Leverage constraints and liquidity*

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ABSTRACT

Do traders' leverage constraints drive equity market liquidity? We use the unique features of the margin trading system in India to identify a causal relationship between traders' leverage constraints and a stock's market liquidity. To quantify the impact of these constraints, we employ a regression discontinuity design that exploits threshold rules that determine a stock's margin trading eligibility. We find that liquidity is higher when stocks become eligible for margin trading and that this liquidity enhancement is driven by margin traders' contrarian strategies. Consistent with downward liquidity spirals due to deleveraging, we also find that this effect reverses during crises.

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1. Introduction

How do traders' leverage constraints impact equity market liquidity? The recent financial crisis has brought increasing attention to the idea that variation in traders' ability to use leverage (i.e., the ability of traders to borrow in order to invest in risky assets) can cause sharp changes in market liquidity. In fact, the assumption that capital constraints drive market liquidity is central to several influential theoretical models (e.g., Gromb and Vayanos (2002), Garleanu and Pedersen (2007), Brunnermeier and Pedersen (2009), Geanakoplos (2010)). When traders such as hedge funds act as financial intermediaries and supply liquidity to markets, frictions related to their ability to obtain leverage can also impact their ability to supply liquidity. While this idea is theoretically appealing, in order to test its validity empirically, one would have to measure traders' leverage constraints and then isolate the variation in these constraints that is not caused by the same economic forces that drive variation in market liquidity. Achieving the latter is particularly problematic when, for example, investor selling pressures due to declines in fundamentals cause leverage constraints to bind and market liquidity to decline simultaneously. This paper exploits the unique margin trading rules in India to provide causal evidence of the impact of trader leverage on liquidity. Importantly, the analysis sheds light on the question of when (i.e., under what market conditions) trader leverage is beneficial to market quality and when it is costly.

Indian equity markets provide a particularly useful laboratory for examining the role of shocks to leverage constraints. In 2004, Indian regulators introduced a formal margin trading system that allows traders to borrow in order to finance their purchases of securities.[1] As in the United States,

[1] The 2004 regulations do not apply to short selling, which has only recently been allowed in India (for a limited number of stocks). We discuss short selling in more detail in Section 2.

under margin trading in India, investors can borrow up to 50% of the purchase price of an eligible stock. Thus, the ability to use margin financing relieves capital constraints and can be considered a positive shock to traders' ability to borrow. We exploit two useful features of the system in India: (i) only some exchange-traded stocks are eligible for margin trading, and (ii) the list of eligible stocks is revised every month and is based on a well-defined eligibility cutoff.

Margin trading eligibility is determined by the average "impact cost," which is the estimated price impact of trading a fixed order size. Impact costs are based on six-month rolling averages of order book snapshots taken at random intervals in each stock every day. Stocks with measured impact costs of less than 1% are categorized as Group 1 stocks and are eligible for margin trading. All remaining stocks are ineligible. The lists of eligible stocks are generated on a monthly basis, and we are able to observe shocks to leverage constraints at the individual stock level.

To identify the causal effect of leverage constraints on market liquidity, we employ a regression discontinuity design, in which we focus the analysis on stocks close to the eligibility cutoff (see Lee and Lemieux, 2009). We compare the liquidity of stocks that are just above and just below the cutoff. Because eligibility is revised every month, we obtain a series of staggered quasi-experiments. This provides important power for our empirical analysis. We conduct our analysis using two widely used measures of liquidity: average bid-ask spreads and the price impact of trading.

Our analysis reveals a causal effect of leverage constraints on stock market liquidity. In the data, we observe a discontinuous change in both spread and price impact measures at the margin trading eligibility cutoff. Formal tests confirm that stock market liquidity is higher when stocks become eligible for margin trading. We conduct placebo analyses in which we repeat our tests around false cutoffs. Unlike the liquidity patterns at the true cutoff, we find no evidence of discontinuous jumps in liquidity at the false eligibility thresholds. This lends further support to the causal interpretation of our findings. Importantly, the finding of liquidity enhancement due to margin trading is robust to alternative definitions of both the local neighborhood around the eligibility cutoffs as well as liquidity measures. In extended analysis, we also find no support in the data for potential alternative explanations of our findings based on stock visibility and index membership or differences in the composition of investors.

Much of the recent discussion in the literature related to the question of how leverage constraints impact markets focuses on the liquidity dry-ups that are observed during crises. Brunnermeier and Pedersen (2009) argue that the deleveraging that occurs during severe market downturns causes downward price spirals and exacerbates reductions in liquidity. To investigate this idea, we relax the restriction that the effect of Group 1 status is constant across states of the market. Once we allow the estimated coefficients to vary with market conditions, the estimated effects of margin trading on liquidity become much larger than those that we observe on average. This is due to an important sign change in the estimated coefficients: we find that the ability to trade on margin is beneficial to liquidity on average; however, it becomes harmful during severe downturns. It is typically very difficult to separate the effects of margin trading from several other effects taking place in times of market stress (such as panic selling or increased aggregate uncertainty). Our research design helps to overcome this empirical obstacle.

Given the evidence of a causal role of leverage constraints on market liquidity, we aim to uncover the mechanisms driving the basic results. One unique feature of our data is that we observe total outstanding margin positions for each stock at the end of each trading day. We use this information to analyze the patterns in margin traders' trading strategies at the daily frequency. We find that margin traders provide liquidity by following contrarian strategies. They reduce their margin positions after positive returns and increase them after negative returns. This contrarian trading behavior competes away returns to reversal strategies for margin eligible stocks. We also find that improvements in liquidity are highest when margin traders are more active. While margin traders are liquidity providers on average, we also find that this role completely reverses and they become liquidity seekers during severe market downturns. As in the liquidity analysis, the margin trading results reveal both the benefits and costs associated with trader leverage.

Our main analysis is at the stock level and exploits cross-sectional variation in leverage constraints. However, we are also interested in the market level question of whether leverage constraints contribute to aggregate patterns in liquidity. It is well known that both U.S. and global stocks exhibit significant liquidity commonality (e.g., Chordia, Roll, and Subrahmanyam (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.[2] In this paper, we examine one potential determinant of commonality: leverage constraints. We analyze stocks near the impact cost threshold and test whether the commonality in liquidity is different for stocks that are eligible for margin trading. We find that marginable stocks have increased commonality with the market in periods of severe market downturns. This evidence is consistent with the idea that large negative shocks cause widespread liquidations and drive commonality in liquidity. Thus, the average liquidity improvements due to margin trading eligibility do come with potential costs during severe downturns.

[2] Thus far, the literature has documented that commonality is higher for stocks with greater institutional ownership and in times of increased foreign capital flow (e.g. Karolyi, Lee, and Van Dijk (2012) and Kamara, Lou, and Sadka (2009)). It also increases when the market is in decline and volatile (Hameed, Kang, and Viswanathan (2010) and Karolyi, Lee, and Van Dijk (2012)). Coughenour and Saad (2004) is perhaps most related to our work. They find that liquidity commonality is higher when stocks share market makers, especially when those market makers are capital constrained. While all of these papers help shed light on important factors related to liquidity commonality, our regression discontinuity design helps us to mitigate some potential challenges in the overall interpretation and highlight the importance of the leverage channel.

Although the intricate relationships between funding constraints and asset prices have long been recognized in the literature (e.g., Kiyotaki and Moore (1997), Kyle and Xiong (2001), Gromb and Vayanos (2002), Krishnamurthy (2003)), there is a growing interest in improving our understanding of these linkages in the aftermath of the recent global financial crisis. Recent theoretical models such as Garleanu and Pedersen (2007), Brunnermeier and Pedersen (2009), and Fostel and Geanakoplos (2012) provide several new insights into the dynamics of funding constraints and the feedback mechanisms that they may trigger. Empirical tests of the impact of funding constraints have generally lagged behind theoretical advances in this area because there are significant challenges associated with (i) measuring financing constraints and (ii) isolating their causal effects.

A growing number of empirical studies have attempted to link funding constraints and market liquidity by using intuitive proxies of aggregate shocks. These include declines in market returns (Hameed, Kang, and Viswanathan (2010)); changes in monetary conditions (Jensen and Moorman (2010)); differences in the yields of on-the-run and off-the-run Treasury bonds (Fontaine and Garcia (2012)); and price deviations of U.S. Treasury bonds (Hu, Pan, and Wang (2011)). Although the results of these papers suggest that funding constraints impact market liquidity and prices, it is often difficult to identify the precise mechanism because these shocks also bring increases in panic sales and informational asymmetries, which also affect market liquidity. Comerton-Forde, Hendershott, Jones, et al. (2010) take a step towards addressing these issues. They aim to capture capital constraints by looking at specialist firms' inventory revenues.[3] They find that spreads are higher if specialist firms have realized overnight losses in the past five days, suggesting a role for capital constraints.[4] Finally, there is a related literature that focuses on hedge funds and provides useful

[3]Gissler (2014) also links liquidity shocks to the balance sheets of liquidity providers for German stocks during the interwar period.

[4] While their empirical strategy improves on identification issues relative to previous studies, it is still challenging to identify the driving force. For example, liquidity declines due to high inventory positions and

findings. Aragon and Strahan (2011) use Lehman's bankruptcy as a funding liquidity shock. Lehman's failure hampered the ability of their client hedge funds to trade their positions, leading to an increase in their failure rate. As a result, stocks held by Lehman-connected funds experienced a decrease in their liquidity. Consistent with Aragon and Strahan (2011), Franzoni and Plazzi (2013) show the role of hedge funds in liquidity provision, and highlight that hedge funds are more vulnerable to changes in aggregate market conditions than other financial institutions.

Our analysis complements these studies because new margin eligibility is easy to interpret as the relaxation of a leverage constraint, and our threshold strategy sharpens the causal interpretation. In many markets, the most important variations in leverage constraints occur during downturns, precisely when there are a number of important market-wide changes that are also affecting stock market liquidity. The monthly changes in eligibility made possible by the Indian regulatory setting produce a series of quasi-experiments over an eight-year period and allow us to address identification concerns. The regression discontinuity design using stock-level variation in margin eligibility helps overcome an important empirical obstacle in that it isolates the impact of leverage constraints and distinguishes it from confounding effects. In this paper, we also uncover the state-dependent effects of margin trading and highlight both the costs and benefits associated with leverage – to the best of our knowledge, our paper is the first to document these causal links. Our focus on the leverage channel (i.e., one specific mechanism within the broad category of funding constraints) provides specific insights into causes and implications of funding constraints. An additional benefit of our analysis is that we are able to study the margin financing activity of all traders, not just a particular type (such as a hedge fund). This is useful when a heterogeneous group of market participants contributes to liquidity provision.

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recent losses are likely to be related to specialists' business models dictating the horizon over which profits are maximized (i.e., risk management practices) or to strategic market maker behavior due to innovations in stock fundamentals.

The remainder of the paper is organized as follows. Section 2 provides a description of the margin trading system in India. Section 3 describes the data and the basic regression discontinuity design. The empirical analyses of the impact of margin trading on stock market liquidity are in Section 4. Section 5 concludes.

2. Institutional Setting

The Securities and Exchange Board of India (SEBI) regulates the margin trading system in India. The system has existed in its current form since April 2004. Prior to that, the main mechanism through which traders in India were able to borrow to purchase shares was a system called Badla. Under Badla, trade settlement was moved to a future expiration date, and these positions could be rolled from one settlement period to another.[5] One problem with Badla was that it lacked good risk management practices – for instance, there were no maintenance margins. Therefore, the practice was eventually banned since it involved "futures-style settlement without futures-style financial safeguards" (Shah and Thomas, 2000).

Crucial to our empirical approach is the fact that not all publicly traded stocks in India are eligible for margin trading. The SEBI uses two measures to determine eligibility. The first is the fraction of days that the stock has traded in the past six months. The second is the average impact cost, defined as the absolute value of the percentage change in price (from bid/offer midpoint) that would be caused by an order size of Rs.1 Lakh (100,000 rupees, or approximately $2,000). Impact costs are based on the last six months of estimated impact costs. They are rolling estimates, using four 10-minute snapshots of the order book, taken at random intervals in each stock per day. Stocks

[5] Berkman and Eleswarapu (1998) use the Badla ban to examine the change in value and trading volume in the 91 stocks that were previously eligible for Badla, and they report a decline in value and trading volume as a result of the ban.

with impact costs of less than 1% and that traded on at least 80% of the days over the past six months are categorized as Group 1 stocks. These stocks are eligible for margin trading.[6] Group 2 stocks are those that have traded on at least 80% of the days over the past six months but do not make the impact cost cutoff. All remaining stocks are classified into Group 3. Group 2 and Group 3 stocks are ineligible for margin trading (i.e., no new margin trades are allowed as of the effective date). Impact costs and the resulting group assignments are calculated on the 15th day of each month. The new groups are announced and become effective on the 1st day of the subsequent month.

Margin trading allows traders to borrow in order to purchase shares. Thus, a stock's entrance to (or exit from) Group 1 can be considered a shock to the ability of a trader to obtain leverage. For eligible stocks, the most important rules for margin trading are similar to those in the United States. Under SEBI rules, 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., after purchase, prices may fall without a margin call as long as the loan is less than 60% of the value of the stock held by the trader). Unlike in the United States, where securities other than cash can be used to provide initial collateral, the initial collateral held in margin accounts in India must be cash or a bank guarantee/deposit certificate.

Brokers who supply margin trading facilities to their clients can use their own funds to do so, or they can borrow from a preapproved list of banks. The SEBI regulations allow for substantial

[6] This is in contrast to the rules in the United States (Regulation T, issued by the Board of Governors of the Federal Reserve System). In the United States, any security registered on a national securities exchange is eligible for margin trading. Among over-the-counter (OTC) stocks, there is variation in margin eligibility; however, the guidelines for eligibility are somewhat vague: "OTC margin stock means any equity security traded over the counter that the Board has determined has the degree of national investor interest, the depth and breadth of market, the availability of information respecting the security and its issuer, and the character and permanence of the issuer to warrant being treated like an equity security traded on a national securities exchange" (Regulation T, 220.2). Importantly, while there are well-defined size and trading activity requirements, the board has sufficient discretion to add or omit stocks (Regulation T, 220.11(f)).

lending: brokers can borrow up to five times their own net worth to provide margin trading facilities. Margin trading is closely monitored. Clients can set up margin trading facilities with only one broker at a time, and brokers must keep records of and report margin trading activities. The margin position data (at the stock level) are subsequently made public on a next-day basis. These data are not available in the case of U.S. equity markets and provide an opportunity (which we exploit later in the paper) to answer questions about the implications and drivers of margin financing activity.

