# Anticipation Versus Direct Effects of Credit Supply on Asset Prices

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**Abstract**

Research on leverage and asset price fluctuations focus on the direct effect of credit enabling financially-constrained investors to bid up prices. In practice, unconstrained investors can anticipate and speculate on when credit becomes available. Anticipation has stability and distributional consequences but is challenging to measure and largely ignored. We disentangle these two effects using the 2010-2015 staggered deregulation of stock margin lending by brokerages and banks in China. Stocks were gradually qualified based on a formula during this bubble-and-crash period. Unconstrained investors bought stocks likely-to-qualify for lending and sold them to constrained investors at high prices after margin became available.

**Preliminary and Incomplete: Do Not Circulate**

# 1 Introduction

An important macro-finance literature, loosely dubbed "credit booms gone wrong", associates leverage cycles and asset price boom-bust patterns using panel regressions involving cross-country variation and long time series (see, e.g., Borio & Lowe (2002), Schularick & Taylor (2012)).[1] Prominent historical examples include the rise of margin lending in the U.S. stock market preceding the Great Depression (Galbraith (2009)) and high loan-to-value ratios in the U.S. housing market preceding the Great Recession. This literature has understandably attracted considerable interest from central bankers and other financial market regulators.

Theories addressing these empirical patterns emphasize the "direct" effect of credit supply shocks leading to higher asset prices and financial fragility through a variety of mechanisms. A non-exhaustive list includes (1) complacency or neglect regarding with the sensitivity of debt structures to downside or tail risk (Minsky (1977), Kindelberger & Manias (1978), Gennaioli *et al.* (2012), Simsek (2013)), (2) reckless lending in the form of lax screening of naive investors (Schumpeter, Dell'Ariccia & Marquez (2006), and Keys *et al.* (2012)) , (3) leverage cycles (Geanakoplos (2010)), and (4) intermediary frictions or balance sheets (Bernanke & Gertler (1989), Kiyotaki & Moore (1997), Adrian & Shin (2010), He & Krishnamurthy (2013), and Brunnermeier & Sannikov (2014)).

Largely neglected in these theories is the role of anticipation, which we define as unconstrained investors' expectations regarding the direct effects of credit supply. In practice, credit expansions are often gradual and predictable, particularly since expansions are frequently associated with government policies. If unconstrained investors are able to speculate in advance of an expansion of credit they may drive up prices, leaving constrained investors to buy at higher prices, and hence higher leverage ratios, when credit becomes available. Such anticipation may have important distributional consequences—as unconstrained investors capture gains from any price increases—as well as impacts on financial fragility resulting from the high prices newly-unconstrained investors must purchase at. A potential example of such anticipation effects was that roll-out of subprime lending across US cities. Investment properties, which as second homes are presumably purchased by unconstrained households, were bought in great numbers in advance of the peak of the housing bubble (see, e.g., Haughwout *et al.* (2011) and DeFusco *et al.* (2017)), particularly in subprime areas. This coincidence of purchases is consistent unconstrained households speculating their expectations of an impending house price boom due to the availability of cheap credit.

Such anticipation effects have been largely neglected since it is hard to measure them in practice. A large literature trying to gauge the effects of credit supply utilize geographical variation in credit supply

[1] An antecedent literature in emerging markets associates banking crises with currency crises and international financial market contagion (see, e.g., Kaminsky & Reinhart (1999)). Recent contributions also include Jordà *et al.* (2013), Mian *et al.* (2017), and Baron & Xiong (2017). Credit booms might also be measured using credit spreads as opposed to leverage ratios (i.e., Krishnamurthy *et al.* (2015) and López-Salido *et al.* (2017)).

(Mian & Sufi (2011), Adelino *et al.* (2017)). But the timing of when the credit supply becomes available is generally not well measured. Moreover, understanding when unconstrained investors have information to form their expectations about impending credit supply, and precisely what information these investors have, is typically a challenge. However, as we show below, the existence of these anticipation effects alters both how we model credit cycles and how we measure the effects of credit supply.

In this paper, we demonstrate that the recent credit cycle in China offers a venue to separate anticipation from direct effects of credit supply on asset prices. From 2010 to 2015, the Chinese stock market had a credit boom gone wrong that mirrors the episodes studied in this macro-finance literature. It witnessed a rapid expansion of stock margin lending to households, provided by both brokerage houses and banks, that peaked at 3.5% of GDP and 4% of market capitalization (see Figure 1). The event was widely watched by the finance community, which pegged this rapid expansion as the fastest and largest in history, dwarfing all other historical developed market experiences. This expansion coincided with the deregulation of stock margin lending by banks over this period. It coincided with high market valuations, a subsequent crash and government bailouts. These bailouts involved among other things purchases of stocks by the state-controlled brokerage firms. Media reports during this episode spoke of unsustainably high levels of margin debt and stock market valuations posing systemic risk to the financial system and indeed even the political system.

Beyond these parallels, what makes the Chinese experience useful is that the government staggered the deregulation of margin lending and hence the availability of credit at the stock level, based formulaically on a stock's index membership, market capitalization and trading volume. Moreover, this stagger occurred over five vintages or cohorts of stocks. We dub as Vintage 0 the original set of 90 stocks in the biggest stock market indices in China and became available for lending in late 2010. This was a pilot program. In 2011, the government announced that another set of stocks in indices (Vintage 1) were qualified for lending. During this time, the government also committed to a formal rule on screening and ranking stocks whereby other stocks were expected to qualify for lending in the future based on market capitalization and trading volume. This screening and ranking procedure is replicable using widely-available public information. There were in total three subsequent extensions before the crash in 2015, affecting roughly 200 stocks per cohort. The last of these was in September 2014, at which point there were 900 of a total of around 2600 stocks that were qualified for margin lending.[2] Figure 2 plots the timing of the vintage roll-outs and subsequent expansion of margin lending.

[2]In addition to the formal margin loan program, investors may borrow from some shadow margin channels, such as P2P lending platforms, to invest into stocks. One may concern how the use of shadow margin changes our results. Unfortunately, data is not available to formally address this issue. But, according to Bian *et al.* (2017), the shadow margin system was not sizeable and popular among investors until the first half of 2015. Given that the last deregulation is effective in September 2014, the conclusion of our analysis is unlikely to be changed if we could take into account shadow margin loans.

This staggered deregulation, including the public announcement of the rule in 2011, allows us to cleanly separate anticipation from direct effects. To the extent that there are no anticipation effects, we should see only price and trading effects when margin becomes available or subsequently after the roll-out. But to the extent there are anticipation effects, we expect prices and trading to rise before the credit supply comes on line. Moreover, there is an anticipation window that should occur after 2011 since the government had not publicly announced their intentions before then. There should not be anticipation effects outside this window. Figures 3–5 indicate that there is a substantial anticipation effect. Figure 3 shows that prices of Vintages 2–4 rise around 6-12 months before the margin lending officially rolls out. Figure 4 shows that this price rise is associated with turnover and Figure 5 shows that it is unconstrained institutional investors who are buying before the roll-out and selling after the roll-out. Notice that this price rise need not be instantaneous and should be gradual since unconstrained investors have holdings costs which would induce horizon effects.

This staggered deregulation is amendable to a quasi-myopic difference-in-difference estimator (see, e.g., Malani & Reif (2015)) to disentangle anticipation versus direct effects. It nests the standard or myopic difference-in-difference estimator. We have the following findings. First, the direct ("ex-post" after margin turns on) effect is on the order 20 to 40 cents for extra $1 of margin debt. This estimate serves as a benchmark and reflects that investors can substitute to other assets. But it is also subject to misspecification since a conventional difference-in-difference estimator compares the treatment effect to a high anticipatory period. Second, we find substantial anticipation effects. Accounting for anticipation effects using the quasi-myopic approach gives estimates of the impact of lending that exceed $1. The anticipation is driven by unconstrained institutional investors who are more likely to buy stocks with highest likelihood of inclusion (calculated using public formula) in next wave of deregulation. In short, we find that accounting for anticipation effects are important.

We view our quasi-experiment as having external validity and the following message. In the verbiage of difference-in-difference estimators, we should expect there to be pre-trends associated with these margin debt roll-outs or credit supply that are driven by anticipation and speculation on the part of unconstrained investors. Our results also mean that in other settings where the parallel trend assumption is satisfied, it does not necessarily mean that there are no anticipation effects per se. It might just be due to the timing of debt roll-outs not being clear to the econometrician but agents in the economy could very well be making such forecasts and anticipation effects might be driving the joint dynamics of asset prices and credit supply.

Our paper proceeds as follows. In Section 2, we provide the background to our empirical design and describe our data. In Section 3, we layout our empirical strategy. In Section 4, we present our results. We conclude in Section 5.

# 2 Background and Data

## 2.1 China's staggered deregulation of margin lending

The Chinese regulatory agency began to allow stock margin lending on February 13th, 2010. Investors with more than 500,000 RMB of assets in their stock brokerage account and six months of trading experience qualified for margin provided by their brokerage firms. As a pilot program, the initial list of 90 stocks (i.e., Vintage 0) were qualified for margin lending through the broker's margin system. This list was determined by the stock's membership in the two major stock market indices: the Shanghai 50 Index and the Shenzhen Component index. These indices comprise the stocks with the largest market capitalizations in the Chinese stock market.

Effective on November 25th, 2011, the Chinese government made the margin lending program for stock trading official and extended the list of marginable stocks based on stocks' membership in broader market indices. The extended list included 278 stocks, 180 stocks from the Shanghai 180 Index and 98 stocks from Shenzhen 100 Index. In the official rule of margin trading, the exchanges explicitly stated that they would extend the list of marginable securities in a staggered manner.[3]

The list of marginable stocks was further extended three times: January 25th 2013, September 6th 2013, and September 12th 2014. Each time, approximately 100 stocks from each of the two exchanges become newly marginable (except 120 stocks for Shanghai exchange on January 25th 2013). At the end of the deregulation period in late 2014, there were approximately 900 stocks that can be bought on margin.[4] Table 1 summarizes the timeline of the deregulation and the number of newly marginable stocks for each extension.

For the last three extensions, the regulator adopted a screening-and-ranking rule to determine a stock's marginability status. This procedure had two steps: (1) screen out stocks that do not satisfy several criteria, i.e., so called Article 24 for Shanghai and Rule 3.2 for Shenzhen, with the purpose of ruling out extremely small, volatile, illiquid and newly listed stocks;[5] and (2) rank the rest of stocks on a formulaic indicator described in Eq.(1) and pick the top 100 as newly marginable stocks in principle with applying some discretions. One can see from Eq.(1) thatthe ranking is based on a value-weighted average of a stock's ranking

[3]See Article 28 in the Rule released by the Shanghai Stock Exchanges.

[4]The concrete number of newly marginable stocks in each extension may be slightly more than 100, as occasionally a few marginable stocks become non-marginable for not stratifying the screening rule.

