The Drivers and Implications of Retail Margin Trading[*]

Jiangze Bian, Zhi Da, Zhiguo He, Dong Lou, Kelly Shue, Hao Zhou

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Abstract

Using granular data covering both regulated (brokerage-financed) and unregulated (shadow-financed) margin accounts in China, we provide novel evidence on retail investors' margin trading behavior and its price implications. First, we show that retail investors' decisions to lever up in stock trading despite the hefty borrowing cost is likely driven by overconfident beliefs and lottery preferences. We then show that margin borrowing indeed affects investors' trading behavior: investors are more likely to liquidate their holdings as they inch closer to margin calls. Third, we show that margin-induced trading aggregates up to affect asset prices and contributes to shock spillovers across stocks.

Keywords: margin-induced trading, leverage, liquidation, contagion

1 Introduction

Margin trading by retail investors has become increasingly popular and volatile in recent years. US households' margin debt increased from 1.8% of GDP in 2010 to a historical peak of nearly 4% of GDP in 2022 before falling back to 2.4% of GDP in 2023.[1] Even more strikingly, margin borrowing by Chinese households rose from close to zero in 2010 to over 3 trillion RMB or 4.5% of GDP at the market peak in 2015, and then fell sharply alongside the market crash and increased regulatory oversight. At the market peak, Chinese retail investors maintained a very high debt-to-asset ratio of 20% (relative to total household stock holdings of around 15 trillion RMB).[2]

The popularity of margin debt among Chinese retail investors is particularly puzzling in light of China's low historical stock market returns (e.g., Allen et al., 2020) and high borrowing costs, which range from 8% in the regulated brokerage margin system to over 25% in the shadow margin system. A natural question arises: why do households engage in so much margin trading—with some borrowing many times their own capital—despite the high borrowing rates and a general lack of trading experience? Given the volatility of margin balances and the tendency of margin investors to rapidly deleverage during market downturns, we are also interested in two related questions with broader implications for asset prices: How does margin borrowing by retail investors affects their trading behavior, and how does margin-induced trading aggregate up to affect asset prices?

In this paper, we provide novel evidence on retail investors' margin trading behavior and its price implications using detailed account-level data in China that track hundreds of thousands of margin investors' borrowing and trading activities. The Chinese economy and its financial markets have experienced tremendous growth in the last three decades.[3] With a total market capitalization of roughly one-third of that of the U.S., the Chinese stock market is now the second largest in the world. Our data cover an extraordinary three-month period of the Chinese stock market, May to July 2015: the market grew steadily in the spring of 2015, continued with a strong run-up from May to mid-June, and then experienced a dramatic crash in mid-June that wiped out nearly 30% of the market value by the end of July 2015.[4]

Retail investors are the dominant players in the Chinese stock market and are the main users of margin borrowing.[5] Our data include two types of margin trading systems: brokerage-financed and shadow-financed margin accounts. Both systems grew rapidly in popularity in early

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[1]US margin debt increased from 265 billion USD in 2010 to over 800 billion USD in 2022 and decreased to 580 billion in 2023. See https://www.finra.org/rules-guidance/key-topics/margin-accounts/margin-statistics.

[2]The references of all these numbers are provided in Section 2. An et al. (2022) show that Chinese households collectively owned 25% of the aggregate market value of roughly 60 trillion RMB in 2015.

[3]See, for example, Carpenter and Whitelaw (2017); Allen et al. (2020).

[4]Excessive leverage and the subsequent leverage-induced fire sales are considered to be contributing factors to many past financial crises. A prominent example is the US stock market crash of 1929 (Schwert, 1989; Galbraith, 2009). Other significant examples of deleveraging and market crashes include the US housing crisis which led to the 2007/08 global financial crisis (Mian et al., 2013), the "Quant Meltdown" of August 2007 (Khandani and Lo, 2011), and the Chinese stock market crash in the summer of 2015 (which will be the focus of this paper).

[5]Trading by retail investors accounts for over 85% of total trading volume, according to Shanghai Stock Exchange Annual Statistics 2015.

2015. The brokerage-financed margin system, which allows retail investors to obtain credit at an annual rate of approximately 8% from their brokerage firms, is tightly regulated by the China Securities Regulatory Commission (CSRC). For instance, investors must be sufficiently wealthy and experienced to qualify for brokerage financing. Further, the CSRC imposes a market-wide maximum level of leverage—the Pingcang Line—beyond which the account is taken over by the lending broker, triggering forced liquidation.[6]

In contrast, the shadow-financed margin system, aided by China's burgeoning FinTech industry, falls in a regulatory grey area. Shadow-financing is largely unregulated by the CSRC, and lenders generally do not impose restrictions on borrower wealth, trading experience, or financial literacy. Borrowing rates often exceed 25% a year, and there is no regulated maximum Pingcang Line for shadow-financed margin accounts. Instead, the maximum leverage limits are market outcomes determined by bilateral matching between the borrower and lender. We find that shadow accounts have significantly higher leverage limits and realized leverage than their brokerage counterparts; for example, the average leverage, defined as assets over equity, is 6.4 for shadow-financed margin accounts and only 1.4 for brokerage-financed accounts.

