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Trader Leverage and Liquidity

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ABSTRACT

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

HOW DOES TRADER LEVERAGE impact equity market liquidity? The recent financial crisis has increased interest in the idea that variation in traders' ability to use leverage (that is, the ability of traders to borrow in order to invest in risky assets) can cause sharp changes in market liquidity. In fact, the assumption that capital constraints drive market liquidity is central to several influential theoretical models (see, for example, Gromb and Vayanos (2002), Garleanu and Pedersen (2007), Brunnermeier and Pedersen (2009), Geanakoplos (2010)). When traders such as hedge funds act as financial intermediaries and supply

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liquidity to markets, frictions related to their ability to obtain leverage can also impact their ability to supply liquidity. While this idea is theoretically appealing, testing its validity empirically is challenging, as it requires that one measure the ability of traders to borrow and then isolate the variation in leverage that is not caused by the same economic forces that drive variation in market liquidity. Achieving the latter is particularly problematic if, for example, investor selling pressures due to a decline in fundamentals simultaneously cause a decline in market liquidity and forced deleveraging. This paper exploits the unique margin trading rules in India to provide causal evidence of the impact of trader leverage on liquidity. Importantly, the analysis sheds light on the question of when (that is, under what market conditions) trader leverage is beneficial to market quality and when it is costly.

Indian equity markets provide a particularly useful laboratory for examining the role of shocks in traders' ability to borrow. 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 stock. Thus, the ability to use margin financing relieves capital constraints and can be considered a positive shock to traders' ability to borrow. We exploit two useful features of the system in India: (i) only some exchange-traded stocks are eligible for margin trading and (ii) the list of eligible stocks is revised every month and is based on a well-defined eligibility cutoff.

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

To identify the causal effect of trader leverage on market liquidity, we employ a regression discontinuity design (RDD) in which we focus on stocks close to the eligibility cutoff (see Lee and Lemieux (2010)). At the cutoff of 1%, the probability of margin trading eligibility jumps from zero to one, which allows us to employ a "sharp" RDD. We compare the liquidity of stocks that are just above and just below the cutoff. Because eligibility is revised every month, we obtain a series of staggered quasi-experiments. This provides important power for our empirical analysis. We conduct our analysis using two widely used measures of liquidity: average bid-ask spreads and the price impact of trading.

Our analysis reveals a causal effect of trader leverage on stock market liquidity. In the data, we observe a discontinuous change in both the spread and the price impact measures at the margin trading eligibility cutoff. Formal tests confirm that stock market liquidity is significantly higher when stocks become

[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 I.

eligible for margin trading. We conduct placebo analyses in which we repeat our tests around false cutoffs. Unlike the liquidity patterns at the true cutoff, we find no evidence of discontinuous jumps in liquidity at the false eligibility thresholds. This lends further support to the causal interpretation of our findings. Importantly, the finding of liquidity enhancement due to margin trading is robust to alternative definitions of the local neighborhood around the eligibility cutoffs as well as to alternative liquidity measures.

Much of the recent literature related to the question of how trader leverage affects market liquidity focuses on the liquidity dry-ups that are observed during crises. Brunnermeier and Pedersen (2009) argue that the deleveraging that occurs during severe market downturns causes downward price spirals and exacerbates reductions in liquidity. To investigate this idea, we relax the restriction that the effect of Group 1 status is constant across states of the market. Consistent with the literature (for example, Hameed, Kang, and Viswanathan (2010)), we find that all stocks experience liquidity declines during severe market downturns. Most importantly, we find that this effect is amplified for stocks that are eligible for margin trading. Thus, there is an important sign change in the estimated effect of eligibility. While the ability to trade on margin is beneficial to liquidity on average, it becomes harmful during severe downturns. It is typically very difficult to separate the effects of margin trading from several other effects taking place in times of market stress (such as panic selling or increased aggregate uncertainty). Our research design helps to overcome this empirical obstacle.

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

Although the intricate relationships between the ability of traders to obtain funding ("funding constraints") and asset prices have long been recognized in the literature (see, for example, Kiyotaki and Moore (1997), Kyle and Xiong (2001), Gromb and Vayanos (2002), Krishnamurthy (2003)), there is a growing interest in improving our understanding of these linkages in the aftermath of the recent global financial crisis. Recent theoretical models such as Garleanu and Pedersen (2007), Brunnermeier and Pedersen (2009), and Fostel and Geanakoplos (2012) provide several new insights into the dynamics of funding constraints and the feedback mechanisms that they may trigger.

Empirical tests of the impact of funding constraints have generally lagged behind theoretical advances in this area because there are significant challenges associated with (i) measuring financing constraints and (ii) isolating their causal effects.

A growing number of empirical studies have attempted to link funding constraints and market liquidity by using intuitive proxies for aggregate shocks. These include declines in market returns (Hameed, Kang, and Viswanathan (2010)), changes in monetary conditions (Jensen and Moorman (2010)), differences in the yields of on-the-run and off-the-run Treasury bonds (Fontaine and Garcia (2012)), and price deviations of U.S. Treasury bonds (Hu, Pan, and Wang (2013)). Although the results of these papers suggest that funding constraints impact market liquidity and prices, it is often difficult to identify the precise mechanism because these shocks also bring increases in panic sales and informational asymmetries, which also affect market liquidity. Comerton-Forde et al. (2010) and Gissler (2014) take a step toward addressing these issues by using shocks to the balance sheets of liquidity providers. Comerton-Forde et al. (2010), for instance, find that spreads are higher if specialist firms have realized overnight losses over the past five days, suggesting a role for capital constraints.[2] Finally, a related literature on hedge funds provides useful findings. Aragon and Strahan (2012) use Lehman's bankruptcy as a funding liquidity shock. Lehman's failure reduced the ability of its client hedge funds to trade their positions, leading to increases in their failure rates. As a result, stocks held by Lehman-connected funds experienced decreases in liquidity. Consistent with Aragon and Strahan (2012), Franzoni and Plazzi (2015) provide evidence of the role of hedge funds in liquidity provision and show that hedge funds are more vulnerable to changes in aggregate market conditions than other financial institutions.

Our analysis complements these studies because new margin eligibility is easy to interpret as an increase in the ability of traders to borrow, and our threshold strategy sharpens the causal interpretation. In many markets, the most important variation in leverage occurs during downturns, precisely when a number of important market-wide changes are affecting stock market liquidity. The monthly changes in eligibility made possible by the Indian regulatory setting produce a series of quasi-experiments over an eight-year period and allow us to address identification concerns. The RDD using stock-level variation in margin eligibility helps overcome an important empirical obstacle in that it isolates the impact of trader leverage and distinguishes it from confounding effects. In this paper, we also uncover the state-dependent effects of margin trading and highlight both the costs and the benefits associated with trader leverage—to the best of our knowledge, our paper is the first to document these

[2] While their empirical strategy improves on identification issues relative to previous studies, it is still challenging to identify the driving force. For example, liquidity declines due to high inventory positions and recent losses are likely to be related to specialists' business models or risk management practices dictating the horizon over which profits are maximized, or to strategic market maker behavior due to innovations in stock fundamentals.

causal links. Our focus on the leverage channel (one specific mechanism within the broad category of funding constraints) provides specific insights into causes and implications of funding constraints. An additional benefit of our analysis is that we are able to study the margin financing activity of all traders, not just a particular type (such as a hedge fund). This is useful when a heterogeneous group of market participants contributes to liquidity provision.

The remainder of the paper is organized as follows. Section I provides a description of the margin trading system in India. Section II describes the data and the basic RDD. The empirical analysis of the impact of margin trading on stock market liquidity is in Section III. Section IV concludes.

I. Institutional Setting

The Securities and Exchange Board of India (SEBI) regulates margin trading 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.[3] One problem with Badla was that it lacked good risk management practices—for instance, there were no maintenance margins. Therefore, the practice was eventually banned since it involved “futures-style settlement without futures-style financial safeguards” (Shah and Thomas (2000, p. 18)).

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 over 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 lakh rupees (100,000 rupees, or approximately $2,000). Impact costs are based on the last six months of estimated impact costs. They are rolling estimates, using four 10-minute snapshots of the order book, taken at random intervals in each stock per day. Stocks 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.[4] 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

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

[4] 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

remaining stocks are classified into Group 3. Group 2 and Group 3 stocks are ineligible for margin trading (that is, no new margin trades are allowed as of the effective date). Impact costs and the resulting group assignments are calculated on the 15th of each month. The new groups are announced and become effective on the 1st of the subsequent month. There is no discretion in allocating stocks to groups; the probability of eligibility shifts unequivocally from zero to one at the 1% cutoff.

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% (that is, a margin trader may borrow up to 50% of the purchase price), and minimum maintenance margins are set at 40% (that is, 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 to provide margin trading facilities. Margin trading is closely monitored. Clients can set up margin trading facilities with only one broker at a time, and brokers must keep records of and report margin trading activities. The margin position data (at the stock level) are subsequently made public on a next-day basis. These data are not available in the case of U.S. equity markets and provide an opportunity (which we exploit later in the paper) to answer questions about the implications and drivers of margin financing activity.

One further 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 is also a short-run advantage associated with Group 1 membership. For noninstitutional traders in India, trade settlement with the broker occurs on 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

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)).

requirements both involve shocks to the supply of leverage, which are in the same direction. Margin trading rules are distinct from the other trading rules in India.[5]

Alternative ways to take leveraged positions are available in India, but they are either restricted to a small group of stocks or costly. For example, stocks have to meet a set of requirements before being eligible for futures and options (F&O) trading. These requirements are significant and are different from the margin trading requirements. The stock has to be in the top 500 stocks based on trading activity over 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 million rupees; there must be at least 20% free float and a value of at least 100 crore rupees (1 billion rupees). As of December 2012, we find 140 stocks that are eligible for F&O trading (whereas 620 stocks are eligible for margin trading in the same month).[6] The shorting market is new (launched in April 2008) and is restricted to stocks that are eligible for F&O trading.[7] 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.[8] Outside of the organized exchanges, investors can also borrow from nonbanking finance companies (NBFCs), which are regulated by Reserve Bank of India (RBI) (the central bank), and use the money to purchase any securities they wish. Doing so is similar to taking a collateralized personal loan to invest in the stock market. Because they are not regulated by the SEBI, NBFCs have more flexibility in setting lending terms than banks do (for example, they can use more flexible collateral, such as land or other property). However, obtaining leverage from this channel also has some important disadvantages. Loans in this channel typically carry higher interest rates (conversations with market participants suggest that they can be more than twice margin loan rates) and include terms that increase the risk of the positions to investors. For instance, NBFCs can liquidate investors' positions without sufficiently early notice, and they do not offer the arbitration mechanisms that exchanges offer. Thus, in the case of a dispute, investors must go to the courts, which can be costly and time-consuming.[9] In sum, there are some alternative ways to obtain leverage;

[5] The master circular issued by the SEBI explains all trading rules. This document is publicly available at http://www.sebi.gov.in/cms/sebi_data/attachdocs/1334312676570.pdf.

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

[7] There are also some tenure restrictions on short positions. Initially, lending tenure was seven days. It was extended to 30 days in October 2008, and to 12 months in January 2010. Despite these efforts to reduce shorting constraints, trading volume in the shorting market remains very low (Suvanam and Jalan (2012)).

