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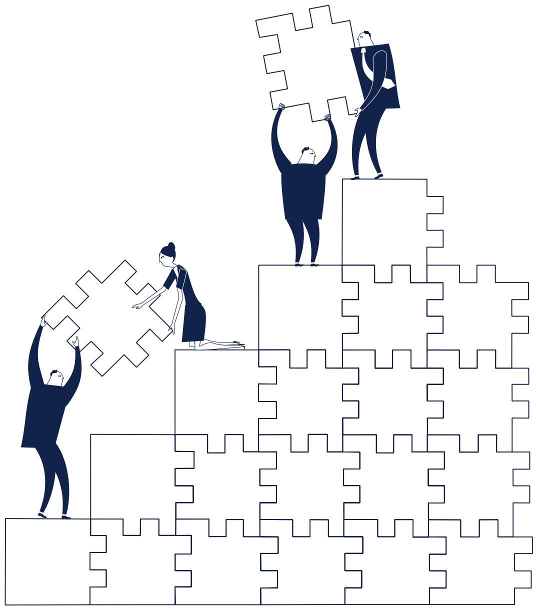

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ABSTRACT

Does trader leverage exacerbate the liquidity co-movement that we observe during crises? We exploit the threshold rules governing margin trading eligibility in India to identify a causal relationship between trader leverage and the extent to which a stock's liquidity covaries with the liquidity of other stocks. We find that trader leverage causes sharp increases in comovement during severe market downturns. For our sample of stocks, the estimates suggest that the trader leverage channel explains about one third of the increase in liquidity commonality that we observe during crises. Consistent with downward price pressure due to the deleveraging of traders who rely on borrowing, we also find that leverage causes stocks to exhibit large increases in return comovement during crises.

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1. Introduction

Does trader leverage exacerbate the liquidity co-movement that we observe during crises? Commonality in liquidity, the tendency of the liquidity of individual stocks to move together, has been well-documented. Recent papers (e.g., Karolyi, Lee, and Van Dijk, 2012, and Hameed, Kang, and Viswanathan, 2010) also report large increases in commonality during crises both in U.S. markets and in markets around the world. The fact that the systematic component of liquidity increases during crises is alarming because these are precisely the times during which traders need liquidity the most. Therefore, it is important to understand the causes of heightened co-movement in liquidity.

Declines in market-wide liquidity could occur when there is panic selling due to economy-wide changes in fundamentals or increased uncertainty. These systemic declines could also be due to supply-side frictions related to traders' ability to maintain levered positions when market prices decline. While both of these explanations of the increased commonality in liquidity that we observe during crises are plausible, disentangling them can pose substantial empirical challenges. To assess the extent to which the ability of traders to use leverage matters, one would need to observe trader leverage as well as variation in leverage constraints. More importantly, one would have to separate the effects of deleveraging from other portfolio demands that can arise during downturns (such as negative sentiment or increased uncertainty). Although the "funding constraints" explanation for heightened liquidity comovement in bad times has received substantial attention in the theoretical literature (e.g., Kyle and Xiong (2001), Gromb and Vayanos (2002), Morris and Shin (2004), Weill (2007), and Gromb and Vayanos (2009), Brunnermeier and Pederson (2009)), we still have a paucity of empirical evidence of its importance.[1] In this paper, we aim to fill this gap. We use the Indian regulatory setting to identify the impact of traders' ability to borrow to purchase shares on commonality in liquidity, particularly during crises.

The margin trading regulations in India make it a useful laboratory for testing the hypothesis that trader leverage drives commonality in liquidity. This is because (i) only some exchange traded stocks are eligible for margin trading and (ii) eligibility is based on a well-defined cutoff. As in the United States, margin trading allows investors to borrow up to 50% of the purchase price of an eligible stock. In India, margin trading eligibility is determined on a monthly basis. It is based on the average

[1] These papers focus on funding constraints of intermediaries. Importantly, Kahraman and Tookes (2016) report evidence that margin traders are stock market liquidity providers. Therefore, we expect negative shocks to their capital to impact commonalty.

"impact cost," which is the estimated price impact of trading a fixed order size (using six-month rolling averages of order book snapshots taken at random intervals in each stock every day). Stocks with measured impact costs of less than 1% are categorized as Group 1 stocks and are eligible for margin trading. All remaining stocks are ineligible.

The discreteness of the margin trading rules in India provides a "sharp" discontinuity (see Lee and Lemieux, 2010) in the ability of traders to borrow. For every stock and month in our sample, we first calculate two widely-used measures of liquidity: average effective bid-ask spreads and the Amihud (2002) illiquidity ratio. Both of these can be interpreted as trading costs, which capture deviations of transactions prices from their fundamental values. Next, we calculate the R^2 of regressions of these liquidity measures on average liquidity in the market. High R^2 is interpreted as high commonality. We then focus the analysis only on stocks that lie close to the eligibility threshold. Using local linear regressions, we compare the commonality of the stocks that are eligible for margin trading with that of stocks that are ineligible.

Like other stock markets throughout the world (see e.g., Karyoli et al., 2012), Indian equity markets are characterized by liquidity commonality that tends to increase during downturns. This pattern is obvious in Figure 1, which shows the time series of commonality, captured by R^2 of a regression of stock level liquidity on market level liquidity for our sample of National Stock Exchange (NSE) stocks during 2004-2012, along with Indian stock market returns. It is clear from the figure that commonality peaks whenever there are large drops in market returns. Figure 2 shows the same times series of commonality, but this time we focus on the subsample of stocks that are very close to the margin trading eligibility threshold. We then separate stocks according eligibility. As discussed above, Group 1 stocks are eligible for margin trading in India and Group 2 stocks are not. The patterns in Figure 2 are even more revealing than those in Figure 1. During almost all market downturns, the liquidity commonality in Group 1 stocks is higher than that of Group 2. During other periods, there are small (if any) differences between the two groups. The figures provide only suggestive evidence of the Brunnermeier and Pedersen (2009) hypothesis that funding constraints can drive commonality; however, the patterns are sufficiently striking to motivate the analysis in this paper.[2]

[2] Throughout the paper, we often refer to Brunnermeier and Pedersen (2009) when we describe the hypothesis that margin constraints of levered liquidity providers causes increased commonality during downturns. We do this in part because it is the most widely cited among the financing constraints-based explanations of the

In the formal regression analysis, we use regression discontinuity design (RDD) to analyze stocks near the impact cost threshold. We test whether the commonality in liquidity is different for stocks that are eligible for margin trading. Consistent with the theoretical literature, our formal tests show that trader leverage is an important driver of commonality in liquidity. Moreover, this effect is driven by crisis periods. While there is an overall increase in commonality in bad times, margin eligibility exacerbates the co-movement in stock liquidity. The magnitudes of our findings are economically large. For instance, when we examine commonality of effective spreads, we find that margin-eligible stocks experience an *additional* 35.3% increase in liquidity co-movement during crisis periods. Not only do our results reveal that trader borrowing causes a large fraction of the increase in liquidity comovement that we observe during crises, they also highlight the importance of econometric specifications that allow the impact of supply-side (and potentially demand-side) proxies to vary with overall market conditions. During non-crisis periods, we find that the impact of trader leverage is negligible.

Our findings contribute to the growing literature on commonality in liquidity. This line of research initially focused on documenting pervasive commonality in U.S. equity markets (Chordia Roll Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Huberman and Kalka, 2001). Subsequent work focused on distinguishing its cause, with a particular focus on whether the evidence is most consistent with supply or demand-side explanations. Under supply-side hypotheses, the capital constraints of market makers who provide liquidity in multiple stocks drive commonality in liquidity. The theoretical work by Kyle and Xiong (2001), Gromb and Vayanos (2002), Morris and Shin (2004), Weill (2007), Gromb and Vayanos (2009) and Brunnermeier and Petersen (2009) all predict or rely on the assumption that the supply-side funding constraints of market makers or arbitrageurs drives commonality, particularly during market downturns. Under demand-side hypotheses, investors' trading demands can impact multiple securities in their portfolios and generate the patterns on commonality that we observe in the data. The recent literature has focused on distinguishing supply versus demand side drivers of commonality because doing so is important for policy-makers looking for the most effective tools to help limit systemic liquidity dry-ups.

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liquidity comovement that we observed during the 2007-2009 financial crisis. However, earlier and contemporaneous papers by, for example, Kyle and Xiong (2001), Gromb and Vayanos (2002), Morris and Shin (2004), Weill (2007), and Gromb and Vayanos (2009) also link capital constraints of liquidity providers to commonality in liquidity.

