Capital Constraints and Market Liquidity: Evidence from India[1]

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ABSTRACT

We use the unique features of the margin trading system in India to test the hypothesis that there is a causal relationship between traders' funding liquidity and a stock's market liquidity (e.g., Brunnermeier and Pedersen (2009)). We employ a regression discontinuity design that exploits the threshold rules that determine a stock's eligibility for margin trading, thus the availability of funding liquidity. Eligibility is revised every month, creating a series of quasi-experiments that provide newly eligible and ineligible stocks with positive or negative funding liquidity shocks. When we compare liquidity changes of treatment and control stocks (stocks that are close to the eligibility threshold), we find a number of results that are consistent with theory. First, we establish that liquidity increases when stocks become eligible for margin trading and decreases following ineligibility. Using available data on margin financing activity at the individual stock level, we find that it is the intense use of margin trading facilities that drives this result. Finally, we explore the dynamics of commonality in liquidity and document some evidence consistent with the view that funding constraints are important drivers of liquidity comovement.

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1. Introduction

Do traders' capital constraints drive equity market liquidity? The recent financial crisis has brought increasing attention to the idea that reductions in funding liquidity can cause sharp declines in market liquidity. Despite its appeal in theoretical models (e.g., Gromb and Vayanos (2002), Garleanu and Pedersen (2007), Brunnermeier and Pedersen (2009), Geanakoplos (2010), Geanakoplos and Fostel (2012)), it is challenging to identify this funding supply effect empirically because there can also be demand effects that confound the overall interpretation (e.g., investors' selling pressures can also cause liquidity declines).

Indian equity markets provide a particularly useful laboratory for examining the role of supply shocks. In 2004, Indian regulators introduced a formal margin trading system that allows traders to borrow in order to finance their purchases of securities. As in the United States, 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 funding liquidity. 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 time-varying and is based on a well-defined eligibility cutoff.[2] We focus our analysis on National Stock Exchange (NSE) stocks. The NSE is an electronic limit order book market and is the most important Indian market, by trading activity.

[2] 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 U.S., 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)).

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 6-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 (and that traded on at least 80% of the days over the past six-months) 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 the time-series and cross-sectional variation in margin eligibility to estimate the impact of changes in eligibility on stock market liquidity.

To identify the causal effect of funding liquidity on market liquidity, we use a regression discontinuity design, in which we focus the analysis on stocks very close to the eligibility cutoffs. 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. We then compare the monthly liquidity changes in stocks that become eligible (or ineligible) for margin trading with liquidity changes in a group of control stocks that lie close to the eligibility cutoffs but for which eligibility did not change. In addition to focusing on treatment and control stocks in a very small region near the eligibility cutoff, we also employ matching techniques to control for sampling variability in our variables of interest. This helps us to further ensure that treatment and control stocks do not differ based on other characteristics that are likely to be correlated with liquidity (returns, volatility, and size). We then test whether changes in liquidity are related to changes in margin trading eligibility.

Our main findings are consistent with a causal effect of funding liquidity made available through margin trading on stock market liquidity. Liquidity increases when stocks become eligible for margin trading and it decreases following ineligibility. These changes are both statistically and economically significant. For example, our results suggest that margin eligibility leads to an estimated 8% reduction in estimated bid-ask spreads in the month following the change in eligibility status.

After presenting evidence of a causal role for funding liquidity on market liquidity, we then try to uncover the mechanisms driving the basic result. In particular, we extend our investigation beyond the extensive margin of eligibility and ask whether the liquidity changes that we observe are driven by traders' large margin positions. Unlike in the United States, data on margin financing in India are available at the individual stock level.[3] Our analysis of actual margin activity reveals that the findings that market liquidity increases (declines) when stocks become eligible (ineligible) for margin trading are driven by the stocks in which investors are more levered.

We also examine the interaction between our main findings and market conditions. Market returns can help guide the interpretation of the main findings because if intermediaries are more willing to lend when market returns are high, then we would expect to observe a larger impact of margin eligibility during high market return periods. Consistent with this prediction, we find that the decrease in estimated spreads that occurs with eligibility is higher when market returns are higher. These results are line with Hameed, Kang and Viswanathan (2010) who report that bid-ask spreads increase following sharp declines in market returns, especially in times when funding liquidity is likely to be more constrained (funding liquidity is not directly observed in their paper, but proxied by commercial paper spread, bank returns and changes in dealer repo positions).

When we repeat the analysis but instead focus on volatility we find that the decreases in estimated spreads that occur upon entry are driven by low-volatility periods. Thus, after price drops and in times of higher volatility (when intermediary funding constraints are more binding), liquidity

[3] To our knowledge, Hardouvelis and Peristiani (1992), is the only other study using actual margin financing data. They study the impact of margin requirements on volatility and trading volume in Japan.

improvements for entry stocks are smaller. While we do not find analogous results in the case of exits, we interpret the results from entry stocks as further evidence of the importance of the funding supply channel.

In addition to testing hypotheses about the impact of funding supply on liquidity levels, we also examine the potential role of funding supply in liquidity comovement. It is well known that stocks exhibit significant liquidity comovement (e.g., Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001)) and that this "commonality in liquidity" is not unique to U.S. stocks (Karolyi, Lee and Van Dijk (2012)). Although it is pervasive, we still do not have a full understanding of what drives it. There is evidence in the literature that commonality is related to both demand- and supply-side variables. For example, Hameed, Kang and Viswanathan (2010) report evidence that liquidity commonality increases when the market is in decline and volatile (consistent with a supply effect). Along similar lines, Coughenour and Saad (2004) find that liquidity commonality is higher when stocks share market makers, especially when those market makers are constrained. There is also evidence consistent with a role for the demand-side. Karolyi, Lee and Van Dijk (2012) find that commonality is higher when market volatility is high and when there is more correlated trading activity. Also consistent with the demand-side view, Kamara, Lou, and Sadka (2009) find that commonality is higher when institutional ownership is higher. While all of these provide important evidence relating commonality to various demand- and supply- side factors, establishing causality remains an empirical challenge.

Our regression discontinuity design allows us to provide the first (to our knowledge) causal evidence that funding liquidity supply impacts commonality in liquidity. We propose two tests to help shed light on the drivers of liquidity commonality. In the first test, we define commonality as the *R-square* of a regression of daily liquidity on market liquidity (as in Karolyi, Lee and Van Dijk

(2012) and Hameed, Kang, and Viswanathan (2010)). We then examine changes in commonality for both treatment and control stocks near changes in margin trading eligibility. Our market liquidity regression differs from that in the earlier papers in that we disaggregate the "market liquidity" for Group 1 and Group 2 stocks and we allow regression coefficients to vary accordingly. In doing so, we are able to conduct our second test, in which we ask whether comovement with Group 1 (2) increases (decreases) for entry stocks following entry. Similarly, we ask whether comovement with Group 1 (2) decreases (increases) for exit stocks.

