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# RIDING THE CREDIT BOOM

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# ABSTRACT

Research on leverage and asset-price fluctuations focuses on the direct effect of lax bank lending enabling financially-constrained investors to take excessive risks. Ignored are unconstrained investors speculating on higher prices during credit booms. To identify these two effects, we utilize China's staggered liberalization of stock-margin lending from 2010-2015—which encouraged a bank/brokerage-credit-fueled stock-market bubble. The direct effect is a 25 cent increase in a stock's market capitalization for each dollar of margin debt. Unconstrained investors led to an even larger increase in valuations of an additional 32 cents as they speculated on stocks likely to qualify for lending.

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# 1 Introduction

An important macro-finance literature associates leverage cycles with asset price boom-bust patterns typically using panel regressions that exploit cross-country variation and long time series (see, e.g., Borio & Lowe (2002), Schularick & Taylor (2012)).<sup>1</sup> Prominent historical examples include the rise of margin lending in the U.S. stock market preceding the Great Depression (Galbraith (2009)) and the growth of loan-to-value ratios in the U.S. housing market preceding the Great Recession in 2008. This literature has understandably attracted considerable interest from central bankers and other financial market regulators.

Theories addressing these empirical patterns emphasize the "direct" effect: an expansion of bank lending to financially constrained households generating higher asset prices and financial fragility through a variety of mechanisms. A non-exhaustive list includes (1) complacent or neglectful creditors underestimating downside or tail risk (Minsky (1977), Kindleberger & O'Keefe (2001), Gennaioli *et al.* (2012)); (2) reckless lending in the form of lax screening of naive investors (Dell'Ariccia & Marquez (2006), Keys *et al.* (2012)); (3) leverage cycles (Geanakoplos (2010), Simsek (2013)); and (4) intermediary frictions or balance sheets (Bernanke & Gertler (1989), Kiyotaki & Moore (1997), Adrian & Shin (2010), Brunnermeier & Sannikov (2014)).

Largely ignored in such narratives is the notion that periods of loose credit supply also draw in unconstrained speculators who, anticipating higher prices, ride and amplify the credit boom, though some have pointed to the importance of such speculation in the recent credit and housing cycle (see, e.g., Glaeser *et al.* (2008)). An anecdotal example: a wave of investment property purchases and a surge in houseflipping—both presumably by relatively unconstrained investors—coincided with the housing bubble (see, e.g., Haughwout *et al.* (2011) and DeFusco *et al.* (2017)), particularly in subprime areas. More generally, empirical research has implicated institutional investors with few financial constraints, e.g. hedge funds and mutual funds, in riding booms such as the Internet Bubble of the late 1990s (Brunnermeier & Nagel (2004) and Griffin *et al.* (2011)) or the South Sea Bubble (Temin & Voth (2004)). Theoretically, speculation of this form, even by sophisticated investors, can greatly magnify asset price movements (De Long *et al.* (1990), Lakonishok *et al.* (1992), Hong & Stein (1999), Abreu & Brunnermeier (2003)).

Our goal in this paper is to quantify and separate both (i) the direct effect of credit booms, i.e. how an exogenous shock to credit supply increases demand for assets by ex-ante *constrained* investors, and (ii) the impacts of anticipatory speculation by ex-ante *unconstrained* investors. While a developing literature utilizes geographical variation in credit supply or banking deregulation to try to gauge the direct effects of

<sup>&</sup>lt;sup>1</sup>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)).

relaxed mortgage credit on home prices (Mian & Sufi (2011), Adelino *et al.* (2017), Favara & Imbs (2015)), there is no work we know of that attempts to separately identify these two effects. Yet such an empirical exercise is needed: if the dangers of credit booms stem from excessive trading or speculation—rather than the extension of credit per-se—policy makers might be better served broadening or shifting their focus from macro-prudential restrictions on leverage or credit to Tobin taxes or other anti-speculative measures.

Our analysis considers the recent credit cycle in China as a venue to disentangle the direct effects of credit supply on asset prices from anticipatory speculation. From 2010 to 2015, the Chinese stock market received a large credit supply shock as a result of the Chinese government liberalizing margin lending and further encouraging banks/brokers to lend to households to buy in the stock market. The liberalization of stock margin lending generated a rapid expansion of margin debt, peaking at 3.5% of GDP and 4% of market capitalization (see Figure 1). In the context of China, the size and rapid expansion of credit can only have been supplied by government-owned banks. At the peak, nearly 2 trillion yuan of margin loans were supplied to Chinese households to purchase in the stock market. Since China has stringent shorting-constraints, speculation and credit gave rise to a bubble (Scheinkman & Xiong (2003), Geanakoplos (2010)), which subsequently gave way to a crash and government bailouts.

In other words, the Chinese stock market had a credit-fueled speculative stock market bubble that given the lack of corresponding productivity increases in China during this period—is suggestive of the "direct" effects narrative found in the literature.<sup>2</sup> However, by exploiting the unique staggered nature of China's margin lending liberalization, we show that market valuations actually rose *prior* to the expansion of margin debt, as unconstrained investors drove up the prices of soon-to-be-marginable stocks in anticipation of deregulation. Furthermore, these unconstrained investors' buying led to an overshooting of prices.

The Chinese experience provides an ideal context in which to differentiate anticipatory speculation, i.e. riding the credit boom, from the direct effects of credit supply for at least three reasons. First, the timing of the credit expansion is precisely observable. New credit became available to Chinese stock market participants as the result of a specifically targeted liberalization program, which introduced margin lending for particular stocks at particular moments in time. Second, the government staggered the deregulation over a series of different *vintages*: including a new cohort of stocks in the margin lending liberalization enables a difference-in-difference approach—comparing marginable stocks to not-yet or never marginable stocks before and after deregulation—but also provides a unique opportunity to isolate anticipation. Because of this feature, we are able to explore whether there are staggered advance increases in asset valuations mirroring

<sup>&</sup>lt;sup>2</sup>This narrative regarding the Chinese context is not dissimilar to arguments as in Mian & Sufi (2011) for an increase in subprime mortgage loans in the face of deteriorating income among those households.

the staggered nature of the liberalization. Third, for the last three of these five vintages the government committed to a formal rule for screening and ranking, whereby new stocks qualified for margin lending in according to a published formula based on publicly available information on market capitalization and trading volume. As a result, we are able to characterize the ex-ante information on the coming credit expansion that was available to investors.

Our empirical strategy attempts to test for and quantify three distinct empirical objects related to credit expansions: (i) anticipatory effects, or ex-ante changes in asset prices in the lead up to a credit boom, (ii) direct effects, the ex-post changes in asset prices that would occur in the absence of anticipation, and (iii) overshooting, or the degree to which ex-ante speculation causes ex-post asset prices to *exceed* the level implied by the direct effect. We proceed in several steps. To begin, we establish the existence of a baseline correlation between margin debt and a stock's market capitalization with a set of OLS regressions. Our most conservative specification, with stock and time fixed effects, suggests that each additional dollar of margin debt is associated with a 40 cent rise in market capitalization. To help interpret this relationship, a useful—if somewhat extreme—benchmark is the case of full pass-through, under which an additional dollar of margin debt would increase market capitalization by a dollar. Of course, it is unsurprising that our estimates are smaller than a dollar, as there is likely to be substitution to other assets by price-sensitive investors to the extent that valuations rise too high.

Next, we turn to explicitly utilizing China's staggered liberalization to understand the effect of margin debt on stock valuations. We start by presenting standard difference-in-difference and IV difference-in-difference estimates that exploit the difference between marginable and non-marginable stocks before and after the roll-out of margin lending as a source of variation in margin debt. We refer to these specifications as *myopic*, as their validity depends on the assumption of no anticipation—a requirement in any textbook difference-in-difference strategy. There is naturally a strong first stage since margin lending cannot begin without regulatory approval. The 2SLS estimates suggest that an extra dollar of margin debt leads to a 25 cent increase in market capitalization, which is smaller than our OLS estimates but nonetheless economically significant. However, the myopic nature of the approach makes it ineffective in capturing a world with anticipation: speculation prior to deregulation generates pre-trends that bias traditional difference-in-difference-in-difference-in-difference-in-difference-in-difference-in-difference-in-difference and the approach makes it ineffective in capturing a world with anticipation: speculation prior to deregulation generates pre-trends that bias traditional difference-in-difference estimators. Furthermore, these specifications are unable to provide tests for or quantify the extent of anticipation, which may be an interesting outcome in and of itself.

To identify the presence of anticipation, and correct the bias in our standard estimates, we then implement a quasi-myopic difference-in-difference estimator (see, e.g., Malani & Reif, 2015). This approach allows for differential ex-ante effects amongst soon-to-be marginable stocks, enabling us to both account for attenuation due to pre-trends and explicitly quantify the role of anticipation. With this strategy, we estimate an overall effect that is much higher than our myopic estimates would suggest: a 57 cent increase in market capitalization per dollar of margin debt. Additionally, we find strong evidence for anticipation: valuations among soon-to-be marginable stocks rise differentially in the periods just before deregulation.

Labeling our estimates as anticipation requires the assertion that the pre-trends we observe are caused by agents in the economy adjusting their behavior in preparation for a publicly known event, rather than reflecting some omitted variable. To this end, we present several pieces of evidence pointing to unconstrained institutional investors speculating on the timing of the margin roll-out across vintages, which are summarized in Figures 3–5. In all figures, vertical lines display the start date of each of the three vintages for which the criteria for a stocks inclusion was published ex-ante. Note that if there are no anticipation effects, we should see price and trading effects for a given stock only at the moment at which or after margin becomes available. Alternatively, if there are anticipation effects, we expect prices and trading—i.e. buying by unconstrained investors—to rise in advance of credit supply becoming available (but after the government publicly announces their intentions). Notice that these increases need not be instantaneous and should be gradual to the extent that unconstrained investors have holding costs or there is uncertainty regarding the likelihood or form of deregulation.

Perhaps the most direct evidence comes as a result of the staggered aspect of the liberalization. While anticipatory speculation would naturally mirror the deregulation, with staggered anticipatory effects concentrated in the periods just prior to the roll-out of each vintage, it is difficult to imagine why a non-anticipatory pre-trend—say due to some omitted variable—would impact these vintages in a staggered fashion. Consistent with anticipation, Figure 3 shows that (residualized) prices of stocks in Vintages 2-4 rise roughly 6-12 months before margin lending is introduced in each specific vintage, with no corresponding pattern in the set of stocks that are never marginable. Furthermore, because it was only after the announcement of the second vintage that the government committed to a deregulation path (and published the screening and ranking formula), we compare the later vintages, where should show stronger anticipation effects, to the first two vintages. As expected, we find significantly stronger ex-ante rises in stock prices in those later vintages.

Further support is provided by sharp ex-ante increases in turnover within each vintage (Figure 5), and the fact that unconstrained institutional investors purchased these vintages differentially just before each roll-out and sold differentially just after (Figure 4).<sup>3</sup> As an additional point of validation, we exploit variation in ex-ante uncertainty over which stocks would become marginable generated by the ranking procedure. We find that anticipatory increases in valuations *within* each vintage are concentrated in the stocks

<sup>&</sup>lt;sup>3</sup>We identify institutional ownership for each stock based both using data on mutual funds, and on shares held by the top 10 shareholders in a company. These owners tend to be institutions and pools of money outside the margin lending system.

most likely to be included in the deregulation ex-ante.