Consistent with the supply-side interpretation, Hameed, Kang, and Viswanathan (2010) report that commonality increases following large market declines. These findings are consistent with binding funding constraints and collateral losses; however the available data in U.S. limits the overall interpretation. As Karolyi, Lee and Van Dijk (2012) note, the findings do not completely rule out panic selling (investor sentiment) during downturns as the driver of commonality. An alternative approach to examining the role of capital constraints in liquidity commonality is to exploit stock-level variation in capital constraints. For example, Coughenour and Saad (2004) focus on traditional New York Stock Exchange specialists, who are responsible for providing liquidity in all of the stocks in which they make markets. They find that liquidity commonality is higher when stocks share market makers, especially when those market makers are capital constrained.[3] Coughenour and Saad (2004) is perhaps most related to our work; however, unlike their paper, we focus our analysis specifically on the leverage channel.[4]

The empirical evidence supporting the demand-side interpretation is perhaps the strongest evidence of the drivers of commonality to date. Karolyi, Lee, and Van Dijk (2012) provide cross-country evidence of commonality. Like in U.S. markets, they confirm that it is widespread and that it tends to rise during crises. When they examine whether a number of intuitive proxies for funding liquidity (i.e., supply-side variables) explain these patterns, they report only very weak evidence. The lack of significance could be due to noise in the proxies or to the challenging identification. However, at face value, their results suggest that the funding constraint mechanisms in Brunnermeier and Petersen (2009) have limited importance. By contrast, Karolyi, Lee, and Van Dijk (2012) report that demand-side proxies, particularly turnover commonality and foreign flows, have considerable explanatory power. Also consistent with the demand-side explanation, Kamara, Lou, and Sadka (2009) find that commonality is higher when institutional ownership is higher. Koch, Ruenzi and Starks (2016) perform what is arguably the cleanest empirical analysis of the demand channel hypothesis to date. They use exogenous shocks to mutual fund flows during the 2003 mutual fund scandals to test the hypothesis that of correlated trading among mutual funds drives commonality.

[3] Quian, Tam and Zhang (2014) examine commonality in China and find evidence that Chinese split-share-structure reform (i.e., the introduction of new tradable shares to the market, which they interpret as a reduction in funding liquidity, and the arrival of new investors to the market) is associated with commonality. While not inconsistent with Brunnermeier and Pedersen (2009), their paper is not a direct test of the leverage spiral channels proposed in their paper.

[4] Gissler (2016) studies commonality in bond markets. Like Coughenour and Saad (2004), he reports that bonds with common dealers exhibit higher comovement.

They report that the specific demand-side determinant that they investigate is, indeed important. Similar to Koch, Ruenzi and Starks (2016), we introduce an identification strategy for a specific channel (in our case, leverage) and we examine the extent to which it can explain commonality, especially during crises. Our approach allows us to make sharp causal statements about the impact of a supply-side factor in liquidity comovement. More than the identification, our specific focus on trader leverage channel provides a new contribution to the literature on commonality and a direct test of the mechanisms proposed in Brunnermeier and Pedersen (2009).[5]

The remainder of this paper is organized as follows. Section 2 provides a description of the regulations that determine margin trading eligibility in India. Section 3 describes the data, commonality measures and the basic regression discontinuity approach. Results of the analysis of the impact of trader leverage on commonality in liquidity are in Section 4. Section 5 concludes.

2. Margin trading in India

Margin trading allows traders to borrow to purchase shares. In India, the margin trading system is regulated by the Securities and Exchange Board of India (SEBI). The current system, in which margin trading is allowed in stocks that meet certain eligibility requirements, has been in place since April 2004.[6] Under SEBI guidelines, two criteria must be met for a stock to be eligible. The first is that the stock must have traded on at least 80% of all trading days during the past six months. The second requirement is that the stock's average impact cost, defined as the absolute value of the percentage change in price from the bid-offer midpoint that would be caused by an order size of 100,000 rupees (approximately $2,000 during our sample period), is less than or equal to 1% . The impact cost used to determine eligibility is based on the average of estimated impact costs over the past 6 months. These are calculated at random 10-minute intervals four times per day.

[5] Our paper is also related to the growing literature on financial contagion and, in particular, the empirical regularities that return spillovers tend to be amplified during downturns. For example, Adams, Fuss and Gropp (2014) show theoretically how intermediaries play a role in transmitting shocks. Dudley and Minalderan (2011) examine futures margins and find that an increase in margins by a factor of 10 increases the probability of contagion of hedge funds by one third. Kyle and Xiong (2001) link investor wealth shocks to price declines across multiple assets. Our paper is related to this line of work as, in extended analysis, we also examine how leverage impacts comovement in returns during crises.

[6] For more details about badla, the prior system used by Indian traders to borrow to purchase shares, see Kahraman and Tookes (2016).

Stocks that meet the impact cost and trading frequency requirements are categorized as Group 1 stocks and are eligible for margin trading. Group 1 status can be considered a shock to the ability of a trader to take a levered position in the stock. Stocks that fail to meet the impact cost requirement, but trade on at least 80% of the days over the past six months are categorized as Group 2 stocks. All remaining stocks are classified into Group 3. Group 2 and Group 3 stocks are ineligible for margin trading (i.e., no new margin trades are allowed as of the effective date). Impact costs and the resulting group assignments are calculated on the 15th day of each month. The new groups are announced and become effective on the 1st day of the subsequent month. For example, when determining eligibility for the month of December, regulators use data from May 15 through November 15 to determine each stock's eligibility. The resulting Group assignments are announced on December 1 and are effective for the entire month of December.

Regression discontinuity relies on the assumption of random assignment near the cutoff. In our context, this means that we should be reasonably certain that there is no manipulation of impact costs near the 1% threshold. Given that the impact cost calculation consists of random order book snapshots, it would be quite costly for an investor to try to strategically move impact costs below the threshold. Consistent with this idea, Figure 4 of Kahraman and Tookes (2016) shows no bunching of impact cost data near the 1% cutoff. If strategic manipulation were occurring, there would be bunching to the left of 1% and possibly a decrease in the frequency of observations immediately to the right of 1%. "Sharp" regression discontinuity design relies on the assumption that there is also no discretion in allocating stocks to groups (i.e., that the probability of assignment jumps from 0% to 1% at the threshold). For stocks that meet the 80% trading frequency requirement, the probability of eligibility shifts unequivocally from 0 to 1 at the 1% impact cost cutoff. This feature of the system allows us to employ a sharp regression discontinuity design.

For eligible stocks, the most important requirements for margin trading in India are similar to those in the United States. Minimum initial margins are set at 50% (i.e., a margin trader may borrow up to 50% of the purchase price), and minimum maintenance margins are set at 40% (i.e., prices may fall without a margin call as long as the loan is less than 60% of the value of the collateral in the margin account). Unlike in the United States, stock-level margin position data are made publicly available on a next-day basis. We exploit this information in our analysis of the impact of margin trading intensity on commonality later in the paper. For a more detailed discussion of the margin trading system in India and comparisons with the U.S., see Kahraman and Tookes (2016) and Securities and Exchange

Board of India (2012). Margin trading rules are distinct from the other trading rules in India. This is important because it allows us to interpret any findings in terms of a trader leverage channel, rather than something else.

3. Data and methodology

Data

The initial sample consists of all equities trading on the National Stock Exchange of India (NSE) from April 2004 through December 2012. The master list of stocks is from the NSE. These are monthly files that contain the International Securities Identification Number (ISIN), stock symbol, impact cost measure and the NSE group assignment for each stock. The daily data are also from the NSE and include symbol, security code, closing price (in Indian Rs), high price, low price, total shares traded and the value of shares traded. We obtain intraday transactions and quote data for all Group 1 and Group 2 NSE stocks from Thomson Reuters Tick History. These data include inside quotes and all transactions during our sample period.[7] We merge the Thomson Reuters Tick data with the other datasets using a map of RIC codes (Thomson unique identifier) to ISINs that was provided to us by Thomson. To ensure reliability of the matching, we remove all matches where the absolute difference between the closing price on the NSE daily files and the last transaction price in the Thomson Tick data is more than 10%.[8] We also require non-missing price and volume information for at least 12 trading days in a given month.

For every stock and month in our sample, we first calculate two widely-used measures of liquidity: average percentage effective bid-ask spread and the Amihud (2002) illiquidity ratio. Effective spread (*espread*) is defined as $100*\frac{|transaction\ price - .5*(bid+ask)|*2}{.5*(bid+ask)}$. The bid and ask prices reflect the prevailing quotes at the time of the trade. The effective spread captures the difference between the transaction price and fundamental value for the average trade. It can be a better proxy for

[7] Fong, Holden and Trzcinka (2014) Thomson Reuters Tick prices to those in Datastream and confirm that the Thomson Tick data are of high quality.

[8] Our sample is the same as that in Kahraman and Tookes (2016). Following Kahraman and Tookes (2016), we also remove: corrected trades; entries with bid or ask prices equal to zero; stocks with extreme price levels (we use the 1% tails of the distribution); stocks with temporary ISIN identifiers, which appear to be an indication of a corporate action such as a merger; stock splits, which we define as a percentage change in shares outstanding that is greater than 50% in absolute value.

transaction costs than quoted spreads since it is based on actual transactions. The effective spreads that we calculate reflect the average effective spreads on all transactions that occur during the month.

The Amihud illiquidity variable (*illiq*) is defined as $1000000 * \frac{|\text{ret}|}{p * vol}$, where $\text{ret} = \frac{p(t) - p(t-1)}{p(t-1)}$; *p* is closing price on day *t*; and *vol* is the (rupee) trading volume on day *t*. *Illiq* captures the change in price generated by daily trading activity of 1 million rupees. This measure is widely used in the literature because it requires only daily data and does well capturing intraday measures of the price impact of trades (Hasbrouck (2009); Goyenko, Holden, and Trzcinka (2009)). Following Amihud (2002), we winsorize the measure at the 1% and 99% levels, and we also remove observations in which daily trading volume is less than 100 shares. Because our focus is on a non-U.S. sample of stocks, we follow Lesmond (2005), who also examines the Amihud (2002) illiquidity measure using international data, and we impose price filters to remove potentially erroneous data from the returns calculations. In particular, whenever the closing price is +/- 50% of the previous closing price, we set that day's price and the previous price equal to missing.

