Leverage constraints and liquidity: What can we learn from margin trading?*

C. Bige Kahraman — **Stockholm School of Economics**

Heather Tookes — **Yale School of Management**

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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 test the hypothesis that there is a causal relationship between traders' leverage constraints (i.e., their ability to borrow to invest in risky assets) and a stock's market liquidity. In India, the list of stocks eligible for margin trading is revised every month, creating a series of quasi-experiments that provide traders of newly eligible and ineligible stocks with shocks to the availability of leverage. We employ a regression discontinuity design that exploits the threshold rules that determine a stock's margin trading eligibility. When we compare the liquidity of eligible and ineligible stocks that lie close to the eligibility threshold, we find that liquidity is higher when stocks become eligible for margin trading and that it decreases with ineligibility. Using available data on margin financing activity at the individual stock level, we try to uncover the mechanisms driving this main finding. We find evidence consistent with the idea that the liquidity enhancement that we observe stems from margin traders' contrarian strategies.

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Author contact information: C. Bige Kahraman, Stockholm School of Economics, Drottninggatan 89, 113 60 Stockholm, Sweden, bige.kahraman@hhs.se. Heather Tookes, Yale School of Management, PO Box 208200, New Haven, CT 06520, heather.tookes@yale.edu.

1. Introduction

Do traders' leverage constraints drive equity market liquidity? The recent financial crisis has brought increasing attention to the idea that reductions in traders' ability to use leverage (i.e., the ability of traders to borrow in order to invest in risky assets) can cause sharp declines 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), Fostel and Geanakoplos (2012)). 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 assumption is theoretically appealing, it is challenging to test its validity empirically. In order to do so, 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 a decline in fundamentals cause leverage constraints to bind and market liquidity to decline simultaneously. This can confound the overall interpretation of any observed positive relationship between market liquidity and leverage constraints.

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, under margin trading in India, investors can borrow up to 50% of the purchase price of an eligible

[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.

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. Because the lists of eligible stocks are generated on a monthly basis, we are able to use both the time-series and cross-sectional variation in margin eligibility to estimate the impact of eligibility on stock market liquidity. We focus our analysis on National Stock Exchange (NSE) stocks. The NSE, an electronic limit order book, is the most important Indian market and the 16th largest in the world by trading activity. As of December 2012, the market capitalization of NSE listed securities was $1.23 trillion.[2]

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. The discreteness of the margin trading rules provides a "sharp" discontinuity (see Lee and Lemieux, 2009). For every stock and month in our sample, we first calculate two widely used measures of liquidity: average (estimated) bid-ask spreads and the Amihud (2002) illiquidity ratio. Both of these can be interpreted as trading costs, which capture deviations of transaction costs from fundamental

[2] World Federation of Exchanges, December 2012, http://www.world-exchanges.org/statistics/monthly-reports.

value.[3] We then compare the liquidity of stocks that are eligible for margin trading with that of stocks that lie close to the eligibility cutoff but are ineligible.

Our main findings are consistent with a causal effect of leverage constraints on stock market liquidity. We find that stock market liquidity is higher when stocks become eligible for margin trading. This effect is both statistically and economically significant. For example, the most conservative estimates from the regression discontinuity analysis of stocks near the eligibility threshold imply that margin eligibility leads to a 2.1% reduction in estimated bid-ask spreads and a 7.9% reduction in the price impact of trades relative to their respective means. Importantly, we do not find similar results when we repeat the eligibility analyses near a placebo margin eligibility cutoff.

The margin trading rules in India are such that investors have time to unwind their positions following ineligibility. Thus, one might expect the effects of new eligibility to be different from ineligibility. When we limit our attention to stocks that are newly eligible or ineligible for margin trading and compare liquidity to a control sample of stocks, we find large implied effects. New eligibility (ineligibility) is associated with substantial decreases (increases) in both spreads and the price impact of trading. The liquidity impact in the case of ineligibility is weaker statistically and occurs over somewhat longer time horizons than in the case of new eligibility. This is expected, and highlights the importance of examining fresh eligibility and ineligibility separately.

Given the strong evidence of a causal role of leverage constraints on market liquidity, we try to uncover the mechanisms driving the basic result. Are margin traders acting as financial intermediaries? While it is possible that they are providing liquidity, it is also possible that margin traders are liquidity demanders or even privately informed traders. Their dominant role is an

[3] Brunnermeier and Pedersen (2009) define market liquidity as the difference between the transaction price and fundamental value. Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010, p. 300) provide similar discussion, in which they map Brunnermeier and Pedersen's (2009) definition of market liquidity to empirical proxies.

empirical question. One unique feature of our data is that we observe daily margin positions at the individual stock level. We use this information to document some basic facts about margin traders' trading strategies. In the spirit of Diether, Lee, and Werner (2008), who characterize the trading strategies of short sellers, we use daily data on margin positions and stock returns at the individual stock level to help us understand the positive impact of eligibility on stock market liquidity.[4] We find that, as a group, margin traders are contrarian in the short run.[5] They tend to buy stock on margin following negative returns, especially when the negative returns are not too extreme (i.e., they do not increase their margin positions during crises, when it is likely that they will face margin calls). Consistent with liquidity provision, the estimates imply that on average, following a 10% decrease in stock prices, margin positions will increase by 1.7%.

In the main analysis, we focus on the relationship between leverage constraints and market liquidity at the individual security level. Although there is considerable interest in understanding these relationships at the aggregate level, our main empirical design exploits the cross-sectional variation in leverage constraints. This approach allows us to mitigate important concerns that market-level variables related to economic fundamentals are driving observed relationships between market and leverage constraints. We are, however, also interested in understanding whether the stock-level results can provide insights into variation in aggregate liquidity. It is well known that both U.S. and global stocks exhibit significant liquidity comovement (e.g., Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), Karolyi, Lee, and Van Dijk (2012)). Although

[4] To our knowledge, Hardouvelis and Peristiani (1992) and Andrade, Chang, and Seasholes (2008) are the only other studies that use actual margin financing data. Hardouvelis and Peristiani (1992) study the impact of margin requirements on volatility and trading volume in Japan. Andrade, Chang, and Seasholes (2008) use weekly margin account data to study the relationship between non-informational trading imbalances and stock returns in Taiwan.

[5] This is consistent with recent empirical work by Franzoni and Plazzi (2013), who find that hedge fund traders who use leverage tend to be contrarian in the short run, thus providing liquidity.

"commonality in liquidity" is pervasive, we still do not have a full understanding of what drives it.[6] We examine one potential determinant of commonality: leverage constraints. We examine stocks near the impact cost threshold and test whether the covariation in liquidity is greater for stocks that trade under similar margin rules. We find that when stocks are in a given margin trading regime, their liquidity tends to comove more with the other stocks in that same category.

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 potential causal effects. Recently, Comerton-Forde, Hendershott, Jones, et al. (2010) and Aragon and Strahan (2011) take important steps toward overcoming some of these issues.

Comerton-Forde, Hendershott, Jones, et al. (2010) link market maker balance sheet and income statement information to liquidity provision at the individual stock level. They find lower stock liquidity when specialists have large positions and when they have recently experienced losses related

[6] Thus far, the literature has documented that commonality is higher for stocks with greater institutional ownership and in times of increased foreign capital flow and higher investment sentiment (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 comovement, our regression discontinuity design helps us to mitigate some potential challenges in the overall interpretation.

to inventory. While their evidence suggests an important role for financing constraints, it is still difficult to fully rule out the hypothesis that market makers' large positions and short-term losses related to inventory represent something other than funding constraints.[7] Aragon and Strahan (2011) use Lehman's bankruptcy as a shock to the funding liquidity of Lehman-connected hedge funds. They document liquidity declines in stocks held by hedge funds that were connected to Lehman. Our analysis complements both of these papers because new margin eligibility is easy to interpret as the relaxation of a funding constraint (due to leverage), and our threshold strategy helps to sharpen the interpretation.[8] 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. Our focus on the leverage channel (i.e., one specific mechanism within the broad category of funding constraints) allows us to provide some specific insights into causes and implications of funding constraints. An additional benefit of our data 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.