There is one related implication of Group 1 membership that deserves mention. In addition to determining eligibility for margin trading (in which margin loans can be maintained as long as margin requirements are met), there is also a short-run advantage associated with Group 1 membership. For non-institutional traders in India, trade settlement with the broker occurs at day $t+1$, at which time full payment is received. Collateral to cover potential losses prior to full payment (called VAR margins) is collected at the time of trade. VAR margin requirements are lower for Group 1 stocks than for Group 2 and Group 3 stocks. This means that, in addition to the longer-term leverage available to traders of Group 1 stocks through margin financing, these stocks also 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 supply of leverage, in the same direction. Margin trading rules are distinct from the other trading rules in India.[7]

Alternative ways to take leveraged positions are available in India, but they are either restricted to a small group of stocks or are costly. For example, stocks have to meet a set of requirements before being eligible for futures and options (F&O) trading. These requirements are significant and

[7] The master circular issued by the Securities and Exchange Board of India explains all trading rules. This document is publicly available at http://www.sebi.gov.in/cms/sebi_data/attachdocs/1334312676570.pdf.

are different from the margin trading requirements. The stock has to be in the top 500 stocks based on trading activity in the previous five months; the average order size required to change the stock price by one-quarter of a standard deviation of daily returns must be less than 1,000,000 Rs; there must be at least 20% free float and a value of at least Rs 100 crore. As of December 2012, we find 140 stocks that are eligible for F&O trading (whereas 620 stocks are eligible for margin trading in the same month).[8] The shorting market is very new (launched in April 2008) and it is restricted to stocks that are eligible for F&O trading.[9] Moreover, while securities are borrowed when investors sell short, short-selling does not free up capital since investors must post cash collateral equal to 100% of the value of the securities being borrowed.[10] Outside of the organized exchanges, investors can also borrow from non-banking finance companies (NBFCs), which are regulated by RBI (the central bank), and use the money to purchase any securities they wish. Doing so is similar to taking a collateralized personal loan to invest in the stock market. Because they are not regulated by the SEBI, NBFCs have more flexibility in setting lending terms than banks do (e.g., they can use more flexible collateral, such as land or other property). However, obtaining leverage from this channel also has some important disadvantages. Loans in this channel typically carry higher interest rates (conversations with market participants suggest that they can be more than twice margin loan rates) and include terms that increase the risk of the positions to the investors. For instance, NBFCs can liquidate investors' positions without a sufficiently early notice, and they do not offer the arbitration mechanisms that exchanges offer. Thus, in the case of a dispute, investors must go to the courts,

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[8] According to an NSE report, F&O trading is mostly concentrated in index products (Kohli, 2010), perhaps due to stringent restrictions.

[9] There are also some tenure restrictions on short positions. Initially, lending tenure was seven days. It was extended to thirty days in October 2008, and to twelve months in January 2010. Despite these efforts to reduce shorting constraints, trading volume in the shorting market remains very low (Suvanam and Jalan (2012)).

[10] Both F&O and shorting market seem quite restricted, and thus are unlikely to have meaningful effects in our analysis. Nevertheless, we still run a robustness check using our data on stock's eligibility in F&O trading (and thus, shorting for the period after April 2008). We show that these alternative mechanisms do not have any impact on our findings.

which can be costly and time-consuming.[11] In sum, there are some alternative ways to obtain leverage; however, these channels appear costly and restrictive. Importantly, the existence of these alternative mechanisms would go against finding significant effects in our empirical analysis.

3. Data and Methodology

3.1 Data

In this paper, we analyze stocks that trade on the National Stock Exchange of India (NSE), which is an electronic limit order book market with the highest trading activity in India. We begin with all stocks traded on the NSE from April 2004 (the month in which margin trading was introduced) through December 2012. We use daily data from the NSE in which we observe symbol, security code, closing price (in Indian Rs), high price, low price, total shares traded, and the value of shares traded. We analyze only equities (securities with the code "EQ"). The intraday transactions and quote data are from Thomson Reuters Tick History and include inside quotes and all transactions for Group 1 and Group 2 NSE stocks during our sample period. Fong, Holden and Trzcinka (2014) compare the Thomson Reuters Tick coverage, price and volume data to Datastream and intraday quote data to Bloomberg for a random selection of stocks. They find very high correlations and conclude that the Thomson Reuters Tick history is of high quality. To merge the Thomson Reuters Tick data with the other datasets, we use a map of RIC codes (Thomson unique identifier) to ISINs provided by Thomson. To ensure reliability of the matching, we remove all matches where the absolute difference between the closing price on the NSE daily files and the last transaction price

[11] Although we observe margin trading positions for each stock, these data do not provide information about the trader type. Using the ownership data from Prowess, which is similar to Compustat but covers Indian Firms, we test whether Group1 stocks are attracting a particular trader type (e.g., retail, institutional, foreign or promoter). We don't see any significant differences in ownership structure between our treatment and control stocks (Table A.3).

in the Thomson Tick data is more than 10%. We also remove corrected trades and entries with bid or ask prices equal to zero from the data and for each stock-month observation, and we require non-missing price and volume information for at least 12 trading days.

The master list of stocks and their impact costs, which determine margin trading eligibility, are from the NSE. These are monthly files that contain International Securities Identification Number (ISIN), stock symbol, impact cost measure, and NSE group assignment for each stock. The stocks eligible for margin trading are in Group 1. As described earlier, these are stocks that have traded on at least 80% of the trading days over the past six months and for which impact cost is less than 1%. The NSE also provided us with data on stocks that are eligible for F&O trading.

Margin data, which begin in April 2004, are from the SEBI daily reports. We obtained these from a local data vendor and the NSE.[12] The margin data are reported at the individual security level and include the *daily* totals of shares outstanding that were purchased with intermediary-supplied funding. Other than Hardouvelis and Peristiani (1992) and Andrade, Chang, and Seasholes (2008), we are not aware of any papers that examine actual margin positions and trading activity.[13] In our data, margin traders' end-of-day stakes in margin-eligible stocks total approximately 4.4 billion

[12] These data are made available in compliance with regulations in Section 4.10 of the SEBI Circular (3/2012): "The stock exchange/s shall disclose the scrip-wise gross outstanding in margin accounts with all brokers to the market. Such disclosure regarding margin trading done on any day shall be made available after the trading hours on the following day, through its website."

[13] There is a small body of older work examining the impact of margin requirements on equity price stability (volatility) and value (Seguin (1990); Hsieh and Miller (1990); Hardouvelis and Peristiani (1992); Seguin and Jarrell (1993); Pruitt and Tse (1996)). The aim of this early work on margin trading is to examine the policy question of whether restricting the extent to which brokers can extend credit for purchase transactions curbs speculation. All of the studies using U.S. data focus either on the years prior to 1974 (the last time margin requirements changed in the United States) or on over-the-counter stocks, where there is variation in margin eligibility. While the evidence is somewhat mixed, perhaps due to identification issues, most of these papers find that margin eligibility is not destabilizing. Unlike the earlier margin trading papers, we focus on the implications of recent theoretical work that suggests potentially important relationships between leverage constraints and market liquidity. The regulatory environment does not allow us to adequately answer these questions using U.S. data.

rupees (about $88 million) on an average day.[14] However, there is substantial time-series variation in this value. When margin trading facilities were first launched, activity was relatively low, but it reaches a level of about 5 billion rupees within a few years. We also observe substantial variation around market downturns. For instance, in early 2008, the total value of margin positions was greater than 10.5 billion rupees and it later dropped to 3.2 billion rupees in the last quarter in the aftermath of the global financial crisis.

We obtain company information from Prowess, a database of Indian firms (analogous to Compustat), 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. We exclude from our sample all stocks that have been suspended, since trading irregularities in suspended stocks are likely to contaminate our liquidity measures.[15]

We impose three additional data filters. First, we exclude stocks with extreme price levels (we use the 1% tails of the distribution). This restriction is similar to that in studies using U.S. data, which commonly focus only on stock prices above $5 and less than $999. Second, we exclude stocks with temporary ISIN identifiers, coded with the text "Dummy" in the NSE data, as this appears to be an indication of a corporate action such as bankruptcy or merger. Finally, although we do not observe corporate actions such as stock splits directly, we attempt to remove these events from our analysis by excluding stocks with percentage changes in shares outstanding that are greater than 50% in absolute value.

[14] In our data, we observe the number of shares purchased using intermediary-supplied capital (e.g., we observe 50 shares for an investor purchasing 100 shares using 50% leverage). To calculate the total value of levered positions, we assume that margin positions represent 50% of the total positions held by margin traders (50% is the minimum initial margin). Because maintenance margins are 40%, the total end-of-day amounts held by margin traders may be up to 25% larger than the values that we report.

[15] We also exclude IPOs from the analysis because the eligibility guidelines for these stocks differ from those that are applied to stocks that are already actively traded. We obtained data on IPOs from Prowess.

Throughout the analysis, we focus on Group 1 and Group 2 stocks. There are 1,842 unique ISINs in Groups 1 and 2 during our sample period. Many stocks move between these groups: of these, there are 1,500 unique ISINs in Group 1 at some point during our sample period, and 1,347 in Group 2.[16] This is consistent with the distribution of the impact cost variable, which has a mean of 2.09 and a standard deviation of 2.76 for the full sample. Of the 1,842 stocks in the sample, 1,100 of them are in the local sample (i.e., with impact costs between 0.78 and 1.22) at some point during the sample period. 995 of these are treatment (Group 1) stocks at least once.

The primarily liquidity variables in the paper are monthly average percent effective spreads *(espread)* and 5-minute price impact of trades (*pimpact*), estimated from order book data. Effective spreads are defined $100*\frac{|transaction\ price - .5*(bid+ask)|*2}{.5*(bid+ask)}$. The bid and ask prices reflect the prevailing quotes at the time of the trade. Unlike quoted spreads, which are defined as $\frac{ask-bid}{.5*(bid+ask)}$, the effective spread takes into account the fact that many trades execute inside the quoted spread (price improvement) or outside of the spread (if the order is large). The effective spread can be a better proxy for actual transactions costs. The effective spreads that we calculate reflect the average effective spreads on all transactions that occur during the month. *Pimpact* is an approximation of the average price impact of a trade, per unit (rupee) volume. Following earlier work (Fong, Holden and Trzcinka (2014); Goyenko, Holden, Trzcinka (2009); Hasbrouck (2009)), for every 5 minute interval for the entire month, we calculate 5-minute returns (log ratio of quote midpoints), *r(t)*. We also calculate *S(t),* which equals the sum of the signed square root of trading

[16] Figure 1 shows the time-series of the number of new entries and exits (i.e., newly eligible and newly ineligible stocks, respectively). As expected, in periods of large market downturns many stocks lose liquidity and no longer make it to the 1% cutoff. Overall, there are exit and entry events in almost every month staggered across time.

volume over the 5-minute interval (in thousands): $S(t) = \sum T * \sqrt{rupee\ volume}$, where T is a trade indicator equal to 1 if the trade is buyer-initiated and -1 if the trade is seller-initiated. Trade initiation is approximated using the Lee and Ready (1991) algorithm with no time adjustment (i.e., assuming no trade reporting delay as in Bessembinder (2003)). We then use OLS to estimate *pimpact*: $r(t) = pimpact * S(t) + e(t)$. *Pimpact* is reported in percentages.

Both *espread* and *pimpact* are calculated at monthly intervals to match the frequency of group assignment and margin trading eligibility of stocks. Both of these measures capture deviations of transaction prices from their fundamental values. Effective bid-ask spreads capture the difference between the transaction price and fundamental value for the average trade. The price impact measure explicitly accounts for the size of trades that we observe. We examine both of these measures and ask whether, when taken together, the results provide a consistent picture of the impact of margin trading on liquidity.

Table 1 provides descriptive statistics for all stocks with impact costs that lie in the neighborhood of the eligibility cutoff of 1% (as we describe in greater detail in Section 3.2, these are stocks with impact costs that range from 0.78% to 1.22%). The most important observation from the table is that liquidity is higher among Group 1 stocks than Group 2 stocks. Mean (median) effective spreads are 60.1 (54.6) basis points for stocks in Group 1 versus 71 (63.4) basis points for stocks in Group 2. The estimated price impacts show similar patterns. Mean price impacts for Group 1 stocks are 53.1 basis points versus 65.8 basis points for stocks in Group 2 and medians are at 44.9 basis points and 55.4, respectively.

3.2 Methodology

Our objective is to understand whether shocks (variation in margin eligibility) to the leverage constraints channel (margin financing) have a causal impact on market liquidity. The Indian regulatory setting is particularly useful for our identification because stocks with measured impact costs just below the cutoff are eligible for margin trading while those with impact costs just above 1% are ineligible. The basic premise of RDD in our context is that group assignment near the cutoff is difficult to control precisely, and this leads to a discontinuous treatment effect stemming from exogenous variation in margin eligibility.[17] That is, while stocks below the 1% cutoff receive the treatment, the ones on the other side of the cutoff do not. RDD is a powerful quasi-experimental design where identification of the treatment effect requires very mild conditions. A comparison of average outcomes just above and just below the threshold identifies the average treatment effect as long as error terms (thus, potential omitted variables) are smooth at the discontinuity point. The identification comes from the fact that the eligibility for margin financing is discontinuous at impact cost equal to 1%, but variation in the other relevant variables is continuous (e.g., Lee and Lemieux (2009); Roberts and Whited (2013)).[18] Our analysis focuses on the "local" sample of stocks, defined as those stocks whose impact costs lie close to the cutoff of 1%. We compare the liquidity of eligible versus ineligible stocks using the regression specification:

[17] It is reasonable to conjecture that impact cost is a noisy measure, and thus cannot precisely capture liquidity. Recall that impact cost is calculated from four random snapshots per day of the limit order book. It is defined as the 6-month average percentage change in price caused by an order size of Rs.1 Lakh (100,000 rupees, or approximately $2,000). Differences in the timing of public information releases, for instance, could produce differences in measured impact costs for stocks with equal liquidity. Consider two identical stocks that differ only in the timing of their earnings news within a given day. If one stock's earnings announcement occurred several hours before a given random snapshot and the other announcement is scheduled to occur just afterward, we would expect large differences in the observed impact costs, even when there is no difference in average liquidity across the stocks.