We find that there are substantial changes in comovement patterns following funding liquidity supply shocks. These changes depend on whether the shock is positive (eligibility/entry) or negative (ineligibility/exit). Consistent with Brunnermeier and Pedersen (2009), we find evidence that negative shocks to funding liquidity result in increased commonality in liquidity with the overall market. We do not, however, find a change in the composition of comovement. In the case of entry, while we do not observe a change in overall commonality, we find evidence of a decrease in comovement with margin ineligible stocks. Taken together, the results suggest that funding liquidity is not only an important driver of overall liquidity commonality, but can also impact the composition of comovement with different categories of stocks. This causal evidence of supply-side drivers of commonality in liquidity is novel.

Although the intricate relationships between funding constraints and asset prices have long been recognized in the literature (e.g., Kiyotaki and Moore (1998), Allen and Gale (1999), Kyle and Xiong (2001), Holmstrom and Tirole (2001), Gromb and Vayanos (2002), Krishnamurthy (2003)), there is a growing interest in improving our understanding of these mechanisms 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 on the dynamics of funding constraints and the feedback mechanisms that they may trigger.

Empirical tests of the impact of funding constraints have lagged behind theoretical advances in this area. This is because empirical researchers face significant challenges associated with measuring funding liquidity and isolating the potential causal linkages. Some recent papers have addressed these issues by using a number of intuitive proxies for funding liquidity. Examples include: shocks to the inventory positions of NYSE specialists (Comerton-Forde, Hendershott, Jones, Moulton and Seasholes (2008)); 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)); price deviations of U.S. Treasury bonds (Hu, Pan, and Wang (2011)); and deviations from well-known arbitrage parities (Pasquariello, 2013). These recent empirical studies provide some evidence consistent with the idea that funding constraints impact market liquidity and prices. Relative to existing work, our paper provides more direct evidence of the impact of funding liquidity because we are able to observe both margin eligibility and margin financing activity. The Indian regulatory setting also allows us to address identification concerns through a regression discontinuity design.

In addition to the recent focus on margins in the context of liquidity crises, stock margin requirements have received some attention in a small body of older literature that examined 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); Puritt and Tse (1996)). The aim of this early work on margin trading was to shed light on the policy question of whether imposing margin requirements (i.e., restricting the extent to which brokers could extend credit for purchase transactions) curbs speculation. All of the studies using United States data focus either on the years prior to 1974 (the last time margin requirements changed in the U.S.) 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 funding liquidity and market liquidity.

This paper provides causal evidence of the impact of margin requirements on liquidity. Our focus on India also allows us to provide new evidence of the impact of market frictions in a market in which frictions are likely to be particularly relevant. 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 liquidity changes 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 Badhla. Under Badhla, trade settlement was moved to a future expiration date, and these positions could be rolled from one settlement period to another. Under Bhadla, 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 percentage change in price (from bid/offer midpoint) 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 (rolling estimates, using four 10-minute snapshots 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. 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. Impact costs and the resulting group assignments are calculated on the 15th of each month. These new groups become effective on the first day of the subsequent month.

Margin trading allows traders to borrow in order to purchase shares. Thus, entrance to (or exit from) Group 1 can be considered funding supply shocks. For eligible stocks, the most important rules for margin trading are similar to those in the United States. 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). The collateral held in margin accounts is 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 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. This transparency makes the Indian market an appealing setting for investigation because it is possible answer questions about the implications and drivers of high levels of margin financing activity.

One additional implication of Group 1 membership 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 funding liquidity 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. The minimum guidelines for these margins are set by SEBI and vary according to stock group. 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 funding liquidity available to traders of Group 1 stocks through margin financing, these stocks also require less short term capital. The existence of additional source of funding liquidity does not change our overall interpretation of Group 1 membership (both the margin financing eligibility and the low VAR margin requirements involve shocks to the supply of funding liquidity, in the same direction). However, the margin position data (available at the stock level) will allow us to conduct further tests to separate the effect of margin trading from the change in VAR margin requirements.

Alternative ways to take leveraged positions are available in India, but not for all stocks. For example, stocks have to meet a set of requirements before being eligible for futures and options (F&O) trading. These requirements are significant: as of May 2013, we found fewer than 150 F&O stocks. For example, 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 ccore (approximately $20 million). 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 only be held for a maximum of two months.

In this paper, we analyze National Stock Exchange (NSE) stocks. The NSE is an electronic limit order book market and, while newer than the Bombay Stock Exchange (BSE), it is now the most important Indian market by trading activity. Of the few other papers in the literature that focus on India, Berkman and Eleswarupu (1998) is most related to ours. The authors examine the change in value and trading volume in the 91 Bombay Stock Exchange stocks that were previously eligible for Badhla when Badhla was banned. Berkman and Eleswarupu (1998) report a decline in value and trading volume as a result of the ban. There are several differences between our paper and theirs. First, our study is motivated by recent papers linking funding liquidity to both market liquidity and liquidity commonality. We test hypotheses about both of these. Second, our discontinuity design helps with the identification. Third, we analyze two liquidity measures that were not available when Berkman and Eleswarupu (1998) published their paper. Both have been shown to be highly correlated with liquidity measures based on intraday data. Turnover, the focus of their study, can have other interpretations (it can, for example, proxy for trader horizon). Finally, the sample size in Berkman and Eleswarupu (1998) is much smaller than ours, increasing the relative power of our tests.

3. Data and Methodology

3.1 Data

Our sample consists of all stocks traded on the NSE from May 2004 (the month after the introduction of the current margin trading system) through December 2012.[4] Daily trading activity and returns data are from the NSE (bhavcopy product). The advantage of using the NSE data (as opposed to Datastream) is that we are able to observe trading activity in all stocks, not just those for which there is coverage in Datastream.[5] 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 and impact cost measure, and NSE group assignment. 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 six-months and for which average impact cost is less than 1%. Impact cost, as described earlier, is calculated as the percentage change in price (from bid/offer midpoint) caused by an order size of 100,000 rupees (approximately $2000).

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 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 that are purchased with intermediary-supplied funding. Other than

[4] 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.

[5] 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.

Hardouvelis and Peritstiani (1992), we are not aware of any papers that examine actual margin trading activity.

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.[6] 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.

We impose three additional data filters to improve data reliability. 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 the 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 seems 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.

