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Open Market Repurchase Programs and Systematic Liquidity

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Abstract

This study examines how open market repurchase (OMR) programs affect firms' exposure to systematic liquidity shocks and liquidity risk. Consistent with the view of repurchasing firms as buyers of last resort, I find: (1) firms experience a significant decline in liquidity commonality during OMR programs; (2) this decline is temporary, with liquidity commonality reverting to pre-program levels once repurchases end; (3) during these programs, firms stabilize against both variation in the demand for liquidity by institutional investors and variation in the supply of liquidity by market makers; and (4) the temporary reduction in liquidity commonality is accompanied by a temporary reduction in firms' liquidity risk. Together, these results highlight a less emphasized aspect of OMR programs: the role of firms' trading activity in shaping their liquidity dynamics and risk exposures.

1 Introduction

Open market share repurchase programs (OMRs) have become the dominant form of corporate payout over the past two decades, surpassing dividends in both the United States and Europe (Anolick et al., 2021). While early research primarily focused on understanding the motivations and valuation effects of OMR announcements, a growing body of literature has shifted attention toward the consequences of firms actively trading their own shares in the market.

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A central topic in this line of research is the effect of OMRs on firms' liquidity. Early work by Barclay and Smith (1988) highlighted the adverse selection costs introduced when informed firms trade their own shares, finding that bid-ask spreads tend to widen during repurchase programs. However, other studies argue that the long duration and flexibility of OMRs allow firms to act as patient liquidity providers, improving market liquidity (Wiggins, 1994; Franz et al., 1995; Nayar et al., 2008; Hillert et al., 2016). Relatedly, Hong et al. (2008) modeled repurchasing firms as buyers of last resort, showing that such intervention reduces short-term return variance and idiosyncratic risk. Similar to this notion, Busch and Obernberger (2017) shows that the stabilizing effect of firms during open market repurchase programs makes prices more efficient and reduces idiosyncratic risk.

While prior studies have focused primarily on firm-level liquidity effects, the implications of open market repurchase programs (OMRs) for systematic liquidity remain largely unexplored. Systematic liquidity, or liquidity commonality, refers to the shared component of liquidity variation across assets. A growing body of empirical evidence documents the presence of liquidity commonality across a wide range of asset classes—including equities, bonds, and derivatives—and across both U.S. and international markets (Chordia et al., 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001; Karolyi et al., 2012).

Importantly, systematic liquidity is not just a microstructure curiosity; it has critical implications for asset pricing. Studies show that a stock's exposure to systematic liquidity risk—that is, whether its liquidity dries up at inopportune times—matters for investors and commands a risk premium (see Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006; Korajczyk and Sadka, 2008). For example, Acharya and Pedersen (2005) develop an asset pricing model where stocks that maintain liquidity during market downturns earn lower average returns, as investors value the option to exit at reasonable cost when market-wide liquidity evaporates.

What explains the existence of systematic liquidity? The literature points to both supply-side and demand-side mechanisms. On the supply side, theoretical models such as Brunnermeier and Pedersen (2009) show that large market declines or spikes in volatility impair the funding liquidity of financial intermediaries (e.g., market makers) who provide liquidity across multiple securities. As these intermediaries face tighter constraints, they reduce liquidity provision broadly, generating co-movement in asset liquidity. Empirically, Coughenour and Saad (2004) find that stocks handled by the same NYSE specialist exhibit stronger liquidity commonality, while Hameed et al. (2010) show that liquidity co-movement intensifies following negative market returns or during periods of high volatility.

On the demand side, liquidity commonality can arise from correlated trading behavior across institutional investors. When institutional investors face liquidity shocks or shifts in risk appetite, their common ownership and synchronized trading across portfolios generate simultaneous liquidity pressures across multiple assets. For example, when mutual funds experience redemptions, they may sell a broad swath of holdings at the same time, producing widespread liquidity stress. Koch et al. (2016) show that stocks with high mutual fund ownership exhibit about twice the liquidity comovement of those with low mutual fund ownership, and Kamara et al. (2008) document that changes in the cross-sectional distribution of liquidity commonality over 1963–2005 can be explained by evolving institutional ownership patterns.

This paper argues that firms engaging in open market repurchase programs (OMRs) occupy a unique position in the market—one that insulates them from, and allows them to counteract, the shocks that typically drive systematic liquidity. Unlike market makers and institutional investors, repurchasing firms are informed traders who use internal cash to buy back a single security—their own shares. As a result, they are largely unaffected by the funding constraints or redemption pressures that amplify supply- or demand-side liquidity shocks. Crucially, these firms not only possess the ability but also the incentive to trade against such shocks, acting as buyers of last resort when liquidity dries up in the broader market. For example, during periods of mutual fund outflows, when systematic selling pressure leads to widespread increases in bid-ask spreads, repurchasing firms can step in to absorb order flow and stabilize liquidity in their own stock. This reasoning leads to a clear empirical prediction: during active OMR programs, firms should exhibit a lower degree of liquidity commonality with the market.

To test this hypothesis, I examine a sample of 1,095 open market repurchase programs announced between 1993 and 2019. For each repurchasing firm, I estimate liquidity commonality using three different liquidity measures: the dollar quoted bid-ask spread, the percentage quoted bid-ask spread, and the Amihud illiquidity ratio. I compute commonality coefficients over three distinct event windows: (1) a pre-repurchase window, defined as the six months preceding the OMR announcement; (2) a repurchase window, covering the six months following the announcement; and (3) a post-repurchase window, which begins one year after the announcement and extends for six months. Comparing firms' liquidity commonality across these windows reveals a striking pattern. From the pre-repurchase period (window 1) to the repurchase period (window 2), liquidity commonality declines sharply and significantly across all three liquidity measures. This reduction is both statistically and economically meaningful; for example, when measured using the percentage quoted bid-ask spread, firms' liquidity commonality falls by an average of 14.9% relative to pre-repurchase levels. Notably, this decline proves to be temporary: in the post-repurchase window (window 3), liquidity commonality rebounds and returns to levels comparable to those observed before the OMR announcement.

To ensure that my findings are not driven by time- or industry-specific factors, I construct a matched sample of non-repurchasing firms. For each firm engaging in an OMR, I identify a matching firm operating in the same industry, belonging to the same size decile, and with a similar book-to-market ratio. I then calculate the adjusted change in liquidity commonality by subtracting the change observed in the matching firm from the change observed in the repurchasing firm (for example, $\Delta\beta_i^{adj} = (\beta_{i,2} - \beta_{i,1}) - (\beta_{match,2} - \beta_{match,1})$). The results confirm the same striking pattern: a significant and economically meaningful decline in liquidity commonality between the pre-repurchase and repurchase windows, followed by a rebound to pre-repurchase levels in the post-repurchase window.