We begin our analysis by examining the types of retail investors that use leverage and are willing to pay a borrowing cost that is many times the average market return.[7] We uncover three sets of results when comparing margin investors to their non-margin peers. First, in terms of investor characteristics, margin investors are older and more likely to be male. Second, in terms of portfolio characteristics, margin investors hold as diversified, if not more diversified, portfolios. They also have higher portfolio turnover than non-margin investors. Finally, in terms of holdings characteristics, margin investors hold smaller stocks with lower book-to-market ratios, smaller market beta, and higher idiosyncratic volatility; there is no clear difference in the past returns of stocks held by margin vs. non-margin investors.

This set of results allows us to reject several plausible explanations for why retail investors engage in expensive margin trading. First, we find that margin trading is not driven by extrapolation of past returns, as margin investors are no more likely to chase past returns than non-margin investors. Margin trading is also not driven by a desire to bet on a single or a few top investment ideas, as margin investors are as diversified as non-margin investors. Finally, margin investors do not appear to be motivated by optimism regarding risky high-beta stocks. Instead, they hold lower market beta stocks than non-margin investors, consistent with margin borrowing acting as a substitute for investments in high beta stocks as a way to amplify market risk (e.g., Frazzini and Pedersen, 2014).

Our results instead point to overconfident beliefs in information advantage as a driver of retail margin trading. Margin investors tend to hold stocks with more scope for "informed trading" –

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[6]The maximum leverage or Pingcang Line corresponds to the reciprocal of the maintenance margin in the U.S. market. "Pingcang" in Chinese means "forced settlement" by creditors.

[7]Allen et al. (2020) show that the average real return of the Chinese stock market since year 2000 is close to zero. With an annual inflation rate of 2-3% during this period, it implies a nominal stock market return of 2-3% a year.

smaller firms with more growth options and higher idiosyncratic volatility. Margin investors also turn over their portfolios at a faster rate than non-margin investors. Finally, margin investors do not outperform the market or non-margin investors in realized portfolio returns. These observations are consistent with overconfidence on the part of margin traders. In other words, part of the reason that some Chinese retail investors are willing to pay a 25% annual borrowing cost in the shadow-financed margin system, despite a far lower average market return, may be that they erroneously believe that they can beat the market.

We further show, perhaps more interestingly, that margin investors have a strong lottery preference (much stronger than that of non-margin investors); that is, they have a strong tendency to hold stocks with positive return skewness. Due to the 10% up and down limits imposed on daily price movements, the statistical definition of skewness does not capture extreme price movements in the Chinese market. We instead use the maximum number of consecutive days in which a stock hits the +10% price limit over the past year to measure its "lottery-ness." For example, consider a stock whose maximum number of consecutive days of hitting the +10% limit is three, its return over this three-day window is more than enough to cover the annual borrowing cost.

The difference in lottery preferences between margin and non-margin investors in our sample is economically large compared to previous estimates of lottery preferences. We show that across a variety of measures of lottery holdings, margin investors hold more lottery stocks than non-margin accounts by approximately 20%.[8] This is significantly larger than those documented in U.S. studies; for instance, Kumar (2009) shows that the demographic characteristics (e.g., being male or Catholic) with the strongest association with preferring lottery stocks are associated with an approximate 3% to 5% increase only.

Collectively, our results point to two drivers of Chinese retail investors' decisions to engage in expensive margin trading: overconfident beliefs in information advantage and lottery preferences. The data are less consistent with extrapolation or optimism about the market as a whole or a particular concentrated position. These empirical patterns among margin investors are closely related to the findings of Liu et al. (2022), who show that perceived information advantage and gambling preferences dominate other behavior biases as the main determinants of non-margin retail trading. We show that similar biases are responsible for driving retail investors to lever up via expensive margin borrowing.

We next study the effect of margin borrowing on investors' trading behavior (as well as the associated price impact) by exploiting the granularity of our daily account leverage and trading data. For each account-date, we compute its "distance-to-margin-call," i.e., the number of standard deviations of downward movements in investors' stock holdings necessary to push the account's leverage to its Pingcang Line. Similar to the distance-to-default measure in a Merton-style model, distance-to-margin-call captures the risk of a margin account hitting its Pingcang Line and consequently

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[8]In a placebo test, we also construct a reverse-lottery measure based on the number of consecutive days of a stock hitting the -10% limit, and find no difference in holdings of reverse lotteries by margin and non-margin investors. Thus, margin investors seem to value positive return skewness rather than higher risk (or kurtosis).

being taken over by its creditor (i.e., when the distance-to-margin-call hits zero). Based on this measure, we develop an empirical framework that is consistent with widely accepted portfolio theory literature with a leverage constraint (Grossman and Vila, 1992; Garleanu and Pedersen, 2011). Providing ample flexibility to accommodate a non-parametric estimation method, our approach embraces a high degree of non-linearity and allows us to empirically investigate the nonlinear effects in question.

We find strong empirical support for margin-induced trading in the data. Specifically, after controlling for account- and stock-date- fixed effects, we show that net buying (selling if negative) is strongly and positively related to the account's distance-to-margin-call (which is labelled "Z"), and to recent changes in this distance (which is labelled "Z-Shock" and is driven by both leverage and account returns). For example, for shadow financed margin accounts, those with $Z \in (0, 1]$ (i.e., accounts that are close to the Pingcang Line) sell 23.2% of their existing risky holdings on that day, relative to non-levered margin accounts, and a one-standard-deviation change in "Z-Shock" increases investor selling by 4.4%; both estimates are statistically significant at the 1% level. In addition, we find that margin investors are relatively more likely to sell non-lottery stocks as distance-to-margin-call shrinks, consistent with the view that margin investors buy and hold lottery stocks for their upside potential, potentially as a way to gamble for resurrection when they move closer to distress.