[5]The criteria to both exchanges are the same: they require stocks to satisfying all of the following criteria: (1) being traded for more than three months; (2) the number of tradable shares is larger than 100 million or market value of tradable shares is larger than 500 million; (3) the number of shareholders is more than 4,000; (4) in the past three months, the following has never happened: a) daily turnover is lower than 20% of the turnover rate of market index, b) the average of absolute value of price changes is higher or lower than that of the market index by 4%, and c) volatility is higher than the market volatility for 500%; (5) has completed the share reform; (6) not special treated stocks; and (7) other conditions. The official document from exchanges does not specify what the other conditions refer to. See rules on stock trading with margin loans on each stock exchange's website.

of size and trading volume within the exchange.[6] The ranking procedure was conducted by Shanghai (SH) and Shenzhen (SZ) exchanges separately.

$$Indicator_i = 2 * \frac{\text{Average Tradable Market Value of Stock } i}{\text{Average Tradable Market Value of All Stocks in SH/SZ}} + \frac{\text{Average Trading Volume in yuan of Stock } i}{\text{Average Trading Volume in yuan of All Stocks in SH/SZ}} \quad (1)$$

According to the regulator's public announcement, the ranking procedure was based on market data over a period before the announcement. Since the data used in the screening-and-ranking procedure is public, we were able to replicate the procedure for each extension on each exchange and find that it explained the membership of newly marginable stocks.

### 2.2 Margin lending and the bubble-crash episode of 2010-2015

Since the deregulation, margin lending expanded rapidly. In Figure 1, we plot the ratio of margin debt to market capitalization and the total market capitalization. One can see that the ratio of total margin debt over market capitalization slowly increased to 0.5% around the end of 2012, and arrived at 1.5% in mid-2014. Since then, the margin debt ratio surges to the highest 4.5% in June 2015. In terms of yuan amount, total margin debt increased from approximately 360 billion in June 2014 to almost two trillion within a year.

Coincident with such high level and rapid growth adoption of margin debt, the Chinese stock market experienced a large boom over this period. As shown in Figure 1, total market capitalization increased from 20 trillion yuan in mid-2014 to over 50 trillion at the peak in June 2015, and the market collapsed more than 20% within two weeks. During the same period, the Shanghai Composite index rose from about 2000 in mid-2014 to the peak, 5,166.35, on June 12, 2015. After, the market crashed to 3709 within three weeks. It is widely believed that the massive use of margin debt pushes the stock prices higher, leading to a bubble, and that forced deleveraging during the crash accelerated the bust of the bubble.

### 2.3 Data and variable construction

We download stock price, trading, and financial information from CSMAR. Formal margin debt balance is released by Shanghai and Shenzhen stock exchanges on a daily basis, and we obtain the data from WIND. Our sample is from 2009/03, one year before margin lending starts, to 2015/10. The pre-crash period is from 2009/03 to 2015/05. The analysis is at monthly level. We exclude stocks on the Growth Enterprise Board

[6] Eq.(1) is released in exchanges' announcements of the second to fourth extension of marginable stocks.

(GEB).

We define the variable $Vintage\_0_i$, which equals one if stock $i$ is in the initial list of marginable stocks and zero otherwise. $Vintage\_1_i$ equals one if stock $i$ becomes newly marginable in the first extension and zero otherwise, and following the same manner we define dummy variables $Vintage\_2_i$, $Vintage\_3_i$, and $Vintage\_4_i$.

The key independent variable of interest in our paper is Margin Debt$_{i,t}$, which refers to the dollar amount balance of margin borrowing for stock $i$ at the end of month $t$. Market Cap$_{i,t}$ is the market value of stock $i$'s all tradable shares. Stocks are sorted into deciles based on the past year's book equity value; we denote decile dummies as $BE_{i,t}$.

Turnover$_{i,t}$ is the number of shares traded over month $t$ scaled by the number of floating shares in Shanghai or Shenzhen stock exchange. Institutional Ownership$_{i,t}$ is the number of shares held by the largest ten shareholders of floating shares scaled by the number of floating shares in Shanghai or Shenzhen stock exchange at the end of month $t$. These owners are predominantly institutions and we use it as our proxy for institutional or large traders who are presumably likely to be unconstrained.

### 2.4 Replicating the screening-and-ranking procedure using public data

We replicate the procedure discussed in Section 2.1 using public stock market data and try to predict the list of marginable stocks for vintages 2–4. It is worthing mentioning that we are subject to a few limitations to exactly back out the outcome. First, it is not clear which time window the exchange exactly uses to implement the procedure. According to some private sources, we learn that they use a three-month period before the formal announcement. Further, it is reasonable that the exchanges have some interval between the formal announcement and the calculation. Here we assume that the most recent month end relative to the announcement day is the end of the three-month evaluation period. Second, the stock exchanges may apply some discretions at the end, which we do not know about. Therefore, we do not expect to be able to precisely predict inclusion— our analysis is somewhat comparable to the first stage of a fuzzy regression discontinuity (RD) design.

For each vintage, we look at the stocks that are non-marginable before the vintage is announced. We follow the screening rule and exclude stocks that do not meet the criteria over the three-month window. Then, we calculate the ranking indicator as specified in Eq.(1) for the rest of stocks and rank them into descending order. We denote stock $i$'s rank for vintage $k$ as $Rank_i^k$, where $k = \{2, 3, 4\}$.

Let $\tau_i^k$ equal one if $Rank_i^k \leq C^k$ and zero otherwise, where $C^k$ is the number of newly marginable stocks in stock $i$'s exchange in vintage $k$. That is, $\tau_i^k$ is the predicted marginable status for stock $i$ for vintage $k$.

Define the indicator of actual marginable status as $D_i^k$, which equals one if stock $i$ becomes marginable for vintage $k$. Because of the discretion that exchanges applied, $\tau_i^k$ does not perfectly predict $D_i^k$ for all stocks. Nonetheless, as long as $\tau_i^k$ is an effective predictor of $D_i^k$, we can still use it to proxy the anticipation effect of credit supply. To formal test this, we follow Chang *et al.* (2014) and run the first-stage regression of the fuzzy RD. That is, for vintage $k$ and stock $i$ satisfying the screening criteria,

$$D_i^k = \alpha_{0l} + \alpha_{1l}(Rank_i^k - C^k) + \tau_i^k[\alpha_{0r} + \alpha_{1r}(Rank_i^k - C^k)] + \epsilon_i \tag{2}$$

If $\tau$ can strongly predict $D$, we expect $\alpha_{0r}$ to be close to one and the R-squared of the regression to be high. Table 2 presents the results for each vintage. While the rankings for stocks are done by exchange, we pool together observations from both exchanges to implement their regression. In column (1), the regression is estimated using the sample of stocks for vintage 4. The point estimate of $\alpha_{0r}$ is 0.87, and $R^2$ equals 0.87, showing that predicted inclusion ($\tau$) can effectively forecast the announced inclusion ($D$). The result also appears to be similarly strong for the other two extensions. In our following analysis, we use the pre-ranking, i.e., $Rank_i$, to identify stocks likely-to-qualify for the margin debt program.

# 3 Empirical Strategy

The primary goal of our empirical analysis is to quantify the impact of China's deregulation of margin lending on stock prices while appropriately accounting for speculation in anticipation of the deregulation. In doing so, we hope to emphasize the necessity of taking anticipatory effects into consideration. We first describe why we expect to see anticipation in this context, why such anticipation will bias or invalidate traditional estimates, the intuition behind our approach to accounting for this, and why our context provides a useful experiment to validate our approach.

While it is not clear that investors were able anticipate the initial roll-out of margin debt (Vintage 0), or the following vintage (Vintage 1), the remains three vintages (2, 3 and 4) proceeded according to a well defined and predictable rule, as described above. As a result, a forward looking investor who expected deregulation to impact prices had substantial time and opportunity to speculate before the margin lending roll-out occurred.

Given the existence of forward looking agents who are unconstrained to some extent, and the expectation that the introduction of margin lending is likely to increase prices, we would expect to see prices begin to rise before deregulation actually occurs. Unconstrained investors will purchase stocks that they expect to become marginable in the future, in order to capture a portion of the price increase that comes with deregulation.

This anticipation has both distributional and destabilizing consequences relative to a world without anticipation. From a distributional perspective, the unconstrained agents are able to capture a portion of the welfare gains that come with deregulation, as they are able to buy at relatively low pre-roll-out prices, and sell to newly unconstrained agents at higher prices when margin trading begins. Because these newly unconstrained agents must buy at higher prices, they wind up more leveraged, and more susceptible to forced deleveraging if asset prices fall.

From the perspective of a traditional difference-in-difference analyses, this sort of anticipation generates a pre-trend in the treatment group. Prices rise for soon to be treated (marginable) stocks, prior to treatment actually occurring. This poses several potential problems for a researcher who is attempting to capture the overall effect of treatment itself on some outcome, which we refer to as the *direct effect*. First, ignoring these pre-trends entirely will lead to biased estimates, as a difference-in-difference approach involves comparing the post-treatment period to a pre-treatment period that has been contaminated by anticipation. If the anticipatory effects are of the same sign as the direct effect, estimated coefficients will be attenuated (or can even change signs).

Alternatively, a researcher might interpret these pre-trends as a sign that treatment is itself endogenous, or that there is some omitted effect impacting the treatment group that renders a difference-in-difference approach invalid. In general, this concern poses a central challenge to appropriately analyzing anticipation: there is no systematic way to distinguish anticipation effects from endogenity of this form.

The value of the staggered nature of margin lending deregulation lies precisely in providing evidence that the pre-trends we see are anticipatory, rather than reflecting some other form of endogeneity. We might typically expect an omitted variable to impact all treated stocks at the same time—and certainly would not expect such a variable to impact different vintages at different times precisely in accordance with the staggered roll-out. On the other hand the timing of pre-trends that are generated by anticipation should correspond exactly to the timing of the roll-out: we would expect to see staggered pre-trends for the different vintages.

The intuition behind our estimation strategy for capturing these anticipation effects is straightforward. Rather than simply comparing the post-treatment period to a contaminated period just pre-treatment , we use the period significantly before the roll-out began as a *pre-period* and separately estimate difference-in-difference coefficients for the treatment period, which we call ex-post or direct effects, and for the periods just before treatment, which we call ex-ante, or anticipatory effects. We refer to this approach as quasi-myopic because it requires the existence of some period significantly before treatment in which anticipation is not present. This could be because agents are truly myopic to some extent—that is they are not infinitely forward looking. Or because anticipation of the event was truly impossible at some horizon.

In the next subsections, we first introduce a baseline set of estimation strategies that follow traditional approaches in the literature, which we refer to as myopic, and then introduce the details of our quasi-myopic approach to capturing anticipation.

## 3.1 OLS

Our OLS specification for the effect of margin debt on stock valuation is the following. For stock $i$ in month $t$, we estimate

$$IHS(\text{Market Cap}_{i,t+1}) = \beta_0 + \beta_1 IHS(\text{Margin Debt}_{i,t}) + \beta_2 BE_{i,t} + \delta_i + \eta_t + \varepsilon_{it},$$

where $IHS(\cdot)$ refers to the inverse hyperbolic sine, $BE_{it}$ are book-equity decile dummies and $\delta_i, \eta_t$ are stock and month×year dummies. $\beta_1$ is expected to be positive, and more importantly, we are interested in the economic magnitude implied from the estimation as we discuss below. We can treat IHS-IHS as roughly similar to a log-log specification and interpret the coefficient of interest $\beta_1$ as an elasticity.