[8] Both F&O and the shorting market seem quite restricted and thus are unlikely to have meaningful effects in our analysis. Nevertheless, we still run a robustness check using our data on a stock's eligibility in F&O trading (and thus, shorting for the period after April 2008). We show that there is no discontinuity in a stock's eligibility in F&O trading at the 1% cutoff.

[9] Although we observe margin trading positions for each stock, these data do not provide information about the trader type. Using the ownership data from Prowess, which is similar to

but, these channels appear costly and restrictive. Importantly, however, the existence of these alternative mechanisms would go against finding significant effects in our empirical analysis.

II. Data and Methodology

A. Data

In this paper, we analyze stocks that trade on the National Stock Exchange of India (NSE), which is an electronic limit order book market with the highest trading activity in India. We begin with all stocks traded on the NSE from April 2004 (the month in which margin trading was introduced) through December 2012. We use daily data from the NSE in which we observe symbol, security code, closing price (in Indian rupees), high price, low price, total shares traded, and the value of shares traded. We analyze only equities (securities with the code "EQ"). The intraday transactions and quote data come from Thomson Reuters Tick History and include inside quotes and all transactions for Group 1 and Group 2 NSE stocks during our sample period. Fong, Holden, and Trzcinka (2014) compare the Thomson Reuters Tick History coverage, price, and volume data to Datastream and the intraday quote data to Bloomberg for a random selection of stocks. They find very high correlations and conclude that the Thomson Reuters Tick History is of high quality. To merge the Thomson Reuters tick data with the other data sets, we use a mapping of Reuters Instrument Code (RIC) codes (Thomson unique identifier) to International Securities Identification Numbers (ISINs) provided by Thomson. To ensure reliability of the matching, we remove all matches where the absolute difference between the closing price on the NSE daily files and the last transaction price in the Thomson tick data is more than 10%. We also remove corrected trades and entries with bid or ask prices equal to zero. Furthermore, we require nonmissing price and volume information for at least 12 trading days.

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

Margin data, which begin in April 2004, are from the SEBI daily reports. We obtained these from a local data vendor and the NSE.[10] The margin data are

Compustat but covers Indian firms, we test whether Group 1 stocks attract a particular trader type (e.g., retail, institutional, foreign, or promoter). We do not see any significant differences in ownership structure between our treatment and control stocks. See Internet Appendix Table IA.I, available in the online version of this article on the *Journal of Finance* website.

[10] 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

reported at the individual security level and include the *daily* totals of shares outstanding that were purchased with intermediary-supplied funding. Other than Hardouvelis and Peristiani (1992) and Andrade, Chang, and Seasholes (2008), we are not aware of any papers that examine actual margin positions and trading activity.[11] In our data, margin traders' end-of-day stakes in margin-eligible stocks total approximately 4.4 billion rupees (about $88 million) on an average day.[12] However, there is substantial time-series variation in this value. When margin trading facilities were first launched, activity was relatively low, but it reached a level of about 5 billion rupees within a few years. We also observe substantial variation around market downturns. For instance, in early 2008, the total value of margin positions was greater than 10.5 billion rupees, and it later dropped to 3.2 billion rupees in the last quarter in the aftermath of the global financial crisis.

We obtain company information from Prowess, a database of Indian firms (analogous to Compustat), which covers approximately 80% of the NSE stocks. Prowess provides information on shares outstanding, index membership, ownership structure (at the quarterly frequency), and trade suspensions. We exclude from our sample all stocks that have been suspended, since trading irregularities in suspended stocks are likely to contaminate our liquidity measures.[13]

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

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."

[11] A small body of older work examines the impact of margin requirements on equity price stability (volatility) and value (Hsieh and Miller (1990), Seguin (1990), Hardouvelis and Peristiani (1992), Seguin and Jarrell (1993), Pruitt and Tse (1996)). The aim of this early work on margin trading is to examine the policy question of whether restricting the extent to which brokers can extend credit for purchase transactions curbs speculation. All of the studies using U.S. data focus either on the years prior to 1974 (the last time margin requirements changed in the United States) or on OTC 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 the ability of traders to borrow and market liquidity. The regulatory environment does not allow us to adequately answer these questions using U.S. data.

[12] In our data, we observe the number of shares purchased using intermediary-supplied capital (e.g., we observe 50 shares for an investor purchasing 100 shares using 50% leverage). To calculate the total value of levered positions, we assume that margin positions represent 50% of the total positions held by margin traders (50% is the minimum initial margin in India).

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

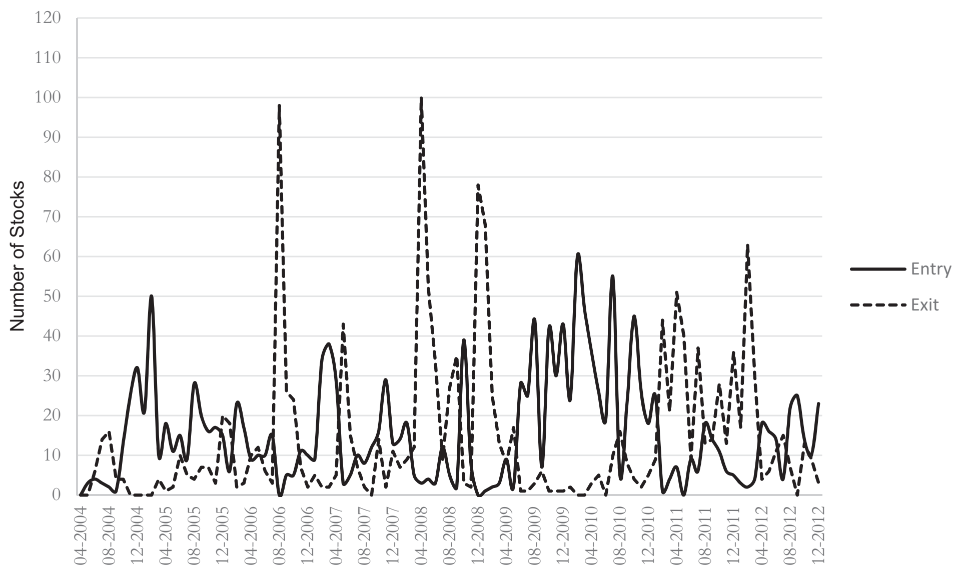


Figure 1. Number of newly eligible and newly ineligible stocks. This figure shows the number of NSE stocks entering and exiting Group 1 between April 2004 and December 2012.

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.

Throughout the analysis, we focus on Group 1 and Group 2 stocks. There are 1,842 unique ISINs in Groups 1 and 2 during our sample period. As Figure 1 shows, many stocks move between these groups; there are 1,500 unique ISINs in Group 1 and 1,347 in Group 2 at some point during our sample period.[14] This is consistent with the distribution of the impact cost variable, which has a mean of 2.09 and a standard deviation of 2.76 for the full sample. Of the 1,842 stocks in the sample, the majority appear in the local sample at some point. For instance, in the local sample used in the price impact regressions, we see 1,100 unique stock observations, of which 995 are treatment (Group 1) stocks at least once.

The two liquidity variables in the paper are monthly average percent effective spreads (*Espread*) and five-minute price impact of trades (*Pimpact*), estimated from order book data. Effective spreads are defined as $100 * \frac{|Transaction price - 0.5*(Bid+Ask)|*2}{0.5*(Bid+Ask)}$. The bid and ask prices reflect the prevailing quotes at the time of the trade. Unlike quoted spreads, which are defined as $\frac{Ask - Bid}{0.5*(Bid+Ask)}$, the effective spread takes into account the fact that many trades

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

execute inside the quoted spread (price improvement) or outside of the spread (if the order is large). The effective spread can be a better proxy for actual transaction costs. The effective spreads that we calculate reflect the average effective spreads on all transactions that occur during the month. The variable *Pimpact* is an approximation of the average price impact of a trade, per unit (rupee) volume. Following earlier work (Goyenko, Holden, and Trzcinka (2009), Hasbrouck (2009), Fong, Holden, and Trzcinka (2014)), for every five-minute interval for the entire month, we calculate five-minute returns (log ratio of quote midpoints), $r(t)$. We also calculate $S(t)$, which equals the sum of the signed square root of trading volume over the five-minute interval (in thousands): $S(t) = \sum T * \sqrt{Rupee volume}$, where T is a trade indicator equal to one if the trade is buyer-initiated and minus one if the trade is seller-initiated. Trade initiation is approximated using the Lee and Ready (1991) algorithm with no time adjustment (that is, assuming no trade reporting delay as in Bessembinder (2003)). We then use OLS to estimate: $r(t) = Pimpact * S(t) + e(t)$. We report *Pimpact* in percentages.

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

Table I provides descriptive statistics for all stocks with impact costs that lie in the neighborhood of the eligibility cutoff of 1%. (As we describe in greater detail in Section II.B, these are stocks with impact costs within one Calonico, Cattaneo, and Titunik (CCT) bandwidth of the cutoff of 1%.) The most important observation from the table is that liquidity is higher among Group 1 stocks than Group 2 stocks. Mean (median) effective spreads are 60.0 (53.4) basis points for stocks in Group 1 versus 71.4 (63.5) basis points for stocks in Group 2. The estimated price impacts show similar patterns. Mean (median) price impacts for Group 1 stocks are 53.1 (44.9) basis points versus 65.8 (55.4) basis points for stocks in Group 2.

B. Empirical Specification

Our objective is to understand whether shocks (variation in margin eligibility) to the leverage channel (margin financing) have a causal impact on market liquidity. The Indian regulatory setting is particularly useful for our identification because stocks with measured impact costs just below the cutoff are eligible for margin trading, while those with impact costs just above 1% are ineligible. The basic premise of RDD in our context is that group assignment near the cutoff is difficult to control precisely, and this leads to a discontinuous

Table I

Descriptive Statistics: Local Group 1 versus Group 2

This table provides summary statistics of liquidity and market characteristics for the sample of National Stock Exchange stocks in the local sample of Groups 1 and 2 for the period April 2004 through December 2012. The local samples are defined based on CCT bandwidths for each variable. All variables are monthly. *Espread* is the average percent effective bid-ask spread for all transactions during month *t*. *Pimpact* is the average percent price impact of trading for stock *i* during month *t*. It is calculated from the OLS regression: $r(t) = Pimpact * S(t) + e(t)$, where $r(t)$is the five-minute quote midpoint return and $S(t)$ equals the sum of the signed square root of trading volume over the five-minute interval (measured in thousands). *Qspread* is the time-weighted average percent quoted spread during month *t*. *Pimpact30* is identical to *Pimpact*, but the coefficient is estimated using data over 30-minute intervals rather than five-minute intervals. *Autocov* is the absolute value of the monthly autocovariance of the daily returns of a stock ($\times 10^3$).

