidity co-movements in market cap indices

In the above 'market model' time series regression, any non-contemporaneous adjustment in liquidity commonality is assumed to be captured by the inclusion of one lag and one lead of the 'market liquidity' index. In a returns-based asset pricing paper, Cartwright and Lee (1987) provide a simple way to solve the problem related to the choice of the number of leads/lags: they propose to replace them by a lagged value of the dependent variable. An additional attractive feature of this approach is the ability to measure liquidity co-movements in the long-run, through the so-called 'long-run beta'.

Tables X and XI report the cross-sectional results of estimating the following equation for each individual stock j included in the large, mid or small market cap index:

$$L_{j,t} = \alpha_j + \beta_j L_{M,t} + \gamma_j L_{j,t-1} + \phi_j V_{j,t} + \sum_{i=-1}^{+1} \delta_{i,j} R_{M,t+i} + \varepsilon_{j,t}. \tag{5}$$

The individual long run beta is computed as follows:[10]

$$\beta_{LR,j} = \beta_j/(1-\gamma_j). \tag{6}$$

For large caps, the proportion of stocks with significantly positive $\beta_{LR,j}$ ranges from 55% (DDEP) to 83% (EWQS). The cross sectional average of the long run liquidity beta is consistently significant and positive for all liquidity measures: the cross-sectional means range from 0.167 (SWPTS) to 0.565 (DEPTH). These findings provide reinforcing positive evidence regarding the pervasiveness of commonality in liquidity among large caps. Interestingly, the adjusted R-squared values reported in Tables X and XI are even higher than those reported in

[10] For the interpretation of the long-run beta to be valid, the absolute value of γ_j needs to be lower than one. In our sample, this condition is satisfied for all stocks, in every market cap category. Although we do not report the results to save space, they are available upon request.

VII and VIII. In addition, the Durbin-Watson statistics indicate that the inclusion of the lagged dependent variable alleviates concern about the goodness of fit of the regression (except in the DEPTH equation).

Mid and small caps exhibit similar long-run liquidity co-movements, both in magnitude and statistical significance. When compared to large caps, these long-run liquidity co-movements are nevertheless weaker, both in magnitude and statistical significance. For example, no sign of long-run liquidity co-movements is found when liquidity is approximated by DEPTH or SVOLU. Results are also not significant for small caps in the EWQSL equation.

Interestingly, the cross-sectional average of γ_j is positively significant for all liquidity measures. Moreover, the vast majority of individual γ_j's are also positive and significant. A positive γ_j points to positive autocorrelation in the evolution of liquidity co-movements as it extends from the short-run to the long-run. This implies that β_{LR} is greater than β_j, or that long-run liquidity co-movements are greater than short-run liquidity co-movements. In the market microstructure literature (for example, see Madhavan, 2000), liquidity (or noise) traders' activity generates a transitory, short-run impact on liquidity while informed traders' activity generates a permanent, long-run impact on liquidity. Informed traders' activity on the NYSE may therefore influence liquidity co-movements to a larger extent than noise traders.[11]

C Volatility regimes and liquidity co-movements in market cap indices

In this last section, a two-step procedure is applied to condition the analysis of liquidity co-movements upon volatility regimes. We first measure volatility for each of the three market cap indices. We follow Andersen and Bollerslev (1998) in defining volatility as the sum of intraday squared returns over the required intervals. As shown by Andersen and Bollerslev (1998), the realized volatility measure provides a model-free estimation of return volatility over a given time interval. We compute the realized volatility (RV) of market cap index c over interval i from 5-minute returns as follows:

$$RV_i^c = r_{i,s+5}^{2,c} + r_{i,s+10}^{2,c} + ... + r_{i,S}^{2,c}, \tag{7}$$

[11] Faff, Kalev, and Sujoto (2005) find the opposite for stocks included in the All Ordinaries Index (AOI) of the pure order-driven Australian stock exchange (ASX).

where $i = [s, S]$ and r_S is the last 5-minute return of interval i, i.e. the 5-minute return corresponding to the [S-5,S] time interval. We standardize the realized volatility measure as described in Section D (as it also exhibits an recurring intraday pattern).

The second step consists in splitting our standardized measures of liquidity into three volatility subsets: low, neutral and high. To construct these three sub-datasets, we apply a three-state Markov switching model à la Hamilton (1989) to the standardized realized volatility series of each market cap index. Using the smoothed transition probabilities, we can immediately determine which volatility observation belongs to which volatility regime. More formally, the standardized measure of realized volatility is assumed to switch regime according to an unobserved variable s_i, where regime 1 is the low-volatility state, regime 2 is the neutral-volatility state, and regime 3 is the high-volatility state. We estimate the parameters of the model using Krolzig's (1997) MSVAR package based on the maximum likelihood EM algorithm. The MSIAH specification with regime-dependent intercept and heteroscedasticity is relied upon. In other words, the standardized realized volatility in state m is equal to μ_m, with variance σ_m^2.

Tables XII and XIII report the cross-sectional results of estimating the following equation for each individual stock j included in the large, mid or small market cap index:

$$L_{j,t} = \sum_{k=1}^{3} D_k(\alpha_{j,k} + \beta_{j,k} L_{M,t} + \gamma_{j,k} L_{j,t-1} + \phi_{j,k} V_{j,t} + \sum_{i=-1}^{+1} \delta_{i,j,k} R_{M,t+i}) + \varepsilon_{j,t}, \quad (8)$$

where D_1 (D_2, D_3) is a dummy variable taking the value of 1 in quiet (normal, volatile) markets and 0 otherwise.

In the large cap index, the cross-sectional average of $\beta_{j,1}$ is consistently significant and positive for all liquidity measures. It ranges from 0.159 (SWPTS) to 0.263 (EWQS) and at least 78% (53%) of large caps have a positive (and significant) $\beta_{j,1}$. Liquidity commonalities in quiet markets for large caps are undisputable. A comparison between liquidity co-movements in the low and high regimes of volatility points to several differences. First, the magnitude of spread-based liquidity co-movements for large caps is greater in quiet markets than in volatile markets: β_1 is greater than β_3 for all spread-based liquidity measures. The opposite is true for the DEPTH variable. Second, β_3 is significantly different from zero in fewer cases than β_1. For example, β_3 is not significantly different from zero for bidimensional liquidity measures and for proportional spread-based measures that rely on transaction prices (i.e. SWPES and SWPTS). For the three proportional quoted spread measures of liquidity, β_3 is only marginally significant.