## 3.2 IV Specifications

We will instrument for margin debt using the staggered margin reforms. For stock $i$ in month $t$, we estimate the second stage regression as ("collapsed instrument specification")

$$IHS(\text{Market Cap}_{i,t+1}) = \beta_0 + \beta_1 IHS(\text{Margin Debt}_{i,t}) + \beta_2 BE_{i,t} + \delta_i + \eta_t + \varepsilon_{it}$$

In the first stage regression, we instrument for Margin Debt with the staggered reform:

$$IHS(\text{Margin Debt}_{i,t}) = \gamma_0 + \gamma_1 \text{Margin Trading Active}_{i,t} + \gamma_2 BE_{i,t} + \theta_i + \tau_t + \upsilon_{it},$$

where Margin Trading Active$_{i,t}$=1 if margin lending is allowed for stock $i$ in month $t$, $IHS(\cdot)$ refers to the inverse hyperbolic sine, $BE_{it}$ are book-equity decile dummies, and $\theta_i, \tau_t$ are stock and month×year dummies.

We can also consider a more elaborate first stage regressions ("all instruments specification") where we allow for the effect of the staggered reform on margin debt to vary by Vintage:

$$IHS(\text{Margin Debt}_{i,t}) = \gamma_0 + \sum_{k=0}^{4} \gamma_1^k \text{Margin Trading Active}_{i,t} \times Vintage\_k_i$$
$$+ \gamma_2 BE_{i,t} + \theta_i + \tau_t + v_{it},$$

where $Vintage\_k_i$ is an indicator equal to one if stock $i$ is in vintage $k$. Thus, Margin Trading Active$_{i,t}$ $\times$ $Vintage\_k_i = 1$ if margin lending is allowed for stock $i$ in vintage $k$.

### 3.3 Reduced-Form Regressions: Baseline (Myopic Approach)

In addition to estimating the 2SLS, we also use a reduced-form specification to quantify the effect of the deregulation of margin trading in China whereby we propose a simple difference-in-difference strategy. We compare stocks that are included in the margin lending roll-out to those that are not, before and after margin lending is introduced for the stock in question. This approach, similar to traditional approaches in the literature, effectively captures the direct effect of the credit supply shock in a myopic world—one in which there is no speculation in anticipation of the shock.

In particular, we consider regressions of the following form:

$$IHS(\text{Market Cap})_{i,t+1} = \beta_0 + \beta_1 \text{Margin Trading Active}_{i,t} + \theta_1 BE_{i,t} + \gamma_i + \delta_t + \varepsilon_{it} \tag{3}$$

where $IHS(\text{Market Cap})_{i,t+1}$ is the inverse hyperbolic sine of market cap for stock $i$ in month $t+1$ , with Market Cap in RMB. Margin Trading Active$_{i,t}$ is equal to one only (i) for stocks that are included in the margin trading roll-out, and (ii) in months after margin trading is active for that stocks. Book-equity deciles refer to dummy variables for inclusion in each decile of book equity at the month level, and $\gamma_i$ and $\delta_t$ are stock and month$\times$ year fixed effects, respectively.

To provide a starting point before directly conducting our analysis of anticipation effects, we consider several variations on this basic regression. While the above specifications collapses the effect of all 5 vintages of the margin-lending roll out into a single difference-in-difference, we also allow for flexible effects across the different vintages. In particular, we (i) estimate the above specification separately for different vintages (including, for each, the set of stocks for which margin trading was never allowed as a control group), and (ii) estimate the following generalization of specification 3

$$IHS(\text{Market Cap})_{i,t+1} = \beta_0 + \sum_{k=0}^{4} \beta_1^k (\text{Margin Trading Active}_{i,t} \times Vintage\_k_i) + \theta_1 BE_{i,t} + \gamma_i + \delta_t + \varepsilon_{it}. \tag{4}$$

Here, $Vintage\_k_i$ is an indicator equal to one if stock $i$ is in vintage $k$, to allow for flexible effects across vintages. In all of these baseline specifications, $\beta_1$ provides a myopic, and hence potentially misleading, estimate of the direct effect of deregulation on market cap.

### 3.4 Accounting for Anticipatory Effects (Quasi-Myopic Approach)

In order to estimate anticipatory effects, and to appropriately measure the direct effects of the deregulation of margin trading in China, we consider quasi-myopic difference-in-difference specifications following Malani and Reif (2015). The basic notion of this approach is to use the period well before the roll-out took place as a pre-period, and to estimate separate difference-in-difference coefficients for (i) the months just before the roll-out took place (anticipatory effects), and (ii) the actual treatment period in which margin lending was active.

Specifically, we consider regressions of the following form:

$$\text{IHS(Market Cap)}_{i,t+1} = \alpha + \beta_0^{quasi}\text{Margin Trading Active}_{i,t} + \sum_{j=1}^{S} \beta_j^{quasi} D_{i,t+j} + \theta_1 BE_{i,t} + \gamma_i + \delta_t + \varepsilon_{it}. \tag{5}$$

Here, $D_{i,t+j}$ is equal to one if margin trading initially becomes active for stock $i$ in period $t+j$, and zero otherwise. Put more simply, $D_{i,t+j}$ is variable that, for a specific stock $i$, indicates that margin lending is about to roll-out. Here, $S$ captures the number of periods in advance investors might feasibly speculate upon the coming introduction of margin lending. The terminology "quasi-myopic" refers to the notion that $S$ is finite—that investors do not anticipate the possibility that lending might roll out at arbitrarily long windows in the future. While in some settings this might be controversial, we believe this is reasonable for deregulation of margin lending in China, particularly since there was no indication of which stocks might become marginable prior to 2011. In our analysis, we consider a variety of windows $S$ to allow for anticipation at different lengths.

In these specifications, $\beta_j^{quasi} > 0$ indicates the presence of anticipatory effects: the market cap of soon-to-be marginable stocks grows relative to a control group in the period leading up to the roll out. Appropriately accounting for anticipation, the coefficient $\beta_0^{quasi}$ captures the direct effect of margin lending.

While market capitalization is the primary variable of interest in our analysis, we also consider quasi-myopic specifications for a variety of other outcomes to support our analysis. In particular, we estimate similar specifications using the proportion of institutional ownership of stocks and turnover of those stocks as dependent variables.

# 4 Results

## 4.1 OLS Estimates

We first consider the effect of margin debt ($IHS$(Margin Debt)) for stock valuations ($IHS$(Market Cap)) using the OLS specification described above. The results are in Table 3. The coefficients of $IHS(\text{Margin Debt}_{i,t})$ are all positive and statistically significant. In column (1) where there are no controls, the coefficient of margin debt is significantly positive at 0.081. In column (2) where we add book-equity decile dummies and industry fixed effects, the coefficient is 0.038. In column (3) where we add book-equity and time effects, the coefficient is .026.

Our most conservative specification is when we have both time effects and stock fixed effects. Even for this conservative specification, there is a precisely measured positive effect. As shown in Column (4), the coefficient equals 0.004. Since market capitalization is two orders of magnitude larger than margin debt, assuming a perfect pass-through where a $1 increase of margin debt leads to an increase of market capitalization by $1, a perfect pass-through scenario implies then an elasticity of 0.01. The estimated elasticity we find is 0.004. So a one dollar increase in margin debt corresponds roughly to a 40 cent increase in stock valuation.

## 4.2 IV Estimates

In Table 4, we present the IV estimates. In the first two columns, we present the results of the collapsed instrument specification. The first column presents the first-stage regression result. The coefficient of interest is 19 and highly significant. There is no issues with weak-instruments. The second stage coefficient of interest is 0.002 and also statistically significant. Recall that the OLS estimate implied that a 1 dollar increase in margin debt is associated with a 40 cent increase in stock valuation. This instrumented regression points to then a more conservative 20 cent increase. In the next two columns, we present the all instrument specification where we allow the first stage regression to vary by vintage. The coefficients of interest are similar in magnitude. This is reflected in Figure 2 where we see that margin debt rises significantly after stocks are qualified for margin lending. The coefficient in the second stage is 0.003 and statistically significant. Our IV specifications point to a one dollar increase in margin being associated with a 20 to 30 cent increase in stock valuation. While not small, these estimates also do not seem to indicate that credit supply might lead to bubbles or financial instability. Another way of putting this is that the direct effect of supply seems modest.

## 4.3 Reduced-Form Myopic Specification

In Table 5, we estimate the reduced-form analog of the IV estimates in Table 4. The independent variable of interest is the dummy variable of when a stock qualifies for margin lending. This corresponds to a traditional difference-in-difference specification which assumes that there are no anticipation effects. The coefficient of interest here is the column labeled Collapsed Roll-Out. The coefficient of 0.047 corresponds to the 20 cent figure for a dollar increase in margin debt associated with the 2SLS. The other coefficients point to the effects being statistically positive in Vintages 3 and 4 and negative or not statistically significant in earlier vintages.

## 4.4 Estimating Anticipatory Effects: Quasi-Myopic Approach

While the myopic difference-in-difference specifications discussed above mirror common techniques in the literature, their ability to capture a direct effect depends on the assumption that no anticipatory effects exist. As noted in Malani & Reif (2015), failing to account for any ex-ante changes in anticipation of the margin lending roll-out will cause a researcher to estimate the true (ex-post) direct effects with bias. In particular, if stock prices rise in anticipation of future margin lending, the myopic approach will *underestimate* the true effects. The intuition here is simple, the myopic difference-in-difference estimator compares a post-treatment price to an artificially high pre-treatment price—which has already risen in anticipation of treatment. Furthermore, these myopic specifications cannot quantify these anticipatory effects, which might be of interest independently.

As Figure 3 makes clear, the assumption of no anticipatory effects appears to be untrue in the context of the deregulation of margin lending in China. The figure, which plots the inverse hyperbolic sine of market cap—after netting out stock, month, and book-equity decile fixed effects—displays evidence of sharp rises in market cap for vintages 2, 3 and 4 in anticipation of the introduction of margin trading for those stocks. In other words, there are evident pre-trends for the treated groups in the pre-treatment periods. While in other settings, it might be difficult to attribute these pre-trends to anticipation—they might, for example, reflect the endogeneity of treatment itself—we believe the staggered nature of the roll-out provides strong support of anticipation. Replicating the roll-out, the increases in market cap are themselves staggered, with the rises for each vintage just preceding deregulation for that vintage.

Table 6 presents results from quasi-myopic specifications intended to capture the patterns presented in Figure 3. The first column, labeled *Myopic*, replicates the collapsed version of the myopic difference-in-difference. With this approach, which requires the assumption of no anticipation, we estimate that on average the introduction of margin lending increased the market cap of marginable stocks by approximately

5 percent. This direct effect is captured by the coefficient labeled *Ex-Post Effect* throughout. The second column shows that even allowing for anticipation in a single month preceding the introduction of margin lending attenuates the downward bias generated by ignoring anticipation: the estimated direct effect rises to approximately 6 percent. Further, there is strong evidence of anticipation: the ex-ante effect in the month prior suggest that prices were on the order of 20 percent higher in the month just prior to deregulation. However, the validity of these estimates still require that no anticipation was present two or more months prior to the roll-out.

To more accurately capture the presence of anticipation, the remaining columns of Table 6 allow for anticipation at significantly longer windows, specifically six months, six quarters, and six half-years. These results further emphasize the importance of accounting for anticipatory effects. When allowing for six months of anticipatory effects, the direct effect of margin lending on stock prices rises to more than 10 percent, and to over 20 percent when accounting for six quarters or six half years. Additionally, the ex-ante effects explicitly show the anticipatory rise in prices in the periods leading up to deregulation. For example, when allowing quarterly lags, the ex-ante effect grows from under 10 percent six quarters prior to deregulation, to over 30 percent in the quarter just before. This increase over time reflects a collapsed discount factor the reflects both cost of carry and any uncertainty investors may have had regarding the specific stocks likely to be included in the next vintage of deregulation.