[18] Although it is likely to be difficult and costly for investors to strategically push impact costs below 1% to enjoy margining (given that the order book snapshots are taken at random intervals and revised every month), we visually inspect a histogram of impact costs to check for evidence of strategic behavior near the threshold (see, e.g., the discussion of threshold strategy validity in Bakke and Whited (2012)). As shown in Figure 4, we do not observe any obvious bunching (i.e., discontinuity in the number of stocks) on either side of the threshold.

$$Liquidity_{it} = \alpha_i + \beta * Group1_t + \gamma * X_t + \varepsilon_{it}. \quad (1)$$

The *Liquidity* variables are *espread* or *pimpact*, and the unit of observation is a stock-month. For both of these measures, higher values are indicative of lower liquidity. *Group 1* is a dummy variable equal to 1 if the stock is in Group 1 and thus eligible for margin trading. The main coefficient of interest is β, which captures the estimated effect of margin trading on stock market liquidity. X_t is a vector of control variables, including one month lagged: standard deviation of stock returns, stock returns, rupee volume and (in some specifications) log equity market capitalization. X_t also contains the lagged dependent variable to control for first-order autocorrelation in liquidity. We also include time fixed effects, we cluster standard errors at the stock level, and we correct for heteroscedasticity.

We use regression analysis to test our formal hypotheses about the impact of leverage constraints on market liquidity; however, it is useful to begin with plots of the liquidity data near the impact cost threshold of 1%. In Figures 2a and 2b, we examine all stocks in the sample with impact costs between 0.25% and 1.75%. We form 30 impact cost bins on each side of the threshold of width 0.025 on each side of the eligibility cutoff and we compute average liquidity within each bin.[19] If there is a treatment effect of margin trading eligibility, we would expect a marked liquidity change at the impact cost cutoff. Indeed, figures 2a and 2b show discontinuous drops in both spreads and the price impact of trading at the cutoff value of 1%. In addition to these, we check the extent to which covariates exhibit discontinuity at the cutoff. Figures 3a through 3d show plots for lagged stock price volatility, stock returns, rupee volume and market capitalization, respectively. In stark contrast with Figures 2a and 2b, we do not observe discontinuous changes in any of these variables.

[19] To control for time series variation, we demean each variable using the average values of all Group 1 and Group 2 stocks for the month.

The evidence in Figures 2a and 2b as well as in Figures 3a through 3d lend strong support for the regression discontinuity design. We conduct formal tests in the regression analysis that follows.

4. Results

4.1 Leverage Constraints and Market Liquidity

One practical issue in the implementation of local regression discontinuity is the choice of bandwidth. That is, how do we define the range of impact costs that lie near the cutoff of 1? As Lee and Lemieux (2009) discuss, there is no perfect answer. The primary objective is to choose a bandwidth that is small enough to capture the effect of the treatment (margin eligibility), but also has a sufficiently large N to provide statistical power in estimation. To limit the discretion involved in choosing a bandwidth, we follow Chava and Roberts (2008) and base our estimation on Silverman's (1986) rule of thumb. Using the distribution of impact costs of stocks (equities only) traded on the NSE during our sample period, we define the optimal bandwidth as $1.06 * \min\left(\sigma,\ R/1.34\right) * N^{-1/5}$, where σ is the standard deviation, and R is the interquartile range of impact cost. This results in a bandwidth of 0.22%.[20] This restriction reduces the sample size in the regressions by more than 85%.

Results of the effective spread regressions are in Table 2, Columns 1 and 2. The estimated coefficient of 0.024 on the Group 1 dummy variable implies that margin trading causes effective spreads to decline by 2.4 basis points. The specification in Column 1 includes controls for lagged volatility (standard deviation of stock returns during month t-1), one-month lagged stock returns, one month lagged dollar trading volume and one-month lagged spreads. In Column 2, we also

[20] The regressions are estimated using monthly data for all stocks with impact costs between 0.78% and 1.22%. Chava and Roberts (2008) use a bandwidth equal to 1.06*R/1.34. To be conservative in our estimate of optimal bandwidth, we take the minimum of this value and 1.06*σ (see the discussion in, e.g., Hardle et al. (2004)). We have repeated the analysis using alternative bandwidths, both smaller and larger than those that we obtain using Silverman's (1986) rule of thumb (alternative bandwidths range from 0.28% to 0.16%). The results are not sensitive to bandwidth choice, as shown in the Appendix Table 1.

control for lagged market capitalization. We obtain this variable from Prowess data. Because not all stocks are in the Prowess subsample, the sample size declines. The coefficients on the control variables are all consistent with what one would expect: liquidity is lower following periods of high volatility and low trading volume, and in stocks with low market capitalization. In Column 2, the estimated coefficient on the Group 1 dummy is 2.5 basis points and is statistically significant. This implies that margin trading improves effective bid-ask spreads by about 3.5% relative to the mean, and 3.9% relative to the median.[21]

The results from the analysis of *pimpact* are presented in Table 2, Columns 3 and 4, and are similar to the *espread* regressions. The estimated coefficient on the Group 1 dummy in Columns 3 and 4 show that margin trading improves the 5-minute price impact of trading. In Column 4, the coefficient of Group1 dummy is 3.1 basis points, implying an improvement of 4.7 % (5.6%) relative to the mean (median). Overall, we observe average improvements in both spreads and the price impact of trading as a result of margin eligibility. Spreads narrow, which suggests more aggressive liquidity providers. The price impact of trades also decreases, consistent with a thickening of the order book. Although it is not a very large difference, we observe more improvements in the price impact than in spreads. This suggests that margin traders are doing somewhat more to provide liquidity at a given price than submitting more aggressive bid and ask prices.

There are a number of reasons why one might expect that the baseline estimates reflect lower bounds on the actual effects of margin trading. First, our empirical design does not allow us to capture potential liquidity spillovers into other stocks (i.e., margin trading can free up capital that

[21] In interpreting the coefficients, it is useful to note that it is entirely possible that the ability to trade a given stock on margin frees up capital to trade all other stocks. Precisely how traders use the additional capital is an empirical question. However, (i) the marginable stock still has to be traded in order for the extra liquidity to be enjoyed, and (ii) spillovers into other stocks would simply dampen any observed effects in the liquidity of the marginable stocks. Thus, the coefficients can be interpreted as lower bounds of the true effect.

can be used to trade elsewhere in the market). Spillover effects would reduce the estimated magnitudes. More importantly, the estimated magnitudes that we observe on average are affected by asymmetries in the rules governing new margin positions versus the unwinding of these trades. Upon exit from Group 1, stocks are ineligible for new margin trading as of the beginning of month *t*. However, existing margin positions do not have to be unwound right away and thus the transition to the "no margin" regime may occur slowly.[22] If margin traders are liquidity providers, one might expect them to unwind slowly, in a way that is consistent with liquidity provision (i.e., sell when there is buy demand in the market). Ignoring these unwinding activities of margin traders in Group 2 stocks would attenuate the estimated effects of margin trading.

To capture the unwinding of margin trades that may occur after stocks move from Group 1 to Group 2, we repeat the analysis in Table 2 but we add a dummy variable (*unwind*), set equal to 1 if a Group 2 stock has experienced a decline in open margin positions during the month. Results are in Table 3. As expected, we find that slow unwinding of margin trades also enhances liquidity, consistent with the idea that margin traders generally provide liquidity when they sell their stocks and exit their positions.[23] More importantly, when we account for this institutional feature of the margin trading rules, the estimated effects of margin eligibility increase substantially. The estimated impact of eligibility on effective spreads doubles, from 2.5 basis points (in Table 2) to 5.0 basis points, implying a decline of 6.5% (7.3%) relative to the mean (median) effective spread. The estimated effect on the price impact of trading also increases, from 3.1 basis points in Table 2 to 5.4 basis points, representing a decline of 7.8% (9.5%) relative to the mean (median).

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[22] As mentioned in Section 2, impact costs and the resulting group assignments are calculated on the 15th day of each month, and these new groups are announced and become effective on the 1st day of the subsequent month. Upon entry, investors can begin levering up immediately, and upon exit, investors lever down. For an orderly liquidation, exchanges allow investors to take their time to unwind their positions. This leads to asymmetric effects due to new eligibility versus new ineligibility. Different from new eligibility, the effects due to ineligibility takes place more slowly.

[23] We also provide evidence for this in Table 8 where we show that margin traders reduce their positions following positive returns (column 3).

In order to assess the economic impact of the reductions in effective spreads and price impacts that we document, it is useful to compare our estimates to recent studies that also analyze the effect of capital constraints on stock liquidity. Aragon and Strahan (2011) report that a one interquartile range change in ownership by Lehman-connected hedge funds increases spreads by 2.9% and they increase the price impact of trading, as captured by the Amihud (2002) illiquidity ratio, by about 3.8%. These effects are comparable to, although somewhat smaller than ours. In their conservative estimates, Comerton et al. (2010) report an increase in daily effective spreads of 0.54 basis points following a one standard deviation shortfall in inventory revenue, which approximately corresponds to a 6-7% change relative to the sample mean. These average effects are in line with ours.[24] As we discuss in Section 4.5, we find strong state-dependent effects when we allow the estimated effects of Group 1 status to vary across states of the market.

4.2 Robustness: Bandwidth Choice and Alternative Liquidity Measures

Before diving deeper to try to understand the mechanisms driving the main findings, a natural question to ask in any regression discontinuity design is whether the results are driven by the choice of bandwidth. We use automatic bandwidth selection techniques to minimize discretion; however, it is useful to examine whether the main results are sensitive to this choice. In the Appendix Table A.1, we present results from analyses in which we both increase and decrease the bandwidth of 0.22 by between 10, 20 and 30 percent. As can be seen from the table, the results are robust across these alternative bandwidths.

[24] See Aragon and Strahan (2001), Tables 4 and 5 and Comerton et al. (2010), Table 4, Column 6. In assessing the economic significance of the effects documented in any of these papers (including ours), it is also important to consider the fact these are transactions costs paid *per trade*. These can be large in markets with substantial trading activity. For example, a rough calculation suggests that over the course of a year, a 5 basis point reduction in trading costs implies an annual savings of 3 million rupees *per stock* (the average Group 1 stock has daily trading volume of 27.27 million Indian rupees). Given that there are more than 1,500 stocks that appear in Group 1 at some point during the sample period, the potential transaction cost savings associated with margin trading eligibility is significant.

We also investigate whether our results are sensitive to the choice of liquidity measure. We focus on effective spreads and the 5-minute price impact of trades in the main analysis. Effective spreads are generally preferred to quoted spreads (the difference between the bid and the ask price) because they take into account the fact that many trades execute at prices that are not equal to the bid and ask and are therefore a better proxy for actual transactions costs than quoted spreads. However, because quoted spreads are also widely used in the literature, we repeat the main analysis using this transaction cost measure. The 5-minute post-trade horizon used in the *pimpact* estimation was chosen for consistency with earlier literature using both U.S. and international data (Fong, Holden and Trzcinka (2014); Goyenko, Holden, Trzcinka (2009); Hasbrouck (2009)); however, a longer interval might be useful if a stock is particularly illiquid. Therefore, we also estimate *pimpact* over 30 minute horizons. Appendix Table A.2 shows results from repeating the analysis for quoted spreads and 30-minute price impacts. The results are similar to those in Table 2.

4.3 Placebo Tests

The identifying assumption in the main analysis is that there is a sharp discontinuity in leverage constraints at the impact cost value of 1%, which defines margin eligibility. One potential alternative interpretation of the main results (in Table 2) is that the measured impact costs predict future liquidity instead of reflecting important variation in leverage constraints 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 a false eligibility cutoff. Because of the importance of this test to the overall interpretation, we examine two false cutoffs, both above and below the true cutoff of 1%. In the first test, Placebo Group 1 stocks have impact costs that are less than or equal to 0.78% (this is one bandwidth below the true cutoff) and Placebo Group 2 stocks have impact costs that are greater than 0.78%. For the regression analysis, the local discontinuity sample consists of Placebo Group 1 stocks with impact costs between 0.56% and 0.78% and the Placebo Group 2 stocks with impact costs between 0.78% and 1.00%. In the second placebo test, we move the cutoff to the right of 1%, to 1.22%. In this case, the Placebo Group 1 stocks have impact costs that are between 1.00% and 1.22% and the Placebo Group 2 stocks have impact costs that are between 1.22% and 1.44%. We then estimate regressions analogous to those in Table 2.

Results from the placebo tests are in Table 4. Unlike the results in Table 2, we do not observe any significant differences in liquidity between Placebo Group 1 and Placebo Group 2 stocks (i.e., the coefficient on the Placebo Group 1 dummy is insignificant in all regressions). This provides support for our identifying assumption that the variation in liquidity observed near the true margin eligibility cutoffs (i.e., defined at impact cost equal to 1%) stems from the discontinuous variation in leverage constraints.

4.4 Alternative Interpretations

Does Group 1 membership capture something other than the ability of traders to use leverage via margin trading? As mentioned in Section 2, outside of lower VAR margin requirements, we are not aware of additional regulatory implications of Group 1 status since margin trading rules are distinct from all other trading rules. However, it is possible that some Group 1 stocks happen to be those stocks for which there are single name futures or options markets. It is also possible that Group 1 stocks are more likely to be in a major index or that particular types of investors (e.g., foreign institutions) have restrictions that limit their ownership to the larger stocks that tend to be in Group 1. In this section, we conduct additional tests to account for these alternative interpretations.

Alternative channels through which investors can lever up to trade individual stocks might drive variation in liquidity. If the single-name derivatives markets are correlated with Group 1 membership status, the concern is that the negative coefficients on the Group 1 dummy in Tables 2 through 4 are driven by derivatives and not margin trading. Along similar lines, if some investors are limited to holding stocks within indexes, the Group 1 dummy might capture index membership. We do not expect the alternative hypotheses to have large effects in our data because only a small fraction of our treatment stocks are eligible for derivatives trading or included in the major Indian index.[25] Nevertheless, to examine these hypotheses, we introduce *derivative*, a dummy variable equal to 1 when futures and/or options trade on the stock[26] and *index,* which is equal to 1 if the stock is in the CNX500 index (Standard and Poor's broad-based index of the Indian Stock market). We include these dummy variables as well as their interaction terms with the *Group 1* dummy.