We follow the market microstructure literature and calculate two measures of market liquidity: bid-ask spreads and the Amihud (2002) illiquidity ratio. Because bid-ask spread data are not directly observable, we estimate them following Corwin and Schulz (2012). The authors suggest using data from daily high and low transaction prices to estimate spreads. Using United States data, they find that this measure has a cross-sectional correlation of 0.83 with effective spreads (difference between transaction price and prevailing quote midpoint). The within-stock (time-series) correlation with

[6] Prowess maintains the last valid firm identifier. This means we are unlikely to match stocks for which significant changes (e.g., restructurings) have occurred. We preformed all of our main analyses with and without requiring Prowess data. None of the primary findings are affected by the use of Prowess data.

effective spreads is 0.65, a substantial improvement over earlier methods for estimating spreads with low frequency data. The general procedure for estimating spreads is as follows (see Corwin and Schulz (2012) for additional details). Let *high*= the high trading price on day *t* and *low*= the low trading price on day *t*. We first calculate $HL = \ln(high / low)$ for every day: the estimated spread is defined as:

$$Spread = HL(t) + HL(t-1) - \ln\left[\frac{\max\left(HIGH(t),\ HIGH(t-1)\right)}{\min\left(LOW(t),\ LOW(t-1)\right)}\right].$$

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: $1000000 * \frac{|\mathrm{ret}|}{p * vol}$.

Where: $\mathrm{ret} = \frac{p(t) - p(t-1)}{p(t-1)}$; 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 one million rupees. *ILLIQ* is widely used in the literature because it requires only data and has been found to do well capturing intraday measures of the price impact of trades (Hasbrouck (2005); Goyenko, Holden, and Trzcinka (2009)). Following Amihud (2002), we winsorize *ILLIQ* at the 1% and 99% levels. We also remove observations in which 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 only on Group 1 and Group 2 stocks that are defined as those stocks that have traded for at least 80% of trading days over the past six-months. We do not include Group 3 stocks because our liquidity measures are 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*). There are a total of 1,887 unique ISINs in Groups 1 and 2 during our sample period. Many stocks move between these groups. There are 1,511 unique ISINs in Group 1 at some point during our sample period, and 1,431 in Group 2. In the final sample, we exclude all month *t* entry (exit) stocks that were exit (entry) stocks in month *t-1*. This helps us isolate the impact of the entry and exit events.

3.2 Methodology

We use a regression discontinuity design to identify shocks (margin eligibility) to the funding supply channel (margin financing) and we test whether funding liquidity has a causal impact on market liquidity. The Indian regulatory setting is particularly useful to 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. We focus on the impact of new eligibility ("entry") and new ineligibility ("exit") events.

We examine changes in 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 transactions costs, where higher values are indicative of lower liquidity. We aggregate the daily data described in the previous section to the monthly level. The unit of observation is a stock-month, and the dependent variable in our main regressions is the change in average liquidity near the new eligibility/ineligibility event. For entries, we measure liquidity changes from month *t-1* to entry month *t*. For exits, we measure liquidity changes from months *t+1* and *t-1* relative to the exit month *t*.[7]

In our entry analysis, we compare the liquidity changes in stocks that become eligible for margin trading to the changes over the same period in a control group of stocks that remain ineligible in both periods *t-1* and *t,* but are very close to the eligibility cutoffs. The control group consists of Group 2 stocks with impact costs less than or equal to 1.1.[8] 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: spreads, Amihud illiquidity ratios, returns, standard deviation of returns, and market capitalization (where available). 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 0.9 and that are the closest match to the exiting stock (using the same matching criteria as in the case of entry).[9]

We choose control stocks close to the eligibility threshold to ensure that treatment and control stocks are as similar as possible. One potential concern with this approach is that investors, anticipating potential future funding concerns, might avoid holding Group 1 stocks that are close to

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[7] The timing difference that we impose in the exit and entry analysis is guided by market rules. Entry stocks are immediately eligible for margin trading (as of the beginning of month *t*). Exit stocks become ineligible for margin trading as of the beginning of month *t,* but existing margin positions do not have to be unwound right away. Traders have 30 days to do so. Because our goal is to isolate the "margin" versus "no margin" regime, we define the event period as the beginning of month *t+1* for exit stocks. This keeps the interpretation of the impact of eligibility similar across the entry and exit analyses.
[8] This value represents the 5th percentile impact cost of all Group 2 stocks.
[9] The 95th percentile of Group 1 impact costs is 0.89.

eligibility cutoffs. While this is a possible strategic behavior, we emphasize that it would bias against any findings of differences between control and treatment stocks.

Summary statistics for the monthly variables are shown in Table 1. There are 1,887 unique ISINs in our sample period. Groups 1 and 2 are shown separately in order to draw comparisons between them. As noted above, monthly *ILLIQ* and *Spread* are the average daily values for each month. Shares outstanding and market capitalization are measured at the end of the month. Monthly return is also measured at the end of the month, and is defined as the percentage change in closing price 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 3.2% for Group 2 stocks, while it is only 2.5% for those in Group 1. Moreover, the median *ILLIQ* (estimated return impact of a 1 million rupee trade) is 0.067 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 lower turnover, lower market capitalization and smaller market capitalization and lower prices than Group 1 stocks.[10] Returns, in contrast, are not very different between the two groups of stocks.

Table 2 gives descriptive statistics for the stocks near the eligibility cutoff during period *t-1* relative to entry/exit. The data include only those stocks in for the sample of treatment and control stocks. As can be seen from the table, the control and treatment stocks look very similar pre-event. Figure 1 shows the time-series of the number of entries and exits during our sample period. There are a total of 1,829 entries and 1,606 exits in the initial sample (before filtering). The number of

[10] 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.

entries per month ranges from zero in July 2006 and November 2008 to 60 in January 2010. Exits range from zero during several months of 2004 and 2010 to a high of 122 in March 2008.

The main regression specification in the entry (eligibility) analysis is as follows:

$$\Delta Liquidity = \alpha + \beta * Entry + \gamma * D + \varepsilon.$$

We include only entry and control stocks, and there is a single liquidity "difference" observation for each treatment and control stock. We exclude the entry stocks that were exit stocks in the previous month and our control sample excludes exiting stocks to isolate the effect of entry from exit. [11]

β, the coefficient on *entry*, is of primary interest. It is interpreted as a "difference-in-difference." The interpretation of the coefficient on the "enter" dummy is therefore a difference-in-difference. It is the change in liquidity from the prior month of newly eligible stocks relative to those stocks with impact factors that are close to the cutoff, but that remained ineligible for margin trading during period *t*. We include a vector *D* of time (month-year) dummies to control for market-wide liquidity movements. This is an important control because entries and exits are clustered in time and are correlated with market returns.