If we consider our the myopic estimates of $0.047$ as the reduced form analogue of our myopic IV specifications— which suggested that a one dollar increase in margin debt increased market cap by 20-30 cents— we can calculate a loose back-of-the-envelope estimate of the impact of margin debt on market cap once anticipation is appropriately accounted for. In particular, our estimates accounting for half year-lags suggest a true direct effect of 0.281, which is 6 times larger than our myopic estimates. Scaling our estimates estimates of the impact of margin debt on market cap similarly, we estimate that a one dollar increase in margin debt increases market cap by 1.20-1.80 dollars.

Table 7 reproduces the results in Table 6, but explicitly for the stocks in the vintages that show the most direct evidence of anticipatory effects: 2, 3, and 4. We also include stocks that were never marginable as a control group. These results mirror those in Table 6, but with significantly stronger anticipatory and direct effects. Even in myopic specifications, these vintages show a larger direct effect of over 10 percent. Furthermore, the anticipatory effects are estimated to be over 30 percent even with a single month lead, and over 40 percent when allowing six quarters or six half years. Once again, there is clear evidence of an increase in the periods leading up to the deregulation, with the ex-ante effects rising from 0 six half-years in advance.

## 4.5 Differential Anticipatory Effects By Likelihood of Inclusion

Table 8 decomposes the anticipation effect depending on the likelihood of a stock being qualified for lending depend on the publicly-known formula. Low Rank is an indicator for the stocks with below median rank (highest likelihood of inclusion) amongst those that were ultimately included in the next vintage according to the formula (i.e., Eq.(1)). We can see that anticipation effects are larger for low rank stocks, This is also illustrated in Figure 6.

## 4.6 Quasi-Myopic Approach: Institutional Ownership

We next turn to outcomes other than market cap. Figure 5 presents evidence of anticipation by unconstrained investors. We plot the proportion of institutional ownership over time for different vintages—once again netting out stock, month, and book-equity decile fixed effects. This figure also shows persuasive evidence of anticipation. For each of vintages 2, 3, and 4 the average proportion of ownership by unconstrained investors rises in the periods just prior to the introduction of margin lending.[7] Interestingly, these high proportions are not sustained once margin lending is introduced, but instead drop off sharply. We interpret this as evidence of unconstrained investors speculating on the introduction of margin lending: buying up shares in advance, and selling these shares to newly unconstrained investors buying on margin.

Table 9 presents quasi-myopic regression specifications intended to capture these patterns in institutional ownership for vintages 2, 3 and 4. In effect, we replicate Table 7 with this alternative outcome. Because we only observe institutional ownership every 6 months, we present results ex-ante effects at one half-year, two half-years, and four half-years, in addition to displaying a myopic specification. The myopic specification highlights the bias generated by failing to account for anticipatory effects. This specification suggests that the introduction of margin lending actually generated a 3 percent *decline* in institutional ownership. However, once anticipatory effects are accounted for, it is clear that the true direct effect of deregulation on institutional ownership was closer to zero. Furthermore, the ex-ante effects display evidence of anticipation: the proportion of institutional ownership rises by 4-4.5 percentage points in the year just before the rollout, with no evidence of an effect 18 months before.

## 4.7 Quasi-Myopic Approach: Turnover

Figure 4 presents similar evidence for turnover. For vintages 2, 3, and 4—and particularly for vintages 2 and 3—there are sharp increases in turnover just prior to the introduction of margin lending. Just as with institutional ownership, there is a precipitous drop in turnover just following deregulation for each of these

[7] For institutional ownership, our data is at a 6 month frequency, so we are only able to display averages each half-year.

vintages. Table 10 presents results from quasi-myopic regression specifications corresponding to these figures. Once again, the myopic approach underestimates the direct effects, which rise from an approximately 10 percent increase in turnover using our myopic specification, to greater than 20 percent account for six quarters or six half years. Additionally, as with market cap, the rise in turnover ramps up monotonically over the course of the periods preceding the roll-out.

# 5 Conclusion

We contribute causal evidence to the credit booms gone wrong literature in macro-finance. Previous empirical studies relied on OLS regressions of financial fragility outcomes on growth of leverage ratios in the economy. We argue that China's 2010-2015 credit boom gone wrong experience driven by the staggered deregulation of margin lending allows for an analysis of the causal role of credit expansion. The expansion was driven by the staggered deregulation of margin trading at the stock level, based formulaically on a stock's market capitalization and liquidity. Using the staggered deregulation to instrument for credit availability points to an estimate of a dollar increase in margin debt leading to a 20 cent increase in stock valuation. There are also important anticipation effects which when accounted for lead to a substantially larger causal impact of credit supply on asset prices.

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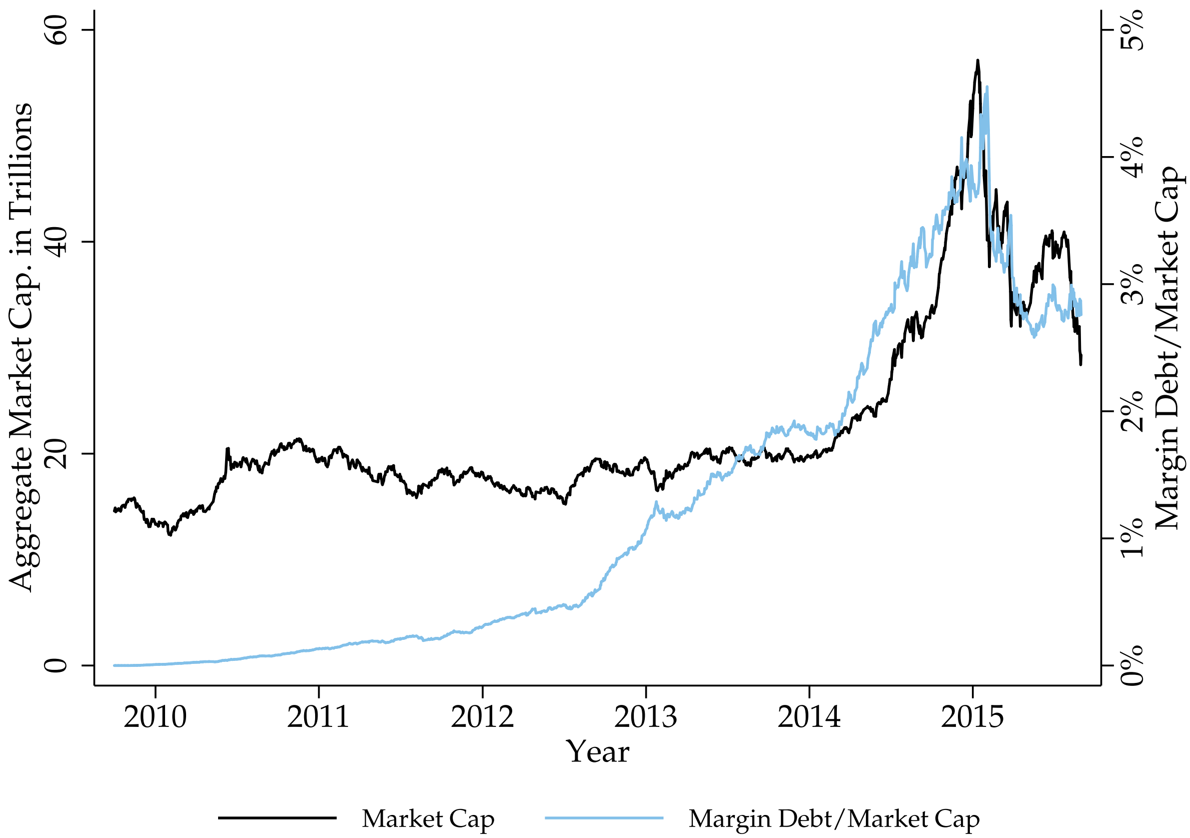
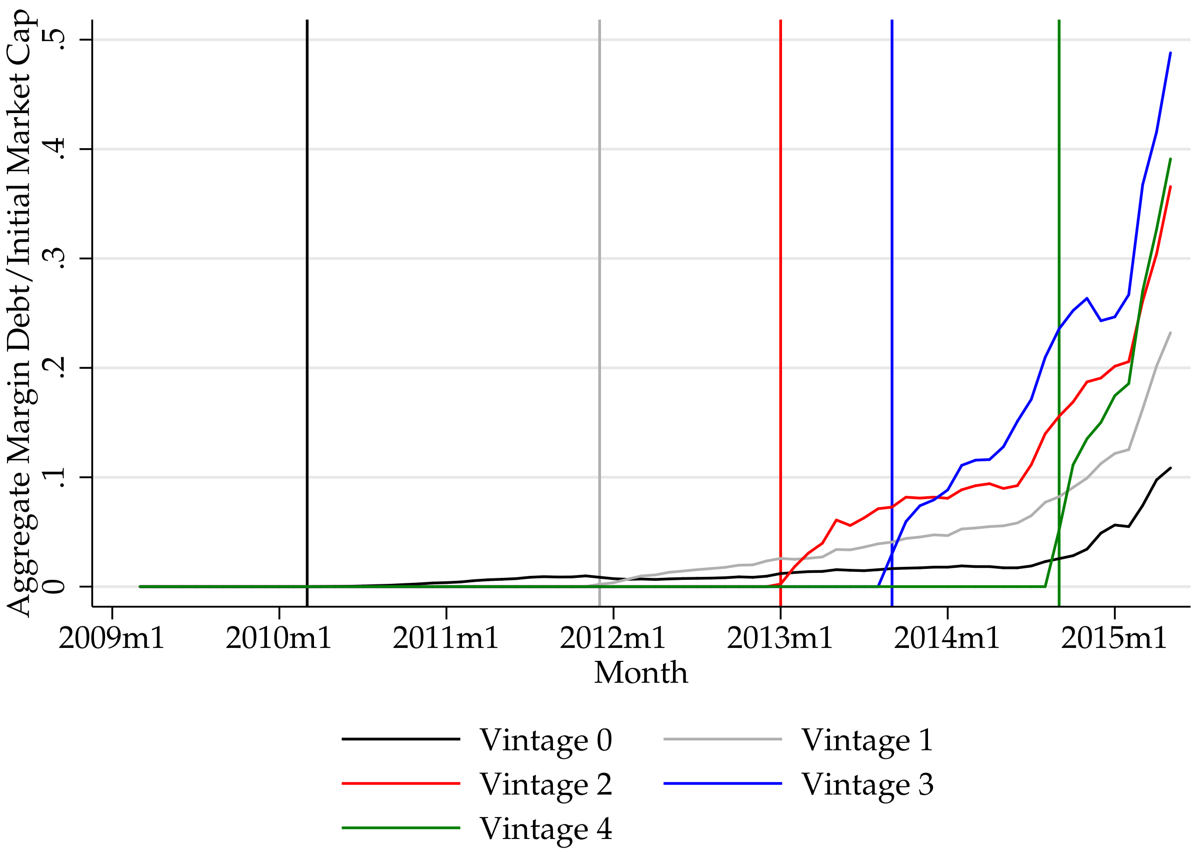
**Figure 1: Aggregate Market Cap. and Margin Debt/Market Cap. Over Time**