We also analyze the role of investor type. Some investors might be inclined to invest in large and visible stocks, and the Group1 dummy might be capturing the differences in the composition of the groups of investors. To test this channel, we consider four main groups of investors: foreign, institutional, individual, and insiders/blockholders ("promoters"). We include *foreign, inst, indiv and promoter,* (dummy variables set equal to 1 if the stock has above-median foreign, institutional, individual, and promoter ownership, respectively), and we interact them with *Group 1* dummy.[27]

Results are presented in Table 5. We find no evidence that the alternative leverage channel, index membership or investor composition have any impact on our main finding of a beneficial role for margin trading eligibility. The statistical and economic significance of the coefficients on the *Group 1* dummy are similar to those in the main specification.

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25 Among treatment observations, about 2% are eligible for derivatives trading, and 13% are included in the index.

26 As discussed in Section 2, this variable also captures the ability to sell shares short in the period after April 2008. Short selling has been available to institutional investors in India since that date.

27 In Appendix Table A.3, we also analyze whether investor composition changes with Group 1 status. We do not observe any significant differences between our treatment and control stocks. We reexamine this issue in this table and also check if results are concentrated in a particular investor group (the Group 1 interactions with investor group variables). Investor composition variables are available at the quarterly frequency. As the results in Appendix Table A.3 indicate that investor composition does not change with Group 1 membership, we populate the quarterly data at the monthly frequency for the purpose of this table; this allows us to compare the results with the ones from the baseline analysis.

In interpreting the finding that Group 1 stocks near the cutoff have higher liquidity than otherwise similar Group 2 stocks (i.e., that margin trading is, on average, beneficial), one additional question that arises is whether margin trading simply causes a migration of trading from Group 2 stocks to otherwise similar Group 1 stocks, and that the liquidity increases that we observe for Group 1 stocks near the cutoff come at the expense of similar Group 2 stocks. If this "cannibalization" effect is driving our results, it should be greatest for the stocks that are most similar to Group 1 stocks (i.e., those that are closest to the cutoff). This would imply that, for Group 2 stocks just to the right of the cutoff, we would observe lower liquidity compared to the other Group 2 stocks with higher impact costs. From Figures 2a and 2b, in which we plot liquidity as a function of impact cost, we see that this alternative interpretation is unlikely.

4.5 Leverage During Market Downturns

Much of the attention in the literature and popular press surrounding the question of how leverage impacts markets has been motivated by the drying up of liquidity we observe during crises. Brunnermeier and Pedersen (2009) argue that the deleveraging that occurs during market downturns causes both downward price spirals and reductions in liquidity. If margin traders are constrained liquidity providers, then their ability to perform this function can be severely limited during downturns. Our empirical design provides a unique opportunity to examine this idea and make causal statements about liquidity changes during downturns.

To understand the role of stock market conditions, we add contemporaneous market return (*mmret*) as a control variable to the analysis and we also interact *mmret* with the Group 1 dummy. We then add a triple interaction term to account for a potential non-linear relationship between market returns and the impact of margin trading during downturns, given the prediction in Brunnermeier and Pedersen (2009) that trader leverage exacerbates liquidity declines during crises. This triple interaction is *group 1* x *mmret* x *severedownturn*, where *severedownturn* is a dummy variable equal to 1 if market returns during month *t* are lower than 10th percentile returns.

Results are shown in Table 6. Columns (1) and (3) show results from the regressions before accounting for the potential impact of severe downturns; Columns (2) and (4) report results from the full specification, in which we explicitly account for these periods. Consistent with the literature, we find that the direct effect of *mmret* is negative and significant. That is, as market conditions improve, liquidity improves. When we examine the extent to which main results vary with market returns, on average, we don't see strong effects (Columns 1 and 3). However, when we analyze severe downturns separately from other periods, we see significant and sign-flipping patterns that are consistent with a harmful effect of leverage during periods of market turmoil. In Columns 2 and 4 (where we include the *group1* x *mmret* and *group1* x *mmret* x *severedownturn* interactions*),* we find positive and significant coefficients on the *group1* x *mmret* interaction term. This implies that, outside severe downturns, Group 1 status is more helpful when market returns are relatively lower. This is expected given that when market returns are very high, market liquidity is also high and thus the incremental gain from the relaxation of margin constraints is lower. Columns (2) and (4) also reveal that the beneficial effect of Group 1 status reverses once market returns become very negative. The coefficient on the triple interaction term (*group 1* x *mmret* x *severedownturn*) is negative, significant and much larger in magnitude than the coefficient on *group1* x *mmret.* This implies that leverage has a harmful effect on the liquidity of Group 1 stocks when market returns become very negative.[28]

The findings in Table 6 not only provide evidence consistent with the liquidity spiral hypothesis in Brunnermeier and Pederson (2009), they also reveal that the average effects that we report in Table 2 do not capture the full magnitude of the impacts due to margin eligibility. Because margin

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[28] Recall that returns are always negative when *severedownturn* = 1, so the negative coefficient on the triple interaction is interpreted as harmful to liquidity.

trading is beneficial during some market conditions and harmful in others, the average effects are attenuated.

4.6 Potential Mechanisms

Overall, the results in Tables 2 through 6 provide consistent evidence of liquidity improvements when stocks become eligible for margin trading and that the average improvement is driven by periods outside severe market downturns. In this section, we aim to uncover the mechanisms driving these results.

4.6.1 Group 1 Status or Margin Trading Activity?

Unlike U.S. equity markets, we are able to observe stock-level daily margin positions for NSE stocks. We exploit this unique feature of our data to help shed light on whether the results are driven by margin trading eligibility or by traders' actual use of leverage (i.e., margin trading activity). To examine this, we calculate daily changes in outstanding margin positions for each stock. The absolute value of these changes is our proxy for margin trading activity. We average these daily changes for each stock during month *t* and divide Group1 stocks into groups based on margin position changes. We introduce a dummy variable *(intense margin trade*) equal to 1 if the stock experiences higher-than-median margin trading during month *t*. The results are in Table 7. For those Group 1 stocks in which margin trading activity is more intense, the estimated coefficients are particularly larger (in absolute terms) – estimates imply that improvements in liquidity are 3 to 4 times higher than those with lower margin trading activity. The statistical significance of the coefficient on the *intense margin trade* indicator is also much higher than that on the Group 1 dummy in all of the specifications. This suggests that it is margin trading activity (i.e., the use of leverage) that drives our results.

4.6.2 Margin Traders as Liquidity Providers

This paper aims to provide insight into how increasing the amount of capital available to liquidity providers impacts stock market liquidity. To deepen our understanding of the mechanisms driving the main results, it is useful to document some basic facts about the margin trading patterns that we observe in the data.

What trading strategies do margin traders employ? Understanding the behavior of traders who use leverage should shed light on what we should expect to observe when these traders become more or less capital constrained. While we do not have transaction-level data on margin account activity, we do observe daily margin positions outstanding at the individual stock level. The daily margin position data allow us to construct a natural proxy for margin trading activity for all margin-eligible stocks: (log) daily changes in outstanding margin positions. In the spirit of Diether, Lee, and Werner (2008), who characterize the trading strategies of short sellers, we use daily data of all marginable stocks to estimate a panel regression that captures the relationship between the margin trading proxy and short-horizon stock returns. The basic specification is as follows:

$$ch\_margin_{it} = \alpha_i + \beta * dret_{t-1} + \gamma_i + \nu_t + \varepsilon_{it},$$

where $dret_{t-1}$ is the one-day lagged stock return and γ_i , ν_t are firm and day fixed effects, respectively. Standard errors are also clustered by firm and date. Results are shown in Table 8. Column 1 reports the results from baseline specification, and in Column 2, we also include the control variables. The results in both columns show that margin traders engage in contrarian strategies. For instance, the estimated coefficient on the one-day lagged stock returns of -0.25 in Column 2 implies that, following a 10% decrease in stock prices, margin positions will increase by 2.5%.[29] Next, we estimate a piecewise linear regression in which we allow the relationship between margin trading activity and returns to vary at different regions of lagged stock returns. As described in Section 2, margin traders can borrow up to 50% of their initial positions in a stock, and must maintain a maintenance margin of at least 40%. This means that margin traders must post additional collateral or liquidate some of their shares once the value of the margin loan exceeds 60% of the value of the stock held by the trader. Given this institutional friction in the ability to maintain margin positions over time, one might expect that margin traders who already have leveraged positions in a given stock are unable to provide additional liquidity during extreme downturns. We define three stock return regions: *positive*, *mild_neg* and *very_neg*. *Positive* returns are one-day lagged stock returns that are greater than or equal to 0%. *Mild_neg* returns are stock returns between 0% and -5%. *Very_neg* returns are defined as stock returns that are less than -5%.

Results are shown in Table 8 Column 3. We observe that margin trading positions increase following decreases in stock prices, unless the past returns are extremely negative. We find the largest sensitivity is in the region of mildly negative and positive returns (estimates -0.24 for *positive* and -0.27 for *mild_neg* vs -0.06 for *very_neg*). This suggests that margin traders not only provide liquidity by establishing initial margin positions following mildly negative returns, but they also behave as liquidity providers by unwinding those positions after periods of positive stock returns. The small magnitude and statistical insignificance of the estimated coefficient on the *very_neg* dummy

[29] It is useful to note that these magnitudes are in line with previous findings on short-selling activity, which has been shown to improve stock market liquidity. For instance, Diether et al. (2008) find that, following a 10% increase in stock prices, short selling activity in NYSE (Nasdaq) stocks increases by 1.6 to 3.7 (1.3 to 2.2) percent (Table 3). In this analysis, we look at the sensitivity to one-day lagged stock returns. It is possible that margin traders might be following contrarian strategies also at different horizons – for instance, part of liquidity provision could be occurring within the day. Since we observe positions only at the end of the day, we cannot capture intraday activities of margin traders. However, the daily analysis is informative: our results show that they are contrarian traders providing liquidity.

variable reveals that this contrarian behavior goes away following extremely negative returns. To further investigate this, in the last columns of Table 8 we remove the day fixed effects to study the aggregate patterns. In particular, we examine the relationship between margin trading and market (rather than individual stock) returns. Different from stock-level contrarian behavior, here we observe significant decreases in margin positions following large market declines. Although they typically provide liquidity to the market, margin traders become liquidity seekers following large negative market shocks.[30] These findings line up with the results in Table 6, which show that traders' leverage becomes costly in times of severe market downturns.

In addition to helping us understand the main results of this paper, the findings in Table 8 are related to the growing literature investigating whether hedge funds, which tend to use leverage, provide liquidity to stock markets (e.g., Aragon (2007), Ben-David, Franzoni, and Moussawi (2012), Franzoni and Plazzi (2013), Hombert and Thesmar (2011), Kruttli, Patton and Ramadorai (2014)). Different from other studies, we observe margin trading activity of all traders (as opposed to a particular type such as a hedge fund or a specialist) and, more importantly, the data allow us to directly observe the positions that are financed by intermediary-supplied capital.[31] These data are not typically available in other markets and allow us to uncover the basic patterns in margin trading activity and to assess directly the role of levered positions on the amplification of negative market shocks. To the best of our knowledge, our paper is the first to isolate the impact of leverage from

[30] This finding that traders do not use more leverage as already negative returns become more extreme is consistent with Adrian and Shin (2010), who find that intermediaries' use of leverage is pro-cyclical.

[31] Financial institutions such as hedge funds obtain capital from various sources, including investor flows and leverage. The currently available datasets do not provide enough information on the financing of their positions. Previous research has shown that hedge funds heavily liquidate their shares in times of severe market downturns. However, given the data limitations, it has been difficult to analyze the extent to which these effects are driven by investor redemptions, leverage constraints or other frictions. A recent study by Franzoni and Plazzi (2013) shows that hedge funds that use high leverage and low restrictions to redemptions are more vulnerable to worsening of aggregate funding conditions. While our paper does not focus on financial institutions (as we are exploiting stock-level variation in margin eligibility), consistent with Franzoni and Plazzi (2013) our paper highlights that the leverage-based trading mechanism is an important driver of the amplification of negative market shocks, as predicted by recent theoretical papers.

other mechanisms that are at work during times of market stress (such as increased informational asymmetries), thanks to the unique institutional features of Indian capital markets that enable a regression discontinuity design.

The results in Table 8 show that margin traders are on average contrarian; however, when stock returns become very negative (as in crises), they no longer engage in contrarian strategies. Another way to examine margin traders' strategies is to look at the trader level. Because the stock level analysis essentially value-weights the position data, it is possible that large traders behave as contrarians, but smaller ones engage in other types of trading strategies. In addition, it is difficult to infer trading horizon without trader-level data. We obtained trader-level position data from the NSE for the 2007-2010 subperiod and we use it to compare each trader's changes in outstanding margin positions to both stock and market returns. There are two important facts that emerge from these data. First, margin traders' horizons are quite short (median of three days and an interquartile range of 1 to 10 days). Second, when we examine the relationship between trade direction and returns, we observe 38% more contrarian trades than momentum at the individual stock return level on average. These two observations are consistent with short-term liquidity provision by margin traders. Also consistent with the crisis analysis in the paper, we find that individual margin traders' strategies substantially change during crises. Contrary to the average results, momentum trades are 85% more likely than contrarian trades during severe market downturns.

Although their contrarian trading strategies are consistent with liquidity provision, it is also possible that margin traders are more informed. To examine this possibility, we investigate whether Group 1 stocks experience changes in the structure of informed trading relative to otherwise similar Group 2 stocks. We use the Thomson Reuters Tick data to classify trades as buys or sells based on transaction prices relative to the prevailing quote midpoints (i.e., following Lee and Ready (1991)).

We then estimate the Probability of Informed Trading (PIN, based on Easley, Kiefer, O'Hara and Paperman (1996)) using the total daily buys and sells. We then estimate the regressions from Table 2 but we replace the dependent variables with PIN. The results are shown in Table 9. We do not observe a significant shift in informed trading for Group 1 stocks. Thus, the evidence is inconsistent with a marked change in informed trading, but it is consistent with an influx of traders providing liquidity via short-horizon contrarian strategies.