Next, we present three tests to identify a causal role of leverage constraints on margin trading behavior. In these tests, our goal is not to completely reject alternative explanations. Indeed, it would be unreasonable to argue that investors never trade in response to portfolio returns or rebalancing motives. Rather, our goal is to rule in a large role specific to leverage and leverage constraints.

First, we identify the role of leverage, as distinct from returns, by exploiting a regulatory discontinuity in brokerage margin eligibility: only brokerage accounts with more than 500K RMB in holdings qualify for margin trading. We compare the trading behavior of brokerage margin investors who just qualified for a margin account and brokerage investors who just failed to qualify for a margin account. We find that the just-eligible margin accounts trade twice as aggressively in response to the same (levered) equity return.

In our second test, we focus on the shadow margin sample in which two accounts can have the same leverage but face different leverage constraints, thanks to differences in their Pingcang Lines. We show that, controlling for each account's leverage and returns, margin investors are more likely to sell when they are closer to their Pingcang Lines (i.e., a tighter leverage constraint). One potential concern of this test is that Pingcang Lines are not randomly assigned. To alleviate this concern, we use an instrument for each shadow margin investor's Pingcang Line by exploiting the fact that shadow margin accounts opened around the same time have similar Pingcang Lines. The variation in average shadow Pingcang Lines over time is likely driven by aggregate shadow credit supply, as opposed to individual credit demand that causes the above identification concern. The results—

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based on the average peer Pingcang Line as a reduced-form instrument for each account's actual Pingcang Line—are virtually unchanged. This suggests that it is indeed the leverage constraint that drives selling activity.

In our third test, we exploit a policy shock that tightened leverage constraints for shadow margin investors but did not affect leverage constraints for brokerage margin investors. On Friday, June 12th 2015, the CSRC banned the creation of additional shadow-financed margin accounts. The announcement also fueled anticipation of future regulatory tightening of shadow leverage. We find strong evidence that selling by shadow investors in response to distance-to-margin-call intensified after the policy shock relative to before. In contrast, there was no significant change in the relation between trading and distance-to-margin-call for brokerage margin investors (who were not directly affected by the policy announcement). Taken together, our results indicate that margin borrowing – and the resulting leverage constraints – can have a significant impact on investors' trading behavior.

As a natural extension to the trading results, we examine whether margin-induced trading aggregates to affect prices. The intuition is that an initial reduction in account value tightens the leverage constraint, leading to additional selling and hence even lower prices. We examine this self-reinforcing mechanism by constructing a stock-level measure of "margin-account linked portfolio returns" ($MLPR$). Specifically, $MLPR$ for a stock is the weighted-average daily return of all margin accounts holding the stock on a particular day, after removing the stock's own contribution to each account's return (to avoid auto-correlations in stock returns). Importantly, the weights are a function of the distance-to-margin-call of each account, to reflect our earlier finding that leverage-induced selling depends on how close the account is to hitting its Pingcang Line.

We find that stocks that are collectively sold by margin investors due to tightening leverage constraints experience negative returns in the short run which are reversed in the following weeks. Specifically, a one-standard-deviation increase in $MLPR$ is associated with a higher return of 10 bps (t-statistic = 2.86) in the following day. A back-of-the-envelope calculation suggests a demand elasticity ($d \ln Q / d \ln P$) in the Chinese stock market during our sample period of around 1.64. This figure is largely in line with the estimates of demand elasticities in the U.S. (e.g., Koijen and Yogo, 2019). For example, Lou (2012) estimates an elasticity of 1.2 using flow-induced mutual fund trading.

Finally, we provide suggestive evidence of spillovers across stocks as a result of margin-induced trading. First, stocks with trading restrictions often have negative returns in China. Since these stocks cannot be sold (due to either outright trading suspensions or hitting the downward daily price limit), margin investors, in response to the tightening leverage constraint, have no choice but to liquidate their other "healthy" holdings. We conjecture that this leads to a spillover of adverse shocks from "non-tradable and unhealthy" to "tradable but healthy" stocks. Second, because margin investors on average overweight lottery stocks but tend to sell non-lottery stocks in response to negative portfolio returns (as shown above), we conjecture that negative shocks to lottery stocks will spill over to non-lottery stocks. We confirm both predictions in the data.

Related literature our paper is closely related to recent studies on the drivers of retail investors' excessive trading and use of margin. For example, Liu et al. (2022) show that perceived information advantages and gambling preferences dominate other behavior biases as the main determinants of non-margin retail trading. Barber et al. (2022) and Heimer and Imas (2022) provide evidence that behavioral biases, such as the disposition effect and overconfidence, may cause levered investors to perform poorly. Both confirming and extending prior results, we show in our unique setting of a bubble-crash episode that overconfident beliefs and lottery preferences are the two main drivers of retail investors' margin trading via expensive margin borrowing. More importantly, we provide causal evidence of margin borrowing and leverage constraints on retail investors' trading behavior, and examine the implications of retail investors' margin-induced trading for asset prices.

