Systematic Liquidity and Leverage*

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ABSTRACT

Does trader leverage exacerbate the liquidity comovement that we observe during crises? Using a regression discontinuity design, we exploit threshold rules governing margin eligibility in India to analyze the impact of trader leverage on systematic liquidity. We find that trader leverage causes sharp increases in comovement during severe market downturns, explaining about one third of the increase in liquidity commonality during these periods. Consistent with downward price pressure due to deleveraging, we also find that trader leverage causes stocks to exhibit large increases in return comovement during these periods of market stress.

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1. Introduction

Does trader leverage exacerbate the liquidity comovement 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 in the literature (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 the heightened comovement.

There are competing explanations for the increased commonality in liquidity that we observe during crisis periods. Liquidity comovement might increase when there is market-wide panic selling due to economy-wide changes in fundamentals or increased aggregate uncertainty. Alternatively, it could be due to frictions related to traders' ability to maintain levered positions when market prices decline. While both of these explanations of increased commonality in liquidity during crises are plausible, disentangling them poses substantial empirical challenges. To assess the extent to which traders' leverage (a form of funding) matters, one would first need to observe variation in trader leverage. Second, and more importantly, one would have to separate the effects of deleveraging from other portfolio demands. This is particularly challenging because, during downturns, investors may liquidate their positions due to negative sentiment or increased uncertainty, which can also affect liquidity comovement.

Although the funding-based 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. In this paper, we aim to fill this gap by examining the impact of trader leverage on liquidity comovement using the margin trading regulations in India.

There are a number of reasons why margin trading in India provides a useful lens through which we can examine frictions due to leverage. First, margin traders might face difficulties in meeting their margin requirements and maintaining their positions when the values of their portfolios decline. Second, brokers may become less willing to provide margin debt during periods of market stress. Both of these can lead to trader deleveraging, which can consume liquidity. The additional advantage of the Indian context is that the regulatory setting helps us overcome the empirical challenges discussed above. In India, only some exchange-traded stocks are eligible for margin trading. Importantly, eligibility is based on a well-defined cutoff. The discreteness of the margin trading rules provides a discontinuity (see Lee and Lemieux (2010)) in the ability of traders to use leverage and therefore provides us an opportunity to perform a regression discontinuity design (RDD) to identify the causal effect of trader leverage on commonality in liquidity.

Like other stock markets throughout the world, 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 along with Indian stock market returns. It is clear from the figure that there is a dramatic increase in commonality (nearly doubles) when there are large drops in market returns. Figure 2 shows the same time series of commonality, but this time for the subsample of stocks that are very close to the margin trading eligibility threshold. The patterns in Figure 2 are even more revealing than those in Figure 1. During almost all market downturns, the liquidity commonality in margin eligible stocks is much higher than that of margin ineligible stocks. During other periods, there are small (if any) differences between the two groups. The figures provide simple, yet striking, evidence consistent with the Brunnermeier and Pedersen (2009) hypothesis that funding constraints in bad times drive commonality.

In the formal regression analysis, we use regression discontinuity design (RDD) to identify the causal effect of trader leverage. Consistent with the theoretical literature, we find that trader leverage exacerbates commonality in stock liquidity. Moreover, this effect is *solely* driven by crisis periods. 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* 30% increase in liquidity comovement during crisis periods. During non-crisis periods, the impact of trader leverage is insignificant. Our results are robust to a battery of tests in which we control for various stock-level characteristics. Importantly, we also conduct placebo tests in which we repeat our analysis around false eligibility cutoffs as well as market rallies and we find no significant effects.

We start our analysis by examining commonality in liquidity because we still do not have a full understanding of the main causes of liquidity crises. However, it is also important to point out that trader leverage can simultaneously drive both commonality in liquidity and commonality in returns (e.g., Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Geanakoplos (2010)). Therefore, we extend our analysis to examine the impact of margin trading on return comovement. Consistent with downward price pressure due to the deleveraging of traders who rely on borrowing, we find that trader leverage amplifies increases in return comovement during crisis periods. Similar to the findings on commonality in liquidity, we find that the economic effect of trader leverage on return comovement is substantial (in crisis periods, there is an additional 28% increase in return comovement due to leverage) and that trader leverage affects return comovement only during periods of market stress.

After establishing the causal impact of trader leverage on commonality in liquidity and commonality in returns, we conduct a number of mechanism tests. In addition to helping us understand the drivers of the patterns that we observe in the data, these tests also allow us to assess the extent to which the same economic forces drive commonality in liquidity and returns. If the main findings are due to frictions related to binding collateral constraints and deleveraging, we would expect the increases in comovement during crises to be strongest between the stocks in which traders tend to use leverage. That is, we would expect pairwise correlations in stocks' liquidity as well as returns to be higher within the set of margin-eligible stocks. This is precisely what we find. These findings are consistent with margin traders, as a group, simultaneously unwinding their positions in multiple stocks when the value of their collateral falls.

Our data allow us to zoom in further to understand potential cross-stock linkages. We can observe, on a daily basis, the entire portfolio of stocks that *each* trader has financed with margin debt. These data include unique trader and broker identification numbers, thus allow us to identify margin trader and broker linkages across stocks. Using this information, we examine the importance of common traders and common brokers on heightened commonality in liquidity and returns during crises. Both the broker and trader channels are of interest. At the trader level, leverage-induced funding constraints might force a trader to liquidate positions in multiple stocks in her portfolio. At the broker level, a negative shock to the overall market might make the broker less willing to provide capital to its customers. We find that margin-eligible stocks that are more connected, through either common margin traders or common brokers, experience much larger increases in pairwise comovement in both liquidity and returns during severe market downturns. The estimated economic effects of common brokers are larger than the economic effects of common traders. This finding contributes to the recent discussions on whether funding constraints arising on the borrower's or the lender's side are more important (e.g., see Brunnermeier and Oehmke (2012) for a review). Our results show that policies which aim to recapitalize or subsidize lenders (instead of borrowers) might be more effective in mitigating systematic liquidity crises.

In addition to revealing the underlying forces behind the main results, this finding indicates that policies which aim to recapitalize or subsidize lenders (instead of borrowers) might be more effective in mitigating systematic liquidity crises.

Our findings contribute to the growing literature on commonality in liquidity. This line of research initially focused on documenting pervasive commonality (Chordia, Roll Subrahmanyam (2000), Hasbrouck and Seppi (2001), Huberman and Kalka (2001)). Subsequent work focused on distinguishing its cause. One strand of theoretical literature points to funding constraints of traders.[1] These studies predict that funding constraints, which include constraints due to margin requirements, drive commonality in liquidity during market downturns. Hameed, Kang, and Vishwanathan (2010) and Coughenour and Saad (2004) support this view. Specifically, Hameed, Kang, and Viswanathan (2010) report that commonality increases following large market declines. Coughenour and Saad (2004) focus on New York Stock Exchange specialists, who provide liquidity in all of the stocks in which they make markets, and show that liquidity commonality is higher when stocks share specialists, especially when specialists are capital constrained.

While the findings in the papers described above are consistent with the idea that funding constraints drive commonality, the overall evidence to date is mixed. Another line of work emphasizes the importance of correlated trading demands that arise from similarities in investors' styles, tastes, or sentiments.[2] Karolyi, Lee, and Van Dijk (2012) find that intuitive proxies for funding constraints (variables such as local interest rates) are not strongly associated with heightened commonality in liquidity in bad times, while turnover commonality (which can be interpreted as a proxy for correlated taste) and foreign flows have considerable explanatory power. Although not paying specific attention

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[1] These include works by Kyle and Xiong (2001), Gromb and Vayanos (2002), Morris and Shin (2004), Weill (2007), Gromb and Vayanos (2009) and Brunnermeier and Petersen (2009), among others.

[2] The idea is that, for instance, due to benchmarking practices, financial institutions tend to have a taste for index stocks, and this exacerbates liquidity comovement across these stocks.

to crisis periods, Kamara, Lou, and Sadka (2008) and Koch, Ruenzi, and Starks (2016) find that commonality is higher when institutional ownership is higher.

One important distinction between these two views is the asymmetry in their predictions. Different from correlated trading due to common investor styles or tastes, which can be important in any market environment, the commonality that arises from funding constraints is expected to be concentrated in times of market downturns, when funding constraints are binding. This asymmetry helps with the interpretation of any empirical findings.

Unlike the previous studies, we use a regression discontinuity design that allows us to isolate the impact of the leverage channel from confounding effects – an empirical challenge faced by previous studies. This makes it possible to make causal statements about the impact of leverage on comovement. Our main finding is that trader leverage dramatically increases commonality, but only during crisis periods. This is not driven by index stocks or differences in ownership structure (such as institutional and foreign ownership), which indicates that leverage channel is distinct from prior findings in the literature. To the best of our knowledge, our paper is the first to provide evidence on the impact of trader leverage on commonality in liquidity.

Our paper is also related to recent work by Kahraman and Tookes (2016), who use the same sample of stocks that we use in this paper, but there are three important differences. First, Kahraman and Tookes (2016), examine the impact of trader leverage on stock liquidity *levels*. They find that, on average, margin-eligible stocks have higher liquidity. Liquidity levels and comovement are fundamentally different and can be driven by different forces. Second, unlike Kahraman and Tookes (2016), we introduce new data at the margin trader and broker level, which helps us uncover the mechanism behind this paper's main results. Our finding that the economic effect of common brokers is larger than that of common traders is, to the best of our knowledge, new to the literature and it has important policy implications. Finally, while Kahraman and Tookes (2016) focus only on liquidity, we also analyze stock returns. A new finding that emerges from our analysis is that, while commonality in stock returns and commonality in liquidity are not strongly correlated in normal times, due to leverage, they become highly linked during times of market stress.

Finally, our findings on return comovement add to the literature on financial contagion. Examples include Bekaert, Harvey, and Ng (2005) and Jotikasthira, Lundblad, and Ramadorai (2012), who document heightened return comovement during crisis periods in international markets. Boyson, Stahel, Stulz (2010) and Billio, Getmansky, Lo, and Pelizzon (2012) provide evidence consistent with contagion among hedge funds. While the theory of contagion is well-studied, empirical evidence on its underlying causes is not conclusive. In this paper, we find that trader leverage is one driver that serves to exacerbate the excess return comovement that we observe during crisis periods.

The paper proceeds as follows: Section 2 discusses the regulations that determine margin eligibility in India. Section 3 describes the data and the regression discontinuity approach. The main results are in Section 4. Section 5 presents mechanism analyses. Section 6 concludes.

2. Margin trading in India

Margin trading allows traders to borrow in order 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.[3] Under current 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 the trading days over the past six months. The second requirement provides the identification that we need for the empirical analysis. The stock's average impact cost, defined as the absolute value of the percentage change in price from

[3] Prior to the current system, the primary borrowing mechanism for traders in India was a system called Badla. Under Badla, trade settlements were rolled from one period to another. The system was eventually banned because it lacked key risk management standards, such as maintenance margins.

the bid-offer midpoint that would be caused by an order size of 100,000 rupees (approximately $2,000 during our sample period), must be 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 six months. These are calculated at random ten-minute intervals four times per day.

Stocks that meet the impact cost and trading frequency requirements are categorized as Group 1 stocks and are eligible for margin trading. Stocks that fail to meet the impact cost requirement, but meet the trading frequency requirement, 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).[4] 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. 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 (i.e., the probability of assignment jumps from 0% to 1% at the threshold).

There are alternative ways that traders can obtain leverage in India outside of the formal margin trading system, but these channels tend to be costly or available for only a small subset of stocks. For example, for a stock to be eligible for futures and options (F&O) trading, there are additional market capitalization, free float, trading activity, and impact cost requirements. As of December 2012, we find only 140 stocks that are eligible for F&O trading (whereas 620 stocks are

[4] When a stock moves from Group 1 to Group 2 or 3, no new margin trades are allowed as the effective date. However, investors who already have outstanding margin positions can take time to unwind them.

eligible for margin trading in the same month). Investors can also borrow from nonbanking finance companies (NBFCs), which are regulated by RBI (the central bank), to finance the purchase of any security. However, NBFC loans typically carry higher interest rates and other terms that are less favorable to investors. It is important to note that, even if these alternative channels are used, their existence would create bias against finding significant effects of margin eligibility.

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 later in the paper.[5] Margin trading rules are distinct from the other trading rules in India.[6] 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

3.1. 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,

[5] For a more detailed discussion of the margin trading system in India, see the Securities and Exchange Board of India (2012). See also the referenced SEBI circular dated March 11, 2003: http://www.sebi.gov.in/legal/circulars/mar-2003/circular-for-risk-management-for-t-2-rolling-settlement_15836.html.

[6] Group 1 membership in India has one additional regulatory advantage in the very short run. For non-institutional traders, trade settlement with the broker occurs at day t+1. Collateral to cover potential losses prior to full payment at settlement is collected at the time of trade (this is called a VAR margin). VAR margin requirements are lower for Group 1 stocks than for Group 2 and Group 3 stocks. Thus, Group 1 stocks require less short-term capital. The existence of an additional source of leverage does not change our overall interpretation of Group 1 membership because the margin financing eligibility and the low VAR margin requirements both involve shocks to the availability of leverage, in the same direction.

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 for which 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%. We also remove cancelled trades and entries with bid or ask prices equal to zero. We require non-missing price and volume information for at least 12 trading days in a given month.

We obtain two datasets with information on daily outstanding margin positions. Both are from the NSE. The first dataset reports the stock-level total outstanding margin trading positions at the end of each trading day. These data are available throughout our sample period. The second dataset contains trader-level data with outstanding margin positions for each stock and trader. These data include unique trader and broker identification numbers and allow us to identify margin trader and broker linkages across stocks. The trader-level data are available only for the 2007 to 2010 subperiod. We complement the NSE data with company information from Prowess, a database of Indian firms, which covers approximately 80% of the NSE stocks. Prowess provides information on shares outstanding, index membership, ownership structure (at the quarterly frequency), and trade suspensions. Prowess data are available throughout our sample period.