Importantly, I also test whether this reduction in liquidity commonality is symmetric across market conditions. Because OMRs only allow firms to buy their own shares, firms can neutralize order imbalances only when there is selling pressure; they cannot intervene when there is excess buying. To account for this asymmetry, I split liquidity commonality into two components—β_i^n, estimated on days when market-wide order imbalance is negative (net selling pressure), and β_i^p, estimated on days with positive order imbalance (net buying pressure). I instrument firm-level order imbalance using the cross-sectional equal-weighted market order imbalance, following Hasbrouck and Seppi (2001), to avoid endogeneity from firms' own repurchase activity. The results reveal that the decline in liquidity commonality between window 1 and window 2, and its subsequent rebound in window 3, is concentrated entirely in β_i^n (negative imbalance days). In contrast, β_i^p remains stable across all windows. This asymmetry strongly supports the interpretation that firms act as buyers of last resort, buffering liquidity shocks specifically during periods of market-wide selling pressure.

I further investigate whether repurchasing firms primarily neutralize demand-side or supply-side liquidity shocks—and find evidence for both. On the demand side, I examine the relationship between institutional ownership and liquidity commonality, estimating separate liquidity betas for negative and positive market order imbalance days. Consistent with prior work (e.g., Kamara et al. (2008)), I find that before and after the repurchase window, firms with higher institutional ownership exhibit stronger liquidity comovement, reflecting the influence of common ownership and correlated trading. However, this relationship disappears during the repurchase window for negative order imbalance days: institutional ownership no longer explains variation in liquidity commonality when firms are actively repurchasing shares. This suggests that repurchasing firms neutralize the institutional channel of systematic liquidity shocks.

On the supply side, I follow the literature in linking market makers' liquidity provision constraints to market volatility and short-term borrowing costs (proxied by the TED spread). I find that pre- and post-repurchase, shocks to volatility and funding costs significantly amplify liquidity commonality, but during repurchase windows, these effects vanish: volatility and TED spread shocks no longer explain variation in firms' liquidity comovement. Together, these results indicate that repurchasing firms buffer their stocks against both demand- and supply-side drivers of systematic liquidity shocks.

Finally, I examine whether the reduction in liquidity commonality during OMR programs translates into a change in firms' liquidity risk. Building on the liquidity-adjusted asset pricing framework of Pástor and Stambaugh (2003) and Acharya and Pedersen (2005), I estimate firms' exposures (betas) to a traded liquidity risk factor, alongside standard market, size, value, and momentum factors. Using a replicated daily liquidity factor portfolio, I find that firms experience a significant decline in liquidity risk during repurchase periods, with no comparable changes in other factor loadings. On average, firms' liquidity betas decrease by approximately 0.06, corresponding to a 1.2% annualized reduction in their cost of capital—a meaningful and economically significant effect. Notably, this reduction proves temporary: once OMR programs conclude, liquidity betas revert to pre-repurchase levels. Correlation analysis confirms that reductions in liquidity commonality and liquidity risk move closely together, supporting the interpretation that OMR programs provide firms with temporary insulation from systematic liquidity risk.

2 Data

I obtain data on share repurchase programs from the SDC Mergers and Acquisitions database, one of the most widely used public sources for tracking repurchase activity, covering U.S. firms since 1984. To construct the sample for this study, I apply several filters designed to ensure clean measurement of firms' liquidity commonality and liquidity risk around open market repurchase (OMR) programs. Specifically, a repurchase program is included if it satisfies the following conditions:

1. The program is labeled as an open market repurchase (OMR), excluding other types such as tender offers, Dutch auctions, odd-lot repurchases, and accelerated repurchase programs.

2. The program is marked as completed in SDC.

3. The security repurchased is a common stock traded on NYSE, NASDAQ, or AMEX.

4. Information on program size (as a percentage of shares outstanding) and completion rate (the fraction of announced shares actually repurchased) is available.

5. The firm has no active repurchase program during the six months prior to the OMR announcement (pre-announcement window) and does not announce a new repurchase program within 18 months following the announcement (ensuring a clean post-repurchase window).

6. Trading and price data are available in TAQ and CRSP over the period spanning six months prior to announcement through 18 months after.

Although these filters reduce the sample size, they are necessary to isolate the effects of firms' trading activity during OMRs. For example, limiting the sample to open market programs ensures that the analysis focuses on discretionary, flexible repurchases, as opposed to one-off or structured transactions. Similarly, requiring the absence of overlapping programs helps ensure that the pre- and post-repurchase windows are free of contamination from other buyback activity. While I limit the sample to programs marked as completed, I note that my main results—particularly the temporary nature of the liquidity commonality reduction—are difficult to explain solely by completion-related selection effects.

After applying these filters, the final sample consists of 1,095 OMR programs announced between April 9, 1993, and October 8, 2019. To provide a sense of firm and program characteristics, Table (1) reports summary statistics. Firms undertaking OMRs tend to be large, with mean (median) size deciles of 7.7 (7), and have relatively high book-to-market ratios, with a mean (median) of 1.9 (1.5), similar to findings in Grullon and Michaely (2004).

Repurchase programs are economically meaningful in size and often span extended periods. The mean (median) program duration is 404 (283) days, with nearly 7% of programs lasting more than two years. Program size, defined as the percentage of shares outstanding announced for repurchase, averages 7.7% (median 5.0%). Although programs are discretionary and non-binding—firms may repurchase less or more than initially announced—the average completion rate is close to 100%, though roughly 5% of programs complete with less than 35% of the announced amount.

Trading data are drawn from the TAQ tools provided via Wharton Research Data Services, covering daily trade characteristics since January 1993. I construct three primary liquidity measures: (1) dollar quoted bid-ask spread (average daily spread in dollars), (2) percentage quoted spread (average daily spread divided by midpoint), and (3) Amihud illiquidity measure, calculated as the ratio of absolute daily return to daily dollar trading volume Amihud (2002). Additionally, I compute daily order imbalance as the dollar value of buy trades minus the dollar value of sell trades for each firm.

Details on the specific design of the event windows used for the main analyses (pre-repurchase, repurchase, post-repurchase) are provided in Section 3.

3 OMR and Liquidity Commonality

3.1 *Baseline and Adjusted Analysis*

To estimate changes in liquidity commonality following the initiation of open market repurchase (OMR) programs, I use a market model similar to that of Chordia et al. (2000). Specifically, in equation (1), $DL_{i,d}$ denotes the percentage change in the liquidity of stock i from trading day $d-1$ to day d, while $DL_{M,d}$ represents the corresponding change in the cross-sectional average liquidity of the market (excluding stock i). The coefficient β_i captures the degree of comovement between the liquidity of stock i and market liquidity. To control for potential confounding effects, I include one lead and one lag of market liquidity, contemporaneous, lead, and lagged market returns, as well as the contemporaneous change in the squared return of the individual stock. The leads and lags account for delayed adjustments in liquidity commonality, the market return controls for spurious dependence between returns and liquidity, and the squared return proxies for stock-level volatility, which may itself influence liquidity.

$$DL_{i,d} = \alpha_i + \beta_i DL_{M,d} + \text{controls} + \epsilon_{i,d} \tag{1}$$

For each stock, the market liquidity measure $DL_{M,d}$ is calculated excluding that stock to avoid mechanical correlation. To ensure robustness, I estimate equation (1) separately using three liquidity measures: dollar quoted bid-ask spread ($QSPR$), percentage quoted bid-ask spread ($PQSPR$), and the Amihud illiquidity measure ($Amihud$).

To capture temporal variation, I define three estimation windows: (1) **Window 1 (pre-repurchase)** — the six months prior to the OMR announcement, (2) **Window 2 (repurchase period)** — the six months following the announcement, and (3) **Window 3 (post-repurchase)** — a six-month window beginning one year after the announcement.

These windows are chosen to ensure sufficient daily observations for reliable coefficient estimates, to align with the typical program duration (median of nine months), and to avoid contamination from overlapping programs (as ensured by the sample filters described in Section 2).

I estimate equation (1) separately for each firm and window, and capture changes in liquidity commonality by examining shifts in the estimated β_i coefficients across periods. Panel A of Table (2) reports the change from Window 1 to Window 2 ($\Delta\beta_i = \beta_i^{\text{window 2}} - \beta_i^{\text{window 1}}$). The results show economically and statistically significant reductions in liquidity commonality across all three measures. Specifically, the mean (median) reductions are -0.176 (-0.092) for $QSPR$, -0.145 (-0.076) for $PQSPR$, and -0.163 (-0.086) for $Amihud$. When normalized by the average pre-repurchase levels, these reductions represent declines of approximately -14.6% (-11.3%), -14.9% (-10.7%), and -15.2% (-11.4%) respectively, underscoring their economic significance.

Panel B of Table (2) examines the change from Window 2 to Window 3 ($\Delta\beta_i = \beta_i^{\text{window 3}} - \beta_i^{\text{window 2}}$). If the observed reduction during Window 2 reflects the stabilizing effects of my repurchasing activity, I would expect liquidity commonality to rebound after the program concludes. Consistent with this prediction, the results show significant increases across all three measures, with mean (median) changes of 0.181 (0.095) for $QSPR$, 0.150 (0.081) for $PQSPR$, and 0.159 (0.084) for *Amihud*.

A comparison of Panels A and B shows that the magnitude of the post-repurchase rebound closely mirrors the earlier decline, and the commonality levels in Window 3 are statistically indistinguishable from those in Window 1. This pattern supports the interpretation that repurchasing firms temporarily act as buyers of last resort, buffering their stocks from systematic liquidity shocks during the program but reverting to market-level comovement once the program ends. Overall, the results in Table (2) provide strong evidence consistent with this stabilizing mechanism.

To address potential concerns about firm-, industry-, or time-specific effects driving the observed patterns, I perform a matched-firm adjustment. Specifically, for each repurchasing firm, I identify a non-repurchasing firm that serves as a control. The matched firm is required to (1) belong to the same industry, (2) fall within the same size decile, and (3) not be engaged in any open market repurchase program during the estimation windows. If multiple firms meet these criteria, I select the one with the closest book-to-market ratio.

For each firm-program observation, I then adjust the change in liquidity commonality by subtracting the corresponding change observed in its matched non-repurchasing firm. Formally, the adjusted change is defined as:

$$\Delta\beta_i^{\text{adjusted}} = \Delta\beta_i - \Delta\beta_{\text{matched}},$$

where $\Delta\beta_i$ is the change in liquidity commonality coefficient for the repurchasing firm between two windows (e.g., Window 2 minus Window 1), and $\Delta\beta_{\text{matched}}$ is the analogous change for the matched firm.

Table (3) presents the adjusted changes in liquidity commonality. The results mirror those observed in Table (2): there is a significant decline in commonality from Window 1 to Window 2, followed by an offsetting increase from Window 2 to Window 3, such that the levels in Window 1 and Window 3 are statistically indistinguishable. The similarity of the raw and adjusted results suggests that the patterns I observe are unlikely to be artifacts of firm-specific characteristics, industry trends, or broad market conditions.

3.2 *Selling vs. Buying Markets*

As discussed earlier, when firms act as buyers of last resort during repurchase programs, they have the potential to counteract both demand- and supply-side liquidity shocks, thereby reducing the comovement between their own liquidity and aggregate market liquidity. The results in Tables (2) and (3) are consistent with this mechanism. However, it is important to note that repurchase programs provide firms with an asymmetric intervention capacity: they allow firms to increase buying activity when facing selling pressure, but they do not permit selling when markets experience excess buying.

This asymmetry leads to a clear empirical prediction: the reduction in liquidity commonality during repurchase programs should be concentrated on days characterized by net selling pressure, with little or no effect observed on days with net buying pressure.

To test this prediction, I use market-wide order imbalance as a proxy for aggregate buying and selling pressure. Specifically, I compute daily order imbalance as the dollar value of buy trades minus the dollar value of sell trades, averaged across all NYSE stocks (equal-weighted), using TAQ data from the Wharton Research Data Services. Because firm-level order imbalance for repurchasing firms is mechanically influenced by their own buyback activity, I rely on market-level order imbalance as an instrument, following Hasbrouck and Seppi (2001), which documents strong cross-firm commonality in order imbalances.

To formally test the asymmetry, I extend equation (1) by allowing for separate liquidity commonality coefficients on days with positive versus negative market order imbalance. Specifically, I estimate the following specification:

$$DL_{i,d} = \alpha_i + \beta_i^p DL_{M,d} \cdot I[IMB_{M,d} \geq 0] + \beta_i^n DL_{M,d} \cdot I[IMB_{M,d} < 0] + \text{controls} + \epsilon_{i,d} \tag{2}$$

where $DL_{i,d}$ is the percentage change in liquidity for firm i on day d, $DL_{M,d}$ is the percentage change in market liquidity (excluding firm i), and $IMB_{M,d}$ is the market-wide order imbalance. The coefficients β_i^p and β_i^n capture liquidity commonality on days of positive and negative market order imbalance, respectively.

I estimate this model for each firm-program observation over the three event windows, focusing on the $QSPR$ liquidity measure for brevity. Panel A of Table (4) reports the change in commonality coefficients from Window 1 to Window 2. Consistent with the prediction, the results show a significant reduction in β_i^n (negative imbalance days), with a mean (median) change of -0.382 (-0.215), while β_i^p (positive imbalance days) shows no significant change over the same period.

Panel B of Table (4) reports the change from Window 2 to Window 3. As with the overall commonality results, we expect the reduction in β_i^n to reverse once the repurchase program concludes. Indeed, the results show a significant increase in β_i^n after the program ends, with a magnitude comparable to the earlier decline. In contrast, β_i^p remains stable across all windows.

Overall, these findings reinforce the interpretation that OMR programs reduce liquidity commonality specifically by mitigating the effects of systematic selling pressure, consistent with firms' asymmetric role as buyers—but not sellers—of last resort.

4 Stabilizing Effect Mechanisms

Liquidity commonality is one of the most robust empirical patterns in the market microstructure literature, and prior research has identified both demand-side and supply-side forces as key contributors. On the demand side, institutional investors with overlapping holdings and correlated trading behaviors generate synchronized liquidity shocks across assets. On the supply side, constraints faced by market makers—such as funding or inventory risk—create cross-asset variation in liquidity provision. Evidence supporting both mechanisms has been documented across multiple markets and time periods, suggesting that both play meaningful roles in driving liquidity comovement.

Having documented that repurchasing firms experience a significant and temporary reduction in liquidity commonality during OMR programs, the next question is: **against which sources of systematic liquidity shocks do firms provide a buffer?** Specifically, do firms primarily neutralize the demand-side effects associated with institutional trading, the supply-side effects linked to market maker constraints, or both? This section investigates these questions.

4.1 *Demand-Side Mechanism*

If institutional ownership and correlated institutional trading are important drivers of liquidity commonality, then firms with higher institutional ownership should exhibit greater liquidity comovement on average. Prior studies support this view: for example, Koch et al. (2016) show that liquidity comovement is roughly twice as high among stocks with heavy mutual fund ownership, while Kamara et al. (2008) link cross-sectional variation in liquidity commonality to institutional holdings.

To assess whether repurchasing firms counteract institutional trading effects, I examine the relationship between institutional ownership and liquidity commonality across the event windows. Institutional ownership data are obtained from the CDA/Spectrum database, measured as the percentage of shares held by institutions in the quarter prior to the OMR announcement (denoted *inst*). For each firm and window, I regress the estimated liquidity commonality coefficients (β_i^p for positive market order imbalance days and β_i^n for negative imbalance days) on *inst*.

Table (5) reports the results. For β_i^p, there is a consistently positive and significant relationship with institutional ownership across all three windows, indicating that higher institutional holdings are associated with greater liquidity comovement on buying-pressure days. For β_i^n, however, the pattern is notably different: institutional ownership is positively related to liquidity commonality before and after the repurchase window, but this relationship disappears during the repurchase period itself. The explanatory power of institutional ownership (as measured by R^2) similarly collapses for β_i^n during the repurchase window, falling from 8% and 7% in the pre- and post-repurchase periods to nearly zero.

These results suggest that firms' repurchasing activity effectively neutralizes the institutional demand-side channel of liquidity commonality, specifically on days with net selling pressure.

4.2 *Supply-Side Mechanism*

To examine whether firms also buffer supply-side liquidity shocks, I focus on two variables commonly associated with market makers' ability to provide liquidity: market volatility and short-term funding costs. Elevated volatility increases inventory risk, while higher short-term rates tighten funding constraints; both mechanisms can amplify cross-asset liquidity comovement Chordia et al. (2000); Brunnermeier and Pedersen (2009); Kamara et al. (2008).

Daily market volatility shocks are estimated following Schwert (1990): I first regress daily market returns on an intercept, weekly dummies, and 22 lags; the absolute residuals from this regression are then regressed on an intercept and 22 lags, with the residuals representing daily volatility shocks ($\sigma_{M,d}$). To capture funding shocks, I use the TED spread—the difference between the three-month Treasury bill rate and three-month LIBOR—where daily shocks (TED_d) are obtained by regressing the TED spread on its

22 lags and extracting the residual.

I then estimate the following model:

$$DL_{i,d} = \alpha_i + \beta_i DL_{M,d} + t_i TED_d \cdot DL_{M,d} + s_i \sigma_{M,d} \cdot DL_{M,d} + \mu_{i,d} \tag{3}$$

where $DL_{i,d}$ is the percentage change in firm-level liquidity, and $DL_{M,d}$ is the cross-sectional average change (excluding firm i). Here, t_i and s_i capture the excess sensitivity of firm i's liquidity commonality to TED spread and volatility shocks, respectively.

Table (6) presents the results. Both t_i and s_i are positive and significant during the pre- and post-repurchase windows, indicating that, consistent with prior literature, higher funding costs and volatility increase liquidity comovement. Strikingly, however, these relationships vanish during the repurchase window: the average and median coefficients become statistically insignificant, and in some cases even flip sign.

Together, these findings indicate that firms not only dampen demand-side liquidity shocks during OMR programs, but also buffer the effects of supply-side shocks related to market maker constraints. This dual stabilizing role highlights the unique position of repurchasing firms as liquidity providers in the market.

5 Liquidity Risk

An extensive literature has explored liquidity as a potential risk factor, emphasizing that liquidity varies over time and that its variation has a systematic component Pástor and Stambaugh (2003); Sadka (2006); Acharya and Pedersen (2005). In particular, Acharya and Pedersen (2005) propose a liquidity-adjusted capital asset pricing model in which expected returns depend not only on market beta but also on several forms of liquidity risk, including the comovement between firm-level and market-level liquidity. This highlights the close conceptual connection between liquidity commonality and liquidity risk.

Given the evidence documented in earlier sections—namely, that liquidity commonality declines significantly during repurchase programs—one would expect a corresponding change in firms' exposure to systematic liquidity risk. This section investigates that connection.

To estimate liquidity risk, I employ a five-factor asset pricing model similar to Pástor and Stambaugh (2003), which allows for the inclusion of a tradable liquidity risk factor alongside the standard Fama-French-Carhart factors (market, size, value, momentum). This model is well suited to my setting because it can be estimated at daily frequency, matching the design of the six-month event windows. Since no publicly available daily series of the Pastor-Stambaugh liquidity factor exists, I replicate the tradable liquidity portfolio following procedures in Pástor and Stambaugh (2003), Li et al. (2019), and Pontiff and Singla (2019). To validate the replication, I compare the monthly returns of my constructed factor to those published by Lucas Stambaugh and the Wharton Research Data Services, finding correlations exceeding 99%.

For each firm-program observation, I estimate the following regression separately over Window 1 (pre-repurchase), Window 2 (repurchase period), and Window 3 (post-repurchase):

$$r_{i,d} = \beta_i^{mkt} MKT_d + \beta_i^{smb} SMB_d + \beta_i^{hml} HML_d + \beta_i^{mom} MOM_d + \beta_i^{ps} PS_d + \epsilon_{i,d} \tag{4}$$

where $r_{i,d}$ is the daily return of firm i, and PS_d is the daily return on the replicated liquidity factor.

Panel A of Table (7) reports the changes in factor loadings from Window 1 to Window 2. While market, value, and momentum betas remain stable, both size and liquidity betas exhibit significant reductions. Notably, the mean (median) reduction in the liquidity beta is -0.06 (-0.07), with p-values below 0.01, indicating a meaningful decline in firms' exposure to systematic liquidity risk during repurchase periods. To gauge the economic significance, I multiply the change in liquidity beta by the average return on the liquidity factor, finding that the reduction in liquidity risk translates into an average annual cost of capital decrease of approximately 1.2% (median 0.88%), significant at the 1% level.

Panel B of Table (7) shows that these changes are temporary: liquidity betas rebound from Window 2 to Window 3, with increases of similar magnitude to the earlier declines, while other factor loadings remain unchanged. This suggests that the liquidity risk reduction coincides specifically with the repurchase window.

To ensure these patterns are not driven by industry-time fixed effects, I apply the matched-firm adjustment described previously. Table (8) presents the adjusted results, which closely mirror the unadjusted findings, reinforcing the robustness of the conclusions.

Finally, I formally test the link between changes in liquidity commonality and liquidity risk by examining the pairwise correlations between the two across measures. Using the three liquidity measures ($QSPR$, $PQSPR$, and $Amihud$), I compute a 4×4 correlation matrix of the changes from Window 1 to Window 2.

Table (9) reveals two key insights. First, changes in liquidity commonality across different liquidity measures are strongly and positively correlated, indicating that firms exhibiting reductions in one measure tend to experience reductions across others. Second, and more critically, changes in liquidity commonality are significantly correlated with changes in liquidity risk. On average, when firms experience a decline in liquidity comovement, they also experience a decline in their exposure to systematic liquidity risk—consistent with the theoretical framework of Acharya and Pedersen (2005), in which comovement between firm and market liquidity is a central form of priced liquidity risk.

6 Robustness

6.1 *Non-Open Market Repurchase Programs*

The earlier analysis showed that firms engaged in open market repurchase (OMR) programs experience a significant and temporary reduction in liquidity commonality, with levels rebounding to their pre-repurchase values once the program concludes. This pattern was interpreted as evidence that firms' trading activity during OMR programs acts as a stabilizing force, reducing exposure to systematic liquidity shocks.

If this mechanism indeed operates through firms' active trading in open market programs, we should not expect to observe similar dynamics in other forms of share repurchase, such as tender offers or Dutch auctions, where firms repurchase shares in bulk without participating in the open market over time.

To test this prediction, I collect non-OMR repurchase programs from the SDC Mergers and Acquisitions database, applying the same filtering criteria described in Section 2, but restricting the sample to transactions explicitly labeled as non-open market. This yields a sample of 360 non-OMR programs. I then apply the same methodology used for the OMR analysis, estimating changes in liquidity commonality across the three event windows.

Table (10) reports the results. Panel A presents changes in liquidity commonality from Window 1 to Window 2, and Panel B reports changes from Window 2 to Window 3. The key finding is that, unlike OMR programs, non-open market repurchases show no significant reduction in liquidity commonality during the repurchase window, nor a subsequent rebound afterward. This suggests that the patterns observed earlier are unique to OMR programs and specifically linked to firms' gradual and flexible trading activity in the open market.

6.2 *Weekly Frequency*

The main analysis in Section 3 was conducted using daily data. While this high-frequency approach allows for precise estimation, it raises the possibility that the observed patterns might be influenced by microstructure noise, non-synchronous trading, or lagged adjustment effects. To address this concern, I re-estimate the main liquidity commonality regressions using weekly data.

Specifically, I estimate the following simplified version of equation (1), excluding control variables due to the smaller number of observations per window:

$$DL_{i,w} = \alpha_i + \beta_i DL_{M,w} + \epsilon_{i,w},$$

where $DL_{i,w}$ is the percentage change in liquidity for stock i from week $w-1$ to w, and $DL_{M,w}$ is the concurrent change in the cross-sectional average market liquidity.

As before, I estimate this equation for each firm-program observation across the three event windows and for the three liquidity measures ($QSPR$, $PQSPR$, and $Amihud$). Table (11) presents the results, with Panel A showing changes from Window 1 to Window 2 and Panel B showing changes from Window 2 to Window 3. The pattern closely replicates the daily-frequency findings: liquidity commonality declines significantly during the repurchase window and reverts to pre-repurchase levels afterward. This provides additional confidence that the main results are robust and not an artifact of high-frequency data, non-synchronous trading, or microstructure effects.

7 Summary and Conclusion

While the motives behind firms' decisions to announce and complete open market repurchase (OMR) programs have been studied extensively, less is known about the microstructural effects of firms' own trading activity during these programs. In particular, prior work has largely focused on how OMRs affect firms' own liquidity levels but has not explored how active repurchasing alters firms' exposure to systematic liquidity shocks or their liquidity risk. This paper seeks to fill that gap. To the best of my knowledge, it is the first study to examine how firms' systematic liquidity comovement and liquidity risk evolve during OMR programs.

The results are consistent with the view that firms act as buyers of last resort, dampening the effects of variation in liquidity demand from institutional investors and liquidity supply from market makers. Specifically, I find that firms experience a significant reduction in liquidity commonality following the initiation of OMR programs. This reduction is temporary, with liquidity commonality reverting to pre-repurchase levels after the program concludes. Importantly, the decline is concentrated on days with negative market order imbalance, underscoring the asymmetric nature of firms' stabilizing role. Further analyses show that the reduction in liquidity commonality is related to both demand-side and supply-side channels, indicating that firms absorb shocks from institutional flows as well as market maker constraints. Finally, I show that the reduction in firms' liquidity commonality is accompanied by a meaningful, though temporary, decline in their exposure to liquidity risk.

Together, these findings highlight an underexplored but important dimension of OMR programs: the role of firms' trading activity in shaping the liquidity dynamics and risk profile of their own shares. By acting as stabilizing agents during periods of systematic liquidity stress, repurchasing firms not only influence their own market microstructure conditions but also reduce their exposure to priced sources of risk, with potential implications for asset pricing and market stability.