Given anticipation, a stocks valuation at the moment of deregulation incorporates any direct effect of margin debt, but might also be influenced by the extent to which anticipatory speculation over-estimated (or under-estimated) this effect. In particular, if unconstrained investors over-estimated the direct effect of margin lending on stock prices, we expect to see prices reverse after credit comes on. As a result, our anticipation corrected estimate—that overall a dollar of margin debt leads to an increase of 58 cents in market capitalization—is actually the sum of two distinct effects of interest: (i) the direct effect of margin debt on market cap, and (ii) overshooting due to anticipation.

To this end, we develop two empirical strategies to to test for the presence of overshooting, and to separate these two effects. The first utilizes the fact that anticipatory increases in valuations are concentrated in those most likely to become marginable. Accordingly, we hypothesize that if anticipation led to overshooting than the ex-post valuations—among the set of all marginable stocks—should be highest for those that were ex-ante most likely to become marginable. Second, under the assumption that prices eventually settle, we measure the direct effect in the period several months *after* the credit roll out. While all these estimates require different assumptions, all produce affirmative evidence of the presence of overshooting. Our conservative estimates for the importance of this effect allow us to decompose our estimate of 57 cents into a direct effect of 25 cents and an overshooting effect of 32 cents.

We next provide correlational evidence that these anticipation effects played a role at the peak of the bubble and crash in 2015, when shadow margin appeared. We have data on shadow margin lending from a peer-to-peer platform that encompassed around 10% of the market during this period. Estimates place shadow margin in 2015 at almost 1 trillion yuan, roughly half of the formal margin amount during at the peak of the bubble and research implicate it in amplifying the market crash (Bian *et al.* (2017a), Bian *et al.* (2017b)). Unconstrained investor holdings of non-marginable stocks going into 2015 went up significantly relative to other stocks. These non-marginal stocks, which had previously under-performed the market, outperformed the market during this period. This buying anticipated the rise in shadow margin lending in the Chinese stock market which was concentrated in these non-marginable stocks. Our earlier findings and these shadow-margin findings are reminiscent of and provide a tighter causal chain on Brunnermeier & Nagel (2004) and Griffin *et al.* (2011) who found that hedge funds rather than shorting internet stocks actually overweighted internet stocks going into the dot-com bubble. More generally, we view our quasi-experiment as having external validity: investors forecasts and anticipation appear to at least partially drive 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 develop our hypothesis. 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 experimenting with margin lending on February 13th, 2010. As a pilot program, an initial set of 90 stocks (Vintage 0) were opened to margin lending. The stocks selected for this initial vintage were simply those included in the two major stock market indices: the Shanghai 50 Index (50 stocks) and the Shenzhen Component index (40 stocks). Investors with at least 500,000 RMB of assets in their stock brokerage account and six months or more of trading experience qualified for margin—provided by their brokerage firms—to buy these stocks.

Effective on November 25th, 2011, the Chinese government officially began the margin lending program for stock trading, extending the list of marginable stocks based on stocks' membership in two broader market indices. The extended list included 278 stocks: 180 stocks from the Shanghai 180 Index and 98 stocks from Shenzhen 100 Index. Throughout, we refer to the stocks added at this point as Vintage 1. In the official regulations released on margin lending, the exchanges explicitly stated that they would extend the list of marginable securities in a staggered manner.<sup>4</sup>

For the later extensions (Vintages 2-4), the regulatory agency adopted a screening-and-ranking rule to determine which stocks would be included in each vintage. This procedure had two steps: (i) Screening out stocks that did not satisfy several criteria that ruled particularly small, volatile, illiquid, and newly listed stocks—the so called Article 24 for Shanghai and Rule 3.2 for Shenzhen.<sup>5</sup> (ii) Ranking the remaining stocks according to the formula described in Equation (1) and selecting the top 100 as the candidates for the next vintage (with some discretion). As shown in Equation 1, the ranking is based on a value-weighted average of a stock's size and trading volume within the exchange. <sup>6</sup> The ranking procedure was conducted by the Shanghai (SH) and Shenzhen (SZ) exchanges separately.

<sup>&</sup>lt;sup>4</sup>See Article 28 in the Rule released by the Shanghai Stock Exchanges.

<sup>&</sup>lt;sup>5</sup>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.

<sup>&</sup>lt;sup>6</sup>Eq.(1) was released in exchanges' announcements of the second to fourth extension of marginable stocks.

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

According to the regulator's public statements, the ranking procedure was based on market data over a period before the start date of each vintage. As both the data used for the screening-and-ranking procedure, and the procedure itself, is public, we were able to fairly successfully replicate the procedure for each extension on each exchange, we discuss this exercise below. More importantly, unconstrained investors would plausibly be able to use these same guidelines starting at the end of 2011 to forecast in the roll-out of margin lending in real time. While the stocks included in Vintages 0 and 1 were potentially difficult to forecast, Vintages 2, 3 and 4 could in principle be predicted fairly easily.

Vintages 2-4 were opened to margin lending on January 25th 2013 (Vintage 2), September 6th 2013 (Vintage 3), and September 12th 2014 (Vintage 4). Each time, approximately 100 stocks from each of the two exchanges become newly marginable (Although there were 120 stocks from the Shanghai exchange included in Vintage 2). After all five of these vintages, there were approximately 900 stocks in total that could be bought on margin across the two exchanges.<sup>7</sup> Table 1 summarizes the timeline of the deregulation and the number of newly marginable stocks for each extension.

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

Since the official announcement of margin deregulation at the end of 2011, margin lending in China expanded dramatically. 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 to total market capitalization increased from 0.5% around the end of 2012 to 4.5% in June 2015. In yuan terms, total margin debt increased from a negligible amount at the beginning of 2012 to almost two trillion yuan in 2015.

Coincident with the high level and rapid growth of margin debt, the Chinese stock market experienced an enormous boom during this period. As shown in Figure 1, total market capitalization increased from 20 trillion yuan in mid-2014 to over 50 trillion at its peak in June 2015, after which the market collapsed by more than 20% within two weeks. Over the same period, the Shanghai Composite index rose from about 2000 in mid-2014 to a peak of 5,166.35, on June 12, 2015. Subsequently, the market crashed to 3709 within three weeks.

<sup>&</sup>lt;sup>7</sup>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.

## 2.3 Data and variable construction

We utilize stock price, trading, and financial information from CSMAR, excluding stocks on the Growth Enterprise Board (GEB). Formal margin debt balance is released by Shanghai and Shenzhen stock exchanges on a daily basis. Our sample is from March 2009, one year before margin lending starts, to October 2015. The pre-crash period is from March 2009 to May 2015. Our analysis is primarily at the monthly level.

The key independent variable of interest in our paper is Margin  $\text{Debt}_{i,t}$ , which refers to the dollar balance of margin borrowing for stock *i* at the end of month *t*. Our primary outcome variable, Market  $\text{Cap}_{i,t}$  is the market value of stock *i*'s tradable shares. We also consider Turnover<sub>*i*,*t*</sub>, the number of shares traded over month *t* scaled by the number of floating shares in Shanghai or Shenzhen stock exchange. As a control, stocks are sorted into deciles based on the past year's book equity value; we denote decile dummies as  $BE_{i,t}$ .

A crucial piece of our analysis regarding anticipation effects revolves around trading behavior of unconstrained investors. While the margin lending deregulation was meant to help constrained households facing financial constraints, there many are institutional investors in China who do not face such constraints, such as insurance companies or mutual funds. We rely on two datasets to get at these investors' trading behavior. The first is an analog of the 13-F quarterly institutional ownership filings in US markets typical used in studies of trading by institutional investors. While data on institutional ownership in China is not quite as high quality, public companies in China do have to disclose the largest ten shareholders and their ownership in quarterly financial reports. This data comes with the names of the investors. The majority of top 10 shareholders are institutional such as insurance companies, brokerages, and occasionally mutual funds. While not a perfect measure of institutional ownership in a stock, this variable is likely to be highly correlated, and to reflect the holdings of relatively unconstrained investors with lots of capital. For our analysis, we sum total ownership across the top 10 holders of floating shares and label it as the Top 10 Investors Ownership Share.

Our second measure of the holdings of unconstrained investors is based on mutual fund data from CSMAR. In China, mutual funds are required to report their stock holdings on a quarterly basis. For each stock, we calculate a Mutual Fund Ownership Share, which is the fraction of floating shares held by all mutual funds.

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

To validate the relevance of the screening and ranking procedure discussed in Section 2.1, we use public stock market data to try to predict the list of marginable stocks for vintages 2-4. It is worth mentioning that there are a handful of limitations that may prevent us from doing so precisely. First, the exact time window

used by the exchange is not clear. However, according to some industry sources, the exchanges use data on a three-month period before the formal announcement of each vintage, although we assume there must be at least some small gap for calculation between the data-collection period and the announcement. Here, we take the end of the most recent month prior to the formal announcement as the end of the three month evaluation period. Second, there is some room at the margins for discretion on the part of the exchanges, with little in the way of published detail. As such, we do not expect to be able to precisely predict inclusion.

For each vintage, we examine the set of stocks that are non-marginable before the vintage is announced. We follow the screening rule and first exclude stocks that do not meet the criteria over the three-month window. Then, we calculate the ranking indicator as specified in Equation 1 for the remaining 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 a fuzzy RD. That is, for vintage *k* and stock *i* satisfying the screening criteria,

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

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 results are similarly strong for the other two vintages. In our following analysis, we use the pre-ranking, i.e., *Rank<sub>i</sub>*, to identify stocks likely-to-qualify for the margin debt program.

# 3 Hypothesis Development

The destabilizing effects of institutional investors speculating on the path of prices are well-established in the literature and can arise in a variety of settings. Here we emphasize a couple of key mechanisms from the theoretical literature that are particularly relevant for our context. First, since China prohibits short-selling, a speculative bubble can emerge as the result of trading on the part of overconfident investors (Scheinkman & Xiong (2003), which we take to be retail household investors (these investors play a significant role in the Chinese stock market). This stock market bubble will increase in size to the extent there is easier access to leverage (Geanakoplos (2010)), which we associate with the government's liberalization of stock margin lending and encouragement of banks to lend large amounts to retail households—as described in the introduction. If unconstrained speculators anticipate that overconfident retail investors will get access to leverage and that prices will rise as a result, it is optimal for them to ride the credit-fueled stock price bubble (Abreu & Brunnermeier (2003)).

The timing of our staggered liberalization setting allows for a test of this anticipatory speculation at the stock vintage or cohort level using a difference-in-difference design. We expect the following robust and testable predictions from the literature.

- The direct effect is positive, i.e. when a stock is qualified for margin lending, buying from households will lead to higher valuations or a larger bubble. This effect assumes that there are not large substitution effects on the part of households into other stocks as a result. This assumption seems plausible since most retail investors hold only a few of their favorite speculative stocks.
- The anticipatory effect is positive, i..e unconstrained investors or arbitrageurs, instead of substituting away from the stocks when credit is rolled out, will instead optimally ride the bubble and start buying stocks that they view as likely to qualify for margin lending in advance of the margin lending deregulation. Notice that their buying and hence price adjustment will be gradual given that there is both uncertainty regarding the policy change and a cost of holding securities.
- To the extent there are enough institutions buying, they will have a price impact and lead to even higher prices or overshooting relative to a world with no such anticipatory speculation. This additional price effect or overshooting is particularly emphasized in De Long *et al.* (1990) and Lakonishok *et al.* (1992).