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

Following the related studies in the literature, we impose sample restrictions to ensure data quality. First, we exclude stocks with extreme price levels (we use the 1% tails of the distribution). This restriction is similar to the restriction imposed in studies using U.S. data, which commonly focus only on stock prices above $5 and less than $999. Second, we exclude the stocks that have been suspended from trade, since trading irregularities in suspended stocks are likely to contaminate our liquidity measures. Finally, although we do not observe corporate actions such as stock splits, bankruptcy, or mergers, we aim to remove these events from the analysis. To do so, we omit stocks with percentage changes in shares outstanding that are greater than 50% (in absolute value) and exclude stocks with temporary ISIN identifiers, as this appears to be an indication of a corporate action.

Throughout the analysis, we focus on Group 1 and Group 2 stocks (as noted above, Group 3 stocks are not frequently traded). There are 1,842 unique ISINs in Groups 1 and 2 during our sample period. Of these, 1,500 are in 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* (the commonality measure using effective spreads) analysis, there are 1,063 unique stock observations, and 954 of these are in the treatment (Group 1) sample at least once. This observation is important to the overall interpretation because it shows that, although our RDD approach focuses only on stocks close to the threshold during a given month, the analysis is not constrained to only a small subset of stocks.

For every stock and month in our sample, we begin the analysis by calculating 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 the fundamental value for the average trade. The effective spreads that we calculate reflect the average daily effective spreads, based 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) and Goyenko, Holden, and Trzcinka (2009)). Following Amihud (2002), we winsorize the measure at the 1% and 99% levels (based on the full sample distribution), and we also remove observations in which daily trading volume is less than 100 shares. The latter restriction impacts only 1% of the full sample of daily data. 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. As in Karolyi, Lee, and Van Dijk (2012) we take logs to reduce the impact of outliers.

If margin traders tend to delever during downturns, the resulting order imbalances are likely to cause increases in both bid-ask spreads and the price impact of trading.[8]

[8] Chordia et al. (2002) find that order imbalances reduce liquidity, for instance, captured by bid-ask spreads. This is consistent with the idea that imbalances introduce additional inventory costs to market makers.

3.2. 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 and month. We define commonality in liquidity as the R^2 statistic from a regression of stock *i's* daily liquidity innovations on market liquidity innovations. We choose to focus on R^2 rather than liquidity betas, which are also used in the commonality in liquidity literature, because liquidity betas estimated at the stock-month level (a frequency crucial to our identification strategy) would introduce excessive noise in the analysis. The papers that use liquidity betas estimate them using data over a full year or more (e.g., Kamara et. al (2008), Hameed et. al (2010), Koch et. al (2016)). Similar to our paper, Karolyi, Lee, and Van Dijk (2012) are interested in commonality at the monthly horizon, and they define commonality based on the R^2 statistic. Because, in principle, a high R^2 can result from either a strong positive or a strong negative correlation with the market, later in the paper, we also examine liquidity correlations (an alternative commonality measure) both with the overall market as well as within Groups 1 and 2. Doing so allows us to clarify both the direction and source of any observed commonality.

Along the lines of the approach in Karolyi, Lee, and Van Dijk (2012), we first calculate liquidity innovations based on a first-stage stock-level regression of daily liquidity on variables known to affect liquidity. Using data for each stock *i* on day *d* during month *t*, we estimate:

$$Liquidity_{i,t,d} = \alpha_i Liquidity_{i,t,d-1} + \gamma_i X_{i,t,d} + \omega_{i,t,d.} \tag{1}$$

X_t is a vector of indicator variable 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 $\omega_{i,t,d.}$, 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 ($\omega_{m,t,d.}$) are defined as the equally weighted average innovations for all Group 1 and Group 2 stocks in the market. We choose to equally weight the liquidity innovations in this paper in order to avoid potential bias that might result from the fact that Group 1 stocks tend to be larger than Group 2 stocks and would therefore receive more weight in the market liquidity innovation calculation.

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: $\omega_{i,t,d} = \alpha_i + \beta_1 \omega_{m,t,d} + \varepsilon_{i,t,d}$. This R^2 measure is also used in Karolyi, 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, our analysis mostly focuses on the Group 1 and Group 2 stocks that lie near the impact cost cutoff of 1%.

We also calculate R^2*return*, a measure of commonality in returns. R^2*return* is defined as the R^2 from a regression of the daily returns of stock *i* on (equal-weighted) market returns during month *t*. After establishing the basic results for commonality in liquidity, we extend our analysis to returns since trader leverage can also play an important role in returns comovement.

It is useful to start by summarizing a couple of important patterns that we observe in the margin position data. First, we observe a significant decline in outstanding margin positions during the global financial crisis, consistent with the intense deleveraging commonly reported in the press. For example, from the first quarter of 2008 to the last quarter of that year, we find that outstanding margin debt declined by approximately 70%. Second, we find that, while margin traders are contrarian traders who provide liquidity during normal times, they become momentum traders who consume liquidity during severe downturns. For instance, there are 38% more contrarian trades than momentum trades in the overall sample. In stark contrast, during crises, momentum trades are 85% more likely than contrarian trades.[9] Motivated by these findings, we aim to understand whether margin trading and deleveraging cause liquidity and return comovement, particularly during market downturns.

3.3. Descriptive Statistics

Table 1 provides basic summary statistics. We report market- and stock-level information for the full sample, as well as subsamples that are defined according to whether a given month corresponds to a severe market downturn. "Severe downturns" refers to months in which Indian market returns (i.e., CNX 500 returns) are below the 10th decile returns, which corresponds to a one-month market return of -9% or less.[10] Panel A of Table 1 reports that the median monthly market return during these periods is -13.2%, with an interquartile range of -18.9% to -10.5%. "Outside of downturns" refers to all months outside of severe downturn periods. Panel A of Table 1 reports median monthly market return of 2.9%, with an interquartile range of -1.2% to 7.4%, outside of severe downturns.

Panel A of Table 1 also reports monthly market liquidity levels, defined as the equal-weighted average daily effective spread (*espread*) or Amihud (2002) illiquidity ratio (*illiq*) of all Group 1 and Group 2 stocks during month *t*. From the table, it is clear that market liquidity is lower during severe downturns. For instance, consistent with previous work by Hameed, Kang and Viswanathan (2010), we observe a 40% increase in *espread* and a 35% increase in *illiq* when there are large market declines.

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[9] Kahraman and Tookes (2016) formally show this using daily stock-level margin positions data. We provide evidence consistent with their result using the trader-level data.

[10] In addition to capturing the recent financial crisis of 2008, this definition also captures severe market downturns that occurred in India during 2005, 2006 as well as in late 2011.

Panels B, C and D of Table 1 show statistics of the commonality measures for the local samples of Group 1 and Group 2 stocks. Consistent with the literature, Panel B reveals that all stocks exhibit commonality, although the average R^2 measures are 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 when one examines extreme downturns. During these periods, commonality in all stocks increases. However, the effect is much larger for Group 1 stocks, for which commonality using the R^2*espread* measure almost doubles and commonality based on R^2*illiq* increases by 50%. These changes are 28%–40% lower for Group 2 stocks than they are for Group 1 stocks. Not surprisingly, the statistics in Panel B are consistent with Figure 2, which shows the time series of commonality for the local samples. The average differences in commonality between Group 1 and Group 2 stocks are driven almost entirely by crisis periods.

Table 1, Panel C describes commonality in liquidity, as captured by liquidity correlations, rather than the R^2 measure. *Corr_espread* is defined as the month *t* correlation of stock *i*'s daily effective spreads with the average daily market effective spread. *Corr_illiq* is the correlation of stock *i*'s daily Amihud illiquidity measure with average market illiquidity. These measures complement R^2 since they can capture the direction of commonality. Panel C reveals that the correlation between stock liquidity and average market liquidity is positive – even the 25th percentile of liquidity correlations is positive under each market condition. Importantly, the patterns based on the R^2 measures that we discuss above are very similar to the patterns that we observe using liquidity correlations. There is an increase in liquidity correlations for all stocks during severe downturns, and these increases are much more pronounced for Group 1 stocks. For instance, we observe about a 70% increase in effective spread correlations for Group 1 stocks, while this change is only 48% for Group 2 stocks. The same pattern holds when correlations are based on the Amihud (2002) illiquidity ratio. Combined with the evidence in Panel A that market liquidity falls during severe downturns, these basic descriptive statistics reveal that the crisis-period increases in R^2 capture increased correlation as stock liquidities *fall*.

Panel D of Table 1 summarizes return comovement during the different market return regimes. The commonality in returns patterns are very similar to what we observe when we examine commonality in liquidity in Panels B and C. Panel D shows that the local sample of Group 1 stocks experience a 70% increase in return comovement during downturns, while that increase is only 52% for local Group 2 stocks. This suggests a potential role for trader leverage in stock return dynamics, which we will explore in extended analysis.

Overall, the summary statistics in Table 1 reveal important variation in commonality across margin eligibility regimes. This motivates a formal examination of trader leverage as a potential driver of commonality.

We use regression analysis to test formally the hypothesis 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 six 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 ten 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 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 (left side Figures 3a and 3b), as well as for periods of severe market downturns (right side of the figures). If there is a treatment effect of margin trading eligibility, we would expect an increase in commonality at the cutoff, particularly during crisis

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

periods. Consistent with this, the regression lines in Figures 3a and 3b show discontinuous drops in commonality measures based on *espread* and *illiq*, respectively, during severe downturns. By contrast, we do not observe discontinuities in the non-crisis period data. The figures provide further (suggestive) evidence of the role of trader leverage in driving commonality.

3.4. Local Regressions: Methodology

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 test whether traders' leverage 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 these tradeoffs, we rely on the optimal bandwidth selection techniques in Calonico, Cattaneo, and Titiunik (CCT, 2014). The CCT bandwidths are based on the data-dependent bandwidths designed for RDD applications in Imbens and Kalyanaraman (IK, 2012), but improve on them by selecting the initial bandwidth optimally. This results in more conservative (smaller) bandwidths than those suggested by IK. For the R^2*espread* variable, the CCT bandwidth is 0.18, and for the R^2*illiq* variable, it is 0.20. These bandwidths result in local samples that are between 85% and 90% smaller than the full sample of Group 1 and Group 2 stocks. In robustness analysis (later in the paper), we 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:

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

Group 1 is an indicator variable equal to 1 if the stock is eligible for margin trading during month *t*. The baseline regression includes a vector of year-month fixed effects. Because the dependent variable is estimated, we bootstrap all standard errors.[12] Our objective is to understand whether shocks (variations 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 in the question of what drives the increases in liquidity comovement that we observe during crises, we remove the year-month fixed effects and 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. The main specification is as follows:

$$\begin{aligned} R^2_{it} &= \alpha + \beta_1 * Group1_{it} + \beta_2 * Group1_{it} * severedownturn_t \\ &+ \gamma * severedownturn_t + \varepsilon_{it}. \end{aligned} \tag{3}$$

The primary coefficients of interest are on the *Group 1* indicator variable and the *Group 1*severedownturn* interaction variable. 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. We also estimate a model in which we replace the direct effect of

[12] We use Stata's *bssize* command to determine the optimal number of replications. We require that our bootstrapped standard errors do not deviate from the ideal bootstrapped value (i.e., the value obtained with infinitely many replications) by more than 10% with probability 0.99. This results in 331 replications.

severedownturn in Equation (3) with month-year fixed effects. We do this to check whether any findings from the main specification are due to unmodeled time-series variation in commonality.

4. Results

4.1. Commonality in Liquidity

The results of the local regressions are in Table 2. In Columns 1 through 3, the dependent variable is R^2*espread,* and in Columns 4 through 6, 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 sample 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% increase in commonality relative to the Group 1 sample mean. Column 3 shows results from the specification in which we replace the direct effect of *severedownturn* with month-year fixed effects. The estimated coefficient on the *Group1*severedownturn* interaction is 0.0358 and remains highly significant. While we use the specification in Column 2 throughout the paper because it allows us to make statements about the impact of margin trading during crises relative to the average increase in commonality across all stocks during crisis periods, the results in Column 3 provide a useful specification check.

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 4 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 *Group 1* is positive, but the t-statistic is only 1.59. When we allow the effect of margin trading eligibility to vary when the market is in a severe downturn (Column 5), we find that commonality in all stocks substantially increases during severe downturns. More importantly, similar to the R^2*espread* regressions, we find that there is an additional increase in commonality for margin-eligible stocks. Specifically, in the case of the Amihud (2002) illiquidity ratio, trader leverage explains nearly 40% of the total crisis-period increase in commonality in Group 1 stocks. Similar to Column 3, the results in Column 6 show that the main findings are robust to replacing the direct effect of *severedownturn* with month-year fixed effects. Overall, the evidence in Table 2 strongly supports the hypothesis that trader leverage drives commonality in crises.

4.1.1. Robustness

In Table 2, the only covariates 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 measures of commonality in liquidity (see, e.g., Chordia et al. (2000), Kamara et al. (2008), Karolyi et al. (2012), and Koch et al. (2016)). The additional controls are lagged: volatility (defined as the standard deviation of daily stock-level returns), stock-level returns, log rupee volume, market capitalization, and lagged dependent variable. 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. Before estimating the regressions, we check the extent to which covariates exhibit discontinuities at the eligibility cutoff during severe downturns. As shown in Appendix Figure A.1, we do not observe discontinuous changes in these variables.

The results of regressions with the 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 are similar to, although slightly larger than, the baseline results from Columns 2 and 5 of Table 2. Not surprisingly, we also find significant relationships between commonality and the covariates. We find that commonality is higher when stock volatility and trading volume are higher and when market capitalization is smaller.[13] We also find that commonality is positively autocorrelated. The relationship between commonality and lagged stock returns depends on the specification. When 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 becomes positive, which might capture some common liquidity improvements as stock market conditions improve. Although they don't really affect the estimates, to remain conservative, we keep the control variables in all subsequent analyses.

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

[13] One might be concerned that the margin trading effect on commonality in liquidity is really a contemporaneous volume effect (assuming margin trading leads to increased volume and commonality in volume which, in turn, might impact commonality in liquidity). In Appendix Table A.1, we repeat the Table 2 and Table 3 regressions, but replace the dependent variables with $R^2volume$, the R^2 from a regression of daily volume innovations on market volume innovations during month *t*. We find no significant relationship between margin trading eligibility and commonality in trading volume. This is true in both normal times, and in times of crisis. Moreover, in the data, we do not observe a differential impact on volume levels of Group 1 stocks during bad times. These finding strongly support the idea that margin trading captures trader leverage, distinct from volume.