Further evidence of the importance of volatility regimes for assessing liquidity commonalities is given by the Wald test, of which the null hypothesis states that the magnitude of liquidity co-movements is statistically equivalent in quiet and stressful markets. On average, around 25% of large caps reject the null. Such an effect is least obvious in the SVOLU equation: β_1 and β_3 are both significant and similar, with only 11% of stocks rejecting the null of the Wald test. Nevertheless, liquidity co-movements for large caps do seem to depend upon the volatility regime of the index to which they belong. Large caps exhibit more spread-based liquidity co-movements in quiet markets than in stressful markets. In contrast, liquidity co-movements measured by the number of shares displayed at the BBO (DEPTH) are larger during stressful than during quiet market times. Therefore, spread adjustments may be more stock specific in stressful than in quiet markets. At the same time, the size displayed at the BBO may be adjusted in a more systematic manner in stressful than in quiet markets. We conjecture that in stressful markets, liquidity providers fight against an increased risk of information asymmetry in a given stock by adjusting the spread rather than the size displayed at the BBO. Conversely, liquidity providers in quiet markets would more often adjust the size rather than the spread, on a stock-by-stock basis.

Consistent with the preceding unconditional analysis of liquidity co-movements, mid caps exhibit smaller β coefficients than large caps. Again, the magnitude of liquidity co-movements is greater in quiet markets. Statistical evidence points to sharp differences in liquidity co-movements between the high and low volatility regimes: while β_1 is significantly different from zero in 10 out of 12 cases, β_3 is positive but insignificant in all cases but one. The Wald test for mid-caps reports similar results to those for large caps. Around 25% of mid-caps reject the null of no difference in liquidity co-movements between the high and low volatility regimes.

Interestingly, the cross-sectional average of $\beta_{j,1}$ for small caps is smaller than the cross-sectional average of $\beta_{j,3}$. However, β_3 is never statistically different from zero. Overall, cross-sectional statistical evidence of liquidity co-movements among small caps is weak in both high and low volatility regimes. Liquidity commonality among small caps would therefore matter during normal market times only, i.e. when the index volatility is neither in the high regime nor in the low regime. The only relevant evidence of different liquidity co-movements between the high and low volatility regimes is reported by the proportional quoted-spread measures of liquidity, as β_1 is significant while β_3 is not. Although there is rather weak cross-sectional evidence of different liquidity co-movements among small caps between the high and low volatility regimes, the Wald test still reveals that around 20% of small caps reject the null of no difference in liquidity co-movements between the two volatility regimes.

IV Conclusion

Liquidity co-movements are studied *within* three different market capitalization indices: small, mid and large. The magnitude of liquidity co-movements is on average positively related to the market capitalization of the index: liquidity co-movements are least intense among small caps and most intense among large caps. The magnitude of concurrent liquidity co-movements is smaller than that found in Chordia, Roll, and Subrahmanyam (2000), but the proportion of individual stocks that is positively and significantly affected by concurrent class-wide liquidity shocks is larger. Interestingly, all three market cap indices exhibit the same degree of pervasiveness in liquidity co-movements. Long-run (vs. short-run) liquidity co-movements within each market cap index are also quantified. In all three market cap indices, we find positive autocorrelation in the evolution of liquidity co-movements as it extends from the short run to the long run. Consequently, long-run liquidity co-movements are greater than short-run liquidity co-movements.

In the last stage of the study, we condition our analysis of systematic liquidity upon volatility regimes. By defining three regimes of volatility (low, normal and high), we analyze how liquidity co-movements among large, mid and small caps are affected by volatility fluctuations. In all market cap indices, a comparison between liquidity co-movements in the low and high regimes of volatility reveals notable differences.

Among both large and mid caps, the magnitude of spread-based liquidity co-movements are greater in quiet markets. Spread adjustments by liquidity providers may therefore be more stock specific in stressful markets than in quiet markets. In contrast, liquidity co-movements measured by the number of shares displayed at the BBO are larger during stressful market times, implying that the size displayed at the BBO may be adjusted by liquidity providers in a more systematic manner in stressful than in quiet markets. We conjecture that in stressful markets, liquidity providers fight against an increased risk of information asymmetry in a given (large or mid cap) stock by individually adjusting the spread rather than the size displayed at the BBO. Conversely, liquidity providers in quiet markets more often adjust the size than the spread on a individual, stock-by-stock basis. For small caps, cross-sectional statistical evidence of liquidity co-movements is weak in both high and low volatility regimes. As a consequence, liquidity commonality among small caps would essentially matter during normal market times, i.e. when the index volatility is neither in the high nor in the low regime. In contrast to large and mid caps, liquidity co-movements among small caps are greater in stressful markets but coefficients are not statistically different from zero.

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Table I
Liquidity measures at the transaction level: definitions.

Name	Symbol	Definition	Unit
Quoted Spread	QS_t	$O_t - B_t$	Dollar
Proportional Quoted Spread	PQS_t	$100 * QS_t / M_t$	Percent
Quoted Depth	$DEPTH_t$	$(B\_Size_t + O\_Size_t)/2$	Shares
Effective Spread	ES_t	$2 * D_t * (P_t - M_{t-5})$	Dollar
Proportional Effective Spread	PES_t	$100 * ES_t / M_{t-5}$	Percent
Share Volume	$SVOLU_t$	P_Size_t	Shares
Quote Slope	QSl_t	$QS_t / log(2 * Depth_t)$	Dollar/Log Shares
Log Quote Slope	$LQSl_t$	$log(QS_t)/log(2 * Depth_t)$	Log Dollar/Log Shares

O denotes the best offer quote (i.e. the lowest, most aggressive selling price available in the market). *B* denotes the best bid quote (i.e. the highest, most aggressive buying price available in the market). *M* is the midquote, that is the sum of *Offer* and *Bid* divided by 2. *P* denotes the price of a trade (i.e. an actual transaction). *D* stands for the direction of the trade: it is equal to 1 (-1) for buy (sell) orders. *O_Size* is the number of shares available at the best offer quote. *B_Size* is the number of shares available at the best bid quote. *P_Size* is the number of shares actually traded. Subscript *t* indicates time as displayed in TAQ.

Table II
Aggregate liquidity measures: summary statistics.