Variable	Mean	Median	P25	P75	Std Dev
		Group 1			
Espread	0.6002	0.5347	0.3946	0.7285	0.2989
Pimpact	0.5312	0.4490	0.2569	0.7043	0.4078
Qspread	0.6343	0.5513	0.3906	0.7825	0.3543
Pimpact30	0.4183	0.3360	0.1784	0.5623	0.3508
Autocov	0.1951	0.1165	0.0477	0.2525	0.2250
		Group 2			
Espread	0.7138	0.6354	0.4657	0.8793	0.3477
Pimpact	0.6575	0.5543	0.3006	0.8910	0.5258
Qspread	0.7902	0.6929	0.4900	0.9935	0.4288
Pimpact30	0.5370	0.4427	0.2201	0.7305	0.4585
Autocov	0.2058	0.1228	0.0549	0.2683	0.2319

treatment effect stemming from exogenous variation in margin eligibility.[15] That is, while stocks at or below the 1% cutoff receive the treatment, those on the other side of the cutoff do not. RDD is a powerful quasi-experimental design in which identification of the treatment effect requires very mild conditions. A comparison of average outcomes just above and just below the threshold identifies the average treatment effect as long as error terms (and potentially omitted variables) are smooth at the discontinuity point. 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

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

(see, for example, Lee and Lemieux (2010), Roberts and Whited (2013)). Our analysis focuses on the "local" sample of stocks, defined as those stocks whose impact costs lie close to the cutoff of 1%. We compare the liquidity of eligible versus ineligible stocks using the regression specification:

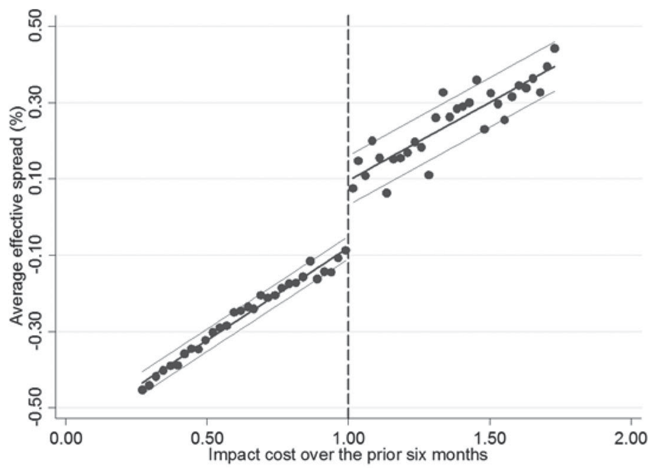
$$Liquidity_{it} = \alpha + \beta * Group\,1_{it} + \gamma * X_{it} + \varepsilon_{it}. \tag{1}$$

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

We use regression analysis to test our formal hypotheses about the impact of leverage on market liquidity. However, it is useful to begin with plots of the data near the impact cost threshold of 1%. As noted in Section I, impact costs that determine eligibility in month t are calculated over the six months prior to month t.[16] In Figure 2, Panels A and B, we examine all stocks in the sample with impact costs between 0.25% and 1.75%. We form 30 impact cost bins on each side of the threshold of width 0.025 on each side of the eligibility cutoff. To control for time-series variation, we demean each variable using the average values of all Group 1 and Group 2 stocks for the month and compute average liquidity within each bin. We then run separate regressions of average liquidity on average impact cost for the observations on each side of 1%. If there is a treatment effect of margin trading eligibility, we would expect a marked liquidity change at the impact cost cutoff. Indeed, the regression lines and robust 95% confidence intervals (based on White (1980) standard errors) in Figure 2, Panels A and B, show discontinuous drops in both spreads and the price impact of trading at the cutoff value of 1%. In addition, we check the extent to which covariates exhibit discontinuity at the cutoff. Figure 3, Panels A through D, show plots for lagged stock price volatility, stock returns, rupee volume, and market capitalization, respectively. In stark contrast to Figure 2, Panels A and B, we do not observe discontinuous changes in any of these variables. Finally, we visually inspect a histogram of impact costs to check for evidence of strategic behavior near the threshold. As shown in Figure 4, we do not observe any obvious bunching (that is, discontinuity in the number of stocks) on either side of the threshold. This is not really surprising; it would be difficult and costly for investors to strategically push impact costs below 1%

[16] More specifically, impact cost is calculated using data from the 15$^{\text{th}}$ of month $t-6$ through the 15$^{\text{th}}$ of month $t-1$. For example, the average impact cost from December 15$^{\text{th}}$ through June 15$^{\text{th}}$ determines eligibility for a stock for the month of July.

Panel A. Effective Spreads



Panel B. Price Impact

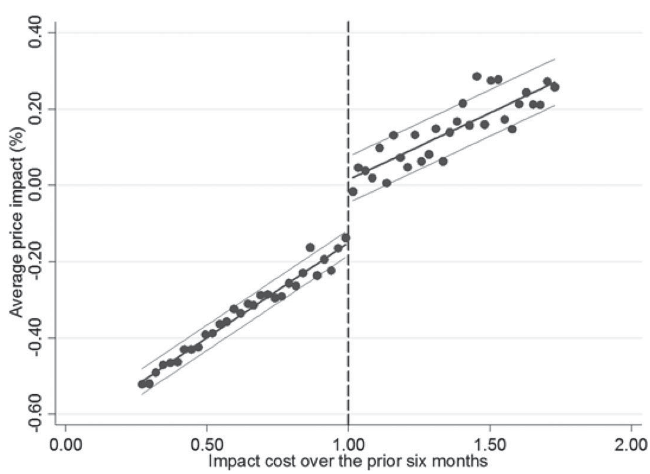


Figure 2. Impact cost, effective spreads, and price impact. The figure plots the average effective spread (Panel A) and price impact (Panel B) during month t as a function of impact cost over the previous six months. Stocks are divided into 30 bins (the X-axis) of width 0.025 on each side of the eligibility cutoff of 1%. To control for time-series variation in market liquidity, we demean each observation using the average values of all Group 1 and Group 2 stocks for the month. We then compute the average effective spread within each bin. Margin-eligible stocks are all those stocks with impact costs that are less than or equal to 1%, which corresponds to bins 1 through 30. Stocks in bins 31 to 60 are ineligible for margin trading during period t. Separate regression lines, along with 95% confidence bands based on robust (White (1980)) standard errors, are shown on both sides of the eligibility cutoff.

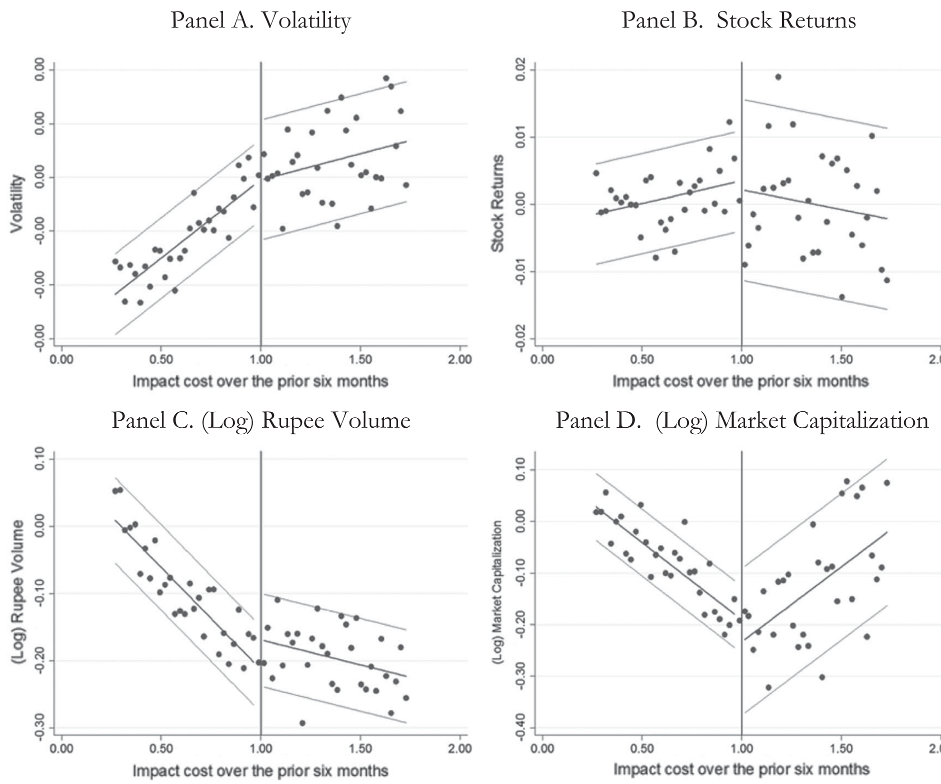


Figure 3. Impact cost and other variables. The figures plot the average one-month lagged stock price volatility (*Std_ret*), stock returns (*Mret*), log dollar volume (*Logvolume*), and log market capitalization (*Logmcap*) as a function of impact cost over the previous six months. All variables are defined in Table II. Stocks are divided into 30 bins of width 0.025 on each side of the eligibility cutoff of 1%. To control for time-series variation, we demean each observation using the average values of all Group 1 and Group 2 stocks for the month. We then compute the averages within each bid. Margin-eligible stocks are all those stocks with impact costs that are less than or equal to 1%, which corresponds to bins 1 through 30. Stocks in bins 31 to 60 are ineligible during period t. Separate regression lines, along with 95% confidence bands based on robust (White (1980)) standard errors, are shown on both sides of the eligibility cutoff.

to enjoy margining given that the order book snapshots are taken at random intervals and revised every month.

As mentioned in Section I, outside of lower VAR margin requirements, there are no additional regulatory implications of Group 1 status since margin trading rules are distinct from all other trading rules. However, it is possible that some Group 1 stocks happen to be those stocks for which there are single name futures or options (thus providing investors an alternative source of leverage). It is also possible that Group 1 stocks are more likely to be in a major index or that particular types of investors (e.g., foreign institutions) have restrictions that limit their ownership to the larger or more

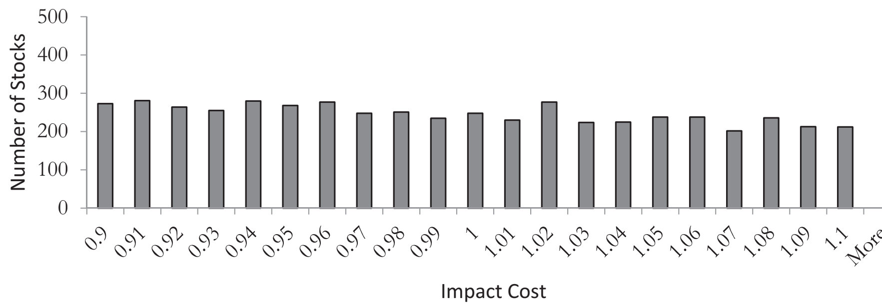


Figure 4. Distribution of stocks around the eligibility cutoff. This figure shows the number of stock-month observations in each impact cost bin (of size 0.01) near the eligibility cutoff of 1%.

liquid stocks that tend to be in Group 1. To examine these possibilities, we identify stocks on which futures/options trade and stocks in the CNX 500 index, as well as the shares owned by foreign, individual, institutional, and blockholder/insider (promoter) investors. Internet Appendix Figure IA.1 shows mean values of these variables for 30 impact cost bins on each side of the threshold. We do not observe any marked discontinuous change in any of these variables.

Overall, the evidence in Figures 2 through 4 and in the Internet Appendix Figure IA.1 lend strong support for the RDD. We conduct formal tests in the regression analysis that follows.