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 Appendix Table A.2, 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 Appendix Table A.2, the main results are robust to bandwidth choice.

Finally, we confirm our main findings using local polynomial regressions. We follow Lee and Lemieux (2010) and use the Akaike information criterion (AIC) to determine the appropriate polynomial orders for a given bandwidth. This approach helps avoid the overfitting problem that can result from estimating polynomial regressions over very narrow bandwidths. We begin with the CCT bandwidth used in main regressions, and we expand it by factors of 1.25 to 1.75. The AIC suggests polynomial orders ranging from 1 to 3 for these bandwidths. Results are reported in Appendix Table A.3. Results show that impact cost polynomials are not significant, and importantly, the inclusion of these polynomials does not have an impact on our findings.

While it is commonly used in the literature, one potential question with the overall interpretation of the R^2 measures is that high R^2 can, in theory, capture important positive *or* negative liquidity comovement. The descriptive statistics presented in Table 1 reveal that the documented patterns in liquidity comovement are due to increases in positive comovement. To test formally whether our results are dependent on the choice of R^2-based commonality measures, we repeat the Table 3 analysis using alternative commonality measures (*Corr_espread* and C*orr_illiq),* which measure the correlation between a stock's daily liquidity with market liquidity. Results are in Table 4. The results in Table 4 are remarkably similar to results using R^2*espread* and R^2*illiq*. For example, the estimated coefficient of 0.1008 on *severedownturn* in the *Corr_espread* regression implies a 42-43% crisis-period increase in commonality for all stocks and the coefficient of 0.0616 on *Group1*severedownturn* in Table

4 implies an additional 26% increase in spread commonality for margin-eligible stocks during crises. That is, trader leverage accounts for more than one third of the total increase in commonality for margin-eligible stocks. These findings show that the effects we document in Tables 2 and 3 are driven by increases in positive liquidity comovement.

4.1.2. 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: the first at one bandwidth above, and the second at one bandwidth below, the true cutoff of 1%.

The results of the placebo analysis are in Panel A of 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 it lends strong support to the causal interpretation of our findings.

What happens during other periods of high market volatility, specifically when there are large rises in the market? If the main findings are due to margin traders whose portfolio constraints cause deleveraging when market conditions deteriorate, we would not expect to observe symmetric effects during extreme up- and down- market conditions. Examining market rallies, rather than severe downturns, can serve as a placebo check for the mechanism driving our results. In Panel B of Table

5, we repeat the Table 3 regression analyses, but we replace *severedownturn* with *market_rally*, a dummy variable equal to 1 if market returns are *higher* than 90th percentile returns. There are two important observations from the table. First, on average, commonality in liquidity is lower during extreme market increases. Second and most importantly, there is no differential impact of margin eligibility on commonality during market rallies, that is, the coefficient on the *market_rally*Group 1* interaction is statistically insignificant. These findings support the leverage-induced funding constraints interpretation of our main results.

4.1.3. Alternative explanations

Karolyi, Lee and Van Dijk (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 are associated with higher commonality. Unlike the trader leverage channel (an effect related to funding constraints), these variables capture effects due to similarity in institutional investment styles or tastes. In interpreting the results in this paper, one might be concerned that Group 1 status is capturing variation in institutional (or foreign) ownership rather than trader leverage. In this section, we analyze this, as well as other potential alternative explanations.

It is useful to start by noting that our main finding arises only during severe downturns. We do not observe significant differences in commonality in liquidity between Groups 1 and 2 stocks outside of downturns. Alternative explanations based on correlated trading channels are unlikely to drive the main results because, if margin traders engage in correlated trading strategies due to similarity in investment style or taste, we would expect margin eligibility to drive correlations in liquidity during normal market conditions and stock market rallies, as well as downturns. To complement this reasoning, we conduct extended robustness tests to assess directly the impact of previously documented channels on our findings.

To examine whether our results are driven by index membership, 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. We also interact them with Group 1 dummy, as well as the *Group 1*severedownturn* interaction variable, to see whether our trader leverage interpretation is actually coming from an alternative mechanism. In addition, we examine whether Group 1 status is proxying for the ability to trade derivatives on the stock. To do so, we introduce *deriv*, a dummy variable equal to 1 if the stock is eligible for futures and options trading.[14]

Results are in Table 6. The estimated coefficients on the direct effects are overall in line with earlier findings. For instance, consistent with Kamara, Lou, and Sadka (2008), we find that, on average, index stocks exhibit more commonality and institutional ownership exacerbates commonality in liquidity. Similar to Karolyi, Lee and Van Dijk (2012), we also find higher commonality in stocks with more foreign ownership. Interestingly, the estimated coefficients on the Group 1 interactions with foreign ownership and index membership are both negative, suggesting that margin eligibility mitigates their effects. While these alternative interpretations are significant on average, they don't have a differential impact on commonality in liquidity during severe downturns. Most importantly, the estimated crisis-period impact of Group 1 status on commonality in liquidity remains very close to the main results in Table 3, even after accounting for these alternative channels.

Finally, using the quarterly ownership data from Prowess, we check for changes in ownership composition during severe downturns. For each stock, we calculate the percentage shares held by

[14] Note that all stocks eligible for futures and options trading are in Group 1; however, it is only a subset of margin-eligible stocks (there are approximately 150 of these stocks). This means that the *group1*deriv* and *deriv* are collinear. Thus, the former are dropped from the analysis.

foreign investors, institutional investors, individual investors, and blockholders/insiders (*foreign perc*, *inst perc*, *indiv perc*, and *promoter perc*, respectively). We also investigate whether the information structure of trading, which might cause changes in commonality, changes during severe downturn periods.[15] We then regress these stockholdings on the *Group 1* dummy as well as its interaction with *severedownturn*. Appendix Table A.4 reports the results. *Group 1*severedownturn* is insignificant in all regressions, indicating that there is no significant change in ownership composition or informed trading during severe downturns.[16]

4.2. Return Commonality

The analysis thus far tests the hypothesis that leverage can drive substantial increases in liquidity comovement during crises. We focus most of the initial analysis on commonality in liquidity because it is pervasive and not well-understood; however, it is important to point out that, in theory (e.g., Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Geanakoplos (2010)), trader leverage will drive both commonality in liquidity and commonality in returns. In this section, we use our research design to test the hypothesis that trader leverage causes return comovement. Our set-up allows us to estimate the portion of return comovement that stems from frictions related to trader leverage.

Before describing the specifics of the empirical analysis, it is important to emphasize that commonality in liquidity does not necessarily imply commonality in returns. As Karolyi, Lee and Van Dijk (2012) note, commonality in liquidity can arise when stocks are facing very different liquidity demands. If one group of stocks experiences intense buying pressure, while the other experiences

[15] To do this, we introduce the Probability of Informed Trading (PIN, based on Easley, Kiefer, O'Hara, and Paperman, (1996)).
[16] As the results in Appendix Table A.4 indicate that investor composition does not change with Group 1 membership, we populate the quarterly ownership data at the monthly frequency for the purpose of Table 6. This allows us to compare the results with the ones from the baseline analysis.

intense selling pressure, we would see increased correlation in liquidity but not an increase in return correlation. However, in the case of the deleveraging that occur during crises, selling pressure that are likely to be similar across stocks might cause returns to comove in ways that are similar to the liquidity patterns that we observe.

To test for evidence of the hypothesized relationship between leverage and returns comovement, we repeat the main Table 2 and Table 3 regressions, but we replace the dependent variable with commonality in returns. Similar to before, 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 7. 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, we add the same additional controls that we include in Table 3. Consistent with the descriptive statistics in Panel D of Table 1, the estimates in Table 7 provide causal evidence of the impact of trader leverage on return comovement during severe downturns.

Columns 1 and 3 show that, on average, there is a significant difference in return comovement between Group 1 and Group 2 stocks, however this difference is quite small. For example, in Column 1, the estimated coefficient on *Group1* dummy implies a 10 basis point increase in return comovement for stocks that are eligible for margin trading, which is a 3.9% increase relative to the average return comovement in the local sample of Group 2 stocks. When we include *severedownturn* dummy as well as its interaction with *Group1* dummy variable in Columns 2 and 4, we see that this difference is entirely driven by crisis periods (as in the case of commonality in liquidity). The coefficient of 0.056 on the *Group 1*severedownturn* interaction in Column 2 of Table 7 implies that trader leverage accounts for a 56 basis point increase in crisis-period return comovement. This represents approximately 28% of the total crisis-period increase in return comovement, which is remarkably similar in magnitude to the results we document for commonality in liquidity. Overall, these findings show that leverage is a key driver of the increase in stock return comovement that we observe during downturns.[17]

Given the results in Tables 2, 3 and 7, and the theoretical linkages between commonality in returns and liquidity, it is natural to ask whether the Group 1 stocks with higher return commonality during downturns also have higher liquidity commonality. The data reveal that this is, indeed, the case. While the correlation between commonality in liquidity and commonality in returns measures for local Group 1 stocks is only 0.2 outside severe downturns, this correlation more than doubles during severe downturns. In Panel B of Table 7, we further examine this by looking at stocks' liquidity and return comovement rankings. In each period, we independently sort Group 1 stocks into 5 groups (in ascending order) based on stock's commonality in liquidity and commonality in returns. Panel B reports the mean commonality in returns rank for each of the 5 groups of stocks ranked on commonality in liquidity.[18] Outside of severe downturns, there is only a mild association between commonality in liquidity and commonality in returns; however, the relationship becomes much stronger during severe downturns. Stocks that have the highest and the lowest commonality in liquidity during severe downturns have an average rank of 4.38 and 2.04, respectively, in R^2*returns.* The crisis-period increase in average R^2*returns* ranks is also strongly monotonic as we move from stocks with the lowest-ranked commonality in liquidity to the ones with the highest rank.

4.3. Mechanism

In this section, we examine margin trading activity and leveraged-based linkages across stocks to shed additional light on the mechanisms driving our main findings. All of the tests include examinations

[17] Appendix Table A.5 contains results of robustness analyses in which we test whether the commonality in returns findings in Table 7 are sensitive to bandwidth choice or to the inclusion of polynomials of impact cost – the RDD checklist robustness tests. These regressions are analogous to those in Appendix Tables A.2 and A.3. As in Tables A.2 and A.3, we find that return commonality results are robust.

[18] For this exercise, we use R^2*espread* as our measure of commonality in liquidity. Results are similar when conduct analyses based on the other measures of commonality that we use in this paper.

of commonality in both liquidity and returns. This helps us understand whether commonality in liquidity is caused by some of the same forces that drive commonality in returns.

4.3.1. Correlated Margin Trading Activity

The results presented so far show that the ability of traders to borrow increases commonality in liquidity and returns. If traders' use of leverage (rather than simply the ability to lever up, captured by the Group 1 dummy variable) is really driving the results, we would also expect the findings to be strongest in stocks in which there is more correlated margin trading activity. We do not have trade-level data on margin trading activity; however, the daily stock-level margin positions data available in India allow us to examine this question (and are a substantial improvement over the monthly market aggregate data available in the U.S.). We use this information to calculate a proxy for correlated margin trading activity: *margin corr* is equal to the correlation between daily changes in a Group 1 stock's outstanding margin positions and the average daily changes in outstanding margin positions in the entire market during each month. Even though we do not observe intraday margin trades, our proxy is likely to be correlated with total margin trading activity.[19]

We repeat the Table 3 and Table 7 regressions, but we include *margin corr*, and interact it with *Group1* and *Group1* Sevredownturn*.[20] If the increase in commonality in liquidity and returns that we observe is due to trader leverage, we expect that the coefficients on the triple interaction term will be positive and significant.

The findings in Table 8 show that this is indeed the case. Results reveal an economically important role for *margin corr* for both commonality in liquidity and commonality in returns. For

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[19] *margin corr* captures daily correlations in changes in outstanding margin positions and is defined over the entire sample period. As reported in Section 3, there is a substantial decline in margin debt for Group 1 stocks during severe downturns, indicating that *margin corr* in such time periods mostly captures correlated deleveraging.

[20] Since *margin corr* is available only for Group 1 stocks (it is set to zero for Group 2 stocks), regressions include only *Group1* Severedownturn*. The interaction *severedownturn * margin corr* and *margin corr* are dropped due to multicollinearity.

instance, the results in Column 1 imply that a one standard deviation increase in correlated margin activity during severe downturns results in a 0.035 (equal to 0.15 * 0.23) increase in R^2*espread*, which is about 50% of the average effect of the increase in R^2*espread* during severe downturns. Note that, unlike the triple interaction term, coefficients on *margin corr*Group1* are not positive and significant, revealing that trader leverage does not increase commonality outside the crises periods. The findings for commonality in liquidity based on R^2*illiq* and commonality in returns are similar (Columns 2 and 3 of Table 8, respectively).

4.3.2. Within-Group Commonality

If the increased commonality of liquidity and returns that we observe in Group 1 stocks during severe downturns is due to binding capital constraints and deleveraging, then one would expect commonality to be higher within the universe of Group 1 stocks. In this section, we analyze commonality within and across Group 1 and Group 2 stocks. To do so, we calculate the pairwise correlations in stocks' liquidity and return measures, and then we test whether within- or across-group commonality is stronger.

For each local stock, we calculate the monthly pairwise correlations of the stock's daily liquidity with the daily stock liquidity of all other stocks in the market (including nonlocal stocks). We also do the same for returns. *Corr_espread* is the monthly pairwise correlation in *espread*. *Corr_illiq* is the monthly pairwise correlation in *illiq*. *Corr_return* is the monthly pairwise correlation in stock returns. We analyze the differences in pairwise correlations for different types of stock pairs. *G1G1* is a dummy variable equal to 1 if both stocks in a given pair are Group 1 members; *G2G2* is a dummy variable equal to 1 if both stocks in a given pair are Group 2 members. The baseline pair is a pair that consists of one Group 1 and one Group 2 stock. We interact both *G1G1* and *G2G2* with *severedownturn* dummy to assess the change in within-group pairwise correlations during downturns. The results are in Table 9. Consistent with our previous findings, all stocks exhibit commonality, especially during downturns.