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.

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[7] For example, liquidity declines due to high inventory positions and recent losses could be related to specialists' business models dictating the horizon over which profits are maximized or to strategic market maker behavior due to innovations in stock fundamentals.

[8] Other recent papers have attempted to link funding constraints and market liquidity by introducing a number of intuitive proxies for funding constraints. These include declines in market returns (Hameed, Kang, and Viswanathan (2010)); changes in monetary conditions due to shifts in Fed monetary policy (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). The results of these recent empirical studies are consistent with the idea that funding constraints impact market liquidity and prices, but it is difficult to establish clear causality.

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. There were few limits (e.g., no maintenance margin). 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 from random intervals in each stock per day. Stocks 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.[9] Group 2 stocks are those that have traded on at least 80% of the days over the past six months but do not

[9] 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)).

make the impact cost cutoff. All remaining stocks are classified into Group 3. Group 2 and Group 3 stocks are ineligible for margin trading. Impact costs and the resulting group assignments are calculated on the 15th day of each month. These new groups are announced and become effective on the first 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 lending: brokers can borrow up to five times their own net worth in the provision of 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 to answer questions about the implications and drivers of high levels 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 are also short-run advantages 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.

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. 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 (approximately $20 million). As of May 2013, we found fewer than 150 F&O stocks. Securities eligible for futures and options are eligible for shorting; however, shorting has been available to institutional investors only since 2008 and short positions can be held for no longer than twelve months.[10] 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. 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

[10] 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).

money to purchase any securities they wish. Doing so is similar to taking a collateralized personal loan from a bank to finance a small business (or even a vacation), except that, because they are not regulated by the SEBI, NBFCs have more flexibility in setting lending terms than banks do. Loans from NBFCs can come with lower margin requirements and more flexible collateral, such as land or other property. At the same time, they typically carry higher interest rates (conversations with market participants suggest that they range from 12% to 18%, twice market rates) and include terms that increase the risk of the positions to the investors (e.g., NBFCs can liquidate investors' positions without notice; there are no arbitration mechanisms, so investors must use the courts to resolve disputes). Because these alternative mechanisms are costly and restrictive, we expect at least some demand for margin trading. Importantly, the existence of these potential alternative leveraging mechanisms biases the analysis against finding a significant role for margin trading.

In this paper, we analyze National Stock Exchange (NSE) stocks. Like many exchanges worldwide, the NSE is an electronic limit order book market. While newer than the Bombay Stock Exchange (BSE), it is now the most important Indian market by trading activity. Of the few papers in the literature that focus on India, Berkman and Eleswarapu (1998) is the most related to ours. The authors use the Badla ban to examine the change in value and trading volume in the 91 BSE stocks that were previously eligible for Badla, and they report a decline in value and trading volume as a result of the ban. Unlike their paper, our study is motivated by recent papers linking funding liquidity to both market liquidity and liquidity commonality. In addition, we analyze events in a much larger sample of stocks over an eight-year horizon and focus on two liquidity measures that were not available when Berkman and Eleswarapu (1998) published their paper.

3. Data and Methodology

3.1 Data

The sample consists of all stocks traded on the NSE from April 2004 (the month in which margin trading was introduced) through December 2012. Daily trading activity and returns data are from the NSE (bhavcopy product). The advantage of using the NSE data relative to Datastream is that we are able to observe trading activity in all stocks, not just those for which there is coverage in Datastream.[11] For each trading day, 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 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. These are stocks that have traded on at least 80% of the trading days over the past sixmonths and for which average impact cost is less than 1%. Impact cost, as described earlier, is calculated as the average percentage change in price (from bid/offer midpoint) caused by an order size of 100,000 rupees (approximately $2000) over the past six months.

Margin data, which begin in April 2004, are from the SEBI daily reports. We obtained these from a local data vendor and the NSE. 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

[11] Corwin and Schulz (2012) use Datastream to estimate spreads for Indian stocks. The number of Bombay Stock Exchange and National Stock Exchange stocks (combined) in Datastream appears comparable to our sample of NSE stocks only.

margin trading done on any day shall be made available after the trading hours on the following day, through its website." The margin data are reported at the individual security level and include *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.[12] In our data, we find that on a typical day, margin traders' end-of-day stakes in margin-eligible stocks are approximately 2.2 billion rupees (about $44 million).[13] This amounts to approximately 1.4% of the total daily trading volume in these stocks.

Shares outstanding and market capitalization data are from Prowess (a database of Indian firms, analogous to Compustat). We observe Prowess information for approximately 80% of the NSE stocks. We do not require Prowess data availability for our main tests; however, we do use Prowess variables in robustness checks. We also obtain a list of stock trading suspensions from Prowess. We exclude from our sample all stocks that have been suspended, because trading irregularities in suspended stocks are likely to contaminate our liquidity measures.[14]

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,

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[12] 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 shed light on 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.

[13] We assume that margin positions represent 50% of the total positions held by margin traders. Because maintenance margins are only 40%, the total amount held by margin traders may be up to 25% larger than the values that we report.

[14] Note that we 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.

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. All of these filters are applied using daily data.

Brunnermeier and Pedersen (2009) define market liquidity as the difference between the transaction price and fundamental value. We focus the analysis on two measures of liquidity that are consistent with this idea and that are commonly used in the market microstructure literature: estimated bid-ask spreads and the Amihud (2002) illiquidity ratio. Bid-ask spreads capture the difference between the transaction price and fundamental value for an investor wishing to trade a small amount of a given security. The Amihud (2002) illiquidity ratio provides an estimate of the price impact of an order of a given size (1 million rupees in our setting). Both of these measures capture deviations of transaction prices from their fundamental values, but they differ in that spreads capture instantaneous costs of executing a small trade, while the Amihud (2002) measure accounts for the size of the order.[15] A benefit of the Amihud (2002) measure is that it can incorporate the costs of larger trades. A cost of the measure is that, because trading volume is in its denominator, substantial noise can be introduced when trading is thin. We therefore 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.

Because bid-ask spreads are not directly observable in the daily data from the NSE, we estimate them following Corwin and Schulz (2012). Starting with the intuition that buy orders are typically

[15] We do not analyze patterns in turnover or trading volume since these are correlated with volatility, which can alter the interpretation. Turnover also can capture investment horizon as well as the arrival of public news.

executed at the daily high price and sell orders are usually executed at the daily low price, the authors suggest using data from daily high and low transaction prices to estimate spreads. The basic idea behind the Corwin and Schulz (2012) measure is that the difference between high and low prices on any single day should reflect the daily price variance plus the spread. Thus, assuming a constant spread over the two-day window, (i) the sum of the difference between high and low prices over two consecutive days should equal two times the daily price variance plus two times the spread, and (ii) the difference between high and low prices over the entire two-day period should be equal to two times the daily price variance, plus the spread. The difference between (i) and (ii) can provide an approximation for the spread. Using U.S. data, Corwin and Schulz (2012) find that their proposed measure has a cross-sectional correlation of 0.83 with effective spreads (the difference between the transaction price and the prevailing quote midpoint). The within-stock (time-series) correlation with effective spreads is 0.65, a substantial improvement over earlier methods for estimating spreads with low frequency data. Moreover, they find that their measure performs particularly well for mid-cap and small-cap U.S. stocks, which are more comparable to the stocks that we analyze in the Indian equity market setting. Note that the Corwin and Schulz (2012) measure may not work well when stocks are traded very infrequently. This does not appear to be a problem in our setting, given that we observe very few zero trading days in our sample of Group 1 and Group 2 stocks. In fact, Corwin and Schulz (2012) use India as an example of a non-U.S. market in which their measure is applicable. The general procedure we use to estimate spreads follows the closed-form solution in Corwin and Schulz (2012), equations (14) and (18).[16]

[16] The SAS code that we use to produce these estimates is posted on Shane Corwin's website: http://www3.nd.edu/~scorwin/HILOW_Estimator_Sample_002.sas. Following Corwin and Schulz (2012), we also adjust for overnight price changes using data from period *t*-1 such that whenever the close on day *t*-1 is higher (lower) than the high (low) on day *t,* we use the day *t*-1 close as the high (low) price for day *t.* In addition, as in Corwin and Schulz (2012), we set negative estimated spreads equal to zero.