C. Bandwidth Selection

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 (2010) discuss, there is no perfect answer to this question. The primary objective is to choose a bandwidth that is small enough to capture the effect of the treatment (margin eligibility), but also has a sufficiently large N to provide statistical power in estimation. Until recently, there was little guidance on bandwidth choice in the regression discontinuity literature and researchers relied on rule-of-thumb (ROT) and cross-validation (CV) approaches from the nonparametric regression literature (see Lee and Lemieux (2010), section 4.3.1). Silverman's (1986) approach is a popular example of an ROT procedure (for example, used in Chava and Roberts (2008)), where the optimal bandwidth is a function of the sample variance of the forcing variable and $N^{1/5}$. As discussed in Lee and Lemieux (2010), CV is a leave-one-observation-out procedure in which a regression is run using all observations except observation i within bandwidth h. The estimated parameters are then used to predict the value of observation i. This is repeated for all observations within the bandwidth. The CV bandwidth is chosen by selecting the value of h that minimizes the MSE of the difference between the predicted and actual values. Both of these approaches have been widely used in earlier studies.

There have been important new advances in the literature on optimal bandwidth selection techniques. Imbens and Kalyanaraman (IK; 2012) use mean squared error (MSE) loss criteria to derive a data-dependent bandwidth for RDD applications. The IK bandwidth depends on initial bandwidth choice, and therefore the optimal bandwidth is not unique. Although the performance of IK bandwidth is typically reasonable, Calonico, Cattaneo, and Titunik (2014a) show that the IK proposed optimal bandwidth can sometimes be too large, leading to biased inference. CCT use the same theoretical derivation developed in IK, but, improve on it by selecting the initial bandwidth optimally. This results in more conservative (smaller) bandwidths than those suggested by IK.

As suggested by DiNardo and Lee (2011) and Lee and Lemieux (2010), we check to see whether the results are stable across more than one plausible approach. To do so, we calculate bandwidths using four bandwidth selection techniques: ROT based on Silverman (1986), CV, IK, and CCT.[17] For analyses of the *Espread* variable, the optimal bandwidths range from 0.22 (ROT) to 0.33 (IK). In the case of *Pimpact*, the range is somewhat larger, ranging from 0.22 (CCT/ROT) to 0.49 (CV). Although the range of suggested bandwidths depends on the distribution of the variable being analyzed, there is also some variation in the bandwidths across different selection techniques. In the analysis that follows, we rely on CCT bandwidths because of their optimality properties and because they are the current state of the art. The CCT bandwidths for effective spread and price impact are 0.23 and 0.22, respectively.

In robustness analysis (later in the paper), we examine how sensitive our main findings are to the bandwidth choice. We first increase and decrease the CCT bandwidths by 0.2, 0.4, and 0.6 (e.g., this results in a bandwidth range of 0.17 to 0.29 for *Espread*). We then reestimate our main regressions. In addition, we estimate the impact of Group 1 status using the local samples based on each of the alternative bandwidth selection approaches. Because all of the techniques except ROT use the distributions of the dependent variables to determine bandwidth, the size of the optimal bandwidths varies depending on the dependent variable we are examining (for example, the CCT bandwidths for our dependent variables are between 0.20 and 0.27). This will cause some

[17] Following the literature on nonparametric techniques in applying Silverman's rule, we use the minimum of the interquartile range and variance (rather than the variance) to correct for the potential failure of the normality assumption embedded in Silverman's rule (see, for example, Hardle et al. (2004)). The ROT bandwidth is given by $1.06 * \min(s, R / 1.34) * N^{-1/5}$, where s and R are the variance and interquartile range of the impact cost, respectively. For CV, IK, and CCT, we use the Stata command *rdbwselect* (estimation details are explained in Calonico, Cattaneo, and Titunik (2014b)). Following Lee and Lemieux (2010), we use the rectangular kernel while calculating the IK and CCT bandwidths. In Section III.B.1, we repeat our analysis using CCT bandwidths calculated using a triangular kernel. Compared to the rectangular kernel, triangular kernel weighting results in wider bandwidths. CCT bandwidths based on triangular kernel weighting for spread and price impact are 0.32 and 0.31, respectively.

Table II

Do Leverage Constraints Impact Liquidity?

This table presents results of the analysis of the impact of margin trading eligibility on market liquidity. The dependent variables are the average effective spread (*Espread*) and the five-minute price impact of trading (*Pimpact*) during month t, where eligibility is effective as of the beginning of month t. The sample includes all stocks in Groups 1 and 2 with impact costs close to the cutoff of 1% (based on CCT bandwidths of 0.23% for the *Espread* regressions and 0.22% for *Pimpact*). The explanatory variables are *Group 1*, a dummy variable equal to one if the control stock is eligible for margin trading during month t, a vector of control variables, and month-year dummies. The control variables include one-month lagged: standard deviation of stock returns (*Std_ret*), stock returns (*Mret*), dollar volume (Logvolume), equity market capitalization (*Logmcap*), and the lagged dependent variables. *Std_ret* is the standard deviation of daily returns during the month. *Mret* is the month t stock return, calculated from the closing prices at the ends of months $t-1$ and t. *Logvolume* is the average daily trading volume, that is, the natural log of the daily closing price (in rupees) times the number of shares traded. *Logmcap* is equity market capitalization, defined as the end of month t closing price, times shares outstanding. Month-year fixed effects are estimated but not reported in the table. All standard errors are clustered by ISIN (stock identifier). t-statistics are in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Variable	(1) *Espread*	(2) *Espread*	(3) *Pimpact*	(4) *Pimpact*
Group 1	−0.024***	−0.025***	−0.043***	−0.031***
	(0.006)	(0.007)	(0.008)	(0.009)
Lag *Std_dret*	−0.711*	−0.375	6.284***	4.490***
	(0.386)	(0.320)	(0.727)	(0.751)
Lag *Mret*	−0.050*	−0.049*	−0.121***	−0.048
	(0.027)	(0.029)	(0.030)	(0.030)
Lag *Logvolume*	−0.025***	−0.030***	−0.094***	−0.087***
	(0.005)	(0.009)	(0.012)	(0.014)
Lag *Logmcap*		0.010*		−0.052***
		(0.006)		(0.006)
Lag *Espread*	0.703***	0.690***		
	(0.058)	(0.076)		
Lag *Pimpact*			0.422***	0.400***
			(0.055)	(0.070)
Observations	8,881	7,512	8,495	7,188
R^2	0.773	0.775	0.493	0.512
Month-Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

differences in the number of observations across regression analyses that have different dependent variables.

III. Results

A. Trader Leverage and Market Liquidity

Results of the effective spread regressions are reported in Table II, columns (1) and (2). The estimated coefficient of 0.024 on the Group 1 dummy variable implies that margin trading causes effective spreads to decline by 2.4 basis points. The specification in column (1) includes controls for lagged volatility (standard deviation of stock returns during month $t - 1$), one-month lagged stock returns, one-month lagged dollar trading volume, and one-month lagged spreads. In column (2), we also control for lagged market capitalization. We obtain this variable from Prowess data. Because not all stocks are in the Prowess subsample, the sample size declines. In column (2), the estimated coefficient on the Group 1 dummy is 2.5 basis points and is statistically significant. This implies that margin trading improves effective bid-ask spreads by about 3.5% relative to the mean and 3.9% relative to the median spread in the control sample of local-sample Group 2 stocks (the mean and median spreads for local Group 2 stocks from Table I are 71.4 basis points and 63.5 basis points, respectively).

Results from the analysis of *Pimpact* are presented in Table II, columns (3) and (4), and are similar to the *Espread* results. The estimated coefficient on the Group 1 dummy in columns (3) and (4) shows that margin trading improves the five-minute price impact of trading. In column (4), the coefficient of the Group 1 dummy is 3.1 basis points, implying an improvement of 4.7% (5.6%) relative to the mean (median) *Pimpact* of local Group 2 stocks, which is 65.7 (55.4) basis points.

The coefficients on the control variables in Table II also deserve mention. Most of these are consistent with what one would expect: liquidity is positively autocorrelated, it is higher following periods of high trading volume, and higher following periods of high stock returns. In the case of volatility, we find that, as expected, price impact is increasing in lagged volatility. The relationship between spreads and lagged volatility is not as consistent. Although it is not a strong relationship, spreads seem to be decreasing in volatility. If the order processing and inventory costs fall more than the information asymmetry component of the spread when volatility is high, it is possible that total spreads will decrease. This might happen near public announcements, when volatility reflects information arrival and improved price efficiency (for example, Krinsky and Lee (1996) emphasize the sometimes opposing behavior of various spread components near earnings announcements). Taken together, the coefficients on the lagged volatility variable suggest that quotes become significantly thinner but possibly more aggressive following high volatility periods.

Overall, the results in Table II show average improvements in both spreads and the price impact of trading as a result of margin eligibility. Spreads narrow, which suggests more aggressive liquidity providers. The price impact of trades also decreases, consistent with a thickening of the order book. Although it is not a very large difference, we observe more improvements in the price impact than in spreads. This suggests that margin traders are doing somewhat more to provide liquidity at a given price than submitting more aggressive bid and ask prices.[18]

[18] We also run a regression in which we repeat the Table II analysis, but we control for up to three lags of changes in the dependent variable to check whether the trends in the dependent variables before the treatment (eligibility) have an impact on our results. We also interact the

There are a number of reasons why one might expect the baseline estimates in Table II to reflect lower bounds on the actual effects of margin trading. First, our empirical design does not allow us to capture potential liquidity spillovers into other stocks (that is, margin trading can free up capital that can be used to trade elsewhere in the market). Spillover effects would reduce the estimated magnitudes. Second, and more importantly, the estimated magnitudes that we observe on average are affected by asymmetries in the rules governing new eligibility versus new ineligibility. Upon entry to Group 1, the stock becomes eligible for margin trading and investors can begin levering up immediately. Upon exit from Group 1, stocks are ineligible for new margin trading as of the beginning of month t. However, existing margin positions do not have to be unwound right away, and thus the transition to the "no margin" regime may occur slowly. If margin traders are liquidity providers, one might expect them to unwind slowly, in a way that is consistent with liquidity provision (that is, sell when there is buy demand in the market). Ignoring these unwinding activities of margin traders in Group 2 stocks would then attenuate the estimated effects of margin trading.

To capture the unwinding of margin trades that may occur after stocks move from Group 1 to Group 2, we repeat the analysis in Table II but we add the dummy variable *Unwind*, which is set equal to one if a Group 2 stock is in an unwinding phase following an exit event and thus has experienced a decline in open margin positions during the month. Table III reports the results. As expected, we find that the slow unwinding of margin trades also enhances liquidity, consistent with the idea that margin traders generally provide liquidity when they sell their stocks and exit their positions.[19] More importantly, when we account for this institutional feature of the margin trading rules, the estimated effects of margin eligibility increase substantially. The estimated impact of eligibility on effective spreads doubles, from 2.5 basis points in Table II to 5.0 basis points, implying a decline of 6.5% (7.3%) relative to the mean (median) effective spread of control stocks. The estimated effect on the price impact of trading also increases, from 3.1 basis points in Table II to 5.4 basis points, representing a decline of 7.8% (9.5%) relative to the mean (median) price impact in the control sample.

Another way to capture the asymmetry in the effects of new eligibility versus ineligibility is to analyze stocks entering and exiting Group 1 separately. Given the findings in Table III and the institutional differences in the rules governing new entry and exit stocks, we would expect eligibility to have a stronger effect on stocks entering Group 1 than on those that are exiting the group. To test this conjecture, we introduce the dummy variables *Entry* and *Exit*, which equal one if a stock is a new Group 1 and Group 2 stock during month t, respectively. To isolate the effect of entry, the control group in the entry analysis includes all

current Group 1 status with these lagged changes in liquidity measures. We find that our results are robust to controlling for this trend. (See Internet Appendix Table IA.II.)