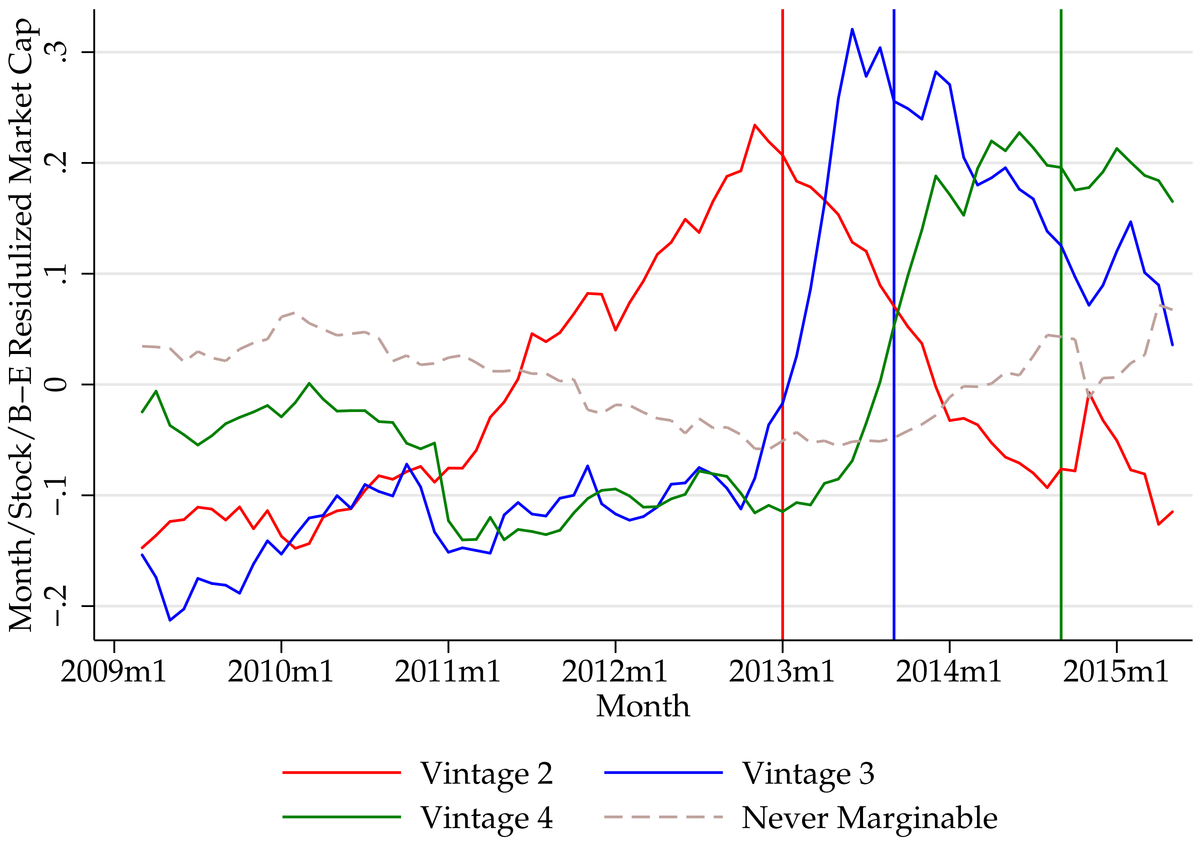

**Notes:** Plot shows monthly aggregate market cap (in black) and the ratio of margin debt to market cap (in blue) for all stocks in sample. Both market cap and margin debt are measured in trillions of yuan.

**FIGURE 2: STAGGERED ROLLOUT OF STOCK MARGIN LENDING—MARGIN DEBT/MARKET CAP BY VINTAGE**



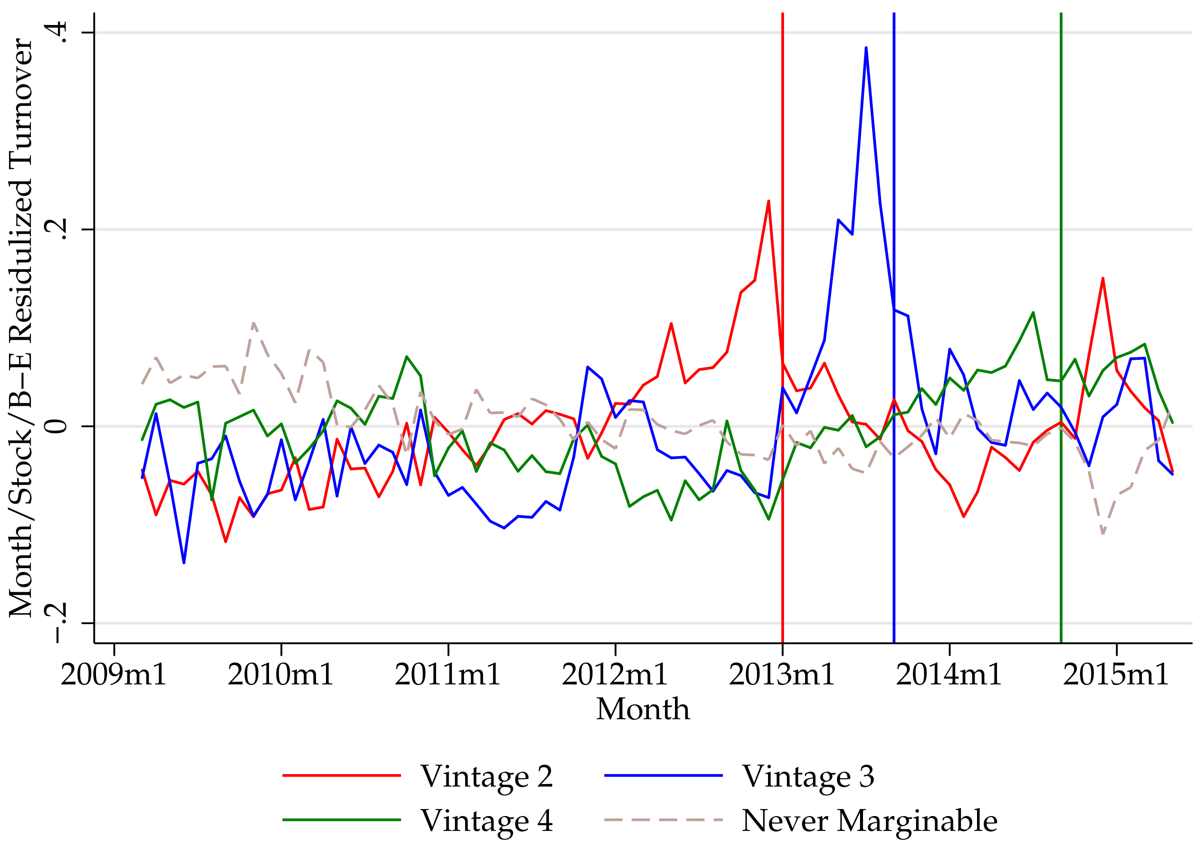

**Notes:** Plot shows the average ratio of margin debt to initial market cap (measured as the 2009 average at the stock level) for each of the five vintages of the margin lending roll-out. Both market cap and margin debt are measured in trillions of yuan. Vertical lines show the starting date of each vintage, with black, gray, red, blue and green representing vintages 0, 1, 2, 3 and 4, respectively.

**FIGURE 3: MARKET ANTICIPATION OF MARGIN LENDING ROLLOUT**
**RESIDUALIZED IHS(MARKET CAP)$_{t+1}$ BY VINTAGE**



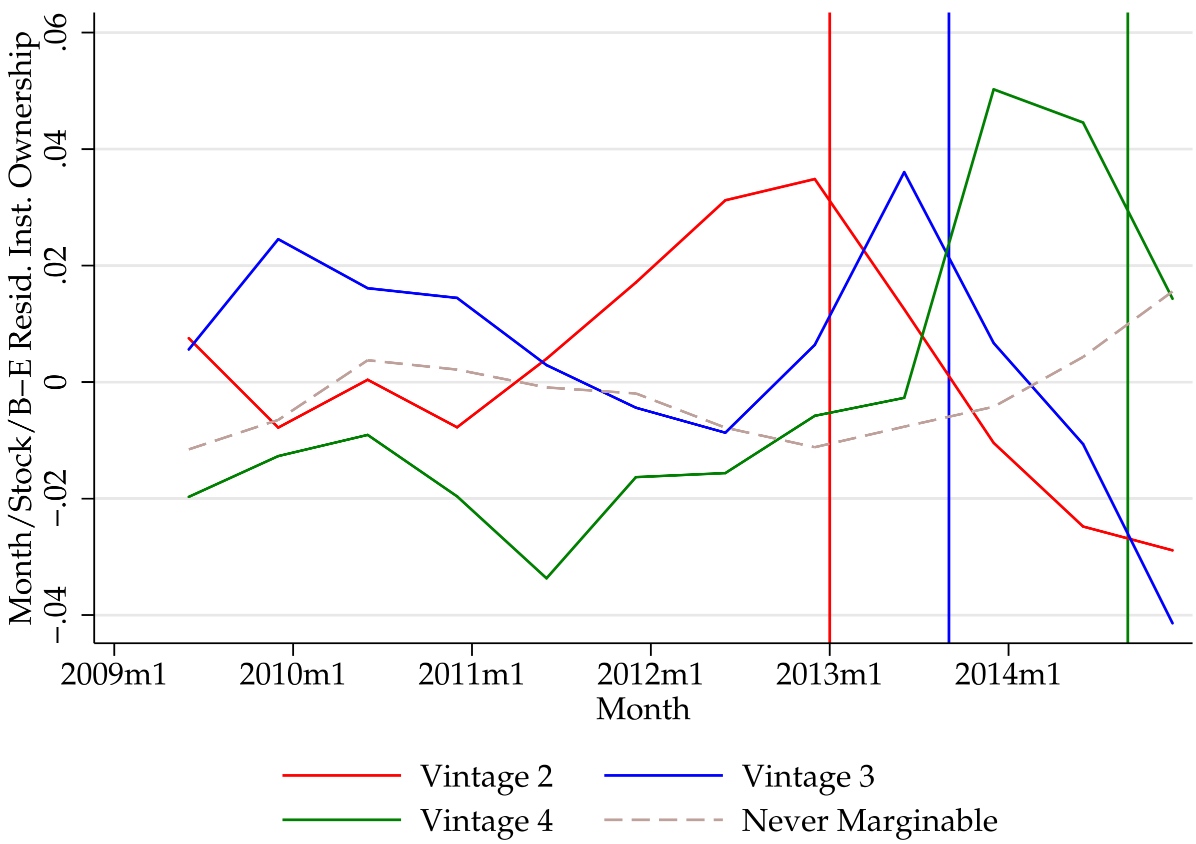

**Notes:** Plots show residuals from regressions of IHS(Market Cap)$_{t+1}$ at the stock-month level on stock fixed effects, month$\times$year fixed effects and dummies for membership in each decile of book equity at the month level. Market cap is measured in yuan. Residuals are calculated from a single regression with all stocks in sample, and plotted separately for vintages 2, 3, and 4 of the margin lending roll-out and for the set of stocks that were never marginable. Vertical lines show the starting date of each vintage, with red, blue and green representing vintages 2, 3 and 4, respectively.