The illiquidity ratio (*ILLIQ*) is from Amihud (2002) and 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 trading volume on day *t*. The interpretation of *ILLIQ* is that it captures the change in price generated by daily trading activity of 1 million rupees. *ILLIQ* 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 *ILLIQ* at the 1% and 99% levels. We also remove observations in which daily trading volume is less than 100 shares. Because our focus is on a non-U.S. sample of stocks, we follow Lesmond (2005), who also examines *ILLIQ* using international data and imposes an additional price filter to try 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.

Throughout the analysis, we focus on Group 1 and Group 2 stocks. There are a total of 1,866 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. Following new eligibility or ineligibility, the typical stock stays in a group for approximately eight months.

Summary statistics for all variables used in the analysis are shown in Table 1. Panel A contains the full sample of Group 1 and Group 2 stocks. Groups 1 and 2 are shown separately in order to draw comparisons between them. Monthly *ILLIQ* and *Spread* are the average daily values for each month. Shares outstanding and market price are measured at the end of the month. Monthly returns are also measured at the end of the month, and are defined as the percentage change in closing price at the end of month *t* from the closing price at the end of the previous month. The standard deviation of returns is defined as the standard deviation of daily returns over month *t*. The most important observation from Table 1 is that liquidity is higher for Group 1 than for Group 2 stocks. The median percentage spread is estimated to be 1.5% for Group 2 stocks, while it is only 1.1% for those in Group 1. Moreover, the median *ILLIQ* (estimated return impact of a 1 million rupee trade) is 0.068 for Group 2 stocks, while it is 0.001 for Group 1 stocks. Our analysis will shed light on whether these differences are, at least partially, driven by the ability to trade Group 1 stocks on margin. There are other differences between Group 1 and Group 2 stocks. Group 2 stocks have higher volatility, lower turnover, lower volume, and lower prices than Group 1 stocks.[17] Returns, in contrast, are not very different between the two groups of stocks.

In Table 1, Panel B, we narrow our lens and present descriptive statistics for 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 0.76% to 1.24%). As can be seen from the table, the Group 1 and Group 2 stocks in this subsample are quite similar. However, we still control for differences in these variables in all of the extended regression specifications to ensure that our results say something about the effect of the ability to obtain margin financing and are not due to variation in another observable.

The identification in all of our analysis comes from stocks moving in and out of Group 1 (this is because we include stock fixed effects in all regressions). Figure 1 shows the time-series of the number of new entries and exits (i.e., newly eligible and newly ineligible stocks, respectively). There are about 3,100 of these events during our sample period. The number of entries per month ranges from zero to 50 (in January 2005). Exits range from zero during several months of 2004 and

[17] Price differences should not have a large impact on spreads (all else equal). Although closing prices are lower for Group 2 stocks, the minimum tick size in India is 0.05 rupees ($0.001), which is small relative to even the 5th percentile closing price for Group 2 stocks.

2010 to a high of 100 in March 2008. Our empirical approach has statistical power because of this frequent movement across groups.

3.2 Methodology

Our main 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 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.

As discussed earlier, we examine two measures of stock market liquidity: estimated bid-ask spreads (*Spread*) and the Amihud (2002) illiquidity ratio (*ILLIQ*). Both of these can be interpreted as transaction costs, where higher values are indicative of lower liquidity. The unit of observation is a stock-month, and the dependent variable in our main regressions is the average daily liquidity of the sample of Group 1 and Group 2 stocks during month *t*.

Following Chava and Roberts (2008), we begin the analysis with panel estimation using the entire sample of Group 1 and Group 2 stocks.[18] We then shift our attention to the "local" sample of stocks, defined as those stocks whose impact costs lie close to the cutoff of 1%. Our primary objective is to compare the liquidity of eligible versus ineligible stocks. The baseline regression specification for the full panel is:

[18] We do not include Group 3 stocks in the full panel estimation. This is because these stocks traded on fewer than 80% of the trading days during the past six months, and liquidity measures can be problematic when stocks do not trade frequently (i.e., *ILLIQ* is undefined on zero volume days and the estimated *Spread* measure relies on price data from both day *t* and trading day *t*-1).

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

The *Liquidity* variables are *Spread* and *ILLIQ*. *Group 1* is a dummy variable equal to 1 if the stock is in Group 1 and eligible for margin trading. The main coefficient of interest is β, which captures the estimated effect of investors' ability to trade on margin on stock market liquidity. X_t is a vector of control variables, including one month lagged: standard deviation of stock returns, stock returns, dollar volume, *Spread*, *ILLIQ*, and equity market capitalization. In most specifications, X_t also contains 5th order polynomial functions for impact cost on both sides of the cutoff.[19] All regressions contain stock fixed effects (α_i), so the identification comes from stocks that switch between Groups 1 and 2. We also include time fixed effects, we cluster standard errors at the stock level, and we correct for heteroskedasticity.

Because imposing a functional form on impact cost may not adequately control for the relationship between impact cost and liquidity, we also employ local linear regressions in which we focus our attention only on stocks that lie close to the threshold. This is perhaps our most important test because the local subsample provides much sharper identification of the effects of leverage constraints.

Critical to the overall interpretation of the analysis is our assumption that the exogenous variation in measured impact cost drives selection of stocks into the margin eligibility groups around the value 1%. We assume that assignment of the close-to-1 observations (from both the left and right) into these groups is largely random. 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

[19] We also examined lower and higher order polynomials. We report results with 5th order polynomials, as the weak significance of polynomial terms completely disappears with orders higher than 5. Results are not sensitive to the order of the polynomial. Moreover, in Table 3, we use local linear regression and the results are qualitatively similar.

price caused by an order size of Rs.1 Lakh (100,000 rupees, or approximately $2,000). While impact cost is related to liquidity, we assume that there is sufficient variation in the limit order books that we expect small differences in measured impact costs across stocks with equal liquidity. This could happen for at least three reasons. First, differences in the timing of public information releases could introduce noise in measured impact costs. 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. Because averages of the past six months are included in the impact cost calculation, a very large impact cost during a public information event for a stock that otherwise has an impact cost of 0.99 could keep the stock out of eligibility for several months. Second, impact costs (within stock) are volatile, so a measured impact cost of 1.24% may not be different from a measured impact cost of 1.00%. We see evidence of this in the data: stocks routinely move in and out of Group 1 and the standard deviation of impact costs is substantial among both groups of stocks, at 0.25 for Group 1 stocks and 3.19 for Group 2 stocks (see Table 1). Finally, the impact cost calculation itself can cause potential variation unrelated to liquidity. As an extreme example, consider two stocks with impact costs of 0.994% and 0.995%. Impact costs are rounded to two decimal points, so after rounding, the former will have an impact cost of 0.99% and the latter of 1.00%. Due to rounding, a true difference of 0.001 becomes a difference of 0.01. For stocks close to the cutoff, this noise can result in some stocks becoming eligible for margin trading while others remain ineligible. That is, the regression discontinuity approach is a valid identification strategy because it is difficult to precisely control assignment near the cutoff (Lee and Lemieux, 2009).[20]

[20] Although we believe that it is difficult for investors to strategically push impact costs below 1% to enjoy

There are a few potential caveats in the interpretation that should be mentioned before moving to the results. First, 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 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. Second, because we focus on margin trading in India, one might be concerned about the extent to which the results can be generalized. While external validity is always difficult to establish, as described in the introduction, there is some corroborating evidence in the literature (albeit without the regulatory features that allow for our identification) that is broadly consistent with the idea that leverage constraints drive variation in liquidity. Finally, margin trading impacts only the ability to purchase. Thus, it may enable traders to provide liquidity in some settings and not others. In an analysis of the mechanisms driving our main results, we examine the link between margin trading activity and stock returns.