The regression specification in the exit (ineligibility) analysis is the same as in the case of entry:

$$\Delta Liquidity = \alpha + \beta * exit + \gamma * D + \varepsilon.$$

[11] We also exclude from the sample of potential control stocks those that are ineligible for margin trading but for which we still observe open margin positions after the end of exit month *t*. Open margin positions are allowed during the exit month because traders have 30 days to unwind their positions.

In the case of exits, the interpretation β is the liquidity change in the exiting stocks, beyond that of the treatment stocks.[12] We estimate both the exit and entry regressions via ordinary least squares, with standard errors clustered by stock.

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 treatment and control 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 price caused by an order size of Rs.1 Lakh (100,000 Rupees, or approximately $2000). While impact cost is related to liquidity, we assume that there is sufficient variation in the limit order books that small differences in measured impact costs are expected across stocks with equal liquidity. This could happen for 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 afterwards, 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 1.1 may not be different from a measured impact cost of 1. We see evidence of this in the data: stocks routinely move in and out of Group 1. Finally, the impact cost calculation itself can cause potential

[12] To isolate the change in liquidity due to exit, we exclude exit stocks that entered Group 1 in $t-1$ or that reenter in $t+1$. That is, we condition the analysis on no change in eligibility during the period in which we measure liquidity changes.

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 design is a valid identification strategy because it is difficult to precisely control assignment near the cutoff (Lee and Lemieux, 2009).

There are a few potential issues with the interpretation that should be discussed 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 (i.e., improves funding liquidity for all stocks). Precisely how traders use the capital is an empirical question. However: (1) the marginable stock still has to be traded in order for the extra liquidity to be enjoyed, and (2) spillovers into other stocks would simply dampen any observed effects in the liquidity of the marginable stocks. Second, we do not study endogenous variation in margin requirements among margin-eligible stocks (which are important in Brunnermeier and Pedersen (2009)). We instead rely on the binary variable that describes margin eligibility. Finally, margining impacts the ability to purchase only. Thus, it may be more useful during some market conditions than in others. In extended analysis (below), we examine the potential interaction of margin trading with overall market returns.

4. Results

4.1 Funding Liquidity and Market Liquidity

Table 3 shows the results from the difference-in-difference analysis of margin eligibility (entry). In Column 1, we show results of the regression for the full sample of treatment and control stocks, where we identify control stocks by matching on pre-entry (month *t-1*): *Spread*, *ILLIQ*, stock return, standard deviation of daily stock returns, and log market capitalization (where available). We find strong evidence of a causal effect of funding liquidity on market liquidity. The estimated coefficient of -0.00244 on the *Enter* dummy in the *Spread* regression suggests that spreads decrease by 24 basis points (7 percent of the mean spread for Group 2 stocks, and 8 percent of the mean pre-entry spread of the treatment stocks) when stocks become eligible for margin trading. The coefficient of -0.0074 in the *ILLIQ* regression suggests that the price impact of one million rupees in daily trading activity decreases by 74 basis points, which is about 2.5 percent of the mean *ILLIQ* for Group 2 stocks and 51 percent of the mean pre-entry *ILLIQ* value for the treatment stocks. Thus, market liquidity improves when funding liquidity increases. These changes are significant both statistically and economically.

In the analysis in Column 1 of Table 1, when market capitalization information is unavailable (i.e., the stock is not in the Prowess data), we exclude market capitalization from the matching criteria. To ensure that any findings are not driven by the lack of Prowess data for some treatment stocks, in Column 2 we restrict our attention to stocks for which market capitalization data are available. The overall results are very similar to what we find in the full sample, and remain statistically significant.

Table 4 presents the results for the case of newly ineligible (exit) stocks. In contrast to the case of entry, we find that market liquidity declines following ineligibility. This asymmetry strengthens the causal interpretation of the Table 3 results. For *Spread*, we find that the estimated coefficients on the exit dummy are positive and statistically significant in all regressions. For *ILLIQ*, the signs of the estimated coefficients are all consistent with what we observe in the *Spread* regressions, but they are statistically insignificant. This is not entirely surprising, given that the distribution of the *Spread* variable is much tighter and more symmetric than *ILLIQ* (see Tables 1 and 2).

The results in Tables 3 and 4 reveal a causal effect of margin eligibility on market liquidity; however, one interesting observation is that the entry analysis results are stronger (both statistically and in economic magnitude) than the exit results. This would be expected if traders begin to unwind their margin positions early. Recall that the groups are determined on the 15th day of the preceding month. It is possible that market participants, anticipating exit, begin to engage in orderly liquidation of their positions beginning in the middle of month *t-1*. It is also possible that eligibility attracts new investors to the stock, whereas ineligibility causes margin traders to reduce their positions up to the amount borrowed via the margin trading facility but not to fully liquidate.

4.2 Potential Mechanisms

4.2.1 Margin Trading

Tables 3 and 4 contain the main results of the paper. To summarize, we find a causal effect of funding liquidity on market liquidity. When stocks become eligible for margin trading, liquidity increases. When stocks become ineligible for margin trading, liquidity declines. Given this basic finding, it is natural to ask about the mechanisms driving this result. In particular, does the ability to obtain margin trading matter (extensive margin) or do the liquidity changes occur because of the amount of margin trading that follows new eligibility (intensive margin)? To examine this question, we exploit data on margin financing activity at the individual stock level. For each entry stock, we calculate the number of shares financed by intermediaries at the end of entry month *t* and divide this by total trading volume during the month (*Margin*).[13] Margin positions for entry stocks during the entry month are (by definition) new. Therefore, *Margin* represents the importance of margin trading relative to all trading activity during month *t*. We interact *Margin* with the *Enter* dummy and repeat the Table 3 regressions.

Estimates of the impact of entry month margin trading activity are given in Table 5, Panel A. They provide strong support for the funding supply interpretation of our results. In particular, when post-entry margin activity is high, we observe greater decreases in both *Spread* and *ILLIQ*. Results of analogous analysis of exit stocks are given in Table 5, Panel B. For exit stocks, we define margin activity as end-of-period *t-1* margin positions, divided by trading volume.[14] As in the case of entry, we find that exit stocks with higher pre-exit margin financing see higher increases in spreads (as in the Table 3 regressions, we do not observe a significant relationship with changes in *ILLIQ*). In fact, we find the effect of exit on spreads is driven by high margin stocks.