**FIGURE 4: ANTICIPATION EFFECTS: RESIDUALIZED TURNOVER BY VINTAGE**




**Notes:** Plots show residuals from regressions of turnover at the stock-month level on stock fixed effects, month×year fixed effects and dummies for membership in each decile of book equity at the month level. Market cap is measured in yuan. Residuals are calculated from a single regression with all stocks in sample, and plotted separately for vintages 2, 3, and 4 of the margin lending roll-out and for the set of stocks that were never marginable. Vertical lines show the starting date of each vintage, with red, blue and green representing vintages 2, 3 and 4, respectively.

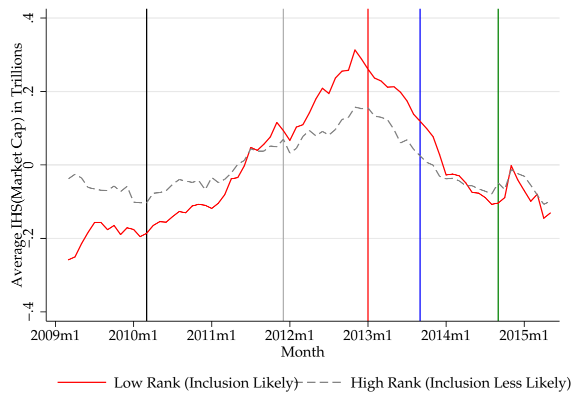
**FIGURE 5: ANTICIPATION EFFECTS: RESIDUALIZED INSTITUTIONAL OWNERSHIP BY VINTAGE**



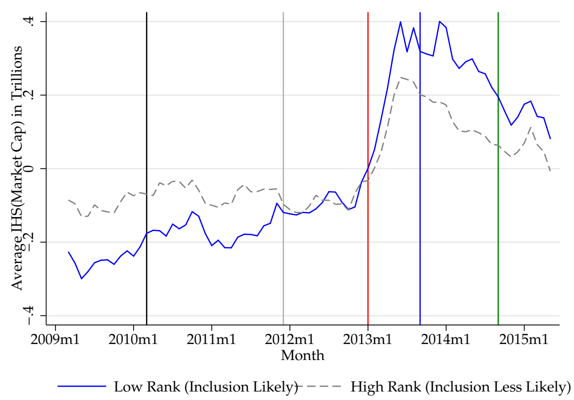

**Notes:** Plots show residuals from regressions of the proportion of institutional ownership at the stock-half year level on stock fixed effects, half-year fixed effects and dummies for membership in each decile of book equity at the month level. Residuals are calculated from a single regression with all stocks in sample, and plotted separately for vintages 2, 3, and 4 of the margin lending roll-out and for the set of stocks that were never marginable. Vertical lines show the starting date of each vintage, with red, blue and green representing vintages 2, 3 and 4, respectively.

## Figure 6: Anticipation Effects: Market Cap by Likelihood of Inclusion

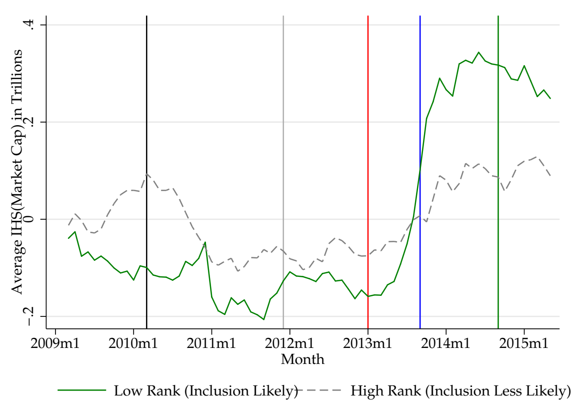
### Panel A: Vintage 2 Stocks




### Panel B: Vintage 3 Stocks




### Panel C: Vintage 4 Stocks




**Notes:** Plots show residuals from regressions of IHS(Market Cap)$_{t+1}$ at the stock-month level on stock fixed effects, month×year fixed effects and dummies for membership in each decile of book equity at the month level. Market cap is measured in yuan. Residuals are calculated from a single regression with all stocks in sample, but plotted separately—within stocks ultimately included in vintages 2, 3 and 4—for stocks with above vs. below median rank on the index that determines inclusion in the vintage. Those with low rank were ex-ante the most likely to be included in the next vintage, whereas those with high rank were ex-ante the least likely to be included. Vertical lines show the starting date of each vintage, with black, gray, red, blue and green representing vintages 0, 1, 2, 3 and 4, respectively.

**TABLE 1: NUMBER OF MARGINABLE STOCKS BY VINTAGE**

| Number of marginable stocks by vintage | | | | |
|---|---|---|---|---|
| | | # of newly marginable | | |
| Vintage # | Effective time | Shanghai | Shenzhen | % of total cap |
| 0 | February 13th, 2010 | 50 | 40 | 51.74% |
| 1 | November 25th, 2011 | 131 | 60 | 66.31% |
| 2 | January 25th, 2013 | 163 | 113 | 75.23% |
| 3 | September 6th, 2013 | 104 | 102 | 77.95% |
| 4 | September 12th, 2014 | 104 | 114 | 78.48% |

## TABLE 2: PREDICTIVE REGRESSIONS OF MARGINABLE MEMBERSHIP (2ND, 3RD, AND 4TH VINTAGE)

| | Vintage 4 | Vintage 3 | Vintage 2 |
|---|---|---|---|
| Dep Var: $D$ | (1) | (2) | (3) |
| $\tau$ | 0.874*** | 0.776*** | 0.778*** |
| | (0.041) | (0.051) | (0.042) |
| $R^2$ | 0.876 | 0.828 | 0.839 |
| N | 1,630 | 1,771 | 1,869 |

Coefficients from predictive regressions of marginable membership for vintages 2–4 as,

$$D_i^k = \alpha_{0l} + \alpha_{1l}(Rank_i^k - C^k) + \tau_i^k[\alpha_{0r} + \alpha_{1r}(Rank_i^k - C^k)] + \epsilon_i$$

where $k = \{2, 3, 4\}$. $D_i^k$ is the indicator, which equals one if stock $i$ is added to the marginable list in vintage $k$; $Rank_i^k$ is stock $i$'s ranking that we produce based on exchanges' procedure. $C^k$ is the number of stocks added to the marginable list in vintage $k$. $\tau_i^k$ equals one if $Rank_i^k - C^k \leq 0$; otherwise zero (i.e., predicted marginable status based on our ranking). The sample only includes non-marginable stocks that satisfy screen criteria in the evaluation period. For each extension, we run the regression using the pooled sample of stocks in Shanghai and Shenzhen. The evaluation window is 2014/06/01-2014/08/31, 2013/06/01-2013/08/31, and 2012/10/01-2012/12/31, for the fourth, third, and second vintage, respectively. The point estimate of is reported and robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

### TABLE 3: OLS ESTIMATES OF ASSOCIATION BETWEEN IHS(MARKET CAP)$_{t+1}$ AND IHS(MARGIN DEBT)

| | IHS(Market Cap)$_{t+1}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| IHS(Margin Debt) | $0.081^{***}$ | $0.038^{***}$ | $0.026^{***}$ | $0.004^{***}$ |
| | $(0.003)$ | $(0.002)$ | $(0.003)$ | $(0.001)$ |
| Mean of Dep. Var. | 22.7 | 22.7 | 22.7 | 22.7 |
| $R^2$ | 0.32 | 0.63 | 0.81 | 0.89 |
| N | 137698 | 137698 | 137696 | 137696 |
| Book-Equity Deciles | No | Yes | Yes | Yes |
| Industry Fixed Effects | No | Yes | No | No |
| Month $\times$ Year Fixed Effects | No | No | Yes | Yes |
| Stock Fixed Effects | No | No | No | Yes |

Coefficients from OLS regressions of the inverse hyperbolic sine (IHS) of market cap in month t+1 on the inverse hyperbolic sine of margin debt in month $t$. Both market cap and margin debt are measured in RMB at the stock-month level. Standard errors, clustered at the stock and month level, are included in parentheses. Sample covers March 2009-May 2015. Mean of dep. var refers to the mean of IHS(Market Cap)$_{t+1}$. Book-equity deciles refer to dummy variables for inclusion in each decile of book equity at the month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

### TABLE 4: IV ESTIMATES OF IMPACT OF IHS(MARGIN DEBT) ON IHS(MARKET CAP)$_{t+1}$

| | Collapsed Instrument | | All Instruments | |
|---|---|---|---|---|
| | First Stage | Second Stage | First Stage | Second Stage |
| IHS(Margin Debt) | | $0.002^{**}$ | | $0.003^{**}$ |
| | | $(0.001)$ | | $(0.001)$ |
| Margin Trading Active | $19.045^{***}$ | | | |
| | $(0.201)$ | | | |
| Vintage 0 Margin Trading Active | | | $18.650^{***}$ | |
| | | | $(0.487)$ | |
| Vintage 1 Margin Trading Active | | | $17.535^{***}$ | |
| | | | $(0.421)$ | |
| Vintage 2 Margin Trading Active | | | $19.581^{***}$ | |
| | | | $(0.191)$ | |
| Vintage 3 Margin Trading Active | | | $19.873^{***}$ | |
| | | | $(0.179)$ | |
| Vintage 4 Margin Trading Active | | | $20.081^{***}$ | |
| | | | $(0.232)$ | |
| Mean of Dep. Var. | 3.50 | 22.7 | 3.50 | 22.7 |
| $R^2$ | 0.95 | 0.89 | 0.95 | 0.89 |
| N | 137696 | 137696 | 137696 | 137696 |
| Book-Equity Deciles | Yes | Yes | Yes | Yes |
| Month $\times$ Year Fixed Effects | Yes | Yes | Yes | Yes |
| Stock Fixed Effects | Yes | Yes | Yes | Yes |