Our paper also contributes to the literature on the role of funding constraints in asset pricing. Theoretical contributions such as Kyle and Xiong (2001), Gromb and Vayanos (2002), Danielsson et al. (2002), Geanakoplos (2010), Fostel and Geanakoplos (2008), Brunnermeier and Pedersen (2009), and Garleanu and Pedersen (2011) help academics and policymakers understand the linkages between funding constraints and asset prices, especially in the aftermath of the recent global financial crisis.[9] There is also an empirical literature that connects various funding constraints to asset prices. Hardouvelis (1990) finds that a tighter margin requirement is associated with lower volatility in the US stock market. This is consistent with an underlying mechanism in which tighter margin requirements discourage optimistic investors from taking speculative positions (this mechanism may also apply to retail investors in the Chinese stock market). Hardouvelis and Theodossiou (2002) further show that the relation between margin requirements and volatility only holds in bull and normal markets. This finding points to the potential benefit of margin credit, in that it essentially relaxes funding constraints. Closely related to our paper is Kahraman and Tookes (2017). By comparing marginable vs. otherwise similar non-marginable stocks in the Indian market, Kahraman and Tookes (2017) analyze the impact of margin trading on stock liquidity as well as commonality in liquidity. Our detailed account-level data allow us to precisely measure how each account manages its leverage ratio (which is not available in the Indian setting) and examine its impact on account trading, and ultimately stock returns.[10] Chen et al. (2021) estimate the value of marginability by studying Chinese corporate bond markets where bonds with identical fundamentals are simultaneously traded on two segmented markets that feature different rules for repo transactions.

Our paper is also related to a large literature on fire sales in various asset markets including the stock market, housing market, derivatives market, and even markets for real assets (e.g., aircraft).

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[9]Another important strand of the literature explores heterogeneous portfolio constraints in a general equilibrium asset pricing framework and its macroeconomic implications, which features an "equity constraint," for instance, Basak and Cuoco (1998); He and Krishnamurthy (2013); Brunnermeier and Sannikov (2014).

[10]The instrument used by Kahraman and Tookes (2017)—that stocks are periodically added to/deleted from the marginable list (a featured also shared by the Chinese market)—is invalid in our setting. This is because a) virtually all margin investors in our sample hold both marginable and non-marginable stocks (a margin investor can use his own money to buy non-marginable stocks and borrowed money to buy marginable stocks), and b) this rule does not apply to shadow-financed margin accounts.

A seminal paper by Shleifer and Vishny (1992) argues that asset fire sales are possible when financial distress clusters at the industry level, as the natural buyers of the asset are financially constrained. Pulvino (1998) tests this theory by studying commercial aircraft transactions initiated by (capital) constrained versus unconstrained airlines, and Campbell et al. (2011) document fire sales in local housing market due to events such as foreclosures. In the context of financial markets, Coval and Stafford (2007) show the existence of fire sales by studying open-end mutual fund redemptions and the associated non-information-driven sales; Mitchell et al. (2007) investigate the price reaction of convertible bonds around hedge fund redemptions; Ellul et al. (2011) show that downgrades of corporate bonds may induce regulation-driven selling by insurance companies. Recently, fire sales have been documented in the market for residential mortgage-backed securities (Merrill et al., 2016) and minority equity stakes in publicly-listed third parties (Dinc et al., 2017). We contribute to this literature by showing how leverage constraints cause investors to sell assets, thereby impacting prices. We also use a variety of techniques to rule in a direct leverage constraint effect, as distinct from a rebalancing channel.

Our paper also complements the recent literature on excess volatility and comovement induced by common institutional ownership (e.g., Greenwood and Thesmar (2011); Lou (2012); Anton and Polk (2014)). These studies focus on common holdings by non-margin investors such as mutual funds. They also focus on transmission via the well-known flow-performance relation. Our paper contributes to this literature by highlighting the role of leverage, in particular leverage-induced selling, in driving asset returns. A unique feature of our leverage channel is that its return effect is asymmetric (Hardouvelis and Theodossiou (2015)); using the recent boom-bust episode in the Chinese stock market as our testing ground, we show that the leverage-induced return pattern is present only in market downturns.

Our analysis of unique shadow margin data also offers insight into how investors behave when new financial innovations relax leverage constraints ahead of regulation. In our case, developments in FinTech spurred rapid growth of unregulated margin borrowing (see e.g., Chen et al., 2018, 2020; Gambacorta et al., 2020). While the available technology obviously differed, our modern Chinese setting can also be viewed as providing a parallel for the US stock market crash of 1929 (see e.g., Schwert, 1989). Leverage for stock market margin trading was also unregulated in the US at the time. Margin credit rose from around 12% of NYSE market value in 1917 to around 20% in 1929. In October 1929, investors began facing margin calls. As investors quickly sold assets to delever their positions, the Dow Jones Industrial Average experienced a record loss of 13% on October 28th, 1929. As a consequence, regulation of margin requirements were introduced through the Securities and Exchange Act of 1934. The rationale for margin requirements at the time was precisely that credit-financed speculation in the stock market may lead to excessive price movements through a "pyramiding-depyramiding" process. It is conceivable that other developing markets may face similar issues.

Finally, given the increasing importance of the Chinese market in the world economy (second

only to the U.S.), understanding the boom and bust episode in 2015 is an informative exercise in and of itself. Taking advantage of our novel account-level data, we provide the first comprehensive evidence of how margin-induced trading may affect asset prices in the cross-section during this extraordinary episode. Focusing on the initial boom of the same episode in China, Hansman et al. (2018) provide evidence that margin debt indeed helped fuel the initial rally in the Chinese stock market, a result that nicely complements ours. They do not, however, study account-level behavior nor the contagion effect as we do. Liao et al. (2022) study the interplay between extrapolative beliefs and the disposition effect using account-level trading records during the same 2014-15 Chinese stock market bubble; they do not, however, analyze the behavior of margin investors during this episode.