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 form 12 impact cost bins of width 0.12 (half the size of the bandwidth that we use for the local discontinuity analysis that follows) on each side of the eligibility cutoff and compute average liquidity within each bin. Margin-eligible stocks are all those stocks with impact costs that are less than or equal to 1%, which corresponds to bins 1 through 6. Ineligible stocks are in bins 7 through 12. Figures 2a and 2b show a drop in both spreads

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margining (given that the order book snapshots are taken at random intervals), we also 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)). We do not observe any obvious bunching on either side of the threshold.

and the Amihud (2002) illiquidity ratio at the cutoff value of 1%. This lends further 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

Full Panel

Results from the baseline specification in Equation (1) are shown in Table 2. The estimated coefficients on β in the *Spread* regressions (Panel A) are significant in all specifications and range from -0.0003 to -0.0071, implying a decrease in spreads due to the ability to trade stocks on margin of between 1.8% and 42% of the mean value for ineligible (Group 2) stocks. The coefficients on β in the *ILLIQ* are significant in four of the five specifications. The statistically significant β estimates range from -0.0029 to -.0859, implying a reduction in the price impact of a 100,000 rupee trade of between 1% and 28% of the mean value for ineligible stocks. The estimated coefficients on all of the control variables are consistent with what one might expect, and with prior literature: liquidity is lower following periods of high volatility and low trading volume, and in stocks with low market capitalization. We also find that both *Spread* and *ILLIQ* are positively autocorrelated.

Local Discontinuity Sample

The results in Table 2 are suggestive of a liquidity-enhancing role for margin financing; however, the full panel regression includes stocks whose impact costs are quite far from 1, and the variability in the magnitudes of estimated coefficients across the specifications also suggests that the assumed functional may be important. Recall that, unlike in the full sample, the Group 1 and Group 2 stocks in the local subsample are very similar to one another (Table 1, Panel B). The relevant difference between them is margin trading eligibility.

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 small enough to capture the effect of the treatment (margin eligibility), but also large enough 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 $1.06*\sigma*N^{-1/5}$, where σ is the standard deviation of impact cost in our sample. This results in a bandwidth of 0.24.[21] This restriction reduces the sample size in the regressions by more than 85%.

Results of the regression using the local regression discontinuity sample are shown in Table 3. We observe statistically significant decreases in both liquidity measures as a result of margin trading. Importantly, the magnitudes of these estimated coefficients tell a consistent story. The estimated coefficients in the *Spread* regressions range from -.0003 to -.0004, implying that the average Group 2 stock near the eligibility cutoff would see a reduction in spreads of between 2.1% and 2.8% if margin trading were allowed. The estimated coefficients in the *ILLIQ* regressions range from -0.0021 to -0.0049, implying reductions in the price impact of trading of between 7.9% to 18.4%. The coefficients on the control variables in the extended specifications are all consistent with those in Table 2.[22]

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[21] The regressions are estimated using monthly data for all stocks with impact costs between 0.76% and 1.24%. We have repeated the analysis using alternative bandwidths, both smaller and larger than those that we obtain using Silverman's (1986) rule of thumb. The results are not sensitive to bandwidth choice.

[22] As discussed in Section 2, there are some Group 1 stocks for which futures and options (F&O) trading is available. We collected F&O eligibility data for all NSE stocks during our sample period. In untabulated analysis, we repeated the regressions in Table 2 and Table 3 analyses, and added a dummy variable to indicate F&O eligibility. As expected, this estimated coefficient on this dummy variable was negative and significant

4.2 Placebo Test

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 results in Tables 2 and 3 is that the measured impact costs predict 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 at impact cost equal to 2. Placebo Group 1 stocks have impact costs that are less than or equal to 2%. Placebo Group 2 stocks have impact costs that are greater than 2%. We then conduct the regression analyses analogous to those in Tables 2 and 3. The local discontinuity sample contains Placebo Group 1 and Placebo Group 2 stocks with impact costs between 1.76% and 2.00% and between 2.00% and 2.24%, respectively.

Results from the placebo analyses are in Table 4. Unlike the results in Tables 2 and 3, 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 strong 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 variation in leverage constraints.

4.3 New Eligibility and Ineligibility

To supplement the main analysis of differences in the liquidity levels of all stocks that lie immediately to the left versus the right of the eligibility cutoff, we shift our focus to the liquidity of newly eligible and newly ineligible stocks. We do this because, ex ante, we expect some asymmetries

in some cases. However, the magnitude and statistical significance of the coefficients on the Group 1 indicator variable remain substantially unchanged in all specifications.

in the effects of eligibility versus ineligibility. Upon entry into Group 1, stocks are immediately eligible for margin trading (as of the beginning of month *t*). Upon exit from Group 1, stocks become ineligible for new margin trading as of the beginning of month *t*, but existing margin positions do not have to be unwound right away. Thus, the transition to the "no margin" regime may be slow. While our main analysis emphasizes a trading channel, Aragon and Strahan (2011) report evidence that the holdings of potential liquidity providers (i.e., hedge funds in their setting) is related to market liquidity. Thus, a slow transition to the "no margin" regime could cause liquidity effects to occur over longer horizons.

In the entry analysis, we compare the liquidity of stocks that become eligible for margin trading during month *t* to the liquidity of a control group of stocks that remain ineligible but are very close to the eligibility cutoffs (i.e., we begin with the local discontinuity sample using the cutoffs from Table 3). The control group consists of Group 2 stocks with impact costs less than or equal to 1.24%. To further ensure that the small differences in measured impact costs between control and treatment stocks are not driven by differences in liquidity or other characteristics, we match on month *t*-1 values of *Spread*, *ILLIQ*, stock returns, standard deviation of stock returns, and rupee volume. For each treatment stock, we then choose the control stock that is the closest match. Matching is based on percentage deviations from the treatment stock in each variable. We also examine exit stocks. To do that, we compare stocks that become ineligible for margin trading to those that remain eligible, but also are very close to the cutoffs. For the exit analysis, the control group is defined as those non-exiting Group 1 stocks with impact costs that are greater than 0.76% and that are the closest match to the exiting stock (using the same matching criteria as in the case of entry).

The main regression specification for both the entry (eligibility) and exit (ineligibility) analyses is the same as that in Equation (1), but the *Group 1* dummy is replaced by dummy variables to indicate whether a stock is newly eligible or ineligible for margin trading (*Enter* and *Exit*, respectively). We include only entry and control stocks in the regressions. In the entry regressions, the coefficient on *Enter* is of primary interest. The interpretation of the coefficient on the *Enter* dummy is that it captures the impact of a relaxation of leverage constraints. It is the difference in liquidity of newly eligible stocks relative to those stocks with impact costs that are close to the cutoff, but that remained ineligible for margin trading during period *t*. The coefficient on *Exit* has an analogous interpretation.