We calculate both *espread* and *Amihud* at the monthly frequency to match the frequency of group assignments. There are 1,842 unique ISINs in Groups 1 and 2 during our sample period. Of these, 1,500 are Group 1 at some point during our sample period and 1,347 are in Group 2. Of the 1,842 stocks in the sample, the majority appear in the local samples at some point. For instance, in the local sample used in the R^2*espread* regressions, we see 1,063 unique stock observations and 954 of these are treatment (Group 1) stocks at least once.

Commonality measure

We use the daily liquidity measures for all Group 1 and Group 2 stocks to construct the commonality in liquidity measure for each stock. In the spirit of Karyoli, Lee and van Dijk (2012) we define commonality in liquidity the R^2 statistic from a regression of stock i's daily liquidity innovations on market liquidity innovations. Following Karyoli, Lee and van Dijk (2012), we first calculate liquidity innovations based on a first-stage stock-level regression of daily liquidity changes on variables known to affect liquidity:

$$\Delta Liquidity_{i,t} = \alpha_i + \gamma_i X_t + \varepsilon_{i,t.}$$

X_t is a vector of indicator variables to indicate day-of-week, month, and whether the trading day falls near a holiday. It also includes a time trend. The daily regression residuals, denoted $\Delta Liq_{i,t}$, are the liquidity innovations that we examine. This method is also used to pre-whiten the liquidity data in Chordia, Sarkar, and Subrahmanyam (2005) and Hameed, Kang, and Viswanathan (2010). Market liquidity innovations ($\Delta Liq_{i,t}$) are defined as the equally weighted average innovations for all Group 1 and Group 2 stocks in the market.

In the second step, for each stock and calendar month, we use daily data to generate a time series of monthly R^2 statistics from the following regression: $\Delta Liq_{i,t} = \alpha_i + \beta_1 \Delta Liq_{m,t} + \varepsilon_{i,t}$. This R^2 measure is also used in Karyoli, Lee and van Dijk (2012) and captures the extent to which the liquidity of a given stock moves with liquidity of the market. We denote these commonality measures as R^2*espread* and R^2*illiq* for the regressions using effective spread and the Amihud (2002) ratio as liquidity measures, respectively. A high R^2 is indicative of high commonality in liquidity. As we emphasize in the introduction, we focus the analysis only on the Group 1 and Group 2 stock stocks that lie near the impact cost cutoff of 1%.

Summary statistics for the local samples of Group 1 and Group 2 stocks are shown in Table 1 (we describe the determination of the relevant "neighborhood" below). As can be seen from Table 1, Panel A, all stocks exhibit commonality, although the R^2 measure is slightly higher for Group 1 stocks than for Group 2 stocks. The average R^2*espread* is 0.146 for Group 1 stocks and 0.138 for Group 2 stocks. For R^2*illiq,* these values are 0.139 and 0.136, respectively. The more interesting variation appears during extreme downturns, defined as months with market returns below the 10 percentile value of -9%.[9] During these periods, commonality in all stocks increase. However, the effect is most obvious for Group 1 stocks, where commonality using R^2*espread* doubles and commonality based on R^2*illiq* increases by 50%. These changes for the Group 2 sample are 28-40 percent lower than they are for Group 1 stocks. Not surprisingly, the statistics in Table 1 are consistent with Figure 2 which shows the time series of commonality for the local samples. In fact, the average differences in commonality between Group 1 and Group 2 stocks are driven almost entirely by crisis periods. Outside of periods of extreme downturns, we observe very small differences in commonality between Group 1 and Group 2 stocks.[10] Table 2, Panel B shows descriptive statistics for return

[9] The median monthly market return for this subset of observations is -13%.
[10] The median monthly market return is 2.8% for these observations.

comovement during the different market return regimes. The patterns are very similar to what we observe in Panel A and suggest an important role for leverage in crisis-period liquidity and return dynamics. These summary statistics motivate more formal analysis of a potential causal role for trader leverage.

We use regression analysis to test formally the hypotheses that trader leverage impacts commonality in liquidity; however, as Lee and Lemieux (2010) suggest, it is instructive to begin with plots of the data near the impact cost threshold. As noted in Section 2, the impact costs that determine eligibility in month *t* are calculated over the 6 months prior to month *t*. In Figures 3a and 3b, we examine all stocks in the sample with impact costs between 0.25% and 1.75%. To do so, we form 10 impact cost bins of equal width on each side of the eligibility cutoff. We choose the number of bins based on the F-tests suggested in Lee and Lemieux (2010).[11] We then compute average commonality within each bin. We then run separate regressions of average commonality on average impact cost for the observations on each side of 1%. We do this for all periods as well as periods of severe market downturns. If there is a treatment effect of margin trading eligibility, we would expect an increase in commonality at the cutoff, particularly during crisis periods. Consistent with this, the regression lines in Figures 3a and 3b show discontinuous crisis-

period drops in commonality based on *espread* and *illiq*, respectively. By contrast, we do not observe discontinuities in the non-crisis period data. The figures provide further (suggestive) evidence of the mechanisms that drive commonality in Brunnermeier in Pedersen (2009).

Local Regressions

Using the time series and cross-sectional variation in the commonality in local Group 1 and Group 2 stocks, we estimate local discontinuity regressions in which we and test whether the ability to lever up via margin trading impacts liquidity commonality. We also examine how any effects that we observe vary with prevailing market conditions. To do this, we first need to define the local sample of stocks. The objective is to choose a bandwidth that is small enough to capture the effect of the treatment (margin eligibility), but with a sufficiently large sample to provide statistical power. To make

[11] We fail to reject the hypothesis of over smoothing when we move to 10 bins from either 20 or 30 bins. We reject the null of over smoothing when we move from 10 bins to 5.

these tradeoffs, we rely on the optimal bandwidth selection techniques in Calonico, Cattaneo and Tittiunik (CCT, 2014). The CCT bandwidths are based on the data dependent bandwidths designed for RDD applications in Imbens and Kalyanaraman (2012), but improves on them by selecting the initial bandwidth optimally. See Kahraman and Tookes (2016) for a more detailed discussion of bandwidth selection approaches. For the *R^2espread* variable, the CCT bandwidth is 0.18 and for the *R^2illiq* variable, it is 0.20. In robustness analysis (later in the paper), we will also examine how sensitive our main findings are to the bandwidth choice.

In the final step, we estimate regressions in which the dependent variable is the monthly R^2 for all stocks in the local discontinuity sample. The basic specification is as follows:

$$R^2_{it} = \alpha + \beta * Group1_{it} + \varepsilon_{it}.$$

Group 1 is an indicator variable equal to 1 if the stock is eligible for margin trading during month t. X_{it} is a vector of year-month fixed effects. We also cluster standard errors at the stock level and correct for heteroscedasticity. Our objective is to understand whether shocks (variation in margin eligibility) to the ability of traders to obtain leverage channel (margin financing) have a causal impact on liquidity comovement. The estimated coefficient on β captures the difference in commonality for stocks that lie just above and just below the threshold and identifies the average treatment effect as long as error terms (and potentially omitted variables) are continuous at the cutoff. The identification comes from the fact that the eligibility is discontinuous at impact cost equal to 1%, but variation in the other relevant variables is continuous (see e.g., Lee and Lemieux (2010)).

Because we are primarily interested the question of what drives the increases in liquidity comovement that we observe during crises, we also add an interaction variable that captures the impact of trader leverage during crises. *Severedownturn* is a dummy variable equal to 1 if monthly market returns are in the bottom decile of the monthly returns during our sample period (this maps to returns below -9%). The extended specification is as follows:

$$\begin{aligned} R^2_{it} &= \alpha + \beta_1 * Group1_{it} + \beta_2 * Group1_{it} * severedownturn_t \\ &+ \gamma * severedownturn_t + \varepsilon_{it}. \end{aligned}$$

The main coefficients of interest are on the *Group 1* indicator variable and the Group 1**severedownturn* interaction variable. Kahraman and Tookes (2016) find that margin traders provide liquidity to markets. If margin calls create financing frictions for margin traders then we would expect Group 1 stocks to exhibit more commonality in liquidity during times in which deleveraging affects many stocks in the market. While it is true that margin investors could trade any stock (an eligible or an ineligible one) to cover a margin call, the stocks that they have borrowed to purchased are more likely than a random stock to be in their portfolios and are therefore more likely to be sold in the event of forced deleveraging.