Symbol	Mean			Median			Stdev		
	L	M	S	L	M	S	L	M	S
EWQS	0.1498	0.1631	0.1906	0.1487	0.1620	0.1873	0.0223	0.0326	0.0513
EWES	0.1027	0.1058	0.1260	0.1017	0.1046	0.1215	0.0168	0.0249	0.0466
EWTS	0.1026	0.1067	0.1263	0.1016	0.1053	0.1212	0.0166	0.0244	0.0458
EWQSl	0.0236	0.0289	0.0457	0.0228	0.0278	0.0416	0.0060	0.0098	0.0227
EWLQSl	0.0004	0.0008	0.0016	0.0004	0.0008	0.0015	0.0001	0.0003	0.0008
EWPQS	0.2617	0.4754	0.7897	0.2576	0.4650	0.7539	0.0473	0.1154	0.2516
SWPQS	0.2684	0.4864	0.8037	0.2639	0.4741	0.7643	0.0511	0.1253	0.2686
TWPQS	0.2536	0.4589	0.7746	0.2492	0.4473	0.7367	0.0481	0.1169	0.2589
SWPES	0.1871	0.3344	0.5386	0.1817	0.3182	0.5006	0.0538	0.1358	0.2778
SWPTS	0.1930	0.3439	0.5558	0.1884	0.3295	0.5199	0.0487	0.1175	0.2459
DEPTH	8174	5695	4128	7192	4551	3067	4393	4172	3673
SVOLU	575406	131907	47371	471384	94558	29209	425132	142146	67771
Symbol	Min			Max			AC(1)		
	L	M	S	L	M	S	L	M	S
EWQS	0.0967	0.0910	0.0881	0.2444	0.3153	0.4770	0.46	0.37	0.37
EWES	0.0585	0.0350	0.0146	0.2094	0.2523	0.4350	0.35	0.25	0.21
EWTS	0.0605	0.0398	0.0167	0.2084	0.2543	0.4371	0.35	0.25	0.21
EWQSl	0.0104	0.0095	0.0097	0.0510	0.0819	0.1950	0.48	0.40	0.44
EWLQSl	0.0002	0.0003	0.0004	0.0008	0.0024	0.0066	0.49	0.44	0.47
EWPQS	0.1569	0.2404	0.3289	0.4573	1.0176	2.1327	0.63	0.53	0.50
SWPQS	0.1555	0.2386	0.3275	0.4753	1.0970	2.3425	0.60	0.51	0.48
TWPQS	0.1524	0.2347	0.3249	0.4911	1.0397	2.1206	0.60	0.52	0.50
SWPES	0.0501	0.0442	0.0225	0.6191	1.4515	2.7557	0.30	0.22	0.21
SWPTS	0.0761	0.0786	0.0511	0.5294	1.1667	2.3099	0.36	0.28	0.27
DEPTH	1438	694	353	34889	35514	31781	0.45	0.44	0.50
SVOLU	76376	7255	1013	4621638	1758003	937346	0.25	0.26	0.23

L denotes the large cap portfolio, including the biggest 100 stocks on the NYSE in terms of market capitalization (MC). *M* denotes the mid cap portfolio, including the first 100 stocks with $\$1B \leq MC < \$4B$. *S* denotes the small cap portfolio, including the first 100 stocks with $\$300M \leq MC < \$1B$.

Table III
Aggregate standardized liquidity measures in the high and low volatility regimes: summary statistics.

Panel A: Low	Mean			Median			Stdev		
Volatility Regime	L	M	S	L	M	S	L	M	S
EWQS	-0.1310	-0.0556	-0.0601	-0.1348	-0.0983	-0.1365	0.9442	0.9777	0.9875
EWES	-0.0952	-0.0421	-0.0693	-0.0652	-0.0612	-0.1566	0.9135	0.9737	0.9831
EWTS	-0.0938	-0.0417	-0.0725	-0.0680	-0.0718	-0.1753	0.9109	0.9722	0.9815
EWQSl	-0.1371	-0.0635	-0.0256	-0.2334	-0.1694	-0.1754	0.9459	0.9593	0.9791
EWLQSl	-0.1616	-0.1321	-0.1348	-0.2404	-0.2374	-0.2774	0.9164	0.9200	0.9188
EWPQS	-0.1327	-0.1410	-0.1963	-0.1607	-0.2025	-0.2808	0.9127	0.9202	0.8939
SWPQS	-0.1094	-0.1271	-0.1836	-0.1440	-0.1966	-0.2725	0.9307	0.9278	0.8993
TWPQS	-0.1392	-0.1415	-0.1922	-0.1770	-0.2166	-0.2840	0.9087	0.9257	0.8940
SWPES	-0.0908	-0.0994	-0.1355	-0.1568	-0.2046	-0.2633	0.9433	0.9385	0.9164
SWPTS	-0.0893	-0.1056	-0.1560	-0.1493	-0.2063	-0.2898	0.9298	0.9294	0.9057
DEPTH	0.0712	0.0063	-0.0359	-0.1639	-0.3070	-0.3281	0.9785	0.9840	0.9313
SVOLU	-0.1410	-0.0755	-0.0390	-0.3615	-0.3248	-0.3013	0.9251	0.9273	0.9411
Panel B: High	Mean			Median			Stdev		
Volatility Regime	L	M	S	L	M	S	L	M	S
EWQS	0.4658	0.2913	0.0805	0.3651	0.2238	0.0106	1.0304	1.0150	0.9741
EWES	0.3940	0.2559	0.0785	0.2488	0.1415	-0.0330	1.1830	1.0947	0.9988
EWTS	0.3851	0.2397	0.0735	0.2387	0.1144	-0.0492	1.1900	1.1106	1.0138
EWQSl	0.4742	0.4285	0.1577	0.3673	0.3097	0.0214	1.0475	1.0908	0.9977
EWLQSl	0.5812	0.5248	0.2613	0.4718	0.3973	0.1100	1.0806	1.1034	1.0311
EWPQS	0.4970	0.3810	0.1994	0.4041	0.2976	0.1112	1.0354	0.9815	0.9763
SWPQS	0.4139	0.3024	0.1632	0.3272	0.2281	0.0714	1.0214	0.9676	0.9683
TWPQS	0.5101	0.3695	0.1809	0.3997	0.2735	0.0964	1.0619	0.9757	0.9661
SWPES	0.3560	0.2742	0.1662	0.2127	0.1227	0.0165	1.0788	1.0300	1.0215
SWPTS	0.3727	0.3051	0.1823	0.2336	0.1481	0.0265	1.1035	1.0670	1.0455
DEPTH	-0.1697	-0.1598	-0.1039	-0.3632	-0.3702	-0.3350	0.8249	0.8032	0.8000
SVOLU	0.4281	0.2899	0.1777	0.1884	0.0408	-0.0959	1.0491	0.9851	0.9612

L denotes the large cap portfolio, including the biggest 100 stocks on the NYSE in terms of market capitalization (MC). *M* denotes the mid cap portfolio, including the first 100 stocks with $1B $\leq$ MC $<$ $4B. *S* denotes the small cap portfolio, including the first 100 stocks with $300M $\leq$ MC $<$ $1B.

Table IV
Aggregate standardized liquidity measures in the high and low volatility regimes: correlation matrix for large caps.