Coefficients from first and second stages of IV regressions of the inverse hyperbolic sine (IHS) of market cap in month t+1 on the inverse hyperbolic sine of margin debt in month $t$. Both market cap and margin debt are measured in RMB at the stock-month level. In the first stage, we instrument for IHS(Margin Debt) with the indicators *Margin Trading Active*: equal to one only (i) for stocks that are included in the margin trading roll-out, and (ii) in months after margin trading is active in those stocks. The columns labeled *Collapsed Instrument* include a single instrument for all stocks included in the rollout at any point. The columns labeled *All Instruments* include separate *Margin Trading Active* indicators for each of the five vintages of stocks that became marginable. Standard errors, clustered at the stock and month level, are included in parentheses. Sample covers March 2009-May 2015. Mean of dep. var refers to the mean of IHS(Market Cap)$_{t+1}$. Book-equity deciles refer to dummy variables for inclusion in each decile of book equity at the month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**TABLE 5: DIFFERENCE-IN-DIFFERENCE ESTIMATES OF IMPACT OF MARGIN LENDING ROLLOUT ON IHS(MARKET CAP)$_{t+1}$**

| | IHS(Market Cap)$_{t+1}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | Restricted Sample | | | | | Full Sample | |
| | Vintage 0 | Vintage 1 | Vintage 2 | Vintage 3 | Vintage 4 | Collapsed Roll-Out | All Vintages |
| Margin Trading Active | −0.107 | −0.069 | 0.039 | 0.243*** | 0.191*** | 0.047** | |
| | (0.067) | (0.043) | (0.049) | (0.052) | (0.039) | (0.022) | |
| Vintage 0 Margin Trading Active | | | | | | | −0.164** |
| | | | | | | | (0.065) |
| Vintage 1 Margin Trading Active | | | | | | | −0.107** |
| | | | | | | | (0.041) |
| Vintage 2 Margin Trading Active | | | | | | | 0.037 |
| | | | | | | | (0.043) |
| Vintage 3 Margin Trading Active | | | | | | | 0.271*** |
| | | | | | | | (0.047) |
| Vintage 4 Margin Trading Active | | | | | | | 0.257*** |
| | | | | | | | (0.039) |
| Mean of Dep. Var. | 22.4 | 22.4 | 22.3 | 22.2 | 22.2 | 22.7 | 22.7 |
| $R^2$ | 0.91 | 0.87 | 0.83 | 0.80 | 0.81 | 0.89 | 0.89 |
| N | 83871 | 90552 | 95705 | 87715 | 88777 | 137696 | 137696 |
| Book-Equity Deciles | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month × Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Coefficients from difference-in-difference regressions of (IHS) of market cap. in month t+1 on indicators for *Margin Trading Active* in period $t$. Market cap is measured in RMB at the stock-month level. *Margin Trading Active*is equal to one only (i) for stocks that are included in the margin trading roll-out, and (ii) in months after margin trading is active in those stocks. Columns labeled *Restricted Sample* include only one of the five vintages of stocks that became marginable, as well as all stocks that were never marginal. The columns labeled *Full Sample* include the full sample, where *Collapsed Roll-Out* includes a single indicator for all stocks included in the rollout at any point, and *All Vintages* includes separate *Margin Trading Active* indicators for each of the five vintages of stocks that became marginable. Standard errors, clustered at the stock and month level, are included in parentheses. Sample covers March 2009-May 2015. Mean of dep. var refers to the mean of IHS(Market Cap)$_{t+1}$. Book-equity deciles refer to dummy variables for inclusion in each decile of book equity at the month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**TABLE 6: IMPACT OF MARGIN LENDING ROLLOUT ON IHS(MARKET CAP)$_{t+1}$: QUASI-MYOPIC APPROACH**

| | IHS(Market Cap)$_{t+1}$ | | | | |
|---|---|---|---|---|---|
| | Myopic | Monthly Lags | | Quarterly Lags | Half Year Lags |
| Ex-Post Effect ($\hat{\beta}_0^{quasi}$) | $0.047^{**}$ | $0.057^{**}$ | $0.109^{***}$ | $0.203^{***}$ | $0.281^{***}$ |
| | (0.022) | (0.023) | (0.025) | (0.030) | (0.036) |
| Ex-Ante Effect (t-1) ($\hat{\beta}_1^{quasi}$) | | $0.225^{***}$ | $0.262^{***}$ | $0.339^{***}$ | $0.390^{***}$ |
| | | (0.044) | (0.045) | (0.035) | (0.036) |
| Ex-Ante Effect (t-2) ($\hat{\beta}_2^{quasi}$) | | | $0.257^{***}$ | $0.295^{***}$ | $0.300^{***}$ |
| | | | (0.050) | (0.029) | (0.035) |
| Ex-Ante Effect (t-3) ($\hat{\beta}_3^{quasi}$) | | | $0.260^{***}$ | $0.255^{***}$ | $0.192^{***}$ |
| | | | (0.044) | (0.028) | (0.034) |
| Ex-Ante Effect (t-4) ($\hat{\beta}_4^{quasi}$) | | | $0.244^{***}$ | $0.200^{***}$ | $0.127^{***}$ |
| | | | (0.037) | (0.029) | (0.029) |
| Ex-Ante Effect (t-5) ($\hat{\beta}_5^{quasi}$) | | | $0.218^{***}$ | $0.150^{***}$ | $0.105^{***}$ |
| | | | (0.032) | (0.028) | (0.030) |
| Ex-Ante Effect (t-6) ($\hat{\beta}_6^{quasi}$) | | | $0.199^{***}$ | $0.092^{***}$ | $0.055^{**}$ |
| | | | (0.026) | (0.028) | (0.026) |
| Mean of Dep. Var. | 22.7 | 22.7 | 22.7 | 22.7 | 22.7 |
| $R^2$ | 0.89 | 0.89 | 0.89 | 0.89 | 0.89 |
| N | 137696 | 137696 | 137696 | 137696 | 137696 |
| Book Equity Deciles | Yes | Yes | Yes | Yes | Yes |
| Year × Month Fixed Effects | Yes | Yes | No | Yes | Yes |
| Stock Fixed Effects | Yes | Yes | Yes | Yes | Yes |

Results from myopic and quasi-myopic difference-in-difference specifications of IHS(Market Cap)$_{t+1}$ on the margin lending roll-out in the vein of Malani and Reif (2015). We report coefficients from the following regression

$$\text{IHS(Market Cap)}_{i,t+1} = \alpha + \beta_0^{quasi}\text{Margin Trading Active}_{it} + \sum_{j=1}^{S} \beta_j^{quasi} D_{i,t+j} + \gamma_i + \delta_t + \varepsilon_{it}$$

Market cap is measured in RMB at the stock-month level. *Margin Trading Active* is equal to one only (i) for stocks that are included in the margin trading roll-out, and (ii) in months after margin trading is active in those stocks. $D_{i,t+j}$ is equal to one if margin trading initially becomes active for stock $i$ in period $t+j$, and zero otherwise. The number of *ex-ante effect* coefficients indicates the value of $S$ for the regression in question. The myopic approach include no ex-ante effects, and is equivalent to the collapsed difference-in-difference approaches presented above. The following five columns include, respectively, separate indicators aimed at capturing ex-ante effects for the month, six months, six quarters, and six half years leading up to the roll-out for each stock. Standard errors, clustered at the stock and month level, are included in parentheses. Sample covers March 2009-May 2015. Mean of dep. var refers to the mean of IHS(Market Cap)$_{t+1}$. Book-equity deciles refer to dummy variables for inclusion in each decile of book equity at the month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**TABLE 7: IMPACT OF MARGIN LENDING ROLLOUT ON IHS(MARKET CAP)$_{t+1}$: QUASI-MYOPIC APPROACH VINTAGES 2, 3 AND 4**

| | IHS(Market Cap)$_{t+1}$ | | | | |
|---|---|---|---|---|---|
| | Myopic | Monthly Lags | | Quarterly Lags | Half Year Lags |
| Ex-Post Effect ($\hat{\beta}_0^{quasi}$) | 0.103*** | 0.114*** | 0.167*** | 0.242*** | 0.277*** |
| | (0.030) | (0.030) | (0.032) | (0.034) | (0.038) |
| Ex-Ante Effect (t-1) ($\hat{\beta}_1^{quasi}$) | | 0.307*** | 0.347*** | 0.419*** | 0.417*** |
| | | (0.038) | (0.039) | (0.033) | (0.036) |
| Ex-Ante Effect (t-2) ($\hat{\beta}_2^{quasi}$) | | | 0.351*** | 0.344*** | 0.272*** |
| | | | (0.032) | (0.028) | (0.037) |
| Ex-Ante Effect (t-3) ($\hat{\beta}_3^{quasi}$) | | | 0.342*** | 0.271*** | 0.158*** |
| | | | (0.030) | (0.033) | (0.035) |
| Ex-Ante Effect (t-4) ($\hat{\beta}_4^{quasi}$) | | | 0.311*** | 0.200*** | 0.097*** |
| | | | (0.025) | (0.032) | (0.028) |
| Ex-Ante Effect (t-5) ($\hat{\beta}_5^{quasi}$) | | | 0.277*** | 0.148*** | 0.045* |
| | | | (0.022) | (0.031) | (0.023) |
| Ex-Ante Effect (t-6) ($\hat{\beta}_6^{quasi}$) | | | 0.236*** | 0.097*** | 0.010 |
| | | | (0.024) | (0.031) | (0.018) |
| Mean of Dep. Var. | 22.4 | 22.4 | 22.4 | 22.4 | 22.4 |
| $R^2$ | 0.82 | 0.82 | 0.83 | 0.83 | 0.83 |
| N | 117735 | 117735 | 117735 | 117735 | 117735 |
| Book Equity Deciles | Yes | Yes | Yes | Yes | Yes |
| Year × Month Fixed Effects | Yes | Yes | No | Yes | Yes |
| Stock Fixed Effects | Yes | Yes | Yes | Yes | Yes |

Results from myopic and quasi-myopic difference-in-difference specifications of IHS(Market Cap)$_{t+1}$ on the margin lending roll-out in the vein of Malani and Reif (2015). We report coefficients from the following regression

$$\text{IHS(Market Cap)}_{i,t+1} = \alpha + \beta_0^{quasi}\text{Margin Trading Active}_{it} + \sum_{j=1}^{S} \beta_j^{quasi} D_{i,t+j} + \gamma_i + \delta_t + \varepsilon_{it}$$

Market cap is measured in RMB at the stock-month level. *Margin Trading Active* is equal to one only (i) for stocks that are included in the margin trading roll-out, and (ii) in months after margin trading is active in those stocks. $D_{i,t+j}$ is equal to one if margin trading initially becomes active for stock $i$ in period $t+j$, and zero otherwise. The number of *ex-ante effect* coefficients indicates the value of $S$ for the regression in question. The myopic approach include no ex-ante effects, and is equivalent to the collapsed difference-in-difference approaches presented above. The following five columns include, respectively, separate indicators aimed at capturing ex-ante effects for the month, six months, six quarters, and six half years leading up to the roll-out for each stock. Standard errors, clustered at the stock and month level, are included in parentheses. Panel A includes stocks in the first two waves of the roll-out (vintages 0 and 1), as well as stocks that were never marginable. Panel B includes stocks in the remaining waves of the roll-out, as well as stocks that were never marginable. Sample covers March 2009-May 2015. Mean of dep. var refers to the mean of IHS(Market Cap)$_{t+1}$. Book-equity deciles refer to dummy variables for inclusion in each decile of book equity at the month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**TABLE 8: IMPACT OF MARGIN LENDING ROLLOUT INTERACTED WITH LIKELIHOOD OF INCLUSION (RANK) ON IHS(MARKET CAP)$_{t+1}$: QUASI-MYOPIC APPROACH—VINTAGES 2, 3 AND 4**