4. Results

The results of the locals are in Table 2. In Columns 1 and 2, the dependent variable is R^2*espread* and in Columns 3 and 4 it is R^2*illiq*. In the case of R^2*espread*, we observe a small positive coefficient on the *Group 1* dummy variable when we constrain the impact of trader leverage to be the same in all market environments (Column 1). The estimated coefficient of 0.0085 suggests that eligibility increases commonality by 8.5 basis points, which is 6.1% higher than the mean of 139 basis points for the local sample of Group 2 stocks. In Column 2, when we allow the effect of eligibility to vary when the overall market is in a severe downturn, the patterns are much more striking. In fact, we find that the results in Column 1 are driven entirely by severe downturn periods. The estimated coefficient on the Group 1 dummy is insignificant. Consistent with earlier work, we find that all stocks exhibit more commonality during downturns. The estimated coefficient of 0.1108 on the *severedownturn* dummy suggests a 111 basis point increase in crisis-period commonality, representing 79.9% and 75.8% increases relative to the averages of 139 basis points and 146 basis points for Group 1 and Group 2 stocks, respectively. Importantly, the positive and significant coefficient of 0.052 on the *Group1*severedownturn* interaction implies that those stocks eligible for margin trading display an additional 52 basis points increase in commonality. These estimates imply that trader leverage accounts for approximately one third of the total crisis-period increase in commonality for Group 1 stocks, and maps to a 35.3 percent increase in commonality relative to the Group 1 sample mean.[12]

When we examine the impact of trader leverage on R^2*illiq,* we find patterns that are similar to what we find for R^2*espread.* In Column 3 of Table 2, in which we restrict the effect of leverage on commonality to be the same across market conditions, we find that the estimated coefficient on the *Group 1* is positive, but the t-statistic is only 1.59. When we allow the effect of margin trading eligibility

[12] Consistent the crisis-period findings, Kahraman and Tookes (2016) also report that the beneficial role of trader leverage on liquidity levels reverses during severe downturns. Unlike this paper, they focus on the impact of trader leverage on liquidity levels and find that, on average, margin traders play a significant role in liquidity provision.

to vary when the market is in a severe downturn (Column 4), we find that commonality in all stocks increases by 48 basis points during severe downturns. This is 34% and 35% higher than the means of R^2*illiq* for Group 1 and Group 2 stocks, respectively. Similar to the R^2*espread* regressions, we find that there is an additional 31 basis point increase in commonality for margin-eligible stocks (i.e., an additional increase of 22% relative to its mean). In the case of the Amihud (2002) illiquidity ratio, trader leverage explains nearly 40 percent of the total crisis period increase in commonality in Group 1 stocks.

Overall, the evidence in Table 2 strongly supports the hypothesis that trader leverage drives commonality in crises. Although their setting is quite different from ours, the estimated magnitudes of the crisis-period impact of trader leverage on commonality are comparable to the demand-side estimates in Koch et al. (2016). They report that a one standard deviation increase in mutual fund ownership is associated with a 27% increase in commonality relative to the mean.

In Table 2, the only control variables in X_t are time fixed effects and the market conditions variable. As Lee and Lemieux (2010) explain, adding covariates can help reduce the sampling variability in the regression discontinuity estimates. Therefore, we add a vector of firm-level control variables to control for factors that are known to be correlated with liquidity. The additional controls are lagged: standard deviation of stock-level returns, stock-level returns, dollar volume, market capitalization, as well as the lagged dependent variable.[13] While including these covariates imposes a linearity assumption, Lee and Lemieux (2010) point out that doing so does not affect the consistency of the RD estimator.

The results of regressions with the additional control variables are presented in Table 3. Overall, as in Table 2, we find that crisis periods are associated with higher commonality, and that margin trading substantially increases this effect. The magnitudes of the estimated effects of margin trading during downturns (Columns 2 and 4) are similar, although slightly larger than, the baseline results from Table 2. Not surprisingly, we also find significant relationships between commonality and the covariates. We find that commonality is higher when volatility and trading volume are higher and when market capitalization is smaller. We also find that commonality is positively autocorrelated. The relationship between commonality and lagged stock returns depends on the specification. When

[13] The market capitalization data are from Prowess, which is similar to Compustat, but covers Indian firms. Because of incomplete Prowess coverage, the regressions that include the control variables have a smaller number of observations than those in Table 2.

we control for month fixed effects, the relationship is negative and marginally significant, suggesting that commonality decreases when stock returns increase. When we instead explicitly control for extreme market downturns, the relationship between commonality and the continuous returns variable returns becomes positive, which might capture liquidity improvements that tend to occur during stock rallies. Because there are several statistically significant relationships between commonality and the additional covariates, we include them in all subsequent analysis.

Having established that the basic results are robust to the inclusion of control variables, we now turn to the question of bandwidth selection (i.e., defining the local "neighborhood" around the impact cost cutoff of 1%). As noted earlier, we rely on CCT bandwidths because of their optimality properties; however, it is still useful to check to see whether the results are robust to a plausible set of alternative bandwidths. The CCT bandwidth for $R^2 espread$ is 0.18 and it is 0.20 for $R^2 illiq$. In Table 4, we increase and decrease these bandwidths in increments of 0.02 (to values that are 30% to 33% greater than and less than the CCT values). As can be seen from Table 4, the main results are robust to bandwidth choice. The number of observations (and the power of the test) naturally decreases with the size of the bandwidth, but the main findings are quite stable.

Placebo tests

Tables 2 through 4 reveal a causal effect of trader leverage on commonality in liquidity during crises. In particular, we observe a discontinuous increase in commonality at the margin trading eligibility cutoff, which lends empirical support for the hypothesis that trader leverage causes commonality, especially during downturns. The identifying assumption in this interpretation is that there is a sharp discontinuity in the ability of traders to borrow at the impact cost value of 1%. One potential alternative interpretation of the main results (in Tables 2 and 3) is that the measured impact costs predict future commonality in liquidity rather than variation in trader leverage and that the regressions capture this relationship. To ensure that our results are not driven by variation in impact cost, we repeat the analysis around false eligibility cutoffs. We examine two false cutoffs, at one bandwidth above and one bandwidth below the true cutoff of 1%.

The results of the placebo analysis are in Table 5. Unlike the liquidity patterns at the true cutoff shown in Tables 2 through 4, we find no evidence of discontinuous jumps in commonality around the false eligibility thresholds. This is true both on average and during crises and lends strong support to the causal interpretation of our findings.

Alternative explanations

Karyoli et al. (2012) find that commonality is higher when stocks are owned by more foreign owners. Kamara, Lou and Sadka (2008) find that institutional ownership and index membership is associated with higher commonality. Unlike the trader leverage channel (a supply-side effect related to funding constraints), the ownership structure and index composition variables are interpreted as proxies for demand-side determinants of commonality. In interpreting the results in this paper, one might be concerned that Group 1 status is capturing variation in these demand side variables rather than trader leverage. For example, some investors might prefer to invest in large and visible stocks, and Group 1 status might capture this visibility. One important feature of our research design is that there would have to be a discontinuous change in these other variables at the impact cost cutoff in order to generate the patterns in Figure 3 and in Tables 2 through 4. Reassuringly, Kahraman and Tookes (2016) fail to find a discontinuity in any of these ownership or index membership variables at the cutoff. Still, to be sure that our results are not driven by these other factors, we including proxies for each of them in extended regression analyses.

To examine whether our results are driven by index inclusion, we introduce a dummy equal to 1 if the stock is in the CNX500 index (Standard and Poor's broad-based index of the Indian Stock market). To investigate the role of investor type, we use quarterly ownership data from Prowess and introduce variables *foreign* and *inst*, which are equal to percentage foreign and institutional ownership, respectively. We repeat the analysis shown in Table 3, but we include all of these direct effects and we also interact them with Group 1 dummy, as well as the *Group 1*severedownturn* interaction variable to see whether our supply-side interpretation is actually coming from demand-side variables. Results are in Table 6.

Most importantly, we find the estimated crisis-period impact of Group 1 status on commonality remains very close the results in Table 3, even after accounting for these alternative channels. The estimated coefficients on the proxies for supply-side effects, vary in significance but are overall in line with earlier findings. Consistent with Kamara, Lou and Sadka (2008), we find that stocks in the CNX 500 exhibit more commonalty (although the effect is small and only marginally significant). Consistent with Karyoli et al (2012), we find higher commonality in stocks with more foreign ownership. Interestingly, the foreign ownership effect goes away when stocks become eligible for margin trading. The increased presence of margin traders during good times might reduce the frictions associated with foreign investor trading activity. We do not find any additional effects of institutional traders on commonality.

Borrowing Activity or Eligibility?

The results presented so far show that the ability of traders to borrow increases commonality. If trader leverage is really driving the results, we would also expect the findings to be strongest in stocks in which margin trading activity is highest. The margin positions data available in India allow us to examine this question. While we do not have margin trading volume information, the daily stock-level positions data are an improvement over margin activity data in most markets. For example, in the United States, the New York Stock Exchange disseminates monthly data describing only aggregate margin positions. In particular, we are able to observe outstanding margin positions for every stock-day in our sample period. We use this information to calculate a proxy for margin trading activity: *margin activity* is the absolute value of daily changes in outstanding margin positions. We do not observe intraday margin trades, but our proxy is likely to be correlated with total margin trading activity.

In the Table 7 regressions, we examine the role of margin trading activity on our results. In our regressions, we include *margin activity* (defined for local Group 1 stocks), and interact it with *Group1* and *Group1* Severedownturn*. If results are being driven by margin activity, the coefficient on this triple interaction term should be positive and significant. The results in Table 7 reveal that this is indeed the case.