Panel A: High Volatility Regime											
	EWQS	EWES	EWTS	EWQSl	EWLQSl	EWPQS	SWPQS	TWPQS	SWPES	SWPTS	DEPTH
EWES	0.5678										
EWTS	0.5771	0.9789									
EWQSl	0.8435	0.5508	0.5571								
EWLQSl	0.7081	0.4800	0.4832	0.8047							
EWPQS	0.6732	0.4043	0.4080	0.5001	0.8320						
SWPQS	0.6272	0.3455	0.3487	0.4411	0.7656	0.9490					
TWPQS	0.6280	0.3873	0.3924	0.4672	0.7837	0.9396	0.9012				
SWPES	0.3678	0.5614	0.5576	0.3144	0.5372	0.5938	0.5548	0.5810			
SWPTS	0.3891	0.5950	0.6050	0.3316	0.5679	0.6294	0.5880	0.6136	0.9587		
DEPTH	-0.2871	-0.1450	-0.1482	-0.5209	-0.3561	-0.0506	-0.0537	-0.0498	-0.0193	-0.0205	
SVOLU	0.1273	0.1208	0.1144	-0.0252	0.0588	0.1973	0.1623	0.2123	0.1975	0.1970	0.2474
Panel B: Low Volatility Regime											
	EWQS	EWES	EWTS	EWQSl	EWLQSl	EWPQS	SWPQS	TWPQS	SWPES	SWPTS	DEPTH
EWES	0.4299										
EWTS	0.4420	0.9668									
EWQSl	0.7977	0.4112	0.4199								
EWLQSl	0.6618	0.3270	0.3310	0.7941							
EWPQS	0.6434	0.2620	0.2659	0.4308	0.7924						
SWPQS	0.6118	0.2227	0.2262	0.3926	0.7392	0.9504					
TWPQS	0.5861	0.2207	0.2294	0.3915	0.7414	0.9364	0.9027				
SWPES	0.2542	0.4631	0.4574	0.1967	0.4376	0.5137	0.4823	0.4898			
SWPTS	0.2687	0.4944	0.5072	0.2056	0.4725	0.5613	0.5269	0.5348	0.9414		
DEPTH	-0.2632	-0.0995	-0.1041	-0.5230	-0.3674	-0.0262	-0.0325	-0.0221	0.0107	0.0159	
SVOLU	0.0498	-0.0128	-0.0187	-0.1047	-0.0069	0.1573	0.1339	0.1647	0.1309	0.1377	0.2463

We follow Hasbrouck and Seppi's (2001) two-step procedure to standardize the data. Volatility regimes are determined according to an endogenous classification rule based on a Markov Switching (MS) three-regime model. We follow Krolzig's (1997) MSIAH specification with regime-dependent intercept and heteroscedasticity. Aggregate 5-minute squared returns are used to approximate volatility.

Table V
Aggregate standardized liquidity measures in the high and low volatility regimes: correlation matrix for mid caps.

Panel A: High Volatility Regime											
	EWQS	EWES	EWTS	EWQSl	EWLQSl	EWPQS	SWPQS	TWPQS	SWPES	SWPTS	DEPTH
EWES	0.5411										
EWTS	0.5492	0.9548									
EWQSl	0.8478	0.5260	0.5323								
EWLQSl	0.7773	0.4711	0.4756	0.9074							
EWPQS	0.8119	0.4258	0.4307	0.6616	0.8355						
SWPQS	0.7495	0.3679	0.3728	0.5860	0.7521	0.9302					
TWPQS	0.7245	0.3673	0.3755	0.5942	0.7611	0.9067	0.8567				
SWPES	0.3962	0.5903	0.5736	0.3606	0.4571	0.5024	0.4656	0.4487			
SWPTS	0.4249	0.6264	0.6520	0.3865	0.4982	0.5521	0.5071	0.4966	0.9240		
DEPTH	-0.2953	-0.1838	-0.1874	-0.4983	-0.4325	-0.1848	-0.1786	-0.1752	-0.1050	-0.1120	
SVOLU	0.0705	0.0374	0.0361	-0.0592	-0.0456	0.0782	0.0397	0.0626	0.1153	0.1012	0.2338
Panel B: Low Volatility Regime											
	EWQS	EWES	EWTS	EWQSl	EWLQSl	EWPQS	SWPQS	TWPQS	SWPES	SWPTS	DEPTH
EWES	0.4198										
EWTS	0.4482	0.9291									
EWQSl	0.8063	0.3955	0.4111								
EWLQSl	0.7546	0.3702	0.3848	0.9016							
EWPQS	0.8164	0.3482	0.3706	0.6142	0.8099						
SWPQS	0.7737	0.3111	0.3330	0.5679	0.7537	0.9458					
TWPQS	0.7320	0.2858	0.3187	0.5507	0.7362	0.9087	0.8722				
SWPES	0.3300	0.5410	0.5208	0.2764	0.3963	0.4581	0.4304	0.4104			
SWPTS	0.3728	0.5848	0.6293	0.3092	0.4497	0.5252	0.4918	0.4752	0.9129		
DEPTH	-0.2302	-0.1044	-0.1080	-0.4821	-0.4090	-0.1187	-0.1161	-0.1111	-0.0463	-0.0509	
SVOLU	0.0302	-0.0116	-0.0171	-0.0947	-0.0686	0.0582	0.0319	0.0369	0.1127	0.0888	0.2000

We follow Hasbrouck and Seppi's (2001)two-step procedure to standardize the data. Volatility regimes are determined according to an endogenous classification rule based on a Markov Switching (MS) three-regime model. We follow Krolzig's (1997) MSIAH specification with regime-dependent intercept and heteroscedasticity. Aggregate 5-minute squared returns are used to approximate volatility.

Table VI

Aggregate standardized liquidity measures in the high and low volatility regimes: correlation matrix for small caps.