Table 5 shows the results from the analysis of margin eligibility (entry). We find strong evidence of a causal effect of a relaxation of leverage constraints on market liquidity. The estimated coefficient of -0.0007 on the *Enter* dummy in the *Spread* regression suggests that spreads are 7 basis points lower (5% of the mean spread for the local discontinuity sample of Group 2 stocks) when stocks become eligible for margin trading. The coefficient of -0.0053 in the *ILLIQ* regression suggests that the price impact of 1 million rupees in daily trading activity decreases by 53 basis points, which is about 20% of the mean *ILLIQ* for the control sample of Group 2 stocks. Thus, complementary to the analyses in Tables 2 and 3, we find that market liquidity improves when leverage constraints become less binding. These changes are significant both statistically and economically.

Table 6 presents the results for the case of newly ineligible (exit) stocks. In the case of exit, we examine liquidity during month *t*, as well as month *t*+1. This is because margin traders have time to unwind their positions. We find that market liquidity is lower in the month following ineligibility (Table 6, Panel A). For *Spread*, we find that the estimated coefficient on the exit dummy is positive (albeit statistically insignificant when we look at month *t*). For *ILLIQ*, the positive and significant coefficient of 0.0097 suggests price impact is nearly 50% higher relative to the pre-exit mean. These effects increase in the subsequent month (Table 6, Panel B).

The results in Tables 5 and 6 reinforce our main findings of a causal effect of margin eligibility on market liquidity. One useful observation is that the entry analysis results are stronger (statistically) than the exit results. This would be expected if traders begin to unwind their margin positions slowly. While new margin positions are not allowed following ineligibility, traders have time to unwind their existing positions beyond the beginning of exit month *t*.

Overall, the results in Tables 2 through 6 provide strong evidence of liquidity improvements when stocks become eligible for margin trading. [23]

4.3.1 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. We focus on margin trading because differences in eligibility provide clear variation in capital availability. However, it is also important to note that there is no theoretical reason why we should expect margin traders to provide liquidity to markets. It is also entirely possible that margin traders are liquidity demanders or even privately informed traders, whose trading activities could negatively impact liquidity. The dominant role of these traders is an empirical question. In order to interpret the main findings in this paper, it is useful to document some basic facts about the margin trading patterns that we observe in the data.

[23] Foucault, Sraer, and Thesmar (2011) use French equity market data to link individual investors' ability to trade within monthly settlement cycles (a way to obtain leverage) to stock price volatility. While they do not focus explicitly on margin trading or liquidity, their finding of increased volatility as a result of retail investors is, at first glance, contrary to ours. However, it is important to note that institutions engage in margin trading in India. This variation in trader type may be important.

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. Following Diether, Lee, and Werner (2008), who characterize the trading strategies of short sellers, we examine the relationship between the margin trading proxy and short-horizon stock returns. We regress the change in each stock's margin trading positions outstanding on one-day lagged stock returns. Results are shown in Table 7, Panel A. The estimated coefficient on the one-day lagged stock returns of -0.207 implies that, following a 10% decrease in stock prices, margin positions will increase by 2%.

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, it is possible that margin traders who already have leveraged positions in a given stock are unable to provide additional liquidity during extreme downturns. To examine this possibility, we repeat the analysis in Table 7, Panel A, but we allow the relationship between margin trading activities and returns to vary across states of the equity market. We introduce two dummy variables, *mild_neg* and *very_neg*, equal to 1 if one-day lagged returns are between 0% and -5% or less than -5%, respectively. We then interact these dummy variables with one-day lagged returns. Given the possibility of margin calls, we expect margin traders to be more contrarian when equity returns are negative, but not in the extreme (i.e., *mild_neg* = 1). Results are shown in Table 7 and are largely consistent with our intuition. We observe greater increases in margin trading when returns are negative (i.e., positive estimated coefficients on both the *mild_neg* and *very_neg* dummy variables). Moreover, the sensitivity of margin trading activity to lagged returns is entirely driven by mild to moderate levels of negative returns. We do not observe this sensitivity following positive returns or following very negative returns.[24]

Short horizon contrarian strategies are only profitable in the presence of return reversals. Table 7, Panel B, shows return autocorrelations of the sample of margin-eligible stocks. We observe one-day momentum followed by reversals. Taken together, the results in Table 7 are consistent with margin traders observing a negative return on day t-1, using leverage to increase their positions in the stock on day t (when returns also tend to be low, as evidenced by the positive first-order autocorrelation in Table 7, Panel B), and enjoying a subsequent return reversal beginning at t+1.

To summarize, three useful observations emerge from the daily price and stock-level margin position data. First, as a group, margin traders follow short-run contrarian strategies. This is consistent with liquidity provision.[25] Second, margin traders' contrarian trading behavior is most evident following moderately negative returns. Finally, it appears margin traders appear to be compensated for their willingness to provide liquidity via short-horizon return reversals. In addition to helping us understand the main results of this paper, the findings in Table 7 contribute to the growing literature investigating whether hedge funds, which tend to use leverage, provide liquidity to stock markets (e.g., Aragon and Strahan (2011), Ben-David, Franzoni, and Moussawi (2012)). Our data allow us to focus on traders beyond hedge funds, and we also observe changes in margin

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

[25] This interpretation is along the lines of that in Kaniel, Saar, and Titman (2008), who find evidence consistent with the idea that individual investors provide liquidity to equity markets through their contrarian trading strategies.

positions at a very high frequency relative to quarterly 13F data, which is typically the primary data source for hedge fund holdings.

4.3.2 Commonality

In Brunnermeier and Pedersen (2009), market declines reduce intermediary capital and therefore reduce their ability to provide liquidity to the entire market. This causes an overall increase in liquidity comovement. 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 comovement is to exploit stock-level variation in capital constraints. For example, Coughenour and Saad (2004) test whether liquidity comovement 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 this section, we conduct basic tests that are similar in spirit to Coughenour and Saad (2004) in that we ask whether stocks with similar margin restrictions tend to comove more than stocks with different restrictions. Because investors can purchase Group 1 stocks on margin, but must fully finance their purchases of Group 2 stocks, we might expect the liquidity of a new Group 1 (2) stock to begin to comove more with the liquidity of other Group 1 (2) stocks. To test this conjecture, we estimate local discontinuity regressions (i.e., the same sample of stocks as in the Table 3 analysis) of stock-level liquidity innovations on market innovations in liquidity.[26]

The commonality analysis is conducted in two steps. We first calculate liquidity innovations based on a first-stage regression of daily liquidity changes on variables known to affect liquidity:

[26] The market is defined as all Group 1 and Group 2 stocks, excluding stock *i*.

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

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 regression residuals (including the intercept) are the liquidity innovations that we examine. This is the same method used to pre-whiten the liquidity data in Chordia, Sarkar, and Subrahmanyam (2005) and in Hameed, Kang, and Viswanathan (2010). Market liquidity innovations ($\Delta Liq1$ and $\Delta Liq2$) are defined as the average innovation for all stocks in each group (equal weighted average, excluding the innovation in stock *i*).

In the second step, we estimate the following regressions, in which the dependent variable is the daily liquidity change for stock *i*:

$$\Delta Liq_{it} = \alpha_i + \beta_1 \Delta Liq1_t + \beta_2 \Delta Liq2_t + \beta_3 \Delta Liq1_t * Group1 + \beta_4 \Delta Liq2_t * Group2 + \beta_5 Group1 + \gamma_i + \varepsilon_{it}.$$

Group 1 is a dummy variable indicating that the stock is in Group 1 on day *t*.[27] *Group 2* indicates that the stock is in Group 2. The coefficients β_3 and β_4 are of particular interest. These capture the differences in the average liquidity comovement of same-group stocks relative to stocks that are not in the same group. To ensure that any findings are not driven by important differences between Group 1 and Group 2 stocks more generally, we focus the analysis on the subsample of stocks with impact costs that are in the neighborhood of 1. In addition, all regressions contain stock fixed effects, and standard errors are clustered by stock.