Group 1 stocks, whose margin traders are more likely to face collateral calls that may cause them to liquidate several stocks in their portfolios, have higher pairwise correlations with both Group 1 and Group 2 stocks during downturns. Most importantly, in those crisis periods, Group 1 stocks have higher pairwise liquidity and return correlations with other Group 1 stocks than they do with Group 2 stocks (*G1G1 and G1G1 * severedownturn* are both positive and significant). Thus, the findings in Tables 2, 3 and 7 not only reflect Group 1 stocks' increased comovement with the market, but that some of this stems from increased comovement with other Group 1 stocks. Group 2 stocks, which are ineligible for margin trading and less likely to have traders facing margin calls, see less pairwise liquidity and return comovement with other Group 2 stocks in both normal times and during crises.

4.3.3. Connected Through Margin Trading

We obtain trader-level margin positions data from the NSE for the 2007 to 2010 subperiod to dive deeper into the idea that common margin traders in Group 1 stocks play an important role in crisis-period commonality. These data are much richer than the monthly market-level margin debt outstanding data available from U.S. exchanges like the NYSE and allow us to conduct more meaningful analyses of the impact of connections that stocks have via levered traders and their brokers.[21] For each stock and each trading day, we observe all traders' individual end-of-day margin trading positions, along with unique trader and broker identification numbers. The identification numbers allow us to identify all of the stocks financed with margin debt by each individual trader, as well as the broker that she uses.[22] Both the trader and broker connections are of interest. At the trader

[21] Bian, Da, Lou, and Zhou (2016) also use trader-level data for margin investors, but they focus on China. They use their data to understand the effect of margin trading and common margin traders on stock returns. Their paper complements ours in that they find evidence that margin investors tend to delever if stocks in their portfolios have done poorly and that this response is strongest during market downturns. Unlike our paper's focus, they neither examine commonality in liquidity nor do they exploit a natural experiment to identify causal linkages.

[22] Chung and Kang (2016) also examine the role of prime brokers in generating commonalities; however, their main goal is to analyze brokers' impact on comovement in hedge fund returns.

level, it is possible that a margin call will force a given trader to liquidate positions in many stocks in her portfolio at once. At the broker level, a negative shock to the overall market might make the broker less willing and able to provide capital to its customers. Both are related to funding constraints, stemming from stress at the trader- and broker-level, respectively.

We start with a few facts about common margin traders and their brokers. There are 85,920 unique margin traders in the sample. These margin traders obtain margin debt from 19 brokers during the sample period.[23] There is a high degree of concentration among these providers of margin debt, with just two to three dominant players in each year. The Herfindahl-Hershman index, based on the average daily rupee value of margin loans, ranges from 2,957 in 2008 to 3,486 in 2010. The median local stock with margin debt outstanding on a given day is connected to 86 other stocks through common margin traders, with an interquartile range of 27 to 140 connected stocks. Not surprisingly, since a single broker is likely to serve more than one client, there are even more connections at the broker level. The median local stock with margin debt outstanding is connected to 415 other stocks through common brokers, with an interquartile range of 340 to 473. Thus, cross-stock connections through margin trading are common.

Using the detailed margin position data, we examine the role of stock-level connectedness through margin trading on commonality in liquidity and returns. We construct our measures of stock-level connectedness in the spirit of Anton and Polk (2014) and Bartram, Griffin, Lim, and Ng (2015). We define *Common traders,* which is the total value of the margin trading positions held by all common margin traders of the two stocks scaled by the total market capitalization of the two stocks. Similarly, *Common broker* is defined as the total value of the margin trading positions lent out by all common brokers of the two stocks scaled by the total market capitalization of the two stocks. These measures

[23] For each broker, all of which are members of the NSE, there may be many sub-brokers. Sub-brokers are not trading members of the NSE, but they act as agents for the brokers. We are only able to observe broker-level data.

are defined for pairs of stocks which are both *Group1* members (this is because only Group 1 stocks are eligible for margin trading). Specifically, measures capture pairwise connections between the local *Group1* stocks and all the other Group 1 stocks in the market. Both *Common traders* and *Common broker* are monthly averages of daily values and are normalized to have zero mean and unit standard deviation so that it is straightforward to compare their coefficients. As in the previous analysis, dependent variables are monthly pairwise correlations in stocks' liquidity and return measures, *Corr_espread*, *Corr_illiq* and *Corr_return.*

Results are reported in Table 10. In Columns 1 through 3, we regress pairwise liquidity and return correlations on *Common traders*, the *severedownturn* dummy, and the *Common traders*severedownturn* interaction. In Columns 4 through 6, we regress pairwise correlations on *Common broker*, *severedownturn,* and their interaction. The patterns are striking. Both *Common traders* and *Common broker* are associated with higher liquidity and return correlations on average, and these effects become much larger during severe market downturns. Interestingly, the magnitudes of the coefficients on the *Common broker* variable during these periods are about twice those of *Common traders.* This suggests that brokers' funding constraints (impacting, for example, their provision of margin debt) during downturns matter more than the collateral calls faced by individual traders. This finding contributes to the recent discussions on whether funding constraints arising on the borrower's or the lender's side are more important (e.g., see Brunnermeier and Oehmke (2012) for a review). Understanding this question is important because it can help regulators develop the appropriate policy tools. Our findings show that policies that aim to recapitalize or subsidize lenders can be more successful in mitigating the negative effects of liquidity crises.

The main finding in this paper is that commonality in liquidity increases substantially during crisis periods for margin-eligible stocks. The same is also true for returns. Tables 8 through 10 are not only consistent with the idea that deleveraging during downturns causes the declines in liquidity and returns for margin-eligible stocks, but also that common margin traders and brokers serve as an important channel through which spillovers can occur. It is worthwhile to discuss external validity and the extent to which these results can generalize outside of the Indian market setting. While difficult to fully rule out these concerns, we do not believe that they should be central to the overall interpretation. This is because our finding that margin-eligible stocks experience substantial increases in commonality during severe downturns is consistent with the same underlying mechanisms that are relevant to developed markets. In particular, large price declines increase traders' leverage and tighten their constraints, which can lead to deleveraging and liquidity declines in all of the stocks in which traders tend to use leverage. This mechanism is at work in both developed and developing markets.

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 by theoretical studies such as Brunnermeier and Pedersen (2009), we find that, while leverage does not have an impact during normal times, it substantially increases commonality in liquidity during crises period. Trader leverage has a similar impact on return comovement.

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 both liquidity and stock returns. The regulatory setting helps us identify the stocks in which crisis-period trading is most likely to induce deleveraging, and importantly, the regression discontinuity design allows us isolate the impact of develeraging from confounding effects – an empirical challenge that has been faced by previous studies. Our findings should help policy-makers and researchers who are interested in identifying effective tools to help prevent the peaks in 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 the equal-weighted average commonality of all Group 1 and Group 2 National Stock Exchange (NSE) stocks during April 2004– December 2012. Commonality is captured by the R^2 of regressions of stock level liquidity innovations on market liquidity innovations. The figure also shows the Indian stock market returns. 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 1a

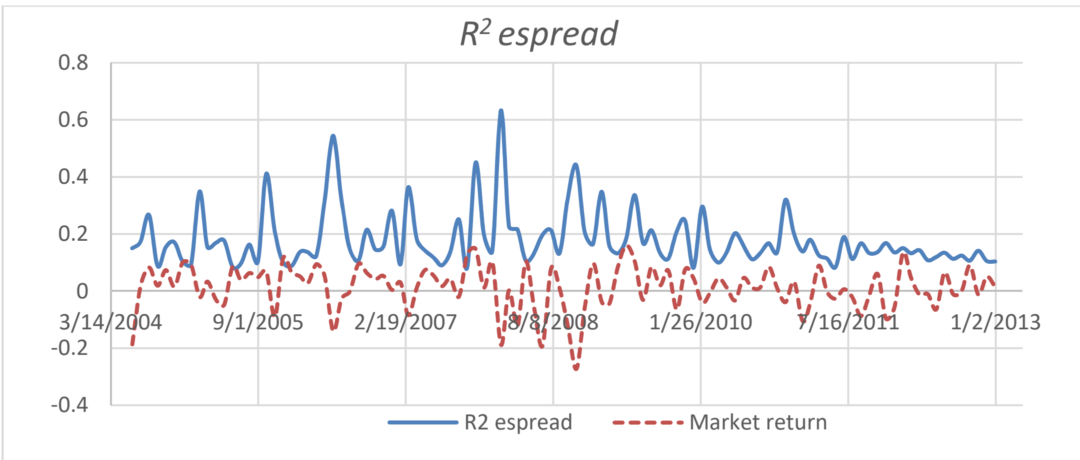


Figure 1b

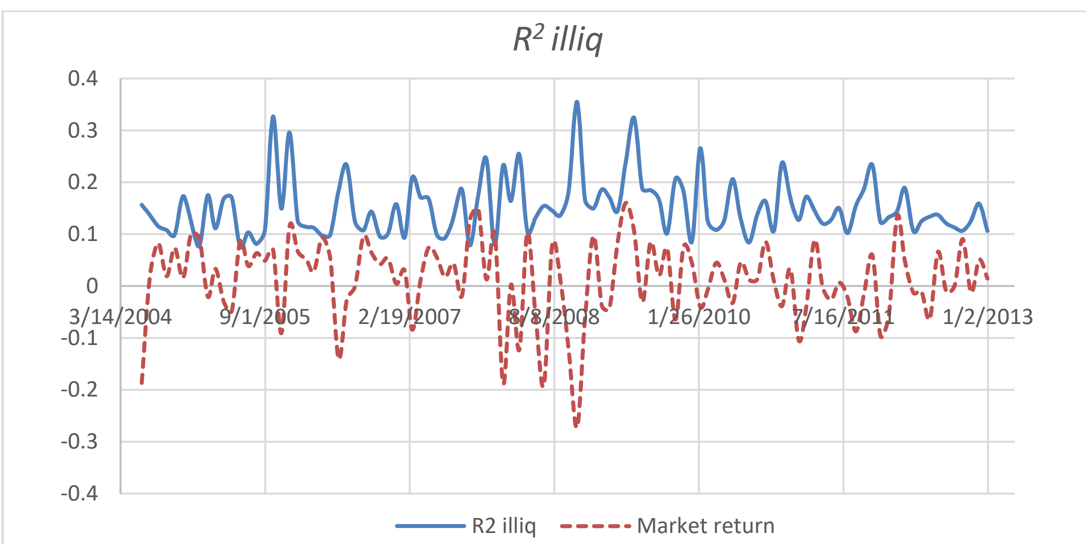


Figure 2: Time Series of Commonality in the Local Sample of Group 1 and Group 2 Stocks

The figures show the time series of the equal-weighted average commonality in the local samples of Group 1 and Group 2 stocks during April 2004– December 2012. Group 1 stocks are eligible for margin trading and Group 2 stocks are ineligible. Commonality is captured by the R^2 of regressions of stock level liquidity innovations on market liquidity innovations. 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. 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. The local samples are defined based on CCT bandwidths, which are 0.18% and 0.20% for R^2*espread* and R^2*illiq,* respectively.

Figure 2a

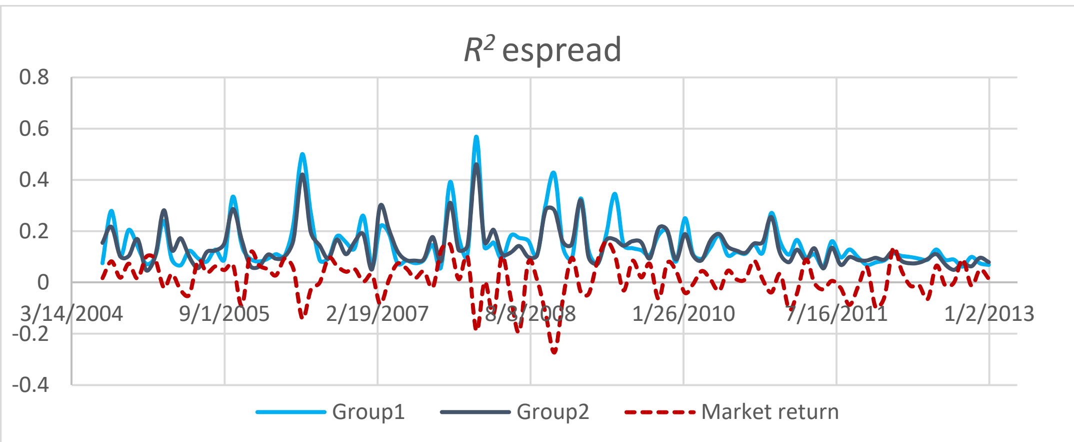


Figure 2b

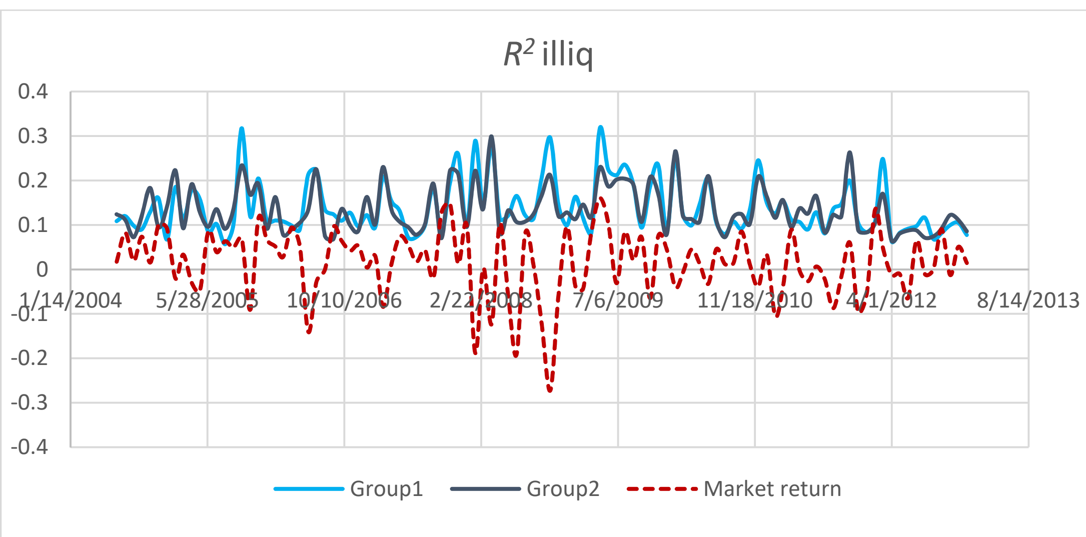


Figure 3: Impact Cost and Commonality

The figures plot the average commonality in liquidity during month *t* as a function of impact cost over the previous six months (which determines month *t* eligibility). In Figure 3a, commonality in liquidity is defined as R^2*espread*, the R^2 from a regression of daily stock level effective spread innovations on market innovations in effective spread. In Figure 3b, commonality is defined as R^2*illiq,* the R^2 from a regression of daily stock level innovations in the Amihud (2002) illiquidity measure on market innovations. Stocks are divided into ten equally sized bins (the X axis) on each side of the eligibility cutoff of 1%. The figures show the average commonality measure within each bin. The number of bins is chosen based on the F-test procedures described in Lee and Lemieux (2010). Margin eligible stocks are all those stocks with impact costs that are less than or equal to 1%, and are located to the left of the vertical line. "Severe downturns" refers to months in which market returns are below the 10th decile returns.

Figure 3a

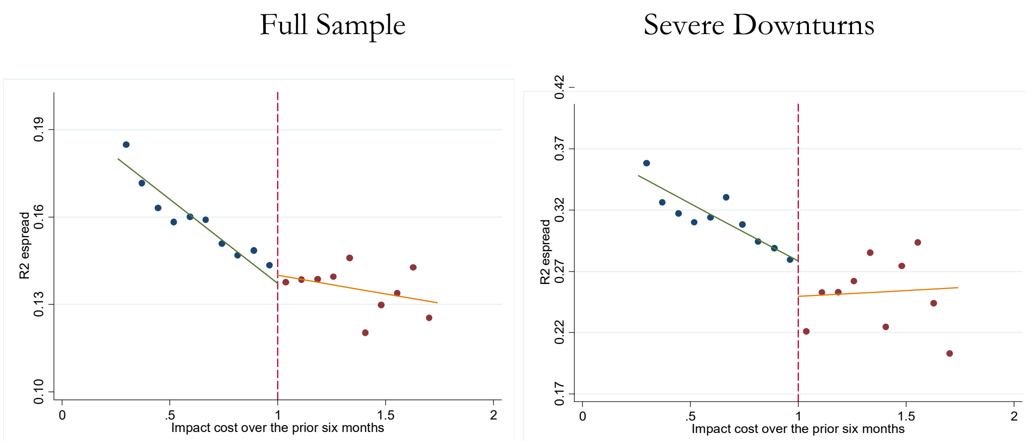


Figure 3b

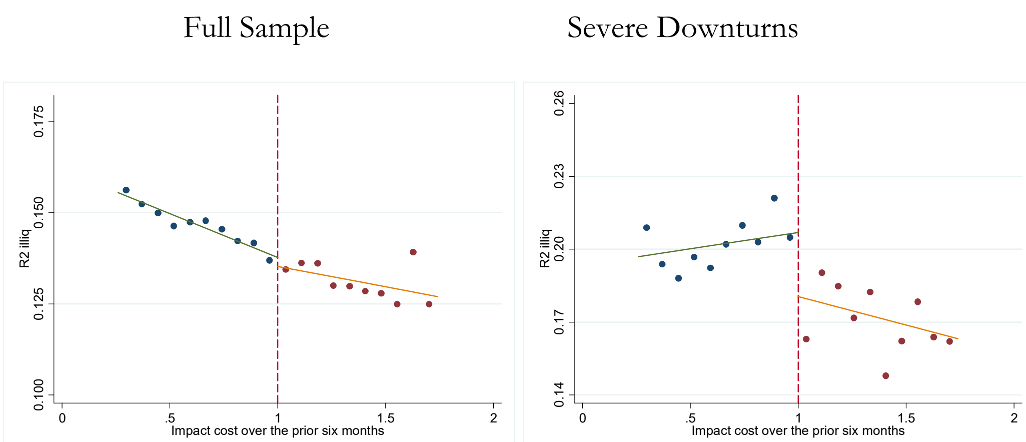


Table 1: Descriptive Statistics

This table provides summary statistics of market liquidity and stock returns, as well as stock-level commonality in liquidity and stock returns. The sample period is from April 2004 through December 2012. Summary statistics are reported for the full sample, and for the subsamples defined according to market conditions. "Severe downturns" refers to months in which market returns (i.e., CNX 500 returns) are below the 10th decile returns. "Outside of downturns" refers to all months outside of severe downturns. Panel A provides summary statistics for market returns and aggregate market liquidity levels, defined as the equal-weighted average effective spread or Amihud (2002) illiquidity ratio of all Group 1 and Group 2 stocks (*Mkt ret*, *Mkt epread* and *Mkt illiq*, respectively). Panels B, C and D provide summary statistics of commonality in liquidity and returns for the local samples of Group 1 and Group 2 stocks, where the local samples are defined based on CCT bandwidths. In Panel B, commonality in liquidity is measured with R^2. R^2*espread* is the R^2 from a regression of daily stock level 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*. CCT bandwidths for R^2*espread* and R^2*illiq* are 0.18% and 0.20%, respectively. Panel C shows descriptive statistics of commonality in liquidity measured with liquidity correlations, *Corr_espread and Corr_illiq*. These are defined as the month *t* correlation of stock *i*'s daily effective spreads and Amihud illiquidity, respectively, with average market liquidity. CCT bandwidths for *Corr_espread* and *Corr_Illiq* are 0.18% and 0.17%, respectively. Panel D shows descriptive statistics for commonality in returns. R^2*returns* is the R^2 from a regression of daily stock returns on market (CNX 500) returns during month *t*. CCT bandwidth for the commonality in returns measure is 0.16%. All variables are monthly.

Panel A: Market Returns and Market Liquidity Levels

	Variable	Mean	Median	P25	P75	Std Dev
Full sample	*Mkt ret*	0.0145	0.0166	-0.0287	0.0679	0.0830
	Mkt espread	0.7441	0.6877	0.4943	0.8637	0.3142
	Mkt illiq	3.5260	2.9380	1.6510	5.0657	2.2404
Severe downturns	*Mrkt ret*	-0.1515	-0.1317	-0.1878	-0.1045	0.0572
	Mkt espread	1.0577	1.0097	0.7170	1.0655	0.4125
	Mkt illiq	4.6150	4.8068	2.3752	6.0916	2.5092
Outside of downturns	*Mrkt ret*	0.0322	0.0290	-0.0123	0.0737	0.0636
	Mkt espread	0.7107	0.6617	0.4776	0.8499	0.2849
	Mkt illiq	3.4101	2.6809	1.6276	4.8626	2.1928

Panel B: Commonality in Liquidity – R^2

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
Severe 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
Severe downturns	R^2*espread*	0.2392	0.1383	0.0296	0.3581	0.2618
	R^2*illiq*	0.1782	0.1166	0.0326	0.2871	0.1784
Outside of downturns	R^2*espread*	0.1284	0.0735	0.0162	0.1940	0.1450
	R^2*illiq*	0.1307	0.0747	0.0189	0.1871	0.1525

Panel C: Commonality in Liquidity – *Corr*

Group 1	Variable	Mean	Median	P25	P75	Std Dev
Full sample	*Corr espread*	0.2558	0.2639	0.0659	0.4473	0.2842
	Corr illiq	0.2459	0.2597	0.0520	0.4490	0.2808
Severe downturns	*Corr espread*	0.4224	0.4256	0.2106	0.7015	0.3397
	Corr illiq	0.3711	0.3979	0.1959	0.5670	0.2727
Outside of downturns	*Corr espread*	0.2387	0.2502	0.0576	0.4299	0.2723
	Corr illiq	0.2322	0.2469	0.0385	0.4355	0.2783
Group 2	Variable	Mean	Median	P25	P75	Std Dev
Full sample	*Corr espread*	0.2453	0.2536	0.0506	0.4456	0.2804
	Corr illiq	0.2374	0.2512	0.0500	0.4335	0.2802
Severe downturns	*Corr espread*	0.3641	0.3428	0.1290	0.5915	0.3271
	Corr illiq	0.3185	0.3392	0.1361	0.5406	0.2806
Outside of downturns	*Corr espread*	0.2330	0.2447	0.0432	0.4314	0.2723
	Corr illiq	0.2283	0.2403	0.0439	0.4211	0.2787

Panel D: Commonality in Returns

Group 1	Variable	Mean	Median	P25	P75	Std Dev
Full sample	R^2*returns*	0.2622	0.2205	0.0807	0.4030	0.2093
Severe downturns	R^2*returns*	0.4422	0.4613	0.2729	0.6155	0.2288
Outside of downturns	R^2*returns*	0.2424	0.2033	0.0726	0.3726	0.1973
Group 2	Variable	Mean	Median	P25	P75	Std Dev
Full sample	R^2*returns*	0.2519	0.2133	0.0818	0.3819	0.2017
Severe downturns	R^2*returns*	0.3822	0.3737	0.1865	0.5694	0.2369
Outside of downturns	R^2*returns*	0.2379	0.2005	0.0758	0.3638	0.1924

Table 2: Does Trader Leverage Impact Commonality in Liquidity?

This table presents the baseline results of the analysis of the impact of margin trading eligibility on commonality in liquidity. 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*. 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*. 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 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%), and we also interact the *Group 1* dummy with *severedownturn*. Columns (3) and (6) are identical to Columns (2) and (4), but we replace the direct effect of *severedownturn* with month-year fixed effects. Bootstrapped standard errors are in parentheses. *** 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*espread*	(4) R^2*illiq*	(5) R^2*illiq*	(6) R^2*illiq*
Group 1	0.0085**	0.0027	0.0051	0.0051*	0.0006	0.0025
	(0.0034)	(0.0039)	(0.0036)	(0.0030)	(0.0031)	(0.0032)
Group 1*severedownturn		0.0516**	0.0358**		0.0307**	0.0250**
		(0.0217)	(0.0162)		(0.0124)	(0.0119)
severedownturn		0.1108***			0.0475***	
		(0.0158)			(0.0088)	
Constant	0.6216***	0.1284***	0.6054***	0.3104***	0.1307***	0.2990***
	(0.0562)	(0.0029)	(0.0547)	(0.0233)	(0.0024)	(0.0247)
Observations	7,291	7,291	7,291	9,609	9,609	9,609
R-squared	0.263	0.060	0.264	0.126	0.017	0.127
Month-Year FE	Yes	No	Yes	Yes	No	Yes

Table 3: **Extended Regressions**

This table presents results of the analysis of the impact of margin trading eligibility on commonality in liquidity. As in Table 2, 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 stock is eligible for margin trading during month *t*; *severedownturn*, a dummy variable equal to 1 if market returns during month *t* are in the lowest decile in our sample; and a vector of control variables. The control variables include one-month lagged: standard deviation of stock returns (*std_ret*), stock returns (*mret*), rupee volume (l*ogvolume*), 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 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. Bootstrapped standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)
VARIABLES	R^2*espread*	R^2*illiq*
Group1	-0.0007	0.0008
	(0.0041)	(0.0036)
Group 1*severedownturn	0.0543***	0.0350**
	(0.0207)	(0.0148)
Severedownturn	0.0824***	0.0390***
	(0.0149)	(0.0110)
Lag std_dret	0.4098*	0.7540***
	(0.2237)	(0.2003)
Lag mret	0.0319**	0.0190
	(0.0159)	(0.0120)
Lag logvolume	0.0170***	0.0144***
	(0.0023)	(0.0021)
Lag logmcap	-0.0130***	-0.0199***
	(0.0021)	(0.0018)
Lag depvar	0.0526***	0.0595***
	(0.0128)	(0.0125)
Constant	0.1407***	0.3212***
	(0.0512)	(0.0396)
Observations	5,859	7,533
R-squared	0.069	0.055

Table 4: **Alternative Commonality Measure (Average Liquidity Correlations)**

This table presents results of the analysis of the impact of margin trading eligibility on alternative commonality in liquidity measures, *Corr_espread* and *Corr_illiq*. These measures are defined as the month *t* correlation of stock *i*'s daily effective spreads and Amihud illiquidity ratio, respectively, with average market liquidity. The regressions include local stocks of Groups 1 and 2 with impact costs close to the cutoff of 1% (based on CCT bandwidths of 0.18% for the *Corr_espread* regressions and 0.17% for *Corr_illiq)*. The explanatory variables and specification are identical to Table 3. Bootstrapped standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)
VARIABLES	*Corr_espread*	*Corr_illiq*
Group1	0.0042	0.0018
	(0.0072)	(0.0074)
Group 1*severedownturn	0.0616**	0.0486**
	(0.0296)	(0.0229)
Severedownturn	0.1008***	0.0727***
	(0.0231)	(0.0185)
Lag std_dret	1.6903***	1.3309***
	(0.3808)	(0.3886)
Lag mret	0.0219	-0.0016
	(0.0236)	(0.0213)
Lag logvolume	0.0184***	0.0259***
	(0.0041)	(0.0037)
Lag logmcap	-0.0228***	-0.0410***
	(0.0039)	(0.0036)
Lag depvar	0.0773***	0.0773***
	(0.0133)	(0.0127)
Constant	0.3909***	0.6902***
	(0.0891)	(0.0758)
Observations	5,859	6,333
R-squared	0.051	0.061

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. In Panel A, 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 consists of 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. Panel B presents results of the analysis of the impact of margin trading eligibility on commonality in liquidity and is identical to Table 3 except that *severedownturn* is replaced with *market_rally*, a dummy variable equal to 1 in months in which market returns are *higher* than 90th percentile returns. Bootstrapped standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

Panel A: Shifting the Margin Eligibility Cutoff

	(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)	(0.003)	(0.004)	(0.004)
Placebo Group1*severedownturn	0.015	-0.010	-0.039	-0.016
	(0.021)	(0.013)	(0.026)	(0.016)
Severedownturn	0.135***	0.073***	0.108***	0.054***
	(0.015)	(0.010)	(0.017)	(0.011)
Lag std_dret	0.715***	0.899***	0.515*	0.767***
	(0.220)	(0.173)	(0.297)	(0.226)
Lag mret	0.055***	-0.003	0.037**	0.039***
	(0.014)	(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)	(0.020)	(0.002)
Lag depvar	0.049***	0.078***	0.045***	0.083***
	(0.012)	(0.011)	(0.015)	(0.016)
Constant	0.127***	0.361***	0.144***	0.237***
	(0.046)	(0.038)	(0.054)	(0.043)
Observations	7,714	10,226	4,423	5,545
R-squared	0.091	0.068	0.064	0.048

Panel B: Extreme Market Increases

VARIABLES	(1) $R^2espread$	(2) $R^2espread$	(3) R^2illiq	(4) R^2illiq
Group1	0.0080*	0.0050	0.0029	0.0051
	(0.0045)	(0.0045)	(0.0037)	(0.0038)
Group 1*market_rally	-0.0033	-0.0054	0.0068	-0.0056
	(0.0112)	(0.0144)	(0.0085)	(0.0097)
market_rally	-0.0139	-0.0040	-0.0169**	-0.0138*
	(0.0085)	(0.0101)	(0.0067)	(0.0074)
Lag std_dret		0.5531**		0.8651***
		(0.2482)		(0.1819)
Lag mret		0.0312**		0.0186
		(0.0154)		(0.0134)
Lag logvolume		0.0156***		0.0134***
		(0.0023)		(0.0021)
Lag logmcap		-0.0119***		-0.0189***
		(0.0022)		(0.0018)
Lag depvar		0.0561***		0.0639***
		(0.0138)		(0.0124)
Constant	0.1406***	0.1410***	0.1377***	0.3179***
	(0.0032)	(0.0537)	(0.0031)	(0.0436)
Observations	7,291	5,859	9,609	7,533
R-squared	0.001	0.028	0.001	0.043

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. In columns 1 through 4, the dependent variable is R^2*espread* during month *t*, where eligibility is effective as of the beginning of month *t*. In columns 5 through 8, the dependent variable is R^2*espread* during month *t*. The local samples and specifications are identical to those in Table 3 except that we add dummy variables for four alternative channels, denoted *alt_channel* in the table. The definitions for *alt_channel* are as follows: *Index* equals 1 if the stock is a member of the CNX 500; *Foreign* is the percentage foreign ownership*;* *Inst* is the percentage institutional ownership; and *Deriv* is a dummy variable set equal to 1 if futures and options trade on the stock. Control variables from Table 3 are included by not reported in the table. Bootstrapped standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) *Index* R^2*espread*	(2) *Foreign* R^2*espread*	(3) *Inst* R^2*espread*	(4) *Deriv* R^2*espread*	(5) *Index* R^2 *illiq*	(6) *Foreign* R^2 *illiq*	(7) *Inst* R^2 *illiq*	(8) *Deriv* R^2 *illiq*
Group 1	0.002	0.004	-0.000	-0.002	0.002	0.002	0.005	0.001
	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Group 1*severedownturn	0.042**	0.063**	0.062*	0.049**	0.026*	0.036**	0.041**	0.031**
	(0.021)	(0.025)	(0.033)	(0.023)	(0.015)	(0.016)	(0.020)	(0.014)
Group 1*severedownturn*alt_channel	0.081	-0.055	-0.044	0.145	0.056*	-0.010	-0.023	0.126*
	(0.061)	(0.058)	(0.119)	(0.089)	(0.034)	(0.029)	(0.069)	(0.066)
Group 1 *alt_channel	-0.020*	-0.030***	-0.000	0.037	-0.008	-0.003	-0.025	-0.008
	(0.011)	(0.010)	(0.025)	(0.051)	(0.009)	(0.009)	(0.020)	(0.028)
Severedownturn*alt_channel	0.000	0.023	0.033	-	-0.009	-0.008	-0.029	-
	(0.048)	(0.044)	(0.093)		(0.025)	(0.023)	(0.052)	
alt_channel	0.017*	0.020**	0.076***	0.069*	0.007	0.004	0.044***	0.043*
	(0.010)	(0.009)	(0.024)	(0.040)	(0.008)	(0.007)	(0.015)	(0.023)
Severedownturn	0.082***	0.077***	0.019	0.083***	0.040***	0.040***	-0.002	0.039***
	(0.016)	(0.018)	(0.017)	(0.016)	(0.012)	(0.012)	(0.016)	(0.010)
Constant	0.166***	0.148***	0.164***	0.179***	0.333***	0.329***	0.301***	0.336***
	(0.048)	(0.053)	(0.056)	(0.051)	(0.045)	(0.045)	(0.048)	(0.044)
Observations	5,859	5,677	5,677	5,859	7,533	7,320	7,320	7,533
R-squared	0.071	0.070	0.068	0.076	0.056	0.055	0.056	0.057
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Does Trader Leverage Impact Commonality in Returns?

Panel A presents results of the analysis of the impact of margin trading eligibility on commonality in stock returns. The specifications are identical to those in Tables 2 and 3 except that we replace the dependent variables with *R^2return*, defined as the R^2 from a regression of the daily returns of stock *i* on market 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 bandwidth of 0.16%*)*. All explanatory variables are defined in Table 3. Bootstrapped standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level. In Panel B, we independently sort stocks into 5 groups (in ascending order) based on the stock's commonality in liquidity (defined as *R^2espread*) and commonality in returns. The panel reports the average rank of *R^2return* for each group of stocks, ranked on *R^2espread*.

Panel A: RDD Regressions

VARIABLES	(1) *R^2return*	(2) *R^2return*	(3) *R^2return*	(4) *R^2return*
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)		(0.015)
Lag std_dret			1.535***	1.737***
			(0.323)	(0.288)
Lag mret			-0.064***	-0.045***
			(0.017)	(0.016)
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***
			(0.014)	(0.014)
Constant	0.670***	0.238***	0.585***	0.501***
	(0.023)	(0.004)	(0.062)	(0.058)
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

Panel B. Average Ranks of Commonality in Returns for Stocks Ranked on Commonality in Liquidity

		Ranks Based on Commonality in Liquidity				
Group 1	Variable	1	2	3	4	5
Severe downturns	*Rank R^2returns*	2.0435	2.6329	2.6923	3.4177	4.3812
Outside of downturns	*Rank R^2returns*	2.7266	2.9625	2.8518	3.1810	3.1845

Table 8: Correlated Margin Trading Activity and Commonality in Liquidity and Returns

This table presents results of the analysis of the relationship between correlated margin trading activity and commonality in liquidity. The dependent variables are R^2*espread*, R^2*illiq* and R^2*return* during month *t*, where eligibility is effective as of the beginning of month *t*. The local samples and specifications are identical to Columns 1 and 2 of Table 3 and Column 4 of Table 7 except that we introduce *margin corr* (defined for local Group 1 stocks), which is equal to the correlation between the daily changes in a stock's outstanding margin positions and the average daily changes in outstanding margin positions in the entire market in each month. We also interact it with *Group1* and *Group1* severedownturn*. Bootstrapped standard errors are in parentheses. *** 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*illiq*	(2) R^2*return*
Group1	0.0005	0.0018	0.0034
	(0.0042)	(0.0040)	(0.0054)
Group1* severedownturn	0.0618***	0.0380**	0.0602***
	(0.0234)	(0.0154)	(0.0199)
Group1* severedownturn * margin corr	0.1558**	0.1308***	0.1240***
	(0.0650)	(0.0400)	(0.0412)
Group1 * margin corr	0.0023	-0.0002	-0.0235**
	(0.0100)	(0.0089)	(0.0119)
Severedownturn	0.0824***	0.0389***	0.1178***
	(0.0158)	(0.0104)	(0.0140)
Lag std_dret	0.2678	0.7290***	1.5437***
	(0.2669)	(0.1924)	(0.2858)
Lag mret	0.0312*	0.0204	-0.0457***
	(0.0159)	(0.0132)	(0.0163)
Lag logvolume	0.0179***	0.0146***	0.0184***
	(0.0025)	(0.0022)	(0.0027)
Lag logmcap	-0.0123***	-0.0192***	-0.0273***
	(0.0026)	(0.0020)	(0.0028)
Lag depvar	0.0505***	0.0603***	0.1974***
	(0.0143)	(0.0122)	(0.0144)
Constant	0.1170**	0.3035***	0.4697***
	(0.0564)	(0.0449)	(0.0631)
Observations	5,403	6,941	5,476
R-squared	0.073	0.058	0.155

Table 9: Within-Group Pairwise Correlations in Stock Liquidity and Returns

This table presents results of the analysis of commonality in liquidity and returns using pairwise correlations. For each local stock, defined as those stocks with impact costs between 0.8% and 1.2%, we calculate the pairwise correlation of the stock's daily liquidity with daily stock liquidity of all other Group 1 and Group 2 stocks in a given month. We do the same for returns. *Corr_espread* is the monthly pairwise correlation in *spread; Corr_illiq* is the monthly pairwise correlation in *illiq*; and *Corr_return* is the monthly pairwise correlation in stock returns. Panel A analyzes the differences in pairwise correlations for different types of stock pairs. *G1G1* is a dummy variable equal to 1 if both stocks in a given pair are Group 1 members; *G2G2* is a dummy variable equal to 1 if both stocks in a given pair are Group 2 members. The baseline pair is a pair that consists of one Group 1 and one Group 2 stock. We also interact *G1G1* and *G2G2* with *severedownturn*. Bootstrapped standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)	(3)
VARIABLES	*Corr_espread*	*Corr_illiq*	*Corr_return*
G1G1	0.0310***	0.0171***	0.0277***
	(0.0004)	(0.0004)	(0.0003)
G1G1 * severedownturn	0.0591***	0.0320***	0.0254***
	(0.0016)	(0.0013)	(0.0011)
Severedownturn	0.1718***	0.0554***	0.1579***
	(0.0010)	(0.0009)	(0.0010)
G2G2	-0.0228***	-0.0144***	-0.0118***
	(0.0005)	(0.0006)	(0.0004)
G2G2 * severedownturn	-0.0270***	-0.0166***	-0.0161***
	(0.0019)	(0.0020)	(0.0014)
Constant	0.1216***	0.0781***	0.1737***
	(0.0002)	(0.0003)	(0.0002)
Observations	2,938,397	3,110,791	3,580,995
R-squared	0.036	0.006	0.036

Table 10: Stock Connections and Pairwise Correlations in Stock Liquidity and Returns

This table examines the relationship between pairwise correlations and stocks' connections through margin trading. Using the trader-level position data, which is available for the 2007 to 2010 subperiod, we construct measures of common margin traders and common brokers. *Common traders* is the total value of the margin trading positions held by all common traders of the two stocks, scaled by the total market capitalization of the two stocks. *Common broker* is the total value of the margin trading positions lent out by all common brokers of the two stocks, scaled by the total market capitalization of the two stocks. Both *Common traders* and *Common broker* are normalized and interacted with *severedownturn*. Since *Common traders* and *Common broker* can be defined for margin eligible stocks, the regressions use only local Group 1 stocks (impact costs between 0.8 % and 1%). Bootstrapped standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

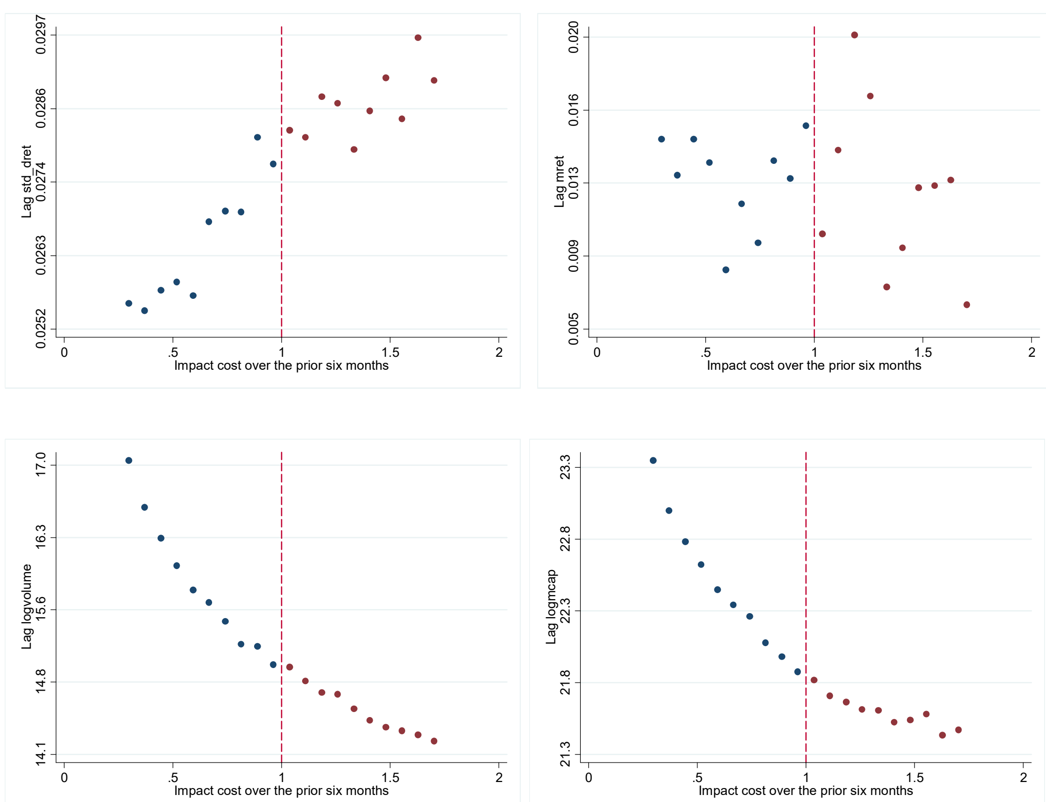
	Common Traders			Common Broker		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Corr_espread*	*Corr_illiq*	*Corr_return*	*Corr_espread*	*Corr_illiq*	*Corr_return*
Common traders	0.0025***	0.0036***	0.0029***			
	(0.0007)	(0.0009)	(0.0006)			
Common traders* severedownturn	0.0153***	0.0148***	0.0165***			
	(0.0049)	(0.0043)	(0.0039)			
Severedownturn	0.3246***	0.1506***	0.2406***	0.3172***	0.1406***	0.2381***
	(0.0020)	(0.0017)	(0.0011)	(0.0021)	(0.0017)	(0.0012)
Common broker				0.0199***	0.0197***	0.0191***
				(0.0007)	(0.0005)	(0.0005)
Common broker * severedownturn				0.0383***	0.0276***	0.0339***
				(0.0024)	(0.0017)	(0.0050)
Constant	0.1872***	0.1114***	0.2219***	0.1869***	0.1102***	0.2239***
	(0.0006)	(0.0005)	(0.0004)	(0.0006)	(0.0005)	(0.0004)
Observations	330,564	415,508	388,323	304,843	383,686	388,323
R-squared	0.069	0.024	0.086	0.072	0.030	0.091

Internet Appendix to Systematic Liquidity and Leverage

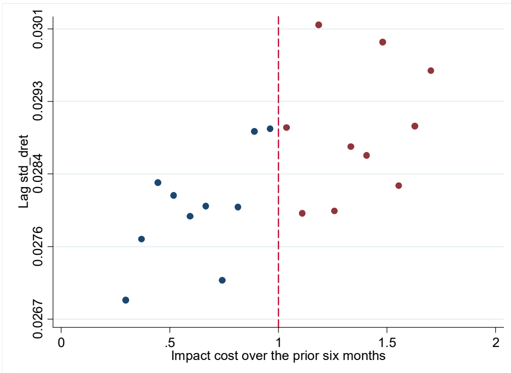
Figure IA.1: Impact Cost and Covariates

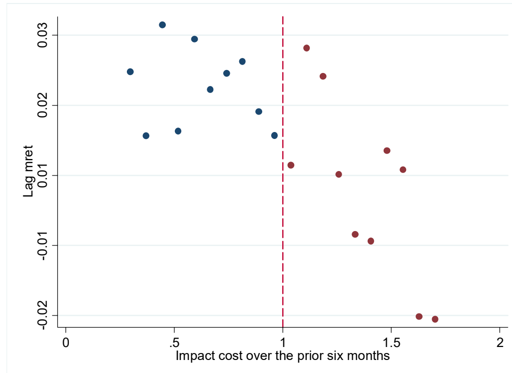
The figure plots the covariates in Table 3 during month *t* as a function of impact cost over the previous six months (which determines month *t* eligibility). The covariates are one-month lagged: standard deviation of stock returns (*std_ret*), stock returns (*mret*), rupee volume (*logvolume*), and equity market capitalization (*logmcap*). *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 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. Stocks are divided into ten equally sized bins (the X axis) on each side of the eligibility cutoff of 1%. The figure shows the average value of the the covariate within each bin. The number of bins is chosen based on the F-test procedures described in Lee and Lemieux (2010). Margin eligible stocks are all those stocks with impact costs that are less than or equal to 1%, which correspond to bins 1 through 10, and are located to the left of the vertical line. Stocks in bins 11–20 are ineligible for margin trading during period *t* and are locaed to the right of the vertical dotted line. Panel A shows plots for the full sample period. Panel B shows plots for severe downturns (months in which market returns are below the 10th decile returns).

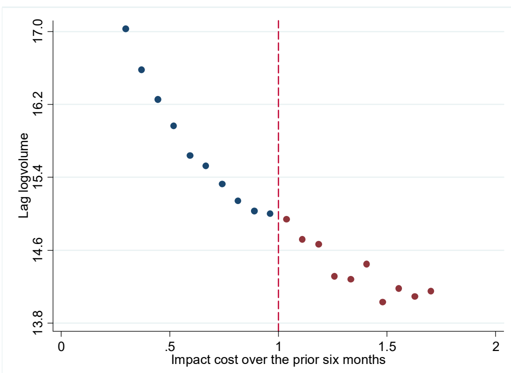
Panel A. Full Sample



Panel B. Severe Downturns







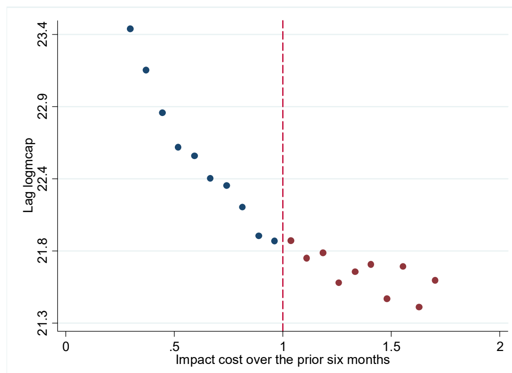
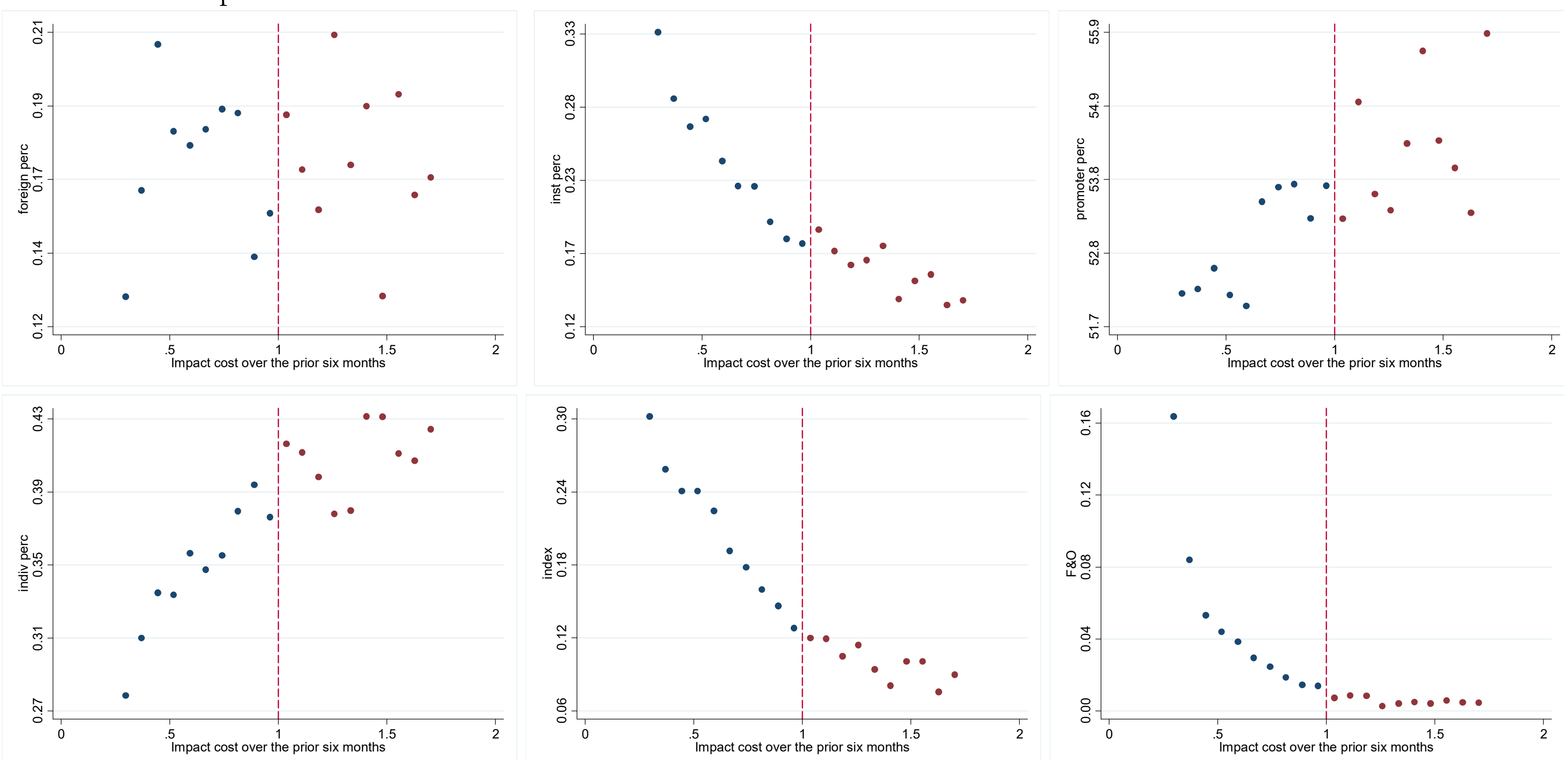


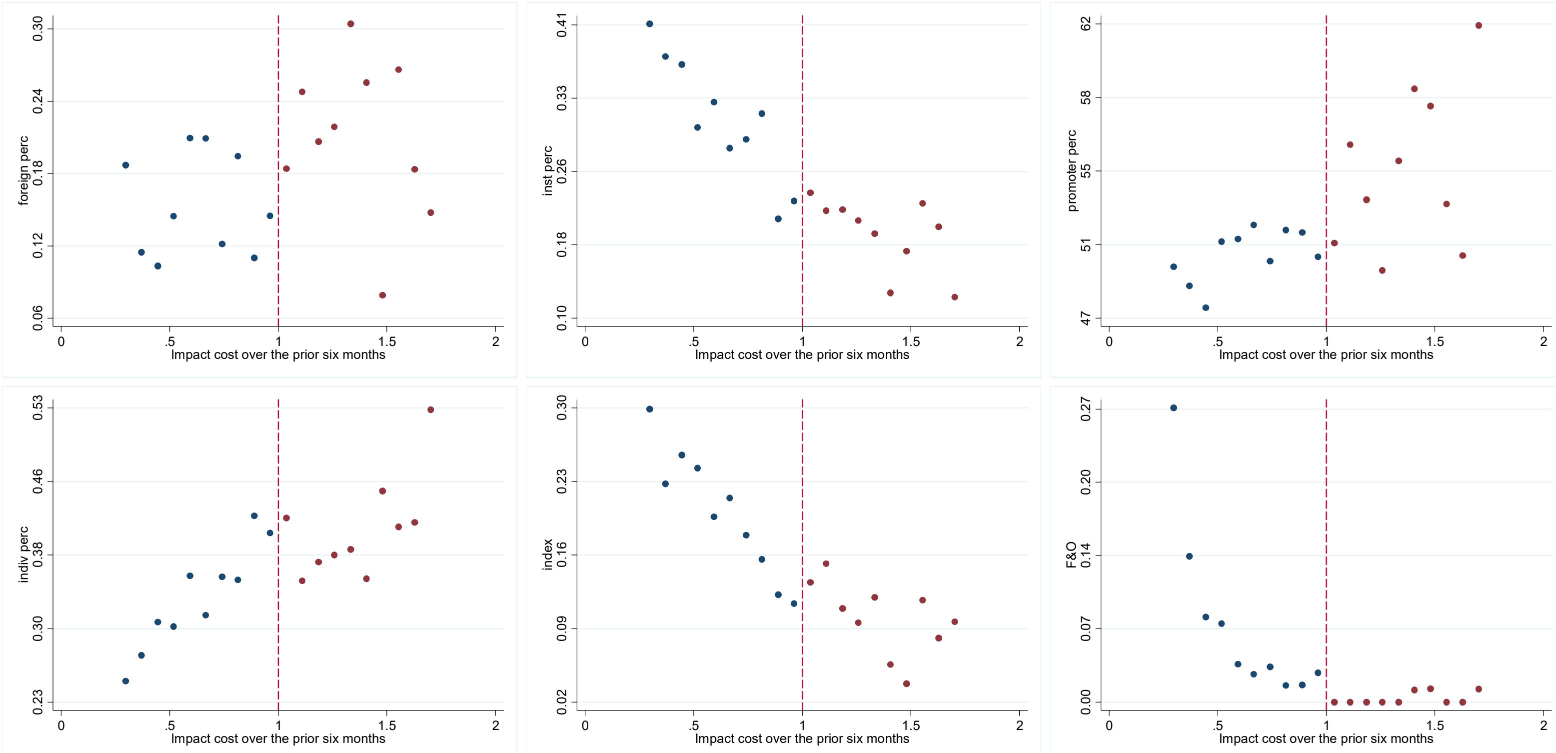
Figure IA.2: Impact Cost and Alternative Channels

The figure plots the alternative channels from Table 6 as a function of impact cost over the previous six months (which determines month *t* eligibility). The alternative channels are: *foreign perc*, the percentage foreign ownership; *inst perc*, the percentage institutional ownership; *promoter perc*, the percentage promoter/insider ownership (in percent); *indiv perc*, the percentage ownership of individuals; *index,* a dummy equal to 1 if the stock is a member of the CNX 500; and *F&O,* a dummy equal to 1 if the stock is eligible for futures and options trading. Stocks are divided into ten equally sized bins (the X axis) on each side of the eligibility cutoff of 1%. The figure shows the average value of the alternative channel within each bin. The number of bins is chosen based on the F-test procedures described in Lee and Lemieux (2010). Margin eligible stocks are all those stocks with impact costs that are less than or equal to 1%, which correspond to bins 1 through 10, and are located to the left of the vertical line. Stocks in bins 11–20 are ineligible for margin trading during period *t* and are locaed to the right of the vertical dotted line. Panel A shows plots for the full sample period. Panel B shows plots for severe downturns (months in which market returns are below the 10th decile returns).

Panel A. Full Sample



Panel B. Severe Downturns



Appendix Table A.1 Commonality in Volume

This table presents results of the analysis of the impact of margin trading eligibility on commonality in trading volume. The regressions are identical to those in Tables 2 and Table 3, except that we replace the dependent variables with R^2*volume*, the R^2 from a regression of daily volume innovations on market volume 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%). The explanatory variables are defined in Tables 2 and 3. Bootstrapped standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(1)	(2)
VARIABLES	R^2*volume*	R^2*volume*	R^2*volume*
Group1	-0.005**	-0.006*	-0.005
	(0.003)	(0.003)	(0.003)
Group 1*severedownturn		0.008	0.001
		(0.010)	(0.012)
Severedownturn		0.020**	0.018*
		(0.008)	(0.010)
Lag std_dret			1.169***
			(0.201)
Lag mret			-0.000
			(0.011)
Lag logvolume			-0.003
			(0.002)
Lag logmcap			-0.003*
			(0.002)
Lag depvar			0.025**
			(0.012)
Constant	0.117***	0.106***	0.182***
	(0.014)	(0.003)	(0.038)
Observations	7,635	7,635	5,954
R-squared	0.198	0.004	0.014
Month-Year FE	Yes	No	No

Appendix Table A.2: 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 that in Table 3 of the main text. 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 explanatory variables are defined in Table 3 in the main text. Columns (1) through (6) increase and decrease the CCT bandwidths by increments of 0.02. Bootstrapped standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

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

VARIABLES	(1) -0.06	(2) -0.04	(3) -0.02	(4) +0.02	(5) +0.04	(6) +0.06
Group 1	0.001	-0.001	0.001	-0.001	0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Group 1*severedownturn	0.042*	0.049**	0.061***	0.054**	0.045**	0.043**
	(0.024)	(0.024)	(0.023)	(0.022)	(0.021)	(0.019)
severedownturn	0.084***	0.078***	0.073***	0.082***	0.087***	0.091***
	(0.019)	(0.017)	(0.016)	(0.016)	(0.015)	(0.014)
Lag std_dret	0.326	0.270	0.393*	0.410*	0.371	0.485**
	(0.282)	(0.264)	(0.230)	(0.231)	(0.229)	(0.203)
Lag mret	0.037**	0.036**	0.034**	0.032**	0.031**	0.032**
	(0.017)	(0.016)	(0.016)	(0.015)	(0.014)	(0.014)
Lag logvolume	0.018***	0.018***	0.017***	0.017***	0.018***	0.017***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lag logmcap	-0.013***	-0.014***	-0.013***	-0.013***	-0.014***	-0.014***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lag depvar	0.066***	0.071***	0.056***	0.053***	0.050***	0.047***
	(0.017)	(0.016)	(0.014)	(0.014)	(0.013)	(0.014)
Constant	0.131**	0.147**	0.151***	0.141***	0.143***	0.144***
	(0.065)	(0.059)	(0.052)	(0.051)	(0.048)	(0.046)
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

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	-0.06	-0.04	-0.02	+0.02	+0.04	+0.06
Group 1	0.000	-0.000	0.001	0.001	0.003	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Group 1*severedownturn	0.045**	0.036**	0.034**	0.035**	0.030**	0.028**
	(0.018)	(0.015)	(0.014)	(0.015)	(0.013)	(0.012)
severedownturn	0.038***	0.040***	0.042***	0.039***	0.040***	0.040***
	(0.013)	(0.012)	(0.011)	(0.012)	(0.010)	(0.009)
Lag std_dret	0.806***	0.806***	0.727***	0.754***	0.781***	0.792***
	(0.213)	(0.214)	(0.196)	(0.188)	(0.165)	(0.170)
Lag mret	0.009	0.014	0.021*	0.019	0.012	0.018*
	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)	(0.010)
Lag logvolume	0.015***	0.015***	0.015***	0.014***	0.015***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lag logmcap	-0.018***	-0.018***	-0.019***	-0.020***	-0.019***	-0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lag depvar	0.068***	0.064***	0.060***	0.059***	0.060***	0.063***
	(0.016)	(0.015)	(0.014)	(0.013)	(0.012)	(0.012)
Constant	0.283***	0.284***	0.291***	0.321***	0.297***	0.304***
	(0.051)	(0.043)	(0.046)	(0.044)	(0.038)	(0.036)
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

Appendix Table A.3: Local Polynomial Regressions

This table presents results of analyses of the impact of margin trading eligibility on market liquidity using local polynomial regressions. Polynomial orders for each bandwidth are determined by the Akaike information criterion (AIC). We begin with the CCT bandwidth used in Table 2, and we expand it by factors of 1.25 to 1.75. Impact cost is centered around the 1% cutoff (i.e., subtract 0.01 from *Impact Cost*). Bootstrapped standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	x1.25	x1.5	x1.75	x1.25	x1.5	x1.75
VARIABLES	*R^2espread*	*R^2espread*	*R^2espread*	*R^2illiq*	*R^2illiq*	*R^2illiq*
Group1	0.0031	0.0043	0.0031	-0.0009	0.0057	0.0119
	(0.0075)	(0.0111)	(0.0134)	(0.0067)	(0.0092)	(0.0117)
Group 1*severedownturn	0.0431**	0.0462**	0.0470***	0.0297**	0.0290**	0.0219**
	(0.0190)	(0.0181)	(0.0167)	(0.0124)	(0.0115)	(0.0103)
Severedownturn	0.0908***	0.0949***	0.0997***	0.0399***	0.0470***	0.0479***
	(0.0141)	(0.0124)	(0.0128)	(0.0089)	(0.0084)	(0.0083)
Impact Cost	0.0388	0.1232	0.1072	-0.0105	0.0437	0.0576
	(0.0453)	(0.1398)	(0.2997)	(0.0343)	(0.1094)	(0.2316)
Impact Cost*Group1	-0.0556	-0.1673	-0.1555	-0.0268	-0.0195	0.1550
	(0.0620)	(0.1733)	(0.3703)	(0.0426)	(0.1364)	(0.2751)
Impact $Cost^2$		-0.4064	-0.6822		-0.1415	-0.1832
		(0.4974)	(2.2550)		(0.3402)	(1.5139)
Impact $Cost^2$*Group1		0.3660	0.4199		0.3175	1.8382
		(0.6234)	(2.8182)		(0.4408)	(1.9083)
Impact $Cost^3$			1.5097			-0.0343
			(4.7866)			(2.7767)
Impact $Cost^3$*Group1			-2.3401			3.0665
			(5.8637)			(3.3618)
Lag std_dret	0.4802**	0.5586***	0.5303***	0.8033***	0.7015***	0.7705***
	(0.2343)	(0.1861)	(0.1832)	(0.1571)	(0.1554)	(0.1410)
Lag mret	0.0322**	0.0393***	0.0477***	0.0182	0.0140	0.0133
	(0.0136)	(0.0125)	(0.0122)	(0.0115)	(0.0102)	(0.0097)
Lag logvolume	0.0175***	0.0160***	0.0168***	0.0148***	0.0154***	0.0148***
	(0.0023)	(0.0018)	(0.0017)	(0.0018)	(0.0017)	(0.0015)
Lag logmcap	- 0.0135***	-0.0136***	-0.0144***	-0.0199***	-0.0200***	-0.0202***
	(0.0019)	(0.0017)	(0.0016)	(0.0017)	(0.0016)	(0.0014)
Lag depvar	0.0475***	0.0469***	0.0473***	0.0665***	0.0777***	0.0782***
	(0.0128)	(0.0107)	(0.0099)	(0.0107)	(0.0105)	(0.0102)
Constant	0.1388***	0.1575***	0.1645***	0.3141***	0.3024***	0.3147***
	(0.0464)	(0.0422)	(0.0396)	(0.0362)	(0.0383)	(0.0336)
Observations	7,216	8,916	10,333	9,500	11,457	13,494
R-squared	0.071	0.075	0.081	0.057	0.061	0.061

Appendix Table A.4: Ownership Structure and the Probability of Informed Trading

This table presents results of the analysis of the impact of margin trading eligibility on the ownership structure and the probability of informed trading in NSE stocks. The sample includes all stocks in Groups 1 and 2 with impact costs close to the cutoff of 1% (based on CCT bandwidths). For each stock, we calculate the percentage shares held by foreign investors, institutional investors, individual investors, and blockholders/insiders (*foreign perc*, *inst perc*, *indiv perc*, and *promoter perc*, respectively). We also calculate the probability of informed trading for each stock and month (PIN, based on Easley, Kiefer, O'Hara and Paperman (1996)). We then regress these dependent variables on the *Group 1* dummy as well as its interaction term with *severedownturn*. The other explanatory variables are defined in Table 3 of the main text. Bootstrapped standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	*foreign perc*	*inst perc*	*indiv perc*	*promoter perc*	*PIN*
Group1	-0.007	-0.001	-0.014	-0.002	-0.004
	(0.015)	(0.008)	(0.010)	(0.002)	(0.003)
Group 1*severedownturn	-0.051	0.018	0.029	-0.001	0.003
	(0.048)	(0.023)	(0.026)	(0.006)	(0.010)
Severedownturn	0.011	0.028*	-0.000	-0.014***	-0.003
	(0.039)	(0.017)	(0.020)	(0.004)	(0.007)
Lag std_dret	1.216	0.335	-0.910*	0.033	-0.488***
	(0.792)	(0.412)	(0.508)	(0.109)	(0.139)
Lag mret	0.098***	-0.023	-0.072***	0.015**	0.022*
	(0.036)	(0.021)	(0.027)	(0.006)	(0.011)
Lag logvolume	-0.056***	0.001	0.018***	-0.009***	-0.010***
	(0.008)	(0.004)	(0.005)	(0.001)	(0.001)
Lag R^2espread	0.049	0.013	-0.001	0.004	0.011***
	(0.042)	(0.021)	(0.028)	(0.006)	(0.002)
Lag R^2illiq	-0.079**	-0.068***	0.039	0.013**	
	(0.039)	(0.022)	(0.030)	(0.006)	
Lag logmcap	0.108***	0.058***	-0.092***	0.021***	
	(0.009)	(0.004)	(0.005)	(0.001)	
Lag_depvar					0.150***
					(0.020)
Constant	-1.380***	-1.099***	2.167***	-0.156***	0.088***
	(0.177)	(0.078)	(0.113)	(0.024)	(0.034)
Observations	2,490	2,490	2,490	2,478	4,985
R-squared	0.089	0.116	0.148	0.176	0.055

Appendix Table A.5: RDD Robustness Tests for Commonality in Returns

This table presents results of the RDD robustness tests for the impact of margin trading eligibility on commonality in returns. Panel A shows results the analysis using alternative bandwidths; Panel D shows the results with local polynomial regressions. The dependent variable is the average *R^2return* during month *t*, where eligibility is effective as of the beginning of month *t*. All variables are defined in Tables 1 and 3. In Panel A, the regression specification is identical to that in Column 4 of Table 7 in the main text. Columns (1) through (6) increase and decrease the CCT bandwidths by increments of 0.02. In Panel B, from Column (1) to Column (3), we expand the CCT bandwidths by factors of 1.25 to 1.75 and include impact cost polynomials as well as the interaction of impact cost polynomials with *Group 1* dummy. Impact cost is centered around the 1% cutoff (i.e., subtract 0.01 from *Impact Cost*). Bootstrapped standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Alternative Bandwidths

	(1)	(2)	(3)	(4)	(5)	(6)
	-0.06	-0.04	-0.02	+0.02	+0.04	+0.06
VARIABLES	*R^2return*	*R^2return*	*R^2return*	*R^2return*	*R^2return*	*R^2return*
Group 1	-0.006	-0.003	-0.003	-0.001	-0.001	0.001
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)
Group 1*severedownturn	0.075***	0.065***	0.071***	0.050***	0.050***	0.045***
	(0.024)	(0.021)	(0.020)	(0.017)	(0.016)	(0.017)
Severedownturn	0.110***	0.121***	0.116***	0.128***	0.125***	0.130***
	(0.017)	(0.016)	(0.016)	(0.012)	(0.012)	(0.013)
Lag std_dret	2.273***	1.932***	1.716***	1.662***	1.828***	1.915***
	(0.361)	(0.317)	(0.284)	(0.257)	(0.249)	(0.236)
Lag mret	-0.054***	-0.045***	-0.048***	-0.038**	-0.042***	-0.042***
	(0.019)	(0.017)	(0.017)	(0.015)	(0.014)	(0.014)
Lag logvolume	0.013***	0.015***	0.018***	0.019***	0.020***	0.020***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Lag logmcap	-0.025***	-0.025***	-0.028***	-0.029***	-0.030***	-0.030***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Lag depvar	0.179***	0.184***	0.195***	0.195***	0.190***	0.193***
	(0.016)	(0.016)	(0.015)	(0.013)	(0.012)	(0.012)
Constant	0.485***	0.467***	0.477***	0.489***	0.507***	0.499***
	(0.073)	(0.069)	(0.059)	(0.055)	(0.053)	(0.054)
Observations	3,709	4,455	5,213	6,737	7,537	8,306
R-squared	0.159	0.159	0.161	0.161	0.165	0.170

Panel B. Local Polynomial Regressions

VARIABLES	(1) x1.25 *R^2return*	(2) x1.5 *R^2return*	(3) x1.75 *R^2return*
Group1	-0.0047	-0.0038	-0.0102
	(0.0096)	(0.0121)	(0.0158)
Group 1*severedownturn	0.0455***	0.0417**	0.0375**
	(0.0166)	(0.0162)	(0.0147)
Severedownturn	0.1266***	0.1317***	0.1367***
	(0.0121)	(0.0120)	(0.0116)
Impact Cost	-0.0110	-0.0376	-0.2255
	(0.0651)	(0.2033)	(0.4060)
Impact Cost*Group1	-0.0177	0.0853	0.1784
	(0.0814)	(0.2548)	(0.4687)
Impact Cost^2		0.1345	1.9909
		(0.8426)	(3.3884)
Impact Cost^2*Group1		0.4109	-2.0537
		(1.0439)	(4.2772)
Impact Cost^3			-4.9933
			(8.0573)
Impact Cost^3*Group1			4.3529
			(9.4650)
Lag std_dret	1.8114***	1.9974***	1.9085***
	(0.2599)	(0.2268)	(0.2126)
Lag mret	-0.0410***	-0.0395***	-0.0407***
	(0.0154)	(0.0134)	(0.0133)
Lag logvolume	0.0199***	0.0181***	0.0185***
	(0.0025)	(0.0022)	(0.0020)
Lag logmcap	-0.0293***	-0.0294***	-0.0301***
	(0.0023)	(0.0022)	(0.0020)
Lag depvar	0.1906***	0.1882***	0.1875***
	(0.0126)	(0.0118)	(0.0108)
Constant	0.4834***	0.5101***	0.5260***
	(0.0477)	(0.0515)	(0.0491)
Observations			
R-squared	7,125	8,681	10,260
Constant	0.164	0.167	0.167