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8 Tables

Table 1: Summary Statistics

This table reports summary statistics for 1,095 open market share repurchase (OMR) programs announced by U.S. firms between April 9, 1993, and October 8, 2019, as recorded in the SDC Mergers and Acquisitions database. The sample is constructed following the filtration criteria detailed in Section 2, which restricts to programs labeled as OMR, completed status, common stock traded on NYSE, NASDAQ, or AMEX, with available data on announced repurchase size (Pct) and completion ratio (Pct_rep), and no overlapping repurchase activity in the surrounding event windows. Size refers to the firm's size decile (based on NYSE breakpoints), and BM is the book-to-market ratio measured in the quarter prior to announcement. Duration is the number of calendar days between program initiation and completion. Pct is the announced repurchase size as a percentage of shares outstanding, and Pct_rep is the percentage of Pct that was actually repurchased by the firm. The table reports mean and median values across three sub-periods and for the full sample.

		size		BM		Duration		Pct		Pct_rep	
	N	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1993-1999	487	7.8	7	1.67	1.41	450	278	6.6	5	98.2	90.0
2000-2009	365	7.9	7	2.3	1.6	462	318	9.7	4.8	121	100.0
2010-2019	243	7.2	7	1.9	1.4	295	227	7.0	5.2	98.8	99.6
All	1095	7.7	7	1.9	1.5	404	283	7.7	5.0	102	100.0

Table 2: Changes in Liquidity Commonality

This table reports changes in the liquidity commonality coefficients of repurchasing firms across three event windows surrounding open market repurchase (OMR) programs. For each firm-program observation, I estimate equation (1) using three liquidity measures: dollar quoted bid-ask spread ($QSPR$), percentage quoted bid-ask spread ($PQSPR$), and the Amihud illiquidity measure ($Amihud$) as defined in Amihud (2002). Window 1 spans the six months prior to the OMR announcement, Window 2 covers the six months following the announcement, and Window 3 begins one year after the announcement and extends for six months.
Panel A reports mean and median changes in liquidity commonality from Window 1 to Window 2; Panel B reports changes from Window 2 to Window 3. Columns (4) and (5) express these changes as percentages of the mean or median coefficient in Window 1. Column (6) shows the fraction of observations exhibiting a reduction or increase. P-values for the mean and median changes are reported in parentheses, based on two-tailed t-tests and Wilcoxon rank-sum tests, respectively.

	Mean	Median	Mean(%)	Median(%)	Fraction (+) or (-)
Panel A: Between window #1 & #2					
$\Delta\beta_{QSPR}$	-0.176	-0.092	-14.6%	-11.3 %	59.2% (-)
	(0.01)	(0.00)			
$\Delta\beta_{PQSPR}$	-0.145	-0.076	-14.9%	-10.7%	61.3% (-)
	(0.02)	(0.00)			
$\Delta\beta_{Amihud}$	-0.163	-0.086	-15.2%	-11.4%	60.0% (-)
	(0.01)	(0.00)			
Panel B: Between window #2 & #3					
$\Delta\beta_{QSPR}$	0.181	0.095	15.0%	11.6%	56.8% (+)
	(0.03)	(0.00)			
$\Delta\beta_{PQSPR}$	0.15	0.081	15.4%	11.4%	58.1% (+)
	(0.01)	(0.00)			
$\Delta\beta_{Amihud}$	0.159	0.084	14.8%	11.3%	59.2% (+)
	(0.02)	(0.00)			

Number of Obs=1095

Table 3: Adjusted Changes in Liquidity Commonality

This table reports changes in liquidity commonality coefficients across three estimation windows, adjusted to account for firm-, industry-, and time-specific effects. For each repurchasing firm, I identify a matched non-repurchasing firm from the same industry and size decile, with the closest book-to-market ratio, and no active repurchase program during the estimation period. The adjusted change is computed as the difference between the repurchasing firm's change and its matched firm's change: $\Delta\beta_i^{\text{adjusted}} = \Delta\beta_i - \Delta\beta_{\text{matched}}$.

Panel A reports mean and median adjusted changes in commonality from Window 1 (pre-repurchase) to Window 2 (repurchase period); Panel B reports adjusted changes from Window 2 to Window 3 (post-repurchase). Columns (4) and (5) express these changes as percentages relative to the mean or median coefficient in Window 1. Column (6) reports the fraction of firms showing reductions (−) or increases (+) in commonality. P-values for the mean and median (columns 2 and 3) are based on two-tailed t-tests and Wilcoxon rank-sum tests, respectively.

	Mean	Median	Mean(%)	Median(%)	Fraction (+) or (-)
Panel A: Between window #1 & #2					
$\Delta\beta_{QSPR}$	-0.185	-0.097	-15.3%	-11.9 %	59.7% (-)
	(0.01)	(0.00)			
$\Delta\beta_{PQSPR}$	-0.15	-0.081	-15.4%	-11.4%	61.5% (-)
	(0.01)	(0.00)			
$\Delta\beta_{Amihud}$	-0.172	-0.094	-16.0%	-12.4%	60.7% (-)
	(0.00)	(0.00)			
Panel B: Between window #2 & #3					
$\Delta\beta_{QSPR}$	0.172	0.089	14.2%	10.8%	56.4% (+)
	(0.03)	(0.00)			
$\Delta\beta_{PQSPR}$	0.142	0.074	14.7%	10.4%	57.8% (+)
	(0.02)	(0.00)			
$\Delta\beta_{Amihud}$	0.148	0.079	13.7%	10.6%	58.8% (+)
	(0.02)	(0.00)			

Number of Obs=1095

Table 4: Changes in Signed Liquidity Commonality Coefficients

This table reports changes in liquidity commonality coefficients separately for days with positive and negative market order imbalance, estimated using $QSPR$ (dollar quoted bid-ask spread) as the liquidity measure. For each firm-program observation, equation (2) is estimated over three windows: Window 1 (pre-repurchase), Window 2 (repurchase period), and Window 3 (post-repurchase). β_i^p denotes the commonality coefficient on days of positive market order imbalance (net buying), while β_i^n denotes the coefficient on days of negative market order imbalance (net selling). Panel A reports the mean and median changes from Window 1 to Window 2; Panel B reports changes from Window 2 to Window 3. Columns (4) and (5) present changes as percentages relative to the Window 1 baseline. Column (6) shows the fraction of firms with reductions (−) or increases (+) in commonality. P-values (in parentheses) are based on two-tailed t-tests (mean) and Wilcoxon rank-sum tests (median).