2 Institutional Background and Characteristics of Margin Investors

Our analysis exploits account-level margin trading data in the Chinese stock market covering the period May 1st to July 31st, 2015. This section provides details of the institutional background and data sources, and describes the characteristics of margin investors.

2.1 Institutional Background

The Chinese stock market experienced a large run-up in the first half of 2015, followed by a dramatic crash in mid-2015. The Shanghai Stock Exchange (SSE) Composite Index started at around 3100 in January 2015, peaked at 5166 in mid-June, and took a nose dive to 3663 at the end of July 2015. Many believed that high levels of margin borrowing and the subsequent leverage-induced fire sales played a role in this episode (e.g., Hu et al., 2021).[11]

There were two types of margin trading systems in China during this time. One is brokerage-financed and the other is shadow-financed. Figure 1 shows the structures and funding sources of the two margin trading systems.[12] Throughout the paper, we use brokerage (shadow) accounts to refer to brokerage-financed (shadow-financed) margin accounts.

2.1.1 Brokerage-financed margin accounts

Margin trading through brokerage firms was introduced in 2010, but saw little utilization until mid-2014, at which point brokerage-financed margin trading started to grow exponentially. The total debt held by brokerage-financed margin accounts stood at 0.4 trillion RMB in June 2014, and more than quintupled to 2.2 trillion RMB after one year.[13] This amounted to approximately 3-4%

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[11]Common beliefs regarding the causes of the crash are discussed, for example, in a Financial Times article, available at https://www.ft.com/content/6eadedf6-254d-11e5-bd83-71cb60e8f08c?mhq5j=e4. Another relevant reading in Chinese is available at http://opinion.caixin.com/2016-06-21/100957000.html.

[12]In Chinese, they are called "Chang-Nei fund matching" and "Chang-Wai fund matching," which literally means "on-site" and "off-site" financing.

[13]This data is publicly available from the China Securities Finance Corporation (CSFC) website, http://www.csf.com.cn/publish/main/1022/1024/1127/index.html. The CSFC is the only institution that provides margin financing loan services to qualified securities companies in China's capital market.

of the total market capitalization of the Chinese stock market in mid-June 2015, similar to the size of margin financing in the U.S. and other developed markets.

Chinese brokerage firms usually provide margin financing by issuing short-term bonds,[14] or borrowing from the China Securities Finance Corporation (CSFC) at a rate slightly higher than the Shanghai Interbank Offered Rate (Shibor, which was about 3.5-4.5% during our sample period). Brokers then lend these funds to margin borrowers at an annual rate of approximately 8-9%.[15] This margin business offered brokers a much higher profit than trading commissions, which were only about 4 basis points of trading volume. It is also important to note that this borrowing cost is relatively high, given a historical real average market return that is close to zero (Allen et al., 2020; see footnote 7 for more details).

Almost all brokerage-financed margin accounts are owned by retail investors.[16] To qualify for brokerage-financed margin trading, an investor needs to have a trading account with the broker for at least 18 months, with a total account value exceeding 500K RMB (or about USD 80,000) averaged during the past 20 trading days. One of our later empirical analyses exploits this rule.

The minimum initial margin set by the CSRC is 50%, so that investors can borrow up to 50% of their own capital when they open their brokerage accounts. More important, the CSRC also imposes a minimum "maintenance margin," which requires that every brokerage account have a margin debt level below 1/1.3 of its total asset value. The minimum "maintenance margin" corresponds one-to-one to the maximum leverage that a margin investor can have. Practitioners in China call this maximum allowable leverage, which equals $Asset/Equity = 1.3/(1.3 - 1) = 4.33$, the "Pingcang Line," which means "forced settlement line" in Chinese. Brokerage firms have discretion to set different Pingcang Lines for their customers, as long as they lie below the regulatory maximum of 4.33. In our sample period, all brokerage firms adopted the 4.33 Pingcang Line.[17] Once the account leverage exceeds the Pingcang Line, and if the borrower is unable to inject equity by the following day, then the account will be taken over by the brokerage firm, who has the sole discretion to sell its stock holdings.

2.1.2 Shadow-financed margin accounts

During the first half of 2015, aided by the burgeoning FinTech industry in China, many retail investors engaged in margin trading via the shadow-financing system in addition to (or instead of)

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[14]For an overview of the Chinese bond market and the China Interbank Market, see Amstad and He (2020).

[15]This is depicted by the left side of Panel A in Figure 1. For an example of the borrowing cost charged by brokerage firms on margin investors, see http://www.chinanews.com.cn/stock/2015/03-03/7096940.shtml.

[16]Professional institutional investors are banned from conducting margin trades through brokers in China.