# 4 Empirical Strategy and Results

Our empirical exercises are designed to address three interrelated goals. First, to test for the presence of anticipatory speculation on the introduction of margin debt by ex-ante unconstrained investors. Second, to test whether this speculation led to a distortion of asset prices: in particular, overshooting relative to the direct effect of margin debt on asset prices in the absence of anticipation. Third, to separate out the impact of anticipation in order to explicitly quantify both the extent of overshooting and the direct effect.

We begin by estimating basic OLS specifications to summarize the relationship between market capitalization and margin lending. We then estimate difference-in-difference IV specifications using the staggered deregulation of margin lending by stock viintages, which would accurately capture the impact of margin debt in a world with no anticipation. We refer to these as *myopic*. Next, we estimate a set of regressions that explicitly allow for anticipation of the margin lending roll-out by unconstrained investors. These specifications, which we refer to as *quasi-myopic*, allow us to more accurately capture the net effects of the margin lending rollout on asset price while also directly testing for the presence of anticipation effects. However, these net effects pool the direct effect of margin debt with any overshooting generated by anticipation. Our final step is to estimate a triple-difference regression, as well as a variation on our quasi-myopic approach, in order to (i) provide direct evidence that anticipation led to overshooting, and (ii) to quantify the direct effect of the rollout of margin debt on asset prices. Below, we discuss each of these in turn.

### 4.1 OLS

Our OLS specification to capture the relationship between margin debt and asset prices is the following. For stock *i* in month *t*, we estimate

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

where IHS (Market Cap)<sub>*i*,*t*</sub> and IHS (Margin Debt<sub>*i*,*t*</sub>) refer to the inverse hyperbolic sine of market cap and margin debt for stock *i* in month t + 1, both in RMB. 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× year fixed effects, respectively.  $\beta_1$  is expected to be positive. We are primarily interested in the economic magnitude of these estimates, and because IHS-IHS as roughly similar to a log-log specification, we interpret the coefficient of interest  $\beta_1$  as an elasticity.

The results from our OLS specifications are shown in Table 3. The coefficients of IHS (Margin Debt<sub>*i*,*t*</sub>), which we interpret as elasticities, 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 .025.

Our most conservative specification includes both time and stock fixed effects. Even for this conservative specification, there is a precisely measured positive effect. As shown in Column (4), the estimated elasticity is 0.005. Given the relative scales of market cap and margin debt in this context (margin debt is nearly two orders of magnitude smaller than market cap), even this conservative estimate is economically sizable.

Evaluated at the means of both variable, this coefficient suggests that a one dollar increase in margin debt corresponds to roughly a 40 cents increase in stock valuation.<sup>8</sup> A useful comparison is the case of perfect pass through, in which a one dollar increase in margin debt would correspondingly increase market cap by one dollar.

## 4.2 Myopic Difference-in-Difference Specifications

To directly capture the variation in margin debt stemming from the staggered margin lending roll-out, we next re-estimate Equation 3 using difference-in-difference IV strategy, and also consider the corresponding reduced form difference-in-difference. In both cases, 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.

Our basic IV specification takes Equation 3 as a second stage. In the first stage, we estimate:

$$IHS(\text{Margin Debt}_{i,t}) = \gamma_0 + \gamma_1 \text{Margin Trading Active}_{i,t} + \lambda_1 BE_{i,t} + \eta_i + \tau_t + v_{it}, \qquad (4)$$

Margin Trading Active<sub>*i*,*t*</sub> is equal to one only (i) if stock *i* is are included in one of the vintages of the margin trading roll-out, and (ii) if margin trading is active for that stock in month *t*. Again,  $IHS(\cdot)$  refers to the inverse hyperbolic sine,  $BE_{it}$  are book-equity decile dummies, and  $\eta_i$ ,  $\tau_t$  are stock and month×year dummies, respectively. We refer to this as the collapsed instrument specification.

We also consider a more elaborate first stage regression. While the above specification 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 ("full instruments specification"):

$$IHS(\text{Margin Debt}_{i,t}) = \gamma_0 + \sum_{k=0}^{4} \gamma_1^k \text{Margin Trading Active}_{i,t} \times Vintage_k_i$$
(5)  
+  $\lambda_1 BE_{i,t} + \eta_i + \tau_t + v_{it},$ 

where  $Vintage_k_i$  is an indicator equal to one if stock *i* is in vintage *k*. Thus, Margin Trading Active<sub>*i*,*t*</sub> ×  $Vintage_k_i = 1$  if margin lending is allowed in month *t* for stock *i* in vintage *k*.

Our myopic reduced form difference-in-difference effectively repeats the first stage regression in Equation 4 above, but replaces  $IHS(Margin Debt_{i,t})$  with  $IHS(Market Cap)_{i,t}$  in order to directly capture the relationship between the introduction of margin lending and asset prices. In particular, we estimate:

<sup>&</sup>lt;sup>8</sup>Average market cap over our sample period is 80.8 times the size of average margin debt.

$$IHS(\text{Market Cap})_{i,t} = \beta_0 + \beta_1 \text{Margin Trading Active}_{i,t} + \theta_1 BE_{i,t} + \gamma_i + \delta_t + \varepsilon_{it}$$
(6)

where again *IHS*(Market Cap)<sub>*i*,*t*</sub> is the inverse hyperbolic sine of market cap for stock *i* in month *t*, with Market Cap in RMB. Margin Trading Active<sub>*i*,*t*</sub> 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× year fixed effects, respectively. In all of these baseline specifications,  $\beta_1$  (which we expect to be positive) provides a myopic estimate of the direct effect of deregulation on market cap, which will be biased in the presence of anticipation.<sup>9</sup>

In Table 4, we present the IV and reduced form myopic estimates. In the first two columns, we display results from the first stage regressions described in Equations 4 and 5. The column labeled collapsed, corresponding to Equation 4, shows that there is a strong, positive, and statistically significant impact of the margin lending rollout on margin debt itself, with a coefficient of just over 19. The column labeled full, corresponding to 5, shows that these effects are relatively constant across the 5 vintages, if marginally smaller in earlier vintages.

The following two columns display the reduced form estimates corresponding to Equation 6, which would effectively capture the net impact of the introduction of margin lending on market cap in a myopic world with no anticipation. The column labeled collapsed displays positive and statistically significant impact of of the introduction of margin lending on market cap, with a coefficient of 0.065. In contrast to the first stage, the column labeled full shows substantial heterogeneity across the different vintages, ranging from negative and statistically significant for the first vintages to positive—and well above 0.065—in the later vintages. We return to this heterogeneity below when discussing the relative ability of investors to anticipate the different vintages.

While the reduced form coefficients are somewhat difficult to interpret in economic terms, the IV specifications, presented in the 5th and 6th columns, directly provide estimated elasticities. The collapsed version, displays an estimated elasticity of 0.003, while the full version displays an estimated elasticity of 0.004. In dollar terms, evaluated at the means of margin debt and market cap, the collapsed elasticity suggests that a one dollar increase in margin debt increases market cap by 24 cents. This 24 cents figure is lower that the 40 cents figure from the OLS specifications as we might expect. But it is nonetheless economically sizeable.

<sup>&</sup>lt;sup>9</sup>We also estimate a reduced form approach analogous to first stage "full instruments specification" in Equation 5.

## 4.3 Accounting for 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 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 this figure—and many that follow—we omit vintages 0 and 1 in order to keep the graphs clear and avoid over-cluttering. As discussed elsewhere, these vintages were difficult to predict and hence (as expected and shown in Table 6) displayed minimal evidence of anticipation.

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.

In order to estimate these anticipatory effects, and to appropriately measure the net 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. As a conservative baseline, we include stocks from all vintages 0 through 4. We later show in Table 6 that the effects are much stronger in vintages 2-4 compared to vintages 0-1.

Specifically, we consider regressions of the following form:

IHS(Market Cap)<sub>*i*,*t*</sub> = 
$$\alpha + \beta_0^{quasi}$$
Margin Trading Active<sub>*i*,*t*</sub> +  $\sum_{j=1}^{S} \beta_j^{quasi} D_{i,t+j} + \theta_1 B E_{i,t} + \gamma_i + \delta_t + \varepsilon_{it}$ . (7)

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 soonto-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 effect of margin lending after adjusting for anticipation.

In order to provide economically interpretable estimates, we also consider IV versions of these specifications. In the second stage, we estimate:

$$IHS(Market Cap)_{i,t} = \alpha + \beta_0 IHS(Margin Debt)_{i,t} + \sum_{j=1}^{S} \beta_j^{quasi} D_{i,t+j} + \theta_1 B E_{i,t} + \gamma_i + \delta_t + \varepsilon_{it}.$$
 (8)

In the first stage, we use Margin Trading Active<sub>*i*,*t*</sub> as an excluded instrument for IHS(Margin Debt)<sub>*i*,*t*</sub> While market cap 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.

Table 5 presents both reduced form and IV evidence from quasi-myopic specifications intended to capture the patterns presented in Figure 3. In the reduced form, the net effect of margin lending is captured by the coefficient labeled *Ex-Post Effect*. The coefficients labeled IHS(Margin Debt) in our IV specifications can be explicitly interpreted as elasticities of margin debt with respect to market cap. As a baseline, the first and fourth columns, labeled *Myopic*, replicate the myopic reduced form and IV specifications shown in Table 4. The remaining columns account for anticipation: columns two and four allow for six months of anticipation, while columns three and six allow for six quarters of anticipation.

Firstly, these estimates provide strong evidence of the existence of anticipatory effects, as evidenced by the positive and significant coefficients labeled as ex-ante effects in these tables. Market cap grows significantly in soon-to-be-marginable stocks in the months or quarters just prior to the margin lending roll-out, when compared with stocks that are not marginable. Additionally, these estimates show that failing to account for anticipation substantially attenuates the net impact of margin lending on market cap. When accounting for six months of anticipatory effects, the estimated reduced form coefficient rises from 0.065 to 0.127, and further to 0.214 when accounting for six quarters of anticipation. The IV estimates, which provide more economically interpretable coefficients, suggest that the elasticity grows from 0.003 with no anticipation, to 0.007 or 0.011 with six months or six quarters. Evaluated at the averages, our six month estimates suggest that—accounting for anticipation—an additional dollar of margin debt leads to a 57 cent increase in market cap, compared to 24 cents in our myopic specification.