4.2.2 Market Conditions

Overall equity market conditions can also help shed light on the mechanisms driving the main result. For example, Hameed, Kang, and Viswanathan, (2010) exploit variation in market returns and they find important asymmetries in the relationship between market returns and liquidity. In particular, they find that the sensitivity of liquidity to returns is greatest when market returns are large and negative. Market returns can help guide the interpretation in our setting as well, because if intermediaries are more willing to lend when market returns are high and volatility is low, then we would expect to observe a larger impact of margin eligibility during high market return/low-volatility

[13] The mean of this variable is 0.116% (or approximately 2.4% of daily trading volume). We right-winsorize *Margin* at the 99th percentile (because the lower bound of this variable is zero, we do not left-winsorize).

[14] The mean of this variable is 0.76% of monthly trading volume (or approximately 15% of daily trading volume). The median is 0.34%. We winsorize at the 99th percentile (because the lower bound of this variable is zero, we do not winsorize at the 1% level).

periods. Alternatively, an explanation based on an interaction of margin financing with investor demand would suggest that, because investors are constrained when market returns are low, the ability to trade on margin is particularly useful during low-market-return and high-volatility periods. To explore these interpretations, we repeat the main regressions (i.e., analyses in Tables 3 and 4), but we interact the *Enter* and *Exit* dummies with one-month-lagged market returns (for example, *enter_mret* is the interaction of *Enter* with market returns, and *enter_mret_neg* is a triple interaction of the *enter_ mret* variable with an indicator for negative market returns. In separate regressions, we also interact the *Enter* and *Exit* dummies with the one-month-lagged change in market return volatility (*dif_enter_std_ret* and *dif_exit_std_ret*, respectively).

The results of the market conditions analysis are shown in Table 6. Panel A shows results for entry. We find that the decrease in spreads that occurs with eligibility is higher when market returns are higher. This is consistent with increased willingness of intermediaries to supply margin financing during market upswings. The positive estimated coefficient on the triple interaction term (*enter_mret_neg*) suggests that the positive impact of market returns on liquidity is dampened during negative returns periods. When we repeat the analysis but instead focus on volatility (the standard deviation of returns in during month *t-1*), we find that the decreases in spreads that occur upon entry are driven by low-volatility periods. Taken together, the results in Panel A reveal that margin trading increases when there are increases in return (this is driven by positive return periods) and during periods of low-volatility, which further supports a supply-side interpretation of the results. Panel B shows the results of the exit regressions. In the case of exit, we do not find evidence that period *t-1* market conditions play a role in the impact of exit on liquidity, except in the case of volatility in *ILLIQ* regression (which, consistent with the supply channel, suggests that the liquidity decline due to exit is higher in high-volatility periods). The relatively low significance in the exit analysis could be due to the fact that the margin positions that were outstanding at exit were accumulated over time, and under market conditions that differed from those that prevailed at exit.

4.2.3 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. However, as suggested by Karolyi, Lee and Van Dijk (2012), an alternative interpretation of this result is that the increase in commonality is driven by panic selling (i.e., demand). Although our setting is different in that we focus on stock-specific shocks to funding liquidity, we are able to move closer to isolating the potential impact of the supply channel.

There are two changes in liquidity comovement that we might expect when stocks move between Group 1 and Group 2. First, 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 commove more with the liquidity of other Group 1 (2) stocks.[15] Second, as suggested by Brunnermeier and Pedersen (2009), liquidity comovement with the entire market can change when funding liquidity shocks occur. Entries result in a jump in funding liquidity. Therefore, we might expect liquidity comovement with the market decline once margin trading begins. We have the opposite prediction for exits. Exits result in decreases in funding liquidity (i.e., margin requirements jump to 1), and these are more extreme than the decreases in

[15] This idea is in the spirit of Barberis, Schleifer, and Wurgler (2005), who use S&P 500 Index additions to test the hypothesis that Index membership is a salient category for investors. They find that when a stock is added to the S&P 500 Index, its price begins to comove more with other stocks in the index.

funding liquidity that would occur in stocks that remain margin-eligible. Thus, the liquidity comovement of exit stocks with the market is expected to increase.

We examine the potential implications for liquidity comovement by estimating regressions of stock-level liquidity innovations on market innovations in liquidity, where the market is defined as all Group 1 and Group 2 stocks, excluding stock i. In order to do so, 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 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 (by group) are defined as the average innovation for all stocks in each group (excluding the innovation in stock i).

We then estimate a "market" model of liquidity, similar to Hameed, Kang, and Viswanathan (2010) and to Karolyi, Lee, and Van Dijk (2012), except that we allow market liquidity betas to vary by group (i.e., we include Group 1 and Group 2 liquidity innovations):

$$\Delta LiqInnovation_{i,t} = \alpha_i + \beta_{i,1} \Delta LiqInnovation_{Group1,t} + \beta_{i,2} \Delta LiqInnovation_{Group2,t} + \varepsilon_{t.}$$

We estimate market liquidity betas for every entry/exit and control stock for the pre- and post-event periods.[16] We then take the differences in the pre-and post- period measures, and we conduct "difference-in-difference" analysis analogous to Tables 3 and 4. The dependent variables of interest are: change in *R-square*; change in Group 1 beta and change in Group 2 beta. As in the previous analyses, we regress each of these changes on the *Enter*/*Exit* dummies, as well as a vector of year-month dummies to control for changes in comovement in the overall market.

Results of the commonality analysis are presented in Table 7. As in the previous tables, the interpretation of the estimated coefficients on the *Enter* and *Exit* dummies is the change in commonality of entry/exit stocks beyond those experienced by the control group. Interestingly, the patterns that we observe in the cases of exit and entry are very different from one another. For entry stocks, we do not observe a change in commonality (i.e., no change in *R-square* beyond that experienced by control stocks). However, we do observe changes in the individual comovement of entering stocks with both Group 1 and Group 2 stocks. In the case of spreads, we observe significant decreases in the Group 2 β and a marginally significant increase in the Group 1 β consistent with the entering stock liquidity behaving less like that of non-marginable stocks and more like that of other marginable stocks. We do not see any significant changes in comovement with in the case of ILLIQ.

In the case of exit, the results in Table 7 reveal a significant increase in commonality. The *R-squares* of the liquidity regressions both increase significantly (for both *Spread* and *ILLIQ*). This is consistent with the idea that the extreme decrease in funding liquidity that occurs when stocks become ineligible for margin trading causes excess comovement with market liquidity. We do not,

[16] We calculate changes from *t-1* to *t* for the entry analysis. For exits, we examine changes from *t-1* to *t+1*. These windows are consistent with those in the main analysis (Tables 3 and 4). Because we estimate the model at the monthly level, coefficients are (not surprisingly) noisy. Therefore, we winsorize the estimated betas at the 1% and 99% levels.

however, find a difference in the composition of comovement for exit stocks. The changes in Group 1 and Group 2 liquidity β's are not different from what we observe in the treatment stocks.

