Effects of Credit Expansions on Stock Market Booms and Busts *

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Abstract

There is causal evidence that mortgage-credit expansions increase house prices. Does an expansion of margin lending increase stock prices? Because unconstrained arbitrageurs are more important for pricing stocks than homes, the impact is not obvious. Tests are limited because sizable shocks to margin lending are rare. We examine a major Chinese margin-lending expansion between 2010-2015. Institutional-holding, regression-discontinuity, and event-study evidence—exploiting the roll-out of margin lending across stocks—shows that arbitrageurs anticipated and bought in advance of a significant causal effect of credit. We develop a model to rationalize our findings. Our estimates suggest that margin debt contributes to stock-market fluctuations.

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1 Introduction

There is causal evidence that expansions in mortgage credit increase house prices.[1] Does an expansion of margin credit for the purchase of equities increase stock prices? The answer is not immediately obvious. Deep-pocketed investors—e.g. hedge funds or other relatively unconstrained actors—play a more pivotal role in price setting for stocks than for real estate (Stein, 1995). Because the impacts of margin credit provided to retail traders and other less liquid investors might be offset by the trades of such agents, it is difficult to extrapolate evidence from housing into equity markets.

Moreover, tests of the effects of credit expansions on stock prices are limited because sharp and sizeable shocks to margin lending are rare. Recent margin deregulations have typically yielded small changes in overall credit. For instance, well-identified studies on margin restrictions (e.g. Foucault *et al.* , 2011; Kahraman & Tookes, 2017) analyze relatively small changes in margin debt, and focus on stock price volatility but not the level of stock prices.[2] As a result, despite theory,[3] historical descriptions (Aliber *et al.* , 2015; Minsky & Kaufman, 2008), and cross-country evidence (Kaminsky & Reinhart, 1999; Borio & Lowe, 2002; Schularick & Taylor, 2012) emphasizing the role of credit in stock market booms and busts, there is little causal evidence.

We address this challenge by examining a major Chinese credit liberalization—the deregulation of margin lending—that occurred between 2010 and 2015. In contrast to other historical changes in margin regulation, the Chinese government actively encouraged banks to lend for stock purchases, in part by establishing a state-owned corporation to provide funding to brokerages. As a consequence, the liberalization fed a wave of margin debt, which rose from virtually nothing to a peak of roughly 4.5% of floating market capitalization (and nearly 10% for many individual

[1]See, e.g. Favara & Imbs (2015); Di Maggio & Kermani (2017); Adelino *et al.* (2023) on the causal effect of mortgage credit, and Dell'Ariccia & Marquez (2006); Mian & Sufi (2009); Keys *et al.* (2012); Adelino *et al.* (2016); Albanesi *et al.* (2022); Kaplan *et al.* (2020); Chodorow-Reich *et al.* (2024), among many others, on the role of mortgage lending in the crisis more generally.

[2]There is a related literature on changes in Fed margin requirements. Excessive margin lending was widely blamed for the bubble that preceded the 1929 crash (Galbraith, 1961), and between 1934 and 1974 margin requirements ranged from 45% to 100%. Since 1974 they have been 50%. As noted in the review by Fortune (2001), a large fraction of these studies find mixed results (e.g. Eckardt & Rogoff, 1976; Hsieh & Miller, 1990; Hardouvelis & Peristiani, 1992; Jylhä, 2018).

[3]A non-exhaustive list includes political economy considerations (Herrera *et al.* (2020)); agency and risk-shifting (Allen *et al.* , 2022; Allen & Gale, 2000); complacent or neglectful creditors underestimating downside or tail risk (Minsky, 1977; Gennaioli *et al.* , 2012); contracting and leverage constraints (Geanakoplos, 2010; Simsek, 2013); and intermediary frictions or balance sheets (Bernanke & Gertler, 1989; Kiyotaki & Moore, 1997; Adrian & Shin, 2010; He & Krishnamurthy, 2013).

stocks).[4] A boom in stock prices followed: the Shanghai Composite Index rose from about 2000 in mid-2014 to a high of 5166 in June 2015.

We exploit the unique implementation of the deregulation to estimate the impacts of credit on stock prices, and to highlight the associated dynamics generated by deep-pocketed investors. Beginning in early 2010, Chinese regulators began to gradually introduce margin debt for different sets of stocks—which we call vintages—over the course of several years. For each of the last several vintages, qualification was determined on the basis of a publicly available formula, which incorporated real-time data on market capitalization and trading volume. These factors allow us to combine an event study strategy based on the staggered introduction of margin debt with a regression discontinuity approach focusing on the formula-based criteria for qualification. Furthermore, detailed data on the trades of speculative institutional investors in the Chinese market allow us to account for their role in the episode.

We find that the introduction of margin lending had a large positive impact on stock prices, and that this impact was largely anticipated and priced in by the market. This suggests that deep-pocketed investors behaved more like front-runners than contrarians in the Chinese stock market. Using a standard event study, we find strong evidence that prices rose gradually but consistently for soon-to-be marginable stocks in the months leading up to the deregulation. There is minimal evidence of a sharp increase in prices, on average, after margin lending was introduced. As the criteria used to determine inclusion was public, the set of to-be marginable stocks was at least partially predictable in advance (although the reliance on real-time data meant that meaningful uncertainty existed until the formal announcement). The return patterns we observe are therefore consistent with a large causal effect of margin lending, albeit one that was foreseen by arbitrageurs.

Indeed, our regression discontinuity approach, which is plausibly untainted by anticipation, provides sharp evidence that the deregulation increased stock prices. Focusing on the formula that determined eligibility, we compare stocks that barely qualified for margin lending to those that just failed to qualify. High frequency variation in the inputs to this formula generated ex-ante uncertainty about the specific set of eligible stocks in a neighborhood around the qualifying threshold for each vintage. Because slight movements in market capitalization or turnover might

[4] While the deregulation technically also allowed shorting, there was negligible short interest during this period because the securities lending market was not well developed. See Appendix Figure A.I for more detail.

cause one stock to qualify or another to be disqualified, investors could not perfectly predict which stocks would be eligible. We find that stocks slightly above the threshold saw a sharp influx of margin debt in the months following the liberalization. This, in turn, corresponded to a non-trivial increase in asset prices. Our estimates suggest that 60-day cumulative returns were roughly 25% higher for eligible stocks compared to stocks that just failed to quality.

Institutional holdings data further supports the evidence that large causal effects were present but priced in by relatively unconstrained investors. We show that institutional buyers anticipated and profited from the deregulation. We find that Chinese mutual funds and other large investors gradually increased their holdings in soon-to-be-marginable stocks as the deregulation approached, in line with the progressive build-up of stock prices. After margin debt was introduced, they began to reduce their positions, likely selling out to new margin buyers. Portfolio-level data shows that funds overweighted stocks they could predict were likely to become marginable (based on contemporaneously available information) and then underweighted qualifying stocks once they became marginable. Our tests, implemented using panel regressions with stock, fund, and time fixed effects, show that mutual funds increased the weights of stocks with a high impending likelihood of marginability by roughly 5% as the next vintage drew near. A test of excess risk-adjusted performance (i.e., an alpha test) shows that institutions profited from this strategy. Within a typical fund portfolio, stocks with a high likelihood of inclusion outperformed stocks with a low likelihood by 2.5% to 3.4% over a six-month holding period.

To rationalize our reduced form findings—a large causal effect that was gradually anticipated by the market—we develop a dynamic competitive stock-pricing model. Our model, which is in the vein of Summers (1986) and De Long *et al.* (1990), has deep-pocketed investors receiving signals about the size of a coming credit liberalization and speculating about its impact on household demand for stocks. New credit leads to an increase in valuations, and this is impounded in prices in advance as information becomes available. We then show that a parametric assumption on the structure of information revelation—specifically, that the uncertainty in investors' signals reduces exponentially as the reform approaches—allows us to match the gradual anticipation that appears in the data. An advantage of this structure is that it provides a simple way of summarizing the basic patterns of the reform, the impact on prices and the path of the anticipatory run-up, with two parameters. These parameters can be easily recovered with a non-linear exponential regression, or with linear dynamic panel regressions in the spirit of Anderson & Hsiao (1981), Arellano & Bond (1991), and Malani & Reif (2015). The key identifying assumption, analogous to a relatively standard difference-in-difference, is that the timing of deregulation is orthogonal to vintage-specific demand shocks for stocks.

Our model estimates indicate an impact of the deregulation on prices that is in line with or marginally larger than the estimates from our event study and regression discontinuity analyses. Furthermore, the model allows us to summarize the speed of the anticipatory run-up. We find that the effect of margin lending was priced in gradually, with an effective monthly discount rate of roughly 7%. This suggests that more than 60% of the effect was priced in even six months prior to the event. While the key parameters are identified from the same pre-deregulation return patterns that inform our event study, the model provides a complementary and parsimonious summary of the impact of margin debt and the patterns of pre-introduction front-running. Given the pervasive nature of anticipation in equity markets, similar exercises may serve as a valuable complement to more standard event studies in contexts outside of our episode.

Following the peak in June of 2015, the Chinese market experienced a rapid decline. The Shanghai Composite Index lost roughly 30% of its value within three weeks. While our empirical strategies do not provide sharp quasi-experimental variation in the presence of margin lending through the top of the market and the crash, we perform a simple extrapolation exercise to account for the role of margin debt in the 2015 boom-bust cycle. To do so, we combine our analysis of the impact of margin lending with data on the total quantity of margin debt through 2015. This allows us to impute the stock price increases implied by our causal estimates. Crucially, our data includes both formal brokerage-provided margin (the focus of our earlier analysis), and shadow margin provided through informal channels, which became popular in 2015.

We find that our imputed change in prices represents roughly 20% of the actual run-up in prices, on average, and that there is a strong correlation between margin debt growth and the boom in the cross-section. Furthermore, we find a strong cross-sectional relationship between the level (and growth) of margin debt as of June 2015 and the severity of the crash. Stocks with the most margin experienced larger reversals or price drops during the aggregate downturn of the market. While we are hesitant to attach a causal interpretation to this evidence, it aligns with popular narratives that highlight margin lending as a key feature in the crash. Overall, our findings indicate that major expansions of credit for stock purchases increase equity prices, and that this may play a meaningful role in stock market booms and busts.

2 Background and Data

2.1 The Staggered Deregulation of Margin Lending

Between 2010 and 2015, Chinese regulators gradually began to allow margin lending for specific stocks listed on the Shanghai and Shenzhen Stock Exchanges. The deregulation occurred in two overall phases. In the first phase, which we refer to as the *pilot*, regulators allowed stocks belonging to major market indexes to be purchased on margin. In the second phase, regulators progressively expanded margin lending, selecting stocks on the basis of a published formula that incorporated market capitalization and share turnover. Because our empirical strategies utilize the details of this formula, we focus our analysis on the second phase.

Throughout both phases, retail investors with at least 500,000 RMB of assets in their brokerage account and six months or more of trading experience qualified for margin—provided by their brokerage firms—with an initial margin requirement of 50%. Prior to 2015, institutional investors were not formally allowed to conduct margin trades through brokers.[5] The government actively promoted and encouraged margin lending, in part by founding a state-owned corporation (China Securities Finance Co.) to provide funding to brokerages.[6] As a consequence, interest rates on margin loans from brokerage firms were generally around 8% to 9% annualized, significantly lower than the rates on the informal shadow margin loans that became popular in 2015 (roughly 25%, according to Bian *et al.* , 2023).

The first phase of the deregulation began on February 13th, 2010, when the 90 stocks included in the two major stock indexes—the Shanghai 50 Index (50 stocks) and the Shenzhen Component

[5] According to the rules posted by the stock exchanges in 2011, margin trading was to be provided only to retail investors. In July 2015, the exchanges revised the margin trading rules and for the first time stated that professional institutional investors qualified for margin trading. See the historical documents from the Shanghai Stock Exchange for more details, http://www.sse.com.cn/lawandrules/sselawsrules/repeal/rules/c/c_20230418_5720123.shtml and http://www.sse.com.cn/aboutus/mediacenter/hotandd/c/c_20150912_3988867.shtml.

[6] According to its website, China Security Finance Co. "aims to facilitate the margin transactions of securities companies in market operation methods, improve China's margin transaction system, complete the functions of China's capital market, and promote the stable development of the same." See: http://www.csf.com.cn/publish/english/1071/1076/index.html.

Index (40 stocks)—were opened to margin lending. We refer to this as *Pilot A*. On November 25th, 2011, the Chinese government extended the list of marginable stocks to two broader market indexes. The extended list included 278 stocks: 180 from the Shanghai 180 Index and 98 from the Shenzhen 100 Index. We refer to this extension as *Pilot B*.

The plan for a second phase, the focus of our analysis, was announced in late 2011. Official regulations were released stating that the list of marginable stocks would be extended in a staggered manner in a series of waves, which we call *vintages*.[7] Ultimately, three vintages were introduced. To determine the set of qualifying stocks for each vintage, the regulatory agency published a screening-and-ranking rule. This procedure had three steps: (i) screening out stocks that did not satisfy a set criteria intended to disqualify particularly small, volatile, illiquid, and newly listed stocks—the so-called Article 24 for Shanghai and Rule 3.2 for Shenzhen;[8] (ii) ranking the remaining stocks according to the formula shown in Equation 1 below; and (iii) selecting the top candidates in each exchange (with some discretion).[9]

$$\begin{aligned}\text{Inclusion Index}_i = \theta \times \frac{\text{Average Tradable Market Value of Stock } i}{\text{Average Tradable Market Value of All Stocks in SH/SZ}} \\ + \gamma \times \frac{\text{Average Trading Volume in Yuan of Stock } i}{\text{Average Trading Volume in Yuan of All Stocks in SH/SZ}}.\end{aligned} \tag{1}$$

This ranking rule, effectively a weighted average of a stock's size and trading volume, was conducted separately in the Shanghai and Shenzhen Stock Exchanges. For all three vintages, the Shenzhen exchange set $\theta = 2$ and $\gamma = 1$, following officially published guidelines. The Shanghai exchange set $\theta = \gamma = 1$ for the first two vintages, and later shifted to $\theta = 2$ and $\gamma = 1$ for the third vintage (see Appendix B for details).

[7] See Article 28 of the rule released by the Shanghai Stock Exchange.

[8] The criteria for both exchanges were the same: they required that stocks: (1) had been traded for more than three months; (2) had either more than 100 million tradable shares or a market value of tradable shares over 500 million; (3) had more than 4,000 shareholders; (4) had not experienced any of the following in the previous three months: (a) daily turnover less than 20% of the turnover rate of the market index; (b) the average of the absolute value price changes more than 4% off of the market index; (c) market volatility higher than the market volatility by 500%; (5) had completed the share reform; (6) were not specially treated stocks; and (7) other conditions (the official documentation does not specify what these other conditions refer to). See the rules on stock trading with margin loans published on each stock exchange's website.

[9] Roughly 100 to 150 new stocks were included in each vintage for each exchange, although the precise number varied slightly, often because formerly marginable stocks became non-marginable due to the screening rule and had to be replaced.

Table 1 summarizes the timeline of deregulation and the number of newly marginable stocks in each vintage. The set of stocks included in *Vintage 1* was announced on January 25th, 2013, and margin lending for these stocks was implemented on January 31st, 2013. *Vintage 2* was announced on September 6th, 2013 and implemented on September 16th. *Vintage 3* was announced on September 12th, 2014, and implemented on September 22nd, 2014. By the time *Vintage 3* was introduced, roughly 900 stocks in total could be bought on margin across the two exchanges.

Figure 1 shows the massive expansion of margin debt that followed the deregulation. The blue line displays margin debt provided by brokers as a fraction of total floating market capitalization in our data. Over the course of the liberalization, margin debt rose from nothing to roughly 4.5% of floating market capitalization. The black line shows the level of total floating market capitalization in our sample, which mirrored the influx of margin debt and spiked in mid-2015. Figure 2 plots the rise of margin debt relative to floating market capitalization separately for each of the three vintages we analyze, with announcement dates denoted by vertical lines. Within each vintage, the quantity of margin debt reached 3% to 5% of floating market capitalization within a few months and peaked between 8% and 10%.

2.2 The Role of Short Selling

The stocks that qualified for margin buying were technically also eligible for short selling. However, as Appendix Figure A.I shows, virtually no shorting took place. Aggregate short interest peaked at 0.02% of floating market capitalization in 2013. This was, at least in part, due to the fact that China's securities lending market was not well established. Its development significantly lagged the expansion of margin lending.[10] Given that the aggregate value of shorted shares was several orders of magnitude below the quantity of margin debt, we abstract from the role of shorting in our analysis.

2.3 The Role of Shadow Margin

In late 2014 and the early part of 2015, retail investors began to heavily use an alternative and less regulated form of borrowing, referred to as *shadow margin*. Shadow margin was offered via online

[10] See, e.g., an April 2015 memo from the China Securities Regulatory Commission that notes the underdeveloped state of the securities lending market: http://www.sse.com.cn/services/tradingservice/margin/rules/c/c_20150912_3987318.shtml.

platforms by FinTech firms that provided margin to retail clients and executed trades on their behalf through standard brokerage accounts. This informal system allowed individual traders to bypass the requirements for opening a margin account and to purchase stocks on margin that were not part of the formal deregulation. The borrowing cost for shadow margin was much higher than the cost for formal margin provided by brokers. Bian *et al.* (2023) report that the annual interest rate on shadow margin was roughly 25%, more than 16 percentage points above the rate for formal margin lending through brokerages.[11]

The formal deregulation we study largely preceded the use or widespread availability of shadow margin debt. While there was a sizable amount of shadow margin outstanding at the time of the 2015 crash, a negligible quantity was borrowed in prior years. To demonstrate this, we utilize proprietary stock-level shadow margin data from one of the major providers of shadow finance in the Chinese system, representing approximately 5% of the market. This echoes Bian *et al.* (2023), who also use proprietary data from large shadow lenders. In Appendix Figure A.II, we plot the time series of the aggregate quantity of formal margin debt alongside an estimate of the aggregate quantity of shadow margin debt, generated by scaling the observed quantity from our provider to match the market as a whole.

We do not observe any shadow margin debt prior to the beginning of 2014, at which point two of the three vintages we study had already been introduced. Furthermore, we estimate that the level of shadow margin in early 2014 was vanishingly small relative to the quantity of formal margin debt (roughly 90 million yuan versus more than 300 billion, respectively, as of January 2014), and remained small through the first half of 2014. When the third and final vintage we study was implemented, in September 2014, the level of shadow margin was still less than one-fifth the level of formal margin debt. It was only towards the middle of 2015 that shadow margin reached even half the quantity of formal margin.[12] While our estimates are based off a single provider and may not perfectly reflect the industry as a whole, the patterns we find mirror the literature. For example, Lu & Lu (2017) report that the industry was small prior to 2014 and went through rapid

[11] Bian *et al.* (2023) also provides an excellent and more thorough introduction to the shadow margin systems and the distinctions between shadow and formal margin debt.

[12] Note that our estimate of the total quantity of shadow margin at the 2015 peak is similar to the estimate from Bian *et al.* (2023), who report a total of 1.0-1.4 trillion yuan, and the estimate from a China Securities Daily article on June 12th, 2015, which reports a total of 1.0-1.5 trillion yuan (Liu, 2015). The total quantity of formal margin at the same point was over 2 trillion.

growth in early 2015.

Given these patterns, the roll-out of formal margin that we study should be seen as the initial introduction of margin lending into the Chinese stock market, with shadow margin coming later. Shadow margin lending appears to have been virtually nonexistent when the first two vintages were introduced, and was still relatively small (and offered with much higher interest rates) when the third vintage was introduced.[13] Furthermore, even at the time of the third vintage, shadow margin was rarely used to purchase stocks that qualified for formal margin. Appendix Table A.I presents basic summary statistics of formal and shadow margin for the set of all marginable stocks just prior to the rollout of the third vintage. For these stocks, the average ratio of formal margin to floating market capitalization was 6.21%, while the average ratio of shadow margin to floating market capitalization was just 0.63%. As a consequence, we largely abstract from shadow margin when studying the initial impact of margin lending on stock prices. We return to our shadow margin data when considering the role of margin debt in the boom and bust cycle as a whole.

2.4 China's Mutual Fund Industry

China started to develop its mutual fund industry in 1998. Unlike other developed markets, mutual funds in China own a substantially smaller fraction of the stock market and are known for their active and speculative trading style. Between 2010 and 2015, mutual funds in total held 4% to 5% of the Chinese stock market, compared to about 30% in the U.S. (Jiang, 2020). Furthermore, Chinese mutual funds charge high fees; the average expense ratio for actively managed mutual funds was 1.2% in 2017 (versus about 0.8% in the U.S.). Jiang (2020) also finds that despite high fees, Chinese mutual funds' net returns do not underperform the market index, suggesting an ability to generate superior returns. In this sense, mutual funds in China are similar to hedge funds in other markets. However, the regulatory reporting framework for mutual funds in China is similar to that in other markets. For example, mutual funds are required to disclose their full equity holdings on a semi-annual frequency.[14]

[13]Our central results are robust to excluding the third vintage.

[14]See Jiang (2020) for more detail on China's mutual fund industry.

2.5 Data

We use stock price, trading, and financial information from CSMAR, excluding stocks on the Growth Enterprise Board (GEB) and newly listed stocks. CSMAR also provides mutual fund data, which includes funds' complete stock holdings on a semi-annual basis, as well as information on each fund's top 10 shareholdings on a quarterly basis. We also observe the ownership share of the largest 10 investors in each stock at a quarterly frequency. We collect outstanding margin debt at the stock level at a daily frequency from the Shanghai and Shenzhen Stock Exchanges. We focus primarily on the period between March 2009 (roughly a year before Pilot A) and May 2015. We obtain proprietary stock-level shadow margin data from one of the major providers of shadow finance in China, representing approximately 5% of the market; this data reports the total shadow margin balance at the stock level at a daily frequency.

3 Reduced Form Evidence on the Reaction of Stock Prices

In this section we provide reduced form evidence showing that the liberalization of margin lending increased stock prices, and that this increase was largely anticipated and priced in by deep-pocketed investors. We begin with two standard strategies. First, event studies show that prices rose consistently for soon-to-be eligible stocks in the months preceding the deregulation, with no indication that prices increased for qualifying stocks at or after the deregulation, on average. Second, regression discontinuity evidence, which is plausibly uncontaminated by anticipation, indicates the presence of a large causal effect on stock prices. We then present direct evidence of front-running based on the holdings of relatively unconstrained investors. Specifically, we show that institutional investors shifted their portfolios toward soon-to-be-marginable stocks—as if they were anticipating a causal effect on prices—and that these investors profited from this strategy.

3.1 Event Studies Comparing Marginable Stocks to Non-marginable Stocks.

We begin with simple event studies that compare marginable and non-marginable stocks in various windows around the deregulation to test whether there is an observable impact of the introduction of margin debt on stock prices. We construct our estimates as follows. For each of Vintages 1, 2 and 3, we consider the cross-section of all stocks that are either (i) included in the corresponding vintage or (ii) never marginable. We pool these together and consider regressions of the form:

$$Ret_i^k = \beta_0 \text{Marginable}_i^k + \theta_k + \varepsilon_i^k. \tag{2}$$

In our benchmark specification, Ret_i^k is the cumulative DGTW-adjusted return for stock i in the relevant window around the announcement/implementation month for vintage k.[15] Marginable$_i^k$ is an indicator equal to one if stock i becomes marginable in vintage k. θ_k is an indicator equal to one if the observation is included in the cross-section corresponding to vintage k, and captures the average return for non-marginable stocks in the relevant window. Our coefficient of interest is then β_0, which captures the deviation in cumulative returns from the average for non-marginable stocks. We cluster our standard errors at the stock level.

Post-Marginability Returns. The first three columns of Panel A in Table 2, labelled "Following Marginability," show that the relative returns for newly marginable stocks were virtually zero in the period immediately following marginability. We see no significant differential return through one, three, or 12 months after the deregulation. These results are inconsistent with an unexpected direct impact of margin debt on the level of asset prices, which would generate positive returns. The fact that these coefficients are effectively zero suggests that for the average stock, either (i) any direct effect of margin debt was already priced in by the time of the deregulation or (ii) there was no average impact of margin debt on asset prices.

Pre-Marginability Returns. Columns 4-6 of Table 2, labelled "Preceding Marginability," provide evidence for the former explanation. The prices of soon-to-be eligible stocks rose in advance of the margin lending deregulation. In these specifications, we repeat the analysis shown in Equation 2, but consider cumulative DGTW-adjusted returns in the one, three, or 12 months prior to the announcement/implementation. We see strong evidence of *positive* returns in the period preceding marginability. Notably, these returns appear gradually over the course of the window. We estimate significant differential returns of 1.9% in the month just prior to implementation, of 6.5% in the three months preceding implementation, and of 24% in the year before implementation.

[15] We follow a Daniel *et al.* (1997) (DGTW) style adjustment using independent sorts of quintiles of size, book-to-market, and past 12-month return to get 125 portfolios. Each stock is assigned to one of these 125 bins. The value-weighted returns in each bin then serve as the benchmark for that stock's adjustment.

Furthermore, these returns did not dissipate following the deregulation. Column 7 shows that cumulative returns from 12 months prior to 12 months after the announcement/implementation month remained at roughly 25%. Similar results hold when considering each vintage independently, indicating that these patterns are not driven by outsized returns for a single vintage. Our estimates are consistent with the market slowly anticipating and pricing in a positive causal effect of margin debt as the deregulation approached.

Robustness. In Panels A and B of Appendix Table A.II we present a set of robustness exercises to show that our choice of regression specification and return adjustment are not driving our results. In Panel A, we repeat the specification in Equation 2 but include all not-yet marginable stocks in each cross-section, including those that become marginable in a later vintage. We find results that are similar to our benchmark specification, although we see relative returns decline slightly in the year following marginability (perhaps due to positive returns in the soon-to-become marginable stocks that make up a portion of the control group in these specifications). In Panel B, we present more traditional one-factor adjusted event studies, which display the mean of cumulative abnormal returns at the same horizons as shown in Table 2. Again, the results are similar to our benchmark specification.

Stronger Anticipatory Returns in High-Ranking Stocks. As further evidence that the deregulation was anticipated by the market, Panel C of Appendix Table A.II shows that the pre-event returns were strongest in the stocks that had the highest ex-ante probability of qualifying. Specifically, we split qualifying stocks at the median of the (within-vintage) ranking according to the inclusion index. The above median (high-ranking) stocks were ex-ante very likely to qualify, whereas the status of below median (low-ranking) stocks was more uncertain. If the returns we observe are indeed anticipatory, we should expect stronger returns for high-ranking stocks. The last four columns of Panel C show that this is the case. We see earlier and larger returns for high-ranking stocks, relative to low-ranking stocks, in the months leading up to the deregulation.

Placebo Tests. One potential concern is that the positive returns we estimate in the months preceding marginability are a mechanical consequence of the ranking criteria used to select marginable stocks (shown in Equation 1). Because market capitalization influences the ranking, it is possible that stocks experiencing high returns in the pre-implementation period are more likely to be selected. Such selection could lead to differential returns as an artifact of the criteria, rather than market anticipation.[16] To address this concern, we implement a series of placebo event studies to test for a mechanical bias generated by the ranking. Our basic approach is to estimate pre-implementation returns after using the ranking procedure to select a "treated" group on randomly selected placebo dates. If the patterns we estimate are truly mechanical, they should appear around placebo dates that are unrelated to the introduction of margin debt.

We conduct 1000 iterations of our placebo strategy. Because our sample is contaminated by the deregulation itself, we consider a wide period prior to the sample period: all months between January 1993 and December 2008.[17] For each iteration, we randomly select three placebo deregulation months, to mirror the three vintages of the deregulation. At each of these dates, we rank stocks according to the inclusion index shown in Equation 1.[18] At the first event month, we replicate the pilot by selecting and removing the top 150 stocks in each exchange. We then assign the top 100 remaining stocks in each exchange as Placebo Vintage 1. At the next date, we exclude stocks in Placebo Vintage 1 or the pilot, and assign the top 100 remaining stocks to Placebo Vintage 2. At the final date we do the same to create Placebo Vintage 3, excluding stocks in any of the earlier placebo vintages. With these vintages defined, we repeat the analysis in Panel A of Table 2 and store the estimated coefficients. We present the results of our placebo exercise in Panel B of Table 2. In each column, we show the mean of our 1000 placebo iterations and 95% confidence intervals drawn from the empirical distribution (anchored by the 2.5th percentile and the 97.5th percentile of our iterations).

We do not find conclusive evidence of a mechanical bias in the months preceding the event dates. At all horizons, the point estimates are relatively small and the empirical 95% confidence intervals comfortably contain zero. While a meaningful fraction of our placebo draws result in negative coefficients, it is notable that the means in both the -3 to 0 and -12 to 0 windows are positive. This suggests that it is possible that the ranking procedure induces an upward bias.

[16]A related source of selection bias could arise if the regulatory agency based the decision to implement the reform on the performance of would-be treated stocks.

[17]We find similar results when focusing on other windows, for example, on the previous stock market bubble that occurred between 2001-2007.

[18]We do not apply the screening procedure as data on the relevant criteria are not available in this earlier sample period.

However, the magnitudes are small in comparison to our main estimates. In the -3 to 0 window, we find a point estimate of 0.014, nearly five times smaller than the estimate in Panel A. In the -12 to 0 window, the point estimate is 0.049, again nearly five times smaller than the corresponding estimate in Panel A. Using the means of these placebo estimates to debias our benchmark estimates implies cumulative returns of 5.1% in the -3 to 0 window and 19.3% in the -12 to 0 window. These estimates are marginally smaller in magnitude, but reflect the same qualitative patterns as our benchmark.

Graphical Evidence. In Appendix Figure A.III we present graphical evidence of the anticipatory returns captured in Table 2. Panel A presents raw price data, displaying the mean price for each of the three vintages we study, as well as the set of never-marginable stocks, between the start of 2012 and the end of 2014. While there are level differences between the groups—and it is somewhat difficult to distinguish pre-trends from broader market movements—there is evidence of anticipation. The colored lines begin to diverge from the black line in advance of the relevant implementation date. Panel B of Appendix Figure A.III presents a cleaner, collapsed version of the same patterns, more directly reflecting the results in Table 2. This figure plots the coefficients β_ℓ from the following regression for stock i, vintage k, and month t:

$$Ret_{ikt} = \sum_{\ell} \beta_\ell \times \mathbb{1}\{t - \tau(k) = \ell\} \times Treated_{ik} + \gamma_{ik} + \lambda_{tk} + \varepsilon_{ikt}. \tag{3}$$

This is effectively a stacked event study. As in Table 2, for each vintage k, we include all stocks i that either (i) become marginable in vintage k ($Marginable_{ik} = 1$) or (ii) never become marginable. $\mathbb{1}\{t - \tau(k) = \ell\}$ is an indicator equal to one if the difference between month t and the implementation date $\tau(k)$ of vintage k is ℓ. We cluster standard errors at the stock level. To show a wider view of the anticipatory patterns prior to the deregulation, we include data from 60 months before the implementation of vintage k to six months after when estimating Equation 3. We measure Ret_{ikt} as the cumulative return beginning 60 months before the implementation of vintage k. To show as raw a version of the data as possible, we do not further adjust returns in these plots.

The estimated coefficients reflect the anticipatory patterns we estimate elsewhere in our analysis. We see prices of soon-to-be marginable stocks rising steadily in the 12 months prior to implementation (relative to never-marginable stocks). Even 24 months prior to the deregulation there is a noticeable difference in returns between the two groups. In general, returns display a roughly exponential curve in the months leading up to the deregulation before peaking and leveling off around the implementation month itself. Our estimates are again consistent with relatively unconstrained investors pre-empting and pricing in a large causal impact of margin debt. We return to the anticipatory patterns shown in Panel B, and the implied magnitudes, when specifying our model in Section 4.

3.2 Regression Discontinuity Estimates

Our event studies provide suggestive evidence that the introduction of margin debt had a sizable impact on the level of asset prices, and that these impacts were largely anticipated and priced in. However, it is always challenging to make causal statements on the basis of a pre-event trend. It is feasible that the positive ex-ante returns we observe were driven by some factor unrelated to the deregulation. To rule out this possibility, we now turn to a regression discontinuity approach that plausibly identifies the causal impacts of the deregulation in a sample that is not tainted by anticipation.

Our strategy focuses on the the set of stocks close to the cut-off in the formula used to determine eligibility for margin lending (we refer to the output of this formula, which is shown in Equation 1, as the inclusion index). Only a fixed number of stocks could be included in each vintage, meaning a discontinuity existed at the value of the index held by the lowest-ranking eligible stock. In principle, stocks above this value qualified for margin debt while stocks below did not. Furthermore, because the formula is based on real-time inputs that vary at high frequency, and because both the date at which the stocks in each vintage were to be chosen and the precise number of stocks included in each vintage were unknown ex-ante, investors could not perfectly predict the set of qualifying stocks. As a result, the introduction of margin debt can be viewed as an unanticipatable shock to credit for stocks in a small neighborhood around the cut-off. This allows us to isolate the effect of the deregulation from local cross-sectional comparisons.

Defining the Inclusion Index and Marginability Threshold. For each stock i, we denote the value of the inclusion index at the time vintage k was introduced as $Index_i^k$, where $k = \{1, 2, 3\}$.

This serves as the running variable in our regression discontinuity. We construct $Index_i^k$ following the screening and ranking procedure described in Section 2 and Equation 1. We define C_E^k to be the inclusion threshold for vintage k in exchange E, and consider all stocks in a window of size one around the threshold. For details on the definition and implementation for each vintage, see Appendix B.1.

No Evidence of Sorting Around the Threshold. There is little evidence that investors or insiders were able to manipulate the rankings of particular stocks locally around the threshold C_E^k. While the basic inputs into the index could have been influenced to some extent, uncertainty over the exact number of stocks included in each vintage made precise control around the threshold effectively impossible. To show this formally, we conduct manipulation tests (in the tradition of McCrary, 2008) following Cattaneo *et al.* (2018). We present the results in Figure 3. We find no evidence of bunching around the threshold: the magnitude of the t-statistic is just below one. Further, Appendix Figure A.IV shows that there are not discontinuities in ex-ante observable characteristics of stocks above versus below the threshold.[19]

A Discontinuity in Marginability and Margin Debt at the Threshold. We begin by showing that the threshold C_E^k is indeed associated with a discontinuity in marginability and the quantity of margin debt. This is displayed most clearly in Panel (a) of Figure 4, which shows sharp jumps in the probability a stock is marginable, the quantity of margin debt, and the ratio of margin debt to floating market capitalization for stocks just above versus just below the threshold.

To show this jump more formally, we take a standard regression discontinuity (RD) approach. Letting Y_i^k be the outcome of interest, consider:

$$Y_i^k = \alpha_{0l} + \alpha_{1l}(Index_i^k - C_E^k) + \tau_i^k[\alpha_{0r} + \alpha_{1r}(Index_i^k - C_E^k)] + \theta_k + \lambda_{ind(i)} + \varepsilon_i^k. \quad (4)$$

Here τ_i^k indicates that stock i is above the marginability threshold, that is, it is equal one if $Index_i^k \geq C_E^k$ and zero otherwise. θ_k represents a vintage fixed effect and $\lambda_{ind(i)}$ represents a industry fixed effect.[20] Our coefficient of interest is α_{0r}, representing the discrete change at the threshold. In our

[19] Appendix Table A.III shows formal tests of covariate smoothness, based on the specification in Equation 4 below. Of the 12 characteristics we examine, one coefficient is significant at the 10% level, and all others are not significant.

[20] The industry classification is based on 2001 CSRC industry code from CSMAR, where we use the first 3-digit for

preferred specifications, we implement a local-linear approach to estimating this parameter, using a triangular kernel, following Cattaneo *et al.* (2024). However, we also present results using a uniform kernel in our robustness exercises, which is equivalent to estimating Equation 4 via OLS. We use the covariate adjusted MSE optimal bandwidths described in Calonico *et al.* (2018) unless otherwise specified, and show standard errors, clustered at the stock level, based upon the three nearest neighbor variance estimators described in Calonico *et al.* (2014) (hereafter, CCT).

Our results from these specifications, shown in Panel A of Table 3, are consistent with Panel A of Figure 4. Crossing the threshold C_E^k is an almost perfect predictor of becoming eligible for margin debt. We estimate a jump in the probability a stock becomes marginable of roughly 96%. This corresponds to a differential influx of 360 million yuan within 60 trading days (or, alternatively, an influx of roughly 5% of floating market capitalization). All estimates are statistically significant and similar whether we use the optimal bandwidth or a fixed bandwidth of 0.1. Together these results show that the threshold C_E^k corresponds to a differential (and plausibly unpredictable) shock to the quantity of margin debt in a local area.

Price Reactions at the Threshold. We next consider the impact on asset prices. We test whether stocks just above the threshold saw higher cumulative returns in the 5, 20, or 60 trading days following the implementation of each vintage. Panel B of Figure 4 presents plots similar to those in Panel A, but with cumulative raw returns at various horizons on the y-axis. The inclusion index is displayed on the x-axis (centered to set C_E^K to 0). These plots introduce the basic results we flesh out more formally below: there is a jump in returns just above the threshold.

In Panel B of Table 3 we show estimates of the impact of margin debt on returns using a reduced-form regression discontinuity approach following Equation 4. For these specifications, the outcome of interest Y_{ik} is the raw cumulative return for stock i in the 5, 20 or 60 trading days following the implementation date of vintage k.[21] As in Panel A, we use a local linear approach with a triangular kernel.

Our results align with the plots shown in Figure 4. In the first three columns, which use the optimal bandwidth, we see a significant impact of roughly 4.5% within five trading days, of nearly

manufacturing industry and the first digit for other industries.

[21]Because the RD strategy allows a comparison of very similar stocks in a small window around C_E^k, we consider raw cumulative returns in our benchmark specification without further adjustment. In robustness exercises, discussed below, we show that our results are not sensitive to using DGTW or market adjusted returns.

8.5% within 20 trading days, and of nearly 25% within 60 trading days. Results are similar in the latter three columns, which use a fixed bandwidth. Panel A of Appendix Figure A.V shows a range of other horizons. The impact on returns appears to stablize after 60 trading days, with similar estimates through 90 trading days. Notice that the price reaction, while rapid and statistically significant at the earliest horizon we examine, does not instantaneously reach this stable level. That is, there is still a degree of price drift following the RD event. We discuss this drift in more detail, and its relationship to the pre-implementation patterns we observe, in Section 3.4 below. Overall, these regression discontinuity estimates suggest that there is a large causal impact of the introduction of margin debt on asset prices.

Robustness for Regression Discontinuity Approach. In Appendix Table A.IV, we show a series of robustness exercises for our regression discontinuity approach. The first two panels show that the qualitative patterns we find are not influenced by using an alternative kernel (uniform) or by including a less thorough set of controls (although the point estimates are slightly smaller and the standard errors are slightly larger for the latter). Panel A considers our analysis of the impact of crossing the threshold on marginability and the quantity of margin debt (which we label the first stage). Panel B considers our analysis of the reduced form impact of crossing the threshold on returns. In the third panel, we show that our reduced form estimates are not sensitive to alternative return adjustments. We repeat our analysis using DGTW adjusted and market adjusted returns.

Heterogeneity in Price Reactions at the Threshold. In Appendix Table A.V we consider heterogeneity in our regression discontinuity estimates by several stock-level characteristics. For each, we repeat the analysis considering only stocks above versus below the median of each characteristic. We fix the bandwidth across all specifications to 0.1 for comparability and consider a 60 trading day horizon. Given the relatively small subsamples considered, we do not include industry fixed effects in these specifications.

We find larger regression discontinuity impacts for stocks with higher past returns, greater sales growth, and higher profits. This indicates that new margin debt is used by retail investors to purchase stocks with positive recent performance. Our findings are consistent with the literature that suggests that retail investors extrapolate based on past price changes that are connected to good fundamental performance.[22] Further, the retail investors using margin in China also appear sensitive to valuation ratios—there are larger effects for stocks with below-median price-to-earnings ratios. A natural interpretation is that Chinese margin traders purchase value stocks with a catalyst—like strong recent price performance or sales growth. Note, however, that point estimates are positive for both above and below median stocks for all characteristics we consider. This suggests that the introduction of margin debt increases prices across the board, even if there are larger effects for particular types of stocks.

Fuzzy Regression Discontinuity to Recover the Causal Effect. To quantify the causal effect of becoming marginable, our final step is to implement a fuzzy regression discontinuity approach that accounts for the fact that the threshold does not perfectly predict marginability. In Panel C of Table 3 we report two-stage least squares regressions in which we instrument for marginability with an indicator for being above the threshold. For more details, see Appendix B.2. Given that our first stage coefficient is close to one, our estimates are marginally larger but otherwise nearly identical to those shown in Panel B. We estimate an impact of returns of nearly 5% at the 5 trading day horizon, 8.5% at the 20 trading day horizon, and 26% at the 60 trading day horizon.

These results indicate the presence of a sizable effect of the margin deregulation on asset prices. Across various specifications, we estimate that eligibility for margin lending generated 60-day cumulative returns of roughly 25%. While large, this quantity must be considered in light of the sharp increase in the market overall during our sample period, and of the large quantities of margin debt that flowed into qualifying stocks. Taken together, our RD and event study approaches suggest that the introduction of margin debt increases equity prices, but that this causal effect was largely priced in by relatively unconstrained—and deep-pocketed—investors by the time the deregulation occurred. We show direct evidence of anticipation by such investors in Section 3.3 below.

[22] Liao *et al.* (2021) show that a large fraction of Chinese retail investors tend to buy stocks that have gone up over the most recent month. An *et al.* (2022) find that Chinese retail investors (particularly those with low account balances) tend to tilt their portfolio towards value stocks. See also Hong *et al.* (2014) and Gao *et al.* (2023) on retail traders in China.

3.3 Front-running by Institutional Investors

In this section, we use data on Chinese mutual funds and other large investors to confirm that relatively unconstrained investors took anticipatory strategies in expectation of the margin lending deregulation. We then conduct tests of risk-adjusted performance to show that mutual funds profited from this strategy.

We begin by showing direct evidence that mutual funds and major stock holders increased their holdings of soon-to-be marginable stocks prior to the deregulation and sold those holdings after margin lending became available. Figure 5 presents coefficients from event study specifications that compare the stock-level ownership share of (i) the largest 10 investors in the stock (Panel A) and (ii) all Chinese mutual funds (Panel B) for soon-to-be marginable versus never-marginable stocks.[23]

For both the mutual fund ownership share and the share held by the top 10 investors, we see steady and significant growth in the quarters leading up to the deregulation. Notably, in both panels, the share peaks the quarter prior to marginability, and begins to steadily decline over the course of at least the next five quarters. Within a year post-marginability, neither share is statistically distinguishable from the share 12 quarters prior to deregulation. This is consistent with institutional players gradually building anticipatory positions, and then gradually winding them down to realize gains as margin debt became available.

Anticipatory Buying at the Fund Level. To show that the anticipatory patterns captured in Figure 5 truly reflect an investor-level strategy (and one that was feasible prior to the introduction of margin debt), we turn to holdings data for mutual funds. We consider semi-annual portfolio disclosures from December 2011 (right after Pilot B was introduced) to June 2014 (right before Vintage 3 was introduced).[24]

We hypothesize that mutual funds tilted their portfolios towards the stocks they expected to become marginable, and did so to a greater extent as the deregulation date approached. Of

[23] Appendix Table A.VI shows the coefficient estimates. These event studies follow the basic specification in Equation 3, but use quarterly stock-level data on the ownership share of each group as the dependent variable. Mutual funds report their complete holdings on only a semi-annual basis, but report their largest shareholds on a quarterly frequency. We assume that holdings do not change between semi-annual reports for for stocks that do not appear in the largest shareholds for a fund.

[24] Our sample covers all (1121) mutual funds who report equity holdings. On average, these funds hold 63.0 stocks in their portfolios (with median of 36).

course, the exact deregulation dates and groups of stocks to be included were unknown beforehand. Therefore, we test if funds shifted their positions based on information that was available to the public ex-ante. Specifically, we ask if they shifted towards a simple strategy based on how highly ranked each stock was according to contemporaneous values of the inputs to the inclusion index (a measure of the likelihood that the stock would be included in the next vintage) and the time elapsed since the most recent vintage (a measure of the likelihood that the next vintage would be announced shortly).

To conduct our analysis, we calculate the inclusion index ($Index_{it}$) based on Equation 1 for all not-yet-marginable stocks using the information available (market cap and trading volume) at time t. This avoids any look-forward bias that might result from using information not available to the funds at the time of investment. We define soon-to-be marginable stocks as the top-ranking stocks according to this formula at time t, regardless of whether they ultimately became marginable. We consider various definitions of top-ranking, including stocks in the *Top Quintile*, the *Top 150* stocks, and the log value of the index itself.

To capture the likelihood that the next vintage would be announced soon, we calculate the number of months between date t and the introduction of the previous vintage, which we denote as *Months Since Last Vintage*$_{it}$.[25] Because the deregulation was expected to roll-out in a relatively standard fashion, a greater time elapsed since the last vintage indicated that the next vintage would probably be introduced shortly. Therefore, we expect mutual funds to increase the weight of soon-to-be marginable stocks in their portfolios as *Months Since Last Vintage*$_{it}$ increases.

To test our hypothesis, we follow the specification in Cohen *et al.* (2008). For each fund j in reporting month t, we calculate stock i's portfolio weight, w_{ijt} as the fund's dollar-value investment in stock i scaled by the fund's total net assets. We conduct the following regression at the semi-annual fund-stock level,

$$w_{ijt} = \alpha + \beta \text{Top Ranking}_{it} \times \text{Months Since Last Vintage}_t + \text{Controls}_{it} + \sigma_i + \theta_j + \gamma_t + \epsilon_{ijt}. \quad (5)$$

Here, *Top Ranking*$_{it}$ is a dummy equal to one if stock i is non-marginable at time t and is high-

[25]For example, for fund holdings reported in June 2014, our variable *Months Since Last Vintage*$_{it}$ is equal to 9 (the number of months since September 2013, when Vintage 2 was introduced). Over our sample, *Months Since Last Vintage*$_{it}$ ranges from 1 to 13 months.

ranking according to one of our metrics based on $Index_{i,t}$ and equal to zero otherwise; we also include a continuous variable equal to the log of the ranking itself in one specification. Our coefficient of interest is β, which captures the tilt of portfolios toward soon-to-be marginable stocks. We include controls for the percentile rank of stock characteristics, including floating market capitalization, book-to-market, turnover rate, past month return, past year return, and the interactions between *Months Since Last Vintage*$_{it}$ and each of these percentile ranks. The interaction terms allow the effect of *Months Since Last Vintage*$_{it}$ to vary with different stock characteristics. This is to account for the fact that the inclusion index (Equation 1) is based on size and volume, so one might be concerned that our findings are driven by large or high turnover stocks. We also include fund, stock, and time fixed effects. Standard errors are clustered by fund.

Table 4 shows our results. In Column 1, we measure top-ranking as the top quintile of non-marginable stocks. The coefficient on the interaction term between *Top Quintile*$_{it}$ and *Months Since Last Vinatage*$_{it}$ is 0.0034 (with a t-statistic of 3.2). In Column 2, we measure top-ranking as the top 150 non-marginable stocks in each exchange based on $Index_{it}$. The coefficient on the interaction term is 0.0027 (with a t-statistic of 2.5). To provide a sense of the economic magnitudes at play, the latter coefficient suggests that, in the 10th month since the previous vintage, mutual funds overweighted the top 150 stocks by 0.027% per stock. This suggests that, overall, mutual funds tilted their investment towards likely-to-be marginable stocks by about 8.1% ($0.027\% \times 150$ stocks $\times$ 2 exchanges), a sizable amount. In Column 3, we consider an alternative specification that replaces the binary $Top\ 150$ or $Top\ Quintile$ with a continuous measure of the stock's ranking (the log of $Index_{it}$, with already-marginable stocks assigned a value of zero). The coefficient on the interaction term remains significant and positive. Together, these results indicate that mutual funds meaningfully adjusted their portfolios in anticipation of the deregulation.

Selling Following the Margin Lending Rollout. We next show portfolio-based evidence that mutual funds unwound their positions after margin debt became available, likely selling out to retail investors using newly acquired margin. To capture selling after qualification, we consider the following regression at the semi-annual fund-stock level:

$$w_{ijt} = \alpha + \beta \text{Marginable}_{it} \times \text{Months Since Marginable}_{it} + \text{Controls}_{it} + \sigma_i + \theta_j + \gamma_t + \epsilon_{ijt}. \quad (6)$$

Here, *Marginable*$_{it}$ equals one if stock i is marginable in month t, and zero otherwise. *Months Since Marginable*$_{it}$ measures the number of months since stock i became marginable, as of time t. Our coefficient of interest is β, which captures the tendency of mutual funds to adjust the portfolio weight of marginable stocks as the number of months since the deregulation increases. We expect β to be negative if funds tilt away from newly marginable stocks after the stocks become eligible. This is similar to the specification in Equation 5, but replaces the *Top Ranking*$_{it}$ variable—an ex-ante prediction of the stocks that are likely to become marginable—with the ex-post marginability of each stock. Controls again include the percentile rank of stock characteristics, including floating market capitalization, book-to-market, the turnover rate, the past month return, the past year return, and interactions between *Months Since Marginable*$_{it}$ and each of the aforementioned percentile ranks.

The fourth column of Table 4 shows our results. The coefficient on the interaction term is -0.0075 and highly significant, mirroring the gradual decline post-marginability shown in Figure 5. This shows that mutual funds unwound their positions in marginable stocks as margin debt became available.

Performance Tests. As a final step, we show evidence that mutual funds profited from the ex-ante strategy of tilting toward soon-to-be-marginable stocks. Specifically, we examine whether mutual funds' soon-to-be marginable holdings earned higher returns compared with the funds' other holdings. To do so, we follow the method of Cohen *et al.* (2008), who test if a fund's connected holdings generate alpha compared to the fund's other positions. At each reporting period, stocks in each mutual fund's portfolio are assigned to one of two portfolios: "To-Be-Marginable" (TBM) and Non-TBM (NTBM). TBM companies are defined as stocks that are ranked within the top quintile or top 150 (following Table 4) within the relevant exchange based on the inclusion index at time t. Again, this distinction is based only on ex-ante available information.

We then compute the monthly returns on TBM and NTBM holdings over the next six months, as well as the returns on a long TBM and short NTBM strategy. We rebalance portfolios every six months and, within a given portfolio, value-weight stocks based on the fund's dollar holdings. The six-month window, which is the best our data allows, implicitly assumes that funds did not change their holdings between semi-annual reports. Finally, we calculate calendar time portfolio returns by averaging across funds. We use raw returns, market-adjusted returns, CAPM alpha, and DGTW returns. CAPM alpha is the intercept from a regression of monthly portfolio excess returns on the market factor. The sample period is from January 2012 to September 2014. We use Newey-West standard errors with a lag of 11 months.

Table 5 presents the results. Over our period, mutual funds allocated 12.98% of AUM into Top Quintile stocks on average (or 12.41%, when defining TBM as the Top 150). Mutual funds' TBM holdings based on the Top Quintile earned 1.65% per month. By comparison, the average return of the NTBM holdings was 1.09%. The portfolio that is long TBM and short NTBM generates a sizable abnormal return of 0.56% per month, which is statistically significant (with a t-statistic of 2.1). We see similar results when using market-adjusted returns (the raw return minus the value-weighted market return). The TBM portfolio generates a significantly positive return of 0.83% per month (with a t-statistic of 2.6), whereas the return on the NTBM portfolio is not significantly different from zero. The return on the long-short portfolio remains positive and significant. The other columns use CAPM alpha and DGTW returns, and the lower row reports the same specification using Top 150 to define TBM stocks. Overall, our main finding is robust: TBM portfolios exhibit significant and positive returns of between 0.55% to 1.65% per month and earn higher returns than mutual funds' other holdings (NTBM). The results suggest that mutual funds earned significant profits by anticipating the demand of constrained investors that was released by the deregulation.

3.4 The Timing of Price Reactions

Our event study and regression discontinuity analyses, paired with our examination of institutional investors, suggest that there was a sizable causal effect of the introduction of margin debt and that this effect was anticipated by the market and priced in for most stocks. A notable feature of our regression discontinuity approach, however, is that the price reaction, although rapid, is not instantaneous. In other words, there appears to be drift in the set of stocks for which eligibility was plausibly a surprise (those very close to the inclusion index threshold). Is this at odds with our finding of anticipation by less-constrained investors?

To recall our regression discontinuity results, there is a sizable and statistically significant reaction of nearly 5% at the earliest horizon we examine. This effect grows over the course of the first month, and reaches a stable level after roughly 60 trading days (See Panel A of Appendix Figure A.V). We view this pattern—a rapid jump, followed by an upward trend over the course of roughly

60 trading days—as consistent with the literature on price drift following earnings announcements and other news events (e.g., Ball & Brown, 1968; Bernard & Thomas, 1989; see Fink, 2021 for a comprehensive review). Even in contexts like earnings announcements, which are closely researched and actively anticipated by analysts and deep-pocketed investors, unexpected news can generate drift that occurs over the course of months. Indeed, in well-developed markets, the accounting literature finds that 60 days is a typical horizon over which earnings surprises are impounded into prices. This is due to a combination of risks and frictions that institutional investors may not be able to fully arbitrage away (e.g., Cohen *et al.* , 2002). The particular features of the Chinese deregulation—including the rate at which retail traders actually took up margin and changes in the trading environment before versus after the reform—help reinforce this interpretation.[26]

4 A Dynamic Panel Model of Stock Prices

The previous section shows evidence that the margin lending deregulation increased stock prices, and that relatively unconstrained investors gradually anticipated and priced in the liberalization. In this section, we ask whether our results can be rationalized in a standard equilibrium stock-trading model with information revelation. We show that a simple set of parametric assumptions within our model enables us to accurately capture the anticipatory patterns in the data—consistent but gradual price growth—with two easy-to-estimate parameters. These parameters allow us to summarize (i) the impact of the deregulation and (ii) the gradual rate of anticipation. The estimates from our model align closely with our reduced form approach.

4.1 A General Information Revelation Model

Consider a market for a stock with shares outstanding of Q. The stock pays dividend $\pi \sim N(0, \sigma_\pi^2)$ at terminal date T, and we consider periods t from $-n < 0$ to $T > 0$. For simplicity, we set the interest rate to zero. There is a unit mass of unconstrained risk-averse investors with CARA utility $-e^{-\gamma W}$ who are price takers.

[26]The last two panels of Appendix Figure A.V show that retail investors entered and took leveraged positions in newly marginable stocks over the course of several months. In fact, the timing of the inflow of margin debt closely matches the drift in prices. Note also that, on average, the holdings of mutual funds and other large investors peak in the quarter prior to the introduction of margin debt (see Figure 5). The same patterns hold if we focus on only low-ranked stocks, which are likely to be close to the inclusion threshold.

Now suppose that at time $t = 0$ there is a shock to credit available for a set of previously constrained investors. In our context, this can be interpreted as the deregulatory date at which margin lending became available. We model the shock, in reduced form, as a permanent price-inelastic demand shock of Δ shares, similar to De Long *et al.* (1990). If this shock was entirely unanticipatable, the price would jump discretely at $t = 0$ by a quantity $m = \Delta\gamma\sigma_\pi^2$.[27] In this context, it is natural to view m as the causal effect of the credit expansion. The unanticipated demand shock of Δ leaves effectively $(Q - \Delta)$ shares for risk-averse unconstrained investors to own.

To capture anticipation, we assume that unconstrained investors begin to receive signals about the demand shock in advance. Specifically, that in each period $t \leq 0$ they receive a signal m_t about m, which we model as $m = \sum_{-n}^{0} m_t$.[28] In other words, investors progressively learn about m as it is realized over time. We assume that the signals m_t are independent normal with mean zero and variance σ_t^2, which may vary across periods. The equilibrium price for any t between $-n$ and 0 (the event itself) is then given by:

$$p_t = p^* + \sum_{j=-n}^{t} m_j - \gamma\left(\sum_{k=t+1}^{0} \sigma_k^2\right)Q. \tag{7}$$

At $t = 0$, the price is simply $p_0 = p^* + m$. Notice that this equation shows two distinct sources of anticipatory pre-trends in prices. First, the summation of m_j terms captures revealed information about future prices. Second, there is a risk discount effect. Risk-averse investors recognize the variance associated with the demand shock and must be compensated to own shares. As time progresses, there is less uncertainty regarding the size of the shock, so the risk discount falls and the stock price rises.

4.2 The Exponential Decay Information Structure

To take our model to data, we propose an information structure that allows unconstrained investors to receive signals about m into the infinite past (formally, we set $n = \infty$). For convenience, we impose the parametric form that, for some $\theta > 0$, the variance of each m_t is given by $\sigma_t^2 = \beta(\theta)^t$.

[27] From the equilibrium price without the shock $p^* = -\gamma\sigma_\pi^2 Q$, to the price after the shock of $p_0 = -\gamma\sigma_\pi^2(Q - \Delta)$.

[28] This dividend structure was first used in Grundy & McNichols (1989) and He & Wang (1995).

Under this assumption, the variance of each signal increases exponentially as the event date approaches (or uncertainty about m reduces exponentially).[29] We view this as reasonable in a broad set of contexts, including our own, as it is relatively flexible (depending on the value of θ, which parameterizes the rate of anticipation), and captures the intuition that more information is likely to be revealed as the event date approaches. Furthermore, as we discuss below, the exponential curve implied by this parameterization provides a parsimonious way of capturing the observed shape of anticipatory pre-trends in the data.

In our setting, we are interested in studying the prices of stocks that ultimately receive a *positive* credit supply shock at time $t = 0$. In the model, this translates to stocks with $m > 0$.[30] We refer to these throughout as *treated* stocks. Given our assumption, in a cross-section of such ex-post treated stocks, the expected price at any time t is given by:

$$E[p_t|m > 0] = \tilde{p} + \beta(\lambda + \gamma) \sum_{j=-\infty}^{t} \mathbb{1}\{j \leq 0\}\theta^j. \tag{8}$$

Here, the constant $\lambda = \frac{\phi(0)}{\Phi(0)} \frac{1}{\sigma_m}$, and the constant $\tilde{p} = p^* - \frac{\gamma\beta}{1-\frac{1}{\theta}}$. We provide details of the derivation of Equation 8 in Appendix C.1.

Implications for Anticipatory Price Trends. The presence of anticipatory pre-trends follows from the expression in Equation 8. The period-to-period price increase is given by:

$$E[p_t - p_{t-1}|m > 0] = \begin{cases} \beta(\lambda + \gamma)\theta^t & \text{if } t \leq 0 \\ 0 & \text{if } t > 0. \end{cases}$$

The parameter θ captures the exponential rate at which prices rise. The red and blue lines to the left of the event date in Panel (a) of Figure 6 show examples of the expected price path for treated stocks—incorporating anticipation on the part of investors—given this information structure. We show two values of θ (holding the size of the ultimate impact on prices fixed). The blue line displays a relatively high value of θ—effectively a very high rate of decay prior to the event. In

[29]Given this assumption, note that the unconditional variance of m can be written as: $\sigma_m^2 = \frac{\beta}{1-\frac{1}{\theta}}$.

[30]In this stylized model all stocks receive a shock and treatment is defined as a positive realization. One can write an analogous model in which m acts as a latent index determining the subset of treated firms receiving a binary credit supply shock, but such a model is less tractable with similar intuition.

this case, anticipation only begins to meaningfully impact prices in the last few periods. The red line shows a lower value of θ. In this case, prices begin to rise in a noticeable way much earlier. The black line shows the limiting case of no anticipation, with a sharp jump in prices exactly at the event date. Panel (b) of Figure 6 shows simulated price paths for individual treated stocks based on our model. The average, captured by the dark blue line, highlights the key feature: anticipatory pre-trends in prices follow (and can be captured by fitting) an exponential curve.

Of course, the implication that pre-trends in prices take an exponential form follows from our assumptions about the information structure. A natural question is whether this assumption is flexible enough to accurately capture the patterns in the data. Panel C of Figure 6 shows that the anticipatory price increases in the data are well approximated with an exponential curve. The black line shows the average pre-marginability price patterns in the data for vintages 1, 2 and 3 (after residualizing and normalizing). The blue line shows the corresponding average price trends implied by the model based on parameters estimated using the same data.[31] This suggests that our exponential structure provides a parsimonious and quantitatively accurate way of capturing the anticipatory trends in the data.

4.3 Panel Estimation Strategy

We now show that Equation 8 translates naturally into a set of empirical specifications. In particular, it suggests a relatively straightforward first-difference approach. For any $t \leq 0$, price changes for treated stocks follow a standard exponential curve:

$$p_{it}^{treated} - p_{it-1}^{treated} = \underbrace{\delta_1}_{\beta(\lambda+\gamma)} \theta^t + \Delta\varepsilon_{it}. \tag{9}$$

Here t again captures the relative time to the treatment date.[32] Using non-linear least squares, we can recover the two key parameters from this equation: δ_1 and θ, from the pre-event price changes for treated stocks. $\delta_1 = \beta(\lambda + \gamma)$ captures the average price increase on the date of the credit

[31] We discuss the details of our estimation in the next section.

[32] $\Delta\varepsilon_{it} = \varepsilon_t - \varepsilon_{t-1}$, where ε_{it} is mean 0 and uncorrelated across stocks. Taken literally, this error term represents the difference between the realized stream of messages for stock i and the conditional expectation for the treated group. $\varepsilon_{it} = \sum_{j=-\infty}^{t} m_j^i - E\left[\sum_{j=-\infty}^{t} m_j^k | m^k > 0\right]$. Of course, in practice ε_{it} will also include any unmodeled stock and time specific factors not captured by the expression in Equation 8.

supply roll-out itself. θ captures the speed of information revelation. For larger θ, anticipation is less important as investors have little information about the existence or size of the credit supply shock far in advance of the event date. The net impact of the deregulation in an economy with anticipation is the average change in prices from $t = -\infty$ to 0. This can be recovered from the two parameters as: $\Delta p_{-\infty} = E[p_0|m > 0] - \tilde{p} = \frac{\delta_1}{1-\frac{1}{\theta}}$.

One could consider taking Equation 9 directly to the data using only a panel of treated firms. However, doing so risks conflating market movements or trends with the parameters of interest. This concern can be avoided with access to a control group—ideally a set of stocks that generally experience the same aggregate movements as treated stocks, but that have no ex-ante possibility of receiving a credit supply shock. Such a control group allows us to difference out general fluctuations in the market and focus on the impact due to the introduction of margin debt.

Linear Difference-in-Difference Style Estimating Equation

We can also estimate the parameters δ_1 and θ with a slight twist on a standard difference-in-difference. Appendix C.2 shows that the price of a treated stock may be written as:

$$p_{it} = \delta_1 D_{it} + \frac{1}{\theta} p_{it+1} + \alpha_i + \eta_t + e_{it}, \tag{10}$$

Here, D_{it} is an indicator equal to one *only* for treated stocks when $t \geq 0$. α_i and η_t represent stock and period fixed effects. This simple equation with two parameters of interest relates the price to one-period-ahead prices and an indicator equal to one after credit formally rolls out.

Estimation of Equation 10 via OLS has known issues that are analogous to those in the literature on dynamic panel models with lagged dependent variables (Arellano & Bond, 1991). However, in Appendix C.3 we show that δ_1 and θ can be estimated by two-stage least squares using a forward looking panel IV approach in the vein of Arellano & Bover (1995) and Malani & Reif (2015).

4.4 Implementation and Results

We estimate our model using both the non-linear approach outlined in Equation 9 and the linear approach outlined in Equation 10. We consider monthly data covering from March 2009 to October 2015 To account for scale effects, we normalize p_{it}, the price of stock i in month t, by the price of that stock in March 2009. As such, p_{it} can also be thought of as the cumulative gross return from the start of our sample.

Evaluating Pre-Event Trends. In both approaches, we use a set of stocks that are not eligible for margin lending to help adjust for aggregate fluctuations in the market, either by considering *excess* price changes relative to the control group, or by using fixed effects. The key assumption is analogous to parallel trends. Changes in prices in the control group must serve as a valid counterfactual for the path prices would have taken in the set of marginable stocks in the absence of the deregulation. While standard tests of pre-trends are likely to be violated, given the anticipatory patterns documented in Section 3, Panel B of Appendix Figure A.III provides suggestive evidence in favor of this assumption. Recall that this plot shows the coefficients from a stacked event study that compares the prices of marginable to never-marginable stocks over a long horizon—60 months—leading up to the introduction of margin debt. As discussed in Section 3.1, there are visible anticipatory pre-trends in the months leading up to the introduction of margin debt.

However, the trends between the two groups are very similar in the period well before the introduction of margin debt. While there is no certain ex-ante point at which meaningful anticipation began, we include a vertical dashed line 55 months prior to the roll-out, which we view as a conservative benchmark. This represents the time between the introduction of the initial pilot vintage and the roll-out of the third and final vintage, the maximum possible window for an investor who began anticipating the final vintage as soon as the pilot began. In the months prior to this dashed line, and for a number of months after, the price trends between the two groups are similar and not statistically distinguishable. While anticipation disrupts our ability to assess the feasibility of parallel trends in the months just prior to the roll-out, this evidence indicates that the set of never-marginable stocks at least provides a reasonable control group in the period before anticipation was likely.

Results. We present our model estimates in Table 6, which displays several specifications of our linear and non-linear approaches. For our non-linear approach, we control for aggregate trends by (i) considering the excess Δp_{it} for soon-to-be marginable stocks, relative to the group of never-marginable stocks and (ii) first residualizing Δp_{it} with respect to time and stock fixed effects using all stocks in our sample. For our linear approach, we show both OLS estimates—which do not account for endogeneity in p_{it+1}—and two-stage least squares IV estimates, which use leads of D_{it} (specifically D_{it+2} and D_{it+3}) as instruments.[33] For all estimates, we show results from a base sample, which includes the three vintages selected using the screening and ranking rule as well as never-marginable stocks, and the full sample, which additionally includes the pilot vintages.

Across specifications, we find evidence that is consistent with our reduced form approaches. The introduction of margin debt led to a substantial increase in stock prices, and this increase was anticipated gradually in advance of the roll-out. In our non-linear strategy we estimate an impact on stock prices of 26% to 37% percent when excluding the pilot sample, and 22% to 26% percent when including the pilot sample. Similarly, in our linear IV approach, we estimate a direct impact of 20% to 39% percent across samples. These effects are in line with the local estimates from our RD analysis, albeit slightly larger in most specifications. Our estimates are also qualitatively in line with, but larger in magnitude than, the corresponding event study estimates recovered in Section 3. This is natural, as our estimation makes a comparison that is similar to those in the event study, but considers returns over a longer anticipatory horizon.

We estimate the parameter θ to be between 1.05–1.10, which suggests that the direct effect was anticipated gradually, with the equivalent of a 5% to 10% monthly exponential rate, as information became available. For example, $\theta \approx 1.07$ in our base IV estimates indicates that more than 60% of the direct effect of credit supply was already priced in even six months prior to deregulation. Put simply, our model estimates reinforce that the introduction of margin debt had a large impact on the prices of treated stocks, and that this impact was gradually realized in the months leading up to the deregulation as information on the precise set of qualifying stocks became available to deep-pocketed investors.

5 Implications for Stock Market Booms and Busts

Finally, we turn to the implications of our findings for the role of margin debt in the broader boom and bust in the Chinese stock market that came to a head in mid-2015, roughly nine months after the introduction of the third and final vintage. While our identification strategies do not

[33] Earlier versions of our paper also employed systems GMM approaches and used a wider array of leads as instruments, with similar results.

provide sharp quasi-experimental variation in the quantity of margin lending through the peak of the boom and the bust, and shadow margin increasingly became important in early 2015, we provide suggestive evidence that stock-market leverage played a meaningful role.

Margin Debt and the Boom. To assess the role of margin debt in the boom, we use our reduced form results to recover a back-of-the-envelope value of the elasticity of demand for stocks with respect to an influx of margin debt. Given our estimates of the effect of marginability on stock prices (26% within 60 trading days, in our benchmark RD specification), and of the observed quantity of margin debt that flowed into eligible stocks (roughly 5% of floating market capitalization within 60 trading days), we can recover an estimate of the elasticity using the following formula:

$$Return = -\frac{1}{\epsilon}\%\Delta Demand. \tag{11}$$

Here, $Return$ is the return associated with the event (i.e. our causal effect). $\Delta Demand$ is the increase in margin debt relative to market capitalization driven by previously constrained retail investors as margin debt becomes available. ϵ is the elasticity of demand of the unconstrained buyers or arbitrageurs in the economy. ϵ approaching $-\infty$ corresponds to infinitely elastic demand curve, while a small negative number corresponds to an inelastic demand curve. Combining our estimates gives $\epsilon = -0.19$, indicating inelastic demand for Chinese stocks. This is perhaps unsurprising, given the frictions and lack of a meaningful market for short-selling in the Chinese market.

We use this elasticity to provide a back-of-the-envelope evaluation of the importance of margin debt in the stock market boom that came to a head in 2015. Specifically, we calculate an *implied boom return* at the stock level based on Equation 11. To do so, we take $\epsilon = -0.19$, and proxy $\Delta Demand$ at the individual stock level using the increase in total margin debt (relative to floating market capitalization) that came in the year prior to the the peak of the boom (June 13th, 2014 to June 12th, 2015). To capture the impact of all forms of borrowing, total margin debt is the stock-level sum of both formal margin debt and our estimate of shadow margin debt. The mean (median) of the *implied boom return* is 23.4% (15.7%), while the mean (median) of the actual realized return over the same period is 112.7% (110.3%). This suggests that the mean implied return is roughly one-fifth of the actual boom. Moreover, a cross-sectional regression of the realized boom return on the *implied boom return* yields a statistically significant coefficient of 0.141 and an R^2 of 18.2%. This is consistent with the influx of margin debt explaining a sizable fraction of the run-up in stock prices.

Margin Debt and the Bust. We next ask whether margin debt contributed to the bust. Specifically, we ask whether stocks with more margin debt at the peak of the boom experienced larger crashes. Table 7 presents a cross-sectional analysis of margin debt and returns during the crash at the stock level. For this analysis, we define *Crash Return* to be the cumulative return between the peak of the market on June 15th and November 27th, 2015—a 24-week window that captures the crash period. We define *Peak Total Margin* as the level of margin debt relative to floating market capitalization on June 15th, 2015, where total again refers to the sum of formal and shadow margin.

Panel A of Table 7 presents summary statistics and shows that stocks with more margin debt, through formal or informal channels, experienced greater declines. For reference, the average crash return is -42.35% with a standard deviation of 26.89%. The mean of *Peak Total Margin* is 6.69% with a standard deviation of 8.46%. For stocks in the top quintile, the average peak total margin is 16.55%, while for stocks outside of the top quintile the average is 3.71%. On average, these top quintile stocks experienced greater drops in the crash. Panel B shows results of cross-sectional regressions of the stock-level *Crash Return* on variables representing the quantity of margin debt. We control for stock characteristics including the log of floating market capitalization, book-to-market, turnover, and the past month and past year returns (as observed at the end of May 2015).

We see a consistent negative relationship between margin debt and returns during the crash. The coefficient on *Peak Total Margin* is -0.263 and is statistically significant at the 5% level. Alternatively, stocks in the top quintile of formal or total margin debt experienced drops during the crash that were six percentage points larger in magnitude than the average for all other stocks.[34] This suggests that there is a meaningful association between total margin debt and the market bust at the stock level.

Of course, the quantity of margin debt in any particular stock is endogenous, and may partly

[34] Results are similar in terms of sign and statistical significance when focusing only on formal margin debt.

reflect expectations regarding a future downturn or other factors that correlate with crash returns. As such, we are hesitant to attach a causal interpretation to this pattern. Still, this analysis suggests that a greater quantity of margin debt at the peak of the boom was associated with a more substantial bust. This aligns with popular and media narratives that highlight margin lending as a key factor in the crash.[35]

6 Conclusion

Credit expansions often coincide with increased valuations in both housing and stock markets. While a broad set of theories has linked credit to asset prices in both settings, well identified empirical studies have typically focused on housing. This is, at least in part, due to the fact that large and cleanly targeted shocks to credit in stock markets are rare. Because stock markets are much more liquid than housing markets, and deep-pocketed investors may have a more pivotal role in pricing, it is difficult to draw conclusions across contexts.

We confront these challenges using the deregulation and unprecedented expansion of margin lending that took place in China in the first half of the 2010s, which preceded a major boom-bust episode peaking in 2015. Reduced form evidence—exploiting the timing and structure of the deregulation—indicates the presence of a positive causal effect of margin lending, which was anticipated and priced in by mutual funds. In other words, in the Chinese stock market, deep-pocketed investors behave more like front-runners than contrarians. We show that these findings can be rationalized by a canonical stock-trading model. Our estimates suggest that major shocks to the quantity of margin lending impact stock prices.

[35] See, e.g. https://www.wsj.com/articles/chinese-firms-discover-margin-lendings-downside-1435653636

References

ADELINO, MANUEL, SCHOAR, ANTOINETTE, & SEVERINO, FELIPE. 2016. Loan originations and defaults in the mortgage crisis: The role of the middle class. *The Review of Financial Studies*, **29**(7), 1635–1670.

ADELINO, MANUEL, SCHOAR, ANTOINETTE, & SEVERINO, FELIPE. 2023. *Credit supply and house prices: evidence from mortgage market segmentation*. Tech. rept. National Bureau of Economic Research.

ADRIAN, TOBIAS, & SHIN, HYUN SONG. 2010. Liquidity and leverage. *Journal of Financial Intermediation*, **19**(3), 418–437.

ALBANESI, STEFANIA, DEGIORGI, GIACOMO, & NOSAL, JAROMIR. 2022. Credit growth and the financial crisis: A new narrative. *Journal of Monetary Economics*, **132**, 118–139.

ALIBER, ROBERT Z, KINDLEBERGER, CHARLES P, & MCCAULEY, ROBERT NEIL. 2015. *Manias, panics, and crashes: A history of financial crises*. Springer.

ALLEN, FRANKLIN, & GALE, DOUGLAS. 2000. Bubbles and crises. *Economic Journal*, **110**(460), 236–255.

ALLEN, FRANKLIN, BARLEVY, GADI, & GALE, DOUGLAS. 2022. Asset price booms and macroeconomic policy: A risk-shifting approach. *American Economic Journal: Macroeconomics*, **forthcoming**.

AN, LI, LOU, DONG, & SHI, DONGHUI. 2022. Wealth redistribution in bubbles and crashes. *Journal of Monetary Economics*, **126**, 134–153.

ANDERSON, THEODORE WILBUR, & HSIAO, CHENG. 1981. Estimation of dynamic models with error components. *Journal of the American statistical Association*, **76**(375), 598–606.

ARELLANO, MANUEL, & BOND, STEPHEN. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, **58**(2), 277–297.

ARELLANO, MANUEL, & BOVER, OLYMPIA. 1995. Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, **68**(1), 29–51.

BALL, RAY, & BROWN, PHILIP. 1968. An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research*, **6**(2), 159.

BERNANKE, BEN, & GERTLER, MARK. 1989. Agency costs, net worth, and business fluctuations. *American Economic Review*, 14–31.

BERNARD, VICTOR L, & THOMAS, JACOB K. 1989. Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting research*, **27**, 1–36.

BIAN, JIANG, DA, ZHI, HE, ZHIGUO, LOU, DONG, SHUE, KELLY, & ZHOU, HAO. 2023. *The Drivers and Implications of Retail Margin Trading*. Tech. rept. Working paper. University of International Business and Economics.

BORIO, CLAUDIO EV, & LOWE, PHILIP WILLIAM. 2002. Asset prices, financial and monetary stability: exploring the nexus. *Bank for International Settlements.*

CALONICO, SEBASTIAN, CATTANEO, MATIAS D, & TITIUNIK, ROCIO. 2014. Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica*, **82**(6), 2295–2326.

CALONICO, SEBASTIAN, CATTANEO, MATIAS D, FARRELL, MAX H, & TITIUNIK, ROCIO. 2018. Regression discontinuity designs using covariates. *Review of Economics and Statistics*.

CATTANEO, MATIAS D, JANSSON, MICHAEL, & MA, XINWEI. 2018. Manipulation testing based on density discontinuity. *The Stata Journal*, **18**(1), 234–261.

CATTANEO, MATIAS D, IDROBO, NICOLÁS, & TITIUNIK, ROCÍO. 2024. *A practical introduction to regression discontinuity designs: Extensions*. Cambridge University Press.

CHODOROW-REICH, GABRIEL, GUREN, ADAM M, & MCQUADE, TIMOTHY J. 2024. The 2000s housing cycle with 2020 hindsight: A neo-kindlebergerian view. *Review of Economic Studies*, **91**(2), 785–816.

COHEN, LAUREN, FRAZZINI, ANDREA, & MALLOY, CHRISTOPHER. 2008. The small world of investing: Board connections and mutual fund returns. *Journal of Political Economy*, **116**(5), 951–979.

COHEN, RANDOLPH B, GOMPERS, PAUL A, & VUOLTEENAHO, TUOMO. 2002. Who underreacts to cash-flow news? Evidence from trading between individuals and institutions. *Journal of financial Economics*, **66**(2-3), 409–462.

DANIEL, KENT, GRINBLATT, MARK, TITMAN, SHERIDAN, & WERMERS, RUSS. 1997. Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of finance*, **52**(3), 1035–1058.

DE LONG, J BRADFORD, SHLEIFER, ANDREI, SUMMERS, LAWRENCE H, & WALDMANN, ROBERT J. 1990. Noise trader risk in financial markets. *Journal of political Economy*, **98**(4), 703–738.

DELL'ARICCIA, GIOVANNI, & MARQUEZ, ROBERT. 2006. Lending booms and lending standards. *The Journal of Finance*, **61**(5), 2511–2546.

DI MAGGIO, MARCO, & KERMANI, AMIR. 2017. Credit-induced boom and bust. *The Review of Financial Studies*, **30**(11), 3711–3758.

ECKARDT, WALTER L, & ROGOFF, DONALD L. 1976. 100% margins revisited. *The Journal of Finance*, **31**(3), 995–1000.

FAVARA, GIOVANNI, & IMBS, JEAN. 2015. Credit supply and the price of housing. *American Economic Review*, **105**(3), 958–92.

FINK, JOSEF. 2021. A review of the post-earnings-announcement drift. *Journal of Behavioral and Experimental Finance*, **29**, 100446.

FORTUNE, PETER. 2001. Margin lending and stock market volatility. *New England Economic Review*, 3–25.

FOUCAULT, THIERRY, SRAER, DAVID, & THESMAR, DAVID J. 2011. Individual investors and volatility. *The Journal of Finance*, **66**(4), 1369–1406.

GALBRAITH, JOHN KENNETH. 1961. *The great crash 1929*. Houghton Mifflin.

GAO, ZHENYU, JIANG, WENXI, XIONG, WEI A, & XIONG, WEI. 2023. *Daily Momentum and New Investors in an Emerging Stock Market*. Tech. rept. National Bureau of Economic Research.

GEANAKOPLOS, JOHN. 2010. The leverage cycle. *NBER macroeconomics annual*, **24**(1), 1–66.

GENNAIOLI, NICOLA, SHLEIFER, ANDREI, & VISHNY, ROBERT. 2012. Neglected risks, financial innovation, and financial fragility. *Journal of Financial Economics*, **104**(3), 452–468.

GRUNDY, BRUCE D, & MCNICHOLS, MAUREEN. 1989. Trade and the revelation of information through prices and direct disclosure. *The Review of Financial Studies*, **2**(4), 495–526.

HARDOUVELIS, GIKAS A., & PERISTIANI, STAVROS. 1992. Margin Requirements, Speculative Trading, and Stock Price Fluctuations: The Case of Japan. *The Quarterly Journal of Economics*, **107**(4), 1333–1370.

HE, HUA, & WANG, JIANG. 1995. Differential information and dynamic behavior of stock trading volume. *The Review of Financial Studies*, **8**(4), 919–972.

HE, ZHIGUO, & KRISHNAMURTHY, ARVIND. 2013. Intermediary asset pricing. *American Economic Review*, **103**(2), 732–70.

HERRERA, HELIOS, ORDOÑEZ, GUILLERMO, & TREBESCH, CHRISTOPH. 2020. Political booms, financial crises. *Journal of Political economy*, **128**(2), 507–543.

HONG, HARRISON, JIANG, WENXI, WANG, NA, & ZHAO, BIN. 2014. Trading for Status. *The Review of Financial Studies*, **27**(11), 3171–3212.

HSIEH, DAVID A, & MILLER, MERTON H. 1990. Margin regulation and stock market volatility. *The Journal of Finance*, **45**(1), 3–29.

JIANG, WENXI. 2020. Investment Funds in China. *Pages 359–382 of: The Handbook of China's Financial System*. Princeton University Press.

JYLHÄ, PETRI. 2018. Margin requirements and the security market line. *The journal of finance*, **73**(3), 1281–1321.

KAHRAMAN, BIGE, & TOOKES, HEATHER E. 2017. Trader leverage and liquidity. *The Journal of Finance*, **72**(4), 1567–1610.

KAMINSKY, GRACIELA L, & REINHART, CARMEN M. 1999. The twin crises: the causes of banking and balance-of-payments problems. *American Economic Review*, **89**(3), 473–500.

KAPLAN, GREG, MITMAN, KURT, & VIOLANTE, GIOVANNI L. 2020. The housing boom and bust: Model meets evidence. *Journal of Political Economy*, **128**(9), 3285–3345.

KEYS, BENJAMIN J, SERU, AMIT, & VIG, VIKRANT. 2012. Lender screening and the role of securitization: evidence from prime and subprime mortgage markets. *The Review of Financial Studies*, **25**(7), 2071–2108.

KIYOTAKI, NOBUHIRO, & MOORE, JOHN. 1997. Credit Cycles. *Journal of Political Economy*, **105**(2), 211–248.

LIAO, JINGCHI, PENG, CAMERON, & ZHU, NING. 2021. Extrapolative Bubbles and Trading Volume. *The Review of Financial Studies*, **35**(4), 1682–1722.

LIU, XIACHUN. 2015. A massive withdrawal of shadow financing is unlikely to come true (in Chinese). *China Securities Journal*, 12 June.

LU, LERONG, & LU, LONGJIE. 2017. Unveiling China's Stock Market Bubble: Margin Financing, the Leveraged Bull and Governmental Responses. *Journal of International Banking Law and Regulation (2017)*, **32**(4), 146–160.

MALANI, ANUP, & REIF, JULIAN. 2015. Interpreting pre-trends as anticipation: Impact on estimated treatment effects from tort reform. *Journal of Public Economics*, **124**, 1–17.

MCCRARY, JUSTIN. 2008. Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of econometrics*, **142**(2), 698–714.

MIAN, ATIF, & SUFI, AMIR. 2009. The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis. *The Quarterly Journal of Economics*, **124**(4), 1449–1496.

MINSKY, HYMAN P. 1977. The financial instability hypothesis: An interpretation of Keynes and an alternative to standard theory. *Challenge*, **20**(1), 20–27.

MINSKY, HYMAN P, & KAUFMAN, HENRY. 2008. *Stabilizing an unstable economy*. Vol. 1. McGraw-Hill New York.

SCHULARICK, MORITZ, & TAYLOR, ALAN M. 2012. Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review*, **102**(2), 1029–61.

SIMSEK, ALP. 2013. Belief disagreements and collateral constraints. *Econometrica*, **81**(1), 1–53.

STEIN, JEREMY C. 1995. Prices and trading volume in the housing market: A model with down-payment effects. *The Quarterly Journal of Economics*, **110**(2), 379–406.

SUMMERS, LAWRENCE H. 1986. Does the stock market rationally reflect fundamental values? *The Journal of Finance*, **41**(3), 591–601.

Tables and Figures

TABLE 1: NUMBER OF MARGINABLE STOCKS BY VINTAGE

		# of newly marginable		
Vintage	Announcement Date	Shanghai	Shenzhen	% of Floating Cap
Pilot A	February 13th, 2010	50	40	51.74%
Pilot B	November 25th, 2011	131	60	66.31%
1	January 25th, 2013	163	113	75.23%
2	September 6th, 2013	104	102	77.95%
3	September 12th, 2014	104	114	78.48%

TABLE 2: EVENT STUDY OF MARGINABILITY

Panel A: Cumulative Returns Before and After the Introduction of Margin Lending

	Following Marginability			Preceding Marginability			Before vs. After
	0 to 1	0 to 3	0 to 12	-1 to 0	-3 to 0	-12 to 0	-12 to 12
Marginable	0.002	-0.004	0.010	0.019^{***}	0.065^{***}	0.242^{***}	0.255^{***}
	(0.004)	(0.007)	(0.015)	(0.005)	(0.008)	(0.014)	(0.021)
N	4087	4076	3986	4098	4098	4098	3986

Panel B: Placebo Estimates

	Following Marginability			Preceding Marginability			Before vs. After
	0 to 1	0 to 3	0 to 12	-1 to 0	-3 to 0	-12 to 0	-12 to 12
Marginable	-0.001	-0.002	-0.011	0.003	0.014	0.049	0.038
	[-0.013, 0.012]	[-0.023, 0.022]	[-0.053, 0.024]	[-0.008, 0.015]	[-0.014, 0.042]	[-0.024, 0.12]	[-0.058, 0.129]

In Panel A, the first three columns show results from stock level regressions of cumulative DGTW adjusted returns from the month of marginability to 1 month, 3 months, or 12 months after on an indicator equal to one for newly marginable stocks. Columns 4-6 consider from 1, 3, and 12 months preceding the introduction to the month of the introduction itself. Column 7 considers the period from 12 months before to 12 months after the introduction. For each of the three vintages we consider a cross-section that includes the newly marginable stocks in that vintage as well as the set of never marginable stocks. Standard errors, clustered at the stock level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel B provides means from placebo replications of the analysis in Panel A. For each of 1000 placebo draws, we mimic the implementation of the reform. We first draw three random event months in the window between January 1993 and December 2008. At the first event month, we replicate the pilot vintages by selecting the top 150 stocks in each exchange. We then sequentially move through each of the three event dates, assigning the top 100 not-yet-selected stocks in each exchange to vintages 1, 2 and 3. With these vintages defined, we conduct event studies at various horizons that compare the treated stocks to the set of stocks that are *never* treated. All draws are with replacement. Brackets contain empirical 95% confidence intervals, displaying the 2.5th and 97.5th percentiles of the distribution of placebo estimates. In both panels, all specifications include dummy variables for each vintage as controls.

TABLE 3: THE IMPACT OF MARGIN DEBT – REGRESSION DISCONTINUITY EVIDENCE

Panel A: Crossing Marginability Threshold Predicts Margin Debt

	Optimal Bandwidth			Fixed Bandwidth		
	Marginable	Margin	$\frac{\text{Margin}}{\text{Market Cap}}$	Marginable	Margin	$\frac{\text{Margin}}{\text{Market Cap}}$
Above Marginable Threshold	0.959***	0.359***	0.049***	0.970***	0.356***	0.052***
	(0.030)	(0.039)	(0.006)	(0.026)	(0.040)	(0.007)
P-Value	0.000	0.000	0.000	0.000	0.000	0.000
CCT Robust P-Value	0.000	0.000	0.000	0.000	0.000	0.000
Bandwidth	0.121	0.103	0.155	0.100	0.100	0.100
N	191	150	229	158	146	146

Panel B: Positive Returns to Crossing Threshold – Reduced Form

	Optimal Bandwidth			Fixed Bandwidth		
	5 Days	20 Days	60 Days	5 Days	20 Days	60 Days
Above Marginable Threshold	0.046***	0.083**	0.246***	0.046***	0.082**	0.242***
	(0.010)	(0.038)	(0.041)	(0.010)	(0.040)	(0.041)
P-Value	0.000	0.030	0.000	0.000	0.039	0.000
CCT Robust P-Value	0.000	0.056	0.000	0.000	0.136	0.000
Bandwidth	0.104	0.109	0.106	0.100	0.100	0.100
N	152	168	156	147	151	146

Panel C: Positive Returns to Marginability – Fuzzy RD

	Optimal Bandwidth			Fixed Bandwidth		
	5 Days	20 Days	60 Days	5 Days	20 Days	60 Days
Marginable	0.047***	0.085**	0.260***	0.047***	0.085**	0.252***
	(0.010)	(0.041)	(0.043)	(0.010)	(0.041)	(0.044)
P-Value	0.000	0.036	0.000	0.000	0.039	0.000
CCT Robust P-Value	0.000	0.071	0.000	0.000	0.145	0.000
Bandwidth	0.129	0.101	0.115	0.100	0.100	0.100
N	193	154	172	147	151	146

Regression discontinuity estimates based upon crossing the vintage-specific threshold of the index used to determine marginability. For each vintage we include the cross-section of all not previously marginable stocks with inclusion index value within the specified bandwidth of the threshold. In panel A, we consider outcomes 60 trading days after marginability. For panels B and C, we consider cumulative returns 5, 20, and 60 trading days after marginability. The first three columns use the covariate adjusted MSE optimal bandwidths described in Calonico, Cattaneo, Farrell, and Titiunik (2017). The latter three columns use a fixed bandwidth of 0.1. Standard errors clustered at the stock level based upon three nearest neighbor variance estimators described in Calonico, Cattaneo, and Titiunik (2014) are included in parentheses. CCT robust P-Value is based upon robust bias correction described in Calonico, Cattaneo, and Titiunik (2014). All columns include local linear regressions with a triangular kernel on either side of the threshold. We include indicators for vintage and industry as covariates. N refers to the effective number of observations within the relevant bandwidth of the threshold. Marginable is a dummy variable equal to one if the stock became marginable in the relevant vintage. Margin debt refers to the stock level quantity of margin debt in billions of yuan. $\frac{\text{Margin}}{\text{Market Cap}}$ refers to the ratio of margin debt to floating market capitalization. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 4: MUTUAL FUND PORTFOLIO WEIGHTS: ANTICIPATORY BUYING AND POST-MARGINABILITY SELLING

	(1)	(2)	(3)	(4)
Top Quintile$_{i,t}$ $\times$ Months Since Last Vintage$_t$	0.0034***			
	(0.0011)			
Top 150$_{i,t}$ $\times$ Months Since Last Vintage$_t$		0.0027**		
		(0.0011)		
log(Index$_{i,t}$) $\times$ Months Since Last Vintage$_t$			0.0016**	
			(0.0007)	
Marginable$_{i,t}$ $\times$ Months Since Marginable$_{i,t}$				-0.0075***
				(0.0027)
Controls	Yes	Yes	Yes	Yes
Stock Fixed Effect	Yes	Yes	Yes	Yes
Fund Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
N	324860	324860	324860	455846
adj. R^2	0.446	0.446	0.446	0.442

The first three columns of this table report the results of regressions following Equation 5. Top Quintile equals one if the stock is ranked in the top 20% among all non-marginable stocks based on the inclusion index, and zero otherwise. Top 150 equals one if the stock is ranked within the top 150 among all non-marginable stocks based on the inclusion index, and zero otherwise. log($Index$) equals the log of the inclusion index for non-marginable stocks and zero for marginable stocks. Months Since Last Vintage equals the number of months between fund reporting and the previous vintage. The fourth column shows results of regressions following Equation 6. Marginable equals one if stock i is marginable in month t, and zero otherwise. Months Since Marginable equals the number of months since stock i became marginable, as of month t. Controls refer to the percentile ranking of stock characteristics, including floating market capitalization, book-to-market, turnover rate, past month return, and past year return, and the interactions between Months Since Last Vintage and the percentile ranking of each stock characteristic. Fund, stock, and time fixed effects are included in all specifications. The sample period is from December 2011 to June 2014 in columns 1-3 and from December 2011 to June 2015 in column 4. Standard errors are clustered by fund and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 5: RETURNS FOR TO-BE-MARGINABLE (TBM) PORTFOLIOS

	TBM Weight (%)	Raw Return (%)			Mkt-adj. Return (%)			CAPM Alpha (%)			DGTW Return (%)		
		TBM	NTBM	L-S	TBM	NTBM	L-S	TBM	NTBM	L-S	TBM	NTBM	L-S
Top Quintile	12.98	1.646	1.089	0.556	0.830	0.273	0.556	0.844	0.285	0.560	0.546	0.119	0.424
		(2.79)	(2.18)	(2.10)	(2.57)	(1.09)	(2.10)	(2.82)	(1.53)	(2.01)	(2.02)	(0.63)	(1.63)
Top 150	12.41	1.656	1.084	0.558	0.840	0.268	0.558	0.852	0.280	0.557	0.551	0.117	0.416
		(2.81)	(2.18)	(2.11)	(2.53)	(1.08)	(2.11)	(2.76)	(1.53)	(1.98)	(1.92)	(0.63)	(1.58)

This table reports returns of mutual funds' TBM, NTBM, and long-TBM-short-NTBM portfolios. For each semi-annual report, stocks in each mutual fund's portfolio are assigned to one of two portfolios: "to-be-marginable" (TBM) and Non-TBM (NTBM). TBM companies are defined as stocks that are ranked within the Top Quintile or Top 150 in each exchange based on the inclusion index. We compute the monthly returns on TBM and NTBM holdings over the next six months and also returns of strategies that long TBM and short NTBM (L-S). Portfolios are rebalanced every six months, and within a given fund portfolio, stocks are value weighted by the funds dollar holdings. Calendar time portfolio returns are calculated by averaging across funds. We use raw returns, market-adjusted returns, CAPM alpha, and DGTW returns. Market-adjusted returns equal the raw return minus value-weighted market returns. CAPM alpha is the intercept on a regression of monthly portfolio excess returns on the market factor. DGTW style adjustments use independent sorts of quintiles of size, book-to-market, and past 12-month return to get 125 portfolios, each stock is assigned to one of these 125 bins, and the value-weighted returns in each bin then serve as the benchmark for that stock's adjustment. TBM Weight (%) is the average portfolio weight of all TBM stocks. The sample period is from January 2012 to September 2014. Newey-West standard errors are used with a lag of 11 months and are reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 6: INFORMATION REVELATION MODEL OF ANTICIPATION

	Non-Linear Estimation				Linear Estimation			
	Excess Δ Price		TWFE		OLS		2SLS	
	Base	Full	Base	Full	Base	Full	Base	Full
θ	1.057^{***}	1.051^{***}	1.099^{***}	1.069^{***}				
	(0.019)	(0.030)	(0.033)	(0.028)				
$\frac{1}{\theta}$					0.880^{***}	0.883^{***}	0.935^{***}	0.944^{***}
					(0.005)	(0.005)	(0.030)	(0.034)
δ_1	0.021^{***}	0.010^{***}	0.025^{***}	0.015^{***}	0.031^{***}	0.013^{***}	0.025^{***}	0.011^{***}
	(0.004)	(0.003)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)
θ	1.057	1.051	1.099	1.069	1.136	1.133	1.069	1.059
Direct Effect	0.382	0.199	0.275	0.227	0.257	0.108	0.393	0.200
First Stage F-Stat (Kleibergen-Paap)							31.4	20.3
Month × Year Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Stock Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes

The first four columns show estimates from the exponential regression outlined in Equation 9: $\Delta p_{it}^{treated} = \delta_1 \theta^t + \Delta\varepsilon_{it}$. Here, t represents the relative time until stock i becomes marginable. We estimate this for each treated stock in the period $t \leq 0$. In the first two columns, $\Delta p_{it}^{treated}$ is measured as the excess price difference, relative to the group of never-marginable control stocks. In the columns labeled TWFE, $\Delta p_{it}^{treated}$ is measured as the price difference residualized with respect to stock and month×year fixed effects. In the remaining regressions, we report coefficients and recovered parameters from the linear specification outlined in Equation 10: $p_{it} = \delta_1 D_{it} + \delta_2 p_{it+1} + \alpha_i + \eta_t + e_{it}$. D_{it} is equal to one only for stocks that are included in the margin trading roll-out in months after margin trading is active. The columns labeled OLS show OLS estimates, and columns labeled IV show two stage least squares estimates with leads $t+2$ and $t+3$ of Margin Trading Active as instruments. Derived parameters are $\theta = \frac{1}{\delta_2}$ and Direct Effect$= \frac{\delta_1}{1-\delta_2}$. We use monthly data from March 2009 to October 2015, and normalize stock prices throughout with the price in March 2009, the first month in our sample. Columns labeled base exclude the pilot vintages, while columns labeled full include the pilot vintages. Standard errors are clustered at the stock level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 7: MARGIN DEBT AND THE BUST

Panel A: Summary Statistics

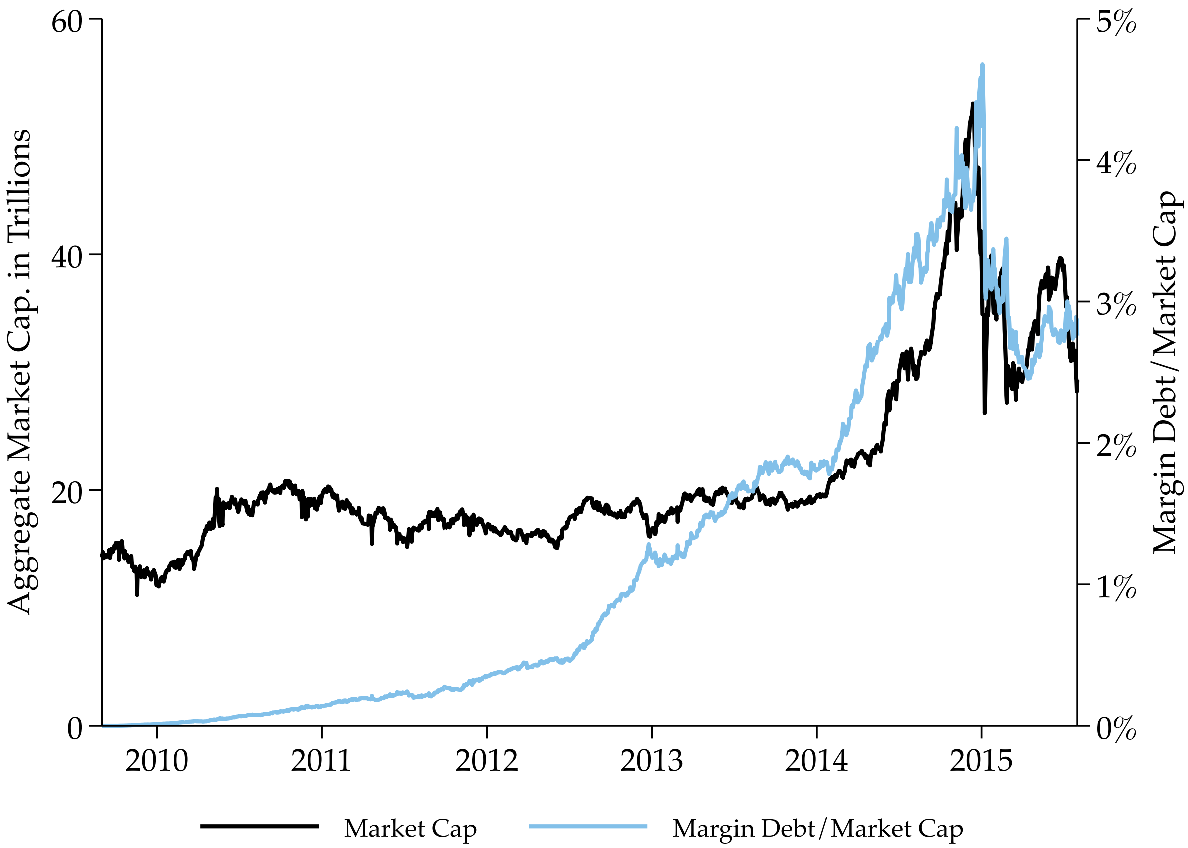
		Crash Return	Peak Total
All stocks			
	Mean	-42.35%	6.69%
	Median	-46.58%	4.64%
	SD	26.89%	8.46%
Sort on Peak Total Margin			
Top Quintile	Mean	-48.54%	16.55%
	Median	-50.68%	13.35%
	SD	21.24%	12.52%
Others	Mean	-40.48%	3.71%
	Median	-44.82%	3.14%
	SD	28.12%	2.76%

Panel B: Regressions of Crash Returns on Margin Debt at the Peak

	(1)	(2)
Peak Total Margin	-0.263**	
	(0.117)	
Top Quintile(Peak Total Margin)		-0.060***
		(0.014)
Controls	Yes	Yes
N	1645	1645

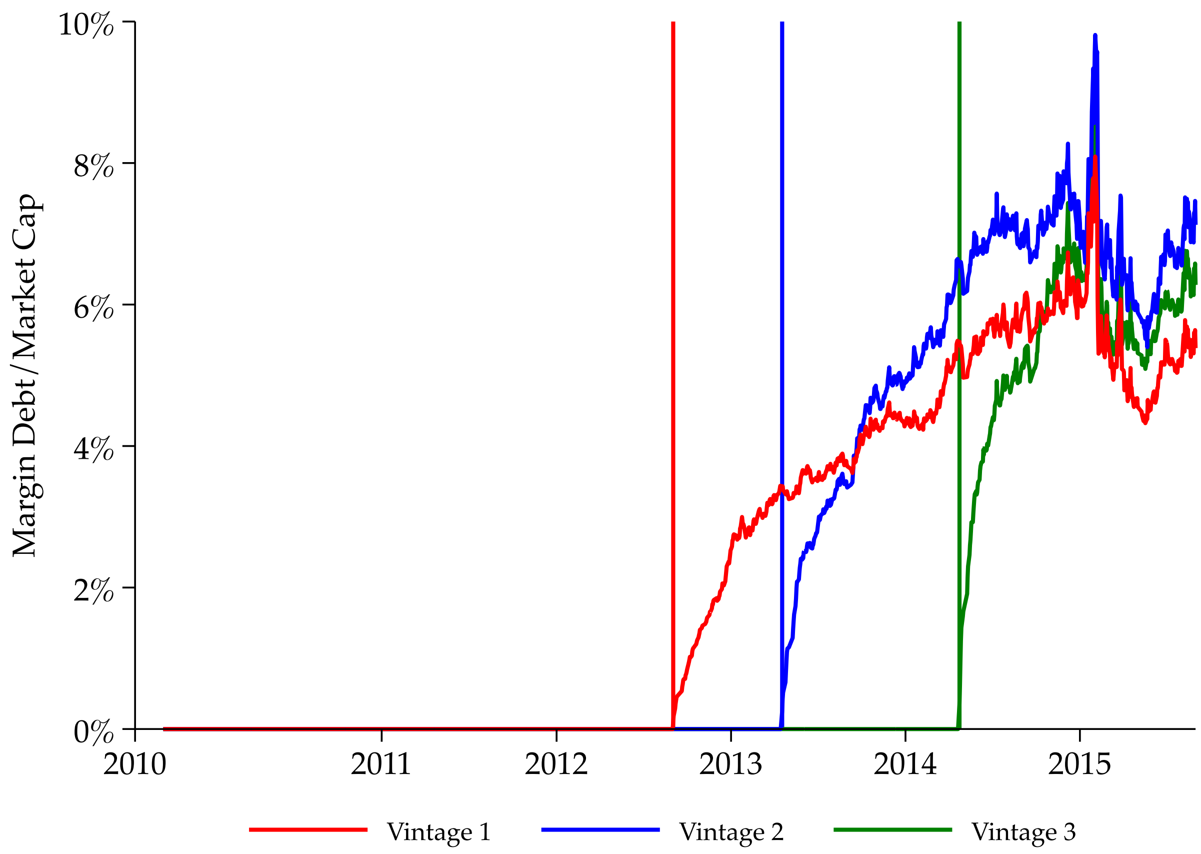
Crash Return refers to the cumulative log return between the peak of margin debt on June 15 and November 27, 2015, a 24-week window capturing the crash period. *Peak Total Margin* refers to the level of formal and shadow margin debt relative to floating market capitalization on June 15, 2015. Panel A shows summary statistics for the bust period. Panel B reports regression results of *Crash Return* on on *Peak Total Margin* in column (1), and on an indicator equal to one if a stock is in the top quintile of *Peak Total Margin* in column (2). We control for stock characteristics including size, book-to-market, the past month return, the past year return, and turnover. Robust standard errors are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE 1: AGGREGATE MARKET CAP. AND MARGIN DEBT/MARKET CAP. OVER TIME



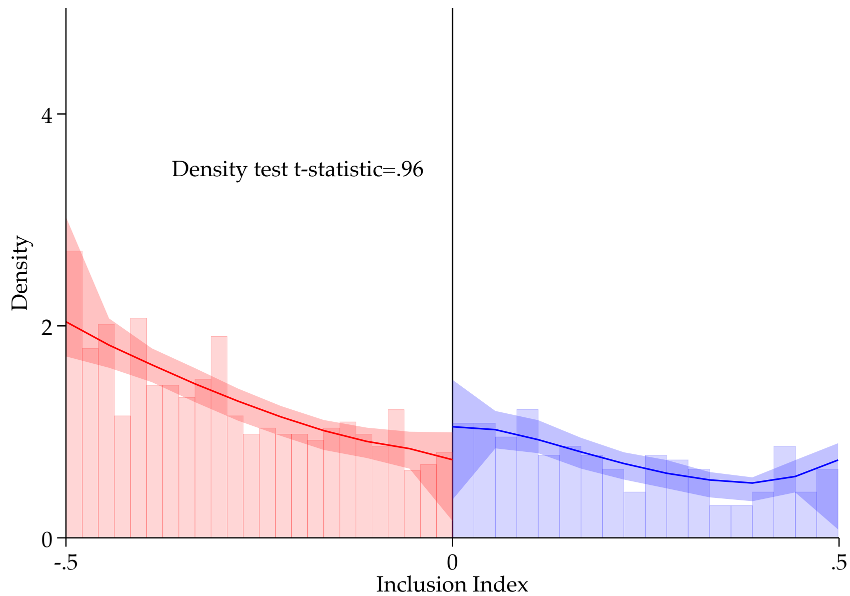
Notes: This plot shows daily aggregate floating market capitalization (in black) and the ratio of aggregate margin debt to aggregate floating market capitalization (in blue) for all stocks in our sample, including those that are never marginable. Floating market capitalization is measured in trillions of yuan.

FIGURE 2: MARGIN DEBT/MARKET CAP. BY VINTAGE



Notes: This plot shows the daily ratio of aggregate margin debt to aggregate floating market capitalization for the three vintages we study. Vertical lines denote starting dates of each vintage.

FIGURE 3: NO EVIDENCE OF BUNCHING AT THRESHOLD

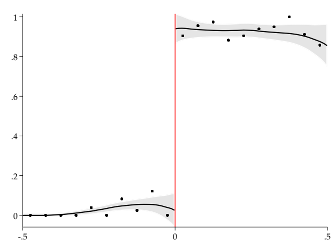


Notes: This plot shows the results of the manipulation tests outlined in Cattaneo *et al.* (2018). Red and blue bars show a histogram of the underlying data, while red and blue lines show local polynomial estimates of the density. We report the robust, bias corrected t-statistic.

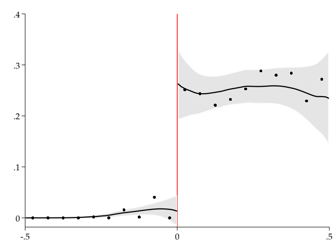
Figure 4: RD Evidence of Impacts of Margin Lending on Equity Prices

Panel A: Inclusion Index Determines Marginability

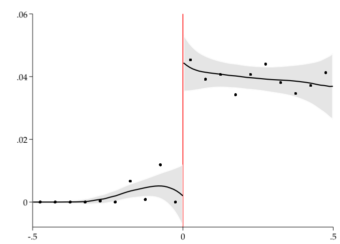
Marginability



Margin Debt

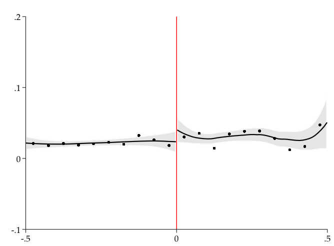


Margin Debt/Market Cap

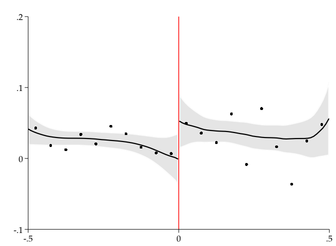


Panel B: Positive Returns to Crossing Marginability Threshold

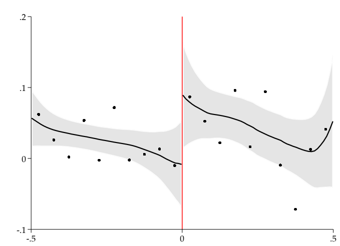
5 Trading Days



20 Trading Days



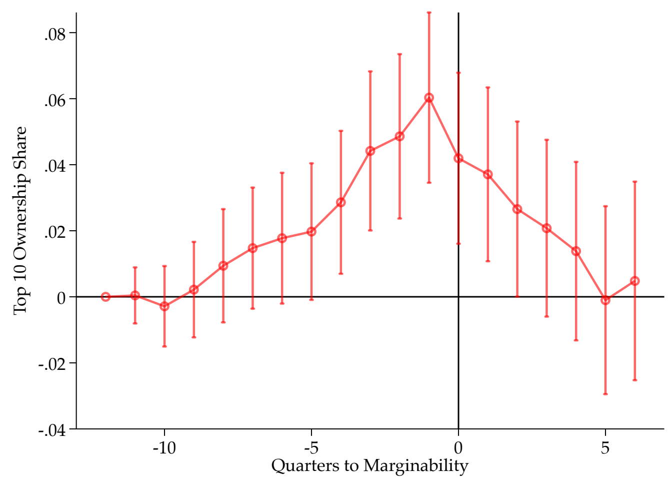
60 Trading Days



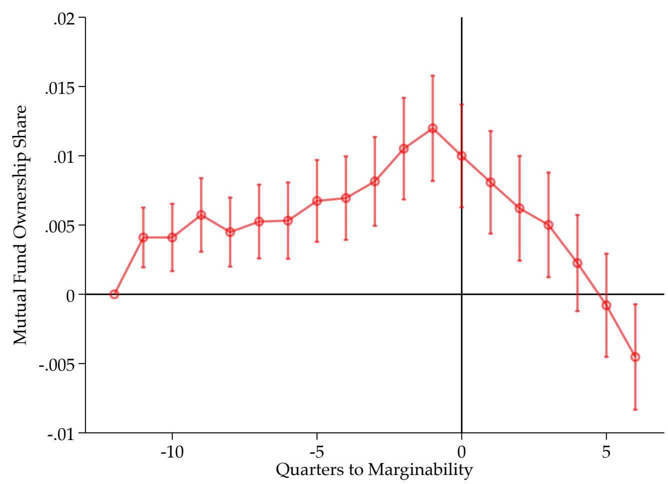
Notes: Panel (a) shows an indicator for marginability, the quantity of margin debt at the stock level, and the stock level ratio of margin debt to floating market capitalization plotted against the inclusion index. Panel (b) shows cumulative returns. The inclusion index is re-centered to set each vintage specific threshold equal to 0. For each vintage, all not-yet marginable stocks with inclusion index within 0.5 of the threshold at the time marginability was determined are included. Marginability, floating market capitalization, and margin debt are measured 60 trading days following the start of each vintage. Points show binned means in equal intervals. Lines shows local linear fits with 95% confidence intervals on either side of the threshold.

Figure 5: Institutional Owners Bought Before the Introduction of Margin Debt and Sold Afterwards

Panel A: Ownership Share of Top 10 Investors



Panel B: Mutual Fund Ownership Share



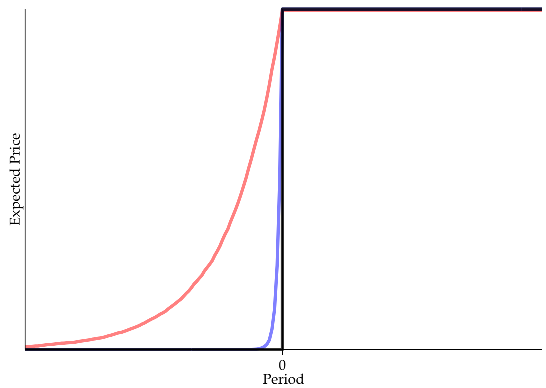
Notes: Coefficients from event-study regressions of ownership by institutions in the quarters surrounding the introduction of margin debt. For each vintage k, we construct a panel of all stocks that become marginable in k (treated stocks) and all never marginable stocks from 12 quarters before the introduction to 6 quarters after. We stack these panels, and plot the coefficients from the following regression for stock j in vintage k and quarter t:

$$\text{Ownership Share}_{jkt} = \sum_{\ell} \beta_\ell \times \mathbb{1}\{t - \tau(k) = \ell\} \times \text{Treated}_{jk} + \gamma_{jk} + \lambda_{tk} + \varepsilon_{jkt}.$$

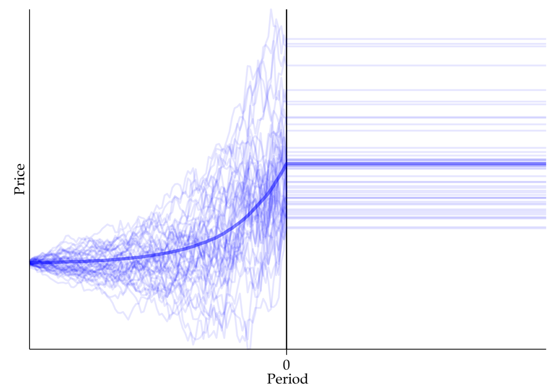
ℓ runs from -11 to 6, with 12 quarters prior to the introduction acting as the omitted group. $\mathbb{1}\{t - \tau(k) = \ell\}$ is an indicator equal to one if the difference between quarter t and the implementation date $\tau(k)$ of vintage k is ℓ. The dependent variables are the stock-level share of ownership by the top 10 investors (panel A) or mutual funds (panel B). Bars represent 95% confidence intervals based on standard errors clustered at the stock level.

Figure 6: Anticipating an Increase in Credit Supply

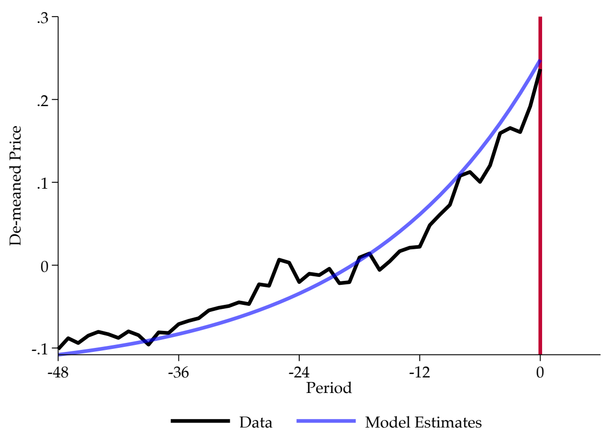
Panel A: Varying the Rate of Anticipation



Panel B: Simulated Price Paths for Treated Stocks



Panel C: Comparing the Model to the Data



Notes: In all figures the y-axis displays price, the x-axis displays time, and the vertical line indicates the event date of a credit supply shock. Panel A shows the expected price path for stocks receiving a credit supply shock at time 0 under three regimes (holding the total price effect constant). The black line shows the expected price path from a model with no anticipation. The blue line shows the expected price path from a version of our model with a large value of θ. The red line shows the expected price path from a low value of θ. Panel B shows price realizations for treated stocks from simulations based on our model. Each lighter blue line represents the price path for an individual stock. The thicker blue line represents the average price for all treated stocks in each period. Panel C plots, in black, average prices for the stocks in vintages 1-3, after normalizing relative to the first month in our sample (March, 2009) and residualizing with respect to stock and month fixed effects (using the set of never-marginable stocks as a control group). In blue, the plot shows the (de-meaned) model implied price path estimated using the same data.

Internet Appendix: For Online Publication

A Appendix Tables and Figures

TABLE A.I: THE USE OF FORMAL AND SHADOW MARGIN IN ELIGIBLE STOCKS

in %	Mean	SD	P25	P50	P75
Formal Margin/Market Cap	6.21	3.86	3.13	5.39	8.79
Shadow Margin/Market Cap	0.63	2.24	0.00	0.07	0.33
N	658				

This table shows summary statistics on the ratio of formal or shadow margin debt to floating market capitalization (in percentage terms) for stocks that qualified for formal margin as of 09/19/2014, the trading day before the rollout of the third vintage. Our data on shadow margin is derived from one of the major providers in the Chinese system, representing roughly 5% of the market. We multiply the observed quantities from this provider by a factor of 20 to estimate the total shadow margin outstanding. Our data on formal margin comes directly from the exchanges. We winsorize both at the 99th percentile day-by-day.

TABLE A.II: ROBUSTNESS FOR EVENT STUDY OF MARGINABILITY

	Panel A: Event Study Including All Not-Yet Marginable Stocks in Control Group						
	Following Marginability			Preceding Marginability			Before vs. After
	0 to 1	0 to 3	0 to 12	-1 to 0	-3 to 0	-12 to 0	-12 to 12
Marginable	-0.000	-0.013^{*}	-0.023	0.016^{***}	0.059^{***}	0.229^{***}	0.207^{***}
	(0.004)	(0.007)	(0.015)	(0.005)	(0.008)	(0.014)	(0.020)
N	4578	4565	4475	4586	4586	4586	4475

	Panel B: Means of One Factor Adjusted Cumulative Abnormal Returns						
	Following Marginability			Preceding Marginability			Before vs. After
	0 to 1	0 to 3	0 to 12	-1 to 0	-3 to 0	-12 to 0	-12 to 12
Cumulative Abnormal Return	0.009	-0.021	0.044	0.012^{*}	0.026^{*}	0.258^{***}	0.302^{***}
	(0.006)	(0.015)	(0.041)	(0.006)	(0.013)	(0.040)	(0.078)
N	475	475	475	475	475	475	475

	Panel C: Event Study for High vs. Low Ranking Stocks						
	Following Marginability			Preceding Marginability			Before vs. After
	0 to 1	0 to 3	0 to 12	-1 to 0	-3 to 0	-12 to 0	-12 to 12
Low Ranking	0.000	0.008	0.012	0.013^{*}	0.047^{***}	0.172^{***}	0.184^{***}
	(0.005)	(0.010)	(0.020)	(0.007)	(0.010)	(0.018)	(0.028)
High Ranking	0.002	-0.020^{*}	0.009	0.024^{***}	0.085^{***}	0.316^{***}	0.327^{***}
	(0.006)	(0.010)	(0.021)	(0.006)	(0.011)	(0.019)	(0.028)
N	4087	4076	3986	4098	4098	4098	3986

In Panels A and C, the first three columns show results from stock level regressions of cumulative DGTW adjusted returns from the month of marginability to 1 month, 3 months, or 12 months after on an indicator equal to one for newly marginable stocks (Panel A) or a set of dummies equal to one for newly marginable stocks that are above or below the median of the relevant exchange and vintage according to the inclusion index (Panel C). Columns 4-6 consider from 1, 3, and 12 months preceding the introduction to the month of the introduction itself. Column 7 considers the period from 12 months before to 12 months after the introduction. In Panel A, we consider a cross-section for each of the three vintages that includes the newly marginable stocks in that vintage as well as the set of not-yet marginable stocks, including those that became marginable in a later vintage. All specifications include dummy variables for each vintage as controls. Panel B presents one-factor adjusted event studies preceding and following the deregulation of margin debt. The first three columns show average cumulative abnormal returns for marginable stocks one, three, and 12 months after marginability. Columns 4-6 show average cumulative abnormal returns in the month before, three months before, and 12 months before marginability. The final column shows cumulative abnormal returns from 12 months before to 12 months after marginability. β for adjustment calculated in the 3 months prior to the 12 month window before the event date for each vintage. In Panel C, we consider a cross-section for each of the three vintages that includes the newly marginable stocks in that vintage as well as the set of never marginable stocks. All specifications include dummy variables for each vintage as controls. Standard errors, clustered at the stock level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.III: NO DISCONTINUITY IN STOCK LEVEL COVARIATES ACROSS THRESHOLD
BALANCE SHEET VARIABLES IN T-1

	Total Assets	Fixed Assets	Current Assets	Total Debt	Total Equity	Leverage (D/E)
Above Marginable Threshold	-0.441	-0.077	-1.024	-0.635	0.280	-0.313
	(3.034)	(0.806)	(1.971)	(2.137)	(1.032)	(0.404)
P-Value	0.884	0.924	0.603	0.766	0.786	0.439
CCT Robust P-Value	0.923	0.888	0.744	0.834	0.696	0.520
Bandwidth	0.151	0.118	0.149	0.146	0.197	0.129
N	211	172	209	208	273	184

	Sales Growth	Net Profit	Market-to-Book	Price-to-Earnings	ROE	ROA
Above Marginable Threshold	0.008	0.238^{*}	0.460	-44.309	-0.002	0.019
	(0.132)	(0.133)	(0.504)	(36.547)	(0.051)	(0.014)
P-Value	0.950	0.072	0.362	0.225	0.962	0.197
CCT Robust P-Value	0.939	0.095	0.335	0.275	0.824	0.324
Bandwidth	0.122	0.112	0.120	0.139	0.112	0.114
N	171	162	173	197	162	165

Regression discontinuity estimates based upon crossing the vintage-specific threshold of the index used to determine marginability. For each vintage we include all not previously marginable stocks in our primary sample with inclusion index value within the specified bandwidth of the threshold at the time marginability was determined. We consider covariates in the year prior to marginability. All columns include local linear regressions with a triangular kernel on either side of the threshold and the covariate adjusted MSE optimal bandwidths described in Calonico, Cattaneo, Farrell, and Titiunik (2017). We include indicators for vintage and industry as covariates. Standard errors clustered at the stock level based upon the three nearest neighbor variance estimators described in Calonico, Cattaneo, and Titiunik (2014) are included in parentheses. CCT robust P-Value is based upon robust bias correction described in Calonico, Cattaneo, and Titiunik (2014). N refers to the effective number of observations within the relevant bandwidth of the threshold. Asset, debt, equity and profit measures are scaled in billions (RMB). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.IV: ROBUSTNESS FOR REGRESSION DISCONTINUITY

Panel A: Alternative Specifications for First Stage

	Alternative Kernel			Minimal Controls		
	Marginable	Margin	$\frac{\text{Margin}}{\text{Market Cap}}$	Marginable	Margin	$\frac{\text{Margin}}{\text{Market Cap}}$
Above Marginable Threshold	0.942^{***}	0.329^{***}	0.048^{***}	0.943^{***}	0.289^{***}	0.047^{***}
	(0.032)	(0.046)	(0.006)	(0.043)	(0.041)	(0.007)
P-Value	0.000	0.000	0.000	0.000	0.000	0.000
CCT Robust P-Value	0.000	0.000	0.000	0.000	0.000	0.000
Bandwidth	0.0752	0.0722	0.120	0.127	0.149	0.149
N	112	95	178	200	223	222

Panel B: Alternative Specifications for Reduced Form

	Alternative Kernel			Minimal Controls		
	5 Days	20 Days	60 Days	5 Days	20 Days	60 Days
Above Marginable Threshold	0.046^{***}	0.094^{**}	0.237^{***}	0.026^{*}	0.069^{*}	0.153^{***}
	(0.010)	(0.038)	(0.049)	(0.014)	(0.041)	(0.053)
P-Value	0.000	0.014	0.000	0.073	0.093	0.004
CCT Robust P-Value	0.000	0.024	0.000	0.094	0.114	0.006
Bandwidth	0.0740	0.0953	0.0815	0.123	0.130	0.115
N	101	144	118	182	196	171

Panel C: Alternative Return Adjustments for Reduced Form

	Market Adjusted			DGTW Adjusted		
	5 Days	20 Days	60 Days	5 Days	20 Days	60 Days
Above Marginable Threshold	0.045^{***}	0.084^{**}	0.228^{***}	0.035^{***}	0.066^{**}	0.163^{***}
	(0.010)	(0.038)	(0.040)	(0.008)	(0.032)	(0.038)
P-Value	0.000	0.027	0.000	0.000	0.040	0.000
CCT Robust P-Value	0.000	0.052	0.000	0.000	0.060	0.000
Bandwidth	0.104	0.111	0.108	0.0991	0.0930	0.0961
N	152	171	160	147	138	138

Regression discontinuity estimates based upon crossing the vintage-specific threshold of the index used to determine marginability. For each vintage we include the cross-section of all not previously marginable stocks with inclusion index value within the specified bandwidth of the threshold. In Panel A, we consider outcomes 60 trading days after marginability. For Panels B and C, we consider returns 5, 20, and 60 days after marginability. All columns use the covariate adjusted MSE optimal bandwidths described in Calonico, Cattaneo, Farrell, and Titiunik (2017) and include standard errors clustered at the stock level based upon the three nearest neighbor variance estimators described in Calonico, Cattaneo, and Titiunik (2014) in parentheses. CCT robust P-Value is based upon robust bias correction described in Calonico, Cattaneo, and Titiunik (2014). N refers to the effective number of observations within the relevant bandwidth of the threshold. Marginable is a dummy variable equal to one if the stock became marginable in the relevant vintage. Margin debt refers to the stock level quantity of margin debt in billions of yuan. $\frac{\text{Margin}}{\text{Market Cap}}$ refers to the ratio of margin debt to floating market capitalization. All specifications are identical to the baseline estimates in the first three columns of Table 3 except for a single modification. In the first three columns of panels A and B we use a local linear approach with a uniform kernel instead of the triangular kernel used in our baseline. In the remaining three columns we exclude industry fixed effects. In Panel C we use alternative return adjustments for the dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.V: Heterogeneity In RD Estimates by Stock Characteristics

	Momentum		Sales Growth		Profits		Price-to-Earnings	
	Below Median	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median	Above Median
Above Marginable Threshold	0.109	0.257***	0.064	0.261***	0.106	0.281***	0.204**	0.124
	(0.094)	(0.075)	(0.066)	(0.080)	(0.081)	(0.084)	(0.088)	(0.089)
Bandwidth	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
N	72	70	61	67	69	63	64	68

Regression discontinuity estimates based upon crossing the vintage-specific threshold of the index used to determine marginability. For each vintage we include the cross-section of all not previously marginable stocks with inclusion index value within the specified bandwidth of the threshold. We consider cumulative returns through 60 trading days after marginability. In all specifications, we fix the bandwidth at 0.1. Standard errors clustered at the stock level based upon the three nearest neighbor variance estimators described in Calonico, Cattaneo, and Titiunik (2014) are included in parentheses. All columns feature local linear regressions with a triangular kernel on either side of the threshold and include indicators for vintage as covariates. N refers to the effective number of observations within the relevant bandwidth of the threshold. Momentum refers to returns in the month prior to the introduction. We measure all other stock characteristic the year prior to the introduction of the vintage. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.VI: INSTITUTIONAL OWNERS BUY BEFORE MARGINABILITY AND SELL AFTERWARDS

	Mutual Fund Ownership Share		Top 10 Ownership Share	
6 Quarters After	0.005	-0.013	-0.005**	-0.010***
	(0.015)	(0.014)	(0.002)	(0.002)
5 Quarters After	-0.001	-0.017	-0.001	-0.006***
	(0.015)	(0.013)	(0.002)	(0.002)
4 Quarters After	0.014	-0.005	0.002	-0.003*
	(0.014)	(0.012)	(0.002)	(0.002)
3 Quarters After	0.021	0.002	0.005***	-0.000
	(0.014)	(0.011)	(0.002)	(0.002)
2 Quarters After	0.027**	0.008	0.006***	0.001
	(0.014)	(0.011)	(0.002)	(0.002)
1 Quarter After	0.037***	0.019*	0.008***	0.003
	(0.013)	(0.010)	(0.002)	(0.002)
Event Quarter	0.042***	0.024**	0.010***	0.005***
	(0.013)	(0.010)	(0.002)	(0.002)
1 Quarter Before	0.060***	0.042***	0.012***	0.007***
	(0.013)	(0.010)	(0.002)	(0.002)
2 Quarters Before	0.049***	0.030***	0.011***	0.005***
	(0.013)	(0.009)	(0.002)	(0.002)
3 Quarters Before	0.044***	0.026***	0.008***	0.003**
	(0.012)	(0.008)	(0.002)	(0.001)
4 Quarters Before	0.029***	0.011*	0.007***	0.002
	(0.011)	(0.006)	(0.002)	(0.001)
5 Quarters Before	0.020*	0.001	0.007***	0.001**
	(0.011)	(0.005)	(0.002)	(0.001)
6 Quarters Before	0.018*		0.005***	
	(0.010)		(0.001)	
7 Quarters Before	0.015		0.005***	
	(0.009)		(0.001)	
8 Quarters Before	0.009		0.004***	
	(0.009)		(0.001)	
9 Quarters Before	0.002		0.006***	
	(0.007)		(0.001)	
10 Quarters Before	-0.003		0.004***	
	(0.006)		(0.001)	
11 Quarters Before	0.000		0.004***	
	(0.004)		(0.001)	
N	69652	48994	69814	49127

Results from stacked event-study regressions in the quarters surrounding the introduction of margin debt. For vintage k, we construct a panel of all stocks that become marginable in k (treated stocks) and all never marginable stocks (control stocks) from 6 (or 12) quarters before the introduction to 6 quarters after. We then show the coefficients from the following regression for stock j in vintage k and quarter t:

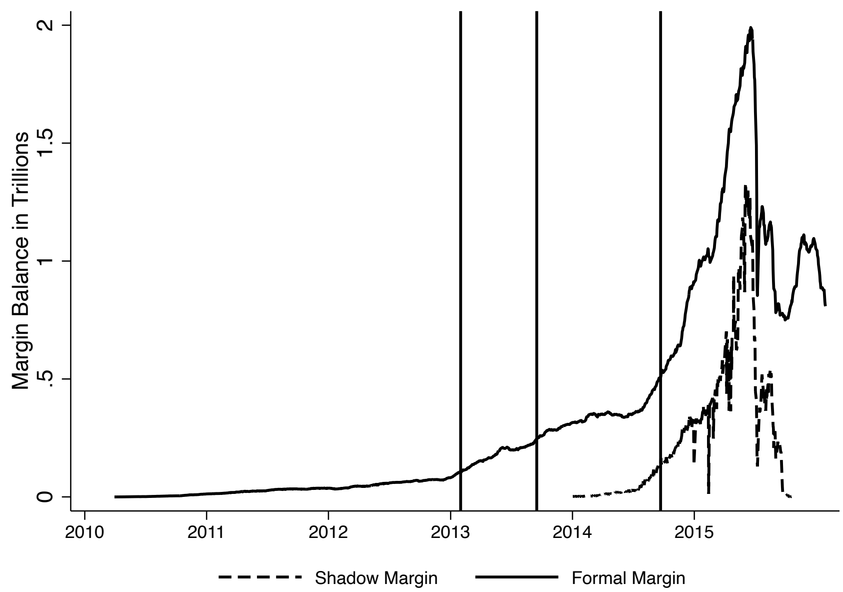
$$\text{Ownership Share}_{jkt} = \sum_{\ell} \beta_\ell \times \mathbb{1}\{t - \tau(k) = \ell\} \times \text{Treated}_{jk} + \gamma_{jk} + \lambda_{tk} + \varepsilon_{jkt}.$$

ℓ runs from -5 or -11 to 6, with the quarter 6 or 12 months prior to the introduction acting as the omitted group. $\mathbb{1}\{t - \tau(k) = \ell\}$ is an indicator equal to one if the difference between quarter t and the implementation quarter $\tau(k)$ of vintage k is ℓ. The dependent variables are the stock-level share of ownership by the top 10 investors and the stock level share of ownership by mutual funds. Standard errors, clustered at the stock level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE A.I: AGGREGATE MARKET CAP. AND SHORTED SHARES/MARKET CAP. OVER TIME

Notes: This plot shows daily aggregate floating market capitalization (in black) and the ratio of the value of all shorted shares to floating market capitalization (in red) for all stocks in our sample. Market cap is measured in trillions of yuan.

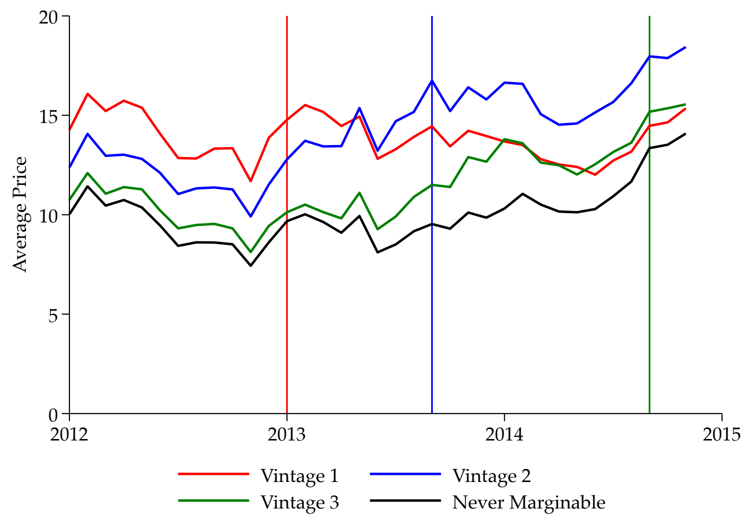
FIGURE A.II: COMPARING THE LEVELS OF SHADOW AND FORMAL MARGIN DEBT



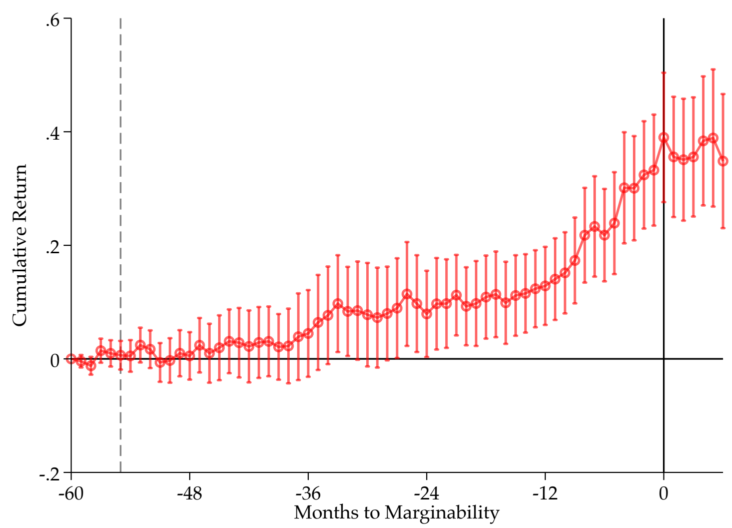
Notes: This plot shows the total amount of formal and shadow margin debt from 2010 to 2015. Formal margin is defined as the sum of brokerage provided margin debt across all marginable stocks, based on data provided by the stock exchanges. Our data on shadow margin is derived from one of the major providers in the Chinese system, representing roughly 5% of the market. The data is available beginning January 1, 2014. We multiply the observed quantities from this provider by a factor of 20 to estimate the total shadow margin outstanding.

FIGURE A.III: GRAPHICAL EVIDENCE OF ANTICIPATION

PANEL A: RAW PRICES VINTAGE BY VINTAGE



PANEL B: DIFFERENTIAL RETURNS OVER A LONG HORIZON

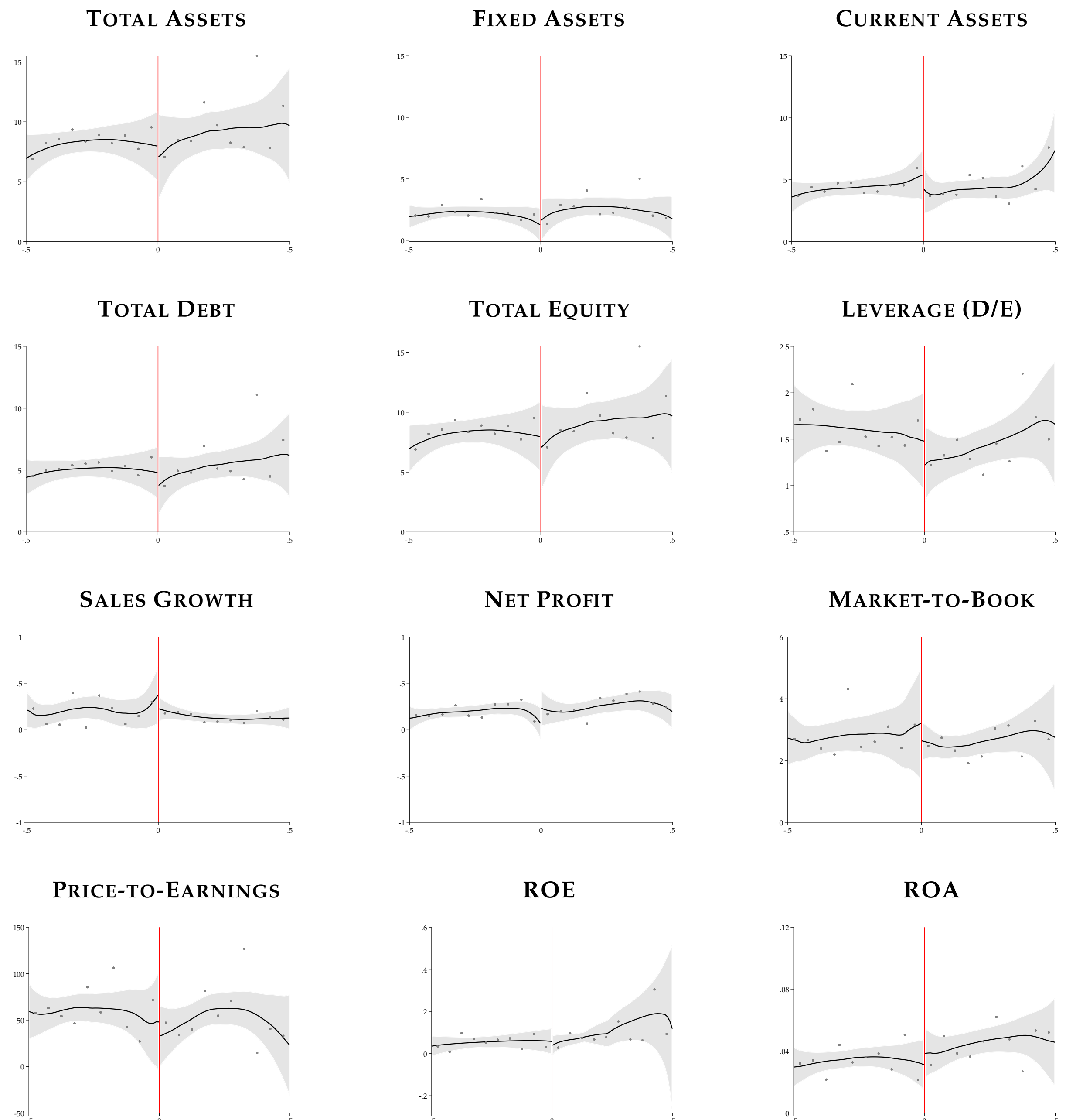


Notes: Panel A plots the average price between 2012 and 2014 for each vintage, as well as the set of never marginable stocks. Vertical lines represent the deregulation month for each vintage. Panel B plots the coefficients β_ℓ from the following regression for stock j, vintage k, and month t:

$$Ret_{ikt} = \sum_{\ell} \beta_\ell \times \mathbb{1}\{t - \tau(k) = \ell\} \times Treated_{ik} + \gamma_{ik} + \lambda_{tk} + \varepsilon_{ikt}.$$

Foreach vintage k, we construct a monthly panel that includes (i) all marginable stocks and (ii) all never marginable stocks, covering from 60 months before to 6 months after the implementation date for k. We then stack these panels and estimate a single regression with stock-vintage and vintage-month fixed effects. Ret_{ikt} represents the cumulative gross return from the first month of the panel for each stock. $\mathbb{1}\{t - \tau(k) = \ell\}$ is an indicator equal to one if the difference between month t and the implementation month $\tau(k)$ of vintage k is ℓ. We cluster standard errors at the stock level and show 95% confidence intervals.

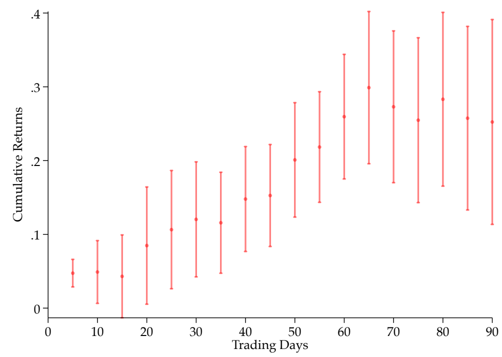
Figure A.IV: Covariates Are Smooth Cross the RD Threshold



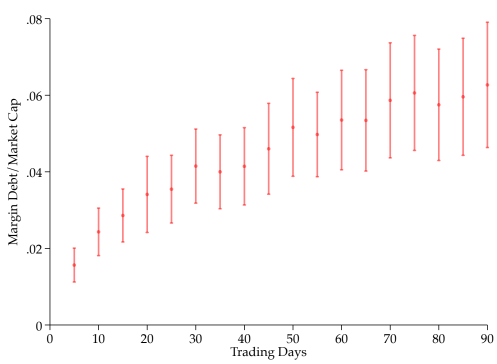
Notes: For each vintage, we consider all not-yet marginable stocks with inclusion index within 0.5 of the threshold at the time marginability was determined. We measure all covariates in the year prior to the rollout of the corresponding vintage. Points show binned means in equal intervals. Lines shows local linear fits with 95% confidence intervals on either side of the threshold. Asset, debt, equity and profit measures are scaled in billions of yuan.

Figure A.V: Post-Implementation Growth in Margin Debt and Realized Returns

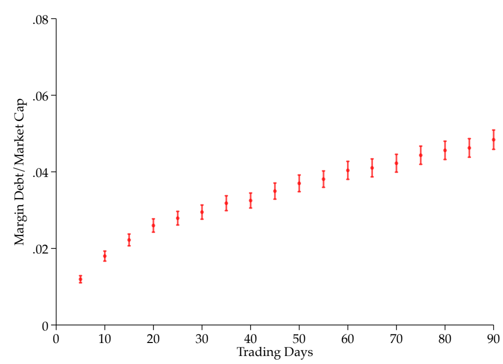
Panel A: Cumulative Returns (RD)



Panel B: Margin Debt/Market Cap (RD)



Panel C: Average Margin Debt/Market Cap



Notes: Panels A and B plot the coefficients from our regression discontinuity design with the dependent variable (cumulative returns or the ratio of margin debt to market cap) measured at various horizons. Other than the horizon, coefficients in Panel A are from specifications identical to the first three columns in the second panel of Table 3. Similarly, other than the horizon, coefficients in Panel B are identical to those in column 3 of the first panel of Table 3. Panel C shows the average ratio of margin debt to floating market cap for all newly marginable stocks in the trading days following the introduction of margin debt. Error bars show 95% confidence intervals.

B Details of Regression Discontinuity

B.1 Defining the Inclusion Index and Marginability Threshold

To construct the inclusion index, we use public stock market data and follow the screening and ranking procedure discussed in Section 2.1. We begin by removing the set of stocks that failed to satisfy the screening criteria. To construct the index itself, we must choose the window in which to measure the key inputs: floating market capitalization and turnover. While the exact window used by regulators was not published, industry sources suggest that the exchanges used a three-month period before the formal announcement of each vintage. There was at least some small gap (five to ten trading days) between data collection and the formal announcement; we choose the three-month window that generates the strongest prediction in the first stage regression for each vintage and exchange. For all but the first vintage, this corresponds to the three calendar months prior to the announcement. For each of the three vintages we calculate the inclusion index for the full set of stocks that had not yet qualified for margin (and satisfied the screening criteria). We denote stock i's index for vintage k as $Index_i^k$, where $k = \{1, 2, 3\}$.

Officially published documents included Equation 1 with the weights $\theta = 2$ and $\gamma = 1$. While this formula accurately describes the classification of all vintages in Shenzhen, and the third vintage in Shanghai, it provides a poor classification of the set of qualifying stocks in Shanghai in the first two vintages. Alternatively, the weights $\theta = 1$ and $\gamma = 1$ provide an almost perfect classification. All outcomes of a grid search of alternative weightings resulted in lower quality predictions. As such, we conclude that Shanghai used an equal weighting scheme in the first and second vintages in practice. In the third vintage, and in all vintages for the Shenzhen exchange, the published weights deliver a high quality classification. We set the threshold C_E^k as the midpoint of the two $Index_i^k$ that maximizes the quality of the prediction of marginability in our regression discontinuity. Our baseline prediction in Table 3 has a coefficient of 0.96, indicating that our formulation of the inclusion index and threshold is able to precisely predict qualification around the threshold.

B.2 Fuzzy Regression Discontinuity

We quantify the direct effect of becoming marginable using a fuzzy regression discontinuity approach that accounts for the fact that the threshold does not perfectly predict marginability. We report two-stage least squares estimates, where the first stage is given by Equation 4 and the second stage is given by:

$$Ret_i^k = \gamma_{0l} + \gamma_{1l}(Index_i^k - C_E^k) + \gamma_{0r}Y_i^k + \gamma_{1r}[\tau_i^k \times (Index_i^k - C_E^k)] + \theta_k + v_i^k. \tag{12}$$

In words, we instrument for marginability (Y_i^k) with an indicator for being above the threshold (τ_i^k). Ret_i^k here represents 5-, 20- or 60-day cumulative returns. Our coefficient of interest is γ_{0r}, which represents the direct impact of marginability on returns.

C Model and Estimation Details

C.1 Equation 8 : A Simple Expression for the Price of Treated Stocks

Given the assumption of an exponential decay information structure, the price at time $t < 0$ (normalizing $Q = 1$ for simplicity) is [36]

$$p_t = p^* + \sum_{j=-\infty}^{t} m_j - \gamma\beta \sum_{j=t+1}^{0} \theta^j.$$

Recalling the normality and independence of the signals m_t, the expected price for treated stocks at any point $t \leq 0$ is:

$$\begin{aligned} E[p_t|m>0] &= p^* + E\left[\sum_{j=-\infty}^{t} m_j|m>0\right] - \gamma\beta \sum_{j=t+1}^{0} \theta^j \\ &= p^* + \beta \underbrace{\frac{\phi(0)}{\Phi(0)} \frac{1}{\sigma_m}}_{\lambda} \sum_{j=-\infty}^{t} \theta^j - \gamma\beta \sum_{j=t+1}^{0} \theta^j. \end{aligned}$$

If we define $\tilde{p} = p^* - \frac{\gamma\beta}{1-\frac{1}{\theta}}$, we may rewrite this as[37]

$$E[p_t|m>0] = \tilde{p} + \beta(\lambda+\gamma) \sum_{j=-\infty}^{t} \theta^j.$$

[36] The price for $t \geq 0$ is simply $p_0 = p^* + m$.

[37] This follows from: $\gamma\beta \sum_{j=-\infty}^{0} \theta^j = \frac{\gamma\beta}{1-\frac{1}{\theta}}$.

Finally, we can generalize the above so that it holds for all t (whether greater or less than 0):

$$E[p_t|m>0] = \tilde{p} + \underbrace{\beta(\lambda+\gamma)}_{\delta_1} \sum_{j=-\infty}^{t} \mathbb{1}\{j \le 0\}\theta^j.$$

C.2 Equation 10: A Linear Difference-in-Difference Style Estimating Equation

Note that an alternative way of writing Equation 8 is:

$$E[p_t|m>0] = \tilde{p} + \underbrace{\beta(\lambda+\gamma)}_{\delta_1} \sum_{j=-\infty}^{0} \theta^j D_{t-j},$$

where D_{t-j} is an indicator equal to one for $j \le t$ (equivalently, $t-j \ge 0$) and zero otherwise. This means, for a given treated stock, we may write

$$p_{it}^{treated} = \tilde{p} + \delta_1 D_{it} + \delta_1 \sum_{j=-\infty}^{-1} \theta^{-j} D_{it-j} + \varepsilon_{it}. \tag{13}$$

Furthermore,

$$\begin{aligned} p_{it+1}^{treated} &= \tilde{p} + \delta_1 \sum_{j=-\infty}^{0} \theta^{-j} D_{it+1-j} + \varepsilon_{it+1} \\ &= \tilde{p} + \delta_1 \theta \sum_{j=-\infty}^{-1} \theta^{j} D_{it-j} + \varepsilon_{it+1}. \end{aligned}$$

Therefore:

$$\delta_1 \sum_{j=-\infty}^{-1} \theta^{-j} D_{it-j} = \frac{1}{\theta}(p_{it+1}^{treated} - \tilde{p} - \varepsilon_{it+1}).$$

Substituting this in the original expression gives

$$p_{it}^{treated} = \underbrace{\left(1-\frac{1}{\theta}\right)\tilde{p}}_{\delta_0} + \delta_1 D_{it} + \frac{1}{\theta} p_{it+1}^{treated} + \underbrace{\varepsilon_{it} - \frac{1}{\theta}\varepsilon_{it+1}}_{e_{it}}. \tag{14}$$

To see how control stocks can be incorporated to generate Equation 10 note first that we may write an analogue of Equation 13 for any t (with p^c representing the price in the control group):

$$p_{it}^{control} = p^c + \varepsilon_{it}.$$

Subtracting and adding $\frac{1}{\theta} p_{it}^{control}$ gives:

$$p_{it}^{control} = \left(1 - \frac{1}{\theta}\right) p^c + \underbrace{\frac{1}{\theta}}_{\delta_2} p_{it+1}^{control} + \underbrace{\varepsilon_{it} - \frac{1}{\theta}\varepsilon_{it+1}}_{e_{it}}.$$

Considering this alongside Equation 14 and letting α_i and η_t absorb the constant term and any individual or time-specific fixed effects gives Equation 10. Importantly, this should not suggest that the parameter θ has a meaningful structural interpretation in the context of control stocks. Given the IV strategy described below, θ is identified strictly off of variation *within* the treatment group.

C.3 Details of Linear Estimation

Estimation of Equation 10 has known issues that are analogous to those in the literature on dynamic panel models with lagged dependent variables (Arellano & Bond, 1991). Most simply, because the error term e_{it} contains ε_{it+1} we generically have

$$Corr(p_{it+1}, e_{it}) \neq 0.$$

However, the panel structure of the data provide a natural set of instruments. Specifically, following a logic similar to that in Malani & Reif (2015), we may construct a forward looking instrument set by allowing leads of D_{it} to act as instruments for p_{it+1}, for example, $D_{it+2}, D_{it+3}, \cdots$. Equation 10 can then be estimated via two-stage least squares or through system GMM approaches in the vein of Arellano & Bover (1995).

Instrument relevance follows directly from Equation 13, which shows that p_{it+1} is a function of all future leads of D_{it}. Because treatment (and hence D_{it}) are defined on an ex-post basis, this holds despite the fact that messages m_t^i are a martingale from the perspective of market participants. A sufficient exclusion restriction is:

$$E[\varepsilon_{it}|D_{it-1}, D_{it}, D_{it+1}, D_{it+2}\cdots] = 0. \tag{15}$$

Note that this restriction implies that e_{it} will be mean independent of D_{it} and its leads. In other words, in any given period, the stock specific error term must not correlate with future treatment status.[38] If Equation 13 is taken literally (i.e., signals m_{it} are the only source of idiosyncratic price fluctuations), then this restriction is satisfied given the rational expectation assumptions of our model. More generally, this restriction is analogous to the assumptions in a standard difference-in-difference setting: that the control allows us to construct a reasonable counterfactual for the price of the treatment group in the absence of any credit supply shock. This would be violated if, for example, the prices of stocks in the treated group were trending differently for reasons unrelated to the shock (e.g., because of differential exposure to some underlying factor), or if some unrelated shock hit the treated group during the sample period.

[38]Note that the primary instruments proposed in Malani & Reif (2015), further leads and lags of the dependent variable itself, will not work in our context because there is inherent autocorrelation in ε_{it}.