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

Table III

The Impact of Unwinding Outstanding Margin Positions

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

Variable	(1) Espread	(2) Pimpact
Group 1	−0.049***	−0.054***
	(0.010)	(0.016)
Unwind	−0.033***	−0.033*
	(0.008)	(0.018)
Lag *Std_dret*	−0.361	4.492***
	(0.320)	(0.750)
Lag *Mret*	−0.054*	−0.054*
	(0.030)	(0.030)
Lag *Logvolume*	−0.030***	−0.086***
	(0.009)	(0.014)
Lag *Logmcap*	0.010*	−0.053***
	(0.006)	(0.006)
Lag *Espread*	0.686***	
	(0.076)	
Lag *Pimpact*		0.401***
		(0.069)
Observations	7,512	7,188
R^2	0.776	0.512
Month-Year FE	Yes	Yes
Controls	Yes	Yes

Group 2 stocks except those that are in the unwinding phase following an exit event. Similarly, the control stocks in the exit analysis consist of all Group 1 local stocks that did not experience a change in eligibility during period t. The results are presented in Internet Appendix Table IA.III. Panel A reports the results for entry and Panel B for exit stocks. Not surprisingly, the estimated magnitude of the *Entry* coefficient is larger than that of the coefficient on the Group 1 dummy in Table II and is in line with estimates in Table III.

We begin the exit analysis by looking at the liquidity effects in the first month of exit. The coefficient on *Exit* is positive, but it is not statistically significant in the first month of exit. Given that traders can take time to unwind their existing margin positions, we might expect the effects of ineligibility to occur over more than one month. Therefore, we also examine month-ahead liquidity for the exit and control stocks (using the stocks that did not experience a change in eligibility from period t to $t + 1$). We find significant liquidity declines. Taken together, the results in Table III and Internet Appendix Table IA.III show that the liquidity changes are larger for stocks transitioning into Group 1 and that the asymmetry in rules governing new eligibility and new ineligibility attenuates the average effects reported in Table II.

To assess the economic impact of our findings, it is useful to compare our estimates to recent studies that also analyze the effect of capital constraints on stock liquidity. Table III shows that the impact of margin eligibility on effective spreads is 5.0 basis points, implying a decline of 6.5% (7.3%) relative to the mean (median) effective spread of control stocks. The estimated effect of eligibility on the price impact of trading is 5.4 basis points, representing a decline of 7.8% (9.5%) relative to the mean (median) price impact in the control sample. Aragon and Strahan (2012) report that a one interquartile range change in ownership by Lehman-connected hedge funds increases spreads by 2.9% and the price impact of trading, as captured by the Amihud (2002) illiquidity ratio, by about 3.8%. These effects are comparable to ours, although somewhat smaller. In their conservative estimates, Comerton-Forde et al. (2010) report an increase in daily effective spreads of 0.54 basis points following a one standard deviation shortfall in inventory revenue, which corresponds to an approximately 6% to 7% change relative to their sample mean. These average effects are in line with ours.[20] As we discuss in Section III.E, we also find strong state-dependent effects when we allow the estimated effects of Group 1 status to vary across states of the market.

B. Robustness and Placebo Tests

B.1. Alternative Bandwidths

Before diving deeper into the mechanisms driving the main findings, a natural question to ask in any RDD is whether the results are driven by the choice of bandwidth. We use current state-of-the-art optimal bandwidth selection techniques to minimize discretion. However, it is useful to examine how sensitive the main results are to this choice. In Table IV, we present results from analyses in which we both increase and decrease the CCT bandwidths (of 0.23 for *spread* and 0.22 for *Pimpact*) by increments of 0.2. This results in bandwidths that are approximately 10% to 30% higher and lower than the CCT bandwidths, from 0.29 to 0.17 for *Epread* and 0.28 to 0.16 for *Pimpact*. When we reestimate the main regression, we find that the results are similar across a wide range of bandwidths. Naturally, the number of observations increases (decreases) as

[20] See Aragon and Strahan (2012), Tables 4 and 5 and Comerton-Forde et al. (2010), Table 4, column 6. In assessing the economic significance of the effects documented in any of these papers (including ours), it is also important to consider the fact that these are transaction costs paid *per trade*. These can be large in markets with substantial trading activity. For example, a rough calculation suggests that over the course of a year, a five basis point reduction in trading costs implies an annual savings of 3 million rupees *per stock* (the average Group 1 stock has daily trading volume of 27.27 million rupees). Given that more than 1,500 stocks appear in Group 1 at some point during the sample period, the potential transaction cost savings associated with margin trading eligibility is significant.

Table IV

Alternative Bandwidths

This table presents results of the analysis of the impact of margin trading eligibility on market liquidity using alternative bandwidths. The regression specification is identical to that in columns (2) and (4) of Table II. The dependent variables are the average *Espread* and *Pimpact* during month t. The explanatory variables are *Group 1*, a dummy variable equal to one if the stock is eligible for margin trading during month t, the control variables (defined in Table II), and month-year dummies. Month-year fixed effects are estimated but not reported in the table. Columns 1 through 6 increase and decrease the CCT bandwidths by increments of 0.02 (approximately 10%, 20%, and 30%). All standard errors are clustered by ISIN (stock identifier). t-statistics are in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Variable	(1) +30%	(2) +20%	(3) +10%	(4) −10%	(5) −20%	(6) −30%
			Panel A: Dependent Variable = *Espread*			
Group 1	−0.026***	−0.026***	−0.026***	−0.026***	−0.025***	−0.023***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Lag *Std_dret*	−0.537*	−0.641**	−0.564*	−0.434	−0.491	−0.646*
	(0.275)	(0.294)	(0.310)	(0.333)	(0.353)	(0.375)
Lag *Mret*	−0.051**	−0.051*	−0.054*	−0.050	−0.043	−0.033
	(0.024)	(0.027)	(0.028)	(0.031)	(0.035)	(0.037)
Lag *Logvolume*	−0.024***	−0.024***	−0.026***	−0.031***	−0.033***	−0.034***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)
Lag *Logmcap*	0.007	0.007	0.008	0.010*	0.011*	0.012*
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
Lag *Espread*	0.721***	0.714***	0.707***	0.680***	0.659***	0.646***
	(0.067)	(0.069)	(0.073)	(0.081)	(0.085)	(0.089)
Observations	9,583	8,887	8,233	6,853	6,170	5,498
R^2	0.776	0.777	0.775	0.773	0.773	0.770
Stock FE	No	No	No	No	No	No
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
			Panel B: Dependent Variable = *Pimpact*			
Group1	−0.034***	−0.034***	−0.032***	−0.029***	−0.030***	−0.029***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Lag *Std_dret*	4.461***	4.364***	4.572***	4.381***	4.555***	4.610***
	(0.645)	(0.667)	(0.721)	(0.800)	(0.858)	(0.906)
Lag *Mret*	−0.058**	−0.064**	−0.062**	−0.061*	−0.047	−0.055
	(0.027)	(0.028)	(0.029)	(0.032)	(0.033)	(0.035)
Lag *Logvolume*	−0.082***	−0.082***	−0.085***	−0.083***	−0.085***	−0.082***
	(0.012)	(0.013)	(0.014)	(0.015)	(0.017)	(0.018)
Lag *Logmcap*	−0.051***	−0.051***	−0.050***	−0.054***	−0.051***	−0.053***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Lag *Pimpact*	0.392***	0.399***	0.398***	0.410***	0.409***	0.423***
	(0.059)	(0.061)	(0.066)	(0.074)	(0.081)	(0.087)
Observations	9,200	8,586	7,859	6,521	5,836	5,161
R^2	0.504	0.511	0.510	0.519	0.521	0.527
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

we increase (decrease) the bandwidths. The main results, however, are very robust.

In addition, we repeat the analysis using alternative bandwidths obtained from other selection techniques. In Internet Appendix Table IA.IV, we use the ROT, CV, and IK bandwidths. We also recalculate the CCT bandwidth using a triangular kernel. The estimates are somewhat larger when the alternative bandwidths are wider (particularly for *Pimpact*), suggesting that CCT bandwidths are in fact more conservative. Overall, the findings are similar to those in the previous tables. We find that margin trading enhances liquidity. To keep the causal interpretation of the results clear, throughout the paper we rely on the more conservative CCT-based estimates.

B.2. Local Polynomial Regressions

As a complement to the local linear regression methodology, we also conduct tests using a parametric approach (specifically, polynomial functional forms). To avoid the overfitting problem that can result from estimating polynomial regressions over very small bandwidths, we follow the guidance in Lee and Lemieux (2010) and use the Akaike information criterion (AIC) to determine the appropriate polynomial orders for a given bandwidth.[21] We begin with the CCT bandwidth (where the appropriate polynomial order is zero, based on the AIC criterion), and we expand (in increments of 0.25) by factors of 1.25 to 2.5. Doing so results in polynomial orders ranging from one to three. In Table V, we report results of regressions over all six additional bandwidths using the AIC-implied polynomial order. We find that the main effect of Group 1 status continues to hold across all specifications.

B.3. Alternative Liquidity Measures

To ensure that our results are not driven by choice of liquidity measure, we also examine whether our results are sensitive to the choice of liquidity measure. In the main analysis, we focus on effective spreads and the five-minute price impact of trades. Effective spreads are generally preferred to quoted spreads (the difference between the bid and the ask) because they take into account the fact that many trades execute at prices that are not equal to the

[21] AIC is used to select the best parametric model among several candidate parametric models. AIC is calculated after each regression, and the model with the lowest AIC is considered the best model. Specifically, in our setting, for a given bandwidth, we run several regressions with different degrees of polynomials. In these regressions, we include the *Group 1* dummy variable, polynomials of impact cost (centered around the 1% cutoff as suggested by Lee and Lemieux (2010)), interactions of the *Group 1* dummy with impact cost polynomials, and control variables. The model with the highest AIC is chosen as the appropriate model. For instance, in regressions for *Espread*, the model with polynomial of degree two is identified as the best model when the bandwidth is 0.46 (two times the CCT bandwidth). Although AIC is not the sole model selection method, it is an easily implementable and commonly used technique in choosing among parametric models (Fabozzi et al. (2014)).