Overall, the results of the commonality analysis suggest an important causal role for the supply channel. Funding liquidity is an important driver of not only overall liquidity commonality, but can also affect the composition of comovement with different categories of stocks.

4.2.4 Market-Wide Margin Activity

The regression discontinuity design has limited our focus to entry/exit stocks and the control stocks near the impact factor cutoff. Because little is known about the drivers of the use of funding liquidity, we briefly turn our attention to the entire universe of Group 1 stocks and we relate market-wide changes in margin activity to overall market conditions. To do so, we first calculate (on a daily basis) the number of shares financed by margin trading facilities, divided by shares outstanding for every Group 1 stock. For each day, we calculate market margin activity by taking the average of margin-to-shares outstanding for all Group 1 Stocks. We then regress daily changes in market margin activity on market returns and volatility (defined as the absolute value of market returns).

If constraints in intermediary supply drive margin activity, then we would expect less margin activity when market returns are low and when volatility is high. If the demand of constrained investors is the primary driver of margin activity, then we would expect less margin activity when returns are high (i.e., when investors are less wealth-constrained and do not need to borrow) and when volatility is low. The results are in Table 8. We observe a positive (albeit insignificant) estimated coefficient on market returns and a significant and negative coefficient on daily volatility. While only suggestive, the results are more consistent with the supply channel.

5. Conclusions

We use the Indian equity market as a laboratory for testing the hypothesis that there is a causal relationship between traders' funding liquidity 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 a 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 changing eligibility to identify the potential effects of funding supply.

There are three main findings. First, we find evidence consistent with a causal effect of funding liquidity on market liquidity. Liquidity increases when stocks become eligible for margin trading and it decreases following ineligibility. Second, our investigation of margin financing activity at the individual stock level suggests that it is the intense use of margin trading facilities that drives the main result. Finally, we find evidence consistent with recent theoretical models in which negative shocks to funding liquidity result in increased commonality in liquidity. Our paper contributes to the literature in its identification of a supply 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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APPENDIX

Figure 1: Number of Entry and Exit Stocks: April 2004 – Dec 2012

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

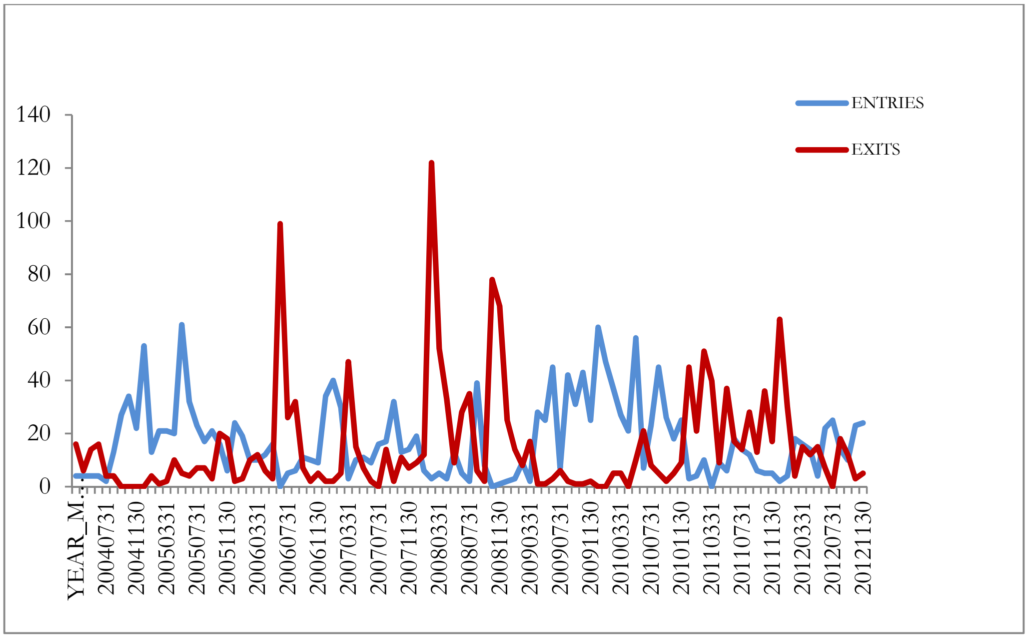

Table 1: Descriptive Statistics: Group 1 vs. Group 2

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 May 2004 through December 2012. All variables are monthly. *ILLIQ* is the Amihud (2002) illiquidity ratio, defined as $\frac{1}{N}\sum_{t=1}^{N} 1000000 * \frac{|\text{ret}|}{p * vol}$. where N is the number of trading days in the month, *ret* 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). *Turnover* is the sum of monthly trading volume (in shares), divided by shares outstanding. *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. *Logmcap* is the (log) equity market capitalization (note that *turnover* and *logmcap* are only available for stocks that are in the Prowess data). *Impact Cost* is the estimated percentage change in price of an order of 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 **Group 1 Stocks**

Variable	Mean	Median	P5	P10	P25	P75	P90	P95	Std Dev
ILLIQ	0.0053	0.0013	0.0000	0.0001	0.0002	0.0047	0.0122	0.0202	0.0221
Spread	0.0269	0.0251	0.0141	0.0162	0.0201	0.0316	0.0397	0.0460	0.0102
Turnover	0.0044	0.0018	0.0002	0.0003	0.0007	0.0043	0.0100	0.0164	0.0095
Mret	0.0098	0.0036	-0.2203	-0.1555	-0.0695	0.0842	0.1808	0.2628	0.1626
Std_ret	0.0258	0.0240	0.0110	0.0132	0.0175	0.0325	0.0414	0.0473	0.0113
Logmcap	23.47	23.36	21.05	21.48	22.25	24.49	25.67	26.41	1.63
Impact cost	0.3961	0.3300	0.0900	0.1100	0.1800	0.5800	0.8000	0.8900	0.2554
Close	323.50	176.15	25.50	39.80	79.05	390.90	784.00	1169.75	406.57

Panel B **Group 2 Stocks**

Variable	Mean	Median	P5	P10	P25	P75	P90	P95	Std Dev
ILLIQ	0.3025	0.0667	0.0036	0.0071	0.0204	0.2746	0.9794	1.6102	0.5479
Spread	0.0347	0.0324	0.0158	0.0193	0.0252	0.0417	0.0529	0.0615	0.0147
Turnover	0.0017	0.0005	0.0001	0.0001	0.0002	0.0014	0.0040	0.0069	0.0046
Mret	0.0259	0.0021	-0.2356	-0.1718	-0.0818	0.1035	0.2497	0.3691	0.1983
Std_ret	0.0321	0.0310	0.0142	0.0170	0.0227	0.0401	0.0487	0.0540	0.0125
Logmcap	20.80	20.74	18.86	19.24	19.95	21.55	22.41	23.00	1.24
Impact cost	3.6816	2.4900	1.0900	1.1800	1.5200	4.8600	8.1200	10.2800	3.0038
Close	127.27	53.20	7.20	11.10	22.60	135.00	303.70	473.15	224.84