Results are shown in Table 8. Consistent with the prior literature documenting commonality in liquidity, we find that all stocks tend to comove (i.e., there are positive and significant coefficients on

[27] We do not include a Group 2 dummy since all stocks in our sample belong to Group 1 or Group 2 (Group 2=1-Group 1).

β_1 and β_2). More importantly, we find positive and significant coefficients on both β_3 and β_4 in both the *Spread* and *ILLIQ* regressions. This suggests that when a stock is in Group 1, its liquidity tends to comove more with the liquidity of other Group 1 stocks. Similarly, when a stock is in Group 2, its liquidity tends to comove more with other Group 2 stocks. Overall, the results in Table 8 provide suggestive evidence in support of the idea that variation in leverage constraints are an important driver of commonality in liquidity.[28]

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. 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. Second, margin traders tend to follow contrarian trading strategies, consistent with liquidity provision. They are most likely to employ these contrarian trading strategies following periods of

[28] It is possible, for example, that when capital constraints of investors begin to bind, the more capital-intensive Group 2 stocks tend to be liquidated together. Along similar lines, during extreme market downturns, margin calls in Group 1 stocks could cause some comovement in these stocks.

moderately negative returns rather than in periods of extreme downturns. Moreover, the investigation of margin financing activity at the individual stock level suggests that the intense use of margin trading facilities is an important driver of the main result. Finally, we provide suggestive evidence consistent with recent theoretical models in which shocks to funding constraints impact commonality in liquidity. Our paper contributes to the literature in its identification of a leverage constraint channel, and the richness of the margin trading data in India also helps us shed light on some of the mechanisms driving the results.

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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 Groups 1 and 2 for the period April 2004 through December 2012. All variables are monthly. *ILLIQ* is the Amihud (2002) illiquidity ratio, defined as $\frac{1}{N}\sum_{t=1}^{N} 1000000 * \frac{|ret|}{p * vol}$, where N is the number of trading days in the month, *ret* is the daily return, p is the closing price, and *vol* is trading volume on day t. *Spread* is the estimated bid-ask spread, calculated according to Corwin and Schulz (2012). Both *Spread* and *ILLIQ* are monthly averages of daily values. *Mret* is the month t stock return, calculated from the closing prices at the ends of months t-1 and t. *Std_ret* is the standard deviation of daily returns during the month. *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. *Turnover* is the average number of shares traded a day, divided by shares outstanding. *Impact Cost* is the estimated percentage change in price of an order size of 100,000 rupees, as calculated by the National Stock Exchange. *Close* is the closing price at the end of month t, in rupees. Panel A shows summary statistics for the full sample of Group 1 and Group 2 stocks. Panel B shows summary statistics for the local discontinuity subsample, which consists of stocks with impact costs near the 1% cutoff (where the bandwidth is set to 0.24%).

Panel A. Full Sample

Group 1	Variable	Mean	Median	P25	P75	Std Dev
	Spread	0.0120	0.0112	0.0086	0.0145	0.0052
	ILLIQ	0.0054	0.0013	0.0002	0.0047	0.0224
	Std_ret	0.0256	0.0236	0.0173	0.0321	0.0113
	Mret	0.0069	0.0020	-0.0708	0.0805	0.1613
	Logvolume	17.1213	16.9822	15.6718	18.4853	1.9502
	Logmcap	23.4963	23.3831	22.2830	24.5184	1.6253
	Turnover	0.0042	0.0017	0.0007	0.0042	0.0088
	Close	328.7071	177.6500	80.0000	396.1500	413.6436
	Impact Cost	0.3942	0.3300	0.1800	0.5800	0.2552
Group 2	Variable	Mean	Median	P25	P75	Std Dev
	Spread	0.0168	0.0151	0.0113	0.0204	0.0085
	ILLIQ	0.3102	0.0683	0.0207	0.2859	0.5559
	Std_ret	0.0317	0.0306	0.0225	0.0396	0.0122
	Mret	0.0192	-0.0006	-0.0839	0.0939	0.1931
	Logvolume	13.3359	13.3492	12.0238	14.6207	1.8905

	Logmcap	20.8289	20.7762	19.9837	21.5869	1.2348
	Turnover	0.0016	0.0005	0.0002	0.0014	0.0045
	Close	128.9658	54.8500	23.0000	138.0000	221.4075
	Impact Cost	4.1883	3.0400	1.7100	5.8300	3.1955

Panel B. Local Sample

Group 1	Variable	Mean	Median	P25	P75	Std Dev
	Spread	0.0136	0.0129	0.0100	0.0164	0.0055
	ILLIQ	0.0196	0.0097	0.0043	0.0195	0.0541
	Std_ret	0.0274	0.0259	0.0187	0.0344	0.0114
	Mret	0.0126	0.0016	-0.0748	0.0907	0.1766
	Logvolume	15.1651	15.0585	14.2313	16.0250	1.3158
	Logmcap	22.0148	21.9411	21.2694	22.7035	1.0314
	Turnover	0.0028	0.0011	0.0004	0.0026	0.0059
	Close	212.7467	114.0500	51.8500	246.2500	290.1540
	Impact Cost	0.8712	0.8700	0.8100	0.9300	0.0720
Group 2	Variable	Mean	Median	P25	P75	Std Dev
	Spread	0.0141	0.0133	0.0103	0.0168	0.0058
	ILLIQ	0.0267	0.0147	0.0064	0.0311	0.0535
	Std_ret	0.0280	0.0266	0.0195	0.0350	0.0113
	Mret	0.0112	-0.0005	-0.0812	0.0887	0.1760
	Logvolume	14.8345	14.6866	13.8506	15.7236	1.3385
	Logmcap	21.7258	21.6079	20.9943	22.3792	1.0451
	Turnover	0.0026	0.0010	0.0004	0.0025	0.0056
	Close	189.3137	97.2000	42.7000	217.4250	270.5821
	Impact Cost	1.1185	1.1200	1.0600	1.1800	0.0694

Table 2
Do Leverage Constraints Impact Liquidity? Full Panel Regressions

This table presents results of the analysis of the impact of margin trading eligibility on market liquidity. We begin with all stocks in Groups 1 and 2. The dependent variables are average *Spread* (Panel A) and *ILLIQ* (Panel B) 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, year-month dummies, and stock fixed effects. We also include a 5^{th} order polynomial function of impact costs in the full specification (Columns 2 and 5). The control variables are defined in Table 1 and include one-month lagged: standard deviation of stock returns (*Std_ret*), stock returns (*mret*), dollar volume (l*ogvolume*), *Spread*, *ILLIQ*, and equity market capitalization (*logmcap*). 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. Spread

VARIABLES	(1) Spread	(2) Spread	(3) Spread	(4) Spread	(5) Spread
Group1	-0.0012***	-0.0071***	-0.0004***	-0.0003***	-0.0037***
	(0.0001)	(0.0009)	(0.0001)	(0.0001)	(0.0008)
lag_std_dret			0.0725***	0.0690***	0.0607***
			(0.0033)	(0.0038)	(0.0039)
lag_mret			-0.0002	-0.0000	-0.0004*
			(0.0002)	(0.0002)	(0.0002)
lag_logvolume			-0.0005***	-0.0004***	-0.0002***
			(0.0000)	(0.0000)	(0.0000)
lag_Spread			0.2343***	0.2353***	0.2217***
			(0.0081)	(0.0091)	(0.0088)
lag_ILLIQ			0.0007***	0.0007***	-0.0002
			(0.0002)	(0.0002)	(0.0003)
lag_logmcap				-0.0005***	-0.0002**
				(0.0001)	(0.0001)
Constant	0.0176***	0.0157***	0.0193***	0.0277***	0.0180***
	(0.0003)	(0.0006)	(0.0005)	(0.0016)	(0.0019)
Observations	89,631	89,631	88,095	72,211	72,211
R-squared	0.231	0.260	0.303	0.307	0.312
Stock FE	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes
Polynomials	No	Yes	No	No	Yes
Controls	No	No	Yes	Yes	Yes