Table V

Local Polynomial Regressions

This table presents results of analyses of the impact of margin trading eligibility on market liquidity using the same specification described in Table II (columns (2) and (4)), except that we add polynomials of the impact cost variable to the specifications. Polynomial orders for each bandwidth are determined by the Akaike information criterion (AIC). We begin with the CCT bandwidth used in Table II and we expand it (in increments of 0.25) by factors of 1.25 to 2.5. All standard errors are clustered by ISIN (stock identifier). Impact cost is centered around the 1% cutoff (i.e., subtract 0.01 from *Impact Cost*). Month-year fixed effects and the control variables from Table II are included in all regressions. t-statistics are in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Variable	(1) CCT×1.25	(2) CCT×1.5	(3) CCT×1.75	(3) CCT×2	(4) CCT×2.25	(5) CCT×2.5
			Panel A: Dependent Variable = *Espread*			
Group 1	−0.023**	−0.021**	−0.028**	−0.032***	−0.029***	−0.040***
	(0.010)	(0.01)	(0.011)	(0.010)	(0.009)	(0.011)
Impact Cost	0.104**	0.141***	0.126	0.047	0.104*	−0.133
	(0.045)	(0.039)	(0.089)	(0.072)	(0.062)	(0.132)
*Impact Cost*Group 1*	−0.047	−0.066*	−0.110	−0.043	−0.093	0.150
	(0.043)	(0.035)	(0.103)	(0.081)	(0.071)	(0.152)
Impact Cost^2			−0.070	0.146	−0.008	1.164*
			(0.232)	(0.158)	(0.122)	(0.605)
Impact Cost^{2*}*Group 1*			−0.104	−0.332*	−0.161	−1.330**
			(0.258)	(0.176)	(0.135)	(0.669)
Impact Cost^3						−1.574**
						(0.737)
Impact Cost^{3*}*Group 1*						1.520*
						(0.788)
Lag *Std_dret*	−0.672**	−0.791***	−0.748***	−0.718***	−0.718***	−0.762***
	(0.297)	(0.268)	(0.239)	(0.219)	(0.200)	(0.183)
Lag *Mret*	−0.052**	−0.062***	−0.065***	−0.070***	−0.069***	−0.065***
	(0.025)	(0.021)	(0.019)	(0.017)	(0.016)	(0.014)
Lag *Logvolume*	−0.024***	−0.019***	−0.018***	−0.016***	−0.016***	−0.015***
	(0.008)	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)
Lag *Logmcap*	0.007	0.005	0.003	0.002	0.001	0.000
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Lag *Espread*	0.711***	0.735***	0.748***	0.770***	0.770***	0.779***
	(0.069)	(0.060)	(0.053)	(0.049)	(0.044)	(0.040)
Observations	9,200	11,322	13,711	16,137	18,235	21,028
R^2	0.778	0.781	0.781	0.789	0.795	0.804
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
			Panel B: Dependent Variable = *Pimpact*			
Group 1	−0.034*	−0.036**	−0.037*	−0.033*	−0.035*	−0.038*
	(0.018)	(0.017)	(0.020)	(0.019)	(0.018)	(0.022)
Impact Cost	0.167**	0.134**	0.172	0.216	0.209	0.428
	(0.079)	(0.065)	(0.187)	(0.171)	(0.137)	(0.294)

(*Continued*)

Table V—*Continued*

Variable	(1) CCT×1.25	(2) CCT×1.5	(3) CCT×1.75	(3) CCT×2	(4) CCT×2.25	(5) CCT×2.5
Panel B: Dependent Variable = *Pimpact*						
*Impact Cost*Group 1*	−0.171*	−0.105	−0.254	−0.211	−0.181	−0.468
	(0.090)	(0.071)	(0.217)	(0.193)	(0.152)	(0.328)
Impact Cost^2			−0.035	−0.170	−0.131	−1.392
			(0.487)	(0.409)	(0.285)	(1.326)
Impact Cost^{2*}*Group 1*			−0.369	0.018	0.008	0.812
			(0.534)	(0.441)	(0.309)	(1.473)
Impact Cost^3						1.990
						(1.658)
Impact Cost^{3*}*Group 1*						−2.634
						(1.752)
Lag *Std_dret*	3.747***	3.660***	3.645***	3.765***	3.399***	3.567***
	(0.607)	(0.565)	(0.495)	(0.470)	(0.422)	(0.440)
Lag *Mret*	−0.038	−0.045**	−0.042**	−0.057***	−0.056***	−0.070***
	(0.025)	(0.022)	(0.020)	(0.020)	(0.018)	(0.019)
Lag *Logvolume*	−0.070***	−0.067***	−0.067***	−0.070***	−0.066***	−0.068***
	(0.011)	(0.010)	(0.009)	(0.008)	(0.007)	(0.007)
Lag *Logmcap*	−0.043***	−0.044***	−0.042***	−0.041***	−0.040***	−0.043***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
Lag *Pimpact*	0.326***	0.317***	0.316***	0.302***	0.302***	0.289***
	(0.057)	(0.050)	(0.043)	(0.039)	(0.035)	(0.035)
Observations	8,758	10,487	12,675	14,700	17,149	19,293
R^2	0.456	0.451	0.459	0.451	0.459	0.476
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

bid and ask and are therefore a better proxy for actual transaction costs than quoted spreads. However, because quoted spreads are also widely used in the literature, we repeat the main analysis using this transaction cost measure. The five-minute posttrade horizon used in the *Pimpact* estimation was chosen for consistency with earlier literature using both U.S. and international data (Goyenko, Holden, Trzcinka (2009), Hasbrouck (2009), Fong, Holden, and Trzcinka (2014)). However, a longer interval might be useful if a stock is particularly illiquid. We therefore also estimate *Pimpact* over 30-minute horizons. Internet Appendix Table IA.V reports results from repeating the analysis for quoted spreads and 30-minute price impacts. The results are very similar to those in Table II.

C. Placebo Tests

The identifying assumption in the main analysis is that there is a sharp discontinuity in the ability of traders to borrow at the impact cost value of 1%, which defines margin eligibility. One potential alternative interpretation of the main results (in Table II) is that the measured impact costs predict future liquidity instead of reflecting important variation in trader leverage and that the regressions capture this relationship. To ensure that our results are not driven by variation in impact costs, we repeat the analysis around a false eligibility cutoff. Because of the importance of this test to the overall interpretation, we examine two false cutoffs, one above and the other below the true cutoff of 1%. In the first test, *Placebo Group 1* stocks have impact costs that are less than or equal to one bandwidth below the true cutoff. For the CCT bandwidth of 0.23%, as in our *Espread* regressions, this implies a false cutoff of 0.77%. *Placebo Group 2* stocks have impact costs that are greater than this value. For the *Espread* regression analysis, the local discontinuity sample consists of *Placebo Group 1* stocks with impact costs between 0.54% and 0.77% and the *Placebo Group 2* stocks with impact costs between 0.77% and 1.00%. In the second placebo test, we move the cutoff to the right of 1%. Using the *Espread* regressions as an example, *Placebo Group 1* stocks have impact costs that are between 1.00% and 1.23%, and the *Placebo Group 2* stocks have impact costs that are between 1.23% and 1.46%.[22] We then estimate regressions analogous to those in Table II.

Results from the placebo tests are in Table VI. Unlike the results in Table II, we do not observe any significant differences in liquidity between *Placebo Group 1* and *Placebo Group 2* stocks (that is, the coefficient on the *Placebo Group 1* dummy is insignificant in all regressions). This supports our identifying assumption that the variation in liquidity observed near the true eligibility cutoffs (defined at impact cost equal to 1%) stems from discontinuous variation in traders' ability to borrow.

D. Alternative Interpretations

D.1. Group 1 Status or Margin Trading Activity?

Does Group 1 membership capture something other than the ability of traders to use leverage via margin trading? If margin trading activity is driving the results, then we would expect to observe stronger effects in markets with more margin trading activity. Unlike U.S. equity markets, we are able to observe stock-level daily margin positions for NSE stocks. We exploit this unique feature of our data to help shed light on whether the results are driven by margin trading eligibility or by traders' actual use of leverage (i.e., margin trading activity).

We test whether the effects that we are observing are stronger when aggregate margin trading activity is higher.[23] To do so, we first calculate daily changes in outstanding margin positions for each stock. The absolute value of these changes, averaged over all Group 1 stocks during month t, is our proxy for margin trading activity. We introduce the dummy variable *Intense margin*

[22] The CCT bandwidth for the *Pimpact* variable is 0.22%. We examine false cutoffs one bandwidth below and above the true one (0.78% and 1.22%, respectively).

[23] We thank an anonymous referee for encouraging this line of analysis.

Table VI
Are Results Driven by Variation in Measured Impact Cost? Placebo Tests

This table presents results of placebo tests, in which we repeat the analyses of the impact of margin trading eligibility on market liquidity from Table II. Instead of measuring eligibility at the impact cost cutoff of 1.0%, we replicate the analysis around a placebo cutoff set at one bandwidth below and above the actual cutoff. The "local sample" used in the analysis are those stocks that lie close to the placebo cutoff using the same bandwidth sizes as in Table II (0.23% for *Espread* and 0.22% for *Pimpact*). The explanatory variables are the *Placebo Group 1* dummy and the same vector of control variables defined in Table II. Month-year fixed effects are estimated but not reported in the table. All standard errors are clustered by ISIN (stock identifier). t-statistics are in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

	Placebo Cutoff Below		*Placebo Cutoff Above*	
Variable	(1) *Espread*	(2) *Pimpact*	(3) *Espread*	(4) *Pimpact*
Placebo Group 1	0.002	0.004	−0.011	−0.012
	(0.006)	(0.008)	(0.007)	(0.014)
Lag *Std_dret*	−0.569***	2.799***	−0.013	6.500***
	(0.204)	(0.439)	(0.377)	(0.942)
Lag *Mret*	−0.035*	−0.114***	−0.047*	−0.121**
	(0.018)	(0.024)	(0.026)	(0.054)
Lag *Logvolume*	−0.006	−0.043***	−0.024	−0.088***
	(0.006)	(0.010)	(0.016)	(0.021)
Lag *Logmcap*	0.004	−0.062***	0.012**	−0.068***
	(0.003)	(0.006)	(0.005)	(0.012)
Lag *Espread*	0.637***		0.573***	
	(0.049)		(0.061)	
Lag *Pimpact*		0.346***		0.329***
		(0.023)		(0.051)
Observations	10,413	9,751	5,431	5,240
R^2	0.846	0.512	0.833	0.480
Month-Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

trade, which is set equal to one if the market has experienced above-median margin trading during month t. The results are in Table VII and show that the main results are driven primarily by those times when aggregate margin trading activity is more intense. This suggests that it is margin trading activity (that is, the use of leverage) that drives our results.[24]

[24] An alternative way to address the question is to examine the impact of intense margin trading at the stock level. A potential concern with this approach is that there might be more margin trading in more liquid stocks (i.e., an endogeneity concern). To examine the impact of variation in margin trading at the stock level while addressing endogeneity concerns, we also conduct stock-level analysis in which we first instrument for daily stock-level margin trading via a first-stage panel regression of a stock's margin trading activity (absolute values of daily changes in margin positions) on one-day lagged stock volatility, turnover, market capitalization, liquidity (measured by effective spreads), and day fixed effects. We use the monthly average of the residuals from this

Table VII

Margin Trading Intensity and Liquidity

This table presents results of the analysis of the relationship between margin trading intensity and market liquidity. The dependent variables are the average effective spread (*Espread*) and the five-minute price impact of trading (*Pimpact*) during month t, where eligibility is effective as of the beginning of month t. The local samples and specifications are identical to columns (2) and (4) of Table II except that we replace the month-year fixed effects with *Intense margin trade*, a dummy variable equal to one if month t aggregate margin trading (defined as the average of the absolute value of changes in margin positions of all Group 1 stocks) is above the sample median. All standard errors are clustered by ISIN (stock identifier). t-statistics are in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Variable	(1) *Espread*	(2) *Pimpact*
Group 1	−0.004	−0.017*
	(0.007)	(0.010)
Intense margin trade	−0.053***	−0.059***
	(0.006)	(0.011)
Lag *Std_dret*	−0.344	6.230***
	(0.536)	(0.823)
Lag *Mret*	−0.089***	−0.257***
	(0.022)	(0.026)
Lag *Logvolume*	−0.016*	−0.067***
	(0.009)	(0.012)
Lag *Logmcap*	−0.007	−0.052***
	(0.005)	(0.005)
Lag *Espread*	0.777***	
	(0.060)	
Lag *Pimpact*		0.487***
		(0.056)
Observations	7,512	7,188
R^2	0.589	0.380
Month-Year FE	No	No
Controls	Yes	Yes

D.2. Potential Cannibalization Effects

In interpreting the finding that Group 1 stocks near the cutoff have higher liquidity than otherwise similar Group 2 stocks (that is, that margin trading is, on average, beneficial), one additional question that arises is whether margin trading simply causes a migration of trading from Group 2 stocks to otherwise similar Group 1 stocks, in which case the liquidity increases that we observe for Group 1 stocks near the cutoff come at the expense of similar Group 2 stocks.

regression as our measure of stock-level margin trading. We set *Intense_margin_trade* to one if the stock experiences above median (relative to all local Group 1 stocks) margin trading during month t. The results are in Internet Appendix Table IA.VI. Consistent with Table VII, we find that the liquidity improvements are greater for high-margin-trading-intensity stocks.