#### 4.3.1 Placebo Test: Heterogeneity in Early Versus Late Vintages

While the stocks included in vintages 2, 3 and 4 were included on the basis of a well defined and publicly available rule, the early vintages were chosen in a less systematic and transparent way. As a result, we expect that the marginable stocks in these vintages were more difficult to predict in advance of the rollout. To test this prediction, we estimate a triple difference version of our quasi-myopic specifications, incorporating the difference between early and later vintages. In particular, we run:

IHS(Market Cap)<sub>*i*,*t*</sub> = 
$$\alpha + \beta_0^{quasi}$$
Margin Trading Active<sub>*i*,*t*</sub> +  $\sum_{j=1}^{S} \beta_j^{quasi} D_{i,t+j}$   
+  $\eta_0^{quasi}$ Margin Trading Active<sub>*i*,*t*</sub> × Late Vintage<sub>*i*</sub> +  $\sum_{j=1}^{S} \eta_j^{quasi} D_{i,t+j}$  × Late Vintage<sub>*i*</sub>  
+  $\theta_1 B E_{i,t} + \gamma_i + \delta_t + \varepsilon_{it}$ . (9)

 $\eta_j^{quasi} > 0$  provides further evidence for anticipatory effects: suggesting that the later, more predictable vintages saw larger increases in market cap in the months prior to the rollout. Additionally, evaluating the hypothesis  $\eta_0^{quasi} > 0$  provides evidence of overshooting, suggesting that the stocks that were more predictable ex-ante also had higher valuations ex-post.

We also estimate IV versions of these specifications, where, in a second stage, we estimate:

$$IHS(Market Cap)_{i,t} = \alpha + \beta_0 IHS(Margin Debt)_{i,t} + \sum_{j=1}^{S} \beta_j^{quasi} D_{i,t+j} + \eta_0 IHS(Margin Debt)_{i,t} \times Late Vintage_i + \sum_{j=1}^{S} \eta_j^{quasi} D_{i,t+j} \times Late Vintage_i + \theta_1 BE_{i,t} + \gamma_i + \delta_t + \varepsilon_{it}.$$
(10)

In a first stage, we include Margin Trading Active<sub>*i*,*t*</sub> and Margin Trading Active<sub>*i*,*t*</sub> × Late Vintage<sub>*i*</sub> as excluded instruments for IHS(Margin Debt)<sub>*i*,*t*</sub> and IHS(Margin Debt)<sub>*i*,*t*</sub> × Late Vintage<sub>*i*</sub>. These IV estimates provide coefficients that can be interpreted as elasticities.

Table 6, which shows estimates from the specifications described in Equation 9, displays significant evidence of both anticipation and overshooting. In monthly and quarterly specifications, there are positive and highly significant differential ex-ante effects for late vintages, suggesting that later more predictable vintages saw significantly larger anticipatory effects. Additionally, there is substantial evidence of overshooting: in all specifications the ex-post effect is significantly larger for later vintages than for early vintages. In particular, the estimated elasticities—evaluated at the means of margin debt and market cap—suggest that, in the monthly specification, an additional dollar of margin debt is associated with a 1.28 dollar larger increase in market cap for later vintages compared with earlier vintages.

### 4.4 Further Evidence from Unconstrained Investors

To confirm that the results above are driven by anticipation, we next directly examine the behavior of two groups of investors we expect to be relatively unconstrained even prior to the introduction of margin lending. Specifically, we examine the holdings of mutual funds, and of the largest holders of each stock—defined as the top ten investors by quantity of shares at the stock-quarter level.

There is strong evidence that these unconstrained investors increased their holdings in anticipation of the roll-out of margin lending. Figure 4 displays the patterns of ownership by both mutual funds and the top 10 investors over our sample period for the vintages that display the most direct evidence of anticipation: vintages 2, 3 and 4. We also include the shares held in never marginable stocks, as a comparison group. The two panels plot residuals of the share of ownership by mutual funds and the top 10 investors, respectively, after netting out stock, quarter, and book equity decile fixed effects. For all three vintages, there is graphical evidence that these relatively unconstrained investors contributed to the anticipatory rise in market cap. Relative to the never marginable group, the share of ownership for these unconstrained investors rose in the months prior to the roll-out date of the vintage (and much farther in advance for vintage 2). Perhaps the most pronounced evidence comes from vintage 4, which shows a steep increase in both groups in relatively close proximity to the roll-out.

Table 8 displays regression results corresponding to Figure 4, but, to be conservative, including stocks in all vintages. The specifications are identical to those in Equation 7, but replace the dependent variable with the share of ownership by unconstrained investors (defined as either mutual funds, or the top 10 investors). They are estimated at the quarterly level, corresponding to the frequency of our data on these investors. In

our quasi-myopic specifications we show two quarters of ex-ante effects to match the 6 months shown in our specifications that utilize monthly data.

The first two columns of this table present results for mutual funds. As a baseline, the column labeled *Myopic* shows results from a myopic difference-in-difference specification that does not account for anticipation. Ignoring anticipation, it appears that there is a marginally significant negative effect of the margin lending rollout on mutual fund holdings. However, the column labeled *Quarterly Lags* shows that this negative effect is largely an artifact of anticipation. Allowing for two quarters of anticipation, the negative effect drops and becomes insignificant.

Perhaps more importantly, there are statistically significant positive coefficients representing ex-ante effects in each of the two quarters preceding the margin lending roll-out. These coefficients suggest that by the quarter just prior to the roll-out, mutual fund holdings increased by 0.7 percentage points on average or 41 percent—relative to never marginable stocks. The top 10 investors show a similar pattern: a negative (although insignificant) coefficient in the myopic specification, which is attenuated when allowing for anticipation. Again, there are positive and statistically significant ex-ante effects for the top 10 investors in the quarters just before the roll-out. These estimates suggest that these investors had increased their holdings in soon to be marginable stocks by 3.6 percentage points, or 7.8 percent, in last quarter before margin lending began.

We also examine whether there is visible evidence of anticipation in turnover for the stocks that qualified for margin lending. Figure 5 shows residualized turnover for vintages 2, 3 and 4, as well as for never marginable stocks, over our sample period. Within each group, this figure plots average turnover after netting out month, stock, and book-equity decile fixed effects. The plot shows sharp increases in turnover for each of the vintages just prior to the margin lending rollout, particularly for vintages 2 and 3. For all three vintages, these spikes recede fairly quickly following the roll-out.

The final two columns of 8 display regression results corresponding to these figures. We once again estimate a version of Equation 7 at the monthly level, but replace the dependent variable with our measure of turnover. There are significant increases in turnover relative to the never marginable group both ex-ante, in the two quarters preceding the roll-out, and after the rollout. The effect on turnover in the quarter before the roll-out, at 0.164, is nearly double the ex-post effect of 0.087. These anticipatory increases in turnover are directly consistent with the presence of unconstrained investors speculating in anticipation of the margin lending roll-out.

## 4.5 Direct Effect versus Price Overshooting from Anticipation

We next develop two strategies that provide further evidence on the presence of anticipation, and allow direct tests of overshooting. In the first, we further interact the quasi-myopic specifications above with a variable intended to capture variation in investors ability to anticipate which stocks were likely to become marginable: the likelihood of inclusion in the coming vintage. In the second, we separate the short run effect of the margin lending—the period just after the roll-out—which ostensibly incorporates both the direct effect of credit supply and the impact of anticipation, from the long run effect, which is more likely to reflect only a stable, direct effect.

#### 4.5.1 High vs. Low Ranking Stocks Within Later Vintages

The later vintages were determined on the basis of a well defined rule based on a stock's ranking in terms of volume and market value at the time of the rollout. As a result, in the months prior to the roll-out itself, there was uncertainty over which stocks would have a sufficient ranking to qualify. We exploit cross-sectional variation in this uncertainty by comparing, within the stocks that qualified for a given vintage, those with the highest rankings (above median rank) to those with the lowest rankings (below median rank). Assuming some stability over time, predicting that the highest ranking stocks would be included in the next vintage was relatively certain. Alternatively, the lowest ranking stocks that were ultimately included were somewhat less certain, as smaller changes in rank might disqualify them. To be explicit, we estimate:

$$IHS(Market Cap)_{i,t} = \alpha + \beta_0^{quasi} Margin Trading Active_{i,t} + \sum_{j=1}^{S} \beta_j^{quasi} D_{i,t+j} + \eta_0^{quasi} Margin Trading Active_{i,t} \times High Rank_i + \sum_{j=1}^{S} \eta_j^{quasi} D_{i,t+j} \times High Rank_i + \theta_1 BE_{i,t} + \gamma_i + \delta_t + \varepsilon_{it}.$$
(11)

 $\eta_j^{quasi} > 0$  provides additional evidence for anticipatory effects: suggesting that stocks that were relatively certain to be included in the next vintage saw larger increases in market cap in the months prior to the rollout. Evaluating the hypothesis  $\eta_0^{quasi} > 0$  provides a direct test of overshooting, suggesting that the stocks that were more likely to be included ex-ante also had higher valuations ex-post.

Just as in our comparison of early and late vintages, we also run IV versions of this specification. In a

second stage, we estimate

$$IHS(Market Cap)_{i,t} = \alpha + \beta_0^{quasi} IHS(Margin Debt)_{i,t} + \sum_{j=1}^{S} \beta_j^{quasi} D_{i,t+j} + \eta_0^{quasi} IHS(Margin Debt)_{i,t} \times High Rank_i + \sum_{j=1}^{S} \eta_j^{quasi} D_{i,t+j} \times High Rank_i + \theta_1 BE_{i,t} + \gamma_i + \delta_t + \varepsilon_{it}.$$
(12)

In a first stage, we include Margin Trading  $Active_{i,t}$  and Margin Trading  $Active_{i,t} \times High Rank_i$  as excluded instruments for IHS(Margin Debt)<sub>*i*,*t*</sub> and IHS(Margin Debt)<sub>*i*,*t*</sub>  $\times$  High Rank<sub>*i*</sub>. These IV estimates provide coefficients that can be interpreted as elasticities.

Figure 6 shows residualized *IHS*(Market Cap) for above and below median rank stocks in vintages 2, 3 and 4. Within each group, this figure displays average *IHS*(Market Cap) after netting out month, stock, and book-equity decile fixed effects. Our results are evident in these plots: within each vintage, the stocks which were likely to be included saw larger increases in the months before the roll-out, and sustained higher levels of market cap ex-post, after the roll-out occurred.

Table 8 shows estimates from the specification described in Equation 11, again providing evidence of both anticipation and overshooting. In all specifications, there are a positive and significant differential ex-ante effects for high ranking stocks when compared to low ranking (keeping in mind that both were ultimately included in one of the vintages). Furthermore, there is substantial evidence of overshooting. The estimated elasticities suggest that an additional dollar of margin debt was associated with a 64 cent larger growth in market cap for high ranking stocks relative to lower ranking stocks.