Panel B. ILLIQ

VARIABLES	(1) ILLIQ	(2) ILLIQ	(3) ILLIQ	(4) ILLIQ	(5) ILLIQ
Group1	-0.0188***	-0.0859***	-0.0029*	0.0012	-0.0562***
	(0.0063)	(0.0255)	(0.0016)	(0.0020)	(0.0205)
lag_std_dret			-0.2490*	-0.6214***	-0.7308***
			(0.1324)	(0.1679)	(0.1625)
lag_mret			0.0146**	0.0245***	0.0121
			(0.0064)	(0.0080)	(0.0079)
lag_logvolume			-0.0067***	-0.0002	0.0032***
			(0.0009)	(0.0011)	(0.0012)
lag_spread			1.0931***	0.9480***	-0.2444
			(0.2426)	(0.2765)	(0.2695)
lag_ILLIQ			0.7398***	0.7461***	0.5773***
			(0.0089)	(0.0090)	(0.0141)
lag_logmcap				-0.0290***	-0.0133***
				(0.0031)	(0.0024)
Constant	0.1502***	0.1229***	0.1499***	0.6848***	0.3314***
	(0.0122)	(0.0237)	(0.0130)	(0.0610)	(0.0557)
Observations	89,606	89,606	88,074	72,194	72,194
R-squared	0.127	0.497	0.601	0.611	0.634
Stock FE	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes
Polynomials	No	Yes	No	No	Yes
Controls	No	No	Yes	Yes	Yes

Table 3
Do Leverage Constraints Impact Liquidity? The Local Discontinuity Sample

This table presents results of the analysis of the impact of margin trading eligibility on market liquidity using the local discontinuity sample. We begin with all stocks Groups 1 and 2 with impact costs are close to the cutoff of 1% (i.e., between 0.76% and 1.24%). The dependent variables are average *Spread* (Panel A) and *ILLIQ* (Panel B) 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, year-month dummies, and stock fixed effects. We also include a 5th order polynomial function of impact costs in the full specification (Columns 2 and 5). The control variables are defined in Table 1 and include one-month lagged: standard deviation of stock returns (*std_dret*), stock returns (*mret*), dollar volume (l*ogdvolume*), *Spread*, *ILLIQ*, and equity market capitalization (*logmcap*). 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) Spread	(2) Spread	(3) Spread	(4) ILLIQ	(5) ILLIQ	(6) ILLIQ
Group1	-0.0004***	-0.0003**	-0.0003**	-0.0049***	-0.0021*	-0.0027***
	(0.0001)	(0.0001)	(0.0001)	(0.0010)	(0.0012)	(0.0010)
lag_std_dret		0.0648***	0.0686***		0.0081	-0.1224
		(0.0079)	(0.0090)		(0.0949)	(0.1166)
lag_mret		-0.0004	-0.0002		0.0168**	0.0225**
		(0.0005)	(0.0005)		(0.0067)	(0.0092)
lag_logvolume		-0.0003***	-0.0003***		-0.0048***	-0.0039***
		(0.0001)	(0.0001)		(0.0010)	(0.0009)
lag_logmcap			0.0000			-0.0029*
			(0.0002)			(0.0017)
lag_spread		0.1203***	0.1309***		-0.0341	0.0730
		(0.0157)	(0.0176)		(0.1296)	(0.1405)
lag_ILLIQ		-0.0017	0.0070*		0.2667**	0.2714***
		(0.0031)	(0.0042)		(0.1103)	(0.0640)
Constant	0.0176***	0.0187***	0.0165***	0.0467***	0.1063***	0.1505***
	(0.0007)	(0.0012)	(0.0042)	(0.0043)	(0.0162)	(0.0355)
Observations	11,656	11,478	9,185	11,656	11,478	9,185
R-squared	0.206	0.231	0.238	0.159	0.200	0.208
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes

Table 4

Are Results Driven by Variation in Measured Impact Cost? A Placebo Test

This table presents results of placebo tests, in which we repeat the analyses of the impact of margin trading eligibility on market liquidity from Tables 2 and 3. Instead of measuring eligibility at the impact cost cutoff of 1.0%, we replicate the analysis around a placebo cutoff of 2.0%. The results from the "Full sample" shown in Columns (1) through (3) consist of *Placebo Group 1* and *Placebo Group 2* stocks. These stocks have impact costs that are less than or equal to 2% and greater than 2%, respectively. The "Local Sample" shown in Columns (4) through (6) are those stocks that lie close to the placebo cutoff using the bandwidth of 0.24%, as in Table 3. The explanatory variables are the *Placebo Group 1* dummy and the same vector of control variables defined in Tables 2 and 3. All standard errors are clustered by ISIN (stock identifier). *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

VARIABLES	(1) Full sample Spread	(2) Full sample Spread	(3) Full sample ILLIQ	(4) Full sample ILLIQ	(5) Local sample Spread	(6) Local sample ILLIQ
Group1	0.0026	-0.0202	-0.2513	-0.3787	-0.0001	-0.0023
	(0.0198)	(0.0210)	(0.5168)	(0.4405)	(0.0002)	(0.0036)
lag_std_dret		0.0506***		-1.0158***	0.0625***	-0.1695
		(0.0070)		(0.3155)	(0.0181)	(0.2484)
lag_mret		-0.0012***		-0.0191	-0.0006	-0.0058
		(0.0004)		(0.0148)	(0.0010)	(0.0105)
lag_dollarvolume		-0.0003***		-0.0003	-0.0001	-0.0076***
		(0.0001)		(0.0025)	(0.0002)	(0.0027)
lag_spread		0.2495***		-0.7827**	0.1485***	0.3485
		(0.0119)		(0.3730)	(0.0299)	(0.4897)
lag_amihud		-0.0006**		0.5955***	0.0024	0.5464***
		(0.0003)		(0.0153)	(0.0052)	(0.0775)
lag_logmcap		-0.0004**		-0.0447***	-0.0010**	-0.0076
		(0.0002)		(0.0074)	(0.0004)	(0.0054)
Constant	0.0145***	0.0209***	0.5025***	1.2381***	0.0331***	0.3493***
	(0.0019)	(0.0043)	(0.1022)	(0.1781)	(0.0082)	(0.1148)
Observations	31,699	26,147	31,679	26,133	3,199	3,199
R-squared	0.213	0.270	0.539	0.679	0.258	0.491
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Polynomials	Yes	Yes	Yes	Yes	No	No

Table 5
Impact of New Eligibility

This table presents results of the analysis of the impact of margin trading eligibility on market liquidity using the sample of entry stocks. We begin with all stocks in the local discontinuity sample described in Table 3. "Entry" stocks are those stocks which become eligible for margin trading in month *t*. Control stocks are those stocks which are not eligible for margin trading but have impact costs that are close to the cutoff (i.e., between 1% and 1.24%) and are the closest matches to the entry stocks. The dependent variables are average *ILLIQ* and *Spread* (defined in Table 1) in month *t*. The explanatory variables are *enter*, a dummy variable equal to 1 if the stock is newly eligible for margin trading, and a vector of year-month dummies. 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) Spread	(2) ILLIQ
Enter	-0.0007**	-0.0053***
	(0.0003)	(0.0013)
Constant	0.0148***	0.0210***
	(0.0010)	(0.0026)
Observations	2,326	2,282
R-squared	0.254	0.290
Month-Year FE	Yes	Yes