4.6.3 Margin Trading and Return Reversals

If margin traders behave as contrarian liquidity providers then an increase in their ability to engage in short-term contrarian strategies should reduce the returns to these strategies and improve the pricing efficiency of Group 1 stocks.[32] Following Nagel (2012), we use the returns of short-term reversal strategies as proxies for the returns to liquidity provision and we estimate the impact of the ability to trade on margin on the returns to these reversal strategies. To do this, we construct several portfolios of stocks. Each portfolio is defined within the universe of the local Group 1 or Group 2 stocks. Following Nagel (2012), we define *Reversals 1day* as the average returns to a reversal strategy that weights stocks in proportion to the negative of market-adjusted returns on days *t-1*. As some stocks may have reversal horizons that go beyond one day, we also calculate returns to reversal strategies that are implemented over relatively longer periods. *Reversals 3day* is the average of returns from three reversal strategies that weight stocks according to the negative of market-adjusted returns on days *t-1, t-2* and *t-3*. Similarly, *Reversals 5day* is the average of five reversal strategies that weight stocks based on returns on days *t-1, t-2, t-3, t-4 and t-5*. We regress the returns of each of these portfolios on an intercept and the Group 1 dummy variable and we cluster the standard errors by month.

[32] We would like to thank an anonymous referee for encouraging this line of inquiry.

Results are reported in Panel A, Table 10. Returns to reversal strategies are reported in percentages. We find positive returns to reversal strategies for both Group 1 and Group 2 stocks. For Group 2 stocks, the portfolio produces returns of 30 basis points over the one-day horizon. As some stocks experience reversals faster than others, we observe that returns gradually decline when the strategy is implemented at longer horizons. For Group 2 stocks, the portfolio produces returns of 16 basis points at 3 days and returns of 12 basis points at 5 day horizons. The most important finding from our analysis is that the magnitudes of the reversal returns are smaller for Group 1 stocks. For instance, the returns to reversal strategies at the one day horizon decline by 8 basis points once stocks are eligible for margin trading. This effect can also be seen at longer horizons.

In Panel B of Table 10, we complement the portfolio-level analyses (where stocks are weighted according to their past returns) with stock-level evidence. For each stock in the local sample, we calculate *Autocov*, which is defined as the absolute value of monthly autocovariance of the daily stock returns (multiplied by 10^3). We regress *Autocov* on a Group 1 dummy variable to test the significance of average differences in daily return autocovariance between Group 1 and Group 2 stocks. Consistent with results in Panel A, we find that Group 1 stocks have significantly lower autocovariances compared to Group 2 stocks. Our interpretation is that short-term intermediaries are constrained when they trade in Group 2 stocks and they are unable to compete away the returns to reversal strategies. This constraint is relaxed when stocks become eligible for margin trading.

4.7 Summary

Thus far, we have documented a causal relationship between traders' leverage constraints and a stock's liquidity. We find that the relaxation of leverage constraints has important effects on liquidity and that these effects strongly depend on market conditions. Although leverage is useful in normal times, it becomes particularly harmful during large market downturns. We analyze the mechanisms driving the results and find that margin traders normally provide liquidity by following short-run contrarian strategies. However, following large negative shocks, they delever their positions and consume liquidity. Before moving to the next section where we examine the implications of this behavior on commonality in liquidity, it is worthwhile to discuss the extent to which our results can be generalized. Because we focus on margin trading in India and because margin trading affects only relatively liquid stocks, one might be concerned about external validity. While it is difficult to completely eliminate concerns about external validity, there are a number of reasons why we believe that such concerns should not be central to the interpretation of this paper. First, when we compare market-level data on margin activity in the United States (stock-level margin trading data are not available in the U.S.) to market-level margin activity in India, we find that the aggregate patterns in margin trading that we observe in India are very similar to those in the U.S.[33] These similarities are not surprising, given our findings that margin traders are liquidity providers who become liquidity seekers during periods of extreme negative returns, and thus consume liquidity. These results are driven by the mechanics of leverage-based trading: large adverse price movements increase traders' leverage and tighten their constraints, which leads to deleveraging. The fact that this mechanism is at work in most markets (if not all) should help mitigate concerns about external validity.[34]

[33] The New York Stock Exchange (NYSE) disseminates aggregate market-level data on outstanding margin positions monthly. While individual stock-level data are not available for the NYSE stocks, we can compare the relationship between monthly market returns and aggregate monthly changes in margin positions outstanding in the two countries. In the United States, we find that this correlation is 0.58 and is statistically significant. In India, the correlation is also positive and significant, at 0.38. Thus, aggregate margin trading activity in India follows broad patterns that are similar to what we observe in the United States.

[34] While the direction of the effects should not depend on the specific market, we acknowledge that it is not immediately obvious how one would generalize the magnitudes that we report in this paper. We do find that the average magnitudes are comparable to results from recent studies that focus on the US market – for instance, to Aragon and Strahan (2011), who study the role of hedge funds in providing liquidity, and to Comerton-Forde et al (2010), who analyze this in the context of NYSE specialist firms. These observations, however, are solely empirical facts based on comparisons with recent related papers. The average magnitudes may not necessarily be the same in every study (e.g., might depend on aggregate conditions during the sample period). The main goal of our paper is to analyze the impacts of leverage constraints on liquidity and establish the causal links, which is often difficult to do in the US setting (variations in leverage are not only

A separate external validity concern, one that is relevant to any regression discontinuity design, is that the test design estimates "local" effects using only observations that are close to the cutoff. The importance of this concern depends on the variation in the forcing variable (the variable that triggers the treatment effect) – if there is substantial variation in the forcing variable, then the local sample can be close to a representative sample. As discussed earlier, there is a good deal of variation in impact costs and substantial movement between Group 1 and Group 2. There are 1,842 unique stocks in Group 1 and Group 2 during our sample period, and 1,110 of them are in the local sample at some point. This indicates that our results are relevant to a large group of stocks.

4.8 Leverage Constraints and Commonality

In Brunnermeier and Pedersen (2009), market declines reduce intermediary capital and therefore reduce the ability of intermediaries to provide liquidity to the entire market. This causes an overall increase in liquidity commonality. The results in Hameed, Kang, and Viswanathan (2010), which show that commonality increases following large market declines, are consistent with this idea. An alternative approach to examining the role of capital constraints in liquidity commonality is to exploit stock-level variation in capital constraints. For example, Coughenour and Saad (2004) test whether liquidity commonality is higher for stocks that share the same specialist firm. They report evidence of greater liquidity commonality among stocks with the same specialist, and that this commonality is higher when specialists are more capital-constrained. In the Indian setting, in which only a subset of stocks is eligible for margin trading, market declines may impact stocks differently. The results in Table 8 reveal that margin positions decline as market returns become very negative.

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unobservable for most securities, but are also thought to be driven mostly by aggregate shocks, which leads to important confounding effects). We believe that we provide useful evidence, but do not claim that every aspect of our findings can be generalized to all possible settings.

If market declines are associated with deleveraging for margin-eligible stocks, the associated selling pressure could cause increased commonality in liquidity for these stocks.

In this section, we conduct basic tests that are similar in spirit to those in Karyoli, Lee and van Dijk (2012). We create a monthly time series of stock-level commonality in liquidity, which we define as the R^2 statistics from regressions of stock i's daily liquidity innovations on market liquidity innovations. We then estimate local discontinuity regressions (i.e., using the same sample of stocks as in the Table 2 analysis) and test whether the ability to lever up via margin trading impacts liquidity commonality. We also examine how any effects that we observe vary with prevailing market conditions.

Following Karyoli, Lee and van Dijk (2012), we first calculate liquidity innovations based on a first-stage regression of daily liquidity changes on variables known to affect liquidity:

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

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

In the second step, for each stock and calendar month we use daily data to generate a time series of monthly R^2 statistics from the following regression: $\Delta Liq_{i,t} = \alpha_i + \beta_1 \Delta Liq_{m,t} + \varepsilon_{i,t}$. This R^2 measure is also used in Karyoli, Lee and van Dijk (2012) and captures the extent to which the liquidity of a given stock moves with liquidity of the market. A high R^2 is indicative of high commonality in liquidity.

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. Explanatory variables are the *Group 1* indicator variable and time fixed effects. The main coefficient of interest is on the *Group 1* indicator variable. If margin calls create financing frictions for margin traders then we might expect Group 1 stocks to exhibit more commonality in liquidity during times in which deleveraging affects many stocks in the market. To examine this hypothesis, we conduct extended analysis in which we interact the Group 1 dummy variable with *severedownturn*.

As in the main analysis, we use effective spreads and price impact as the key liquidity variables. However, because the commonality in liquidity analysis requires the use of daily data, in this analysis, we use the price impact measure of Amihud (2002) as the low-frequency analog to *pimpact*.[35] The Amihud variable 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*. This measure captures the change in price generated by daily trading activity of 1 million rupees. This measure is widely used in the literature because it requires only daily data and does well capturing intraday measures of the price impact of trades (Hasbrouck (2009); Goyenko, Holden, and Trzcinka (2009)). Following Amihud (2002), we winsorize the measure at the 1% and 99% levels, and we also remove observations in which daily trading volume is less than 100 shares. Because our focus is on a non-

[35] While effective spreads can be measured with as little as one transaction in a day, the *pimpact* coefficient is estimated from a regression and requires many more transactions to eliminate the noise in the measure. Following Fong, Holden and Trzcinka (2014), we estimate *pimpact* by using all transactions in a month. This is more appropriate in the analyses that use monthly data, and it also helps substantially with computing time. Table 1 shows that R^2 statistics constructed from both liquidity measures are remarkably similar. Thus, we believe that using the low-frequency analog of *pimpact* is unlikely to have important impact on our results.

U.S. sample of stocks, we follow Lesmond (2005) (who also examines this measure using international data) and impose price filters to remove 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.

Results are shown in Table 11. The positive and significant coefficients on the Group 1 dummy variable in Columns 1 and 3 indicate that, while liquidity improvements are enjoyed when stocks move into Group 1, a potential cost is that liquidity commonality with the market also increases. When we further explore the time series patterns of this result, we find that the increase in liquidity commonality is driven entirely by periods of large negative market returns. The estimated coefficients on the *Group 1* and *severedownturn* interaction variables (in Columns 2 and 4) are positive and significant. R^2 statistics estimated from spread and price impact measures are both substantially higher for Group 1 stocks in times of severe market declines. Estimates for comovement in spreads imply a 20.8% higher liquidity commonality for Group1 stocks in bad times, and the effect is similar, about 19.4% higher, for Group 1 stocks when we use the price impact measure.[36] Finally, consistent with Hameed, Kang, and Viswanathan (2010), we find a positive and significant coefficient on the *severedownturn* indicator variable, indicating that all stocks exhibit more liquidity commonality during market downturns.

The analysis and results in Table 11 provide evidence to support the idea that variation in leverage constraints is an important driver of commonality in liquidity. Commonality tends to be higher for stocks in which traders use leverage and the effect is driven by periods of extremely negative market returns, consistent with the idea that margin traders' use of leverage results in widespread liquidations during downturns. These results complement the earlier results and

[36] The average R^2 *spread* and R^2 *price impact* for Group2 stocks during severe downturn are 0.24 and 0.18, respectively.

highlight an important cost associated with trader leverage: it amplifies liquidity commonality when markets are in crises.

5. Conclusions

We use the Indian equity market as a laboratory for testing the hypothesis that there is a causal relationship between traders' leverage constraints and a stock's market liquidity. In 2004, Indian regulators introduced a formal margin trading system with two useful features: (1) only some stocks are eligible for margin trading, and (2) the list of eligible stocks is time-varying and is based on a well-defined eligibility cutoff. We use regression discontinuity design in which we focus the analysis on stocks close to the eligibility cutoffs and we exploit variation in the data generated by eligibility to identify the potential effects of leverage constraints on stock market liquidity.

There are three main findings. First, we find evidence consistent with a causal effect of leverage constraints on stock market liquidity. Liquidity is higher when stocks become eligible for margin trading on average; however, this effect reverses during crises. These findings show both the costs and benefits of leverage. On average, margin trading is beneficial; however, it comes with the cost of amplification of negative shocks in times of market stress. This causal statement about the impact of leverage constraints on liquidity should be of particular interest to policy makers thinking about imposing or relaxing restrictions on leverage. In the aftermath of the recent financial crisis, there is an increased interest in understanding the role of leverage in driving systematic crises and developing policies to avoid its potential harmful effects. For instance, in a recent paper, Geanakoplos and Pedersen (2011) highlight the importance of monitoring leverage. They propose various ways in which the Federal Reserve Bank could gather detailed data on loans and develop policies to track the overall changes in leverage in the market. Similarly, there are a number of developing markets that are considering revisions to margin trading policies in attempts to better manage large market swings (e.g., 2015 margin trading policy changes in China). Our causal statements about the impact of leverage constraints on stock market liquidity can contribute to future policy discussions. Our findings indicate both costs and benefits associated with leverage. Policy makers could use our findings to improve decision-making by considering relative weights that they place on normal times versus downturns.

The second important finding in the paper is that margin traders tend to follow contrarian trading strategies, consistent with liquidity provision. They are most likely to employ contrarian trading strategies following periods of moderately negative or positive returns. Following extreme downturns they become liquidity demanders. Several theoretical papers point out that large negative shocks can cause deleveraging and downward spirals. Our paper is, to our knowledge, the most direct evidence of this effect in the current literature.

Finally, we provide evidence consistent with recent theoretical models in which shocks to funding constraints drive commonality in liquidity. Our paper contributes to the literature in its identification of a leverage constraint channel.

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Figure 1: Number of Newly Eligible and Newly Ineligible Stocks

This figure shows the number of NSE stocks entering and exiting Group 1 between April 2004 and December 2012.