If this "cannibalization" effect is driving our results, it should be greatest for those Group 2 stocks that are most similar to Group 1 stocks (that is, those that are closest to the cutoff). This would imply that, for Group 2 stocks just to the right of the cutoff, we would observe lower liquidity compared to other Group 2 stocks with higher impact costs. From Figure 2, Panels A and B, where we plot liquidity as a function of impact cost, we see that this alternative interpretation is unlikely.

E. Leverage during Market Downturns

Much of the attention in the literature and popular press surrounding how leverage impacts markets has been motivated by the drying up of liquidity that we observe during crises. Brunnermeier and Pedersen (2009) argue that the deleveraging that occurs during market downturns causes downward price spirals and exacerbates reductions in liquidity. Although a number of studies in the literature aim to document this effect, they have faced challenges due to identification problems because important variation in leverage generally occurs during downturns, precisely when a number of other market-wide changes are also affecting stock market liquidity. Our RDD using stock-level variation in margin eligibility provides a unique opportunity to make causal statements about liquidity changes during market downturns.

To understand the role of stock market downturns, we remove the month fixed effects from our baseline specification and add the dummy variable *Severedownturn*, which equals one if market returns during month t are lower than 10^{th} percentile returns in the market over our sample period, as well as the interaction term *Group 1* × *Severedownturn* to capture the differential impact of Group 1 status on liquidity during crises. Table VIII reports the results. When we analyze severe downturns separately from other periods, we see significant sign-flipping patterns that are consistent with a harmful effect of leverage during periods of market turmoil.

Consistent with the literature (for example, Hameed, Kang, and Viswanathan (2010)), we see that all stocks experience liquidity declines during severe market downturns. More importantly, the liquidity declines are amplified for stocks that are eligible for margin trading, as would be predicted by Brunnermeier and Pedersen (2009). For both the *Espread* and *Pimpact* measures, while the main effect of Group 1 status remains negative, we find positive and significant coefficients on the *Group 1* × *Severedownturn* interaction terms. The coefficients on the interactions are more than double the average effect of Group 1 status in periods outside of severe market downturns. The sign flip captured in Table VIII also implies that the average effects that we report in Table II (where we compare Group 1 stocks to all Group 2 stocks in the local sample) are somewhat attenuated. The estimated coefficients on the Group 1 dummy in Table VIII imply a 5.2% decline in spread and a 7.4% reduction in price impact (relative to the local Group 2 means outside severe market downturns). In Table II, we document a 3.5% and 4.7% decline (relative to the local Group 2 means) in spread and price impact, respectively. Taken together, the

Table VIII

Market Conditions and the Effect of Leverage Constraints on Liquidity

This table presents results of the analysis of the relationship between equity market conditions and the impact of margin trading eligibility on market liquidity. The dependent variables are the average effective spread (*Espread*) and the five-minute price impact of trading (*Pimpact*) during month t, where eligibility is effective as of the beginning of month t. The local sample and basic regression specifications are the same as in columns (2) and (4) of Table II except that we replace month-year fixed effects with *Severedownturn*, a dummy variable equal to one if market returns during month t are in the lowest decile in our sample. We also interact *Severedownturn* with *Group 1*. All standard errors are clustered by ISIN (stock identifier). t-statistics are in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Variable	(1) *Espread*	(2) *Pimpact*
Group 1	-0.028^{***}	-0.046^{***}
	(0.007)	(0.009)
Group 1 × *Severedownturn*	0.073^{***}	0.101^{***}
	(0.011)	(0.020)
Severedownturn	0.238^{***}	0.247^{***}
	(0.011)	(0.022)
Observations	7,512	7,188
R^2	0.645	0.431
Month-Year FE	No	No
Controls	Yes	Yes

findings in Table VIII show both the costs and benefits of margin trading (or traders' leverage). While the average effect of trader leverage is beneficial, it has a harmful effect on liquidity when market returns become very negative.[25]

F. Potential Mechanisms

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

[25] The harmful effects of leverage during downturns may stem from changes in liquidity comovement, as predicted by Brunnermeier and Pedersen (2009). If levered traders are forced to delever during market downturns, Group 1 stocks might be more vulnerable to market-wide negative shocks. This is because, while margin investors can trade any stock to cover a margin call, the stocks that they have borrowed to purchase are more likely than a random stock to be in their portfolios and are therefore more likely to be sold in the event of forced deleveraging. Consistent with this idea, Kahraman and Tookes (2016) report that trader leverage causes significant increases in liquidity comovement during severe downturns.

F.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. To deepen our understanding of the main results, it is useful to document some basic facts about the margin trading patterns that we observe in the data.

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

$$Ch\_margin_{it} = \alpha + \beta * Dret_{it} + \gamma_i + \nu_t + \varepsilon_{it}, \tag{2}$$

where $Dret_t$ is the contemporaneous stock return and γ_i and ν_t are firm and day fixed effects, respectively.[26] Standard errors are also clustered by firm and day. Table IX reports the results. Column (1) reports the results for the baseline specification, and column (2) includes the control variables. The results in both columns show that margin traders engage in contrarian strategies. For instance, the estimated coefficient on the one-day lagged stock returns of −0.367 in column (2) implies that, following a 10% decrease in stock prices, margin positions increase by 3.67%.[27] Next, we estimate a piecewise linear regression in which we allow the relationship between margin trading activity and returns to vary at different regions of lagged stock returns. As described in Section I, margin traders can borrow up to 50% of their initial positions in a stock and must maintain a maintenance margin of at least 40%. This means that margin traders must post additional collateral or liquidate some of their shares once the value of the margin loan exceeds 60% of the value of the stock held by the trader. Given this institutional friction in the ability to maintain margin positions over time, one might expect margin traders who already have leveraged

[26] We use contemporaneous returns based on the idea that liquidity provision occurs if margin traders increase their positions whenever a price decline occurs (similar intuition can be found in, for example, Anand et al. (2013)). Given the daily frequency of the data, one might be concerned that the contemporaneous returns capture intraday price changes that may have occurred after the margin positions were opened/closed. To account for this, we repeated the analysis using one-day lagged stock returns (Internet Appendix Table IA.VII). All results are qualitatively similar.

[27] It is useful to note that these magnitudes are in line with previous findings on short-selling activity, which has been shown to improve stock market liquidity. For instance, Diether, Lee, and Werner (2008) find that, following a 10% increase in stock prices, short-selling activity in NYSE (NASDAQ) stocks increases by 1.6% to 3.7% (1.3% to 2.2%) (table 3).

Table IX

Margin Traders' Short-Horizon Trading Patterns

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

Variable	*Ch_margin*	*Ch_margin*	*Ch_margin*	*Ch_margin*
Dret	-0.3790^{***}	-0.3670^{***}		-0.2716^{***}
	(0.0179)	(0.0196)		(0.0166)
Very Neg			−0.0017	
			(0.0190)	
Mild Neg			-0.3798^{***}	
			(0.0223)	
Positive			-0.2934^{***}	
			(0.0237)	
Lag *Dret* × *Severedownturn*				0.3497^{***}
				(0.0522)
Severedownturn				-0.0421^{***}
				(0.0029)
Lag *Ch_margin*		-0.0708^{***}	-0.0703^{***}	-0.0696^{***}
		(0.0021)	(0.0020)	(0.0021)
Lag *Turnover*		0.1230^{***}	0.1258^{***}	0.1499^{***}
		(0.0336)	(0.0317)	(0.0338)
Lag *Mcap*		−0.0002	0.0001	0.0004
		(0.0003)	(0.0003)	(0.0003)
Lag *Volatility*		0.0523^{***}	0.0533^{***}	-0.0306^{***}
		(0.0096)	(0.0095)	(0.0086)
Lag *Dret*		-0.2518^{***}	-0.2565^{***}	-0.2556^{***}
		(0.0124)	(0.0124)	(0.0125)
Observations	898,435	739,250	739,250	739,250
R^2	0.0034	0.0182	0.0182	0.0170
Day FE	Yes	Yes	Yes	No

positions in a given stock to be unable to provide additional liquidity during extreme downturns. We define three stock return regions: *Positive*, *Mild_Neg*, and *Very_Neg*, where *Positive* returns are one-day lagged stock returns that are greater than or equal to 0%, *Mild_Neg* returns are stock returns between 0% and −5%, and *Very_Neg* returns are defined as stock returns that are less than −5%.

Table IX, column 3, reports the results. We observe that margin trading positions increase following decreases in stock prices unless past returns are extremely negative. We find the largest sensitivity is in the region of mildly negative and positive returns (estimates −0.293 for *Positive* and −0.380 for *Mild_Neg*, versus −0.002 for *Very_Neg*). This suggests that margin traders not only provide liquidity by establishing initial margin positions following mildly negative returns, but also behave as liquidity providers by unwinding those positions after periods of positive stock returns. The small magnitude and statistical insignificance of the estimated coefficient on the *Very_Neg* dummy variable shows that this contrarian behavior goes away following extremely negative returns. To further investigate this pattern, in the last columns of Table IX we remove the day fixed effects to study the aggregate patterns. In particular, we examine the relationship between margin trading and market (rather than individual stock) returns. Different from stock-level contrarian behavior, here we observe significant decreases in margin positions following large market declines. Although they normally provide liquidity to the market, margin traders become liquidity seekers following large negative market shocks. This result is consistent with Adrian and Shin (2010), who find that intermediaries' use of leverage is procyclical. Taken together, these findings are in line with the results in Table VIII, which show that traders' leverage becomes costly in times of severe market downturns.

In addition to helping us understand the main results of this paper, the findings in Table IX are related to the growing literature investigating whether hedge funds, which tend to use leverage, provide liquidity to stock markets (for example, Aragon (2007), Ben-David, Franzoni, and Moussawi (2012), Hombert and Thesmar (2014), Kruttli, Patton, and Ramadorai (2014), Franzoni and Plazzi (2015)). Different from other studies, we observe margin trading activity of all traders (as opposed to a particular type, such as a hedge fund or a specialist) and, more importantly, we observe directly the positions that are financed by intermediary-supplied capital.[28] These data are not typically available in other markets and allow us to both uncover the basic patterns in

[28] Financial institutions such as hedge funds obtain capital from various sources, including investor flows and leverage. The currently available data sets do not provide enough information on the financing of their positions. Previous research shows that hedge funds heavily liquidate their shares in times of severe market downturns. However, given the data limitations, it has been difficult to analyze the extent to which these effects are driven by investor redemptions, trader leverage, or other frictions. A recent study by Franzoni and Plazzi (2015) shows that hedge funds that use high leverage and low restrictions to redemptions are more vulnerable to a decline in aggregate funding conditions. While our paper does not focus on financial institutions (as we are exploiting stock-level variation in margin eligibility), consistent with Franzoni and Plazzi (2015),

margin trading activity and assess directly the role of levered positions on the amplification of negative market shocks. To the best of our knowledge, our paper is the first to isolate the impact of leverage from other mechanisms that are at work during times of market stress (such as increased informational asymmetries), thanks to the unique institutional features of Indian capital markets that enable an RDD.