#### 4.5.2 Short- versus Long-run Approach

Our results above suggest that anticipatory speculation by unconstrained investors led to inflated stock valuations both before margin lending began, and in the period directly after. As a final strategy, we separate the short run effect of the margin lending—the period just after the roll-out—which ostensibly incorporates both the direct effect of credit supply and the impact of anticipation, from the long run effect, which is more likely to reflect only a stable, direct effect. In our specifications, we separately estimate difference-difference coefficients for (i) the period just before the margin lending roll-out, and (ii) the entire period after the roll-out ("long-run") while (iii) allowing for differential effects in the period immediately after the rollout. (i) Captures any anticipatory effects, (ii) captures the direct effect, and (iii) separately estimates the impact of

overshooting. Specifically, we estimate:

$$IHS(Market Cap)_{i,t} = \alpha + \beta_0^{quasi} Margin Trading Active_{i,t} + \sum_{j=-(S-1)}^{S} \beta_j^{quasi} D_{i,t+j} + \theta_1 B E_{i,t} + \gamma_i + \delta_t + \varepsilon_{it}.$$
(13)

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. For positive values of *j*,  $D_{i,t+j}$  indicates that margin lending is about to roll-out. For negative values, it indicates that margin lending has just rolled-out. Together, the positive and negative values allow for differential effects in the periods just before and just after the roll-out. We interpret  $\beta_0^{quasi}$  as the long run direct effect of margin lending on stock valuations, with one caveat: the choice of *S*, the period in which the direct effect is contaminated by anticipatory effects, is somewhat arbitrary. In our preferred specification, we set *S* to six months, and interpret our estimates as an upper-bound on the direct effects.

$$IHS(Margin Debt)_{i,t} = \alpha + \beta_0^{quasi} Margin Trading Active_{i,t} + \sum_{j=-(S-1)}^{S} \beta_j^{quasi} D_{i,t+j} + \theta_1 B E_{i,t} + \gamma_i + \delta_t + \varepsilon_{it}.$$
(14)

In a second stage, we then estimate

IHS(Market Cap)<sub>*i*,*t*</sub> = 
$$\alpha + \beta_0$$
IHS(Margin Debt)<sub>*i*,*t*</sub> +  $\sum_{j=-(S-1)}^{S} \beta_j^{quasi} D_{i,t+j} + \theta_1 B E_{i,t} + \gamma_i + \delta_t + \varepsilon_{it}$ . (15)

Table 9 presents results from these specifications. There are two primary takeaways. First, these specifications are consistent with an interpretation of overshooting. In the months immediately after the roll-out, market cap was significantly higher for marginable stocks, as evidenced by the positive and significant coefficients on the ex-post effects in the six months (or quarters) following the roll-out.

Furthermore, our IV estimates allow us to quantify the direct effect of margin debt on market cap. Our preferred specification, which includes monthly lags, gives an estimated and statistically significant elasticity of 0.004. Evaluated at the means of market cap and margin debt, this suggests that an additional dollar of margin debt causally increases stock valuation by 32 cents. This stands in contrast to the 57 cents we reported in Table 5, based on estimates that pool the direct effect of margin debt with the impact of speculation by unconstrained investors.

## 4.6 Anticipating Shadow Margin the Peak of the Bubble in 2015

While our analysis has been constrained thus far to the official deregulation of margin lending, the notion of anticipation we describe should, in principle, apply to any foreseeable expansion of credit. To conclude

our analysis, we briefly consider the expansion of what is often referred to shadow margin: the provision of margin via peer-to-peer platforms distinct from formal brokerages, allowing smaller investors to informally buy *any* stock on margin. Although the introduction of shadow margin was not as precisely delineated as lending through formal channels, the process expanded rapidly in late 2014 and early 2015. Estimates place shadow margin in 2015 at almost 1 trillion yuan, roughly half of the formal margin amount during at the peak of the bubble.

The patterns in Panel A of Figure 7 (which reproduces the later period of Figure 4). suggest that mutual funds began to increase their relative positions in non-marginable stocks after the introduction of Vintage 4, the final official set of marginable stocks. Similar patterns can be seen for the top 10 investors, to a lesser extent, in Figure 4. We now argue that this buying anticipated the rise in shadow margin lending in the Chinese stock market which was concentrated in these non-marginable stocks. The non-marginable stocks, which had previously under-performed the market, outperformed the market during the final period prior to the crash (Figure 3).

To show that this is indeed the case, we gather data on shadow margin lending from a peer-to-peer platform that encompassed around 10% of the market during this period. We measure the presence of shadow margin at the stock level using data from a large technology provider. This technology company routed the trades of 180 peer-to-peer platforms that provided leverage for stock purchases. Each platform had a master account which qualified for margin with the stock exchange. This master account was subdivided into smaller managed accounts for individual households that could then buy stocks on margin provided by the platform. The technology company managed the website and routing of trades. As a result, it aggregated for us all the buys and sells from the 180 peer-to-peer platforms. They calculate for us the net buys and sells each day and the cumulative net buys and sells over time for each stock, which we then use as a proxy for shadow margin. This shadow margin figure is not identical to the margin balance data from the exchanges since the net buys and sells is marked to market daily. But it does provide a measure of shadow margin activity across different stocks. In our analysis, we scale shadow margin by a factor of 10 to reflect that the peer-to-peer platform we collected data only accounts for 10% of the market.

Panel B of Figure 7 plots shadow margin debt for the different vintages, and for all stocks that were not part of any vintage, in the latter part of our sample. Unsurprisingly, shadow margin begins to expand later in the sample, around the end of 2014, suggesting that it is not a major concern for our primary analysis. Further, the majority of shadow margin debt is concentrated in non-marginable stocks, suggesting that mutual funds and unconstrained investors were at least matching—if not anticipating—the flows of shadow margin debt. These findings are reminiscent of Brunnermeier & Nagel (2004) and Griffin *et al.* (2011) who found that hedge funds rather than shorting internet stocks actually overweighted internet stocks going into the dot-com bubble. The collection of these forces surely contributed to the dramatic surge and subsequent crash in the non-marginable stocks (along with the rest of the market) in 2015.

# 5 Conclusion

In this paper we provide causal evidence that credit expansions lead to potentially destabilizing asset price growth both through direct channels and via anticipation by unconstrained investors. Furthermore, we show that this anticipation may, in practice, lead to overshooting—causing asset prices to rise above the level they would reach through a direct effect alone. To do so, we exploit the staggered deregulation of margin lending in China that took place between 2011 and 2014. At five different points across those years, the Chinese regulators opened a new vintage (group of stocks) to margin lending. By the final vintage, about 900 stock qualified for margin lending (out of approximately 2500 listed stocks). This deregulation enabled a huge influx of margin lending, peaking at nearly 5% of market capitalization. For at least the last three vintages, the margin lending roll-out was highly predictable: the stocks included in each vintage were chosen on the basis of a published formula based on public data.

To identify the impact of this credit expansion on asset prices, we employ a quasi-myopic differencein-difference estimator that compares stocks in each of the five vintages to non-marginable stocks, before and after the vintage in question became marginable. To test for anticipation—and to correct the bias in ex-post effects generated by anticipation driven pre-trends—the quasi-myopic estimator allows for differential effects in the treatment group (marginable stocks) in the periods just before deregulation. In these specifications we find convincing evidence of anticipation, prices rise in soon-to-be marginable stocks in the period before margin lending is allowed. Additionally, this approach enables us to estimate an overall ex-post effect of margin debt on asset prices. Our results suggest that an additional dollar of margin debt is associated with a 57 cent rise in market capitalization.

We argue that this 57 cent estimate is the sum of two distinct effects: the direct effect of margin debt on asset prices, and overshooting caused by anticipatory speculation. To disentangle these two effects, we consider two additional generalizations of our quasi-myopic approach. The first, a triple difference, compares—within each vintage of marginable stocks—the stocks that were ex-ante more versus less likely to become marginable. We find that there are larger speculative increases in the stocks that investors could be confident would become marginable. Furthermore, these higher prices were sustained in the early period after the stocks actually became marginable, suggesting that speculation led to overshooting. Our second approach differentiates the period just after margin lending becomes available, in which we expect the impacts of anticipation effects to linger, to later periods in which prices have in principle converged to a level that appropriately reflects the direct effect of margin lending. This approach provides what we argue is a conservative estimate of the importance of overshooting due to anticipation: speculation by unconstrained investors was responsible for 32 of the 58 cent increase in market capitalization per dollar of margin debt, implying that the direct effect is responsible for the remaining 25 cents.

The anticipatory speculation we highlight has both distributional and destabilizing consequences. Demand by unconstrained investors in advance of a credit expansion leads to larger price increases, limiting the amount constrained agents can buy when credit becomes available (and potentially increasing the leverage they choose to take). Furthermore, the magnitudes of the effects we uncover suggest a potential shift in policy discussions away from macroprudential regulations on credit access. Carefully designed restrictions on speculative behaviors may allow regulators to avoid the boom-bust cycles associated with credit expansions without imposing onerous restrictions on borrowers.

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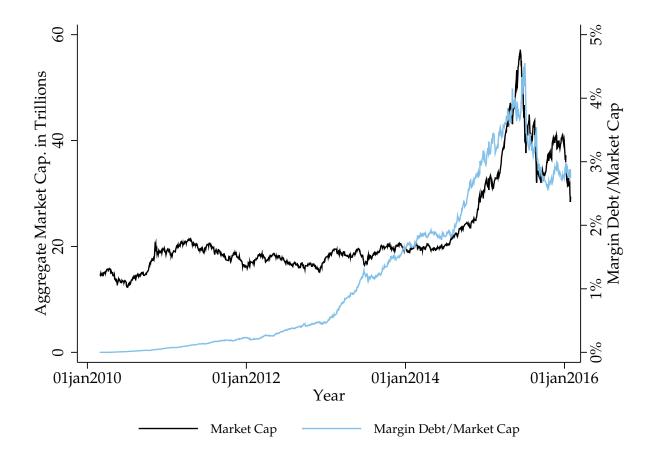
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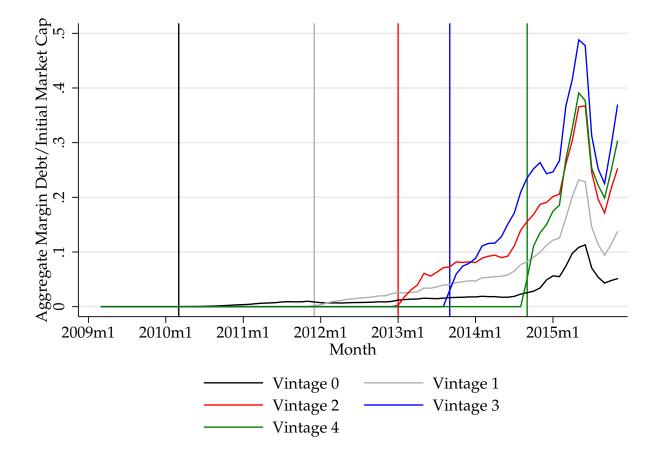
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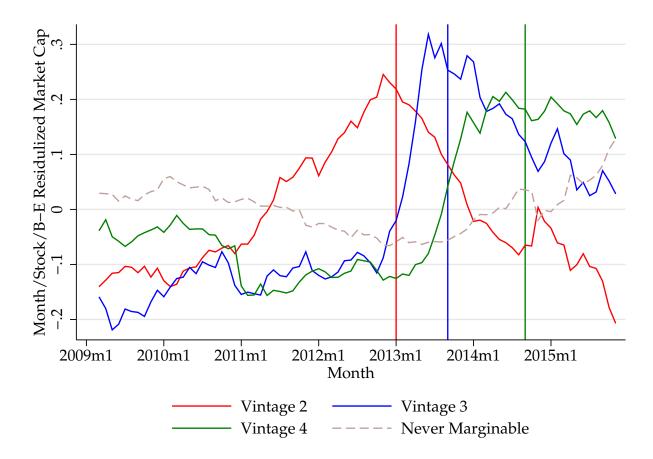
# FIGURE 1: AGGREGATE MARKET CAP. AND MARGIN DEBT/MARKET CAP. OVER TIME

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

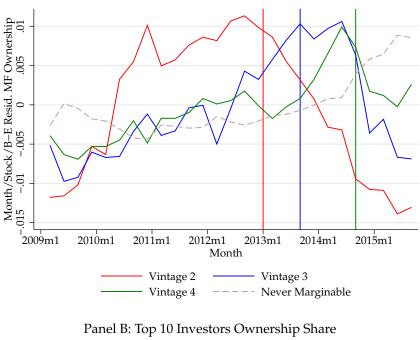
**Notes:** Plot shows the average ratio of margin debt to initial market cap (measured as the 2009 average at the stock level) for each of the five vintages of the margin lending roll-out. Both market cap and margin debt are measured in trillions of yuan. Vertical lines show the starting date of each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



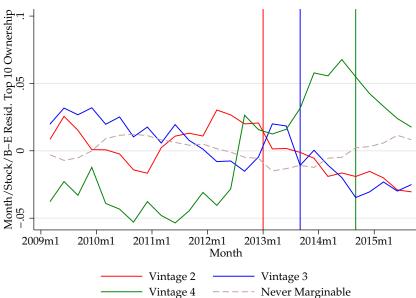
## FIGURE 3: MARKET ANTICIPATION OF MARGIN LENDING ROLLOUT: RESIDUALIZED IHS(MARKET CAP)<sub>t+1</sub> by Vintage

**Notes:** Plots show residuals from regressions of IHS(Market Cap)<sub>t+1</sub> 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.