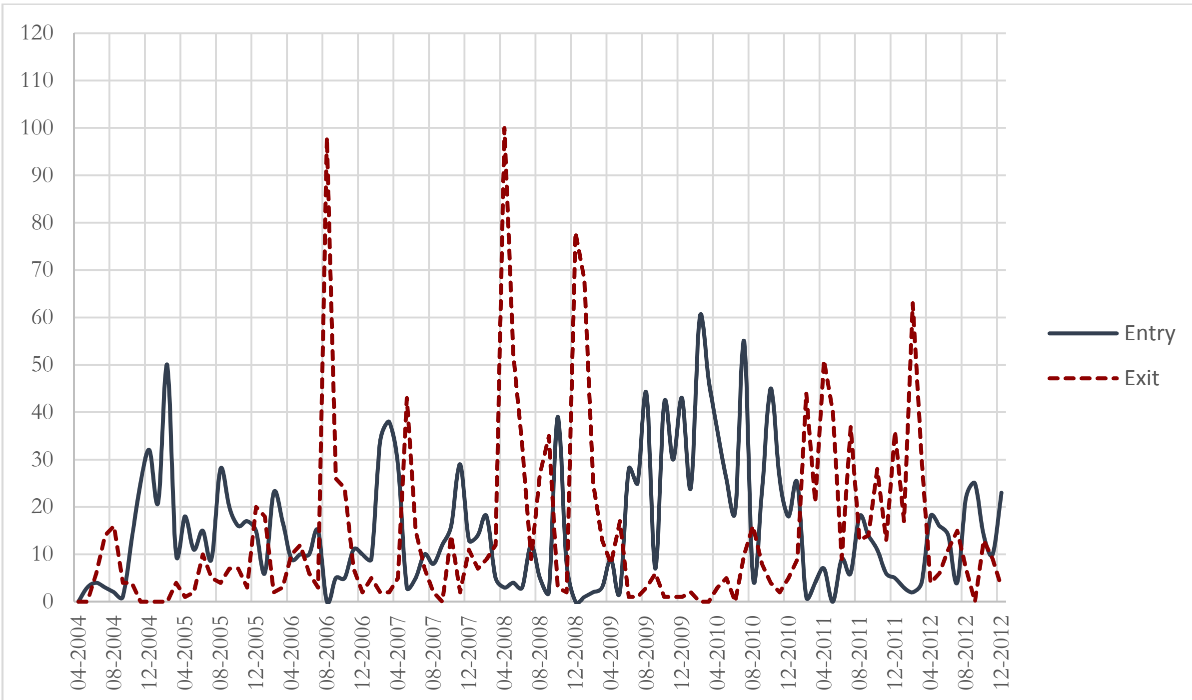


Figure 2a: Impact Cost and Effective Spreads

The figure plots the the average effective spread during month *t* as a function of month *t* impact cost. Stocks are divided into 30 bins (the X axis) of width 0.025 on each side of the eligibility cutoff of 1%. To control for time series variation in market liquidity, we demean each observation using the average values of all Group 1 and Group 2 stocks for the month. We then compute the average effective spread within each bin Margin eligible stocks are all those stocks with impact costs that are less than or equal to 1%, which corresponds with bins 1 through 30 (in blue). Stocks in bins 31-60 (in red) are ineligible for margin trading during period *t*.

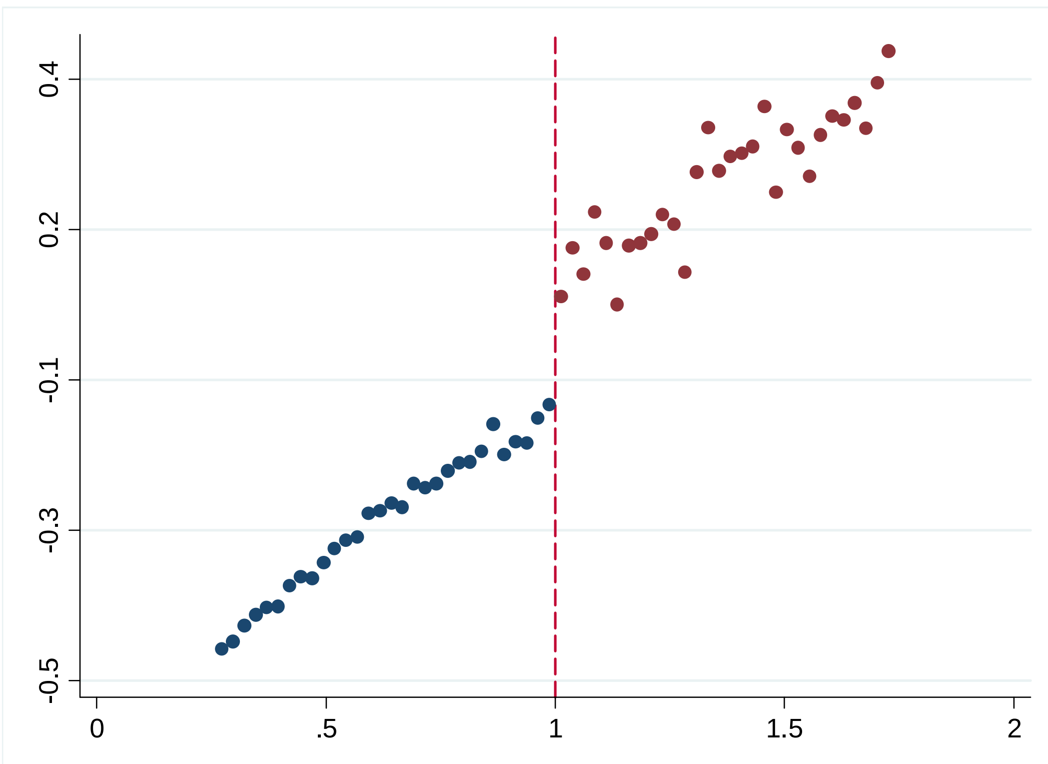
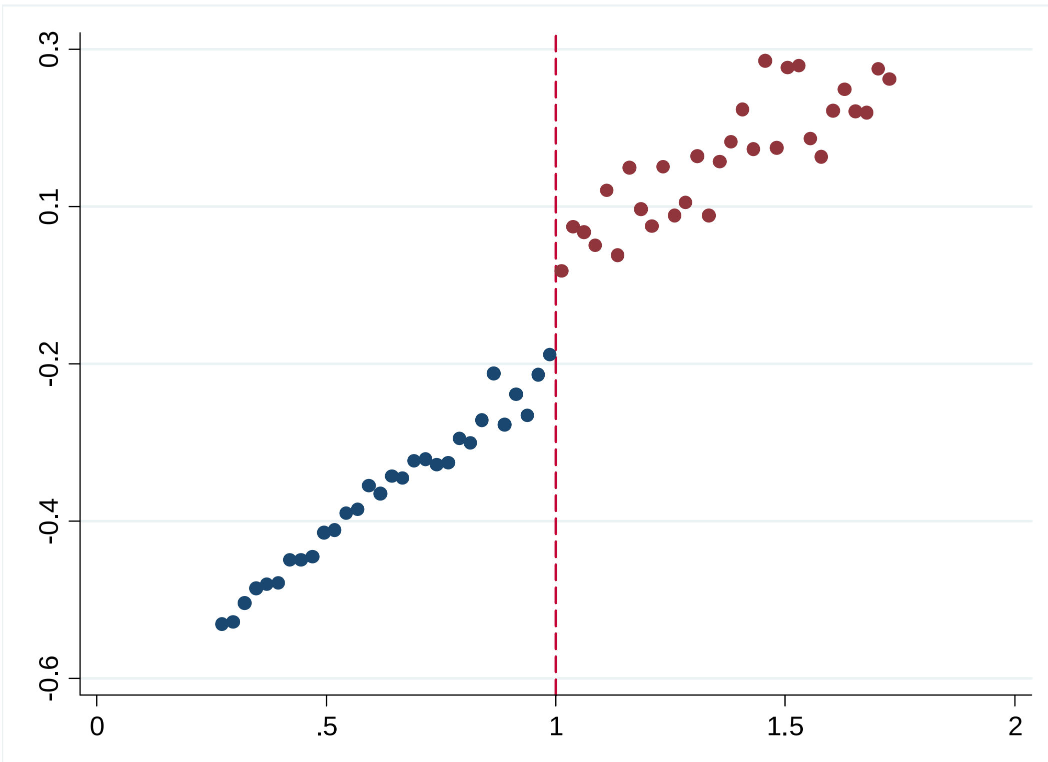


Figure 2b: Impact Cost and Price Impacts

The figure plots the the average 5-minute price impact of trading during month *t* as a function of month *t* impact cost. Stocks are divided into 30 bins (the X axis) of width 0.025 on each side of the eligibility cutoff of 1%. To control for time series variation in market liquidity, we demean each observation using the average values of all Group 1 and Group 2 stocks for the month. We then compute the average price impact within each bid. Margin eligible stocks are all those stocks with impact costs that are less than or equal to 1%, which corresponds with bins 1 through 30 (in blue). Stocks in bins 31-60 (in red) are ineligible for margin trading during period *t*.



Figures 3a - 3d Impact Cost and Other Variables

The figures plot the the average one-month lagged stock price volatility (*std_ret*), stock returns (*mret*), log dollar volume (*logvolume*) and log market capitalization (*logmcap*) as a function of month t impact cost. All variables are defined in Table 2. Stocks are divided into 30 bins of width 0.025 on each side of the eligibility cutoff of 1%. To control for time series variation, we demean each observation using the average values of all Group 1 and Group 2 stocks for the month. We then compute the averages within each bid. Margin eligible stocks are all those stocks with impact costs that are less than or equal to 1%, which corresponds with bins 1 through 30 (in blue). Stocks in bins 31-60 (in red) are ineligible for margin trading during period *t*.

Figure 3a: Volatility

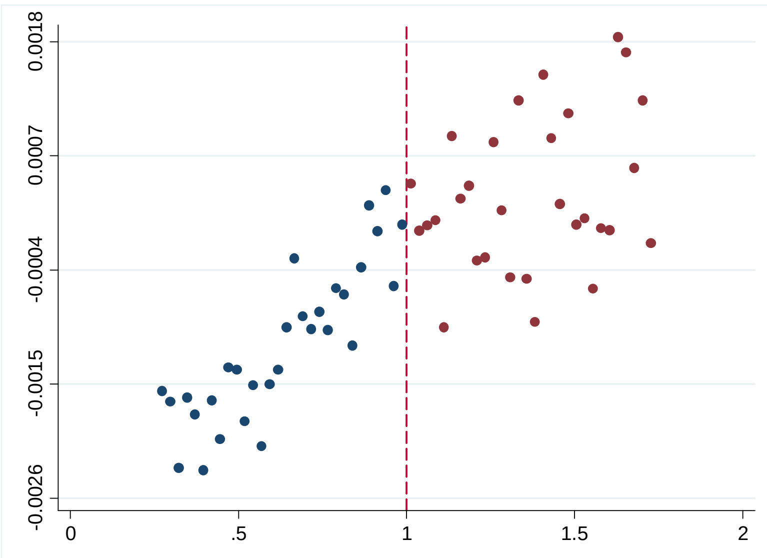


Figure 3b: Stock Returns

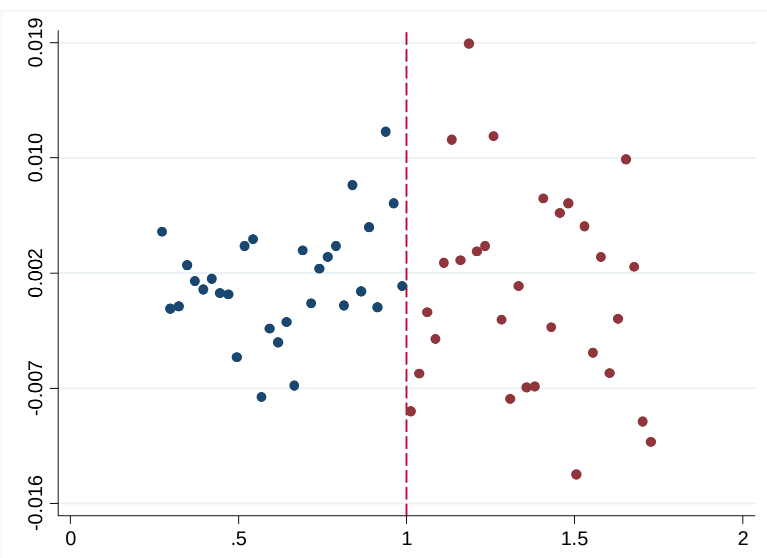


Figure 3c: (Log) Rupee Volume

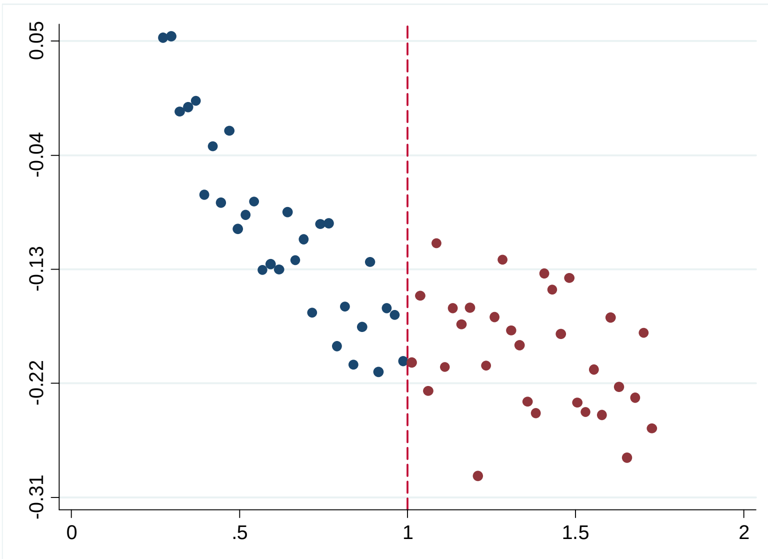


Figure 3d: (Log) Market Capitalization

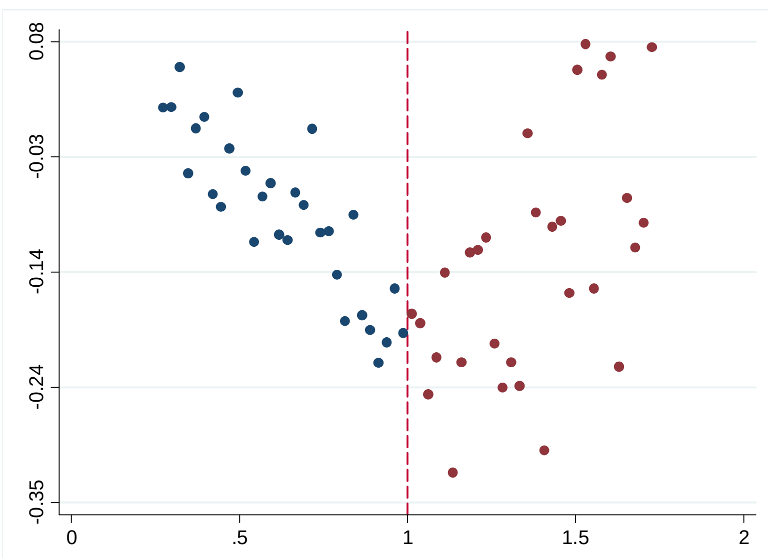


Figure 4
Distribution of Stocks around the Eligibility Cutoff

This figure shows the number of stock-month observations in each impact cost bin (of size 0.01) near the eligibility cutoff of 1%.