[17]Besides regulating leverage, the CSRC also mandated that only the most liquid stocks (usually blue-chips) are marginable, i.e., eligible for obtaining margin financing. However, this regulation is not binding for most investors, as investors can use cash from previous sales to buy other non-marginable stocks, as long as their accounts remain below the Pingcang Line. In our data, 23% of stock holdings in brokerage-financed margin accounts are non-marginable stocks in the week of June 8-12, 2015 (the week leading up to the crash). When the account engaged in either preemptive sales to avoid reaching the Pingcang Line or forced sales after crossing the Pingcang Line, investors sold both marginable and non-marginable stocks, rendering the initial margin eligibility largely irrelevant. Moreover, shadow-financed margin accounts were not regulated and could always buy non-marginable stocks on margin.

the brokerage-financing system. The shadow-financing system, as many financial innovations in the past, existed in a regulatory gray area. Shadow-financing was not initially regulated by the CSRC, and lenders did not require borrowers to have a minimum level of wealth or trading history. In turn, borrowers paid higher interest rates to shadow financing lenders. In a limited subsample where interest rate information is available, we find that the shadow borrowing rate is about 25%, approximately 16.5 percentage points higher than that in the brokerage-financed market (and way higher than the average market return between 2000 and 2014; see footnote 7).

Shadow-financing usually operated through a web-based trading platform that facilitated trading and borrowing.[18] The typical platform featured a "mother-child" dual account structure, where each mother account offered trading access to many (in most cases, hundreds of) child accounts; these were also referred to as "Umbrella Trusts." Panel B of Figure 1 depicts such a "mother-child" structure. The mother account (the middle box) is connected to a distinct trading account registered in a brokerage firm with direct access to stock exchanges (the top box). The mother account belongs to the lender, usually a professional financing company. Each mother account is connected to multiple child accounts, and each child account is managed by an individual retail margin trader (the bottom boxes).

On the surface, a mother account appears to be a normal non-margin brokerage account, with large asset holdings and trading volume; while in fact it is used by a FinTech platform to transmit the orders submitted by associated child accounts in real time to stock exchanges. As shown in Panel B of Figure 1, the professional financing company that manages the mother account provides margin credit to child accounts. Its funding sources include its own capital as mezzanine financing as well as borrowing from the shadow banking sector. Through this umbrella-style structure, a professional financing company lends funds to many shadow margin traders, while maintaining different leverage limits for each child account.

Similar to brokerage accounts, each shadow (child) account has a maximum allowable leverage limit—i.e., the Pingcang Line—beyond which the child account (the debtor) will be taken over by the mother account (the creditor), triggering forced sales. Often, this switch of ownership was automated by the FinTech platform, through the expiration of the borrower's password and immediate activation of that of the creditor.

Unlike the brokerage-financed margin system, the shadow-financed margin system was unregulated (before the policy shock, as explained below). Two points are worth emphasizing. First, there were no regulations concerning the maximum allowable leverage for each child account; the creditor and the debtor set an account-specific Pingcang Line that never changes during the life of the account, and in our sample, unregulated shadow accounts have much higher Pingcang Lines than their regulated brokerage peers (11 vs. 4.3, median, Table 1 Panel C). Second, the shadow margin businesses were operated in a more "discretion-based" way due to lax regulation, while brokerage margin businesses were more "rule-based." For instance, in the brokerage system, processing of debt

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[18]HOMS, MECRT, and Royal Flush were the three leading electronic margin trading platforms in China in the first half of 2015.

financing is automated, and margin investors can borrow within the system without delay as long as their accounts remain in good standing. In contrast, the shadow margin system often lacked standardized procedures and internal controls; typically, each new request for margin financing needed to be reviewed by the mother account in an ad-hoc way.

Whereas funding for brokerage accounts came from either the brokerage firm's own borrowed funds or the CSFC, the shadow-financed margin system sourced its funding from a broader set of channels that are directly, or indirectly, linked to the shadow banking system in China. The right side of Figure 1 Panel A lists these sources of financing. Besides the capital by financing companies who were running the platform and equity from shadow margin traders, the three major funding sources were: Wealth Management Products (WMP) sold to bank depositors, Trust and Peer-to-Peer (P2P) informal lending, and borrowing through pledged stock rights. As hinted by the gray color on the right hand side of Figure 1 Panel A, the shadow-financed margin system operated in the "shadow"—regulators did not know its size nor its leverage. One educated guess of the total debt held by shadow-financed margin system was about 1 trillion RMB at its peak.[19]

On Friday, June 12th, 2015, the CSRC released a set of draft rules that would strengthen the self-examination requirement of services provided to shadow-financed margin accounts and explicitly ban the creation of additional shadow-financed margin accounts. The announcement raised investor anticipation that coming regulations would require shadow lenders to tighten their offered leverage constraints on existing borrowers.[20] A stock market crash began the following trading day, Monday, June 15th, 2015, wiping out almost 30% of the market index, until the market stabilized in mid-September 2015.

2.2 Data Sources

Recall our sample period covers the episode between May 1st to July 31st, 2015. We use a combination of proprietary and public data from several sources. The first proprietary dataset contains the complete records of stock holdings, cash balances, and trading activity of all accounts from multiple large brokerage firms in China. This sample contains data on nearly five million accounts, over 95% of which are retail accounts. Approximately 77,000 of these accounts are eligible for brokerage-financed margin trading, hereafter referred to as "brokerage-financed margin accounts" or "brokerage accounts." (The rest of accounts are called "non-margin" accounts.) After applying our data filtering criteria, the total credit to these brokerage-financed margin accounts represents about 5% of the outstanding brokerage margin credit to the entire stock market in China during our sample period.