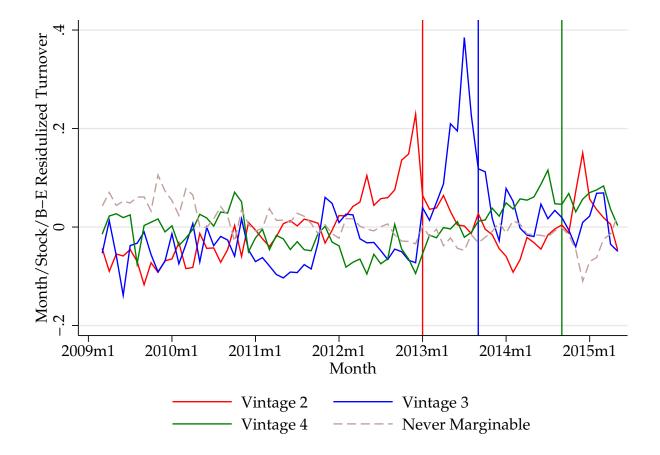
## FIGURE 4: UNCONSTRAINED INVESTORS' ANTICIPATION OF MARGIN LENDING ROLLOUT: Residualized Institutional Ownership by Vintage



Panel A: Mutual Fund Ownership Share



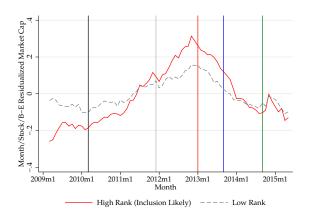
**Notes:** Plots show residuals from regressions of the proportion of institutional ownership at the stock-quarter level on stock fixed effects, quarter fixed effects and dummies for membership in each decile of book equity at the month level. Residuals are calculated from a single regression with all 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 5: ANTICIPATION MARKET ACTIVITY: RESIDUALIZED TURNOVER BY VINTAGE

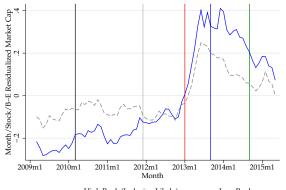
**Notes:** Plots show residuals from regressions of turnover at the stock-month level on stock fixed effects, month  $\times$  year fixed effects and dummies for membership in each decile of book equity at the month level. Market cap is measured in yuan. Residuals are calculated from a single regression 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 6: DIFFERENTIAL ANTICIPATION FOR PREDICTABLY MARGINABLE STOCKS: Residualized IHS(Market Cap) $_{t+1}$ by Likelihood of Inclusion



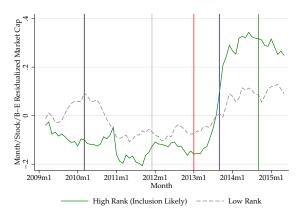
#### PANEL A: VINTAGE 2 STOCKS

PANEL B: VINTAGE 3 STOCKS



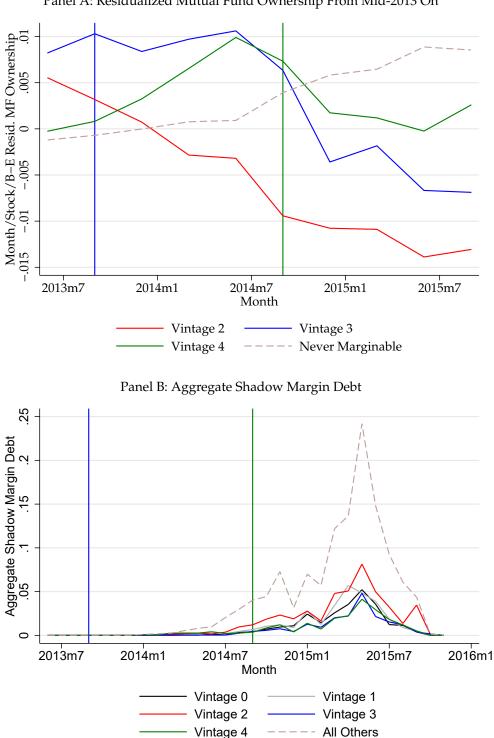
High Rank (Inclusion Likely) ----- Low Rank

#### PANEL C: VINTAGE 4 STOCKS



**Notes:** Plots show residuals from regressions of IHS(Market Cap)<sub>t+1</sub> 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.





Panel A: Residualized Mutual Fund Ownership From Mid-2013 On

Notes: Panel A shows residuals from regressions of the proportion of mutual fund ownership at the stock-quarter level on stock fixed effects, quarter 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. Panel B shows aggregate shadow margin debt by vintage in trillions of yuan, calculated by scaling our observed shadow margin debt by a factor of 10. Vertical lines show the starting date of each of the last two vintages, with blue and green representing vintages 3 and 4, respectively.

Number of marginable stocks by vintage								
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 1: NUMBER OF MARGINABLE STOCKS BY VINTAGE

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

	Vintage 4	Vintage 3	Vintage 2
Dep Var: D	(1)	(2)	(3)
τ	0.874***	0.776***	0.778***
	(0.041)	(0.051)	(0.042)
R <sup>2</sup>	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.

	IHS(Market Cap)						
	(1)	(2)	(3)	(4)			
IHS(Margin Debt)	$\begin{array}{c} 0.081^{***} \\ (0.003) \end{array}$	$\begin{array}{c} 0.038^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.025^{***} \\ (0.003) \end{array}$	$\begin{array}{c} 0.005^{***} \\ (0.001) \end{array}$			
Mean of Dep. Var. $R^2$ N	22.7 0.32 137698	22.7 0.63 137698	22.7 0.82 137696	22.7 0.89 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			

# TABLE 3: OLS ESTIMATES OF ASSOCIATION BETWEEN IHS(MARKET CAP) AND IHS(MARGIN DEBT)

Coefficients from OLS regressions of the inverse hyperbolic sine (IHS) of market cap in month t 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)<sub>t</sub>. Book-equity deciles refer to dummy variables for each decile of book equity in the previous fiscal year. \* p < 0.10, \*\*\* p < 0.05, \*\*\*\* p < 0.01.

	First Stage: IHS(Margin Debt)		Reduced Form: IHS(Market Cap)		IV IHS(Mark	
	Collapsed	Full	Collapsed	Full	Collapsed	Full
IHS(Margin Debt)					$0.004^{***}$ (0.001)	$\begin{array}{c} 0.003^{***} \\ (0.001) \end{array}$
Margin Trading Active	$\begin{array}{c} 19.045^{***} \\ (0.201) \end{array}$		$0.065^{***}$ (0.023)			
Vintage 0 Margin Trading Active		$18.650^{***}$ (0.487)		$-0.168^{**}$ (0.065)		
Vintage 1 Margin Trading Active		$17.535^{***}$ (0.421)		$-0.098^{**}$ (0.041)		
Vintage 2 Margin Trading Active		$\begin{array}{c} 19.581^{***} \\ (0.191) \end{array}$		$\begin{array}{c} 0.062 \\ (0.043) \end{array}$		
Vintage 3 Margin Trading Active		$\begin{array}{c} 19.873^{***} \\ (0.179) \end{array}$		$0.301^{***}$ (0.047)		
Vintage 4 Margin Trading Active		$20.081^{***} \\ (0.232)$		$0.272^{***}$ (0.040)		
Mean of Dep. Var. $R^2$ N	3.50 0.95 137696	3.50 0.95 137696	22.7 0.89 137696	22.7 0.89 137696	22.7 0.89 137696	22.7 0.89 137696
Book-Equity Deciles	Yes	Yes	Yes	Yes	Yes	Yes
Month $\times$ Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

#### TABLE 4: IMPACT OF MARGIN LENDING ROLLOUT ON IHS(MARGIN DEBT) AND IHS(MARKET CAP)

Coefficients from regressions of IHS(Margin Debt) and IHS(Market Cap) on the indicators *Margin Trading Active*, as well as from IV regressions of IHS(Margin Debt) on IHS(Market Cap) instrumented by *Margin Trading Active* indicators. These indicators are 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* include a single indicator for all stocks included in the rollout at any point. The columns labeled *Full* include separate *Margin Trading Active* indicators for each of the five vintages of stocks that became marginable. The first two columns represent the first stage of IV specifications, with IHS(Margin Debt) regressed on *Margin Trading Active*. The final two columns display reduced form specifications of IHS(Market Cap) regressed on *Margin Trading Active*. The final two stocks-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(Margin Debt) or IHS(Market Cap). Book-equity deciles refer to dummy variables for each decile of book equity in the previous fiscal year. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