Table 2: Descriptive Statistics: Treatment and Control Stocks Pre-Event

This table provides summary statistics of liquidity and the market characteristics used to match the newly eligible (entry) and newly ineligible (exit) stocks with the control stocks. The sample consists of National Stock Exchange stocks during the period May 2004 through December 2012. Entry stocks are those stocks that are newly eligible for margin trading as of the 1st day of month t. Control stocks are defined as those Group 2 stocks with impact factors between 1.0 and 1.1 that are the best match with the exit stock, based on the pre-exit Amihud (2012) illiquidity ratio, estimated spread, return, volatility, and market capitalization. Exit stocks are no longer eligible for margin trading as of the 1st day of month t. Control stocks are defined as those Group 1 stocks with impact factors between 0.9 and 1.0 that are the best match with the exit stock. All variables are monthly and are calculated as of month t-1 relative to entry and exit. *ILLIQ* is the Amihud (2002) illiquidity ratio, defined as $\frac{1}{N}\sum_{t=1}^{N} 1000000 * \frac{|\text{ret}|}{p * vol}$. Where N is the number of trading days in the month, *ret* 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). *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. *Logmcap* is the (log) equity market capitalization.

Panel A	**Entry Stocks**					
	Variable	Mean	Median	P25	P75	Std Dev
Treatment	ILLIQ	0.0146	0.0061	0.0030	0.0117	0.0702
	Spread	0.0305	0.0300	0.0240	0.0357	0.0101
	Mret	0.0733	0.0417	-0.0377	0.1475	0.1879
	Std_dret	0.0290	0.0283	0.0205	0.0364	0.0115
	Logmcap	21.72	21.56	20.98	22.36	1.04
Control	ILLIQ	0.0170	0.0103	0.0060	0.0161	0.0321
	Spread	0.0299	0.0291	0.0249	0.0350	0.0088
	Mret	0.0789	0.0551	-0.0517	0.1768	0.2051
	Std_dret	0.0283	0.0260	0.0206	0.0354	0.0108
	Logmcap	21.44	21.20	20.68	21.93	1.02

Panel B	**Exit Stocks**					
	Variable	Mean	Median	P25	P75	Std Dev
Treatment	ILLIQ	0.0430	0.0305	0.0181	0.0489	0.0575
	Spread	0.0351	0.0325	0.0258	0.0418	0.0135
	Mret	-0.0932	-0.0800	-0.1935	0.0089	0.1730
	Std_dret	0.0325	0.0311	0.0221	0.0412	0.0128
	Logmcap	21.67	21.58	20.97	22.34	1.02
Control	ILLIQ	0.0346	0.0272	0.0181	0.0437	0.0318
	Spread	0.0361	0.0333	0.0279	0.0426	0.0121
	Mret	-0.0847	-0.1045	-0.1867	0.0153	0.1743
	Std_dret	0.0326	0.0310	0.0236	0.0414	0.0122
	Logmcap	21.86	21.78	21.18	22.47	1.09

Table 3: Does Funding Supply Impact Liquidity? The Impact of Margin Eligibility

This table presents results of the difference-in-difference analysis of the impact of margin trading eligibility on market liquidity. The sample consists of "entry" stocks, which become eligible for margin trading, and the control group, defined as those stocks with impact factors between 1.1 and 1, which are not eligible for margin trading and are the closest matches with the entry stocks. The dependent variables are the changes in *ILLIQ* and *Spread* (defined in Table 1) from month t-1 to month t, where eligibility is effective as of the beginning of month t. The explanatory variables are *enter*, a dummy variable equal to one if the control stock is eligible for margin trading, and a vector of year-month dummies. All standard errors are clustered by ISIN (stock identifier). Columns (1) and (2) show results for the full sample. Columns (3) and (4) show results for the subsample of firms for which we have market capitalization data. ***denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

Dependent Variable	Spread	ILLIQ	Spread	ILLIQ
	(1)	(2)	(3)	(4)
Intercept	-0.0018	0.0051***	-0.0032	0.0029
	0.0021	0.0025	0.0028	0.0031
Enter	-0.0024***	-0.0074***	-0.0018**	-0.0084**
	0.0007	0.0024	0.0009	0.0034
Month-Year FE	Yes	Yes	Yes	Yes
N	1321	1276	932	911
R-square	0.23	0.049	0.2416	0.041

Table 4: Does Funding Supply Impact Liquidity? The Impact of Margin Ineligibility

This table presents results of the difference-in-difference analysis of the impact of the loss of margin trading eligibility on market liquidity. The sample consists of "exit" stocks, which become ineligible for margin trading, and the control group, defined as those stocks with impact factors between .9 and 1, which remain eligible for margin trading and are the closest matches with the entry stocks. The dependent variables are the changes in *ILLIQ* and *Spread* (defined in Table 1) from month t-1 to month t+1, where eligibility is effective as of the beginning of month t. The explanatory variables are *exit*, a dummy variable equal to one if the control stock is eligible for margin trading, and a vector of year-month dummies. All standard errors are clustered by ISIN (stock identifier). Columns (1) and (2) show results for the full sample. Columns (2) and (3) show results for the subsample of firms for which we have market capitalization data. ***denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

Dependent Variable	Spread	ILLIQ	Spread	ILLIQ
	(1)	(2)	(3)	(4)
Intercept	-0.0031	0.0085	-0.0031	0.0088
	0.0039	0.0074	0.0039	0.0072
Exit	0.0017**	0.0030	0.0018**	0.0024
	0.0008	0.0026	0.0009	0.0025
Month-Year FE	Yes	Yes	Yes	Yes
N	2185	2181	1784	1780
R-square	0.419	0.269	0.412	0.262

Table 5: The Role of Margin Financing Activity

This table presents results of the analysis of the impact of margin financing activity on the increase (decrease) in liquidity experienced following eligibility (ineligibility). The regression specification in Panel A is the same as that in Table 3, except *enter_margin*, defined as end-of-month t margin financing, divided by month t trading volume, is added as an additional explanatory variable. The regression specification in Panel B is the same as that in Table 4 except *exit_margin*, defined as end-of-month t-1 margin financing divided by month t-1 trading volume, is added as an additional explanatory variable. The other explanatory variables are the *enter* and *exit* dummies 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: Entry Stocks