	Mean	Median	Mean(%)	Median (%)	Fraction (+) or (-)
Panel A: Between window #1 & #2					
$\Delta\beta^n$	-0.382	-0.215	-33.7%	-28.4%	67.3% (-)
	(0.00)	(0.00)			
$\Delta\beta^p$	-0.075	0.005	-6.9%	0.6 %	50.1% (+)
	(0.15)	(0.82)			
Panel B: Between window #2 & #3					
$\Delta\beta^n$	+0.335	+0.152	29.5%	20.0%	63.7% (+)
	(0.00)	(0.00)			
$\Delta\beta^p$	0.062	0.056	5.7%	6.7%	50.9% (+)
	(0.23)	(0.27)			

Number of Obs=1095

Table 5: Relation Between Institutional Ownership and Liquidity Commonality

This table reports the results of six univariate regressions examining the relationship between institutional ownership and liquidity commonality. The explanatory variable, *inst*, is defined as the percentage of firm shares held by institutional investors in the quarter prior to the OMR announcement, sourced from the CDA/Spectrum database. Panel A reports regressions where the dependent variable is β_i^p, the liquidity commonality coefficient on days of positive market order imbalance (net buying), estimated separately for Window 1 (pre-repurchase), Window 2 (repurchase period), and Window 3 (post-repurchase). Panel B reports regressions where the dependent variable is β_i^n, the liquidity commonality coefficient on days of negative market order imbalance (net selling), across the same three windows. Reported coefficients show the estimated relation between institutional ownership and commonality; R^2 values indicate the explanatory power of institutional ownership in each regression. P-values are shown in parentheses.

Panel A:			
	$\beta^{p,window1}$	$\beta^{p,window2}$	$\beta^{p,window3}$
$inst$	0.96	1.09	1.07
	(0.00)	(0.00)	(0.00)
R^2	0.11	0.10	0.12
Panel B:			
	$\beta^{n,window1}$	$\beta^{n,window2}$	$\beta^{n,window3}$
$inst$	1.67	.14	1.45
	(0.00)	(0.71)	(0.01)
R^2	0.08	0.00	0.07
N	1010	1010	1010

Table 6: Effects of Market Volatility and Short-Term Interest Rate Shocks on Liquidity Commonality

This table reports the estimation results of equation (3), which examines how liquidity commonality responds to supply-side shocks. For each firm-program observation and estimation window, I estimate the firm-level coefficients t_i and s_i, which capture the excess sensitivity of liquidity commonality to short-term funding shocks (TED spread residuals) and market volatility shocks, respectively. Specifically, t_i measures the additional comovement in firm i's liquidity with the market on days of positive TED spread shocks (tight funding conditions), while s_i captures excess liquidity comovement on days of elevated market volatility. Daily TED spread shocks are computed as residuals from an autoregressive model of the TED spread, and daily volatility shocks are calculated following the residual-based procedure of Schwert (1990).The table reports the mean and median values of t_i and s_i across firms in each of the three event windows: Window 1 (pre-repurchase), Window 2 (repurchase period), and Window 3 (post-repurchase). P-values in parentheses are based on two-tailed t-tests (means) and two-tailed Wilcoxon rank tests (medians).

	$t_1(TED)$		$s_1(Volatility)$	
	Mean	Median	Mean	Median
Window 1:				
	2.40	0.99	2.16	1.25
	(0.00)	(0.00)	(0.03)	(0.00)
Window 2:				
	-0.33	0.25	-0.04	0.24
	(0.33)	(0.73)	(0.97)	(0.39)
Window 3:				
	1.57	0.42	1.08	1.43
	(0.06)	(0.07)	(0.08)	(0.07)

Number of Obs=1095

Table 7: Changes in Risk Betas Across Estimation Windows

This table reports the changes in risk factor loadings (betas) for firms undergoing open market repurchase (OMR) programs, estimated using the five-factor asset pricing model. The model includes the standard Fama-French-Carhart factors—market (β^{mkt}), size (β^{smb}), value (β^{hml}), and momentum (β^{mom})—as well as a tradable liquidity risk factor (β^{ps}) constructed following Pástor and Stambaugh (2003), Li et al. (2019), and Pontiff and Singla (2019). For each firm-program observation, we estimate betas separately over three windows: Window 1 (pre-repurchase, six months prior to announcement), Window 2 (repurchase period, six months post-announcement), and Window 3 (post-repurchase, starting one year after announcement). Panel A reports the mean and median changes in betas from Window 1 to Window 2; Panel B reports changes from Window 2 to Window 3. The final column shows the fraction of firms with positive (+) or negative (−) changes. P-values in parentheses are based on two-tailed t-tests (mean) and Wilcoxon rank tests (median).

	Mean	Median	Fraction (+) or (-)
Panel A: Between window #1 & #2			
$\Delta\beta^{mkt}$	−0.02	0.02	50.7%(+)
	(0.13)	(0.63)	
$\Delta\beta^{smb}$	−0.04	−0.04	54.3%(−)
	(0.02)	(0.00)	
$\Delta\beta^{hml}$	+0.01	−0.02	50.9%(−)
	(0.17)	(0.20)	
$\Delta\beta^{mom}$	−0.01	−0.02	50.8%(−)
	(0.67)	(0.24)	
$\Delta\beta^{ps}$	−0.06	−0.07	62.3%(−)
	(0.00)	(0.00)	
Panel B: Between window #2 & #3			
$\Delta\beta^{mkt}$	0.01	0.01	50.8%(+)
	(0.54)	(0.78)	
$\Delta\beta^{smb}$	0.02	0.01	51.0%(+)
	(0.28)	(0.41)	
$\Delta\beta^{hml}$	−0.01	−0.01	50.3%(−)
	(0.76)	(0.81)	
$\Delta\beta^{mom}$	0.01	−0.01	50.4%(−)
	(0.63)	(0.61)	
$\Delta\beta^{ps}$	0.06	0.06	60.3%(+)
	(0.00)	(0.00)	

Number of Obs=1095

Table 8: Adjusted Changes in Risk Betas Across Estimation Windows

This table reports the adjusted changes in risk factor loadings (betas) for firms undergoing open market repurchase (OMR) programs. To control for industry-time fixed effects, each repurchasing firm is matched to a non-repurchasing firm from the same industry and size decile (selected based on the closest book-to-market ratio), as described in Section 3.1. Adjusted changes are computed as the difference between the change in the repurchasing firm's beta and the corresponding change in its matched control: $\Delta\beta_i^{\text{adjusted}} = \Delta\beta_i - \Delta\beta_{\text{matched}}$. The asset pricing model (equation 4) includes market (β^{mkt}), size (β^{smb}), value (β^{hml}), momentum (β^{mom}), and tradable liquidity risk (β^{ps}) factors, estimated over three event windows: Window 1 (pre-repurchase), Window 2 (repurchase period), and Window 3 (post-repurchase). Panel A reports adjusted mean and median beta changes from Window 1 to Window 2; Panel B reports adjusted changes from Window 2 to Window 3. The final column shows the fraction of firms with positive (+) or negative (−) changes. P-values are reported in parentheses, based on two-tailed t-tests (mean) and Wilcoxon rank tests (median).