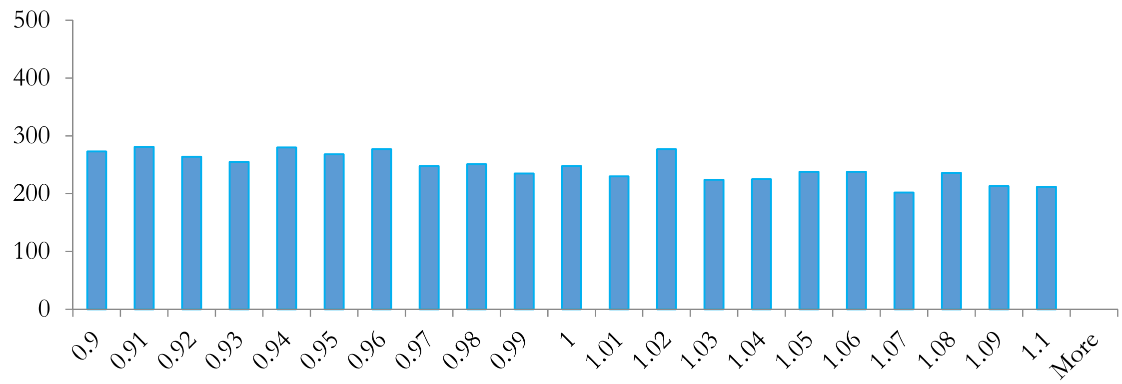


Table 1
Descriptive Statistics: Group 1 vs. Group 2

This table provides summary statistics of liquidity and market characteristics for the sample of National Stock Exchange stocks in the local sample of Groups 1 and 2 for the period April 2004 through December 2012. All variables are monthly. *Espread* is the average percent effective bid-ask spread for all transactions during month t. *Pimpact* is the average percent price impact of trading for stock *i* during month *t*. It is calculated from the OLS regression: $r(t) = pimpact * S(t) + e(t)$, where $r(t)$ is the 5-minute quote mid point return and $S(t)$ equals the sum of the signed square root of trading volume over the 5-minute interval (measured in thousands). *Qspread* is the time-weighted average percent quoted spread during month t. *Pimpact30* is identical to pimpact, but the coefficient is estimated using data over 30 minute intervals rather than 5-minutes. *Autocov* is the absolute value of monthly autocovariance of the daily returns of a stock (x 10^3). R^2 *espread* and R^2 *pimpact* are estimated following the two-step procedure in Karolyi, Lee and van Dijk (2012).

Group 1	Variable	Mean	Median	P25	P75	Std Dev
	Espread	0.6009	0.5364	0.3965	0.7300	0.2968
	Pimpact	0.5312	0.4490	0.2569	0.7043	0.4078
	Qspread	0.6458	0.5665	0.3981	0.7972	0.3557
	Pimpact30	0.4230	0.3463	0.1816	0.5689	0.3536
	Autocov	0.1865	0.1167	0.0483	0.2533	0.2269
	R^2 espread	0.1464	0.0804	0.0194	0.2100	0.1764
	R^2 pimpact	0.1363	0.0728	0.0173	0.2003	0.1616
Group 2	Variable	Mean	Median	P25	P75	Std Dev
	Espread	0.7109	0.6344	0.4644	0.8772	0.3448
	Pimpact	0.6575	0.5543	0.3006	0.8910	0.5258
	Qspread	0.7801	0.6856	0.4830	0.9757	0.4197
	Pimpact30	0.5302	0.4341	0.2177	0.7207	0.4570
	Autocov	0.2055	0.1228	0.0548	0.2668	0.2315
	R^2 espread	0.1382	0.0777	0.0175	0.2014	0.1621
	R^2 pimpact	0.1304	0.0714	0.0158	0.1928	0.1531

Table 2
Do Leverage Constraints Impact Liquidity?

This table presents results of the analysis of the impact of margin trading eligibility on market liquidity. The sample includes all stocks Groups 1 and 2 with impact costs close to the cutoff of 1% (i.e., between 0.78% and 1.22%). The dependent variables are average effective spread (*espread)* and the 5-minute price impact of trading (*pimpact)* during month *t*, where eligibility is effective as of the beginning of month *t*. The explanatory variables are *Group 1*, a dummy variable equal to 1 if the control stock is eligible for margin trading during month *t*, a vector of control variables and year-month dummies. The control variables include one-month lagged: standard deviation of stock returns (*std_ret*), stock returns (*mret*), dollar volume (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 average daily trading volume, that is, the natural log of the daily closing price (in rupees) times the number of shares traded. *Logmcap* is the equity market capitalization, defined as the end of month *t* closing price, times shares outstanding. Month-year fixed effects are estimated but not reported in the table. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

VARIABLES	(1) espread	(2) espread	(3) pimpact	(4) pimpact
Group1	-0.024***	-0.025***	-0.043***	-0.031***
	(0.006)	(0.007)	(0.008)	(0.009)
Lag std_dret	-0.810**	-0.507	6.284***	4.490***
	(0.401)	(0.325)	(0.727)	(0.751)
Lag mret	-0.045*	-0.045	-0.121***	-0.048
	(0.027)	(0.030)	(0.030)	(0.030)
Lag logvolume	-0.025***	-0.030***	-0.094***	-0.087***
	(0.005)	(0.009)	(0.012)	(0.014)
Lag logmcap		0.010*		-0.052***
		(0.006)		(0.006)
Lag espread	0.698***	0.683***		
	(0.059)	(0.078)		
Lag pimpact			0.422***	0.400***
			(0.055)	(0.070)
Observations	8,495	7,188	8,495	7,188
R-squared	0.774	0.775	0.493	0.512
Month-Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 3
The Impact of Unwinding Outstanding Margin Positions

This table presents results of the analysis of the impact of margin trading eligibility on market liquidity. The sample includes all stocks Groups 1 and 2 with impact costs close to the cutoff of 1% (i.e., between 0.78% and 1.22%). The dependent variables are average effective spread (*espread)* and the 5-minute price impact of trading (*pimpact)* during month *t*, where eligibility is effective as of the beginning of month *t*. The specification is identical to that in Columns 2 and 4 of Table 2 except that *unwind*, a dummy variable equal to 1 if a Group 2 stock has experienced a decline in open margin positions during the month, is included as an additional explanatory variable. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

VARIABLES	(1) espread	(2) pimpact
Group1	-0.050***	-0.054***
	(0.010)	(0.016)
Unwind	-0.034***	-0.033*
	(0.009)	(0.018)
Lag std_dret	-0.489	4.492***
	(0.325)	(0.750)
Lag mret	-0.050*	-0.054*
	(0.030)	(0.030)
Lag logvolume	-0.030***	-0.086***
	(0.009)	(0.014)
Lag logmcap	0.010*	-0.053***
	(0.006)	(0.006)
Lag espread	0.680***	
	(0.078)	
Lag pimpact		0.401***
		(0.069)
Observations	7,188	7,188
R-squared	0.776	0.512
Month-Year FE	Yes	Yes
Controls	Yes	Yes

Table 4

Are Results Driven by Variation in Measured 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 market liquidity from Table 2. Instead of measuring eligibility at the impact cost cutoff of 1.0%, we replicate the analysis around a placebo cutoff below and above the actual cutoff (at 0.78% and 1.22%, respectively). The "Local Sample" used in the analysis are those stocks that lie close to the placebo cutoff using the bandwidth of 0.22%, as in Table 2. The explanatory variables are the *Placebo Group 1* dummy and the same vector of control variables defined in Table 2. Month-year effects are estimated but not reported in the table. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)	(3)	(4)
	Placebo Cutoff= 0.78%		*Placebo Cutoff = 1.22%*	
VARIABLES	espread	pimpact	espread	pimpact
Placebo Group1	0.000	0.004	-0.012	-0.012
	(0.005)	(0.008)	(0.007)	(0.014)
Lag std_dret	-0.584***	2.799***	-0.072	6.500***
	(0.214)	(0.439)	(0.383)	(0.942)
Lag mret	-0.036*	-0.114***	-0.043	-0.121**
	(0.019)	(0.024)	(0.027)	(0.054)
Lag logvolume	-0.006	-0.043***	-0.025	-0.088***
	(0.007)	(0.010)	(0.017)	(0.021)
Lag logmcap	0.004	-0.062***	0.012**	-0.068***
	(0.004)	(0.006)	(0.005)	(0.012)
Lag espread	0.635***		0.566***	
	(0.051)		(0.062)	
Lag pimpact		0.346***		0.329***
		(0.023)		(0.051)
Observations	9,751	9,751	5,240	5,240
R-squared	0.845	0.512	0.830	0.480
Month-Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 5 Extended Analyses

This table presents results of extended analyses of the impact of margin trading eligibility on market liquidity using the local discontinuity sample and specification described in Table 2 (columns 2 and 4). We introduce 6 new variables: (1) a dummy to indicate the ability to trade single-stock derivatives (*derivative*); (2) a dummy variable to indicate CNX 500 index membership (*index*); (3) a dummy to indicate high percentage foreign ownership (*foreign);* (4) a dummy to indicate high percentage institutional ownership (*inst);* (4) a dummy to indicate high percentage individual ownership (*indiv*); (4) a dummy to indicate high percentage blockholder and insider ownership (*promoter*). These new variables, as well as their interactions with the Group 1 dummy variable are included in the regressions. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

Panel A: Dependent variable =*espread*

VARIABLES	(1) Derivative	(2) Index	(3) Foreign	(4) Inst	(5) Indiv	(6) Promoter
Group1	-0.026***	-0.023***	-0.024***	-0.021***	-0.021**	-0.027***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)
Group1 x derivative	0.038					
	(0.023)					
Group1 x index		-0.013				
		(0.013)				
Group1 x foreign			-0.006			
			(0.009)			
Group1 x inst				-0.011		
				(0.009)		
Group1 x indiv					-0.005	
					(0.009)	
Group1 x promoter						0.002
						(0.008)
derivative	-0.027					
	(0.019)					
index		0.003				
		(0.013)				
foreign			0.014			
			(0.010)			
inst				0.004		
				(0.008)		
indiv					-0.002	
					(0.007)	
promoter						0.012
						(0.007)
Observations	7,188	7,188	6,968	6,968	6,968	6,936
R-squared	0.775	0.775	0.776	0.776	0.776	0.775
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 5 Panel B: Dependent Variable = *pimpact*

VARIABLES	(1) Deriv	(2) Index	(3) Foreign	(4) Inst	(5) Indiv	(6) Promoter
Group1	-0.031***	-0.032***	-0.030***	-0.032***	-0.027*	-0.029**
	(0.009)	(0.010)	(0.011)	(0.012)	(0.015)	(0.013)
Group1 x derivative	0.072					
	(0.059)					
Group1 x index		0.010				
		(0.018)				
Group1 x foreign			-0.006			
			(0.019)			
Group1 x inst				-0.000		
				(0.016)		
Group1 x indiv					0.001	
					(0.019)	
Group1 x promoter						-0.010
						(0.017)
derivative	-0.095*					
	(0.052)					
index		-0.025*				
		(0.015)				
foreign			0.001			
			(0.015)			
inst				-0.021		
				(0.015)		
indiv					-0.017	
					(0.015)	
promoter						0.042***
						(0.014)
Observations	7,188	7,188	6,968	6,968	6,968	6,936
R-squared	0.512	0.512	0.509	0.509	0.509	0.510
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 6
Market Conditions and the Effect of Leverage Constraints on Liquidity

This table presents results of the analysis of the relationship between equity market conditions and the impact of margin trading eligibility on market liquidity. The sample includes all stocks Groups 1 and 2 with impact costs are close to the cutoff of 1% (i.e., between 0.78% and 1.22%). The dependent variables are average effective spread (*espread)* and the 5-minute price impact of trading (*pimpact)* during month *t*, where eligibility is effective as of the beginning of month *t*. In Columns (1) and (3), the specification is identical to that in Columns 2 and 4 of Table 2 except that *mmret*, defined as the Indian market returns during month t is added as an additional explanatory variable. We also interact *mmret* with the group 1 indicator variable. In Columns (2) and (4), we also add *severedownturn*, a dummy variable equal to 1 if market returns during month *t* are in the lowest decile in our sample. We also add a triple interaction of *severedownturn* with *group1 x mmret*. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

VARIABLES	(1) espread	(2) espread	(3) pimpact	(4) pimpact
Group1	-0.014**	-0.030***	-0.029***	-0.053***
	(0.006)	(0.007)	(0.010)	(0.010)
Group1 x mmret	0.108	0.454***	0.269*	0.803***
	(0.091)	(0.084)	(0.154)	(0.148)
Group1 x mmret x severedownturn		-0.802***		-1.266***
		(0.160)		(0.289)
mmret	-1.061***	-0.908***	-1.403***	-1.427***
	(0.073)	(0.069)	(0.126)	(0.128)
severedownturn		0.067***		-0.011
		(0.018)		(0.032)
Observations	7,188	7,188	7,188	7,188
R-squared	0.648	0.658	0.426	0.431
Month-Year FE	No	No	No	No
Controls	Yes	Yes	Yes	Yes

Table 7
Margin Trading Intensity and Liquidity
This table presents results of the analysis of the relationship between margin trading intensity and market liquidity. The sample includes all stocks Groups 1 and 2 with impact costs close to the cutoff of 1% (i.e., between 0.78% and 1.22%). The dependent variables are average effective spread (*espread*) and the 5-minute price impact of trading (*pimpact*) during month *t*, where eligibility is effective as of the beginning of month t. The specification is identical to Table 2 except that we add *intense margin trade*, a dummy variable equal to 1 if a Group 1 stock experiences higher-than-median margin trading during month t. Margin trading activity is calculated based on the absolute value of daily changes in outstanding margin positions. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)
VARIABLES	espread	pimpact
Group1	-0.014*	-0.016*
	(0.008)	(0.009)
Intense margin trade	-0.031***	-0.047***
	(0.005)	(0.009)
Lag std_dret	-0.444	4.052***
	(0.326)	(0.660)
Lag mret	-0.044	-0.043
	(0.032)	(0.031)
Lag logvolume	-0.026***	-0.076***
	(0.010)	(0.014)
Lag logmcap	0.007	-0.052***
	(0.006)	(0.006)
Lag espread	0.699***	
	(0.087)	
Lag pimpact		0.411***
		(0.072)
Observations	6,887	6,887
R-squared	0.784	0.523
Month-Year FE	Yes	Yes
Controls	Yes	Yes