Returns commonality

So far, we have focused the on the idea leverage can drive substantial increases in commonality in liquidity during crises. Leverage can also impact commonality in returns (Gromb and Vayanos (2002); e.g., Brunnermeier and Pedersen (2009); Geanakoplos (2010)). In this section, we test the hypothesis that trader leverage causes return comovement. Our research design allows us to estimate the portion of return comovement that stems from frictions related to trader leverage. Before describing the specifics of the empirical approach, it is important to emphasize that commonality in liquidity does not necessarily imply commonality in returns. As Karyoli et al. (2012) note, commonality in liquidity can arise when stocks when are facing very different liquidity demands. If one group of stocks experiences intense buying pressure while the other experiences intense selling pressure, we would see increased correlation in liquidity, but not an increase in return correlation. However, in the case of the forced deleveraging that can occur during crises, the order imbalances that are likely to be similar across stocks and might cause returns comovement to exhibit patterns that line up with the liquidity patterns that we observe.

To test for the hypothesized relationship between leverage and returns comovement, we repeat the main Table 3 regressions, but we replace the dependent variable with commonality in returns. Along the lines of Morck, Yueng and Yu (2000), we use the R^2 from a regression of stock i's returns on the market index to capture return commonality. The results are in Table 8. Columns 1 and 2 are analogous to the Table 2 regressions. They show results of regressions without the stock-level control variables. In Columns 3 and 4 of Table 8, we add the same additional controls that we include in Table 3. Consistent with the descriptive statistics in Table 1, Panel B, the estimates in Table 8 provide causal evidence of the impact of trader leverage on average return comovement (Columns 1 and 3); however, this average effect is relatively small. For example, the estimated coefficient of 0.01 in Column 1 implies a 10 basis point increase in return comovement when a stock becomes eligible for margin trading. This is an increase of 3.9% relative to the local Group 2 mean return comovement of 251 basis points. During downturns, we see a sharp increase in the effect of trader leverage. The coefficient of 0.056 on the *Group 1*severedownturn* interaction implies that trader leverage accounts for a 56 basis point increase in crisis period return comovement. This represents approximately 23% of the total comovement in Group 1 and Group 2 stocks during non-crisis periods. Thus, leverage is a key driver of the increase in stock return comovement that we observe during downturns.

Note that our findings are different from those in Seguin and Jarrell (1993), who report that margin-eligible securities did not have lower returns following the crash of 1987. In the United States, exchange traded stocks are all eligible for margin trading. The variation that Senguin and Jarrell (1993) report comes from differences between eligible and ineligible over-the-counter stocks. Unlike in India, Under Regulation T, the Federal Reserve Board has some discretion in assigning eligibility and takes into account "national investor interest, the depth and breadth of market, the availability of information respecting the security and its issuer, and the character and permanence of the issuer to warrant being treated like an equity security traded on a national securities exchange" (Regulation T, 220.2). There are well-defined size and trading activity requirements, but the Board also has discretion to add or omit stocks (Regulation T, 220.11(f)). Thus, the results in Seguin and Jarrell (1993) might be due to other differences between margin eligible and ineligible stocks in their sample and highlights the advantage of our identification strategy.

The results in Table 8 are related to recent work by Greenwood and Thesmar (2016) who show that stocks can commove when different owners have correlated trading demands. Using data on mutual fund holdings, they find that this "co-fragility" is significantly associated with stock return co-movement. Our analysis is related to theirs in that we identify a supply side (trader leverage) channel through which co-fragility can occur. The finding that Group 1 status is associated with increases in co-movement during crises is also related to Barberis, Schleifer and Wurgler (2005), who find that excess co-movement can be explained by frictions (as opposed to fundamentals). This can occur when, in their setting, investors only invest in a subset of securities belonging to the same stock index. Table 8 shows that trader leverage is another important friction driving excess co-movement.

5. Conclusion

It is well-known that both U.S. and global stocks exhibit significant liquidity commonality (e.g., Chordia et al., 2000, Hasbrouck and Seppi, 2001, Karolyi, Lee, and Van Dijk, 2012). Although commonality in liquidity is pervasive, we still do not have a full understanding of what drives it. In this paper, we exploit the features of the margin trading system in India to test whether there is a causal effect of trader leverage on commonality in liquidity. Consistent with the funding liquidity mechanism proposed in Brunnermeier and Pedersen (2008) we find that, while leverage has a negligible effect during normal times, it substantially increases commonality in liquidity during crises.

Our analysis provides the most direct test (to our knowledge) of the hypothesis that declines in the collateral values of levered traders can cause commonality in liquidity. The identification strategy allows us to identify the stocks in which crisis period trading demands are most likely to include forced deleveraging. Much of the empirical evidence to date is consistent with the idea that demand-side channels are the key drivers of commonality (e.g., index inclusion, foreign ownership, institutional ownership). While the average effects of the supply-side channel that we investigate are small, we document a large economic effect of trader borrowing during crises. These findings should help policy-makers and researchers who are interested in identifying effective tools to help reduce the friction-induced comovement in liquidity and stock returns that we observe during periods of extreme market stress.

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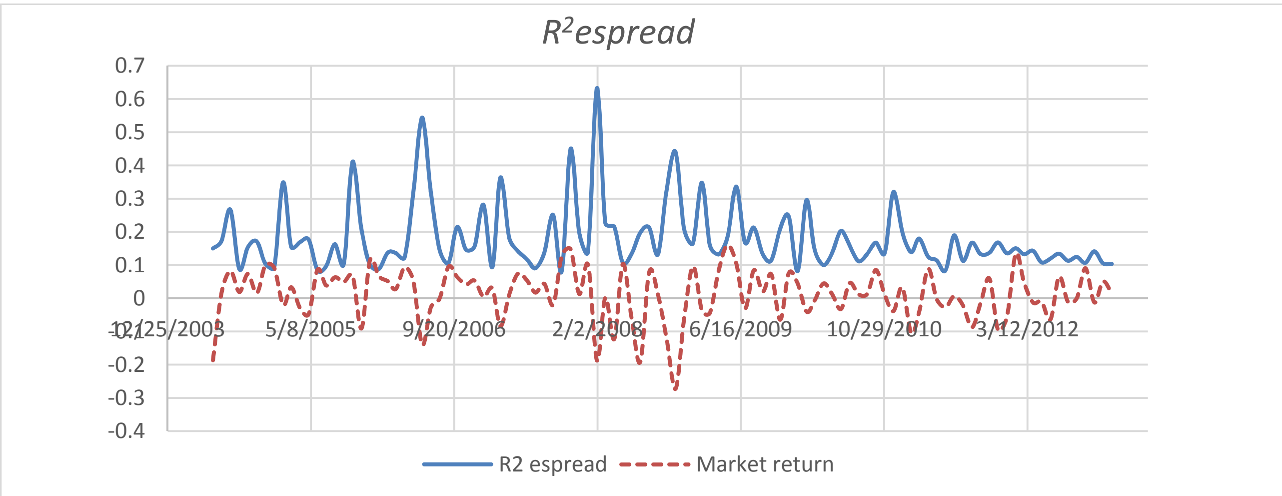
Figure 1: Time Series of Commonality and Market Returns

The figures show the time series of commonality, captured by the R^2 of regressions of stock level liquidity on market liquidity for all Group 1 and Group 2 National Stock Exchange (NSE) stocks during 2004-2012. Indian stock market returns are also shown (right-axis). In Figure 1a, commonality in liquidity is based on commonality in effective spreads. In Figure 1b, it is based on the Amihud (2002) illiquidity ratio. Indian stock market returns are defined as the CNX 500 returns, which is Standard and Poor's broad-based index of the Indian Stock market.



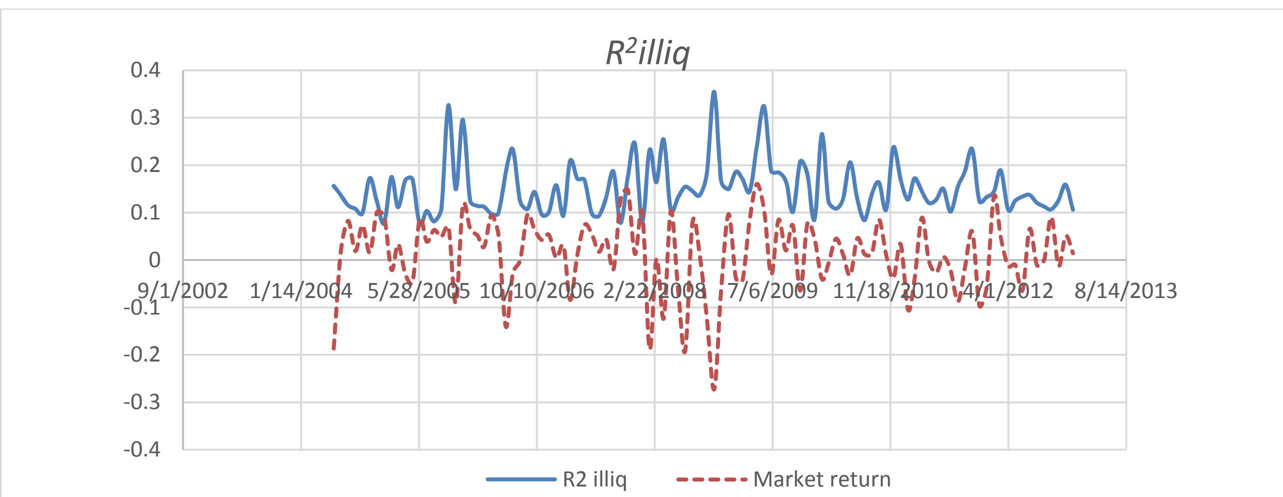
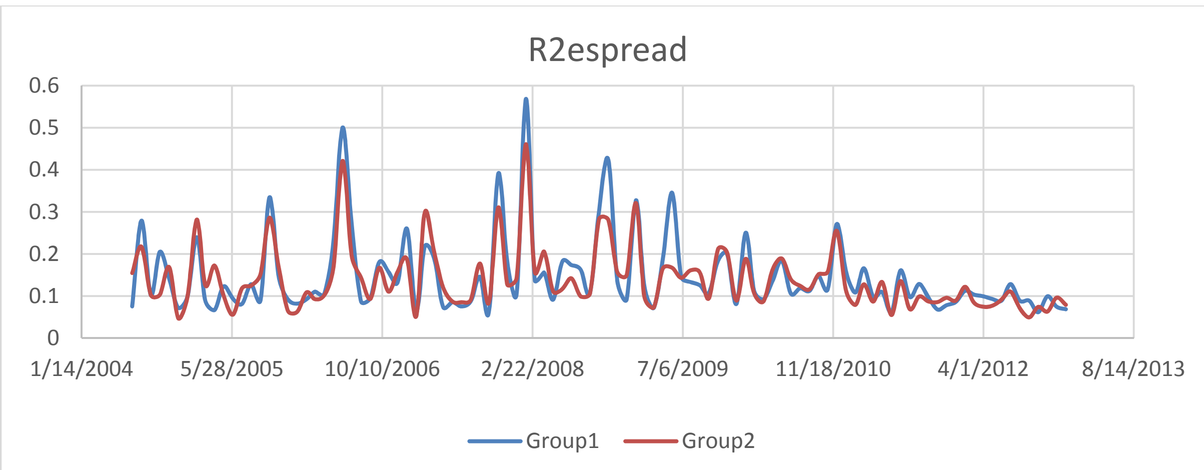