| | IHS(Market Cap)$_{t+1}$ | | | | |
|---|---|---|---|---|---|
| | Myopic | Monthly Lags | | Quarterly Lags | Half Year Lags |
| Ex-Post Effect ($\hat{\beta}_0^{quasi}$) | 0.046 | 0.054 | 0.095** | 0.148*** | 0.165*** |
| | (0.034) | (0.034) | (0.036) | (0.040) | (0.045) |
| Ex-Post Effect × Low Rank | 0.119*** | 0.124*** | 0.152*** | 0.198*** | 0.235*** |
| | (0.045) | (0.046) | (0.049) | (0.054) | (0.061) |
| Ex-Ante Effect (t-1) × Low Rank | | 0.205*** | 0.232*** | 0.271*** | 0.300*** |
| | | (0.031) | (0.039) | (0.046) | (0.056) |
| Ex-Ante Effect (t-2) × Low Rank | | | 0.221*** | 0.256*** | 0.224*** |
| | | | (0.042) | (0.046) | (0.056) |
| Ex-Ante Effect (t-3) × Low Rank | | | 0.230*** | 0.214*** | 0.129** |
| | | | (0.038) | (0.046) | (0.053) |
| Ex-Ante Effect (t-4) × Low Rank | | | 0.221*** | 0.162*** | 0.085* |
| | | | (0.038) | (0.044) | (0.047) |
| Ex-Ante Effect (t-5) × Low Rank | | | 0.211*** | 0.114*** | 0.055 |
| | | | (0.036) | (0.040) | (0.042) |
| Ex-Ante Effect (t-6) × Low Rank | | | 0.205*** | 0.072* | 0.047 |
| | | | (0.038) | (0.040) | (0.032) |
| Ex-Ante Effect (t-1) ($\hat{\beta}_1^{quasi}$) | | 0.208*** | 0.235*** | 0.288*** | 0.273*** |
| | | (0.045) | (0.046) | (0.040) | (0.043) |
| Ex-Ante Effect (t-2) ($\hat{\beta}_2^{quasi}$) | | | 0.245*** | 0.221*** | 0.164*** |
| | | | (0.041) | (0.033) | (0.042) |
| Ex-Ante Effect (t-3) ($\hat{\beta}_3^{quasi}$) | | | 0.232*** | 0.168*** | 0.096** |
| | | | (0.037) | (0.034) | (0.040) |
| Ex-Ante Effect (t-4) ($\hat{\beta}_4^{quasi}$) | | | 0.205*** | 0.123*** | 0.057 |
| | | | (0.033) | (0.033) | (0.034) |
| Ex-Ante Effect (t-5) ($\hat{\beta}_5^{quasi}$) | | | 0.175*** | 0.093*** | 0.018 |
| | | | (0.024) | (0.031) | (0.029) |
| Ex-Ante Effect (t-6) ($\hat{\beta}_6^{quasi}$) | | | 0.137*** | 0.063** | −0.013 |
| | | | (0.024) | (0.027) | (0.023) |
| Mean of Dep. Var. | 22.4 | 22.4 | 22.4 | 22.4 | 22.4 |
| $R^2$ | 0.82 | 0.82 | 0.83 | 0.83 | 0.83 |
| N | 117735 | 117735 | 117735 | 117735 | 117735 |
| P-Value (Joint Test of Rank Ex-Ante) | | 0.000 | 0.000 | 0.000 | 0.001 |
| Book Equity Deciles | Yes | Yes | Yes | Yes | Yes |
| Year × Month Fixed Effects | Yes | Yes | No | Yes | Yes |
| Stock Fixed Effects | Yes | Yes | Yes | Yes | Yes |

Results from myopic and quasi-myopic (in the vein of Malani and Reif (2015)) difference-in-difference specifications of IHS(Market Cap)$_{t+1}$ on the interaction between the margin lending roll-out and the ex-ante likelihood that a stock is included in the roll-out. We report coefficients from the following regression

$$\text{IHS(Market Cap)}_{i,t+1} = \alpha + \beta_0^{quasi}\text{Margin Trading Active}_{it} + \eta_0^{quasi}\text{Margin Trading Active}_{it} \times \text{Low Rank}_{it} + \sum_{j=1}^{S}\left[\beta_j^{quasi} D_{i,t+j} + \eta_j D_{i,t+j} \times \text{Low Rank}_{it}\right] + \gamma_i + \delta_t + \varepsilon_{it}$$

Market cap is measured in RMB at the stock-month level. *Low Rank* is an indicator for the stocks with below median rank (highest likelihood of inclusion)—amongst those that were ultimately included in the next vintage–according to the formula described by rule 3.2. *Margin Trading Active* is equal to one only (i) for stocks that are included in the margin trading roll-out, and (ii) in months after margin trading is active in those stocks. $D_{i,t+j}$ is equal to one if margin trading initially becomes active for stock $i$ in period $t + j$, and zero otherwise. The number of *ex-ante effect* coefficients indicates the value of $S$ for the regression in question. The myopic approach include no ex-ante effects. The following five columns include, respectively, separate indicators aimed at capturing ex-ante effects for the month, six months, six quarters, and six half years leading up to the roll-out for each stock. Standard errors, clustered at the stock and month level, are included in parentheses. Reported P-Values are from joint tests of *Ex-Ante Effect × Low Rank* coefficients. This table includes stocks in vintages 2,3, and 4, as well as stocks that were never marginable. Sample covers March 2009-May 2015. Mean of dep. var refers to the mean of IHS(Market Cap)$_{t+1}$. Book-equity deciles refer to dummy variables for inclusion in each decile of book equity at the month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

### TABLE 9: IMPACT OF MARGIN LENDING ROLLOUT ON INSTITUTIONAL OWNERSHIP: QUASI-MYOPIC APPROACH—VINTAGES 2, 3, AND 4

| | Proportion of Institutional Ownership | | | |
|---|---|---|---|---|
| | Myopic | Half Year Lags | | |
| Ex-Post Effect ($\hat{\beta}_0^{quasi}$) | $-0.034^{**}$ | $-0.027^{*}$ | $-0.019$ | $-0.016$ |
| | (0.011) | (0.012) | (0.013) | (0.015) |
| Ex-Ante Effect (t-1) ($\hat{\beta}_1^{quasi}$) | | $0.033^{***}$ | $0.041^{***}$ | $0.044^{***}$ |
| | | (0.007) | (0.008) | (0.010) |
| Ex-Ante Effect (t-2) ($\hat{\beta}_2^{quasi}$) | | | $0.035^{***}$ | $0.038^{***}$ |
| | | | (0.010) | (0.012) |
| Ex-Ante Effect (t-3) ($\hat{\beta}_3^{quasi}$) | | | | 0.008 |
| | | | | (0.009) |
| Ex-Ante Effect (t-4) ($\hat{\beta}_4^{quasi}$) | | | | 0.006 |
| | | | | (0.005) |
| Mean of Dep. Var. | 0.40 | 0.40 | 0.40 | 0.40 |
| $R^2$ | 0.70 | 0.70 | 0.70 | 0.70 |
| N | 18411 | 18411 | 18411 | 18411 |
| Book-Equity Deciles | Yes | Yes | Yes | Yes |
| Month × Year Fixed Effects | Yes | Yes | Yes | Yes |
| Stock Fixed Effects | Yes | Yes | Yes | Yes |

Results from myopic and quasi-myopic difference-in-difference specifications of the proportion of institutional ownership in half year $t$ on the margin lending roll-out in the vein of Malani and Reif (2015). We report coefficients from the following regression

$$\text{Prop. Institutional Ownership}_{i,t} = \alpha + \beta_0^{quasi}\text{Margin Trading Active}_{it} + \sum_{j=1}^{S} \beta_j^{quasi} D_{s,t+j} + \gamma_i + \delta_t + \varepsilon_{it}$$

*Margin Trading Active* is equal to one only (i) for stocks that are included in the margin trading roll-out, and (ii) in half-years after margin trading is active in those stocks. $D_{i,t+j}$ is equal to one if margin trading initially becomes active for stock $i$ in period $t+j$, and zero otherwise. The number of *ex-ante effect* coefficients indicates the value of $S$ for the regression in question. The myopic approach include no ex-ante effects. The following three columns include, respectively, separate indicators aimed at capturing ex-ante effects for the half-year, two-half years, and four-half years leading up to the roll-out for each stock. Standard errors, clustered at the stock and half year level, are included in parentheses. This table includes stocks in vintages 2,3, and 4, as well as stocks that were never marginable. Sample covers March 2009-May 2015. Mean of dep. var refers to the mean of IHS(Market Cap)$_{t+1}$. Book-equity deciles refer to dummy variables for inclusion in each decile of book equity at the month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

### TABLE 10: IMPACT OF MARGIN LENDING ROLLOUT ON TURNOVER: QUASI-MYOPIC APPROACH—VINTAGES 2, 3, AND 4

| | Turnover$_t$ | | | | |
|---|---|---|---|---|---|
| | Myopic | Monthly Lags | | Quarterly Lags | Half Year Lags |
| Ex-Post Effect ($\hat{\beta}_0^{quasi}$) | 0.050** | 0.057*** | 0.087*** | 0.120*** | 0.135*** |
| | (0.019) | (0.018) | (0.018) | (0.019) | (0.023) |
| Ex-Ante Effect (t-1) ($\hat{\beta}_1^{quasi}$) | | 0.221*** | 0.244*** | 0.270*** | 0.229*** |
| | | (0.058) | (0.058) | (0.036) | (0.030) |
| Ex-Ante Effect (t-2) ($\hat{\beta}_2^{quasi}$) | | | 0.274*** | 0.157*** | 0.120*** |
| | | | (0.064) | (0.021) | (0.023) |
| Ex-Ante Effect (t-3) ($\hat{\beta}_3^{quasi}$) | | | 0.200*** | 0.120*** | 0.067*** |
| | | | (0.027) | (0.023) | (0.020) |
| Ex-Ante Effect (t-4) ($\hat{\beta}_4^{quasi}$) | | | 0.164*** | 0.090*** | 0.058*** |
| | | | (0.035) | (0.017) | (0.020) |
| Ex-Ante Effect (t-5) ($\hat{\beta}_5^{quasi}$) | | | 0.115*** | 0.045*** | −0.003 |
| | | | (0.016) | (0.015) | (0.018) |
| Ex-Ante Effect (t-6) ($\hat{\beta}_6^{quasi}$) | | | 0.103*** | 0.058*** | 0.009 |
| | | | (0.015) | (0.016) | (0.016) |
| Mean of Dep. Var. | 0.53 | 0.53 | 0.53 | 0.53 | 0.53 |
| $R^2$ | 0.45 | 0.45 | 0.46 | 0.46 | 0.46 |
| N | 117735 | 117735 | 117735 | 117735 | 117735 |
| Book Equity Deciles | Yes | Yes | Yes | Yes | Yes |
| Year × Month Fixed Effects | Yes | Yes | No | Yes | Yes |
| Stock Fixed Effects | Yes | Yes | Yes | Yes | Yes |

Results from myopic and quasi-myopic difference-in-difference specifications of turnover in month $t$ on the margin lending roll-out in the vein of Malani and Reif (2015). We report coefficients from the following regression

$$\text{Turnover}_{i,t} = \alpha + \beta_0^{quasi}\text{Margin Trading Active}_{it} + \sum_{j=1}^{S} \beta_j^{quasi} D_{s,t+j} + \gamma_i + \delta_t + \varepsilon_{it}$$

*Margin Trading Active* is equal to one only (i) for stocks that are included in the margin trading roll-out, and (ii) in half-years after margin trading is active in those stocks. $D_{i,t+j}$ is equal to one if margin trading initially becomes active for stock $i$ in period $t+j$, and zero otherwise. The number of *ex-ante effect* coefficients indicates the value of $S$ for the regression in question. The myopic approach include no ex-ante effects. he following five columns include, respectively, separate indicators aimed at capturing ex-ante effects for the month, six months, six quarters, and six half years leading up to the roll-out for each stock. Standard errors, clustered at the stock and half year level, are included in parentheses. This table includes stocks in vintages 2,3, and 4, as well as stocks that were never marginable. Sample covers March 2009-May 2015. Mean of dep. var refers to the mean of IHS(Market Cap)$_{t+1}$. Book-equity deciles refer to dummy variables for inclusion in each decile of book equity at the month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.