			IHS(Mar	ket Cap)		
	Ι	Difference-in-Dif	ference		IV	
	Myopic	Monthly Lags	Quarterly Lags	Myopic	Monthly Lags	Quarterly Lags
Ex-Post Effect $(\hat{\beta}_0^{quasi})$	$\begin{array}{c} 0.065^{***} \\ (0.023) \end{array}$	$\begin{array}{c} 0.127^{***} \\ (0.025) \end{array}$	$\begin{array}{c} 0.214^{***} \\ (0.031) \end{array}$			
IHS(Margin Debt)				$0.003^{***}$ (0.001)	$0.007^{***}$ (0.001)	$0.011^{***}$ (0.002)
Ex-Ante Effect (t-1) ( $\hat{\beta}_1^{quasi}$ )		$0.266^{***}$ (0.051)	$\begin{array}{c} 0.337^{***} \\ (0.034) \end{array}$		$0.266^{***}$ (0.052)	$0.336^{***}$ (0.035)
Ex-Ante Effect (t-2) ( $\hat{\beta}_2^{quasi}$ )		$0.272^{***}$ (0.044)	$\begin{array}{c} 0.281^{***} \\ (0.027) \end{array}$		$\begin{array}{c} 0.272^{***} \\ (0.045) \end{array}$	$0.280^{***}$ (0.028)
Ex-Ante Effect (t-3) ( $\hat{\beta}_3^{quasi}$ )		$0.252^{***}$ (0.039)	$\begin{array}{c} 0.245^{***} \\ (0.029) \end{array}$		$0.252^{***}$ (0.040)	$\begin{array}{c} 0.244^{***} \\ (0.029) \end{array}$
Ex-Ante Effect (t-4) ( $\hat{\beta}_4^{quasi}$ )		$0.228^{***}$ (0.033)	$0.186^{***}$ (0.028)		$0.228^{***}$ (0.034)	$\begin{array}{c} 0.185^{***} \\ (0.027) \end{array}$
Ex-Ante Effect (t-5) ( $\hat{\beta}_5^{quasi}$ )		$0.207^{***}$ (0.027)	$\begin{array}{c} 0.133^{***} \\ (0.027) \end{array}$		$0.207^{***}$ (0.028)	$\begin{array}{c} 0.131^{***} \\ (0.027) \end{array}$
Ex-Ante Effect (t-6) ( $\hat{\beta}_6^{quasi}$ )		$0.199^{***}$ (0.027)	$0.086^{***}$ (0.027)		$0.198^{***}$ (0.028)	$\begin{array}{c} 0.084^{***} \\ (0.027) \end{array}$
Mean of Dep. Var. $R^2$ N	22.7 0.89 137696	22.7 0.89 137696	22.7 0.89 137696	22.7 0.89 137696	22.7 0.89 137696	22.7 0.89 137696
Book-Equity Deciles	Yes	Yes	Yes	Yes	Yes	Yes
Month $\times$ Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

# TABLE 5: MARKET ANTICIPATION OF IMPACT OF MARGIN LENDING ROLLOUT ON IHS(MARKET CAP): QUASI-MYOPIC APPROACH

Results from myopic and quasi-myopic difference-in-difference and IV specifications of IHS(Market Cap)<sub>t</sub> on the margin lending roll-out in the vein of Malani and Reif (2015). For our difference-in-difference specifications we report coefficients from the following regression

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

For the second stage of IV specifications, we replace Margin Trading Active with IHS(Margin Debt) in the above, and use Margin Trading Active as an instrument for IHS(Margin Debt) in a first stage. Market Cap and Margin Debt are 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 includes no ex-ante effects, and is equivalent to the collapsed difference-in-difference approaches presented above. Quasi-myopic specifications include indicators aimed at capturing ex-ante effects for the six months and six quarters 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)<sub>t</sub>. Book-equity deciles refer to dummy variables for each decile of book equity in the previous fiscal year. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

	IHS(Market Cap)						
	I	Difference-in-Dif	ference		IV		
	Myopic	Monthly Lags	Quarterly Lags	Myopic	Monthly Lags	Quarterly Lags	
Ex-Post Effect× Late Vintage	$\begin{array}{c} 0.272^{***} \\ (0.045) \end{array}$	$\begin{array}{c} 0.311^{***} \\ (0.047) \end{array}$	$0.263^{***}$ (0.048)				
Ex-Post Effect ( $\hat{\beta}_0^{quasi}$ )	$-0.109^{***}$ (0.036)	$-0.087^{**}$ (0.040)	$\begin{array}{c} 0.016 \\ (0.045) \end{array}$				
IHS(Margin Debt) $\times$ Late Vintage				$0.014^{***}$ (0.002)	$0.016^{***}$ (0.003)	$0.013^{***}$ (0.003)	
IHS(Margin Debt)				$-0.006^{***}$ (0.002)	$-0.005^{**}$ (0.002)	0.001 (0.003)	
Ex-Ante Effect (t-1)× Late Vintage		$\begin{array}{c} 0.422^{***} \\ (0.039) \end{array}$	$0.364^{***}$ (0.041)		$0.423^{***}$ (0.035)	$0.364^{***}$ (0.041)	
Ex-Ante Effect (t-2)× Late Vintage		$\begin{array}{c} 0.374^{***} \\ (0.043) \end{array}$	$\begin{array}{c} 0.352^{***} \\ (0.045) \end{array}$		$0.376^{***}$ (0.042)	$\begin{array}{c} 0.352^{***} \\ (0.045) \end{array}$	
Ex-Ante Effect (t-3)× Late Vintage		$\begin{array}{c} 0.344^{***} \\ (0.039) \end{array}$	$0.323^{***}$ (0.038)		$0.345^{***}$ (0.037)	$\begin{array}{c} 0.323^{***} \\ (0.039) \end{array}$	
Ex-Ante Effect (t-4)× Late Vintage		$0.303^{***}$ (0.039)	$\begin{array}{c} 0.248^{***} \\ (0.036) \end{array}$		$0.304^{***}$ (0.037)	$0.248^{***}$ (0.036)	
Ex-Ante Effect (t-5)× Late Vintage		$0.230^{***}$ (0.048)	$0.203^{***}$ (0.038)		$0.231^{***}$ (0.048)	$\begin{array}{c} 0.202^{***} \\ (0.039) \end{array}$	
Ex-Ante Effect (t-6)× Late Vintage		$0.195^{***}$ (0.043)	$\begin{array}{c} 0.184^{***} \\ (0.046) \end{array}$		$0.196^{***}$ (0.043)	$0.183^{***}$ (0.046)	
Ex-Ante Effect (t-1) ( $\hat{\beta}_1^{quasi}$ )		-0.053 (0.032)	0.059 (0.037)		$-0.054^{**}$ (0.027)	$0.060 \\ (0.038)$	
Ex-Ante Effect (t-2) ( $\hat{\beta}_2^{quasi}$ )		-0.015 (0.032)	$0.096^{**}$ (0.036)		-0.016 (0.027)	$0.096^{**}$ (0.037)	
Ex-Ante Effect (t-3) ( $\hat{\beta}_3^{quasi}$ )		-0.014 (0.033)	$0.205^{***}$ (0.033)		-0.015 (0.030)	$0.205^{***}$ (0.033)	
Ex-Ante Effect (t-4) ( $\hat{\beta}_4^{quasi}$ )		-0.010 (0.033)	$0.145^{***}$ (0.027)		-0.011 (0.032)	$0.146^{***}$ (0.027)	
Ex-Ante Effect (t-5) ( $\hat{\beta}_5^{quasi}$ )		0.019 (0.042)	$0.106^{***}$ (0.028)		0.017 (0.041)	$0.105^{***}$ (0.028)	
Ex-Ante Effect (t-6) ( $\hat{\beta}_6^{quasi}$ )		0.034 (0.029)	$0.058^{**}$ (0.028)		0.033 (0.026)	$0.058^{**}$ (0.028)	
Mean of Dep. Var.	22.7	22.7	22.7	22.7	22.7	22.7	
$R^2$	0.89	0.89	0.89	0.89	0.89	0.89	
N	137696	137696	137696	137696	137696	137696	
Book-Equity Deciles	Yes	Yes	Yes	Yes	Yes	Yes	
Month $\times$ Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	

# TABLE 6: DIFFERENCE IN IMPACT OF MARGIN LENDING ROLLOUT ON IHS(MARKET CAP): EARLY (UNPREDICTABLE) VS. LATER (PREDICTABLE) VINTAGES

Results from myopic and quasi-myopic triple-difference specifications of IHS(Market Cap)<sub>t</sub> on the margin lending roll-out, differentiated by early versus late vintages. For our triple-difference specifications we report coefficients from the following regression

 $\text{IHS(Market Cap)}_{i,t} = \alpha + \beta_0^{quasi} \text{Margin Trading Active}_{it} + \eta_0^{quasi} \text{Margin Trading Active}_{it} \times \text{Late Vintage}_{it}$ 

$$+ \sum_{i=1}^{S} \left[ \beta_{j}^{quasi} D_{i,t+j} + \eta_{j} D_{i,t+j} \times \text{Late Vintage}_{it} \right] + \gamma_{i} + \delta_{t} + \varepsilon_{i}$$

For the second stage of IV specifications, we replace Margin Trading Active with IHS(Margin Debt) everywhere in the above, and use Margin Trading Active and Margin Trading Active  $_{it}$  × Late Vintage $_{it}$  is instruments for IHS(Margin Debt) and IHS(Margin Debt)  $_{it}$  × Late Vintage $_{it}$  in a first stage. Market Cap and Margin Debt are measured in RMB at the stock-month level. Late Vintage is a dummy variable that indicates stocks in vintages 2, 3 and 4. *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 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 includes no ex-ante effects, and is equivalent to the collapsed difference-in-difference approaches presented above. Quasi-myopic specifications include indicators aimed at capturing *ex*-ante effects for the six months and six quarters 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)<sub>t</sub>. Book-equity deciles refer to dummy variables for each decile of book equity in the previous fiscal year. \* p < 0.01, \*\* p < 0.05, \*\*\* p < 0.01.

	IHS(Market Cap)							
	Mutua	al Fund Share	Тој	p 10 Share	Turnover			
	Myopic	Quarterly Lags	Myopic	Quarterly Lags	Myopic	Quarterly Lags		
Ex-Post Effect ( $\hat{\beta}_0^{quasi}$ )	$-0.006^{*}$ (0.003)	-0.004 (0.003)	-0.016 (0.011)	-0.009 (0.013)	$0.055^{***}$ (0.016)	$0.087^{***}$ (0.016)		
Ex-Ante Effect (t-1) ( $\hat{\beta}_1^{quasi}$ )		$0.007^{***}$ (0.002)		$0.036^{**}$ (0.016)		$0.164^{***}$ (0.034)		
Ex-Ante Effect (t-2) ( $\hat{\beta}_2^{quasi}$ )		$0.006^{***}$ (0.002)		$0.033^{**}$ (0.014)		$0.081^{***}$ (0.022)		
Mean of Dep. Var. $R^2$ N	0.017 0.51 38819	0.017 0.51 38819	0.46 0.62 38819	0.46 0.62 38819	0.50 0.47 137696	0.50 0.47 137696		
Book-Equity Deciles	Yes	Yes	Yes	Yes	Yes	Yes		
Month $\times$ Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes		
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes		

# TABLE 7: IMPACT OF MARGIN LENDING ROLLOUT ON INSTITUTIONAL OWNERSHIP AND TURNOVER: QUASI-MYOPIC APPROACH

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

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

Where  $y_{i,t}$  represents either the proportion of ownership by mutual funds of each stock, the proportion of ownership by the top 10 investors in each stock, or turnover. The first two are at a quarterly frequency, while turnover is at a monthly frequency. *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. For each outcome, we include a myopic approach with no ex-ante effects and a quasi-myopic approach with two quarters of anticipation. Sample covers March 2009-May 2015. Mean of dep. var. refers to the mean of  $y_{i,t}$  Book-equity deciles refer to dummy variables for each decile of book equity in the previous fiscal year. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