	Mean	Median	Fraction (+) or (-)
Panel A: Between window #1 & #2			
$\Delta\beta^{mkt}$	-0.01	0.02	50.5%(+)
	(0.37)	(0.59)	
$\Delta\beta^{smb}$	-0.04	-0.05	54.7%(−)
	(0.01)	(0.00)	
$\Delta\beta^{hml}$	-0.01	-0.02	50.9%(−)
	(0.24)	(0.27)	
$\Delta\beta^{mom}$	-0.02	0.00	50.1%(+)
	(0.71)	(0.81)	
$\Delta\beta^{ps}$	-0.07	-0.07	62.4%(−)
	(0.00)	(0.00)	
Panel B: Between window #2 & #3			
$\Delta\beta^{mkt}$	0.01	0.00	50.1%(+)
	(0.71)	(0.88)	
$\Delta\beta^{smb}$	0.01	0.01	50.9%(+)
	(0.25)	(0.39)	
$\Delta\beta^{hml}$	+0.00	-0.01	50.4%(−)
	(0.17)	(0.20)	
$\Delta\beta^{mom}$	0.01	0.01	50.8%(+)
	(0.65)	(0.31)	
$\Delta\beta^{ps}$	0.07	0.06	60.6%(+)
	(0.00)	(0.00)	

Number of Obs=1095

Table 9: Correlation matrix between changes in liquidity commonality coefficients and changes in liquidity risk beta

This table reports the pairwise correlation matrix between changes in liquidity commonality coefficients and changes in liquidity risk beta from Window 1 (pre-repurchase) to Window 2 (repurchase period). $\Delta\beta_{QSPR}$, $\Delta\beta_{PQSPR}$, and $\Delta\beta_{Amihud}$ represent the changes in liquidity commonality coefficients based on the dollar quoted bid-ask spread ($QSPR$), percentage quoted bid-ask spread ($PQSPR$), and Amihud illiquidity measure, respectively. $\Delta\beta^{ps}$ denotes the change in the liquidity risk beta estimated from the Pastor-Stambaugh liquidity factor in the five-factor asset pricing model. Correlations are computed across the full sample of 1,095 firm-program observations. Numbers in parentheses are p-values testing the null hypothesis of zero correlation.

	$\Delta\beta_{QSPR}$	$\Delta\beta_{PQSPR}$	$\Delta\beta_{Amihud}$	ΔPS
$\Delta\beta_{QSPR}$	1			
$\Delta\beta_{PQSPR}$	0.91	1		
	(0.00)			
$\Delta\beta_{Amihud}$	0.82	0.89	1	
	(0.00)	(0.00)		
$\Delta\beta^{ps}$	0.26	0.32	0.30	1
	(0.03)	(0.01)	(0.01)	

Number of Obs=1095

Table 10: Changes in liquidity commonality, non-open market repurchase programs

This table reports changes in liquidity commonality coefficients between three estimation windows for non-open market repurchase programs (non-OMRs), including tender offers and Dutch auctions. For each liquidity measure—dollar quoted bid-ask spread ($QSPR$), percentage quoted bid-ask spread ($PQSPR$), and Amihud illiquidity ($Amihud$)—I estimate equation (1) separately over Window 1 (six months pre-announcement), Window 2 (six months post-announcement), and Window 3 (months 12–18 post-announcement). Panel A presents the mean and median change in liquidity commonality from Window 1 to Window 2; Panel B reports changes from Window 2 to Window 3. Columns (4) and (5) express changes as percentages of the mean and median levels in Window 1, and column (6) reports the fraction of observations showing a reduction (-) or increase (+). P-values in parentheses are based on two-tailed t-tests (means) and two-tailed Wilcoxon rank tests (medians). The sample consists of 360 non-OMR repurchase programs drawn from the SDC Mergers and Acquisitions database.

	Mean	Median	Mean(%)	Median(%)	Fraction (+) or (-)
Panel A: Between window #1 & #2					
$\Delta\beta_{QSPR}$	0.05	0.03	3.3%	3.4 %	50.5% (+)
	(0.20)	(0.60)			
$\Delta\beta_{PQSPR}$	0.068	-0.042	5.4%	-5.3%	50.1% (-)
	(0.56)	(0.90)			
$\Delta\beta_{Amihud}$	0.051	-0.033	3.9%	-4.0%	50.7% (-)
	(0.66)	(0.47)			
Panel B: Between window #2 & #3					
$\Delta\beta_{QSPR}$	0.042	0.031	2.8%	3.5%	50.4% (+)
	(0.62)	(0.53)			
$\Delta\beta_{PQSPR}$	0.028	0.016	2.2%	2.0%	50.6% (+)
	(0.82)	(0.41)			
$\Delta\beta_{Amihud}$	0.031	0.029	2.3%	3.5%	50.9% (+)
	(0.88)	(0.61)			

Number of Obs=360

Table 11: Changes in liquidity commonality, weekly frequency

This table reports changes in liquidity commonality coefficients between three estimation windows, using weekly rather than daily observations. For each firm-program observation, I estimate equation (1) over Window 1 (six months prior to repurchase announcement), Window 2 (six months following the announcement), and Window 3 (months 12–18 post-announcement), focusing on three liquidity measures: dollar quoted bid-ask spread ($QSPR$), percentage quoted bid-ask spread ($PQSPR$), and Amihud illiquidity ($Amihud$). To account for the reduced number of weekly observations, regressions exclude control variables. Panel A reports the mean and median changes in liquidity commonality from Window 1 to Window 2; Panel B reports changes from Window 2 to Window 3. Columns (4) and (5) present changes as percentages of the mean and median levels in Window 1, while column (6) shows the percentage of observations with reductions (-) or increases (+). P-values for means and medians are based on two-tailed t-tests and Wilcoxon rank tests, respectively.

	Mean	Median	Mean(%)	Median(%)	Fraction (+) or (-)
Panel A: Between window #1 & #2					
$\Delta\beta_{QSPR}$	-0.115	-0.072	-11.8%	-8.2 %	59.5% (-)
	(0.03)	(0.00)			
$\Delta\beta_{PQSPR}$	-0.105	-0.065	-10.5%	-6.6%	60.7% (-)
	(0.03)	(0.00)			
$\Delta\beta_{Amihud}$	-0.121	-0.071	-11.5%	-7.4%	60.5% (-)
	(0.02)	(0.00)			
Panel B: Between window #2 & #3					
$\Delta\beta_{QSPR}$	0.121	0.075	12.4%	8.6%	58.8% (+)
	(0.03)	(0.00)			
$\Delta\beta_{PQSPR}$	0.11	0.071	11.0%	7.2%	58.4% (+)
	(0.04)	(0.00)			
$\Delta\beta_{Amihud}$	0.132	0.084	12.5%	8.8%	58.9% (+)
	(0.01)	(0.00)			

Number of Obs=1095