Table 6
Impact of New Ineligibility

This table presents results of the analysis of the impact of margin trading ineligibility on market liquidity using the sample of exit stocks. We begin with all stocks in the local discontinuity sample described in Table 3. "Exit" stocks are those stocks which become ineligible for margin trading during month *t*. Control stocks are those stocks which remain eligible for margin trading but have impact costs that are close to the cutoff (i.e., between 0.76% and 1%) and are the closest matches to the exit stocks. The dependent variables are average *ILLIQ* and *Spread* (defined in Table 1) in month *t*. The explanatory variables are *exit,* a dummy variable equal to 1 if the stock is newly ineligible for margin trading, and a vector of year-month dummies. 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. Liquidity in Month *t*

VARIABLES	(1) Spread	(2) ILLIQ
Exit	0.0001	0.0097***
	(0.0003)	(0.0016)
Constant	0.0109***	0.0058*
	(0.0013)	(0.0030)
Observations	2,320	2,308
R-squared	0.293	0.246
Month-Year FE	Yes	Yes

Panel B. Liquidity in Month *t*+1

VARIABLES	(1) Spread	(2) ILLIQ
Exit	0.0006*	0.0151***
	(0.0003)	(0.0016)
Constant	0.0107***	0.0031
	(0.0011)	(0.0049)
Observations	1,948	1,940
R-squared	0.264	0.255
Month-Year FE	Yes	Yes

Table 7

Margin Traders' Short-Horizon Trading Patterns

This table presents results of the analysis of daily margin trading activity and short-horizon stock returns. In Panel A, 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. *Lret* is the one-day lagged stock return. In the extended specifications, we allow the relationship between margin trading activity and lagged stock returns to vary with stock market conditions. *Mild_neg* is a dummy variable equal to 1 if lagged stock returns are between -5% and 0%. *Very_neg* is a dummy variable equal to 1 if lagged stock returns are less than -5%. All standard errors are clustered by ISIN (stock identifier) and trading day. In Panel B, we show return autocorrelations at the individual stock level. *Lret2*, *Lret3*, *Lret4* and *Lret5* are 2-, 3-, 4-, and 5- day lagged stock returns, respectively. The mean values reported in Panel B represent the average coefficients from the stock-level regressions. *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

Panel A. Margin Trading Activity and Past Returns

	(1)	(2)
VARIABLES	ch_margin	ch_margin
Lret	-0.1731***	-0.0179
	(0.0156)	(0.0277)
Very_neg		0.0280***
		(0.0093)
Mild_neg		0.0044***
		(0.0009)
Mild_neg_lret		-0.2963***
		(0.0447)
Very_neg_lret		0.1312
		(0.1481)
Constant	0.0028***	-0.0023***
	(0.0003)	(0.0006)
Observations	1,084,969	1,084,969
R-squared	0.0002	0.0003
Day FE	Yes	Yes

Panel B. Return Autocorrelations

VARIABLES	Mean estimates
Let	0.0432***
Lret2	-0.0228**
Lret3	-0.0135*
Lret4	-0.0013
Lret5	-0.0110
Observations	1,279

Table 8
Commonality in Liquidity

This table presents results of the commonality in liquidity analysis. We use daily data from the local discontinuity subsample (described in Table 3) for the period April 15, 2004, through December 2012. We regress daily innovations in stock *i*'s liquidity on average innovations for all Group 1 (*∆Liq1*) and Group 2 (*∆Liq2*) stocks. The regressions also include group membership interactions to measure the incremental sensitivity to own-category stocks. *Group 1* is a dummy variable equal to 1 if the stock is a category 1 stock. *Group 2* is a dummy that indicates whether the stock is in category 2. All regressions include stock fixed effects 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.

VARIABLES	(1) ΔSpread	(2) ΔILLIQ
ΔLiq1	0.4590***	0.0645***
	(0.0402)	(0.0142)
ΔLiq2	0.4266***	0.0155
	(0.0415)	(0.0098)
ΔLiq1*Group1	0.1367**	2.1378***
	(0.0537)	(0.2500)
ΔLiq2*Group2	0.1127*	0.3430***
	(0.0603)	(0.0407)
Group1	-0.0000	-0.0001*
	(0.0000)	(0.0001)
Constant	-0.0000***	-0.0000
	(0.0000)	(0.0000)
Observations	222,674	211,814
R-squared	0.055	0.002
Stock FE	Yes	Yes

Figure 1: Number of Entry and Exit Stocks

This figure shows the number of NSE entry and exit stocks from Group 1 (the group of stocks that are eligible for margin trading) between April 2004 and December 2012.

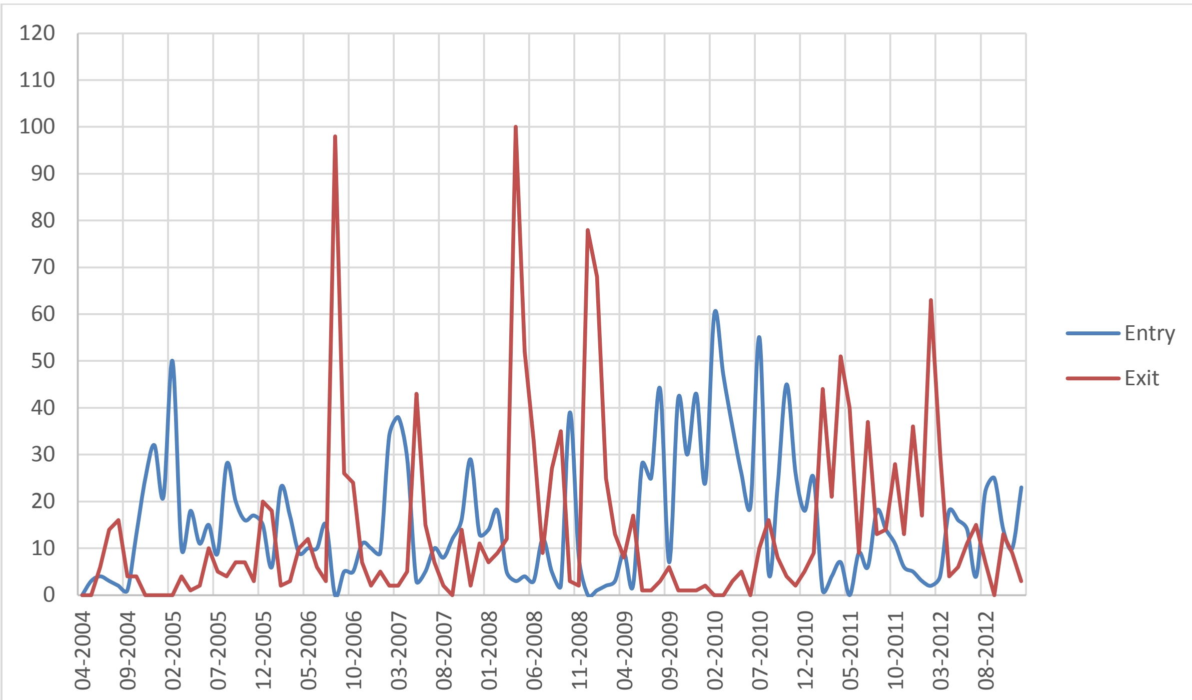

Figure 2: Liquidity and Impact Cost

These figures show the average liquidity (spread and Amihud illiquidity ratio, minus the market change) in month *t* as a function of month *t* impact cost. Stocks are divided into 12 bins (the X axis) of size 0.12, around the eligibility cutoff (from 0.28 to 1.72), and we fit a 2nd order polynomial to the data points that are to the left and right of the cutoff. Margin eligible stocks are all those stocks with impact costs that are less than or equal to 1, which corresponds with bins 1 through 6 (in blue). Stocks in bins 7-12 are ineligible for margin trading during period *t*.