Panel A: High Volatility Regime											
	EWQS	EWES	EWTS	EWQSl	EWLQSl	EWPQS	SWPQS	TWPQS	SWPES	SWPTS	DEPTH
EWES	0.5495										
EWTS	0.5516	0.9403									
EWQSl	0.8131	0.5024	0.4998								
EWLQSl	0.7410	0.4578	0.4554	0.9026							
EWPQS	0.8174	0.4495	0.4513	0.6367	0.8078						
SWPQS	0.7715	0.4122	0.4160	0.5787	0.7407	0.9435					
TWPQS	0.7264	0.3948	0.3986	0.5712	0.7349	0.9038	0.8621				
SWPES	0.4197	0.6643	0.6381	0.3598	0.4633	0.5340	0.5049	0.4751			
SWPTS	0.4519	0.7041	0.7438	0.3883	0.5067	0.5865	0.5547	0.5241	0.9051		
DEPTH	-0.2871	-0.1588	-0.1613	-0.4660	-0.4065	-0.1578	-0.1507	-0.1525	-0.0945	-0.1079	
SVOLU	0.1273	0.0242	0.0203	-0.0763	-0.0629	0.0485	0.0227	0.0137	0.1075	0.0891	0.2031
Panel B: Low Volatility Regime											
	EWQS	EWES	EWTS	EWQSl	EWLQSl	EWPQS	SWPQS	TWPQS	SWPES	SWPTS	DEPTH
EWES	0.4930										
EWTS	0.5011	0.9275									
EWQSl	0.8031	0.4454	0.4477								
EWLQSl	0.7522	0.4152	0.4174	0.9300							
EWPQS	0.8583	0.4258	0.4320	0.6612	0.7963						
SWPQS	0.8112	0.3920	0.3983	0.6073	0.7362	0.9460					
TWPQS	0.7562	0.3752	0.3876	0.5905	0.7179	0.8924	0.8524				
SWPES	0.3861	0.6627	0.6290	0.3275	0.4066	0.4791	0.4535	0.4207			
SWPTS	0.4271	0.7093	0.7627	0.3608	0.4567	0.5419	0.5106	0.4836	0.8871		
DEPTH	-0.2219	-0.1247	-0.1255	-0.4341	-0.3895	-0.1424	-0.1330	-0.1381	-0.0668	-0.0743	
SVOLU	0.0129	-0.0072	-0.0066	-0.0889	-0.0769	0.0285	0.0079	-0.0048	0.0886	0.0663	0.1804

We follow Hasbrouck and Seppi's (2001) two-step procedure to standardize the data. Volatility regimes are determined according to an endogenous classification rule based on a Markov Switching (MS) three-regime model. We follow Krolzig's (1997) MSIAH specification with regime-dependent intercept and heteroscedasticity. Aggregate 5-minute squared returns are used to approximate volatility.

Table VII
Liquidity co-movements in market cap indices.

Symbol	EWQS			EWES			EWTS		
	L	M	S	L	M	S	L	M	S
Concurrent	0.291	0.138	0.117	0.225	0.103	0.075	0.230	0.104	0.073
t-stat	4.401	2.154	2.244	3.278	1.767	1.572	3.292	1.707	1.488
% +	99.60	93.20	91.00	96.80	90.20	85.40	95.40	90.40	82.80
% + significant	94.00	63.40	62.80	75.20	51.60	48.00	77.60	50.20	46.60
Lag	0.031	0.031	0.027	0.025	0.026	0.028	0.022	0.029	0.032
t-stat	0.603	0.492	0.537	0.407	0.364	0.578	0.336	0.400	0.619
% +	66.00	63.20	61.20	62.00	60.40	64.20	59.80	61.40	65.60
% + significant	27.00	20.40	24.40	20.60	17.00	20.00	19.60	18.20	22.20
Lead	0.013	0.024	0.029	0.031	0.026	0.033	0.033	0.030	0.036
t-stat	0.208	0.346	0.601	0.404	0.326	0.704	0.463	0.391	0.745
% +	56.00	59.00	62.60	57.60	55.20	68.60	59.80	57.40	70.60
% + significant	24.00	20.20	23.40	23.40	18.20	22.40	25.20	18.20	22.40
Sum Mean	0.335	0.193	0.173	0.281	0.155	0.136	0.285	0.162	0.141
t-stat	5.901	3.539	2.995	4.712	2.907	2.430	4.541	3.063	2.550
Sum Median	0.302	0.148	0.158	0.210	0.102	0.107	0.220	0.101	0.109
t-stat	5.318	2.718	2.745	3.510	1.912	1.911	3.499	1.905	1.970
Adj. R^2 Mean	0.336	0.200	0.146	0.344	0.220	0.160	0.348	0.225	0.164
Adj. R^2 Median	0.289	0.156	0.119	0.323	0.180	0.130	0.324	0.182	0.132
Symbol	EWQSl			EWLQSl			EWPQS		
	L	M	S	L	M	S	L	M	S
Concurrent	0.221	0.086	0.048	0.209	0.117	0.098	0.250	0.178	0.208
t-stat	4.007	1.816	1.131	3.418	1.714	1.632	3.255	1.997	2.267
% +	97.40	90.80	80.20	97.40	92.20	91.20	94.20	92.80	91.40
% + significant	89.00	54.40	35.00	86.00	53.00	48.40	79.20	62.80	68.00
Lag	0.025	0.015	0.017	0.040	0.042	0.033	0.062	0.075	0.039
t-stat	0.548	0.319	0.377	0.817	0.671	0.671	0.950	0.977	0.717
% +	63.80	60.20	61.20	72.20	70.60	65.00	76.00	74.60	66.60
% + significant	28.00	14.40	18.80	28.00	22.20	27.80	30.80	31.40	27.40
Lead	-0.002	0.007	0.019	-0.002	0.030	0.035	0.031	0.060	0.035
t-stat	0.040	0.158	0.433	0.025	0.473	0.686	0.454	0.781	0.688
% +	50.00	54.00	61.80	46.20	62.80	66.40	59.40	70.20	63.40
% + significant	25.02	15.00	19.60	17.60	20.20	27.20	23.20	28.20	27.60
Sum Mean	0.243	0.108	0.083	0.248	0.190	0.165	0.342	0.313	0.282
t-stat	3.615	1.677	1.239	3.875	3.162	2.662	5.950	6.016	5.130
Sum Median	0.252	0.113	0.087	0.231	0.187	0.156	0.328	0.293	0.251
t-stat	3.755	1.752	1.286	3.620	3.120	2.516	5.694	5.635	4.555
Adj. R^2 Mean	0.232	0.124	0.080	0.318	0.223	0.166	0.420	0.341	0.286
Adj. R^2 Median	0.218	0.110	0.066	0.304	0.194	0.141	0.373	0.304	0.245

Equally-weighted cross-sectional means of time series slope coefficients are reported, with their corresponding t-statistics. Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors are computed, using Newey and West's (1994) automatic truncation lag procedure. SUM = concurrent + lag + lead coefficients. '%+' reports the percentage of positive slope coefficients while '%+ significant' gives the percentage of positive slope coefficients which are statistically different from zero at the 5% level.

Table VIII
Liquidity co-movements in market cap indices.