Table 8

Margin Traders' Short-Horizon Trading Patterns

This table presents results of the panel regression analysis of daily margin trading activity and short-horizon stock returns. In Column 1, we regress the change in daily margin positions outstanding on lagged daily returns. We use daily margin position data to calculate the margin trading proxy (c*h_margin*), defined as the log ratio of day *t* margin positions outstanding to day *t*-1 margin positions outstanding. *Lag dret* is the one-day lagged daily stock return. Column 2 adds control variables that have been shown to be related to trading activity. These are one-day lagged: stock turnover, defined as the average number of daily shares traded divided by shares outstanding; log market capitalization; and stock price volatility, defined as the difference between the daily high and the low prices, divided by the daily high price. Contemporaneous daily stock returns (*dret*) and lagged c*h_margin* are also included as controls. In Column 3, we estimate a piecewise linear regression in which we allow the relationship between margin trading activity to vary in different regions of lagged daily stock returns. *Very neg* is the lagged return when lagged returns are less than -5%, otherwise *Very neg* is set equal to -5%. *Mild neg* equals: zero when returns are less than or equal to -5%; lagged return plus 5% when lagged returns are between -5% and 0%; and 5% when lagged returns are greater than or equal to 0%. *Positive* equals the lagged return when lagged returns are greater than 0% and is zero otherwise. The specifications in Columns (1) through (3) include stock and day fixed effects. In Column 4, we remove the day fixed effects and add a dummy variable, *severedownturn*, which equals 1 if market returns during month *t* are less than the bottom decile returns and 0 otherwise. All standard errors are clustered by ISIN (stock identifier) and trading day. *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)	(3)	(4)
VARIABLES	ch_margin	ch_margin	ch_margin	ch_margin
Lag dret	-0.1913***	-0.2518***		-0.1727***
	(0.0104)	(0.0124)		(0.0106)
Very neg			-0.0680	
			(0.0601)	
Mild neg			-0.2706***	
			(0.0205)	
Positive			-0.2404***	
			(0.0190)	
Lag dret x severedownturn				0.3103***
				(0.0523)
Severedownturn				-0.0373***
				(0.0029)
Lag ch_margin		-0.0708***	-0.0707***	-0.0696***
		(0.0021)	(0.0021)	(0.0021)
Lag turnover		0.1230***	0.1193***	0.1545***
		(0.0336)	(0.0336)	(0.0340)
Lag mcap		-0.0002	0.0002	0.0002
		(0.0003)	(0.0003)	(0.0003)
Lag volatility		0.0523***	0.0562***	-0.0036
		(0.0096)	(0.0105)	(0.0073)
Dret		-0.3670***	-0.3660***	-0.2673***
		(0.0196)	(0.0197)	(0.0168)
Observations	898,149	739,250	739,250	739,250
R-squared	0.0009	0.0182	0.0182	0.0169
Number of ISINs	1,241	994	994	994
Stock FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	No

Table 9
Margin Trading and the Probability of Informed Trading (PIN)

This table presents results of analysis of the impact of margin trading eligibility on 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% (i.e., between 0.78% and 1.22%). For each stock and month, we estimate the PIN following Easley, O'Hara and Paperman (1996). The dependent is the month *t* PIN. The explanatory variables are *Group 1*, a dummy variable equal to 1 if the control stock is eligible for margin trading during month *t*, a vector of control variables and year-month dummies. The control variables are defined in Table 2 and include one-month lagged: standard deviation of stock returns (*std_ret*), stock returns (*mret*), dollar volume (l*ogvolume*), equity market capitalization (*logmcap*) and as well as the lagged liquidity variables, *espread* and *pimpact*. Month-year fixed effects are estimated but not reported in the table. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

VARIABLES	(1) PIN
Group1	-0.002
	(0.003)
Lag std_dret	-0.996***
	(0.207)
Lag mret	-0.020
	(0.016)
Lag logvolume	-0.000***
	(0.000)
Lag logmcap	0.009***
	(0.002)
Lag espread	0.054***
	(0.006)
Lag pimpact	-0.020***
	(0.005)
Observations	6,903
R-squared	0.072
Month-Year FE	Yes
Controls	Yes

Table 10

This table compares returns to short-horizon return reversal strategies in Group 1 versus Group 2 stocks in the local sample. Returns (in %) from analyzing a number of portfolios are reported in Panel A, with each portfolio defined within the universe of the local Group 1 or Group 2 samples. *Reversals 1day* is the average returns to a reversal strategy that weights stocks proportional to the negative of market-adjusted returns on days *t-1*. *Reversals 3day* is the average of returns from three reversal strategies that weight stocks proportional to the negative of market-adjusted returns on days *t-1, t-2* and *t-3*. Similarly, *Reversals 5day* is the average of five reversal strategies that weight stocks based on returns on days *t-1, t-2,.., t-5*. We regress the returns of each of these portfolios on an intercept and the Group 1 dummy variable; standard errors are clustered by month. Panel B provides stock-level evidence. *Autocov* is the absolute value of monthly autocovariance of the daily returns of a stock (x 10^3). We use the local discontinuity sample and specification described in Table 2 (columns 2 and 4). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

Panel A. Portfolio Returns

	Reversals 1day	Reversals 3day	Reversals 5day
Intercept	0.2979***	0.1638***	0.1183***
	(0.0503)	(0.0475)	(0.0377)
Group 1	-0.0808**	-0.0435*	-0.0345*
	(0.0326)	(0.0252)	(0.0201)
Observations	4,228	4,228	4,228
R-Squared	0.0004	0.0002	0.0002

Panel B. Stock-level Covariance

VARIABLES	Autocov
Group1	-0.012**
	(0.006)
Lag std_dret	3.021***
	(0.463)
Lag mret	-0.087***
	(0.029)
Lag volume	0.017***
	(0.004)
Lag logmcap	-0.009***
	(0.003)
Lag autocov	-0.002
	(0.017)
Observations	7,188
R-squared	0.171
Month-Year FE	Yes
Controls	Yes

Table 11
Commonality in Liquidity

This table presents results of the commonality in liquidity analysis. The dependent variable is the monthly r-square from a regression of stock i's liquidity innovation on the market's liquidity innovation. *R^2 espread* indicates the R-square from the monthly *espread* innovation regressions; *R^2 pimpact* is the R-square from the monthly regressions using the Amihud (2002) illiquidity ratio. *Group 1* is a dummy variable equal to 1 if the stock is a Group 1 stock. In the specifications shown in Columns (1) and (3), we include the *Group 1* indicator variable, as well as time fixed effects. In Columns (2) and (4), we add a dummy variable to indicate very negative market returns. *Severe downturm* equals 1 if market returns during month *t* are in the bottom decile of market returns and 0 otherwise. All regressions include year-month fixed effects (estimated but not reported in the table) and standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)	(3)	(4)
VARIABLES	R^2 espread	R^2 espread	R^2 pimpact	R^2 pimpact
Group1	0.0062*	0.0005	0.0110***	0.0034
	(0.0037)	(0.0037)	(0.0039)	(0.0040)
Group1 x severedownturn		0.0504**		0.0346**
		(0.0205)		(0.0163)
Severedownturn		0.0900***		0.0430***
		(0.0139)		(0.0118)
Lag std_dret	0.3909	0.3606*	0.8402***	0.8683***
	(0.2474)	(0.2157)	(0.2392)	(0.1987)
Lag mret	-0.0350**	0.0333**	-0.0487***	-0.0220*
	(0.0152)	(0.0140)	(0.0152)	(0.0129)
Lag dollarvolume	0.0120***	0.0175***	0.0038	0.0104***
	(0.0023)	(0.0022)	(0.0023)	(0.0023)
Lag logmcap	-0.0103***	-0.0119***	-0.0182***	-0.0157***
	(0.0020)	(0.0021)	(0.0022)	(0.0021)
Lag R^2 espread	0.0308**	0.0437***		
	(0.0128)	(0.0131)		
Lag R^2 pimpact			0.0618***	0.0609***
			(0.0135)	(0.0139)
Observations	6,826	6,826	6,826	6,826
R-squared	0.258	0.072	0.200	0.043
Controls	Yes	Yes	Yes	Yes
Month-Year FE	Yes	No	Yes	No

Appendix Table A.1

Alternative Bandwidths

This table presents results of the analysis of the impact of margin trading eligibility on market liquidity using the local discontinuity sample with alternative bandwidths, ranging between 0.16% and 0.28%. The regression specification is identical to that in Table 2. The dependent variables are average *espread* and *pimpact* during month t, where eligibility is effective as of the beginning of month *t*. The explanatory variables are *Group 1*, a dummy variable equal to 1 if the control stock is eligible for margin trading during month *t*, the control variables defined in Table 2, and year-month dummies. The year-month fixed effects are estimated but not reported in the table. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

Panel A: Dependent Variable = *espread*

VARIABLES	(1) 0.28%	(2) 0.26%	(3) 0.24%	(4) 0.22%	(5) 0.20%	(6) 0.18%	(7) 0.16%
Group1	-0.026***	-0.026***	-0.025***	-0.025***	-0.026***	-0.024***	-0.024***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Lag std_dret	-0.626**	-0.702**	-0.481	-0.507	-0.504	-0.485	-0.648
	(0.288)	(0.302)	(0.322)	(0.325)	(0.345)	(0.364)	(0.395)
Lag mret	-0.047*	-0.054**	-0.055*	-0.045	-0.045	-0.036	-0.029
	(0.025)	(0.027)	(0.029)	(0.030)	(0.032)	(0.035)	(0.038)
Lag logvolume	-0.024***	-0.024***	-0.027***	-0.030***	-0.031***	-0.033***	-0.035***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.011)
Lag logmcap	0.007	0.007	0.010*	0.010*	0.010	0.012*	0.012*
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Lag espread	0.718***	0.710***	0.698***	0.683***	0.672***	0.651***	0.633***
	(0.068)	(0.071)	(0.075)	(0.078)	(0.082)	(0.086)	(0.092)
Observations	9,200	8,586	7,859	7,188	6,521	5,836	5,161
R-squared	0.777	0.777	0.775	0.775	0.773	0.770	0.769
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Dependent Variable = *pimpact*

VARIABLES	(1) 0.28%	(2) 0.26%	(3) 0.24%	(4) 0.22%	(5) 0.20%	(6) 0.18%	(7) 0.16%
Group1	-0.034***	-0.034***	-0.032***	-0.031***	-0.029***	-0.030***	-0.029***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Lag std_dret	4.461***	4.364***	4.572***	4.490***	4.381***	4.555***	4.610***
	(0.645)	(0.667)	(0.721)	(0.751)	(0.800)	(0.858)	(0.906)
Lag mret	-0.058**	-0.064**	-0.062**	-0.048	-0.061*	-0.047	-0.055
	(0.027)	(0.028)	(0.029)	(0.030)	(0.032)	(0.033)	(0.035)
Lag logvolume	-0.082***	-0.082***	-0.085***	-0.087***	-0.083***	-0.085***	-0.082***
	(0.012)	(0.013)	(0.014)	(0.014)	(0.015)	(0.017)	(0.018)
Lag logmcap	-0.051***	-0.051***	-0.050***	-0.052***	-0.054***	-0.051***	-0.053***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Lag pimpact	0.392***	0.399***	0.398***	0.400***	0.410***	0.409***	0.423***
	(0.059)	(0.061)	(0.066)	(0.070)	(0.074)	(0.081)	(0.087)
Observations	9,200	8,586	7,859	7,188	6,521	5,836	5,161
R-squared	0.504	0.511	0.510	0.512	0.519	0.521	0.527
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix Table A.2
Alternative Liquidity Variables

This table presents results of the analysis of the impact of margin trading eligibility on market liquidity using alternative liquidity measures. The sample includes all stocks in Groups 1 and 2 with impact costs close to the cutoff of 1% (i.e., between 0.78% and 1.22%). The dependent variables are the time-weighted average quoted spread (*qspread)* and the 30-minute price impact of trading (*pimpact30)* during month *t*, where eligibility is effective as of the beginning of month *t*. The specification is identical to that in Columns 2 and 4 of Table 2. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)
VARIABLES	qspread	pimpact30
Group1	-0.026***	-0.026***
	(0.008)	(0.008)
Lag std_dret	-0.331	4.624***
	(0.410)	(0.719)
Lag mret	-0.064***	-0.034
	(0.024)	(0.026)
Lag logvolume	-0.030***	-0.098***
	(0.008)	(0.007)
Lag logmcap	0.014**	-0.048***
	(0.007)	(0.005)
Lag qspread	0.751***	
	(0.058)	
Lag pimpact30		0.284***
		(0.042)
Observations	7,188	6,990
R-squared	0.789	0.446
Month-Year FE	Yes	Yes
Controls	Yes	Yes

Appendix Table A.3
Margin Eligibility and Ownership Structure
This table presents results of analysis of the impact of margin trading eligibility on the ownership structure of NSE stocks. The sample includes all stocks Groups 1 and 2 with impact costs close to the cutoff of 1% (i.e., between 0.78% and 1.22%). 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 then regress these stockholdings on the Group 1 dummy and the control variables defined in Table 2, as well as the lagged liquidity variables, *espread* and *pimpact*. Month-year fixed effects are estimated but not reported in the table. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

	(1)	(2)	(3)	(4)
VARIABLES	foreign perc	inst perc	indiv perc	promoter perc
Group1	-0.014	0.003	-0.012	-0.0883
	(0.016)	(0.008)	(0.009)	(0.651)
Lag std_dret	1.283	-0.606	-1.647**	87.011
	(1.106)	(0.582)	(0.712)	(52.986)
Lag mret	0.027	-0.078***	0.072*	7.766***
	(0.055)	(0.028)	(0.038)	(2.569)
Lag logvolume	-0.054***	0.000	0.021***	-3.388***
	(0.015)	(0.008)	(0.008)	(0.660)
Lag logmcap	0.108***	0.047***	-0.109***	8.107***
	(0.022)	(0.008)	(0.009)	(0.724)
Lag espread	0.102*	-0.006	-0.029	-1.256
	(0.055)	(0.022)	(0.027)	(1.870)
Lag pimpact	-0.072**	-0.013	0.009	1.091
	(0.031)	(0.012)	(0.017)	(1.226)
Observations	2,462	2,462	2,462	2,451
R-squared	0.120	0.179	0.261	0.219
Month-Year FE	Yes	Yes	Yes	Yes