Figure 2: Time Series of Commonality: Local Group 1 and Group 2 Stocks

The figure shows the time series of commonality, captured by R^2 of regressions of stock level liquidity on market liquidity for the local samples of Group 1 and Group 2 stocks during 2004-2012. Group 1 stocks are eligible for margin trading and Group 2 stocks are ineligible. In Figure 2a, commonality in liquidity is based on commonality in effective spreads. In Figure 2b, it is based on the Amihud (2002) illiquidity ratio.



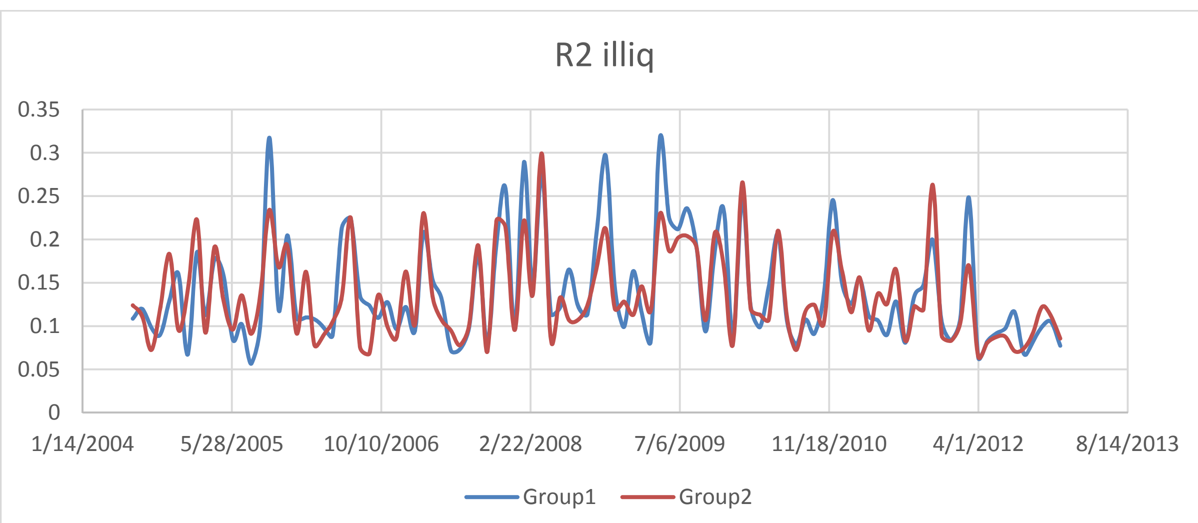
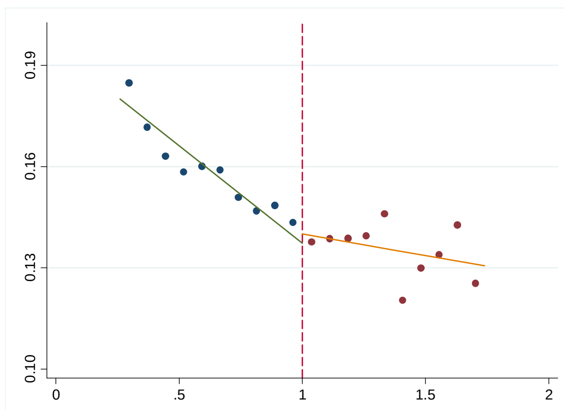


Figure 3a: Impact Cost and Commonality (*R^2espread*)

The figure plots the average *R^2espread* during month *t* as a function of impact cost over the previous 6 months (which determines month *t* eligibility). *R^2espread* is the R^2 from a regression of daily effective spread innovations on market innovations. Stocks are divided into 10 equally sized bins (the X axis) on each side of the eligibility cutoff of 1%. The number of bins is chosen based on the F-test procedures described in Lee and Lemieux (2010). We then compute the average *R^2espread* within each bin. Margin eligible stocks are all those stocks with impact costs that are less than or equal to 1%, which corresponds with bins 1 through 10. Stocks in bins 11-20 are ineligible for margin trading during period *t*. "Extreme downturns" refers to months in which market returns are below the 10th decile returns.

Full Sample



Extereme Downturns

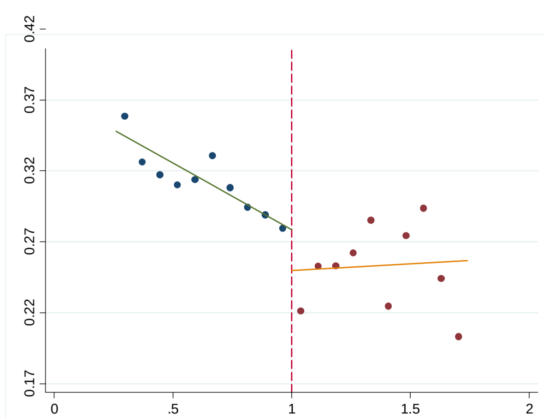
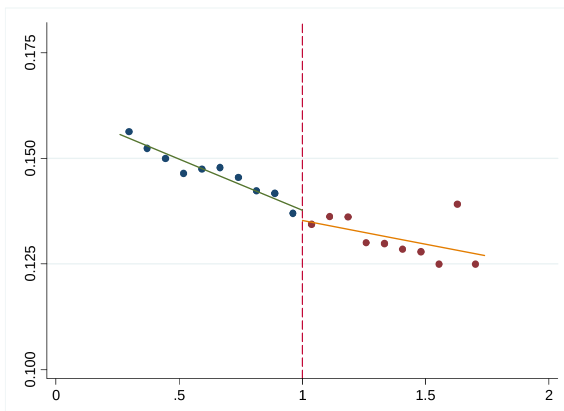


Figure 3b: Impact Cost and Commonality (*R^2illiq*)

The figure plots the average *R^2illiq* during month *t* as a function of impact cost over the previous 6 months (which determines month t eligibility. *R^2illiq* is the R^2 from a regression of daily innovations in the Amihud (2002) illiquidity measure on market innovations. Stocks are divided into 10 equally sized bins (the X axis) on each side of the eligibility cutoff of 1%. The number of bins is chosen based on the F-test procedures described in Lee and Lemieux (2010). We then compute the average *R^2 illiq* within each bin. Margin eligible stocks are all those stocks with impact costs that are less than or equal to 1%, which corresponds with bins 1 through 10. Stocks in bins 11-20 are ineligible for margin trading during period *t*. "Extreme downturns" refers to months in which market returns are below the 10th decile returns.

Full Sample



Extreme Downturns

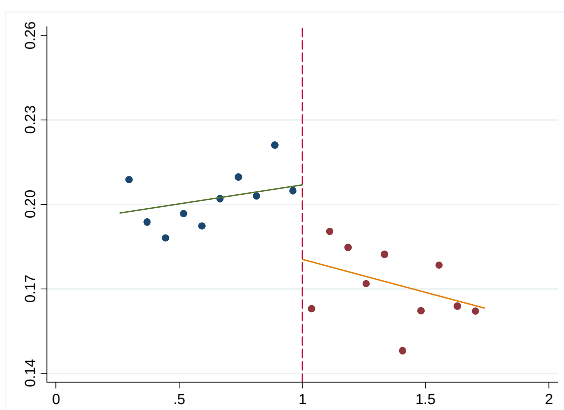


Table 1

Descriptive Statistics: Local Group 1 vs. Group 2

Panel A provides summary statistics of commonality liquidity and returns for the local sample National Stock Exchange stocks for the period April 2004 through December 2012. The local samples are defined based on CCT bandwidths for each variable. All variables are monthly. R^2*espread* is the R^2 from a regression of daily effective spread innovations on market effective spread innovations during month *t*. R^2*illiq* is the R^2 from a regression of daily innovations in the Amihud (2002) illiquidity measure on market innovations during month *t*. "Extreme downturns" refers to months in which market returns are below the 10th decile returns (-9%). "Outside of downturns" refers to all months outside of extreme downturns. Panel B shows descriptive statistics for commonality in returns. R^2*Returns* is the R^2 from a regression of daily stock returns on CNX 500 returns during month t.