Symbol	SWPQS			TWPQS			SWPES		
	L	M	S	L	M	S	L	M	S
Concurrent	0.254	0.163	0.187	0.229	0.172	0.210	0.176	0.095	0.094
t-stat	3.263	1.863	2.014	2.957	1.910	2.290	2.806	1.541	1.546
% +	94.60	92.80	90.80	94.60	90.20	91.80	95.80	86.00	86.60
% + significant	81.60	58.40	60.60	77.60	61.60	65.60	65.60	49.00	46.60
Lag	0.052	0.074	0.043	0.064	0.074	0.041	0.001	0.029	0.029
t-stat	0.811	0.941	0.734	0.961	0.988	0.732	-0.025	0.463	0.500
% +	70.40	74.80	66.00	76.40	75.20	65.20	48.00	62.60	64.80
% + significant	27.00	31.40	28.00	32.00	29.80	29.80	14.20	19.00	20.00
Lead	0.026	0.062	0.040	0.038	0.063	0.034	0.009	0.031	0.025
t-stat	0.391	0.782	0.717	0.483	0.827	0.683	0.120	0.472	0.443
% +	61.60	67.80	62.80	60.00	68.00	64.20	52.00	59.80	61.00
% + significant	22.00	28.40	27.20	24.60	32.20	28.20	17.60	17.00	20.00
Sum Mean	0.331	0.299	0.270	0.330	0.310	0.284	0.186	0.155	0.147
t-stat	5.754	5.732	4.957	5.633	5.932	5.063	3.323	3.273	2.898
Sum Median	0.316	0.268	0.243	0.302	0.294	0.260	0.145	0.118	0.119
t-stat	5.492	5.148	4.465	5.158	5.636	4.623	2.595	2.494	2.352
Adj. R^2 Mean	0.362	0.295	0.251	0.404	0.307	0.249	0.269	0.215	0.222
Adj. R^2 Median	0.303	0.245	0.209	0.365	0.266	0.201	0.246	0.191	0.200
Symbol	SWPTS			DEPTH			SVOLU		
	L	M	S	L	M	S	L	M	S
Concurrent	0.118	0.073	0.090	0.195	0.073	0.039	0.224	0.074	0.041
t-stat	1.631	0.993	1.331	3.285	1.190	0.639	4.462	1.580	0.933
% +	78.60	78.00	83.00	97.20	83.40	72.20	98.40	89.20	80.00
% + significant	45.40	32.00	42.60	79.80	35.80	19.40	89.60	48.40	26.20
Lag	0.032	0.056	0.046	0.021	0.024	0.022	-0.016	0.004	0.005
t-stat	0.500	0.808	0.709	0.404	0.309	0.302	-0.425	0.074	0.097
% +	61.80	72.60	70.20	57.80	58.40	57.40	37.80	55.00	55.20
% + significant	21.00	27.80	26.60	24.40	16.60	18.20	7.00	6.40	6.40
Lead	0.034	0.052	0.044	0.013	0.021	0.019	-0.010	0.003	0.008
t-stat	0.438	0.714	0.717	0.252	0.301	0.255	-0.241	0.031	0.151
% +	60.00	68.80	67.00	56.80	56.00	55.80	43.40	52.60	56.80
% + significant	21.00	24.60	27.40	23.20	16.60	16.20	7.20	6.00	8.00
Sum Mean	0.184	0.182	0.180	0.229	0.119	0.080	0.198	0.081	0.054
t-stat	3.367	3.870	3.503	3.924	1.895	1.179	2.871	1.361	0.926
Sum Median	0.145	0.132	0.156	0.212	0.091	0.062	0.195	0.082	0.053
t-stat	2.656	2.815	3.034	3.632	1.453	0.913	2.820	1.373	0.903
Adj. R^2 Mean	0.299	0.258	0.257	0.137	0.067	0.045	0.215	0.128	0.118
Adj. R^2 Median	0.275	0.233	0.231	0.088	0.035	0.021	0.194	0.110	0.090

Equally-weighted cross-sectional means of time series slope coefficients are reported, with their corresponding t-statistics. Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors are computed, using Newey and West's (1994) automatic truncation lag procedure. SUM = concurrent + lag + lead coefficients. '%+' reports the percentage of positive slope coefficients while '%+ significant' gives the percentage of positive slope coefficients which are statistically different from zero at the 5% level.

Table IX
Liquidity co-movements in market cap indices: Wald and F-tests.

Symbol	EWQS			EWES			EWTS		
	L	M	S	L	M	S	L	M	S
H0:$\beta_{1,j}+\beta_{2,j}+\beta_{3,j}=0$									
% reject at 5%	82.40	63.80	64.60	71.20	49.40	51.00	70.80	49.60	51.00
H0:$\gamma_j=\delta_{-1,j}=\delta_{0,j}=\delta_{1,j}=0$									
% reject at 5%	86.80	91.00	90.20	85.40	96.40	93.60	87.20	96.60	95.20
F-Test									
% reject at 1%	98.40	94.20	94.40	94.80	95.80	92.20	94.60	95.00	92.80
Symbol	EWQSl			EWLQSl			EWPQS		
	L	M	S	L	M	S	L	M	S
H0:$\beta_{1,j}+\beta_{2,j}+\beta_{3,j}=0$									
% reject at 5%	75.60	53.00	43.00	80.80	68.80	62.20	83.80	81.20	80.20
H0:$\gamma_j=\delta_{-1,j}=\delta_{0,j}=\delta_{1,j}=0$									
% reject at 5%	84.20	87.40	82.60	97.40	97.40	92.80	96.20	97.40	96.60
F-Test									
% reject at 1%	95.80	91.20	80.20	99.20	98.00	95.40	100.00	99.00	99.40
Symbol	SWPQS			TWPQS			SWPES		
	L	M	S	L	M	S	L	M	S
H0:$\beta_{1,j}+\beta_{2,j}+\beta_{3,j}=0$									
% reject at 5%	83.00	77.00	79.80	83.80	81.00	81.80	59.60	58.20	60.00
H0:$\gamma_j=\delta_{-1,j}=\delta_{0,j}=\delta_{1,j}=0$									
% reject at 5%	93.60	95.20	96.00	95.20	95.40	93.80	93.40	98.40	98.60
F-Test									
% reject at 1%	99.80	98.20	98.20	99.60	98.00	98.00	98.80	99.00	98.40
Symbol	SWPTS			DEPTH			SVOLU		
	L	M	S	L	M	S	L	M	S
H0:$\beta_{1,j}+\beta_{2,j}+\beta_{3,j}=0$									
% reject at 5%	60.20	63.60	67.80	73.00	50.60	43.60	70.60	38.00	26.80
H0:$\gamma_j=\delta_{-1,j}=\delta_{0,j}=\delta_{1,j}=0$									
% reject at 5%	94.20	99.00	98.00	56.20	50.20	41.20	85.20	87.80	89.00
F-Test									
% reject at 1%	98.40	99.00	97.80	86.40	59.20	41.40	99.00	86.00	80.80

Each test is applied on a stock by stock basis. We report the percentage of stocks which significantly reject the null hypothesis at the 5% level for the Wald tests and at the 1% level for the F-test.

Table X

Long-run liquidity co-movements in market capitalization indices.