The second proprietary dataset covers more than 150,000 accounts from a large web-based trading platform in China, i.e., "shadow-financed margin accounts" or "shadow accounts." These shadow accounts are based on two distinct FinTech software systems: YJ and QJ, accounting for

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[19]This number is consistent with the estimates provided by China Securities Daily on June 12th, 2015. For detailed estimation for each category, see Appendix A.1.

[20]See a review article in Chinese on this event at http://opinion.caixin.com/2016-06-21/100957000.html.

49.45% and 50.55% of the sample, respectively.[21] Unfortunately, the QJ accounts do not provide enough cash flow information for us to compute their daily account leverages. In addition, all their Pingcang Lines are recorded as 10. In our empirical analyses, we therefore focus on YJ accounts, for which we have detailed trading, holding, interim cashflows, and leverage information for the child accounts, and more importantly, account-specific Pingcang Lines. The account-specific Pingcang Lines allow us to design further tests to differentiate the impact of leverage constraints from that of leverage itself. After further applying the filters detailed in Appendix A.2, we retain a final sample of 53,972 shadow accounts with valid and complete information. The total debt in this sample reached 26.4 billion RMB in June 2015. For comparison, recall that in Section 2.1.2 we estimate that the debt associated with shadow accounts peaked at around 1 trillion RMB; therefore our sample covers a bit below 3% of the shadow-financed margin system.

A key advantage of our proprietary brokerage and shadow samples, besides detailed information on every transaction, is that we observe both the assets and liabilities of each margin account. An implicit assumption in our analysis is that both data samples are representative of the two margin-based financing systems in China. Though it is impossible to verify the representativeness of our sample of shadow-financed margin accounts (we are the first to analyze shadow-financed margin trading), we find a correlation – across all stocks on the Shanghai Stock Exchange – in daily trading of 87% between brokerage margin investors in our sample and all brokerage margin investors in the market.[22] The average correlations in buy trades and sell trades between our sample of margin investors and all margin investors in the market are 85% and 83%, respectively.

During our sample period in China, investors were not allowed to have brokerage margin accounts with multiple security firms. However, brokerage margin investors could potentially participate in the shadow-financed margin system. Since we lack data on investor identities in our shadow sample, it is possible that the same investor traded in both the brokerage and shadow margin samples. It is unclear how multiple margin accounts tied to a single investor will bias our empirical findings other than the well-known issue of unobservable wealth effects, which is typical for this type of account-level data without investor wealth information.

We obtain daily closing prices, trading volume, stock returns and other stock characteristics from the RESSET Financial Research Database (RESSET/DB), which is widely regarded as the leading academic data vendor for Chinese financial markets. In China, each individual stock was allowed to move by a daily maximum of 10% from the previous closing in either direction, before triggering a trading halt (see, e.g., Chen et al., 2019 for a detailed analysis). While the stock could technically continue to be traded within the 10% range, in practice a stock's trading volume will drop significantly once it reaches its daily price limit. Finally, throughout we exclude stock-date

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[21]YJ stands for Yongjin and QJ stands for Qianjiang in Chinese.

[22]Specifically, for each day, we calculate the cross-sectional correlation between trading (buy+sell) in individual stocks on the Shanghai Stock Exchange (SSE) by brokerage margin investors in our sample and trading by all margin investors in the market. (We only observe aggregate margin trading for stocks on the SSE, which accounts for about 2/3 of all margin trading across the two exchanges in China). We then take the time-series average of the correlations for our sample period of May to July 2015.

observations when stocks that are suspended from trading, which is common during our sample period (Huang et al., 2018).

2.3 Characteristics of Margin Investors

In this subsection, we discuss the characteristics of margin investors (both brokerage and shadow) versus those of non-margin investors who do not have access to leverage.

2.3.1 Account and portfolio characteristics

We first examine the types of retail investors that use leverage and are willing to pay a borrowing cost many times the average market return, which is estimated to be 2-3% since 2000 by Allen et al. (2020). We study three sets of investor and portfolio characteristics. First, in Table 1 Panel A, the first three columns report the differences in investor characteristics between non-margin and brokerage margin accounts. (We do not observe investor characteristics of shadow margin accounts.) Brokerage margin investors, relative to non-margin investors, are slightly more experienced (8 vs. 7 years of trading experience), older (44.5 vs. 43 years old), and less likely to be female (36% vs. 46%).

We then examine the portfolio characteristics of brokerage margin, shadow margin, and non-margin accounts. As shown in Panel A of Table 1, margin investors hold as diversified portfolios as non-margin investors. More specifically, brokerage margin investors on average hold 4.5 stocks and shadow margin investors hold 2.8 stocks; while non-margin investors stand in the middle by holding 3.4 stocks in their portfolios, which close to the average of both margin accounts. (For reference, Ivković et al. (2008) show that the average retail investor in the US holds 3.9 stocks in her portfolio.) Alternatively, using the Herfindahl index as a measure of portfolio concentration, we find that three classes of investors have similar Herfindahl indexes (around 0.6); brokerage margin investors have slightly lower Herfindahl index (0.56), consistent with they holding a relatively larger number of stocks in their portfolios. Shadow margin investors also have a much higher portfolio turnover; their average daily portfolio turnover rate is 21.4%, which is much higher that of brokerage margin investors (11.7%) and that of non-margin investors (10.7%).