Panel A: Commonality in Liquidity

Group 1	Variable	Mean	Median	P25	P75	Std Dev
Full sample	R^2*espread*	0.1462	0.0807	0.0200	0.2059	0.1757
	R^2*illiq*	0.1392	0.0797	0.0181	0.2064	0.1589
Extreme downturns	R^2*espread*	0.2935	0.1877	0.0609	0.4983	0.2802
	R^2*illiq*	0.2096	0.1619	0.0522	0.3157	0.1980
Outside of downturns	R^2*espread*	0.1311	0.0751	0.0182	0.1901	0.1534
	R^2*illiq*	0.1313	0.0739	0.0168	0.1933	0.1519

Group 2	Variable	Mean	Median	P25	P75	Std Dev
Full sample	R^2*espread*	0.1388	0.0772	0.0171	0.2029	0.1628
	R^2*illiq*	0.1355	0.0781	0.0197	0.1956	0.1560
Extreme downturns	R^2*espread*	0.1383	0.0296	0.3581	0.2618	0.2392
	R^2*illiq*	0.1166	0.0326	0.2871	0.1784	0.1782
Outside of downturns	R^2*espread*	0.1311	0.0751	0.0182	0.1901	0.1534
	R^2*illiq*	0.1313	0.0739	0.0168	0.1933	0.1519

Panel B: Commonality in Returns

Group 1	Variable	Mean	Median	P25	P75	Std Dev
Full sample	R^2*espread*	0.2622	0.2205	0.0807	0.4030	0.2093
Extreme downturns	R^2*espread*	0.4422	0.4613	0.2729	0.6155	0.2288
Outside of downturns	R^2*espread*	0.2424	0.2033	0.0726	0.3726	0.1973

Group 2	Variable	Mean	Median	P25	P75	Std Dev
Full sample	R^2*espread*	0.2519	0.2133	0.0818	0.3819	0.2017
Extreme downturns	R^2*espread*	0.3822	0.3737	0.1865	0.5694	0.2369
Outside of downturns	R^2*espread*	0.2379	0.2005	0.0758	0.3638	0.1924

Table 2: Does Trader Leverage Impact Commonality in Liquidity?

This table presents results of the analysis of the impact of margin trading eligibility on commonality in liquidity. The dependent variables are the average *R^2espread* and the average *R^2illiq* during month *t*, where eligibility is effective as of the beginning of month *t*. *R^2espread* is the R^2 from a regression of daily effective spread innovations on market effective spread innovations during month *t*. *R^2illiq* is the R^2 from a regression of daily innovations in the Amihud (2002) illiquidity measure on market innovations during month *t*. The sample includes all stocks in Groups 1 and 2 with impact costs close to the cutoff of 1% (based on CCT bandwidths of 0.18% for the *R^2espread* regressions and 0.20% for *R^2illiq)*. The explanatory variables are *Group 1*, a dummy variable equal to 1 if the control stock is eligible for margin trading during month *t* and a vector of year-month dummies. In Columns (2) and (4), we replace the month-year fixed effects with *severedownturn*, a dummy variable equal to 1 if market returns during month *t* are in the lowest decile in our sample (less than -9%). All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)	(3)	(4)
VARIABLES	*R^2espread*	*R^2espread*	*R^2illiq*	*R^2illiq*
Group1	0.0085**	0.0027	0.0051	0.0006
	(0.0035)	(0.0037)	(0.0032)	(0.0034)
Group 1*severedownturn		0.0516**		0.0307**
		(0.0209)		(0.0120)
severedownturn		0.1108***		0.0475***
		(0.0158)		(0.0089)
Observations	7,291	7,291	9,609	9,609
R-squared	0.263	0.060	0.126	0.017
Month-Year FE	YES	NO	YES	NO

Table 3: **Additional Covariates**

This table presents results of the analysis of the impact of margin trading eligibility on commonality in liquidity. As in Table 1, the dependent variables are the average R^2*espread* and the average R^2*illiq* during month *t*, where eligibility is effective as of the beginning of month *t*. The sample includes all stocks in Groups 1 and 2 with impact costs close to the cutoff of 1% (based on CCT bandwidths of 0.18% for the R^2*espread* regressions and 0.20% for R^2*illiq)*. The explanatory variables are *Group 1*, a dummy variable equal to 1 if the control stock is eligible for margin trading during month *t*, a vector of control variables and year-month dummies. The control variables include one-month lagged: standard deviation of stock returns (*std_ret*), stock returns (*mret*), dollar volume (*logvolume*), equity market capitalization (*logmcap*) and the lagged dependent variables. *Std_ret* is the standard deviation of daily returns during the month. *Mret* is the month *t* stock return, calculated from the closing prices at the ends of months *t*-1 and *t*. *Logvolume* is the average daily trading volume, that is, the natural log of the daily closing price (in rupees) times the number of shares traded. *Logmcap* is the equity market capitalization, defined as the end of month *t* closing price, times shares outstanding. We also include *lag_depvar*, the one-month lagged dependent variable. In Columns (2) and (4), we replace the year-month fixed effects with *severedownturn*, a dummy variable equal to 1 if market returns during month *t* are in the lowest decile in our sample. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

VARIABLES	(1) R^2*espread*	(2) R^2*espread*	(3) R^2*illiq*	(4) R^2*illiq*
Group1	0.0058	-0.0007	0.0077**	0.0008
	(0.0039)	(0.0041)	(0.0036)	(0.0037)
Group 1*severedownturn		0.0543**		0.0350**
		(0.0227)		(0.0138)
severedownturn		0.0824***		0.0390***
		(0.0158)		(0.0104)
Lag std_dret	0.5173**	0.4098*	0.8889***	0.7540***
	(0.2586)	(0.2317)	(0.2300)	(0.1882)
Lag mret	-0.0301*	0.0319**	-0.0223	0.0190*
	(0.0183)	(0.0153)	(0.0137)	(0.0114)
Lag logvolume	0.0104***	0.0170***	0.0092***	0.0144***
	(0.0025)	(0.0024)	(0.0021)	(0.0021)
Lag logmcap	-0.0110***	-0.0130***	-0.0212***	-0.0199***
	(0.0020)	(0.0023)	(0.0022)	(0.0020)
Lag depvar	0.0365**	0.0526***	0.0674***	0.0595***
	(0.0149)	(0.0143)	(0.0130)	(0.0130)
Observations	5,859	5,859	7,533	7,533
R-squared	0.251	0.069	0.176	0.055
Month-Year FE	Yes	No	Yes	No

Table 4: Alternative Bandwidths

This table presents results of the analysis of the impact of margin trading eligibility on commonality in liquidity using alternative bandwidths. The regression specification is identical to Columns (2) and (4) of Table 3. The dependent variables are average R^2*espread* and the average R^2*illiq* during month *t*, where eligibility is effective as of the beginning of month *t*. The explanatory variables are defined in Table 3. Columns (1) through (6) increase and decrease the CCT bandwidths by increments of 0.02 (i.e., bandwidths up to 33% larger and smaller than the R^2*espread* CCT bandwidth of 0.18 and 30% larger and smaller than the R^2*illiq* bandwidth of 0.20). All standard errors are clustered by ISIN (stock identifier). ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: Dependent Variable = R^2*espread*

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	-0.06	-0.04	-0.02	+0.02	+0.04	+0.06
Group 1	0.001	-0.001	0.001	0.001	0.001	0.001
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Group 1*severedownturn	0.042*	0.049**	0.061***	0.045**	0.043**	0.053***
	(0.024)	(0.025)	(0.023)	(0.021)	(0.020)	(0.019)
severedownturn	0.084***	0.078***	0.073***	0.087***	0.091***	0.090***
	(0.019)	(0.017)	(0.016)	(0.015)	(0.014)	(0.013)
Lag std_dret	0.326	0.270	0.393	0.371*	0.485**	0.619***
	(0.303)	(0.273)	(0.253)	(0.219)	(0.211)	(0.208)
Lag mret	0.037**	0.036**	0.034**	0.031**	0.032**	0.038***
	(0.019)	(0.017)	(0.016)	(0.014)	(0.014)	(0.013)
Lag dollarvolume	0.018***	0.018***	0.017***	0.018***	0.017***	0.016***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Lag logmcap	-0.013***	-0.014***	-0.013***	-0.014***	-0.014***	-0.013***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Lag depvar	0.066***	0.071***	0.056***	0.050***	0.047***	0.041***
	(0.017)	(0.016)	(0.015)	(0.014)	(0.013)	(0.012)
Observations	3,879	4,543	5,184	6,547	7,216	7,889
R-squared	0.068	0.068	0.066	0.069	0.071	0.075