Symbol	EWQS			EWES			EWTS		
	L	M	S	L	M	S	L	M	S
Beta LR	0.325	0.185	0.170	0.268	0.148	0.116	0.273	0.154	0.121
t-stat	7.579	4.137	3.433	6.281	3.511	2.582	6.365	3.775	2.789
% +	93.20	85.60	84.80	89.60	84.60	84.40	89.60	85.00	83.20
% + significant	83.40	66.60	65.80	70.80	56.80	54.00	71.60	55.20	53.20
Gamma	0.330	0.297	0.321	0.211	0.164	0.166	0.207	0.155	0.155
t-stat	8.440	7.656	8.025	4.852	4.122	3.973	4.779	3.866	3.703
% +	100.00	100.00	100.00	99.20	98.40	98.80	99.00	98.00	97.80
% + significant	100.00	99.60	99.40	91.20	87.40	87.20	90.20	82.20	83.60
DW Mean	2.015	2.027	2.041	1.976	1.984	2.002	1.970	1.981	2.000
DW Median	2.008	2.020	2.032	1.981	1.978	1.993	1.973	1.976	1.992
Adj. R^2 Mean	0.423	0.281	0.244	0.382	0.246	0.188	0.385	0.249	0.189
Adj. R^2 Median	0.404	0.252	0.227	0.381	0.218	0.161	0.379	0.215	0.159
Symbol	EWQSl			EWLQSl			EWPQS		
	L	M	S	L	M	S	L	M	S
Beta LR	0.242	0.105	0.077	0.233	0.166	0.146	0.322	0.289	0.266
t-stat	3.781	1.703	1.234	3.825	2.797	2.452	6.863	6.293	5.461
% +	88.40	80.80	75.40	93.00	87.00	86.60	91.00	90.40	92.00
% + significant	73.80	52.80	43.40	82.00	67.80	61.40	80.00	80.00	79.20
Gamma	0.426	0.414	0.447	0.385	0.395	0.426	0.466	0.384	0.373
t-stat	11.516	10.708	10.964	10.244	10.164	10.474	13.879	10.426	9.653
% +	100.00	100.00	99.80	100.00	100.00	99.80	100.00	100.00	99.80
% + significant	100.00	99.60	99.60	100.00	99.60	99.20	100.00	99.60	99.40
DW Mean	2.062	2.058	2.078	2.044	2.056	2.068	2.132	2.108	2.093
DW Median	2.037	2.049	2.064	2.030	2.049	2.062	2.096	2.077	2.065
Adj. R^2 Mean	0.394	0.291	0.279	0.442	0.362	0.333	0.586	0.458	0.400
Adj. R^2 Median	0.386	0.282	0.271	0.438	0.334	0.317	0.583	0.442	0.360

Equally-weighted cross-sectional means of time series slope coefficients are reported, with their corresponding t-statistics. Newey and West's (1987) heteroskedasticity and autocorrelation consistent standard errors are computed, using Newey and West's (1994) automatic truncation lag procedure. '%+' reports the percentage of positive slope coefficients while '%+ significant' gives the percentage of positive slope coefficients which are statistically different from zero at the 5% level. DW statistic is the cross sectional average of the Durbin Watson test statistic.

Table XI
Long-run liquidity co-movements in market capitalization indices.

Symbol	SWPQS			TWPQS			SWPES		
	L	M	S	L	M	S	L	M	S
Beta LR	0.321	0.279	0.254	0.308	0.286	0.270	0.191	0.143	0.131
t-stat	6.937	6.082	5.221	5.958	6.137	5.364	3.947	3.544	3.209
% +	92.00	89.80	90.20	91.00	90.40	91.80	88.80	86.40	86.40
% + significant	81.40	77.80	77.60	79.80	80.40	81.20	62.80	62.80	61.00
Gamma	0.436	0.360	0.351	0.446	0.377	0.378	0.175	0.106	0.108
t-stat	12.445	9.457	8.835	12.163	9.951	9.668	4.042	2.551	2.553
% +	100.00	100.00	99.80	100.00	99.80	100.00	96.40	94.40	95.40
% + significant	100.00	99.60	99.20	99.60	98.80	99.20	82.00	66.80	65.40
DW Mean	2.153	2.108	2.092	2.126	2.110	2.099	2.048	2.024	2.020
DW Median	2.110	2.079	2.067	2.099	2.082	2.077	2.022	2.012	2.006
Adj. R^2 Mean	0.515	0.400	0.354	0.557	0.420	0.366	0.303	0.227	0.235
Adj. R^2 Median	0.502	0.374	0.316	0.572	0.396	0.327	0.284	0.201	0.214
Symbol	SWPTS			DEPTH			SVOLU		
	L	M	S	L	M	S	L	M	S
Beta LR	0.167	0.160	0.157	0.565	0.713	0.246	0.255	0.082	0.052
t-stat	3.592	3.944	3.833	2.551	1.307	0.721	3.789	1.578	1.043
% +	75.80	82.20	84.40	86.39	78.60	65.58	93.40	86.40	79.60
% + significant	54.60	61.00	64.80	63.93	40.00	25.93	80.80	49.40	30.60
Gamma	0.218	0.145	0.146	0.644	0.663	0.669	0.429	0.320	0.258
t-stat	5.062	3.522	3.484	8.017	8.042	7.919	8.717	5.813	4.366
% +	99.20	97.80	98.40	100.00	100.0	100.00	100.00	100.00	98.00
% + significant	90.20	82.60	80.20	100.00	100.0	100.00	99.80	96.40	88.80
DW Mean	2.072	2.038	2.035	1.781	1.691	1.586	2.043	2.076	2.060
DW Median	2.042	2.019	2.015	1.779	1.699	1.593	2.038	2.059	2.050
Adj. R^2 Mean	0.345	0.279	0.279	0.262	0.222	0.213	0.399	0.243	0.201
Adj. R^2 Median	0.327	0.254	0.261	0.230	0.206	0.201	0.406	0.220	0.161

Equally-weighted cross-sectional means of time series slope coefficients are reported, with their corresponding t-statistics. Newey and West's (1987) heteroskedasticity and autocorrelation consistent standard errors are computed, using Newey and West's (1994) automatic truncation lag procedure. '%+' reports the percentage of positive slope coefficients while '%+ significant' gives the percentage of positive slope coefficients which are statistically different from zero at the 5% level. DW statistic is the cross sectional average of the Durbin Watson test statistic.

Table XII

Conditioning liquidity co-movements upon volatility regimes in market capitalization indices.

Symbol	EWQS			EWES			EWTS		
	L	M	S	L	M	S	L	M	S
β_1	0.263	0.139	0.102	0.258	0.122	0.075	0.262	0.128	0.080
t-stat	4.636	2.881	1.662	4.344	2.385	1.125	4.364	2.519	1.205
% +	93.20	86.00	81.20	92.40	81.00	76.60	91.60	80.80	77.20
% + significant	80.20	54.40	49.00	71.40	44.20	32.80	72.80	44.40	34.60
β_3	0.212	0.139	0.133	0.222	0.134	0.106	0.228	0.150	0.108
t-stat	2.162	1.143	1.158	2.628	1.385	0.966	2.677	1.445	0.961
% +	89.80	74.40	78.60	91.20	77.40	73.00	90.60	76.20	74.00
% + significant	57.00	32.60	36.60	64.40	40.20	29.20	67.40	40.20	29.20
Adj. R^2 Mean	0.439	0.295	0.259	0.404	0.266	0.208	0.408	0.269	0.210
Adj. R^2 Median	0.429	0.268	0.245	0.416	0.252	0.190	0.418	0.250	0.188
% reject H0:$\beta_1 = \beta_3$ at 5%	22.00	21.00	17.00	26.00	26.80	18.00	28.00	27.60	17.60
Symbol	EWQSl			EWLQSl			EWPQS		
	L	M	S	L	M	S	L	M	S
β_1	0.171	0.065	0.036	0.197	0.116	0.076	0.231	0.197	0.178
t-stat	3.044	1.296	0.680	3.273	2.080	1.202	4.447	3.867	2.499
% +	87.60	78.40	69.60	94.00	83.20	82.00	91.60	87.00	91.00
% + significant	69.40	39.80	23.80	76.60	56.80	38.40	80.60	73.20	67.20
β_3	0.146	0.084	0.065	0.149	0.115	0.120	0.173	0.155	0.208
t-stat	1.564	1.005	0.549	1.556	0.985	1.027	1.780	1.080	1.563
% +	83.60	67.40	63.60	85.60	70.40	72.20	83.20	73.00	80.80
% + significant	47.20	31.80	23.60	44.20	33.80	35.00	50.80	38.40	45.00
Adj. R^2 Mean	0.409	0.304	0.294	0.458	0.372	0.344	0.600	0.467	0.410
Adj. R^2 Median	0.403	0.295	0.288	0.453	0.343	0.325	0.612	0.454	0.375
% reject H0:$\beta_1 = \beta_3$ at 5%	20.60	22.00	18.20	25.80	23.40	21.00	27.80	25.00	20.20

Equally-weighted cross-sectional means of time series slope coefficients are reported, with their corresponding t-statistics. Newey and West's (1987) heteroskedasticity and autocorrelation consistent standard errors are computed, using Newey and West's (1994) automatic truncation lag procedure. β_1 measures the average sensitivity of individual stock liquidity to contemporaneous market-wide liquidity in the low volatility regime (i.e. in quiet markets). β_3 measures the average sensitivity of individual stock liquidity to contemporaneous market-wide liquidity in the high volatility regime (i.e. in stressful markets). '%+' reports the percentage of positive slope coefficients while '%+ significant' gives the percentage of positive slope coefficients which are statistically different from zero at the 5% level. For the Wald test, we report the percentage of stocks which significantly reject, at the 5% level, the null hypothesis that $\beta_1 = \beta_3$.

Table XIII
Conditioning liquidity co-movements upon volatility regimes in market capitalization indices.

Symbol	SWPQS			TWPQS			SWPES		
	L	M	S	L	M	S	L	M	S
β_1	0.233	0.192	0.172	0.231	0.191	0.178	0.213	0.137	0.095
t-stat	4.432	3.761	2.400	4.323	3.703	2.517	3.573	2.591	1.466
% +	92.20	88.00	90.00	91.20	87.20	90.80	91.80	85.80	80.40
% + significant	79.60	71.40	64.00	80.40	70.60	68.40	71.20	52.80	44.00
β_3	0.172	0.121	0.200	0.165	0.180	0.211	0.112	0.074	0.110
t-stat	1.667	0.923	1.436	1.732	1.074	1.559	1.135	0.635	0.888
% +	82.80	70.00	79.60	83.20	71.60	80.60	75.40	64.20	72.40
% + significant	48.80	35.00	41.80	48.60	37.80	44.60	32.60	23.60	30.80
Adj. R^2 Mean	0.529	0.409	0.364	0.572	0.428	0.374	0.324	0.239	0.250
Adj. R^2 Median	0.521	0.383	0.326	0.588	0.405	0.336	0.309	0.218	0.232
% reject H0:$\beta_1 = \beta_3$ at 5%	24.80	26.20	18.60	30.20	28.40	17.60	29.00	27.00	19.60
Symbol	SWPTS			DEPTH			SVOLU		
	L	M	S	L	M	S	L	M	S
β_1	0.159	0.140	0.106	0.165	0.096	0.042	0.199	0.064	0.033
t-stat	2.866	2.681	1.599	3.440	2.072	0.919	3.310	1.333	0.659
% +	78.00	80.20	77.60	97.20	87.20	71.20	99.00	84.00	72.60
% + significant	53.00	50.60	44.60	81.60	55.20	30.60	87.20	42.20	21.80
β_3	0.120	0.086	0.152	0.268	0.200	0.118	0.203	0.091	0.080
t-stat	1.201	0.650	1.137	2.884	2.219	1.153	2.628	1.401	0.848
% +	75.80	64.00	74.20	94.80	87.80	79.40	93.00	76.60	71.60
% + significant	34.20	27.00	35.40	73.40	57.20	36.00	71.40	38.60	28.20
Adj. R^2 Mean	0.365	0.292	0.294	0.321	0.272	0.259	0.423	0.258	0.220
Adj. R^2 Median	0.348	0.267	0.277	0.299	0.252	0.228	0.426	0.241	0.188
% reject H0:$\beta_1 = \beta_3$ at 5%	24.40	26.20	20.80	21.40	25.80	17.80	11.00	19.60	14.80

Equally-weighted cross-sectional means of time series slope coefficients are reported, with their corresponding t-statistics. Newey and West's (1987) heteroskedasticity and autocorrelation consistent standard errors are computed, using Newey and West's (1994) automatic truncation lag procedure. β_1 measures the average sensitivity of individual stock liquidity to contemporaneous market-wide liquidity in the low volatility regime (i.e. in quiet markets). β_3 measures the average sensitivity of individual stock liquidity to contemporaneous market-wide liquidity in the high volatility regime (i.e. in stressful markets). '%+' reports the percentage of positive slope coefficients while '%+ significant' gives the percentage of positive slope coefficients which are statistically different from zero at the 5% level. For the Wald test, we report the percentage of stocks which significantly reject, at the 5% level, the null hypothesis that $\beta_1 = \beta_3$.