Dependent Variable	Spread	ILLIQ
	(1)	(2)
Intercept	-0.0017	0.0046**
	0.0021	0.0024
Enter	-0.0025***	-0.0061***
	0.0008	0.0023
Enter_Margin	-0.2294**	-0.6451
	0.1047	0.6419
Month-Year FE	Yes	Yes
N	1321	1276
R-square	0.2473	0.0563

Panel B: Exit Stocks

Dependent Variable	Spread	ILLIQ
	(1)	(2)
Intercept	-0.0029	0.0086
	0.0040	0.0074
Exit	0.0012	0.0028
	0.0008	0.0034
Exit_Margin	0.0855***	0.0888
	0.0331	0.1615
Month-Year FE	Yes	Yes
N	2185	2181
R-square	0.4214	0.2743

Table 6: Market Conditions: Returns and Volatility

This table presents results of the analysis of the impact of market conditions on the increase (decrease) in liquidity experienced following eligibility (ineligibility). The regression specification in Panel A is the same as that in Table 3, but month t-1 market conditions are added as explanatory variables. The regression specification in Panel B is the same as that in Table 4 except but month t-1 market conditions are added as explanatory variables. In both Panels A and B, Columns 1 and 2 show results of the analysis of market returns. *mmret* is the market return (CNX 500 index), *enter_mmret* is the interaction of *mmret* with the *enter* dummy variable, *exit_mmret* is the interaction of *mmret* with the *exit* dummy variable, *neg* is a dummy variable equal to 1 if *mmret* is negative, *enter_mmret_neg* is the triple interaction of *mmret*, *enter*, and *neg*. *exit_mmret_neg* is the triple interaction of *mmret*, *exit* and *neg*. In Columns 3 and 4 of the tables, lagged market returns are replaced by the lagged change in the standard deviation of daily returns, *Dif_std_mret*. The other explanatory variables in the regressions are the *enter* and *exit* dummies, as well as 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: Entry Stocks

	Market Returns		Market Volatility	
Dependent Variable	Spread	ILLIQ	Spread	ILLIQ
	(1)	(2)	(3)	(4)
Intercept	-0.0039	0.0004	-0.0009	0.0098
	0.0027	0.0077	0.0022	0.0040
Enter	0.0012	0.0068	-0.0031***	-0.0071**
	0.0011	0.0068	0.0009	0.0030
Enter_mmret	-0.0901***	-0.2188*		
	0.0291	0.1315		
Enter_mmret_neg	0.1261***	0.5766*		
	0.0451	0.3415		
Enter_std_mdret			0.4466**	0.8354
			0.2122	0.6900
Lag_mmret	0.0506	0.0626		
	0.0389	0.1348		
Neg	-0.0001	0.0424		
	0.0033	0.0283		
Dif_std_mret			0.1276	2.8963**
			0.2070	1.1581
Month-Year FE	Yes	Yes	Yes	Yes
N	1321	1276	1321	1276
R-square	0.287	0.084	0.277	0.093

Panel B: Exit Stocks

	Market Returns		Market Volatility	
Dependent Variable	Spread	ILLIQ	Spread	ILLIQ
	(1)	(2)	(3)	(4)
Intercept	0.0149***	0.0831**	-0.0029	0.0071
	0.0046	0.0416	0.0039	0.0087
Exit	0.0021	0.0002	0.0017*	0.0072***
	0.0014	0.0040	0.0010	0.0036
Exit_mmret	-0.0050	0.0517		
	0.0185	0.0641		
Exit_mmret_neg	0.0104	-0.0801		
	0.0278	0.0892		
Exit_std_mdret			0.0010	1.1639***
			0.1138	0.4709
Lag_mmret	-0.0354*	-1.2129		
	0.0213	0.2618		
Neg	-0.0186***	-0.0883**		
	0.0024	0.0424		
Dif_std_mret			1.0961***	4.0523
			0.2095	4.3771
Month-Year FE	Yes	Yes	Yes	Yes
N	2185	2181	2185	2181
R-square	0.4209	0.2738	0.4211	0.2773

Table 7: Commonality in Liquidity

This table presents results of the commonality in liquidity regressions. For each stock-month, daily changes in liquidity innovations are regressed on changes in average changes in liquidity for Group 1 and Group 2 stocks. We then calculate the changes in Group 1 liquidity beta (*ch_group1_beta*), Group 2 liquidity beta (*ch_group2_beta*), and regression R-square (*ch_rsq*) in all treatment and control stocks. For the entry regressions in Panel A, changes are calculated from month t-1 to month t. For the exit regressions in Panel B, they are based on changes from month t-1 to month t+1. The dependent variables in the regressions are: *ch_rsq*, *ch_group1_beta*, and *ch_group2_beta.* The explanatory variables are the *enter* and *exit* dummies 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: Entry Stocks

Dependent Variable	Spread			ILLIQ		
	(1)	(2)	(3)	(1)	(2)	(3)
	Group1 β	Group2 β	R-square	Group1 β	Group2 β	R-square
Intercept	-0.8620	-0.2387	-0.0128	0.1957	0.1694**	0.0314
	0.8808	1.1129	0.0467	1.5154	0.0745	0.0470
Enter	0.5081	-0.4925*	-0.0162	-0.6854	-0.0411	0.0236
	0.3161	0.2889	0.0189	0.4541	0.0304	0.0174
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1254	1254	1254	1195	1195	1195
R-square	0.1254	0.1237	0.2473	0.1426	0.145	0.23

Panel B: Exit Stocks

Dependent Variable	Spread			ILLIQ		
	(1)	(2)	(3)	(1)	(2)	(3)
	Group1 β	Group2 β	R-square	Group1 β	Group2 β	R-square
Intercept	-0.6095	0.2924	-0.0349	-3.2088*	0.2263*	-0.1460**
	1.3316	3.2101	0.0542	1.5239	0.1308	0.0677
Exit	0.2123	-0.0003	0.0303*	0.7694	-0.0238	0.0469***
	0.2002	0.2161	0.0174	0.4901	0.0280	0.0144
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2153	2153	2153	1995	1995	1995
R-square	0.07225	0.07423	0.2173	0.1128	0.1153	0.3476

Table 8: Market-wide margin activity

Daily changes in market-wide margin activity are regressed on daily market returns (*mdret*, based on the CNX 500 index) and the absolute value of market returns. Market wide margin activity is calculated on a daily basis and is defined as the average number of shares financed by margin trading facilities, divided by shares outstanding, for all Group 1 stocks. ***denotes significance at the 1% level.

Dependent Variable: Average Margin/Shares Outstanding		
	Estimate	Std Error
Intercept	0.000000800	0.000000707
Mdret	0.000013000	0.000010800
Abs_mdret	-0.0000679***	0.000027500
N	2125	
R-square	0.0019	