	IHS(Market Cap)						
	Ι	Difference-in-Dif	ference		IV		
	Myopic	Monthly Lags	Quarterly Lags	Myopic	Monthly Lags	Quarterly Lags	
Ex-Post Effect $\times$ High Rank	$0.131^{***}$ (0.045)	$\begin{array}{c} 0.163^{***} \\ (0.049) \end{array}$	$0.206^{***}$ (0.054)				
Ex-Post Effect ( $\hat{\beta}_0^{quasi}$ )	$0.067^{*}$ (0.034)	$\begin{array}{c} 0.114^{***} \\ (0.036) \end{array}$	$0.162^{***}$ (0.040)				
IHS(Margin Debt) $\times$ High Rank				$0.006^{***}$ (0.002)	$0.008^{***}$ (0.002)	$0.010^{***}$ (0.003)	
IHS(Margin Debt)				$0.003^{**}$ (0.002)	$0.006^{***}$ (0.002)	$0.008^{***}$ (0.002)	
Ex-Ante Effect (t-1) $\times$ High Rank		$0.227^{***}$ (0.044)	$0.271^{***}$ (0.046)		$0.226^{***}$ (0.043)	$0.271^{***}$ (0.046)	
Ex-Ante Effect (t-2) $\times$ High Rank		$\begin{array}{c} 0.233^{***} \\ (0.038) \end{array}$	$0.247^{***}$ (0.046)		$0.233^{***}$ (0.035)	$\begin{array}{c} 0.247^{***} \\ (0.046) \end{array}$	
Ex-Ante Effect (t-3) $\times$ High Rank		$\begin{array}{c} 0.231^{***} \\ (0.039) \end{array}$	$\begin{array}{c} 0.198^{***} \\ (0.047) \end{array}$		$0.230^{***}$ (0.037)	$\begin{array}{c} 0.198^{***} \\ (0.047) \end{array}$	
Ex-Ante Effect (t-4) $\times$ High Rank		$0.217^{***}$ (0.038)	$\begin{array}{c} 0.151^{***} \\ (0.044) \end{array}$		$0.217^{***}$ (0.035)	$0.150^{***}$ (0.043)	
Ex-Ante Effect (t-5) $\times$ High Rank		$0.208^{***}$ (0.039)	$0.104^{**}$ (0.042)		$0.208^{***}$ (0.037)	$0.104^{**}$ (0.042)	
Ex-Ante Effect (t-6) $\times$ High Rank		$\begin{array}{c} 0.194^{***} \\ (0.039) \end{array}$	$0.071^{*}$ (0.039)		$\begin{array}{c} 0.194^{***} \\ (0.037) \end{array}$	$0.071^{*}$ (0.038)	
Ex-Ante Effect (t-1) ( $\hat{\beta}_1^{quasi}$ )		$0.252^{***}$ (0.043)	$0.281^{***}$ (0.038)		$0.252^{***}$ (0.043)	$0.282^{***}$ (0.038)	
Ex-Ante Effect (t-2) ( $\hat{\beta}_2^{quasi}$ )		$0.241^{***}$ (0.038)	$0.198^{***}$ (0.032)		$0.242^{***}$ (0.038)	$0.198^{***}$ (0.032)	
Ex-Ante Effect (t-3) ( $\hat{\beta}_3^{quasi}$ )		$0.211^{***}$ (0.033)	$0.159^{***}$ (0.035)		$0.212^{***}$ (0.032)	$0.158^{***}$ (0.035)	
Ex-Ante Effect (t-4) ( $\hat{\beta}_4^{quasi}$ )		$0.183^{***}$ (0.024)	$0.108^{***}$ (0.032)		$0.183^{***}$ (0.021)	$0.108^{***}$ (0.032)	
Ex-Ante Effect (t-5) $(\hat{\beta}_5^{quasi})$		$0.144^{***}$ (0.025)	$0.083^{***}$ (0.029)		$0.144^{***}$ (0.021)	$0.082^{***}$ (0.029)	
Ex-Ante Effect (t-6) ( $\hat{\beta}_6^{quasi}$ )		$0.136^{***}$ (0.034)	$0.056^{**}$ (0.027)		$0.136^{***}$ (0.033)	$0.055^{**}$ (0.027)	
Mean of Dep. Var. $R^2$ N	22.4 0.82 117735	22.4 0.83 117735	22.4 0.83 117735	22.4 0.82 117735	22.4 0.83 117735	22.4 0.83 117735	
Book-Equity Deciles	Yes	Yes	Yes	Yes	Yes	Yes	
Month × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	

# TABLE 8: DIFFERENCE IN IMPACT OF MARGIN LENDING ROLLOUT ON IHS (MARKET CAP): HIGH RANK (LIKELY TO BE MARGINABLE) VS. LOW RANK (LESS LIKELY TO BE MARGINABLE) STOCKS

Results from myopic and quasi-myopic triple-difference specifications of IHS(Market Cap)<sub>t</sub> on the margin lending roll-out, differentiated by high vs. low ranking stocks amongst those included in each vintage. For our triple-difference specifications we report coefficients from the following regression

IHS(Market Cap)<sub>*i*,*t*</sub> =  $\alpha + \beta_0^{quasi}$ Margin Trading Active<sub>*i*t</sub> +  $\eta_0^{quasi}$ Margin Trading Active<sub>*i*t</sub> × High Rank<sub>*i*t</sub>

$$+ \sum_{j=1}^{S} \left[ \beta_{j}^{quasi} D_{i,t+j} + \eta_{j} D_{i,t+j} \times \text{High Rank}_{it} \right] + \gamma_{i} + \delta_{t} + \varepsilon_{it}$$

For the second stage of IV specifications, we replace Margin Trading Active with IHS(Margin Debt) everywhere in the above, and use Margin Trading Active and Margin Trading Active  $_{it} \times$  High Rank $_{it}$  as instruments for IHS(Margin Debt) and IHS(Margin Debt) $_{it} \times$  High Rank $_{it}$  in a first stage. Market Cap and Margin Debt are measured in RMB at the stock-month level. High rank is a dummy variable that indicates stocks in each vintage that are above median rank within the vintage according to the index that determines inclusion. *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*<sub>i,t+j</sub> 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 includes no ex-ante effects, and is equivalent to the collapsed difference-in-difference approaches presented above. Quasi-myopic specifications include indicators aimed at capturing exante effects for the six months and six quarters leading up to the roll-out for each stock. Standard errors, clustered at the stock and month hevel, are included in parentheses. Sample covers March 2009-May 2015. Vintages 0 and 1 are excluded as inclusion in those vintages was not based upon a pre-defined rule. Mean of dep. var refers to the mean of IHS(Market Cap)<sub>t</sub>. Book-equity deciles refer to dummy variables for each decile of book equity in the previous fiscal year. \* p < 0.05, \*\*\* p < 0.05.

	IHS(Market Cap)						
	Difference-in-Difference			IV			
	Myopic	Monthly Lags	Quarterly Lags	Myopic	Monthly Lags	Quarterly Lags	
Ex-Post Effect (Long-Run)	$\begin{array}{c} 0.065^{***} \\ (0.023) \end{array}$	$0.070^{**}$ (0.028)	$0.048 \\ (0.039)$				
IHS(Margin Debt)				$0.003^{***}$ (0.001)	$0.004^{**}$ (0.001)	$0.002 \\ (0.002)$	
Ex-Post Effect (t)		$0.180^{***}$ (0.045)	$0.256^{***}$ (0.038)		$0.191^{***}$ (0.042)	$\begin{array}{c} 0.259^{***} \\ (0.036) \end{array}$	
Ex-Post Effect (t+1)		$\begin{array}{c} 0.182^{***} \\ (0.035) \end{array}$	$0.246^{***}$ (0.037)		$0.185^{***}$ (0.033)	$\begin{array}{c} 0.246^{***} \\ (0.037) \end{array}$	
Ex-Post Effect (t+2)		$\begin{array}{c} 0.171^{***} \\ (0.035) \end{array}$	$0.203^{***}$ (0.033)		$\begin{array}{c} 0.172^{***} \\ (0.035) \end{array}$	$\begin{array}{c} 0.202^{***} \\ (0.033) \end{array}$	
Ex-Post Effect (t+3)		$0.163^{***}$ (0.035)	$\begin{array}{c} 0.181^{***} \\ (0.032) \end{array}$		$0.163^{***}$ (0.034)	$\begin{array}{c} 0.180^{***} \\ (0.032) \end{array}$	
Ex-Post Effect (t+4)		$\begin{array}{c} 0.174^{***} \\ (0.035) \end{array}$	$0.160^{***}$ (0.032)		$0.174^{***}$ (0.035)	$\begin{array}{c} 0.161^{***} \\ (0.032) \end{array}$	
Ex-Post Effect (t+5)		$0.167^{***}$ (0.039)	$\begin{array}{c} 0.121^{***} \\ (0.029) \end{array}$		$0.166^{***}$ (0.038)	$\begin{array}{c} 0.122^{***} \\ (0.029) \end{array}$	
Ex-Ante Effect (t-1) ( $\hat{\beta}_1^{quasi}$ )		$0.250^{***}$ (0.052)	$0.304^{***}$ (0.036)		$0.250^{***}$ (0.053)	$0.304^{***}$ (0.036)	
Ex-Ante Effect (t-2) ( $\hat{\beta}_2^{quasi}$ )		$0.256^{***}$ (0.045)	$0.257^{***}$ (0.028)		$0.256^{***}$ (0.046)	$0.256^{***}$ (0.028)	
Ex-Ante Effect (t-3) ( $\hat{\beta}_3^{quasi}$ )		$0.241^{***}$ (0.041)	$0.224^{***}$ (0.028)		$0.241^{***}$ (0.042)	$\begin{array}{c} 0.223^{***} \\ (0.027) \end{array}$	
Ex-Ante Effect (t-4) ( $\hat{\beta}_4^{quasi}$ )		$0.217^{***}$ (0.035)	$0.165^{***}$ (0.026)		$0.217^{***}$ (0.035)	$0.165^{***}$ (0.025)	
Ex-Ante Effect (t-6) ( $\hat{\beta}_6^{quasi}$ )		$0.188^{***}$ (0.025)	$0.077^{***}$ (0.023)		$0.188^{***}$ (0.025)	$0.076^{***}$ (0.023)	
Mean of Dep. Var. $R^2$ N	22.7 0.89 137696	22.7 0.89 137696	22.7 0.89 137696	22.7 0.89 137696	22.7 0.89 137696	22.7 0.89 137696	
Book-Equity Deciles	Yes	Yes	Yes	Yes	Yes	Yes	
Month $\times$ Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	

#### TABLE 9: SHORT VS. LONG RUN IMPACT OF MARGIN LENDING ROLLOUT ON IHS(MARKET CAP)

Results from myopic and quasi-myopic difference-in-difference and IV specifications of IHS(Market Cap)<sub>t</sub> on the margin lending roll-out expanding on Malani and Reif (2015). For our difference-in-difference specifications we report coefficients from the following regression

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

For the second stage of IV specifications, we replace Margin Trading Active with IHS(Margin Debt) in the above, and use Margin Trading Active as an instrument for IHS(Margin Debt) in a first stage. Market Cap and Margin Debt are 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. Note that contrary to previous tables, here we include indicators for both the periods just before and just after the roll-out. The number of *ex-ante effect* and *ex-post effect* coefficients indicates the value of *S* for the regression in question. The myopic approach includes no ex-ante or ex-post effects, and is equivalent to the collapsed difference-in-difference approaches presented above. Quasi-myopic specifications include at the stock and month level, are included in parentheses. Sample covers March 209-May 2015. Mean of dep. var refers to the mean of IHS(Market Cap)<sub>t</sub>. Book-equity deciles refer to dummy variables for each decile of book equity in the previous fiscal year. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.