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

Although their contrarian trading strategies are consistent with liquidity provision, it is also possible that margin traders are more informed. To examine this possibility, we investigate whether Group 1 stocks experience changes in the structure of informed trading relative to otherwise similar Group 2 stocks. We use the Thomson Reuters tick data to classify trades as buys or sells based on transaction prices relative to the prevailing quote midpoints (following Lee and Ready (1991)). We then estimate the Probability of Informed Trading (PIN; based on Easley et al. (1996)) using total daily buys and sells and estimate the regressions from Table II, after replacing the dependent variables with PIN. Table X reports the results. We do not observe a significant shift in informed trading for Group 1 stocks. Thus, the evidence is inconsistent with a marked change in informed trading, but consistent with an influx of traders providing liquidity via short-horizon contrarian strategies.

F.2. Margin Trading and Return Reversals

If margin traders behave as contrarian liquidity providers then an increase in their ability to engage in short-term contrarian strategies should reduce the re-

our paper highlights that the leverage-based trading mechanism is an important driver of the amplification of negative market shocks, as predicted by recent theoretical papers.

Table X

Margin Trading and the Probability of Informed Trading (PIN)

This table presents results of analysis of the impact of margin trading eligibility on the probability of informed trading in NSE stocks. The sample includes all stocks in Groups 1 and 2 with impact costs between 0.78% and 1.22% (the CCT bandwidth). For each stock and month, we estimate the PIN following Easley, O'Hara, and Paperman (1996). The dependent variable is the month t PIN. The explanatory variables are *Group 1*, a dummy variable equal to one if the control stock is eligible for margin trading during month t, a vector of control variables, and month-year dummies. The control variables are defined in Table II and include one-month lagged: standard deviation of stock returns (*Std_ret*), stock returns (*Mret*), dollar volume (*Logvolume*), equity market capitalization (*Logmcap*), and the lagged liquidity variables, *Espread* and *Pimpact*. Month-year fixed effects are estimated but not reported in the table. All standard errors are clustered by ISIN (stock identifier). t-statistics are in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Variable	PIN
Group 1	−0.002
	(0.003)
Lag *Std_dret*	−0.996***
	(0.207)
Lag *Mret*	−0.020
	(0.016)
Lag *Logvolume*	−0.000***
	(0.000)
Lag *Logmcap*	0.009***
	(0.002)
Lag *Espread*	0.054***
	(0.006)
Lag *Pimpact*	−0.020***
	(0.005)
Observations	6,903
R^2	0.072
Month-Year FE	Yes
Controls	Yes

turns to these strategies and improve the pricing efficiency of Group 1 stocks.[29] Following Nagel (2012), Lehman (1990), and Lo and MacKinlay (1990), we use the returns of short-term reversal strategies as proxies for the returns to liquidity provision. We then estimate the impact of the ability to trade on margin on the returns to these reversal strategies. To do so, we construct several portfolios of stocks. Each portfolio is defined within the universe of the local Group 1 or Group 2 stocks. Following Nagel (2012), we define *Reversals 1 day* as the average returns to a reversal strategy that weights stocks in proportion to the negative of market-adjusted returns on days $t-1$. As some stocks may have reversal horizons that go beyond one day, we also calculate returns to reversal strategies that are implemented over relatively longer periods: *Reversals 3 day* is the average of returns from three reversal strategies that weight stocks

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

according to the negative of market-adjusted returns on days $t-1$, $t-2$, and $t-3$. Similarly, *Reversals 5 day* is the average of five reversal strategies that weight stocks based on returns on days $t-1$, $t-2$, $t-3$, $t-4$, and $t-5$. We regress the returns of each of these portfolios on an intercept and the Group 1 dummy variable, and we cluster the standard errors by month.

Table XI, Panel A, reports the results. Returns to reversal strategies are reported in percentages. We find positive returns to reversal strategies for both Group 1 and Group 2 stocks. For Group 2 stocks, the portfolio produces returns of 29 basis points over the one-day horizon. As some stocks experience reversals faster than others, we observe that returns gradually decline when the strategy is implemented at longer horizons. For Group 2 stocks, the portfolio produces returns of 16 (11.5) basis points at the three-day (five-day) horizon. The most important finding from our analysis is that the magnitudes of the reversal returns are smaller for Group 1 stocks. For instance, the returns to reversal strategies at the one-day horizon decline by about 8 basis points once stocks are eligible for margin trading. This effect can also be seen at longer horizons.

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

G. Interpretation

We have documented a causal relationship between traders' ability to borrow and a stock's liquidity. Unlike the earlier literature, which focuses on empirical settings in which it is very difficult to rule out the possibility that latent variables are driving both leverage and liquidity, the Indian equity market setting allows us to establish causality. We find that traders' ability to trade on margin has important effects on liquidity and that these effects depend strongly on market conditions. Although trader leverage is useful in normal times, it becomes particularly harmful during large market downturns. We analyze the mechanisms driving these results and find that margin traders normally provide liquidity by following short-run contrarian strategies, but following large negative shocks, they delever their positions and consume liquidity.

Before concluding, it is worthwhile to discuss the extent to which our results can be generalized outside of the specific institutional context that we study. While it is difficult to completely eliminate concerns about external validity, we believe that these concerns should not be central to the interpretation of this

Table XI

Return Reversals

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

Panel A: Portfolio Returns

	Reversals 1 day	*Reversals 3 day*	*Reversals 5 day*
Intercept	0.2920***	0.1610***	0.1152***
	(0.0505)	(0.0479)	(0.0382)
Group 1	−0.0763**	−0.0399*	−0.0294*
	(0.0323)	(0.0234)	(0.0172)
Observations	4,229	4,229	4,229
R^2	0.0004	0.0002	0.0002

Panel B: Stock-Level Covariance

Variable	*Autocov*
Group 1	−0.013**
	(0.005)
Lag *Std_dret*	2.983***
	(0.455)
Lag *Mret*	−0.083***
	(0.028)
Lag *Volume*	0.016***
	(0.004)
Lag *Logmcap*	−0.009***
	(0.003)
Lag *Autocov*	−0.005
	(0.016)
Observations	7,512
R^2	0.168
Month-Year FE	Yes
Controls	Yes

paper. Most importantly, although recent models of funding constraints have been written with developed markets in mind, our finding that margin trading is harmful during severe downturns is consistent with the same underlying mechanisms that are relevant to developed markets. In particular, large adverse price movements increase traders' leverage and tighten their constraints, which leads to deleveraging and liquidity declines. This mechanism is at work in most markets (if not all) and should help mitigate concerns about external validity. Indeed, when we compare market-level data on margin activity in the United States (stock-level margin trading data are not available in the United States) to market-level margin activity in India, we find that the aggregate patterns in margin trading that we observe in India are very similar to those in the United States.[30] These similarities are not surprising, given our findings that margin traders are liquidity providers who become liquidity seekers during periods of extreme negative market returns.

While similar mechanisms for leverage-based trading across markets alleviates external validity concerns about this paper's main findings (a causal impact of margin trading on liquidity), the extent to which the reported magnitudes translate to other markets is less obvious. Indian stocks are smaller and less liquid than a typical stock in a more developed market such as the United States. The average Group 1 stock's liquidity is comparable to that of a small or midcap U.S. stock, and the local sample, crucial for identification, consists of the relatively smaller stocks within Group 1. To put the magnitudes of estimated coefficients in perspective and to ease comparisons with related papers, we discuss the economic effects of margin eligibility in terms of percentage changes with respect to the mean (or median) liquidity levels of the control stocks. For instance, in the discussion of Table III, we report that the impact of eligibility on price impact is 5.4 basis points, which implies a decline of 7.8% relative to the mean price impact of the local control stocks. It is reassuring to note that the economic effects that we report are comparable to results from recent studies that focus on the U.S. equities market—for instance, to Aragon and Strahan (2012), who study the role of hedge funds in providing liquidity, and to Comerton-Forde et al. (2010), who analyze this question in the context of NYSE specialist firms.

Although Indian stocks are less liquid than U.S. equities, they are more liquid than, for instance, many U.S. corporate bonds (for example, Goldstein, Hotchkiss, and Sirri (2007)). The fact that trader leverage is also relevant to

[30] NYSE disseminates aggregate market-level data on outstanding margin positions monthly. While individual stock-level data are not available for NYSE stocks, we can compare the relationship between longer-horizon (monthly) market returns and aggregate monthly changes in margin positions outstanding in the two countries. In the United States, we find that this correlation is 0.58 and is statistically significant. In India, the correlation is also positive and significant, at 0.38. Thus, aggregate margin trading activity in India follows broad patterns that are similar to what we observe in the United States. Although the focus of this paper is different in that we exploit stock-level (rather than market-level) variation in margin constraints over short horizons, the monthly correlation analysis is instructive for purposes of cross-market comparisons.

this important but less liquid market in developed economies should also help alleviate external validity concerns.

A separate external validity concern, one that is relevant to any RDD, is that the test design estimates "local" effects using observations that are close to the cutoff. The importance of this concern depends on the variation in the forcing variable (the variable that triggers the treatment effect)—if there is substantial variation in the forcing variable, then the local sample can be close to a representative sample. There are 1,842 unique stocks in Group 1 and Group 2 during our sample period, of which 1,110 of them are in the local sample (defined as observations with impact costs between 0.78 and 1.22) at some point. This indicates that our results are relevant to a large group of stocks.

IV. Conclusions

We use the Indian equity market as a laboratory for testing the hypothesis that there is a causal relationship between traders' ability to borrow 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. Using an RDD in which we focus the analysis on stocks close to the eligibility cutoffs, we exploit variation in the data generated by eligibility to identify the potential effects of trader leverage on stock market liquidity.

Our analysis delivers three main findings. First, we find evidence consistent with a causal effect of trader leverage on stock market liquidity. Second, we find that this effect reverses during crises. These first two findings highlight both the costs and the benefits of leverage: On average, margin trading is beneficial; however, it amplifies negative shocks during times of market stress. These causal statements about the impact of borrowing on liquidity should be of particular interest to policy makers thinking about imposing or relaxing restrictions on trader leverage. In the aftermath of the recent financial crisis, there is increased interest in understanding the role of leverage in driving systematic crises and in developing policies to avoid its potential harmful effects. For instance, Geanakoplos and Pedersen (2011) highlight the importance of data collection and of monitoring of leverage. In addition, a number of developing markets are considering revisions to margin trading policies in an attempt to better manage large market swings (e.g., the 2015 margin trading policy changes in China). Our causal statements about the benefits and costs of trader borrowing on stock market liquidity can contribute to future policy discussions. Specifically, policy makers could use our findings to improve decision-making by considering the relative weights that they place on normal times versus downturns.

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

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix