Do Speculators Exacerbate Managerial Myopia? Evidence from Margin Traders in China

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ABSTRACT

This paper exploits a regulatory experiment that lifts the margin trading ban in China to examine the real effects of speculative retail investors. Using a regression discontinuity design, I find that margin trading eligibility causes an increase in share turnover and stock prices, and that marginable firms cater to investor short-termism by manipulating earnings and reducing long-term investment. Consistent with managerial myopia, marginable firms experience a decline in operating profit and equity valuation in the long run. My results suggest that margin traders, as short-term speculators, pressure the manager to focus on current earnings and sacrifice long-term growth.

JEL Classification: G14, G31, M40, M41.

Keywords: Investor Short-Termism, Managerial Myopia, Margin Trading, Retail Speculators, Earnings Management, Long-Term Investment

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I. Introduction

Managerial myopia, the phenomenon that managers pursue short-term performance at the expense of firms' long-term growth, has raised substantial concerns in the past three decades. A long tradition of economic research blames this on short-term speculators because they tend to overweight current earnings in the stock price (Porter, 1992; Froot et al., 1992). Consistent with this view, survey evidence by Graham et al. (2005) suggests that respectively 80% and 56% of executives are willing to reduce discretionary spending and delay a profitable project, just in pursuit of an earnings target possibly desired by speculators. Beyer et al. (2014) find from another survey that two-thirds of companies would deviate from strategic decisions and focus on current performance under the pressure of short-term investors. Over time, this perspective has been supported by not only executives but industry professionals and policymakers.[1]

Yet causal evidence of this widespread short-termism remains scarce, as it requires identifying speculators and then isolating the variation in speculative activities that is not driven by the same economic forces that affect corporate behaviors.[2] The latter is easily violated if, for example, firms with a recent structure optimization may simultaneously reduce discretionary expenses and attract informed speculators. Using a rank-based margin trading deregulation in China, I address these difficulties by comparing corporate reporting, operational, and investment decisions for firms that barely passed the experiment cutoff to those of firms that just missed it. A key identification assumption, that margin traders are more speculative and short-term orientated than non-leveraged investors, has long been recognized in the literature due to the leverage risk and borrowing cost of margin trading (Hardouvelis, 1990; Brunnermeier and Pedersen, 2009; Heimer and Simsek, 2019).

[1]For example, Hillary Clinton, the presidential candidate, proposed a sharp increase in the tax rate on short-term investments in 2015 and claimed that it would reduce firms' pressure to show near-term gains (https://www.wsj.com/articles/clinton-capital-gains-taxes-on-short-term-investments). BlackRock consecutively wrote annual letters (2012–2019) to all companies it invested in and urged them to fight against speculators' short-term demand and focus on long-term growth (https://www.blackrock.com/corporate/investor-relations/2016-larry-fink-ceo-letter).

[2]To my knowledge, there is no paper that identifies the causal effect of speculators (or short-term investors) on myopic corporate behaviors. The closest one is Cremers et al. (2020), who find a negative correlation between transient institutional ownership and long-term investment around firms' addition to the Russell 2000 index. However, unlike the plausibly exogenous index inclusion, the investor ownership in their setting is endogenously decided.

In a recent rule to restrict leveraged derivatives, the SEC even listed excessive borrowing as one of the most important driving factors for undue speculation.[3]

The theoretical link between speculators and managerial myopia has been well established. Most closely related to this paper is the catering theory proposed by Baker et al. (2006), where managers rationally cater to prevailing investor demand for earnings target and free cash flows, and make corporate decisions that can encourage overvaluation. Speculators are willing to pay a premium for these catering stocks either due to rational reasons, such as the option to sell the stock to other optimistic investors (Bolton et al., 2006), or behavioral bias like underestimating the extent of myopia (Goldman and Slezak, 2006). This mispricing can persist, at least in the short run, due to limits of arbitrage widely accepted in the literature (Miller, 1977). Meanwhile, managers can benefit directly from stock-based compensation and implicitly from the reputation for maintaining stock price (Narayanan, 1985). Earlier theories also attribute managerial myopia to investors' trading sensitivity to earnings news (Stein, 1989; von Thadden, 1995), a feature that particularly accords with leveraged speculators due to overconfidence and margin requirements (Garleanu and Pedersen, 2011; Barber et al., 2020). Unlike the catering theory, stock prices in these models are unaffected because markets see through managers' incentives to manipulate earnings.

China equity markets provide an ideal laboratory to examine the role of short-term speculators. Although having the world's second-largest stock market, China has long banned margin trading in fear of causing irrational speculation among retail investors. From 2013 to 2015, Chinese regulators ranked all stocks based on their market value and trading volume and made those top-ranked stocks eligible for margin trading. This natural experiment lends itself to my research question for two reasons. First, margin traders in China are short-term retail investors who, on average, only hold stocks for two weeks compared to a four-month holding period of an average investor (Section II). Second, firms close to the experiment cutoff can be seen as randomly chosen for the margin trading eligibility. Firms are not likely to manipulate their rankings close to the cutoff because both the event day and the number of treated firms are unknown ex-ante.

[3]See details in the SEC final rules: 17 CFR Parts 239, 249, 270, and 274 released on November 2, 2020 (https://www.sec.gov/rules/final/2020/ic-34084.pdf).

To identify the causal effect of margin traders, I employ a fuzzy regression discontinuity (RD) design where I focus on stocks close to the experiment cutoff. The experiment is implemented over three rounds with approximately one year in between, which mitigates the concern that margin trading eligibility may coincide with other firm-level shocks that affect corporate decisions. Moreover, since RD's treatment is as good as randomly assigned local to the cutoff (Lee and Lemieux, 2010), my setting efficiently alleviates the anticipation effect, in which firms may predict future treatment and adjust corporate decisions beforehand (Hansman et al., 2021).

I begin by examining the effect of margin trading eligibility on stock market reactions. Relative to non-treated peers, marginable stocks experience a 46–56% increase in share turnover, which corresponds to a 32–36% decline in investor average holding period. This frequent trading pattern clearly demonstrates margin traders' short-term orientation, a key feature that leads to managerial myopia under the catering theory in Baker et al. (2006). Moreover, I find positive returns for marginable stocks that rise from 2% during event days to 11% over three months. Since firms around the cutoff can be seen as randomly treated, the abnormal returns are unlikely to reflect any fundamental changes. Instead, this overvaluation is consistent with the notion that, in equilibrium, investors expect managers' catering behaviors and trade against each other to profit in the speculative bubble (Bolton et al., 2006).

Given the effect on share turnover and stock prices, I test whether marginable firms cater to investor short-termism and undertake myopic actions to encourage, or at least maintain, the overvaluation. Specifically, I examine the top two shortsighted behaviors chosen by executives in the survey of Graham et al. (2005), namely earnings management and long-term investment cuts. Relative to non-treated peers, marginable firms increase absolute discretionary accruals by 5.4% and reduce discretionary expenses by 1.7%. As for investment decisions, marginable firms reduce their capital expenditures by 4.6% relative to the control group (all scaled by beginning-of-year total assets). A similar decline happens to the asset growth rate of marginable firms as well.

I consider several alternative explanations for my results. One potential interpretation is that margin traders may monitor firms' operating activities and prevent the long-existing overinvestment and overspending. In contradiction to this monitoring hypothesis, I find that marginable firms experience a continuous decline in operating profit and equity valuation starting from the next year of the deregulation. Another explanation is that discretionary accruals may reflect changes in firms' investment and growth opportunities (Fairfield et al., 2003). This is less of a problem in my setting since accruals are measured one year before the investment variables due to the implementation timeline (more details in Section V.E.2). Nonetheless, I consider several ways to control for firm growth and investment and find that my results hold with multiple specifications.

Managerial myopia has long been recognized in the literature. Theoretical evidence attributes this myopia to various reasons, such as CEO reputation (Narayanan, 1985), takeover threats (Stein, 1988), and earnings inflation (Stein, 1989). In the wake of the research on the real effect of financial markets, recent models such as Bolton et al. (2006) and Goldman and Slezak (2006) show that short-term speculators may encourage managerial myopia by weighing the executive compensation more heavily on the current stock price. However, empirical tests have generally fallen behind due to the difficulty of identifying speculators and isolating their causal impact.

A growing number of empirical studies have attempted to link managerial myopia to investor short-termism. In his early works, Bushee shows that transient institutional investors tend to overweight current earnings and are associated with lower R&D expenditures (Bushee, 1998, 2001). Using Bushee's classification of institutions, other studies find similar results in the setting of acquisition monitoring (Chen et al., 2007) and around firms' addition to the Russell index (Cremers et al., 2020). However, since institutional ownership is inevitably correlated with many firm characteristics, existing literature still calls for causal evidence of this horizon alignment hypothesis. Moreover, the effect of retail investors, an active and important group of short-term traders, on managerial myopia is largely ignored.

This paper makes three contributions. First, my results confirm the survey evidence of widespread managerial myopia driven by short-term speculators (Graham et al., 2005; Beyer et al., 2014). In order to tackle the long debating endogeneity issue in this field, I exploit a natural experiment that shocks the participation of margin traders in China and provide some of the first causal evidence for this speculation-induced myopia. Notably, this paper relates to yet differs greatly in the investor composition with the literature that examines the effect of blockholder horizon on manager incentives. Besides the studies using Bushee's institution classifications, the existing literature tends to proxy for shareholder horizon using specific controlling blockholders with myopic incentives, say, venture capitalists (Cadman and Sunder, 2014), or option vesting conditions that implicitly indicate blockholder short-termism (Edmans et al., 2017). Therefore, one thing in common is that these studies all focus on large institutions and controlling blockholders and leave the role played by retail investors untouched. Others attempt to tackle this issue by examining investment decisions under general capital market pressure, such as public listing and increased reporting frequency (Asker et al., 2015; Kraft et al., 2018). Benefiting from the unique institutional setting in China, this paper is also among the first to examine the real effect of retail speculators.

Second, this paper demonstrates at least one channel through which trading in secondary financial markets can affect firms' operating decisions (Bond et al., 2012). Rather than assuming investors play a role through implicit channels such as closed-door intervention and exit threat (McCahery et al., 2016), I show that unleashed retail speculators dramatically increase the share turnover and stock prices. Consistent with the catering theory, managers are pressured to cater to investor short-termism and join the notorious earnings game to maintain the inflated prices (Fuller and Jensen, 2010). My findings also echo the heated discussion about a speculative bubble driven by retail traders, especially with the rapidly growing Robinhood during COVID-19 (Welch, 2020). A clear example, undoubtedly, is the recent GameStop short squeeze that boosts its stock price by nearly 30 times in a month.

Third, my findings contribute to the policy debate on the benefits and costs of margin trading. Prior work suggests that margin trading can facilitate information flow (Seguin, 1990), provide liquidity (Kahraman and Tookes, 2017), yet, on the other hand, may also cause destabilizing speculation (Hardouvelis, 1990), generate liquidity spirals (Brunnermeier and Pedersen, 2009), and encourage risk-taking (Ben-David et al., 2018). As one of the first papers to study the real effect of margin trading, I find that margin traders can exert short-term pressure on firms and lead to myopic corporate behaviors. Consistent with Heimer and Simsek (2019), my results suggest that margin trading should be cautiously regulated, especially in a retail investor concentrated market.

The remainder of the paper is organized as follows. Section II provides a description of the margin trading system in China. Section III describes the data and the variable definitions. Section IV explains the RD design. The empirical analysis of the impact of margin trading eligibility on stock performance and corporate decisions is in Section V. Section VI concludes.

II. Institutional Setting

Ever since the re-establishment of the stock market in the early 1990s, China has long banned margin trading in fear of causing irrational speculation among retail investors. Aiming to further develop its financial market, China launched a pilot scheme in March 2010 to lift the margin trading ban for designated stocks. As the counterpart of the SEC, the China Securities Regulatory Commission (CSRC) then announced that this pilot scheme would become a routine practice for both the Shanghai Stock Exchange and Shenzhen Stock Exchange. From early 2010 to late 2014, over 950 stocks were approved for margin trading throughout five major rounds.[4]

The pilot scheme was implemented in two phases. In the first phase, Pilot A and B, firms in the corresponding market indexes were selected. On February 13, 2010, firms included in the Shanghai 50 Index and Shenzhen 40 Index got approved for margin trading. On November 25, 2011, the extended list further accommodated firms included in the Shanghai 180 Index and Shenzhen 100 Index.[5] However, this first phase has raised great concerns for identification. First, firms can easily predict future treatment and adjust operating decisions beforehand (Hansman et al., 2021). For example, suppose a firm in the Shanghai 180 Index reduces discretionary spending in

[4]The CSRC implemented another round in late 2019. However, compared to the original 50% initial margin requirement (same as the U.S.), this newest round requires a much higher minimum initial margin at 100%, meaning a margin trader has to pay all the purchase price with a leverage ratio of zero. Although securities may be discounted to provide initial collateral, this adjustment substantially lowered margin traders' borrowing ability.

[5]These market indexes generally include firms with the highest market value within each exchange. The Shanghai 50 Index covers the largest 50 firms in the Shanghai Exchange. Likewise, the Shanghai 180 Index covers the top 180 firms, including the aforesaid 50 firms. The Shenzhen 40 Index (also known as the Shenzhen Component Index) and the Shenzhen 100 Index are established in the same manner.

preparation for the next round and adjusts back to normal afterward. In that case, we could even find an opposite effect of margin trading eligibility on firm operating decisions using the standard difference-in-differences approach. Second, stocks inside and outside the market indexes inevitably differ in many crucial features such as institutional ownership, ETF tracking, and board structure, leading to poorer comparability between treated and non-treated firms (Appel et al., 2016).

Therefore, this paper focuses on the second phase, including the next three rounds, where China uses a ranking procedure to decide the experiment eligibility. Specifically, the CSRC first excluded stocks that were extremely small and volatile.[6] Then, within each exchange, either Shanghai (SH) or Shenzhen (SZ), the CSRC ranked the remaining stocks according to the formula in Equation (1) and chose the top-ranked stocks to add to the margin trading list. The formula essentially calculates a weighted average of a stock's equity value and trading volume scaled by the entire exchange. Using this procedure, the CSRC further implemented three rounds: (1) 276 firms in Round 1 on January 31, 2013; (2) 206 firms in Round 2 on September 16, 2013; (3) 218 firms in Round 3 on September 22, 2014. The event day and the number of treated firms are both unknown ex-ante, making it unlikely, at least around the cutoff, to predict future margin trading eligibility.

$$\begin{aligned}\text{Ranking Index}_\text{i} =& 2 \times \frac{\text{Average Tradable Market Value of Stock i}}{\text{Average Tradable Market Value of All Stocks in SH/SZ}} \\ &+ \frac{\text{Average Trading Volume of Stock i}}{\text{Average Trading Volume of All Stocks in SH/SZ}}\end{aligned} \tag{1}$$

Table 1 summarizes the eligibility decision rule, event day, and the number of newly marginable stocks for both stock exchanges across five rounds. My sample from Round 1 to Round 3 mainly covers mid-cap and small-cap firms that take up about 20% of the market value.

Margin trading rules in China are generally similar to those applied in the United States. For eligible stocks, minimum initial margins are set at 50% (that is, a margin trader may borrow up

[6] Requirements: (1) have been traded for more than three months; (2) have either more than 200 million tradable shares or a market value over 800 million; (3) have more than 4,000 shareholders; (4) have not experienced any of the followings in the previous three months: (a) daily share turnover less than 20 percent of the share turnover of the market index; (b) the average of the absolute value of the daily price change deviates from that of the market index by more than 4 percent; (c) the maximum price difference scale by the average price is higher than that of the market index by five times; (5) have completed the share reform; (6) are not specially treated stocks; and (7) other unspecified conditions.

to 50% of the purchase price), and the minimum maintenance margins are set at 37.5% (that is, after purchase, a margin call will occur once the loan takes up more than 62.5% of the value of the stock held by the trader). Securities can be used to provide initial collateral with a pre-determined discount rate based on asset class and risk level (for example, 65% for stocks and 90% for ETFs), another feature shared with the United States. To prevent margin traders from using some of the borrowed money on non-marginable stocks, the CSRC set up a much higher requirement to extract cash from the margin account. I will discuss this feature and how margin accounts work in practice in more detail in the Appendix.

Alternative ways to obtain leverage in China are associated with extra costs and strict restrictions. Throughout the sample period of this paper, stock futures are only available for the market indexes, which means that investors can only increase their leverage by investing in the entire market.[7] Besides borrowing directly from the brokerage firms, investors may also take leveraged positions through informal channels, such as private financing companies, peer-to-peer lending, and wealth management products from commercial banks. However, there are some crucial drawbacks to these informal channels. First, interest rates provided by these shadow financing lenders are around 25%, much higher than the 8.5% interest rates of brokerage firms (Bian et al., 2021). Second, these shadow financing contracts are not regulated or protected by the CSRC, which means investors have to bear an additional risk upon the already pressured leverage position. Importantly, any alternative channel would go against finding significant results in my empirical analysis.

Margin trading takes up a significant portion of the market value in China. Figure 1 plots the average outstanding margin debt scaled by total tradable market capitalization for newly marginable stocks in each round. All three rounds display a steep jump of the outstanding margin debt after the event day, then reach a stable level at 5%–7%. Compared with the 2% margin debt in the United States, margin trading plays a much more important role in China.

[7] As of December 2016, only three stock index futures are available in China, including Shanghai/Shenzhen 300 Index, China Securities 500 Index, and Shanghai 50 Index.

Due to the leverage risk and borrowing cost, margin trading has long been recognized as a short-term trading strategy. Moreover, almost all margin accounts are owned by retail investors.[8] To ensure market stability, the CSRC requires a qualified investor to have a trading account for at least six months, with a total account value of more than 500,000 RMB (USD 80,000). Unlike U.S. equity markets, China provides stock-level daily margin positions and trading data. In Figure 2, I estimate the average holding period for margin traders and that of average investors for all marginable stocks in rounds 1, 2, and 3. The holding period of margin traders (average investors) is calculated as the reciprocal of the stock-level/market-level share turnover of margin (total) trading activities from 2013 to 2016. Margin traders, on average, only hold stocks for two weeks, while an average investor in China holds stocks for 13 to 16 weeks. This difference is even more dramatic when we include firms in the pilot rounds or exclude margin trading activities when calculating average investors' holding period. Overall, margin traders are extremely short-term orientated in China.

A policy-related concern is that margin trading and short selling are simultaneously approved for designated stocks. However, short selling in China has long been criticized for its minimal functionality. Previous studies such as Chang et al. (2014) attribute this deficiency to several reasons, including the high transaction cost, the up-tick rule, and the fact that most retail investors in China steer clear of short selling due to insufficient understanding of its mechanism. But most importantly, Chinese retail investors face a highly limited supply of security lending, especially for those mid-cap and small-cap firms examined in this paper.[9] As a result, the total outstanding shares of short selling take up less than 1% of those of margin trading; from a cross-nation perspective, daily shorting volume accounts for merely 0.49% of total trading volume during the sample period, which is negligible as compared to that of 20% in the United States (Boehmer and Wu, 2013). Moreover, my findings of positive *event-time* returns after the experiment (Section V.B.2) further help to distinguish between margin trading and short selling. While short selling can better incorporate negative information and lead to lower stock prices (Grullon et al., 2015), margin trading, on the contrary,

[8]Institutional investors are banned from conducting margin trades through brokers in China.

[9]Many media and professionals raised concern for the limited supply of security lending in China. For more details, please refer to the following websites: (1) http://finance.sina.com.cn/stock/quanshang/qsyj/20140710 (in Chinese); (2) https://www.globalinvestorgroup.com/articles/3431778/china-a-shares-lending-slow-to-progress (in English).

often stirs up speculation and boosts the stock price above its fundamental value (Hardouvelis, 1990). Benefiting from the RD design, I am able to identify positive *event-time* returns for treated stocks, which is consistent with the above consensus that margin trading dominates short selling in China. Importantly, however, since short-sellers have been shown to monitor and discipline firms' reporting and operating decisions (Massa et al., 2015; Fang et al., 2016), any synchronous short-selling activities would prevent me from identifying the myopic corporate actions driven by margin traders.

III. Sample, Data, and Variable Definitions

This paper investigates public firms that trade on the Shanghai Stock Exchange and the Shenzhen Stock Exchange in China. I collect information on the implementation details and daily margin trading data from the official exchange websites. Daily stock market data and annual accounting information come from CSMAR (analogous to a combination of Compustat, CSRP, and I/B/E/S). My sample period is from January 2011, two years before Round 1 began, through December 2016. I exclude firms that have been treated more than once and firms in the financial industry.[10]

After excluding stocks not eligible for the ranking procedure, the full sample from Round 1 to Round 3 includes 672 newly-treated stocks and 4,083 non-treated stock-round observations (1,868 unique stocks). By design, the RD sample includes stocks close to the experiment cutoff in each round. As suggested by Calonico, Cattaneo, and Titiunik (2014), denoted CCT hereafter, I choose the bandwidth using a data-driven MSE-optimal selector (more details in Section IV.C). On average, the local sample covers 40% of the treated firms, more or less, depending on the examined outcome variable, and 57% have entered the local sample for one or more tests.

The two myopic behaviors in the paper are earnings management and long-term investment cuts. To measure accrual-based earnings management, I use the absolute value of discretionary

[10]Marginable firms with negative earnings for two consecutive years (ST firms) may be removed from the margin trading list and rejoin later when their earnings turn positive. These firms take up less than 1% of my sample and do not affect my results. Besides the convention of removing the financial industry in the literature, financial firms also directly or indirectly serve as the leverage provider for margin traders.

accruals calculated from the modified Jones model and refer to it as *ADA* throughout the analysis.[11] Discretionary accruals are estimated from cross-sectional regressions of total accruals on changes in sales and PP&E within each industry. Therefore, higher *ADA* indicates that a firm reports accruals far from its industry standard. For real earnings management activities, I use abnormal discretionary expenses measured as the change of SG&A expenses and denote it as $\Delta DISEXP$ hereafter. Reducing such spending will boost current period earnings and lead to higher current period cash flows if firms generally pay such expenses in cash.

I use the abnormal capital expenditures $\Delta CAPEX$ and changes in total assets $\Delta ASSETS$ as measures of corporate investment.[12] $\Delta CAPEX$ is equal to the annual change in capital expenditures scaled by beginning-of-year total assets. $\Delta ASSETS$ is equal to the percent change in total assets. Throughout this paper, I mainly examine the annual change of those non-stationary variables to alleviate the impact of any omitted time-invariant firm characteristics. A detailed variable construction is provided in the Appendix.

Table 2 reports descriptive statistics for firm-round observations local to the eligibility cutoff. As these statistics depend on the bandwidth, I provide results for multiple bandwidth choices. The mean book value of assets of local firms is around 800 million RMB (about 125 million US dollars). As an important validity test for the RD design, I verify that none of the fundamental variables displays a significant discontinuity at the cutoff in Section V.D.3.

[11] Since margin trading eligibility is almost permanent in China, firms with excessively high profits are incentivized to save "extra" earnings through accruals in a repeated game. Moreover, because earnings smoothing is even more important than hitting earnings target in the eyes of executives (Graham et al., 2005), *ADA* is the appropriate measure to use to determine whether earnings management occurs (e.g., Bergstresser and Philippon (2006) or Cornett et al. (2008)). In contrast, real earnings management is always directional because firms face huge costs adjusting operating decisions and cannot accurately control the manipulation results like in the "accruals game".

[12] I omit R&D in the main analysis because: (1) R&D data in China is of relatively low quality and reduces my sample by about 30%; (2) R&D spending can be attributed to both real earnings management and long-term investment cuts, making it difficult to differentiate between these two myopic behaviors. My results do hold when including R&D in either of these two activities (Section V.D.4).

IV. Empirical Methodology

This section explains the replication of the ranking procedure and the fuzzy regression discontinuity design. For each round, non-marginable firms are first ranked based on Equation (1) and will then be added to the margin trading list if their ranking order is higher than the number of treated firms. Therefore, my identification strategy comes from the discontinuity in margin trading eligibility at the experiment cutoff.

A. Defining the Standardized Forcing Variable

Following CSRC's rules, for each non-marginable stock eligible for the ranking procedure, I calculate its index using Equation (1) and denote stock i's index for round k as $Index_i^k$, where $k = 1, 2, 3$.[13] Next, as suggested by Hansman et al. (2021), I determine the experiment cutoff as follows. First, for each round and each exchange, I sort all stocks based on their ranking indexes. Second, I take the exact number X of treated stocks in that round and set the cutoff to be the ranking index of the Xth highest-ranked stock, regardless of whether that stock is treated or not. This procedure ensures that the ranking index solely decides whether a firm is placed above or below the experiment cutoff. The cutoff for round k and exchange E is denoted as C_E^k.

Lastly, I normalize the cutoff to zero and generate a standardized forcing variable for stocks in each round and each exchange. This procedure makes the forcing variable comparable across different rounds and identifies the average treatment effect on the observed distribution of individuals close to the cutoff.[14] For example, a standardized forcing variable V_i^k of 1 (-1) indicates that stock i has a ranking index one standard deviation higher (lower) than the experiment cutoff in round k.

[13]The time window used to calculate the ranking index is not officially confirmed by the CSRC. Following Hansman et al. (2021), I use three calendar months before the announcement date because: (1) the 3-month window aligns with the calculation window listed in the screening criteria; (2) industry sources also suggest a 3-month pre-event window.

[14]Another advantage of round standardization is that it makes the final sample equally distributed among three rounds. Since the ranking formula generates a score scaled by the entire exchange, firms in Round 3 (slightly smaller) are naturally more densely distributed around the threshold than firms in Round 1 (slightly larger). Without round normalization, the final sample would include a disproportionate number (45%) of firms in Round 3.

A requirement for the regression discontinuity design is that firms cannot accurately manipulate their ranking to be treated or not *close* to the experiment cutoff (McCrary, 2008). In my setting, firms are not likely to do so because: (1) firms do not know the event day and the number of treated firms ex-ante; (2) the inputs for the ranking formula are determined by investors' daily trading activities with high-frequency variations. Figure 3 plots the frequency density of firm-round observations within each bin of the forcing variable around the cutoff. I also plot local polynomial density estimates (solid blue and red) and robust bias-corrected confidence intervals (shaded blue and red). There is no evidence of bunching at the cutoff. Following Cattaneo et al. (2020), I further run a manipulation test at the cutoff. The final test result is $T = 0.3326$, with a p-value of 0.7394, suggesting no statistical evidence of manipulation either.

B. Fuzzy RD Regression Specifications

I use a fuzzy regression discontinuity design to study the causal effect of margin trading eligibility. The treatment discontinuity is not perfectly sharp at the cutoff because: (1) the specific window used to calculate the ranking index is not officially confirmed by the CSRC; (2) the CSRC occasionally exercises its discretion to decide a firm's inclusion. Therefore, I use a standard two-stage least squares (2SLS) estimation for this fuzzy RD setting.

The first stage is given by Equation (2), where I use an indicator of being above the cutoff as an instrument variable for margin trading eligibility.

$$Marginable_i^k = \beta_1 \cdot \mathbf{1}[V_i^k > 0] + R(V_i^k) + L(V_i^k) + \eta^k + \epsilon_i^k \tag{2}$$

Here, $Marginable_i^k$ is a dummy variable that equals one if stock i is added to the margin trading list in round k, and zero otherwise. $\mathbf{1}[V_i^k > 0]$ is an indicator that equals to one if stock i is ranked above the cutoff in round k, and zero otherwise. Gelman and Imbens (2019) suggest that using high-order polynomials in RD analysis is a flawed approach due to its noisy estimates, order-sensitive results, and poor coverage of confidence intervals. Therefore, I include separate linear controls of the forcing variable V_i^k that allow for different slopes on the right-hand side of the cutoff $R(V_i^k)$ and on the left-hand side of the cutoff $L(V_i^k)$. η^k represents the round fixed effect. There is no need for firm fixed effects since non-marginable firms are only treated once in the experiment. The resulting estimates of β_1, representing the additional probability of being marginable when ranked above the cutoff, are reported in Section V.A.

For the second stage, I estimate a similar relationship between margin trading eligibility and the outcome variable. For each outcome variable, I estimate the following equation:

$$Y_i^k = \beta_2 \cdot \widehat{Marginable}_i^k + R(V_i^k) + L(V_i^k) + \eta^k + \epsilon_i^k \tag{3}$$

$\widehat{Marginable}_i^k$ is the predicted value of margin trading eligibility from the first stage. The resulting estimate of β_2 represents the effect of margin trading eligibility on the outcome variable Y_i^k. Different control variables are included depending on the outcome variable examined.

C. Bandwidth Selection

RD design restores the treatment randomness by focusing on firms close to the experiment cutoff. Therefore, choosing a proper bandwidth is important in my setting. The main objective is to maintain the exogenous treatment variation (smaller bandwidth) and provide sufficient statistical power in estimation (larger bandwidth). In the analysis that follows, I choose a fully data-driven bandwidth selector suggested by Calonico, Cattaneo, and Titiunik (2014). As the current state of the art, CCT stand out in the RD literature because they provide mean squared error optimal bandwidths and reduce the inference bias caused by overestimated bandwidths in alternative methods.[15]

Since there is no perfect bandwidth, I examine alternative bandwidth choices in the robustness check. Specifically, I increase/decrease the CCT bandwidth by 10% and 25% (which expand/shrink

[15]Alternative methods include rule-of-thumb, cross-validation, and other MSE-optimal bandwidth selectors (Imbens and Kalyanaraman, 2012). MSE-optimal selectors gradually take the place of the former two methods because they provide solid theoretical support and a data-driven algorithm. Of the last category, Calonico et al. (2014) improve on prior studies by offering a more conservative bandwidth with smaller inference bias. See a more detailed review of these methods in Kahraman and Tookes (2017).

my sample size by about 15% and 35%) and redo the RD analysis. Because CCT choose the optimal bandwidth based on the distribution of the dependent variable, the bandwidth and sample size slightly varies with the outcome variable we are examining.

V. Results

A. First-Stage Regressions

In this section, I show that there is indeed a discontinuity in the margin trading eligibility at the cutoff. Figure 4 plots the margin trading eligibility against the forcing variable. I include all firms within the CCT bandwidth, and each point denotes the average probability of being marginable for firms within each evenly-spaced bin. Separate regression lines, along with 90% confidence intervals based on heteroscedasticity-consistent standard errors, are shown on both sides of the eligibility cutoff. As expected, the RD plot shows a sharp discontinuity in the treatment probability at the experiment cutoff. Table 3 reports the first-stage regression, directly running margin trading eligibility on the indicator of being above the cutoff. Consistent with Figure 4, regression results show a dramatic jump of the treatment probability of 54% at the cutoff. The estimates are almost identical with the triangular kernel, and I use the uniform (rectangular) kernel for my main analysis hereafter.[16]

Both the RD plot and regression results confirm an evident discontinuity in margin trading eligibility at the cutoff. Besides the evidence of no bunching at the cutoff (Section IV.A), I further confirm there is no significant discontinuity of any firm characteristics in Section V.D.3. Overall, the margin trading deregulation in China is a great fit for the regression discontinuity design.

[16]The triangular kernel gives a higher (lower) weight for firms close to (far from) the cutoff, while the uniform kernel equally weights all firms within the CCT bandwidth. The uniform kernel better suits my setting because: (1) the coefficient of estimates is easier to interpret; (2) firms closer to the cutoff in the fuzzy RD design are more likely to be non-compliers, that is, treated (untreated) when ranked below (above) the cutoff. My results do hold with different kernel choices.

B. Stock Market Reactions

In this section, I examine the impact of margin trading eligibility on share turnover and stock prices. Under the catering theory (Baker et al., 2006), managers cater to short-term traders' demand for earnings target and free cash flows, and take myopic actions that can encourage overvaluation. In equilibrium, investors expect managers' catering behaviors and trade against each other to profit in the speculative bubble (Bolton et al., 2006). Therefore, we expect to see an increase in share turnover, indicating the short-term horizon of margin traders, and an increase in stock prices, representing the overvaluation driven by the competing speculators.

B.1. Share Turnover

In this section, I test whether marginable stocks experience an increase in abnormal share turnover, measured as the change of share turnover before and after the implementation date using event windows of 4 weeks, 8 weeks, and 12 weeks.[17] The share turnover itself is defined as the daily share volume over tradable shares outstanding (Lo and Wang, 2000). Besides the benefit of controlling time-invariant omitted variables, using abnormal share turnover also alleviates the concern that trading volume is included in the ranking formula. Any pre-event volume difference has been excluded in this procedure. Figure 5 plots the abnormal share turnover against the forcing variable. To control for time-series variation, I demean the outcome variable using the average values of all stocks within the CCT bandwidth for the round. Each point denotes the average abnormal share turnover within each bin of width 0.05. Separate regression lines along with 90% confidence intervals are shown on both sides of the eligibility cutoff. All figures display an evident discontinuity in abnormal share turnover at the threshold.

Panel A of Table 4 reports the reduced form regression in which I run the abnormal share turnover on the indicator of being above the cutoff. Therefore, the estimated coefficient of 0.569 matches closely with the cutoff jump of abnormal share turnover in the 8-week case of Figure 5. Panel B

[17]The pre-event window is fixed at 12 weeks before the event day, the same length as the ranking procedure.

reports the fuzzy RD results using 2SLS estimation. The outcome variable is the abnormal share turnover, and the main explanatory variable of interest is an indicator variable of margin trading eligibility. Following Chordia et al. (2007), I control for the previous month's absolute stock return, stock price, analyst following, forecast dispersion, and other annual frequency variables including earnings surprise, leverage, book-to-market ratio, market capitalization, and beta. Although these controls are not exhaustive, one of the biggest advantages of the RD design is that it compares similar firms, which renders it fairly robust to omitted variables. Depending on different event windows, marginable stocks experience a 0.8–1% (18–22%) increase in daily (monthly) share turnover relative to non-marginable peers. For a representative firm with a median monthly share turnover of 39% in my sample, margin trading eligibility leads to a 46–56% increase in share turnover, corresponding to a 32–36% decline of investor average holding period. Both the economic magnitude and the statistical significance of these results are large, suggesting that margin trading eligibility leads to a significant decline in the average shareholder horizon.

B.2. Returns

This section examines the impact of margin trading eligibility on stock prices, measured with the cumulative returns over event days and in a longer post-event window of three months. Figure 6 plots the cumulative returns against the forcing variable. All specifications are the same as before. Both figures display an evident jump in stock returns at the cutoff. Table 5 reports the reduced form regression and the fuzzy RD regression using 2SLS estimation. The outcome variable is the stock returns, measured as the raw/market-adjusted cumulative abnormal returns (CAR) right after the implementation day (event window [0,1]) and raw/DGTW-adjusted cumulative returns in a longer post-event window of three months.[18] Relative to non-treated peers, marginable stocks experience positive returns of 2.3–2.4% during event days and 9–11% over three months.[19]

[18] I follow the same procedure as in Daniel et al. (1997) and sort all stocks into 125 ($5 \times 5 \times 5$) portfolios based on size, book-to-market ratio, and momentum. The equal-weighted returns for each portfolio serve as the benchmark return for all stocks in the same portfolio.

[19] My results are consistent with Hansman et al. (2021), who find positive returns for marginable stocks over three months and twelve months. Although I find similar results for a longer period, I remain conservative about the post-event window since the shortest time gap between rounds is eight months.

Overall, I find that margin trading eligibility leads to higher stock prices. Since firms around the cutoff can be seen as randomly treated, this abnormal return is unlikely to reflect any fundamental changes. Instead, the gradually increasing prices are consistent with the equilibrium investor-manager dynamics in the catering theory, where investors expect managers' catering behaviors and trade against each other to profit in the speculative bubble.

C. Managerial Myopia

In this section, I test whether managers cater to investor short-termism and undertake myopic behaviors to encourage, or at least maintain, the mispricing. Following survey evidence of Graham et al. (2005), I examine the top two shortsighted behaviors chosen by executives, namely earnings management and long-term investment cut.

C.1. Earnings Management

I use absolute discretionary accruals *ADA* to measure accrual-based earnings management and abnormal discretionary expenses Δ*DISEXP* to proxy for real earnings management. Higher *ADA* means a firm adjusts accruals far from its industry-standard. On the other hand, lower Δ*DISEXP* suggests a decline in firms' discretionary spending, a common approach to boost current period earnings and increase cash flows. Figure 7 plots *ADA* and Δ*DISEXP* against the forcing variable. All specifications are the same as before. RD plots show an evident jump of *ADA* and a clear drop of Δ*DISEXP* at the cutoff.

Table 6 reports the reduced form regression and the fuzzy RD regression using 2SLS estimation. The outcome variables are *ADA* and Δ*DISEXP*, and the main explanatory variable of interest is an indicator variable of margin trading eligibility. Following Hribar and Nichols (2007) and Yu (2008), I control for market capitalization, market-to-book ratio, leverage, operating ROA, operating cash flow, cash flow volatility, the growth rate of assets, and lagged discretionary accruals. I also report pre-event (one year before the experiment) results as a placebo test. Relative to non-treated peers, marginable firms increase discretionary accruals by 5.4% and reduce discretionary expenses by 1.7% (scaled by total assets), suggesting an increase in both accrual-based and real earnings management. In contrast, there is no discontinuity in the pre-event period, indicating my results are not driven by any mechanical difference between treatment and control groups. In Section V.D.4, I examine alternative measures, including abnormal discretionary accruals ΔADA and a slightly modified version of $\Delta DISEXP$ that includes R&D expenses, and find similar results.

The magnitude of these effects is generally in line with magnitudes documented in other studies on the impact of short-termism on earnings management. For example, Cornett et al. (2008) find a one-sigma increase in the option compensation variable is associated with an increase in absolute discretionary accruals that takes up 4.5% of total assets. Ali and Zhang (2015) find that CEOs in their earlier years are associated with 0.95% lower abnormal discretionary expenses as scaled by assets, which further goes up to 1.94–2.67% after controlling for different monitoring parties such as institutional investors, analysts, and independent boards. Although these studies focus directly on the manager horizon itself, they provide a valuable reference to analyze the impact of investor short-termism in my setting.

Due to the specific timeline of the experiment, ADA is measured one period before $\Delta DISEXP$. This is because, unlike the accruals earnings management that takes as little time as a firm would spend on preparing the annual report, operational decision making requires multiple rounds of board meetings and even more time in the actual implementation (Badertscher, 2011). Therefore, I calculate discretionary accruals using annual reports published after the deregulation (Iliev, 2010) and require real earnings management (as well as investment variables in the next section) to overlap at least six months to be counted in a fiscal year (Grullon et al., 2015). Since all three rounds are implemented at the end of the year, ADA is measured one year before $\Delta DISEXP$.[20] The insignificant pre-event results provide additional support that the estimation period for each outcome variable is valid. Notably, my results may not suggest a substitutive relation between accrual-based and

[20]All firm fiscal years end in December in China. Although Round 1 was implemented in January, firms still have enough time for accruals management. This is because less than 1% of firms publish annual reports in January, and more than 95% do so after March. My results do hold with only firms that publish annual reports after February or March.

real earnings management since the lag of $\Delta DISEXP$ may well result from insufficient time for operational adjustment in my setting (Zang, 2012).

C.2. Long-Term Investment

I use abnormal capital expenditures $\Delta CAPEX$ and changes in total assets $\Delta ASSETS$ to measure long-term investment. Figure 8 plots $\Delta CAPEX$ and $\Delta ASSETS$ against the forcing variable. All specifications are the same as before. RD plots show a noticeable drop of both $\Delta CAPEX$ and $\Delta ASSETS$ at the experiment cutoff. Table 7 reports the reduced form regression and the fuzzy RD regression using 2SLS estimation. As mentioned in the last section, investment variables are required to overlap at least six months to be counted in a fiscal year. Following Grullon et al. (2015), I control for variables that may affect firm investment in event studies, including operating cash flow, lagged total assets, and past profitability (operating ROA).

Relative to non-treated peers, marginable firms reduce capital expenditures by 4.6% and lower their asset growth rates by 28%. Although the effects on asset growth rates appear to be large, they should be considered together with the average asset growth rate of 19% during the sample period. In other words, the actual decline in asset growth for a marginable firm is around 9%. Once again, there is no discontinuity in the pre-event period. In the robustness check, I include R&D expenses in the long-term investment and find similar results. The magnitude of these effects is generally in line with other studies on the impact of capital market pressure on long-term investment. For example, Asker et al. (2015) find that public firms are associated with 2.4–4.9% lower gross investment and 9.1% lower asset growth rates compared to private firms. Kraft et al. (2018) find a slightly smaller decline in capital expenditures that takes up 1.8–1.9% of total assets along with the transition of firms from annual reporting to quarterly reporting. Considering the dramatic change in share turnover and stock prices in China, my results that are about the same level as the public listing status and twice that of the increased reporting frequency are fairly reasonable.

My results suggest that margin trading eligibility leads to a decline in firms' long-term investment. Survey evidence of Graham et al. (2005) shows that 56% of the executives are willing to delay profitable projects and capital expenditures in pursuit of investors' demand for current period earnings and cash flows. My findings confirm this consensus and provide one of the first pieces of evidence on a causal link between short-term speculators and managerial myopia.

D. Robustness Check

D.1. Alternative Bandwidths

Regression discontinuity design stands out in field studies since it restores the treatment randomness by focusing on firms close to the experiment cutoff. Hence a proper bandwidth is important in the RD setting. Throughout the main analysis, I let the CCT data-driven selector choose the optimal bandwidth for each outcome variable. In this section, I check whether my results are sensitive to alternative bandwidth choices. Table 8 reports the fuzzy RD results with alternative bandwidths. Specifically, I increase/decrease the CCT bandwidth by 10% and 25% (which expand/shrink my sample size by about 15% and 35%) and redo the RD analysis for all outcome variables, including the abnormal share turnover, returns, *ADA*, Δ*DISEXP*, Δ*CAPEX*, and Δ*ASSETS*. Overall, my findings are robust to alternative bandwidths.

D.2. Placebo Tests

Like any other RD design study, one alternative interpretation is that the ranking index itself can predict future corporate behaviors and market reactions. To ensure that my results are not driven by variation in the ranking procedure, I repeat the RD analysis around multiple placebo cutoffs. Specifically, I set placebo cutoffs above and below the actual cutoff 0, using a fixed distance of 0.5 and a flexible distance based on the CCT bandwidth for each outcome variable. There is no need for a 2SLS estimation since, for placebo tests, the first stage regression is no longer predictive. Table 9 reports the reduced form RD regression results for all outcome variables at placebo cutoffs. Unlike the main analysis, I do not observe a significant cutoff discontinuity in any outcome variables. Therefore, the ranking index itself is unlikely to explain my results.

D.3. Validity Tests

I have confirmed no pre-event discontinuity of any dependent variable in the main analysis. In this section, I check the extent to which covariates exhibit discontinuity at the cutoff. Validity tests are important in the RD design because discontinuity in pre-event covariates may indicate that firms above and below the cutoff are systematically different. Table 10 reports the fuzzy RD results for all control variables used in this study, measured one year before the margin trading deregulation. All specifications are the same as the main analysis. Overall, there is no significant discontinuity in any control variables at the cutoff.

D.4. Alternative Measures

In this section, I examine whether my results are sensitive to alternative measures. For accrual-based earnings management, I use *ADA* rather than ΔADA in the main analysis because the latter may not be suitable for event studies. Since discretionary accruals are defined as the residuals of cross-sectional regressions within each industry year, a change of *ADA* does not necessarily imply a firm engage in accruals management. In other words, ΔADA not only depends on firms themselves but also on their industry peers. However, like other outcome variables, ΔADA has the advantage of alleviating ex-ante accruals difference between firms above and below the cutoff.

R&D is another widely used variable in managerial myopia literature. However, R&D data is of relatively low quality in China. Throughout my sample period, only two-thirds of firms in the local sample report R&D information. Even for those disclosing firms, R&D expenses merely take up 30% of capital expenditures and 20% of SG&A expenses. Compared with an almost 1:1 ratio between R&D and CAPEX in the United States, R&D plays a much less important role in Chinese firms' investment policy. Moreover, reducing R&D expenditures has been attributed to both real earnings management and long-term investment cuts in the literature, making it difficult to differentiate between these two myopic behaviors. Nonetheless, I respectively include R&D in abnormal discretionary expenses ($\Delta DISEXPRD$) and in long-term investment ($\Delta CAPEXRD$) and redo the analysis.

Table 11 reports the regression results for all variables discussed above. For a better comparison with previous results, I use the same bandwidth as that of the main analysis for each outcome variable. Overall, my results are robust to these alternative measures.

E. Alternative Explanations

So far, my results suggest that margin traders, as short-term speculators, pressure the manager to focus on current earnings and sacrifice long-term growth. In this section, I evaluate multiple alternatives to this explanation.

E.1. Managerial Myopia or External Monitoring?

One explanation for my results is that margin traders may monitor firms' operating activities and prevent long-existing overinvestment and overspending. This monitoring hypothesis is questionable in the first place because margin traders in China are retail investors with limited information sources and little involvement in the board meeting. Nonetheless, firms may still choose to reduce overinvestment simply because they fear getting caught for suboptimal operating decisions when put in the spotlight. Since firms' optimal operating strategy is unobservable, it remains an empirical question whether reducing investment and discretionary spending is beneficial in the long run.

I examine the long-term performance of marginable firms to test whether they adjust operating decisions in a myopic way. Myopic behaviors, by definition, would lead to a decline in long-term operating profitability, as well as lower equity valuation when markets find out firms' real sacrifice. Notably, the standard RD design no longer applies because non-treated firms in an earlier round may enter the treatment group in the next one. To tackle this issue, I adopt a dynamic version of the regression discontinuity design and estimate the following equation:

$$Y_{i,t+\tau} = \beta^{\tau} \cdot Marginable_{it} + R^{\tau}(V_{it}) + L^{\tau}(V_{it}) + \alpha_{\tau} + \eta_c + \lambda_{it} + \epsilon_{it\tau} \quad (4)$$

This specification follows expression (7) in Cellini et al. (2010). $Marginable_{it}$ is a dummy variable that equals one if stock i is approved for margin trading at time t, and zero otherwise. The term β^{τ} estimates the effect of margin trading eligibility at time t on outcome variables τ periods later. For example, $\beta^{\tau=2}$ estimates the treatment effect two years after the deregulation. For each firm-round (i, t), I include observations for firm i from period $t-2$ (two years before) to $t+4$ (four years after) and exclude the event year t. Therefore, the effect on future outcome variables is estimated based on pre-event firm characteristics. The coefficient β^{τ} and separate linear controls of the forcing variable $R^{\tau}(V_{it})$ and $L^{\tau}(V_{it})$ are allowed to vary for $\tau > 0$, and constrained to zero for $\tau < 0$, and standard errors are clustered at the firm level. The parameters α_{τ} and η_c are fixed effects for time periods relative to the event and calendar years. Additionally, pooling multiperiod data allows me to include firm-round fixed effect λ_{it} and control for time-invariant firm characteristics. However, the CCT bandwidth selector cannot be applied to the dynamic RD design. For robustness, I report results for multiple bandwidth choices.

Table 12 presents the effect of margin trading eligibility on firm long-term performance. Marginable firms experience a decline in operating ROA starting from the next year of the deregulation. The estimated coefficient -0.02 corresponds to a ROA drop of 36%, representing 27% of the standard deviation (mean and standard deviation of ROA are 0.056 and 0.074, respectively). This declining profitability persists in years $t+3$ and $t+4$, although only marginally significant. Stock returns show similar results, where marginable firms experience a 17% price decline in the next year and a slightly downward trend after that. Overall, my results are against the interpretation that margin traders serve as external monitors and prevent suboptimal operating decisions.

E.2. Accruals, Growth, and Investment

Prior literature shows that a firm's accruals correlate with its growth opportunity and investment level (Fairfield et al., 2003; Zhang, 2007; Wu et al., 2010). Since I use discretionary accruals to proxy for accrual-based earnings management, an alternative explanation is that the accruals discontinuity may result from an investment change.

Before diving into a more detailed analysis, I would like to explain why this alternative explanation is unlikely in the first place. In my setting, discretionary accruals are measured one year before the investment variables (more details in Section V.C.1). This unique feature benefits from the fact that accruals management takes as little time as a firm would spend on preparing the annual report, while, in contrast, operating decisions require multiple rounds of board meetings and even more time in the actual implementation. This sequential relation between accruals and investment makes it almost impossible for firm investment to reversely affect accruals in the preceding year.

Nonetheless, I adopt several controls for firms' investment and growth to thoroughly investigate this concern. Besides the asset growth rate $\Delta ASSETS$ that I have already controlled in the main analysis, I further add $\Delta CAPEX$ to control for firms' growth opportunities. The results are reported in Table 13. I include $\Delta CAPEX$ in column (1) and the squared terms of both $\Delta ASSETS$ and $\Delta CAPEX$ to account for a nonlinear effect of investment on accruals. The coefficient on the margin trading eligibility, $Marginable_i^k$, are barely affected by the inclusion of these controls. In columns (3) and (4), I construct a slightly modified version of $\Delta CAPEX$ by including R&D expenses and denote it $\Delta CAPEXRD$. Again, the results are similar to those reported in Table 6.

F. Discussion

Before concluding, I would like to discuss the extent to which my finding can be generalized outside of the institutional setting in this paper. Although recent models of managerial myopia have been written with developed markets in mind, the core assumption of these models—information asymmetry and heterogeneous beliefs—also applies, if not more, to emerging markets. Moreover, besides the common underlying mechanism, China and the U.S. are comparable in market size, regulation rules, and margin trading patterns. As of the end of 2015, China's stock market capitalization stood at $8.2 trillion, the second-largest in the world, ranking behind only the U.S. equity markets ($25 trillion). China also set up almost identical minimum requirements of initial margins (50%) and maintenance margins (37.5%) as those of the United States. Not surprisingly, margin traders in China and the U.S. display similar trading patterns in which they increase margin positions when the stock market performs better and decrease them when the market gets worse.[21] All the similarities listed above, coupled with the overwhelming blame on speculators from the U.S. entrepreneurs, alleviate the external validity concern on the causal link between investor short-termism and managerial myopia.

The magnitude of these myopic effects, however, may be larger in China than in the United States. An outstanding feature of China is that retail investors dominate the stock markets and account for 85% of the total trading volume (25% in the U.S.). As a result, Chinese stocks generally have higher share turnover and a shorter average holding period. Notably, this higher share turnover itself should not affect my findings since I essentially compare the abnormal share turnover for firms on either side of the experiment cutoff. It is the possibility—overconfident or irrational retail investors freed from financial constraints may generate higher speculative pressure than institutional investors do—that might contribute to a larger impact of margin trading eligibility in China than in the United States. Nevertheless, in the wake of retail investor participation along with the rapidly growing Robinhood (Welch, 2020), this concern should not be central to the generalization of my results. The recent short squeeze of GameStop best demonstrates that even in a developed financial market like the United States, speculative retail investors can well push the stock price far above its fundamental value. In a word, although the magnitude of the effects in China may not be identical to developed markets, my paper still provides a valuable reference to future regulations around the world.

Finally, an RD-specific external validity concern is whether firms close to the experiment cutoff are representative of the China economy. This is less of a problem in my setting since, out of the 672 treated firms in my sample period, 383 or 57% of firms have entered the local sample for one or more tests. Except for those extremely large and tiny firms, my results can apply to a large group of firms in China.

[21]Since NYSE only discloses monthly market-level margin positions, I compare the correlation between monthly market returns and monthly changes in outstanding margin positions in the two countries. This correlation is 0.64 in China and is 0.60 in the United States, both positive and significant.

VI. Conclusions

This paper investigates whether speculative retail investors impact stock prices and distort corporate operating decisions. To provide causal evidence, I exploit a rank-based margin trading deregulation in China and compare corporate reporting, operational, and investment decisions for firms that barely passed the experiment cutoff to those of firms that just missed it. Building on prior literature, my key identification assumption is that, on average, margin traders are more speculative and short-term orientated than non-leveraged investors. The data supports this assumption.

My results show that relative to non-treated peers, marginable stocks experience a dramatic increase in share turnover and hence a decline in investor average holding period. This frequent trading pattern clearly demonstrates margin traders' short-term orientation, a key feature that leads to managerial myopia under the catering theory. Moreover, I find gradually increasing returns for marginable stocks, consistent with the notion that in equilibrium, investors expect managers' catering behaviors and trade against each other to profit in the speculative bubble. On the other side of the coin, managers cater to investor short-termism and undertake myopic behaviors such as earnings management and long-term investment cuts to encourage or maintain this overvaluation. Lastly, consistent with managerial myopia, marginable firms experience a continuous decline in operating performance and equity valuation starting from the next year of the deregulation.

My findings highlight investor short-termism as a key driving factor for managerial myopia. A number of authors have emphasized the adverse effect of short-term institutions and controlling blockholders. However, the role played by retail investors, an active and important group of short-term traders, is largely ignored. Benefiting from the unique institutional setting in China, my paper not only confirms the myopic effect of speculative retail investors but also contributes to the broader literature that studies the real effect of secondary financial markets. My results give support to a worldwide policy change that aims for a longer investment horizon as well as a tightening of the leverage constraint in both China and the United States.

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Appendix A: Variable Definitions

TABLE A.1: Description of Main Variables

Variable	Definition
Share Turnover	*Share Turnover* is defined as the daily share volume over tradable shares outstanding (in percentage). *Abnormal Share Turnover* measures the change of *Share Turnover* before and after the implementation day using multiple event windows.
Returns	The detailed construction of stock returns is provided in the main analysis.
ADA	Using the modified Jones model, I estimate the absolute discretionary accruals *ADA* as follows. I first run the following cross-sectional OLS regression within each industry year based on the 2012 CSRC industry classification: $$\frac{TA_{i,t}}{A_{i,t-1}} = \beta_1 \frac{1}{A_{i,t-1}} + \beta_2 \frac{\Delta REV_{i,t}}{A_{i,t-1}} + \beta_3 \frac{PPE_{i,t}}{A_{i,t-1}} + \epsilon_{i,t}$$ where i indexes firm and t indexes year. Total accruals $TA_{i,t}$ are defined as the net income minus operating cash flows, $A_{i,t-1}$ is total assets at the beginning of year t, $\Delta REV_{i,t}$ is the change in sales revenues from the preceding year, and $PPE_{i,t}$ is property, plant, and equipment. The non-discretionary accruals are calculated as $$NDA_{i,t} = \hat{\beta}_1 \frac{1}{A_{i,t-1}} + \hat{\beta}_2 \frac{\Delta REV_{i,t} - \Delta AR_{i,t}}{A_{i,t-1}} + \hat{\beta}_3 \frac{PPE_{i,t}}{A_{i,t-1}} + \epsilon_{i,t}$$ where ΔAR_{it} is the change in account receivables. *ADA* is defined as the absolute value of the difference between total accruals $\frac{TA_{i,t}}{A_{i,t-1}}$ and non-discretionary accruals $NDA_{i,t}$.
$\Delta DISEXP$	Abnormal discretionary expenses, measured as the annual change of SG&A expenses (selling, general, and administrative) scaled by beginning-of-year total assets.
$\Delta CAPEX$	Abnormal capital expenditures, measured as the annual change of capital expenditures scaled by beginning-of-year total assets.
$\Delta ASSETS$	Asset growth rate, measured as the annual change in total assets scaled by beginning-of-year total assets.
ΔADA	Abnormal discretionary accruals, measured as the annual change of *ADA*.

Variable	Definition
Δ*DISEXPRD*	A slightly modified version of Δ*DISEXP*, measured as the annual change of SG&A and R&D expenses scaled by beginning-of-year total assets. R&D is set to zero if missing.
Δ*CAPEXRD*	A slightly modified version of Δ*CAPEX*, measured as the annual change of capital expenditures and R&D expenses scaled by beginning-of-year total assets. R&D is set to zero if missing.
$Marginable_i^k$	A dummy variable that equals one if firm i is approved for margin trading in round k.
V_i^k	The standardized forcing variable used to rank the non-marginable stocks.
$\mathbf{1}[V_i^k > 0]$	A dummy variable that equals one if stock i's ranking index is above the experiment cutoff in round k.
Total Assets	Book value of total assets.
Market Cap.	Market value of equity.
B/M	Book-to-market ratio, calculated as the book value of equity divided by the market value of equity.
ROA	Operating return on assets, calculated as the operating income over beginning-of-year total assets.
Leverage	Long-term debt plus current liabilities scaled by the book value of debt and equity.
Asset Growth	Same definition as Δ*ASSETS*; control variable for earnings management.
Cash Flow	Cash flow from operations over beginning-of-year total assets.
Cash Flow Vol.	Cash flow volatility is estimated by the standard deviations of cash flows of a firm in the sample period, scaled by beginning-of-year total assets.
Δ*NI*	Earnings surprise, defined as the absolute value of the current ROA (return on assets) minus last year's ROA.
Analyst No.	Previous month's number of analysts who follow a firm and report forecasts.
Dispersion	Previous month's analyst forecast dispersion, defined as the standard deviations of earnings per share forecasts reported by analysts.
Beta	Stock-level beta in the preceding year, calculated from the CAPM model using daily returns.

Appendix B: Margin Account Details

This section describes the details of margin accounts in China and explains why investors can only leverage their position on marginable stocks. Let me first introduce some definitions for clarity. Since the term "margin" has been overused to denote multiple concepts in this field, I will try to use more specific terms when possible. In this Appendix, I will also use the original definition of the *initial* and *maintenance* ratios listed in the official CSRC rules. To facilitate the understanding, I have converted such ratios to the standard U.S. version in the main body. A demonstration of the conversion procedure is also provided in this Appendix.

- *Cash Deposit* (*CD*): the initial money or securities that an investor has to deposit with the broker to increase their purchasing power. For simplicity, I assume the deposit to be purely cash of 200 RMB. This can also be achieved by depositing 308 RMB worth of securities based on the 65% security discount rate or a combination between cash and securities. With 200 RMB worth of *Cash Deposit*, an investor has a purchasing power of 200/50% = 400 RMB that can only be spent on marginable stocks.

- *Initial Equity* (*IE*): the value of securities an investor actually purchased; can fall in between 0 and 400 RMB (*Cash Deposit*/50%). I will only consider the case that *Initial Equity* is larger than *Cash Deposit*. Otherwise, the margin account is essentially identical to a cash account.

- *Margin Debt* (*MD*): the net amount of money an investor borrows from the broker; equals *Initial Equity* − *Cash Deposit*. A term commonly used in the U.S. but not as much in China.

- *Current Equity* (*CE*): the floating equity value after the establishment of *Initial Equity*.

- *Initial Deposit Ratio* (*IR%*): the ratio of *Cash Deposit* over *Initial Equity*; cannot be smaller than 50%. The 50% *IR%* is identical to the required minimum initial margin of 50% in the United States.

- *Maintenance Deposit Ratio* (*MR%*): the ratio of (*Cash Deposit*+*Current Equity*) over *Initial Equity*, ignoring any interest rate or transaction fee. A margin call would happen when *MR%* is lower than 130%. An investor can only extract cash from the margin account if *MR%* is higher than 300% and must keep it at at least 300% afterward.

Row 1–4 of Table A.2 illustrates the initial phase, where an investor opens a margin account and deposit their 200 RMB cash. As the investor increases *Initial Equity* from 250 to 400 RMB, their *Initial Deposit Ratio* falls from 80% to the minimum requirement of 50% (in red). *Maintenance Deposit Ratio* does not come into play in the initial phase since, by design, it is higher than 130% even at a 50% *Initial Deposit Ratio*.

The rest of Table A.2 illustrates the later phase where *Initial Equity* has been established in the initial phase and remains the same after that. The stock price fluctuates over time, leading to a changing *Current Equity*. Row 5–8 considers the situation when *Maintenance Deposit Ratio* hits the lower limit of 130% for a margin call (in red). For a *Initial Deposit Ratio* of 50% (row 8), a price drop of 20% would lead to a margin call ([200 + 320]/400 = 130%; [320 − 400]/400 = −20%).

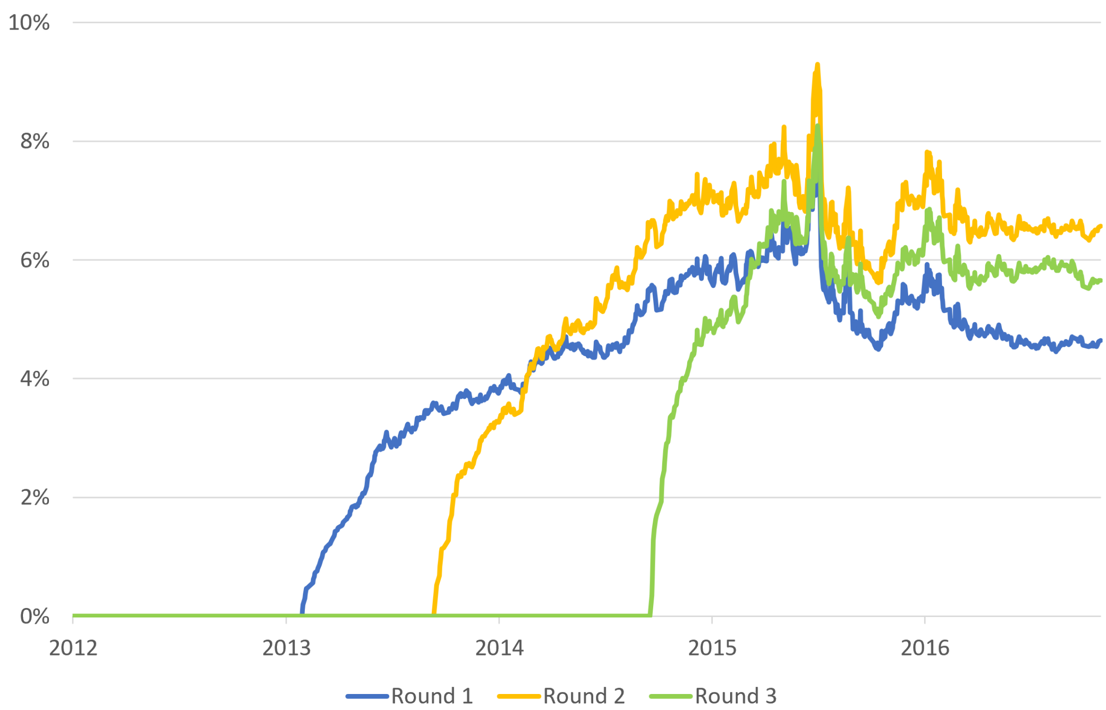
For investors with lower leverage (say, 80% *Initial Deposit Ratio*), the price has to decrease by 50% to trigger the margin call. In the United States, *maintenance margin* is defined as the amount of equity that an investor must maintain in the margin account over the current market value of the stock held by the investor. Therefore, the minimum *maintenance margin* is met in China when an investor receives a margin call with a minimum *Initial Deposit Ratio* of 50% (row 8), which equals $(\textit{Current Equity} - \textit{Margin Debt})/\textit{Current Equity} = (320 - 200)/320 = 37.5\%$. This is comparable to the 30–40% minimum *maintenance margin* required by major U.S. brokerage firms.

Another key feature is the cash extraction requirement as described in Row 9–12, which is the underlying mechanism why investors cannot leverage their positions on non-marginable stocks in China. A reasonable concern is that investors may borrow 400 RMB altogether, use half of it on marginable stocks, and transfer the other half to a separate cash account eligible for non-marginable stocks. However, the CSRC requires that all traders cannot extract any cash from their margin accounts unless *Maintenance Deposit Ratio* reaches 300% (in red). For investors with a *Initial Deposit Ratio* of 50% (row 12), they can only extract money when their stock value rises to 2.5 times the purchase price ($[200 + 1000]/400 = 300\%$; $1000/400 = 2.5$), an event unlikely to happen to the majority of margin traders within a short period. The same dilemma even happens to investors with a much higher *Initial Deposit Ratio* of 80%, requiring *Current Equity* to be at least 2.2 times the *Initial Equity*. But perhaps more importantly, the extracted cash, even invested on non-marginable stocks through a separate cash account, is no longer used as collateral and cannot provide any leverage.

TABLE A.2: Initial and Maintenance Margin Requirements

Phase	Events	Row	*CD*	*IE*	*MD*	*CE*	Price%	*IR%*	*MR%*
Initial		1	200	250	50	250	0%	80%	180%
		2	200	300	100	300	0%	67%	167%
		3	200	350	150	350	0%	57%	157%
		4	200	400	200	400	0%	50%	150%
Later	Margin Call	5	200	250	50	125	-50%	80%	130%
		6	200	300	100	190	-37%	67%	130%
		7	200	350	150	255	-27%	57%	130%
		8	200	400	200	320	-20%	50%	130%
Later	Cash Extract	9	200	250	50	550	120%	80%	300%
		10	200	300	100	700	133%	67%	300%
		11	200	350	150	850	143%	57%	300%
		12	200	400	200	1000	150%	50%	300%

Figure 1: Outstanding Margin Debt by Round

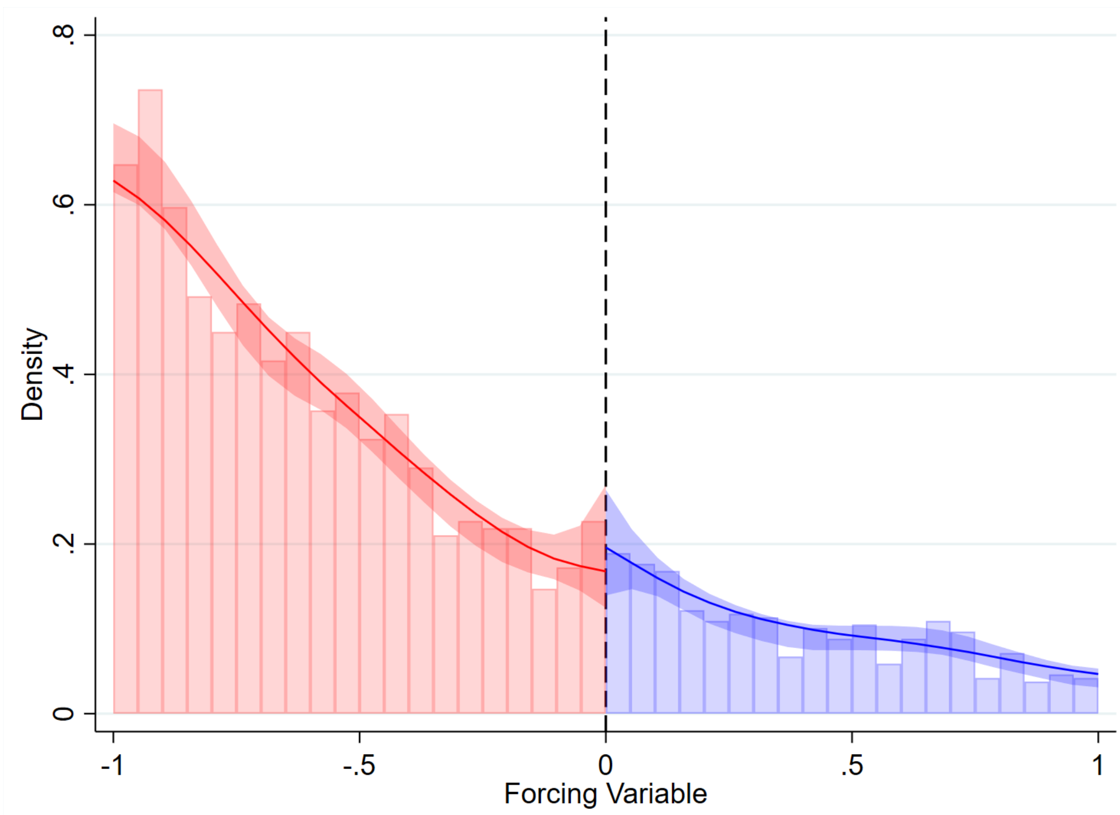


This figure plots the average stock-level outstanding margin debt scaled by total tradable market capitalization for newly marginable stocks in rounds 1, 2, and 3.

Figure 2: Average Holding Period: Margin Trader vs. Average Investor

This figure plots the average holding period of margin traders and average investors for all newly marginable stocks in rounds 1, 2, and 3. The left column calculates the average holding period of margin traders (average investors) as the reciprocal of the *stock-level* share turnover of margin (total) trading activities from 2013 to 2016. The right column instead uses the *market-level* share turnover of the margin (total) trading activities. For margin trading, the share turnover is calculated as the daily repay amount scaled by outstanding margin debt; for total trading activities, the share turnover is calculated as the daily share volume over tradable shares outstanding.

Figure 3: Distribution of Stocks around the Eligibility Cutoff

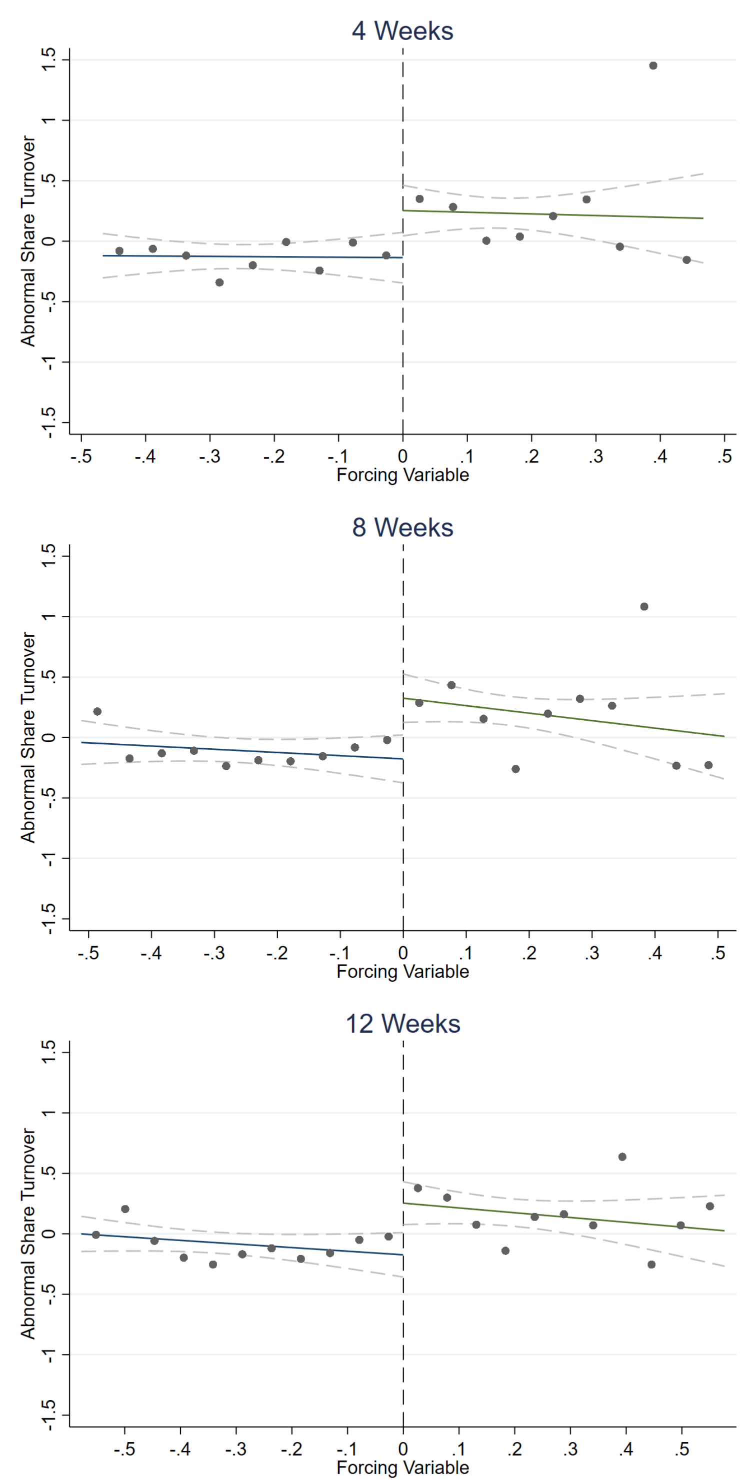


This figure shows the frequency density of firm-round observations in each bin of the forcing variable around the eligibility cutoff. Vertical bars represent the histogram estimate of the forcing variable. Following Cattaneo et al. (2020), I plot local polynomial density estimates (solid blue and red) and robust bias-corrected confidence intervals (shaded blue and red) on both sides of the experiment cutoff.

Figure 4: Discontinuity in Margin Trading Eligibility at the Cutoff

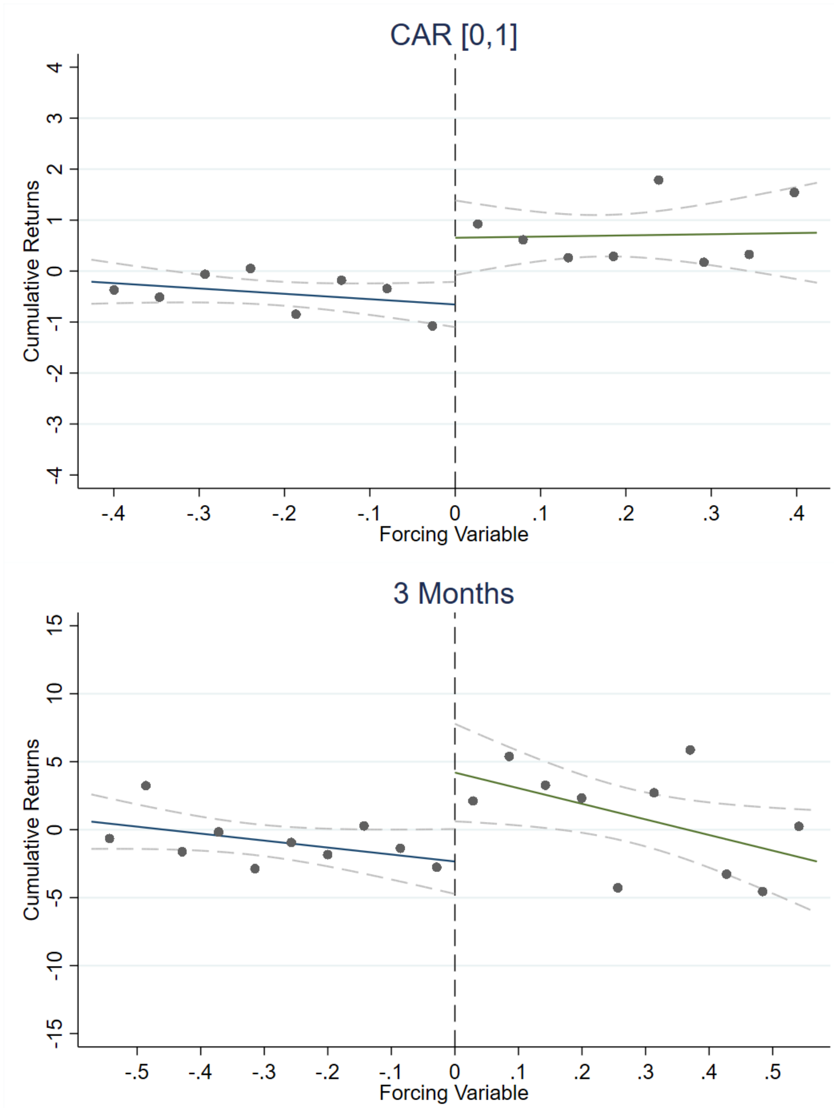
This figure plots the margin trading eligibility against the forcing variable. I include all firms within the CCT bandwidth, and each point denotes the average probability of being marginable for firms within each evenly-spaced bin. Separate regression lines, along with 90% confidence intervals based on heteroscedasticity-consistent standard errors, are shown on both sides of the eligibility cutoff.

Figure 5: Discontinuity in Abnormal Share Turnover at the Cutoff



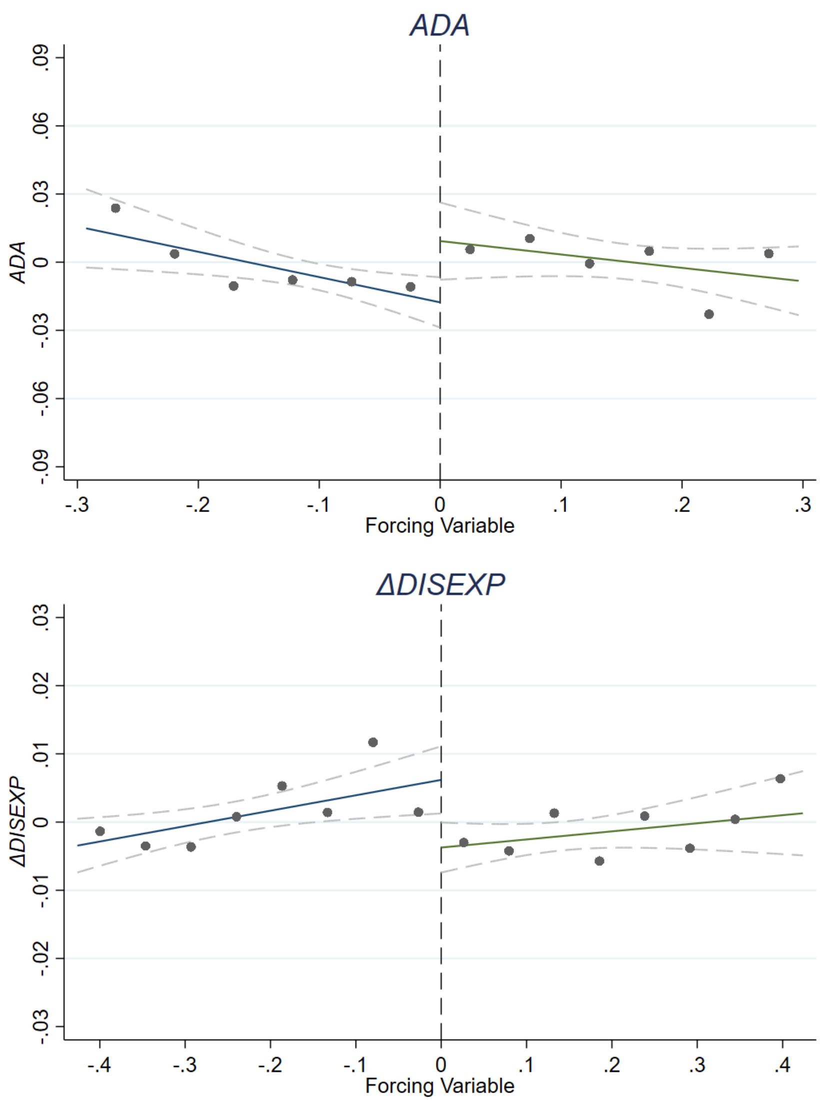
This figure plots the abnormal share turnover against the forcing variable. I include all firms within the CCT bandwidth and measure the abnormal share turnover as the change of daily share turnover before and after the implementation date using event windows of 4 weeks, 8 weeks, and 12 weeks. To control for time-series variation in abnormal share turnover, I demean each firm-round observation using the average values of all stocks in that round. Each point denotes the average abnormal share turnover within each bin of width 0.05. Separate regression lines, along with 90% confidence intervals based on heteroscedasticity-consistent standard errors, are shown on both sides of the eligibility cutoff.

Figure 6: Discontinuity in Returns at the Cutoff



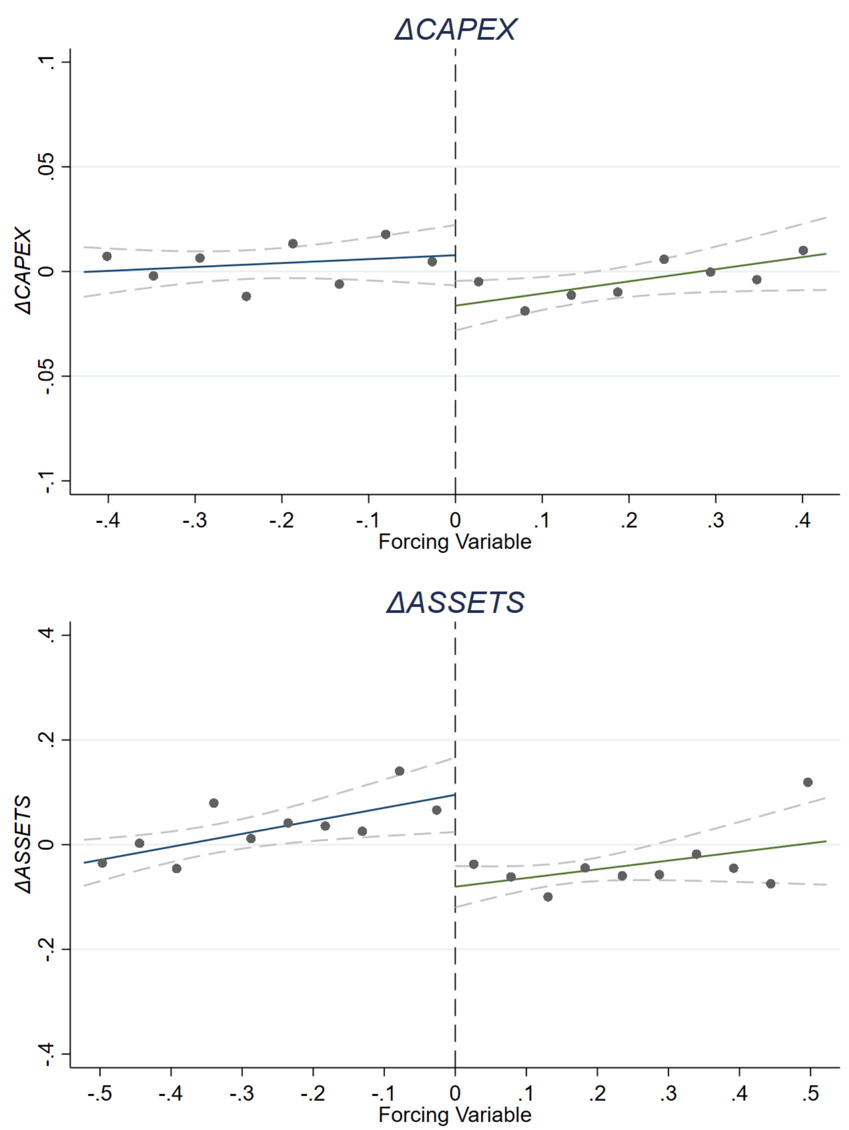
This figure plots the cumulative returns against the forcing variable. I include all firms within the CCT bandwidth and measure the outcome variable as the cumulative returns right after the implementation day (event window [0,1]) and cumulative returns in a longer post-event window of three months. To control for time-series variation in returns, I demean each firm-round observation using the average values of all stocks in that round. Each point denotes the average cumulative returns within each bin of width 0.05. Separate regression lines, along with 90% confidence intervals based on heteroscedasticity-consistent standard errors, are shown on both sides of the eligibility cutoff.

Figure 7: Discontinuity in Earnings Management at the Cutoff



This figure plots *ADA* and Δ*DISEXP* against the forcing variable for all firms within the CCT bandwidth. To control for time-series variation in accrual-based and real earnings management, I demean each firm-round observation using the average values of all stocks in that round. Each point denotes the average of the outcome variable within each bin of width 0.05. Separate regression lines, along with 90% confidence intervals based on heteroscedasticity-consistent standard errors, are shown on both sides of the eligibility cutoff.

Figure 8: Discontinuity in Long-Term Investment at the Cutoff



This figure plots Δ*CAPEX* and Δ*ASSETS* against the forcing variable for all firms within the CCT bandwidth. To control for time-series variation in corporate investment, I demean each firm-round observation using the average values of all stocks in that round. Each point denotes the average of the outcome variable within each bin of width 0.05. Separate regression lines, along with 90% confidence intervals based on heteroscedasticity-consistent standard errors, are shown on both sides of the eligibility cutoff.

TABLE 1: Implementation Timeline

Round #	Eligibility Decision	Event Day	# of Treated Stocks by Round		
			Shanghai	Shenzhen	Both
Pilot A	Market index	March 31, 2010	50	40	90
Pilot B	Market index	December 5, 2011	130	59	189
1	Ranking formula	January 31, 2013	163	113	276
2	Ranking formula	September 16, 2013	104	102	206
3	Ranking formula	September 22, 2014	104	114	218

TABLE 2: Summary Statistics

	Bandwidth = 0.4			Bandwidth = 0.5			Bandwidth = 0.6		
Variable	Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median	S.D.
Total Assets	8.42	4.37	12.10	8.08	4.22	11.48	7.75	4.09	10.94
Market Cap.	7.39	6.12	6.20	7.22	5.92	5.94	6.99	5.85	5.55
B/M	0.45	0.37	0.32	0.44	0.37	0.31	0.45	0.38	0.31
ROA	5.61	4.69	7.37	5.57	4.69	7.42	5.52	4.46	7.27
Leverage	0.48	0.49	0.21	0.47	0.48	0.21	0.47	0.48	0.21
Cash Flow	5.74	5.27	8.86	5.63	5.14	8.92	5.36	5.10	8.91
Cash Flow Vol.	11.18	7.57	14.22	11.30	7.56	14.92	11.50	7.61	14.89
ΔNI	3.33	1.61	6.03	3.45	1.68	6.31	3.57	1.72	6.48
Analyst No.	7.32	3.00	12.02	6.92	3.00	11.62	6.67	3.00	11.21
Dispersion	11.15	5.82	15.14	10.94	4.96	15.13	10.88	4.36	15.42
Beta	1.12	1.11	0.32	1.13	1.11	0.32	1.13	1.12	0.31
Share Turnover	2.50	1.79	2.18	2.51	1.83	2.20	2.52	1.84	2.21
ADA	6.83	4.52	7.53	6.93	4.43	7.90	6.93	4.48	7.81
$\Delta DISEXP$	1.66	0.83	2.70	1.64	0.82	2.73	1.58	0.81	2.69
$\Delta CAPEX$	1.18	0.14	6.87	1.22	0.17	7.00	1.16	0.15	6.98
$\Delta ASSETS$	19.26	12.37	35.39	18.88	12.09	34.61	19.19	12.00	35.37

This table reports descriptive statistics for observations local to the eligibility cutoff within the bandwidth of 0.4, 0.5, and 0.6. All firm characteristics are measured in the fiscal year closest to the implementation date. Variable definitions are provided in the Appendix. All variables are winsorized at the 1% and 99% levels. *Total Assets* and *Market Cap.* are in 100 millions RMB. *ROA*, *Cash Flow*, *Cash Flow Vol.*, ΔNI, *Dispersion*, *Share Turnover*, *ADA*, $\Delta DISEXP$, $\Delta CAPEX$, and $\Delta ASSETS$ are in percentage points.

TABLE 3: First Stage: Discontinuity in Margin Trading Eligibility at the Cutoff

	Marginable	
Above the Cutoff	0.539***	0.524***
	(0.064)	(0.070)
Firms Below	332	409
Firms Above	234	253
CCT Bandwidth	0.342	0.401
Kernel	Uniform	Triangular

This table reports the first-stage regression results estimated by the following equation:

$$Marginable_i^k = \beta_1 \cdot \mathbf{1}[V_i^k > 0] + R(V_i^k) + L(V_i^k) + \eta^k + \epsilon_i^k$$

$Marginable_i^k$ is a dummy variable that equals one if stock i is approved for margin trading in round k. $\mathbf{1}[V_i^k > 0]$ is a dummy variable that equals one if stock i's ranking index is above the experiment cutoff in round k. $R(V_i^k)$ and $L(V_i^k)$ are linear controls of the forcing variable on the right-hand and left-hand side of the cutoff. η^k represents the round fixed effect. The bandwidth is automatically chosen by a data-driven algorithm as described in Calonico et al. (2014). All standard errors are calculated using the heteroskedasticity-robust nearest-neighbor estimator (Calonico et al., 2019). I show coefficient estimates of β_1 and report standard errors in parentheses. All estimates are similar among different kernel choices, and I use the uniform (rectangular) kernel for the main analysis hereafter. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 4: Abnormal Share Turnover

Panel A: Reduced Form

	4 Weeks	8 Weeks	12 Weeks
Above the cutoff	0.453***	0.569***	0.455***
	(0.164)	(0.169)	(0.154)

Panel B: Fuzzy RD

	4 Weeks	8 Weeks	12 Weeks
Marginable	0.796***	0.972***	0.748***
	(0.300)	(0.303)	(0.260)
Firms Below	468	528	636
Firms Above	264	277	305
CCT Bandwidth	0.468	0.512	0.578
Controls	Yes	Yes	Yes

Panel A reports the reduced form regression in which I run the outcome variable on the indicator of being above the cutoff. Panel B reports the fuzzy RD regression results using 2SLS estimation.

$$Y_i^k = \beta_2 \cdot Marginable_i^k + R(V_i^k) + L(V_i^k) + X_i^k + \eta^k + \epsilon_i^k$$

The outcome variable Y_i^k is the abnormal share turnover (in percentage) for firm i in round k, measured as the change of daily share turnover before and after the implementation date using event windows of 4 weeks, 8 weeks, and 12 weeks. The main explanatory variable of interest $Marginable_i^k$ is an indicator variable that equals one if firm i is approved for margin trading in round k. An indicator of whether stock i's ranking index is above the cutoff, $\mathbf{1}[V_i^k > 0]$, is used as an instrument for $Marginable_i^k$. Control variables X_i^k are as follows: previous month's absolute stock return and log stock price; log(1+*Analyst No.*), where *Analyst No.* is the previous month's number of analysts who follow a firm and report forecasts; previous month's forecast dispersion, defined as the standard deviations of earnings per share forecasts reported by analysts; earnings surprise defined as the absolute value of the current ROA minus last year's ROA; other annual frequency controls including leverage, book-to-market ratio, market capitalization, and beta. $R(V_i^k)$ and $L(V_i^k)$ are separate linear controls of the forcing variable V_i^k on the right-hand and left-hand side of the cutoff. η^k represents the round fixed effect. The bandwidth is automatically chosen by the CCT data-driven algorithm as described in Calonico et al. (2014). All standard errors are calculated using the heteroskedasticity-robust nearest-neighbor estimator (Calonico et al., 2019). I show coefficient estimates of β_2 and report standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 5: Returns

Panel A: Reduced Form

	CAR [0,1]		3 Months	
Adjustment	Raw	Market	Raw	DGTW
Above the cutoff	1.308**	1.345**	6.540**	5.365**
	(0.539)	(0.559)	(2.710)	(2.397)

Panel B: Fuzzy RD

	CAR [0,1]		3 Months	
Adjustment	Raw	Market	Raw	DGTW
Marginable	2.335**	2.427**	10.597**	9.023**
	(0.977)	(1.026)	(4.443)	(4.088)
Firms Below	430	387	684	618
Firms Above	254	248	328	311
CCT Bandwidth	0.427	0.403	0.573	0.535

Panel A reports the reduced form regression in which I run the outcome variable on the indicator of being above the cutoff. Panel B reports the fuzzy RD regression results using 2SLS estimation.

$$Y_i^k = \beta_2 \cdot Marginable_i^k + R(V_i^k) + L(V_i^k) + \eta^k + \epsilon_i^k$$

The outcome variable Y_i^k is the stock returns (in percentage) for firm i in round k. I measure raw/market-adjusted cumulative abnormal returns (CAR) right after the implementation day (event window [0,1]) and raw/DGTW-adjusted cumulative returns in a longer post-event window of three months. The main explanatory variable of interest $Marginable_i^k$ is an indicator variable that equals one if firm i is approved for margin trading in round k. An indicator of whether stock i's ranking index is above the cutoff, $\mathbf{1}[V_i^k > 0]$, is used as an instrument for $Marginable_i^k$. $R(V_i^k)$ and $L(V_i^k)$ are separate linear controls of the forcing variable V_i^k on the right-hand and left-hand side of the cutoff. η^k represents the round fixed effect. The bandwidth is automatically chosen by the CCT data-driven algorithm as described in Calonico et al. (2014). All standard errors are calculated using the heteroskedasticity-robust nearest-neighbor estimator (Calonico et al., 2019). I show coefficient estimates of β_2 and report standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 6: Earnings Management

Panel A: Reduced Form

	ADA		*ΔDISEXP*	
	Post	Pre	Post	Pre
Above the Cutoff	0.028***	−0.006	−0.009***	−0.005
	(0.011)	(0.010)	(0.003)	(0.004)

Panel B: Fuzzy RD

	ADA		*ΔDISEXP*	
	Post	Pre	Post	Pre
Marginable	0.054***	−0.011	−0.017***	−0.009
	(0.021)	(0.019)	(0.006)	(0.007)
Firms Below	253	335	447	417
Firms Above	179	232	255	247
CCT Bandwidth	0.297	0.362	0.427	0.417
Controls	Yes	Yes	Yes	Yes

Panel A reports the reduced form regression in which I run the outcome variable on the indicator of being above the cutoff. Panel B reports the fuzzy RD regression results using 2SLS estimation.

$$Y_i^k = \beta_2 \cdot Marginable_i^k + R(V_i^k) + L(V_i^k) + X_i^k + \eta^k + \epsilon_i^k$$

The outcome variables Y_i^k are respectively *ADA* and $\Delta DISEXP$ for firm i in round k. The main explanatory variable of interest $Marginable_i^k$ is an indicator variable that equals one if firm i is approved for margin trading in round k. An indicator of whether stock i's ranking index is above the cutoff, $\mathbf{1}[V_i^k > 0]$, is used as an instrument for $Marginable_i^k$. Control variables X_i^k include market capitalization, market-to-book ratio, leverage, operating return on assets, cash flow volatility, asset growth rate, operating cash flow, and lagged discretionary accruals. I also report pre-event results (one year before the deregulation) as a placebo test. $R(V_i^k)$ and $L(V_i^k)$ are separate linear controls of the forcing variable V_i^k on the right-hand and left-hand side of the cutoff. η^k represents the round fixed effect. The bandwidth is automatically chosen by the CCT data-driven algorithm as described in Calonico et al. (2014). All standard errors are calculated using the heteroskedasticity-robust nearest-neighbor estimator (Calonico et al., 2019). I show coefficient estimates of β_2 and report standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 7: Long-Term Investment

Panel A: Reduced Form

	$\Delta CAPEX$		$\Delta ASSETS$	
	Post	Pre	Post	Pre
Above the Cutoff	-0.025^{**}	0.012	-0.171^{***}	0.022
	(0.011)	(0.009)	(0.049)	(0.053)

Panel B: Fuzzy RD

	$\Delta CAPEX$		$\Delta ASSETS$	
	Post	Pre	Post	Pre
Marginable	-0.046^{**}	0.019	-0.286^{***}	0.042
	(0.021)	(0.015)	(0.085)	(0.100)
Firms Below	450	567	605	330
Firms Above	258	287	305	229
CCT Bandwidth	0.428	0.521	0.523	0.343
Controls	Yes	Yes	Yes	Yes

Panel A reports the reduced form regression in which I run the outcome variable on the indicator of being above the cutoff. Panel B reports the fuzzy RD regression results using 2SLS estimation.

$$Y_i^k = \beta_2 \cdot Marginable_i^k + R(V_i^k) + L(V_i^k) + X_i^k + \eta^k + \epsilon_i^k$$

The outcome variables Y_i^k are respectively $\Delta CAPEX$ and $\Delta ASSETS$ for firm i in round k. The main explanatory variable of interest $Marginable_i^k$ is an indicator variable that equals one if firm i is approved for margin trading in round k. An indicator of whether stock i's ranking index is above the cutoff, $\mathbf{1}[V_i^k > 0]$, is used as an instrument for $Marginable_i^k$. Control variables X_i^k include past profitability (operating ROA), operating cash flow, and lagged total assets. I also report pre-event results (one year before the deregulation) as a placebo test. $R(V_i^k)$ and $L(V_i^k)$ are separate linear controls of the forcing variable V_i^k on the right-hand and left-hand side of the cutoff. η^k represents the round fixed effect. The bandwidth is automatically chosen by the CCT data-driven algorithm as described in Calonico et al. (2014). All standard errors are calculated using the heteroskedasticity-robust nearest-neighbor estimator (Calonico et al., 2019). I show coefficient estimates of β_2 and report standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 8: Alternative Bandwidths

Panel A: Dependent Variable = Abnormal Share Turnover				
Bandwidth	+25%	+10%	−10%	−25%
Marginable	0.772***	0.740***	0.800***	0.665**
	(0.213)	(0.237)	(0.290)	(0.328)
Observations	1277	1074	830	671
Panel B: Dependent Variable = Returns				
Bandwidth	+25%	+10%	−10%	−25%
Marginable	1.807**	2.220**	2.934***	3.197***
	(0.837)	(0.946)	(1.053)	(1.135)
Observations	833	724	567	481
Panel C: Dependent Variable = *ADA*				
Bandwidth	+25%	+10%	−10%	−25%
Marginable	0.047**	0.052***	0.051**	0.044*
	(0.018)	(0.019)	(0.022)	(0.025)
Observations	532	478	388	325
Panel D: Dependent Variable = Δ*DISEXP*				
Bandwidth	+25%	+10%	−10%	−25%
Marginable	−0.013***	−0.014**	−0.018***	−0.016**
	(0.005)	(0.006)	(0.007)	(0.007)
Observations	928	785	626	529
Panel E: Dependent Variable = Δ*CAPEX*				
Bandwidth	+25%	+10%	−10%	−25%
Marginable	−0.037**	−0.036*	−0.046**	−0.049**
	(0.017)	(0.018)	(0.023)	(0.025)
Observations	937	793	629	533
Panel F: Dependent Variable = Δ*ASSETS*				
Bandwidth	+25%	+10%	−10%	−25%
Marginable	−0.266***	−0.282***	−0.256***	−0.296***
	(0.064)	(0.076)	(0.089)	(0.109)
Observations	1201	1012	793	648

This table reports the fuzzy RD results with alternative bandwidths. Specifically, I increase/decrease the CCT optimal bandwidth by 10% and 25% and redo the RD analysis for all outcome variables, including the 12-week abnormal share turnover, event-day returns, *ADA*, Δ*DISEXP*, Δ*CAPEX*, and Δ*ASSETS*. All specifications and control variables are the same as the main analysis. I show coefficient estimates of β_2 and report standard errors in parentheses, along with the firm-round observations within each alternative bandwidth. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 9: Placebo Cutoffs

Panel A: Dependent Variable = Abnormal Share Turnover				
Cutoff	+0.5	−0.5	+CCT	−CCT
Marginable	−0.092	−0.094	−0.172	0.244
	(0.223)	(0.168)	(0.235)	(0.151)
Observations	636	859	441	980
Panel B: Dependent Variable = Returns				
Cutoff	+0.5	−0.5	+CCT	−CCT
Marginable	−0.740	0.114	−0.142	0.276
	(0.753)	(0.391)	(0.663)	(0.370)
Observations	543	1105	744	1345
Panel C: Dependent Variable = *ADA*				
Cutoff	+0.5	−0.5	+CCT	−CCT
Marginable	−0.002	−0.007	−0.003	0.011
	(0.010)	(0.007)	(0.008)	(0.008)
Observations	543	1103	966	1061
Panel D: Dependent Variable = Δ*DISEXP*				
Cutoff	+0.5	−0.5	+CCT	−CCT
Marginable	0.004	−0.004	0.002	−0.001
	(0.004)	(0.003)	(0.004)	(0.003)
Observations	625	1054	651	1403
Panel E: Dependent Variable = Δ*CAPEX*				
Cutoff	+0.5	−0.5	+CCT	−CCT
Marginable	−0.006	0.005	−0.002	0.010
	(0.013)	(0.008)	(0.012)	(0.008)
Observations	437	1295	615	1713
Panel F: Dependent Variable = Δ*ASSETS*				
Cutoff	+0.5	−0.5	+CCT	−CCT
Marginable	0.034	0.014	0.046	0.035
	(0.043)	(0.040)	(0.063)	(0.038)
Observations	1001	986	615	1129

This table reports results of placebo tests, in which I replicate the RD analysis around placebo cutoffs set at 0.5, −0.5, and one CCT bandwidth above and below the actual cutoff 0. Outcome variables include the 12-week abnormal share turnover, event-day returns, *ADA*, Δ*DISEXP*, Δ*CAPEX*, and Δ*ASSETS*. All specifications and control variables are the same as the main analysis. I show coefficient estimates of β_1 from the reduced form regression and report standard errors in parentheses, along with firm-round observations within the CCT bandwidth auto-selected at each placebo cutoff. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 10: Validity Tests

Variables	*Total Assets*	*Market Cap.*	*B/M*	*ROA*	*Leverage*	*Asset Growth*
Marginable	2.549	0.920	0.132	0.713	−0.021	0.065
	(3.508)	(1.657)	(0.098)	(2.045)	(0.058)	(0.103)
Firms	566	629	565	539	568	559
Variables	*Cash Flow*	*Cash Flow Vol.*	*ΔNI*	*Analyst No.*	*Dispersion*	*Beta*
Marginable	−0.396	0.556	−1.654	−4.593	1.782	0.068
	(2.862)	(3.646)	(1.739)	(4.079)	(4.689)	(0.080)
Firms	554	728	536	794	473	600

This table reports the fuzzy RD regression results using 2SLS estimation.

$$Y_i^k = \beta_2 \cdot Marginable_i^k + R(V_i^k) + L(V_i^k) + \eta^k + \epsilon_i^k$$

The outcome variables Y_i^k include all control variables used in the main analysis for firm i in round k, measured one year before the margin trading deregulation. $Marginable_i^k$ is an indicator variable that equals one if firm i is approved for margin trading in round k. An indicator of whether stock i's ranking index is above the cutoff, $\mathbf{1}[V_i^k > 0]$, is used as an instrument for $Marginable_i^k$. $R(V_i^k)$ and $L(V_i^k)$ are separate linear controls of the forcing variable V_i^k on the right-hand and left-hand side of the cutoff. η^k represents the round fixed effect. The bandwidth is automatically chosen by the CCT data-driven algorithm as described in Calonico et al. (2014). All standard errors are calculated using the heteroskedasticity-robust nearest-neighbor estimator (Calonico et al., 2019). I show coefficient estimates of β_2 and report standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 11: Alternative Measures

Panel A: Reduced Form

	ΔADA	$\Delta DISEXPRD$	$\Delta CAPEXRD$
Above the Cutoff	0.027^{***}	-0.011^{***}	-0.027^{**}
	(0.010)	(0.004)	(0.011)

Panel B: Fuzzy RD

	ΔADA	$\Delta DISEXPRD$	$\Delta CAPEXRD$
Marginable	0.053^{**}	-0.020^{***}	-0.049^{**}
	(0.021)	(0.007)	(0.021)
Firms Below	244	447	450
Firms Above	173	255	258
CCT Bandwidth	0.297	0.427	0.428
Controls	Yes	Yes	Yes

Panel A reports the reduced form regression in which I run the outcome variable on the indicator of being above the cutoff. Panel B reports the fuzzy RD regression results using 2SLS estimation.

$$Y_i^k = \beta_2 \cdot Marginable_i^k + R(V_i^k) + L(V_i^k) + X_i^k + \eta^k + \epsilon_i^k$$

The outcome variables Y_i^k are defined as follows: ΔADA is the annual change of ADA, representing the abnormal portion of accrual-based earnings management; $\Delta DISEXPRD$ is a slightly modified version of $\Delta DISEXP$, defined as the annual change of SG&A and R&D expenses scaled by beginning-of-year total assets; $\Delta CAPEXRD$ is a slightly modified version of $\Delta CAPEX$, defined as the annual change of capital expenditures and R&D expenses scaled by beginning-of-year total assets. All specifications and control variables are the same as before. The same bandwidth as that of the main analysis is used for each outcome variable. All standard errors are calculated using the heteroskedasticity-robust nearest-neighbor estimator (Calonico et al., 2019). I show coefficient estimates of β_2 and report standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 12: Long-Term Performance

	ROA			*Returns*		
Bandwidth	0.3	0.4	0.5	0.3	0.4	0.5
One year later, $t+1$	−0.017**	−0.018**	−0.016**	−0.176**	−0.163**	−0.167***
	(0.008)	(0.008)	(0.008)	(0.068)	(0.067)	(0.061)
Two years later, $t+2$	−0.019**	−0.021**	−0.021**	−0.077	−0.089	−0.080
	(0.010)	(0.009)	(0.009)	(0.060)	(0.059)	(0.054)
Three years later, $t+3$	−0.018*	−0.017	−0.014	−0.058	−0.066*	−0.063*
	(0.011)	(0.011)	(0.010)	(0.040)	(0.038)	(0.035)
Four years later, $t+4$	−0.018	−0.018*	−0.011	−0.041	−0.045	−0.052
	(0.011)	(0.011)	(0.010)	(0.043)	(0.041)	(0.039)
R^2	0.521	0.513	0.505	0.483	0.483	0.480
Observations	2912	3870	5060	2894	3848	5034
No. of firm-rounds	493	655	856	493	655	856

This table presents the effect of margin trading eligibility on firm long-term performance using a dynamic regression discontinuity model.

$$Y_{i,t+\tau} = \beta^\tau \cdot Marginable_{it} + R^\tau(V_{it}) + L^\tau(V_{it}) + \alpha_\tau + \eta_c + \lambda_{it} + \epsilon_{it\tau}$$

The outcome variables are operating ROA (return on assets) and stock returns. $Marginable_{it}$ is an indicator of margin trading eligibility, and β^τ estimates the effect of margin trading eligibility at time t on firm outcomes at $t+\tau$. β^τ and separate linear controls of the forcing variable $R^\tau(V_{it})$ and $L^\tau(V_{it})$ are allowed to vary for $\tau > 0$, and constrained to zero for $\tau < 0$, and standard errors are clustered at the firm level. The parameters α_τ, η_c, and λ_{it} are fixed effects for time periods relative to the event, calendar years, and firm-rounds. The bandwidth is respectively set at 0.3, 0.4, and 0.5. I show coefficient estimates of β^τ ($\tau = 1, 2, 3, 4$) and report standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 13: The Effect of Margin Trading Eligibility on *ADA* Controlling for Investment Growth

	Absolute Discretionary Accruals (*ADA*)			
	(1)	(2)	(3)	(4)
$Marginable_i^k$	0.051**	0.050**	0.052**	0.051**
	(0.021)	(0.021)	(0.021)	(0.021)
V_i^k	−0.125**	−0.125**	−0.126**	−0.125**
	(0.054)	(0.053)	(0.054)	(0.053)
$R(V_i^k)$	0.038	0.038	0.035	0.034
	(0.070)	(0.069)	(0.070)	(0.069)
Market Cap.	−0.001**	−0.001**	−0.001**	−0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Leverage	0.023	0.029*	0.023	0.030*
	(0.017)	(0.018)	(0.018)	(0.018)
MB	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Cash Flow	−0.056	−0.060	−0.056	−0.062
	(0.057)	(0.055)	(0.057)	(0.055)
Cash Flow Vol.	0.053	0.052	0.054	0.051
	(0.051)	(0.050)	(0.051)	(0.050)
ROA	0.019	0.072	0.018	0.073
	(0.095)	(0.091)	(0.095)	(0.091)
Lagged ADA	0.204***	0.193***	0.207***	0.196***
	(0.064)	(0.064)	(0.064)	(0.064)
$\Delta ASSETS$	0.040***	0.003	0.042***	0.001
	(0.016)	(0.021)	(0.016)	(0.022)
$\Delta CAPEX$	0.048	0.014		
	(0.054)	(0.062)		
$\Delta ASSETS^2$		0.000		0.000
		(0.000)		(0.000)
$\Delta CAPEX^2$		0.002		
		(0.003)		
$\Delta CAPEXRD$			0.030	0.010
			(0.047)	(0.060)
$\Delta CAPEXRD^2$				0.002
				(0.003)
Constant	0.005	0.006	0.005	0.005
	(0.015)	(0.015)	(0.015)	(0.015)
R^2	0.264	0.277	0.263	0.276
Observations	432	432	432	432

This table presents the effect of margin trading eligibility on *ADA* after controlling for firms' investment and growth. All regression specifications are the same as before. Besides the control variables used in the main analysis, I further include $\Delta CAPEX$ in column (1) and the squared terms $\Delta ASSETS^2$ and $\Delta CAPEX^2$ in column (2). In columns (3) and (4), I use a slightly modified version of $\Delta CAPEX$ by including both capital expenditures and R&D expenditures and denote it $\Delta CAPEXRD$. Heteroscedasticity-consistent standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.