Volatility regimes and liquidity co-movements in cap-based portfolios

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Abstract

In contrast with prior studies focused on market-wide liquidity co-movements, we study class-wide liquidity co-movements and condition the analysis on volatility regimes using the Markov switching methodology. By defining three regimes of volatility (low, normal and high), we can investigate whether, and to what extent, liquidity co-movements in cap-based portfolios are affected by volatility fluctuations. As our analysis points out, class-wide shocks dominate stock-specific shocks in low volatility regimes for both large and mid caps. For small caps, cross-sectional statistical evidence of liquidity co-movements is weak in both high and low volatility regimes. Evidence indicates that failure to recognise the importance of volatility to determine class-wide variations in liquidity could significantly alter the performance and risk of size-based portfolios.

Keywords: commonality, liquidity, volatility, regime, market, capitalisation, portfolio.

JEL classifications: G12, G14, C32, C53, G14

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1 Introduction

In asset pricing theory, expected stock returns are sensitive to variations of some key 'state' variables. Market-wide liquidity, which characterizes co-movements between liquidity of different stocks, has been shown to be such a priced state variable in both theoretical and empirical studies (Amihud and Mendelson 1986, Jacoby, Fowler and Gottesman 2000, Amihud 2002, Pástor and Stambaugh 2003, Gibson and Mougeot 2004, Acharya and Pedersen 2005). Evidence on the existence of such co-movements in spreads or depth is reported by Chordia, Roll and Subrahmanyam (2000) for a sample of 1,169 stocks trading on the New York Stock Exchange in 1992. Concurrent investigations at the daily or intraday frequencies highlight the significance of this systematic liquidity risk on the NYSE (Huberman and Halka 2001, Hasbrouck and Seppi 2001). In contrast with the 'market model' regressions used in Chordia et al. (2000) where individual liquidity measures are regressed against the liquidity of the market and a set of control variables, Hasbrouck and Seppi (2001) use the principal component and canonical correlation analyses to examine the existence of common factors in the returns, order flows and liquidity of the Dow 30 stocks in 1994. The reported evidence points to weaker intraday co-movements in spreads and depth than in returns and order flows.

Among the potential determinants of such co-movements, the literature has identified the specific design of the market. Specialists appear to significantly influence the magnitude of liquidity co-movements, with stronger correlated changes in the liquidity of stocks managed by the same specialists (Coughenour and Saad 2004). Weaker co-movements are expected in quote-driven market structures (Brockman and Chung 2002). Another reason for common variations in liquidity is index inclusion. For example, Brockman and Chung (2006) show that arbitrageurs or fund managers on the Hong Kong Stock Exchange play a significant role in determining the correlated changes in spreads or depth of stocks included in an index.

Brockman, Chung and Pérignon (2009) provide evidence of a global common component in the cross-sectional dynamics of liquidity and stress the importance for regulators to monitor the evolution of liquidity. They argue that a spillover of liquidity commonalities beyond single market structures conveys valuable information regarding the contagion of risk across instruments or markets. The current financial crisis reveals all the significant adverse effects that such a global common component in the cross-sectional dynamics of liquidity can have on diversification. Faced with the current financial crisis, all the major regulatory authorities around the world highlight the urgent need to accurately reflect in risk models the adverse effect of such common liquidity variations.[1]

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 capitalisation classes: small, mid, and large caps. More precisely, we examine whether, and to what extent, liquidity risk due to co-movements is similar within each class of market capitalisation. For instance, this approach allows us to compare liquidity co-movements among small caps to liquidity co-movements among large caps. This is an important and timely topic as style and/or cap-based investment strategies are becoming more and more popular with active investment managers (e.g. mutual funds focusing on small-cap stocks, or small-cap value stocks vs. mutual funds investing solely in large-cap stocks, or large-cap growth stocks). If co-movements in liquidity for small-cap and large-cap stocks feature

[1] As an illustration, the Financial Times on Thursday, June 19, 2008, ran a story in its column quoting Nout Wellink, chairman of the Basel committee, as saying: 'The Basel committees goal is to significantly raise the bar for the management and supervision of liquidity risk at banks'.

different dynamics, this implies that the systematic liquidity risk for both type of stocks should diverge. Hence, for example, the global cost of rebalancing small-cap or large-cap stocks could be quite different. 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 liquidity co-movements is conditioned on volatility regimes. From an econometric point of view, the volatility regime states are determined by an endogenous classification rule based on Markov switching models (see Section 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. This part of our work provides market practitioners and stock exchange regulators with a general assessment of the evolution of liquidity in periods of heightened pressure.

As both market microstructure theories and empirical studies point out, illiquid stocks tend to be more volatile (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). Evidence at the aggregate level is however not conclusive: the positive relation between illiquidity and volatility reported in Pástor and Stambaugh (2003) diverges from the findings of Chordia, Roll and Subrahmanyam (2001). As Domowitz, Glen and Madhavan (2001) point out, the direct influence of an increase in volatility on turnover and its indirect impact on transaction costs makes it extremely difficult to predict

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

how liquidity will react to an increase in the level of stress in the market. The asymmetric reaction of liquidity to market stress between order-driven and quote-driven markets reported in Brockman and Chung (2008) further suggests that this remains an empirical issue. To the best of our knowledge, these two aspects of our work are new.

Our results can be summarised as follows. First, the magnitude of liquidity co-movements is on average positively related to the market capitalisation of the portfolio: 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 indices routinely traded by portfolio managers. Compared to market-wide liquidity co-movements (Chordia et al. 2000), the magnitude of concurrent class-wide 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. As hinted at above, this has important implications for portfolio managers implementing style and/or size strategies. Indeed, this seems to indicate that the systematic cost of rebalancing small-cap stocks funds can be less an issue than when large-cap stocks are dealt with. Note that this relates to co-movements of small-cap stocks, not the individual liquidity of small-cap stocks which is of course much poorer than for large-cap stocks. Another related consequence is that the proportion of individual vs class-wide liquidity risk may be different for small-cap and large-cap stocks, class-wide liquidity risk being more a problem for large-cap stocks.

Second, the magnitude of class-wide liquidity co-movements are, on a cross-sectional basis, typically greater in quiet markets for both large and mid caps. In addition, on a stock-by-stock basis, around 20% of mid caps (versus 30% of large caps) display significantly higher common liquidity movements in quiet periods than in periods of heightened pressure. Consequently, class wide price and volatility shocks dominate stock-specific price and volatility shocks in low volatility regimes for large and mid caps. When volatility is in the low regime, common variation in both inventory and adverse selection costs (inducing common liquidity movements) would dominate stock-specific variation in both these costs. The opposite is true in stressful markets: stock-specific price and volatility shocks dominate class wide price and volatility shocks. 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.

The remainder of the paper is structured as follows. In Section 2, we present the data set and describe the liquidity measures used in this paper. We discuss the empirical results in Section 3 and conclude in Section 4.

2 Data

In line with the existing literature (Chordia et al. 2000, Chakravarty, Van Ness and Van Ness 2005), we restrict the universe of securities listed on the New York Stock Exchange to class A shares.[3] Following Standard and Poor's definition of large, mid and small market capitalisation classes, we select the first hundred stocks in each category at the beginning of each year and define three cap-based portfolios accordingly. [4]

[3]Preferred stocks, warrants, rights, derivatives, trusts, closed-end investment companies, ADRs, units, shares of beneficial interest and realty trusts are thus excluded from our sample.

[4]Large, mid and small caps respectively represent those companies with a market capitalisation larger than USD 4 billions, between USD 1 billion and USD 4 billions, and between USD 300 millions and USD 1 billion.

Tick-by-tick records of transactions and quotations are extracted from the Trades and Quotes (TAQ) database provided by the NYSE. The sample period covers a five-year period starting on January 1, 1995 and ending on September 30, 1999, which represents a total of 1199 trading days. The filtered trades and quotes data sets are matched after correcting for an average 5-second delay in the time of trades .[5] Similar to Chordia et al. (2000), the direction of each transaction is determined by the Lee and Ready's (1991) widely-used algorithm[6]

Our analysis relies on liquidity proxies estimated from the information set available to market participants before and after executing a transaction. To approximate ex ante liquidity, we compute for every quotation the proportional quoted spread (PQS_t) and the quoted depth ($DEPTH_t$). The two measures are computed as follows: $PQS_t = (O_t - B_t)/M_t$, where O_t is the best offer quote available in the market at time t (as displayed in TAQ), B_t is the best bid quote at time t, and M_t is the mid-quote, that is, the sum of O_t and B_t divided by 2; $DEPTH_t = (B\_Size_t + O\_Size_t)/2$, where B_Size_t is the number of shares available at the best bid quote at time t and O_Size_t is the number of shares available at the best offer quote at time t. To approximate ex post liquidity, we compute for every transaction the proportional effective spread (PES_t) and the proportional traded spread (PTS_t). The two measures are

[5]We discard trades and quotes recorded outside the regular trading hours on the NYSE, that is, before 09:30 or after 16:00 (or 13:00 when the Exchange closed early). Consistent with the filtering applied in Chordia et al. (2001) or Huang and Stoll (1996), transaction records are further eliminated if (i) the trade price or size is negative or equal to 0, (ii) the trade price is outside the USD 5 - USD 999 range, or (iii) the trade was subsequently corrected or canceled. Erroneous recording of quotes is similarly assumed (i) when the (bid or ask) price or size is negative or equal to 0, (ii) when the quoted spread is negative or wider than USD 4, or (iii) when the proportional quoted spread is wider than 40%. A proportional effective spread greater than four times the proportional quoted spread (Chordia et al. 2001) or an absolute change larger than 10% (for the trade price, bid or ask quote) lead to the deletion of the record. On average, those filters reject 0.4% of the original trade records and 0.06% of the quotes.

[6]As a number of papers in the literature points out, this algorithm is a standard and accurate method for signing transactions (see, e.g., Easley, O'Hara and Paperman (1998), Madhavan and Sofianos (1998), Chordia, Roll and Subrahmayam (2002) or Hvidkjaer (2006)). This algorithm performs best for NYSE transactions: 93% of transactions are correctly classified in the sample examined in Lee and Radhakrishna (2000) while Finucane (2000) and Odders-White (2000) report 85% of accurate trade directions.

computed as follows: $PES_t = [2 * D_t * (P_t - M_{t-5})]/M_{t-5}$, where P_t denotes the price of a trade at time t, D_t stands for the direction of the corresponding trade at time t (+1 and -1 for buy and sell orders respectively), and M_{t-5} is the mid-quote taking the average 5-second delay into account; at the transaction level, $PTS_t = PES_t/2$.

We then aggregate those tick-by-tick liquidity measures over three intraday intervals: (i) the morning, from 09:30 to 12:00, (ii) the lunchtime, from 12:00 to 14:00, and (iii) the afternoon intervals, from 14:00 to 16:00. Three aggregation techniques are applied. First, the equally-weighted average is used to compute the equally-weighted average proportional quoted spread (EWPQS) and depth (DEPTH). It represents the simplest aggregate measure of ex-ante liquidity since every observation inside an interval gets the same weight. The second aggregation technique is the size-weighted average which gives more weight to tick-by-tick liquidity measures that imply higher depth or higher traded volume. First, we compute the size-weighted average proportional quoted spread (SWPQS) by weighting each PQS_t by the depth available at time t. Second, we compute the size-weighted average proportional effective spread (SWPES) by weighting each PES_t by the number of shares traded at time t. Third, we compute the size-weighted average proportional traded spread (SWPTS) by combining the average effective half-spreads of buy and sell orders, each PTS_t being weighted by the number of shares traded at time t (similar to Stoll, 2003). Finally, the third aggregation technique is the time-weighted average whereby each tick-by-tick liquidity measure is weighted by its duration, that is, the number of seconds its corresponding quote remains unchanged in the market. This technique is used to compute the time-weighted average proportional quoted spread (TWPQS).

Table 1 gives some cross-sectional statistics of (time series) means for each of the six liquidity measures defined above. All measures point to larger liquidity costs for small caps than for large caps. Consistent with previous studies, there is some positive skewness, that is, sample means exceeding medians. Positive skewness seems to be more pronounced for small caps than for large caps. As expected, the proportional effective and traded spreads are smaller than the proportional quoted spread for all three market cap portfolios. Taking into account the cross-sectional average of mean price levels, liquidity cost measures are more than three times higher for small than for large caps.

Size-weighted proportional quoted spreads (SWPQS) are systematically larger than equally-weighted proportional quoted spreads (EWQS), 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 that tighter spreads are posted on average for longer periods of time. These observations hold for all market cap classes. 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 (SWPTS) are larger than the corresponding effective spreads, in each of the three market cap categories. Interestingly, depth points to the sharpest difference in liquidity between large and small caps since it is more than ten times lower for small caps than for large caps. Finally, liquidity measures for large caps exhibit stronger first-order autocorrelation than either mid and small caps.

Our liquidity measures are finally adjusted for the presence of intraday seasonality. The aggregate data are standardised in a two-step procedure (Hasbrouck and Seppi 2001). First, we compute the equally-weighted average and the standard deviation over the sample within each of the three intraday intervals for each of our proxies. Second, we standardise each liquidity proxy by subtracting the equally-weighted mean and dividing by the standard deviation. By construction, each standardised measure has a mean of 0 and a standard deviation of 1 over each intraday interval.

Table 2 reports descriptive statistics on standardised liquidity measures in both the high and low volatility regimes.[7] 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 tend to fall in quiet markets. Interestingly, depth displays positive means for large and mid caps and negative medians for all types of stock. In quiet markets, displaying higher sizes at the best bid and offer (BBO) does not seem to be a systematic behaviour of liquidity providers. In the high volatility regime, the means of all spread-based standardised liquidity measures are above 0, suggesting that illiquidity is positively correlated to volatility (as found, e.g., in Pástor and Stambaugh (2003)). In each market cap class, depth exhibits negative standardised means and medians, with standard deviations below one. This also points to a positive correlation between illiquidity and volatility and suggests that spreads and depth depend upon volatility regimes. While the average number of shares displayed at the BBO shrinks in volatile markets, the standardised average spreads in the high volatility regime are wider than the unconditional standardised average (equal to 0).[8]

[7]The econometric methodology used to define the three regimes of volatility (low, normal, high) is explained in Section 3.

[8]The cross-sectional means of the correlations between the standardised liquidity measures in both high and low volatility regimes are not reported to save space. All measures of spread are positively correlated to each other across time and negatively correlated with depth. Although correlations between liquidity measures are

3 Empirical Analysis

The empirical analysis is carried out in two steps. First, co-movements within each market capitalisation class are assessed using 'market model' time series regressions à la Chordia et al. (2000). Second, the Markov switching methodology is used to define three regimes of volatility which the analysis of liquidity co-movements is conditioned upon.

To assess liquidity co-movements within each of the three market capitalisation classes (small, mid, and large), we first follow Chordia et al.'s (2000) methodology. We run 'market model' time series regressions, in which the liquidity proxy of an individual stock is regressed on the *class*-wide liquidity proxy.[9] The class-wide liquidity proxy is the value-weighted average of individual liquidity measures of all stocks belonging to the same market capitalisation class (excluding the dependent-variable stock). We share Hasbrouck and Seppi's (2001) concern that differencing our liquidity measures in the absence of evidence of a unit root may negatively affect the accuracy of the estimated parameters.[10] In addition, although we do not differentiate our proxies, we use *proportional* (and not absolute) measures of liquidity, as described in Section 2. We therefore avoid the potential bias that the tick size reduction (from 1/8th to 1/16th) on 24 June 1997 may introduce when actual values are relied upon.

higher overall in the high volatility regime than in the low one, the differences are not large. Finally, levels of correlation are very similar across market capitalisation classes. Tables are available upon request.

[9]A market-wide liquidity proxy is not appropriate since we study liquidity co-movements within cap-based portfolios. Large caps *automatically* display stronger commonalities in liquidity than small caps when a unique value-weighted index is employed.

[10]Overdifferenciation may lead to inefficient parameter estimates and spurious correlation in the residuals (Plosser and Schwert 1977).

Table 3 reports the cross-sectional averages of estimating the following equation for each individual stock j included in the large, mid or small market cap portfolio:

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

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 capitalisation class as stock j,[11] $L_{M,t+1}$ and $L_{M,t-1}$ are one lead and one lag of $L_{M,t}$ to account for any non-contemporaneous correlated movement in our liquidity proxy, $V_{j,t}$ is the concurrent change in the volatility of stock j, and R_M are market returns, of which the concurrent, lead, and lag values are included.

Table 3 shows evidence of liquidity co-movements within market cap portfolios.[12] For example, the equally-weighted proportional quoted spread (EWPQS) of large caps displays an average value of 0.25 for β_1.[13] The highest value for β_1 is obtained for the size-weighted proportional quoted spread (SWPQS). Looking at the values of the different β_1's, class-wide commonalities seem to be lower than market-wide commonalities, as measured by Chordia et al. (2000) in 1992 (only, but) for 1,169 stocks (mixing large, mid and small caps). However, the liquidity of a larger proportion of individual stocks are positively and significantly affected by concurrent class-wide liquidity shocks. Indeed, 94.2% of the individual $\beta_{1,j}$'s are positive and statistically greater than 0 at the 5% level in a one-tailed upper t-test (with a critical value of 1.645).

[11] This is not a prerequisite in Chordia et al.'s (2000) study.

[12] Because the tables are already voluminous, we do not report coefficients for the nuisance variables: the market return and squared stock return.

[13] β_1 measures the average sensitivity of individual stock liquidity to contemporaneous class-wide liquidity.

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 focused on market-wide liquidity, 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 et al. (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. EWPQS, SWPQS, and TWPQS). Consistent with Chordia et al. (2000), SWPES, SWPTS, and DEPTH show the weakest sign of liquidity co-movements.

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 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 all spread-based 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 3 cases (out of 6), 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 indices.

In light of these recent research developments, our results regarding large and small caps are therefore not surprising.

Table 4 reports the results of three tests. First, we apply a Wald test on a stock-by-stock basis. The null hypothesis is defined as $H_0 : \beta_{1,j} + \beta_{2,j} + \beta_{3,j} = 0$. We report the percentage of stocks which significantly reject the null at the 5% level. While the magnitude of class-wide liquidity co-movements is measured by the β and SUM coefficients reported in Table 3, the Wald test gives information on the pervasiveness of liquidity co-movements within market cap classes. Looking at proportional measures of liquidity, Table 4 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 Table 3 point to liquidity co-movements of greater magnitude among 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. We apply a second Wald test with the null hypothesis defined as $H_0 : \gamma_j = \delta_{-1,j} = \delta_{0,j} = \delta_{1,j} = 0$. 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.

The second step of our analysis consists in conditioning 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 realised volatility measure provides a model-free estimation of return volatility over a given time interval. We compute the realised volatility (RV) of market cap index c over interval i from 5-minute returns as follows:

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

where $i = s, ..., S$ and r_S is the last 5-minute return of interval i, that is, the 5-minute return corresponding to the [S-5,S] time interval. We standardise the realised volatility measure as described in Section 2 (as it also exhibits a recurring intraday pattern).

We then split our standardised measures of liquidity into three volatility subsets: low, neutral and high. To construct these three sub-data sets, we apply a three-state Markov switching model à la Hamilton (1989) to the standardised realised 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 standardised measure of realised 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 standardised realised volatility in state m is equal to μ_m, with variance σ_m^2.

Table 5 reports the cross-sectional results of estimating the following equation for each individual stock j included in the large, mid or small market cap portfolio:

$$L_{j,t} = \sum_{k=1}^{3} D_{k,t}(\alpha_{j,k} + \beta_{j,k}L_{M,t} + \gamma_{j,k}L_{j,t-1} + \phi_{j,k}V_{j,t} + \sum_{i=-1}^{+1} \delta_{i,j,k}R_{M,t+i}) + \epsilon_{j,t}, \qquad (3)$$

where $D_{1,t}$ ($D_{2,t}$, $D_{3,t}$) is a dummy variable taking the value of 1 in quiet (normal, volatile) markets and 0 otherwise.

In the large cap portfolio, all our liquidity proxies exhibit positive and significant cross-sectional average values for the $\beta_{j,1}$ coefficient. Correlated movements of liquidity in the quiet regime of volatility are accordingly strongest for SWPQS (0.233) and weakest for SWPTS (0.159). In this regime, at least 79% (53%) of large caps have a positive (and significant) $\beta_{j,1}$. Liquidity commonalities in quiet markets for large caps are indisputable. 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 0 in fewer cases than β_1. For example, β_3 is not significantly different from 0 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 among large caps is given by the Wald test. The null hypothesis of the Wald test states that the magnitude of liquidity co-movements is statistically equivalent in quiet and stressful markets. In other words, the null states that liquidity co-movements for large caps do not depend upon the volatility regime of the portfolio to which they belong. When we look at spread-based liquidity co-movements, the null is not rejected for around 65% of large caps. However, around 30% of large caps reject the null against the alternative that liquidity co-movements are greater in quiet markets. Interestingly, such an effect is also true, albeit less obvious, regarding depth-based liquidity co-movements: less than 20% of stocks reject the null of the Wald test against the upper one-tailed test. So, quote-based and spread-based liquidity co-movements among large caps react to volatility in a similar way. All in all, large caps exhibit significantly greater liquidity co-movements in quiet markets than in stressful markets. Therefore, spread and quote adjustments may be more stock-specific in stressful than in quiet markets. The logical implication is that class wide price and volatility shocks dominate stock-specific price and volatility shocks in low volatility regimes, i.e. quiet markets. When volatility is in the low regime, common variation in both inventory and adverse selection costs (inducing common liquidity movements) would dominate stock-specific variation in both these costs. The opposite is true in stressful markets: stock-specific price and volatility shocks dominate class wide price and volatility shocks. At first sight, such evidence goes against Brunnermeier and Pedersen (2009) who relate market liquidity to funding liquidity. They show that commonalities in liquidity are related to the financing constraints that liquidity providers (e.g. market-makers and arbitrageurs) face following a negative shock on market prices. These constraints amplify the effect of the initial shock on prices and therefore lead simultaneously to an increase in both liquidity co-movement and volatility. One would therefore expect co-movements in liquidity to be higher when volatility is high. However, the three volatility regimes used in our study are endogenously determined and are not conditioned upon funding liquidity constraints. In other words, volatility can be high even if liquidity providers do not face any financing constraint, which prevents us from testing the Brunnermeier and Pedersen theoretical model.

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. Cross-sectional statistical evidence points to sharp differences in liquidity co-movements between the high and low volatility regimes: while β_1 is always positive and significant, β_3 is positive but insignificant in all cases but one. The Wald test indicates that around 25% of mid-caps reject the null of no difference in liquidity co-movements between the high and low volatility regimes. Around 20% of mid caps (versus 30% of large caps) display significantly higher common liquidity movements in quiet periods than in periods of heightened pressure.

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 on a cross-sectional basis. So, statistical evidence of liquidity co-movements among small caps is weak in the high volatility 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 15% of small caps reject the null of no difference in liquidity co-movements between the two volatility regimes, in favor of greater liquidity co-movements in quiet markets.

4 Conclusion

Liquidity co-movements are studied within three different market capitalisation portfolios: small, mid and large. The magnitude of liquidity co-movements is on average positively related to the market capitalisation of the index: liquidity co-movements are least intense among small caps and most intense among large caps. The magnitude of concurrent class-wide liquidity co-movements is smaller than market-wide liquidity movements as measured by Chordia et al. (2000). However, the proportion of individual stocks that is positively and significantly affected by concurrent class-wide liquidity shocks is larger. Interestingly, all three market cap portfolios exhibit the same degree of pervasiveness in class-wide liquidity co-movements, as measured by the percentage of stocks with statistically positive beta coefficients.

In the last stage of the study, we condition our analysis of class-wide liquidity co-movements upon volatility regimes. By defining three regimes of volatility (low, neutral and high), we analyse 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 interesting differences.

The magnitude of liquidity co-movements among large caps is, on a cross-sectional basis, typically greater in quiet markets. In addition, on a stock-by-stock basis, around 30% of large caps exhibit significantly greater liquidity co-movements in quiet markets than in stressful markets. Consequently, class wide price and volatility shocks dominate stock-specific price and volatility shocks in low volatility regimes for large caps. When volatility is in the low regime, common variation in both inventory and adverse selection costs (inducing common liquidity movements) would dominate stock-specific variation in both these costs. The opposite is true in stressful markets: stock-specific price and volatility shocks dominate class wide price and volatility shocks.

In the mid cap portfolio, cross-sectional statistical evidence points to sharp differences in class-wide liquidity co-movements between the high and low volatility regimes. While the magnitude of liquidity co-movements among mid caps is also greater in quiet markets, it remains below the sensitivity of large caps to class wide liquidity variations. In addition, around 20% of mid caps (versus 30% of large caps) display significantly greater class wide liquidity movements in quiet periods than in periods of heightened pressure.

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, that is, when the index volatility is neither in the high nor in the low regime.

This general assessment of the provision of liquidity on the NYSE arguably conveys valuable information for stock exchange regulators monitoring the operation of the market and the behaviour of specialists. Our results additionally suggest that financial managers should update their models to account for the risk of systematic changes in liquidity across stocks. The implementation of portfolio decisions and the management of market risks are indeed critically influenced by the liquidity of the underlying instruments. As our analysis points out, failure to recognise the importance of this systematic liquidity risk could significantly alter the performance and risk of portfolios.

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Table 1: Aggregate liquidity measures - Summary Statistics

Symbol	Mean			Median			Stdev		
	L	M	S	L	M	S	L	M	S
$EWPQS$	0.262	0.475	0.790	0.258	0.465	0.754	0.047	0.115	0.252
$SWPQS$	0.268	0.486	0.804	0.264	0.474	0.764	0.051	0.125	0.269
$TWPQS$	0.254	0.459	0.775	0.249	0.447	0.737	0.048	0.117	0.259
$SWPES$	0.187	0.334	0.539	0.182	0.318	0.501	0.054	0.136	0.278
$SWPTS$	0.193	0.344	0.556	0.188	0.330	0.520	0.049	0.118	0.246
$DEPTH$	8174	5695	4128	7192	4551	3067	4393	4172	3673
Symbol	Min			Max			AC(1)		
	L	M	S	L	M	S	L	M	S
$EWPQS$	0.157	0.240	0.329	0.457	1.018	2.133	0.63	0.53	0.50
$SWPQS$	0.156	0.239	0.328	0.475	1.097	2.343	0.60	0.51	0.48
$TWPQS$	0.152	0.235	0.325	0.491	1.040	2.121	0.60	0.52	0.50
$SWPES$	0.050	0.044	0.023	0.619	1.452	2.756	0.30	0.22	0.21
$SWPTS$	0.076	0.079	0.051	0.529	1.167	2.310	0.36	0.28	0.27
$DEPTH$	1438	694	353	34889	35514	31781	0.45	0.44	0.50

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

Table 2: Aggregate standardised 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
$EWPQS$	-0.133	-0.141	-0.196	-0.161	-0.203	-0.281	0.913	0.920	0.894
$SWPQS$	-0.110	-0.127	-0.184	-0.144	-0.197	-0.273	0.931	0.928	0.899
$TWPQS$	-0.139	-0.142	-0.192	-0.177	-0.217	-0.284	0.909	0.926	0.894
$SWPES$	-0.091	-0.099	-0.136	-0.157	-0.205	-0.263	0.943	0.939	0.916
$SWPTS$	-0.089	-0.106	-0.156	-0.149	-0.206	-0.290	0.930	0.929	0.906
$DEPTH$	0.071	0.006	-0.036	-0.164	-0.307	-0.328	0.979	0.984	0.931
Panel B: High	Mean			Median			Stdev		
Volatility Regime	L	M	S	L	M	S	L	M	S
$EWPQS$	0.497	0.381	0.199	0.404	0.298	0.111	1.035	0.982	0.976
$SWPQS$	0.414	0.302	0.163	0.327	0.228	0.071	1.021	0.968	0.968
$TWPQS$	0.510	0.370	0.181	0.400	0.274	0.096	1.062	0.976	0.966
$SWPES$	0.356	0.274	0.166	0.213	0.123	0.017	1.079	1.030	1.022
$SWPTS$	0.373	0.305	0.182	0.234	0.148	0.027	1.104	1.067	1.046
$DEPTH$	-0.170	-0.160	-0.104	-0.363	-0.370	-0.335	0.825	0.803	0.800

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

Table 3: Liquidity co-movements in market capitalisation portfolios

Symbol	EWPQS			SWPQS			TWPQS		
	L	M	S	L	M	S	L	M	S
Concurrent	0.250	0.178	0.208	0.254	0.163	0.187	0.229	0.172	0.210
t-statistic	3.255	1.997	2.267	3.263	1.863	2.014	2.957	1.910	2.290
% +	94.20	92.80	91.40	94.60	92.80	90.80	94.60	90.20	91.80
% + significant	79.20	62.80	68.00	81.60	58.40	60.60	77.60	61.60	65.60
Lag	0.062	0.075	0.039	0.052	0.074	0.043	0.064	0.074	0.041
t-statistic	0.950	0.977	0.717	0.811	0.941	0.734	0.961	0.988	0.732
% +	76.00	74.60	66.60	70.40	74.80	66.00	76.40	75.20	65.20
% + significant	30.80	31.40	27.40	27.00	31.40	28.00	32.00	29.80	29.80
Lead	0.031	0.060	0.035	0.026	0.062	0.040	0.038	0.063	0.034
t-statistic	0.454	0.781	0.688	0.391	0.782	0.717	0.483	0.827	0.683
% +	59.40	70.20	63.40	61.60	67.80	62.80	60.00	68.00	64.20
% + significant	23.20	28.20	27.60	22.00	28.40	27.20	24.60	32.20	28.20
Sum Mean	0.342	0.313	0.282	0.331	0.299	0.270	0.330	0.310	0.284
t-statistic	5.950	6.016	5.130	5.754	5.732	4.957	5.633	5.932	5.063
Sum Median	0.328	0.293	0.251	0.316	0.268	0.243	0.302	0.294	0.260
t-statistic	5.694	5.635	4.555	5.492	5.148	4.465	5.158	5.636	4.623
Adj. R^2 Mean	0.420	0.341	0.286	0.362	0.295	0.251	0.404	0.307	0.249
Adj. R^2 Median	0.373	0.304	0.245	0.303	0.245	0.209	0.365	0.266	0.201
Symbol	SWPES			SWPTS			DEPTH		
	L	M	S	L	M	S	L	M	S
Concurrent	0.176	0.095	0.094	0.118	0.073	0.090	0.195	0.073	0.039
t-statistic	2.806	1.541	1.546	1.631	0.993	1.331	3.285	1.190	0.639
% +	95.80	86.00	86.60	78.60	78.00	83.00	97.20	83.40	72.20
% + significant	65.60	49.00	46.60	45.40	32.00	42.60	79.80	35.80	19.40
Lag	0.001	0.029	0.029	0.032	0.056	0.046	0.021	0.024	0.022
t-statistic	-0.025	0.463	0.500	0.500	0.808	0.709	0.404	0.309	0.302
% +	48.00	62.60	64.80	61.80	72.60	70.20	57.80	58.40	57.40
% + significant	14.20	19.00	20.00	21.00	27.80	26.60	24.40	16.60	18.20
Lead	0.009	0.031	0.025	0.034	0.052	0.044	0.013	0.021	0.019
t-statistic	0.120	0.472	0.443	0.438	0.714	0.717	0.252	0.301	0.255
% +	52.00	59.80	61.00	60.00	68.80	67.00	56.80	56.00	55.80
% + significant	17.60	17.00	20.00	21.00	24.60	27.40	23.20	16.60	16.20
Sum Mean	0.186	0.155	0.147	0.184	0.182	0.180	0.229	0.119	0.080
t-statistic	3.323	3.273	2.898	3.367	3.870	3.503	3.924	1.895	1.179
Sum Median	0.145	0.118	0.119	0.145	0.132	0.156	0.212	0.091	0.062
t-statistic	2.595	2.494	2.352	2.656	2.815	3.034	3.632	1.453	0.913
Adj. R^2 Mean	0.269	0.215	0.222	0.299	0.258	0.257	0.137	0.067	0.045
Adj. R^2 Median	0.246	0.191	0.200	0.275	0.233	0.231	0.088	0.035	0.021

Equally-weighted cross-sectional means of time series slope coefficients are reported, with their corresponding t-statistics. Newey and West's (1987) heteroscedasticity 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 in a one-tailed upper t-test.

Table 4: Liquidity co-movements in cap-based portfolios - Wald and F-tests

	EWPQS			SWPQS			TWPQS		
	L	M	S	L	M	S	L	M	S
H0:$\beta_{1,j} + \beta_{2,j} + \beta_{3,j} = 0$									
% reject at 5%	83.80	81.20	80.20	83.00	77.00	79.80	83.80	81.00	81.80
H0:$\gamma_j = \delta_{-1,j} = \delta_{0,j} = \delta_{1,j} = 0$									
% reject at 5%	96.20	97.40	96.60	93.60	95.20	96.00	95.20	95.40	93.80
F-Test									
% reject at 1%	100.00	99.00	99.40	99.80	98.20	98.20	99.60	98.00	98.00
	SWPES			SWPTS			DEPTH		
	L	M	S	L	M	S	L	M	S
H0:$\beta_{1,j} + \beta_{2,j} + \beta_{3,j} = 0$									
% reject at 5%	59.60	58.20	60.00	60.20	63.60	67.80	73.00	50.60	43.60
H0:$\gamma_j = \delta_{-1,j} = \delta_{0,j} = \delta_{1,j} = 0$									
% reject at 5%	93.40	98.40	98.60	94.20	99.00	98.00	56.20	50.20	41.20
F-Test									
% reject at 1%	98.80	99.00	98.40	98.40	99.00	97.80	86.40	59.20	41.40

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 5: Conditioning liquidity co-movements upon volatility regimes in cap-based portfolios

Symbol	EWPQS			SWPQS			TWPQS		
	L	M	S	L	M	S	L	M	S
β_1	0.231	0.197	0.178	0.233	0.192	0.172	0.231	0.191	0.178
t-statistic	4.447	3.867	2.499	4.432	3.761	2.400	4.323	3.703	2.517
% +	91.60	87.00	91.00	92.20	88.00	90.00	91.20	87.20	90.80
% + significant	80.60	73.20	67.20	79.60	71.40	64.00	80.40	70.60	68.40
β_3	0.173	0.155	0.208	0.172	0.121	0.200	0.165	0.180	0.211
t-statistic	1.780	1.080	1.563	1.667	0.923	1.436	1.732	1.074	1.559
% +	83.20	73.00	80.80	82.80	70.00	79.60	83.20	71.60	80.60
% + significant	50.80	38.40	45.00	48.80	35.00	41.80	48.60	37.80	44.60
Adj. R^2 Mean	0.600	0.467	0.410	0.529	0.409	0.364	0.572	0.428	0.374
Adj. R^2 Median	0.612	0.454	0.375	0.521	0.383	0.326	0.588	0.405	0.336
% reject H0:$\beta_1 = \beta_3$ vs H1:$\beta_1 > \beta_3$	30.20	19.40	15.60	25.40	19.80	14.40	33.80	22.80	14.40
% reject H0:$\beta_1 = \beta_3$ vs H1:$\beta_1 < \beta_3$	3.20	7.20	5.60	3.60	6.40	4.60	2.40	6.40	3.60
Symbol	SWPES			SWPTS			DEPTH		
	L	M	S	L	M	S	L	M	S
β_1	0.213	0.137	0.095	0.159	0.140	0.106	0.165	0.096	0.042
t-statistic	3.573	2.591	1.466	2.866	2.681	1.599	3.440	2.072	0.919
% +	91.80	85.80	80.40	78.00	80.20	77.60	97.20	87.20	71.20
% + significant	71.20	52.80	44.00	53.00	50.60	44.60	81.60	55.20	30.60
β_3	0.112	0.074	0.110	0.120	0.086	0.152	0.268	0.200	0.118
t-statistic	1.135	0.635	0.888	1.201	0.650	1.137	2.884	2.219	1.153
% +	75.40	64.20	72.40	75.80	64.00	74.20	94.80	87.80	79.40
% + significant	32.60	23.60	30.80	34.20	27.00	35.40	73.40	57.20	36.00
Adj. R^2 Mean	0.324	0.239	0.250	0.365	0.292	0.294	0.321	0.272	0.259
Adj. R^2 Median	0.309	0.218	0.232	0.348	0.267	0.277	0.299	0.252	0.228
% reject H0:$\beta_1 = \beta_3$ vs H1:$\beta_1 > \beta_3$	31.80	19.20	16.80	35.20	19.40	18.00	18.00	19.20	14.40
% reject H0:$\beta_1 = \beta_3$ vs H1:$\beta_1 < \beta_3$	2.60	8.60	4.20	2.00	7.20	4.20	3.40	7.60	4.80

Equally-weighted cross-sectional means of time series slope coefficients are reported, with their corresponding t-statistics. Newey and West's (1987) heteroscedasticity 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 class-wide liquidity in the low volatility regime (i.e., in quiet markets). β_3 measures the average sensitivity of individual stock liquidity to contemporaneous class-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 $\beta_1 = \beta_3$.