Panel b: Dependent Variable = R^2illiq

VARIABLES	(1) -0.06	(2) -0.04	(3) -0.02	(4) +0.02	(5) +0.04	(6) +0.06
Group 1	0.000	-0.000	0.001	0.003	0.005	0.005
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Group 1*severedownturn	0.045***	0.036**	0.034**	0.030**	0.028**	0.031***
	(0.017)	(0.016)	(0.015)	(0.013)	(0.012)	(0.012)
severedownturn	0.038***	0.040***	0.042***	0.040***	0.040***	0.043***
	(0.012)	(0.012)	(0.011)	(0.010)	(0.009)	(0.009)
Lag std_dret	0.806***	0.806***	0.727***	0.781***	0.792***	0.763***
	(0.228)	(0.217)	(0.202)	(0.186)	(0.179)	(0.171)
Lag mret	0.009	0.014	0.021*	0.012	0.018*	0.017*
	(0.014)	(0.013)	(0.012)	(0.011)	(0.010)	(0.010)
Lag dollarvolume	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lag logmcap	-0.018***	-0.018***	-0.019***	-0.019***	-0.020***	-0.019***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lag depvar	0.068***	0.064***	0.060***	0.060***	0.063***	0.068***
	(0.016)	(0.015)	(0.014)	(0.012)	(0.012)	(0.012)
Observations	5,210	5,951	6,733	8,302	9,084	9,905
R-squared	0.056	0.054	0.055	0.054	0.055	0.059

Table 5: Are Results Driven by Variation in Impact Cost? Placebo Tests

This table presents results of placebo tests, in which we repeat the analyses of the impact of margin trading eligibility on commonality in liquidity from Table 3, Columns 2 and 4. Instead of measuring eligibility at the impact cost cutoff of 1.0%, we replicate the analysis around placebo cutoffs set at one bandwidth below and above the actual cutoff. The "Local Sample" used in the analyses are those stocks that lie close to the placebo cutoff using the same bandwidth sizes as in Tables 2 through 4 (0.18% for R^2*espread* and 0.20% for R^2*illiq*). The explanatory variables are the *Placebo Group 1* dummy and the same vector of control variables defined in Table 3. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)	(3)	(4)
	Placebo cutoff below		*Placebo cutoff above*	
VARIABLES	R^2*espread*	R^2*illiq*	R^2*espread*	R^2*illiq*
Placebo Group1	0.005	0.009	0.002	0.006
	(0.004)	(0.007)	(0.005)	(0.004)
Placebo Group1*severedownturn	0.015	-0.010	-0.039	-0.016
	(0.021)	(0.012)	(0.025)	(0.015)
severedownturn	0.135***	0.073***	0.108***	0.054***
	(0.016)	(0.010)	(0.019)	(0.011)
Lag std_dret	0.715***	0.899***	0.515*	0.767***
	(0.230)	(0.163)	(0.269)	(0.239)
Lag mret	0.055***	-0.003	0.037**	0.039***
	(0.013)	(0.011)	(0.016)	(0.014)
Lag logvolume	0.018***	0.016***	0.015***	0.013***
	(0.002)	(0.002)	(0.003)	(0.002)
Lag logmcap	-0.013***	-0.023***	0.054***	-0.016***
	(0.002)	(0.002)	(0.019)	(0.002)
Lag depvar	0.049***	0.078***	0.045***	0.083***
	(0.013)	(0.012)	(0.015)	(0.020)
Observations	7,714	10,226	4,423	5,545
R-squared	0.091	0.068	0.064	0.048

Table 6
Alternative Channels

This table presents results of the analyses of the relationship between commonality and liquidity and both index membership and ownership structure. The dependent variables are the average *R^2espread* and *R^2illiq* during month *t*, where eligibility is effective as of the beginning of month *t*. The local samples and specifications are identical to those in Columns 2 and 4 of Table 3 except that we add the dummy variables of *index*, which equals 1 if the stock is a member of the CNX 500; *foreign*, which is the percentage foreign ownership*;* and (iii) *inst*, which is the percentage institutional ownership. Standard errors are clustered by ISIN (stock identifier).). ***, ** and * denotes significance at the 1%, 5% and 10% levels, respectively.

Panel A: *R^2espread*

	(1)	(2)	(3)
VARIABLES	*R^2espread*	*R^2espread*	*R^2espread*
Group 1	0.002	0.004	-0.000
	(0.004)	(0.004)	(0.006)
Group 1*severedownturn	0.042*	0.063**	0.062*
	(0.025)	(0.025)	(0.033)
severedownturn	0.082***	0.077***	0.076***
	(0.017)	(0.018)	(0.024)
Group 1*severedownturn*index	0.081		
	(0.059)		
Group1*index	-0.020		
	(0.012)		
Severedownturn*index	0.000		
	(0.042)		
index	0.017*		
	(0.010)		
Group 1*severedownturn*foreign		-0.055	
		(0.058)	
Group1*foreign		-0.030***	
		(0.010)	
severedownturn*foreign		0.023	
		(0.044)	
foreign		0.020**	
		(0.009)	
Group 1*severedownturn*inst			-0.044
			(0.119)
Group1*inst			-0.000
			(0.025)
severedownturn*inst			0.033
			(0.093)
inst			0.019
			(0.017)
Observations	5,859	5,677	5,677
R-squared	0.071	0.070	0.068
Controls	Yes	Yes	Yes

Local Panel:Extended Checks

VARIABLES	(1) *R^2illiq*	(2) *R^2illiq*	(3) *R^2illiq*
Group 1	0.002	0.002	0.005
	(0.004)	(0.004)	(0.005)
Group 1*severedownturn	0.026*	0.036**	0.041**
	(0.015)	(0.016)	(0.020)
severedownturn			
	0.040***	0.040***	0.044***
Group 1*severedownturn*index	(0.012)	(0.012)	(0.015)
	0.056*		
Group1*index	(0.034)		
	-0.008		
Severedownturn*index	(0.009)		
	-0.009		
index	(0.025)		
	0.007		
Group 1*severedownturn*foreign	(0.008)		
		-0.010	
Group1*foreign		(0.029)	
		-0.003	
severedownturn*foreign		(0.009)	
		-0.008	
foreign		(0.023)	
		0.004	
Group 1*severedownturn*inst		(0.007)	
			-0.023
Group1*inst			(0.069)
			-0.025
severedownturn*inst			(0.020)
			-0.029
inst			(0.052)
			-0.002
			(0.016)
Observations	7,533	7,320	7,320
R-squared	0.056	0.055	0.056
Controls	Yes	Yes	Yes

Table 7

Margin Trading Intensity and Commonality

This table presents results of the analysis of the relationship between margin trading intensity and commonality in liquidity. The dependent variables are the average *R^2espread* and *R^2illiq* during month *t*, where eligibility is effective as of the beginning of month *t*. The local samples and specifications are identical to Columns 2 and 4 of Table 3 except that we introduce *margin activity* (defined for local Group 1 stocks), equal to the (log) absolute value of changes in utstanding margin positions. We also interact it with *Group1* and *Group1* severedownturn*. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

VARIABLES	(1) *R^2espread*	(2) *R^2illiq*
Group1	-0.0054	-0.0014
	(0.0056)	(0.0047)
Group1* severedownturn	0.0435**	0.0315**
	(0.0185)	(0.0150)
Group1* severedownturn * margin activity	0.4219**	0.2122*
	(0.1874)	(0.1234)
Group1 * margin activity	0.0768*	0.0431
	(0.0458)	(0.0384)
Severedownturn	0.0822***	0.0389***
	(0.0114)	(0.0094)
Lag std_dret	0.3364	0.7463***
	(0.2355)	(0.1908)
Lag mret	0.0274**	0.0194*
	(0.0132)	(0.0108)
Lag dollarvolume	0.0169***	0.0146***
	(0.0024)	(0.0020)
Lag logmcap	-0.0117***	-0.0198***
	(0.0023)	(0.0019)
Lag depvar	0.0524***	0.0615***
	(0.0133)	(0.0118)
Observations	5,601	7,197
R-squared	0.073	0.058
Month-Year FE	No	No
Controls	Yes	Yes

Table 8
Does Trader Leverage Impact Commonality in Returns?

This table presents results of the analysis of the impact of margin trading eligibility on commonality in liquidity. The specifications are identical to those in Tables 2 and 3 except that we replace the dependent variables with R^2*return*, defined as the R^2 from a regression of the daily returns of stock *i* on the CNX 500 returns during month *t*. The sample includes all stocks in Groups 1 and 2 with impact costs close to the cutoff of 1% (based on the CCT bandwidths of 0.16%). All variables are defined in Tables 1 and 3. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)	(3)	(4)
VARIABLES	R^2*return*	R^2*return*	R^2*return*	R^2*return*
Group1	0.010**	0.004	0.008*	-0.002
	(0.004)	(0.005)	(0.004)	(0.005)
Group 1*severedownturn		0.056***		0.059***
		(0.018)		(0.020)
severedownturn		0.144***		0.118***
		(0.014)		(0.014)
Lag std_dret			1.535***	1.737***
			(0.322)	(0.299)
Lag mret			-0.064***	-0.045***
			(0.017)	(0.015)
Lag logvolume			0.010***	0.018***
			(0.003)	(0.003)
Lag logmcap			-0.031***	-0.029***
			(0.003)	(0.003)
Lag depvar			0.181***	0.190***
			(0.015)	(0.014)
Observations	7,635	7,635	5,954	5,954
R-squared	0.283	0.067	0.343	0.157
Month-Year FE	Yes	No	Yes	No