Finally, we examine the differences in margin and non-margin investors' holding characteristics. As shown in Panel B of Table 1, relative to non-margin investors, margin investors hold stocks with smaller size, lower book-to-market ratios (0.44 for brokerage margin accounts and 0.41 for shadow margin accounts vs. 0.71 for non-margin accounts), lower market beta (0.72 for brokerage margin accounts and 0.54 for shadow margin accounts vs. 0.90 for non-margin accounts), higher idiosyncratic volatility (6.7% annualized for brokerage margin accounts and 7.4% for shadow margin accounts vs. 6.2% for non-margin accounts), and higher turnover (2.4% for brokerage margin accounts and 2.8% for shadow margin accounts vs. 1.9% for non-margin accounts).[23] Interestingly,

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[23]The stock turnover measure in Table 1 Panel B has a qualitatively similar pattern across different investor groups as the account turnover measure reported in Panel A, al beit with smaller magnitudes as the former is measured

there is no visible difference in past returns of the stocks held by margin vs. non-margin investors; this is true for returns measured in the past day (Momentum Short in Panel B Table 1), month (Momentum Medium), or six months (Momentum Long).

As discussed in Section 2.1, Chinese retail margin investors incur high borrowing costs relative to historical average market returns. The above summary statistics allow us to reject several plausible explanations of why retail investors engage in expensive margin trading. First, we find that margin trading is not driven by extrapolation of past returns, as margin investors are no more likely to chase past returns than non-margin investors. Margin trading is also not driven by a desire to bet on a single or a few top investment ideas; margin investors are at least as diversified as non-margin investors. Finally, margin investors do not appear to be motivated by optimism regarding risky high-beta stocks. Instead, they hold lower market beta stocks than non-margin investors, consistent with margin borrowing acting as a substitute for investments in high beta stocks as a way to amplify market risk (e.g., Frazzini and Pedersen, 2014).

Our results instead point to overconfident beliefs in information advantage as a potential driver of retail margin trading. Margin investors tend to hold stocks with more scope for "informed trading"—smaller firms with more growth options and higher idiosyncratic volatility. Margin investors also turn over their portfolios at a much faster rate than non-margin peers. Moreover, as shown in Table 1 Panel A, in our sample period during which the Chinese stock market experienced a boom and bust cycle, margin investors—with a -16.5bps daily return for brokerage margin investors and a -63.9bps daily return for shadow margin investors, and a combined daily return of -26.6bps for all margin investors—do not outperform non-margin investors (with a daily return of -25.8bps) in realized portfolio returns. These observations are consistent with overconfidence on the part of margin traders. In other words, part of the reason that some Chinese retail investors are willing to pay a 25% borrowing cost, despite a far lower average market return, may be that they erroneously believe that they can beat the market.

2.3.2 Lottery preferences

Perhaps more interestingly, we show that margin investors have a much stronger lottery preference than non-margin investors; that is, margin investors are more likely to hold stocks with positive return skewness than non-margin investors. Due to the 10-percent up- and down- limits imposed on daily price movements, the traditional definition of skewness does not capture extreme price movements in the Chinese market. We instead use the maximum number of consecutive days in which a stock hits the +10% price limit over the past year to measure its "lottery-ness." One way to think about our lottery-ness measure is that it captures the maximum daily return in absence of the daily price limit.

The difference in lottery preferences between margin and non-margin investors is economically large in our sample, compared to previous estimates of lottery preferences. Kumar (2009), for

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based on stock turnover in the prior year (May 2014 to May 2015).

example, shows that the demographic characteristics most strongly associated with tendencies to hold lottery stocks (e.g., being male or Catholic) are associated with an approximate 3% to 5% increase in the lottery preference measure. In contrast, Panel B of Table 1 shows that across a variety of measures of lottery holdings, margin investors hold more lottery stocks than non-margin accounts by approximately 20%. For example, the weighted-average maximum number of consecutive days of hitting the +10% price limit of all stocks in the portfolio (labelled "Lottery-ness") is 2.43 and 2.56 days for brokerage and shadow margin investors respectively, and that of non-margin investors is 2.07 days, so a (statistically significant) difference between margin and non-margin investors of more than 20%.[24]

We also consider alternative definitions of lottery stocks. For instance, in the row labelled "Lottery Holding 3," we define lottery stocks as those that have had at least three consecutive days of hitting the +10% price limit; this corresponds to a cumulative return of over 30% in just three days, enough to cover the borrowing cost in the shadow-margin system. Based on this definition, both brokerage and shadow margin accounts invest 34%, while non-margin accounts invest 28%, of their portfolios in lottery stocks, a difference of nearly 30%. We obtain similar results if we instead define lottery stocks as those that have had at least two (Lottery Holding 2) or four (Lottery Holding 4) consecutive days of hitting the up price limit.

In a placebo test, we also construct a reverse-lottery measure based on the number of consecutive days of a stock hitting the -10% price limit. As reported in the row of "Lottery Reverse Holding" in Panel B of Table 1, we find no difference in holdings of reverse lotteries by margin and non-margin investors. Thus, margin investors seem to value positive return skewness rather than higher tail risk or kurtosis.

Taken together, our results point to two potential drivers of the decision to lever up in trading in the Chinese stock market: overconfident beliefs in information advantage and lottery preferences. These findings extend the conclusions of Liu et al. (2022), which shows that perceived information advantage and gambling preferences dominate other behavior biases as the main drivers of unlevered retail trading. We find that margin traders exhibit even stronger versions of these biases relative to unlevered retail traders, and these biases help explain the decision to engage in expensive margin borrowing.

3 Empirical Framework

We describe in this section a simple empirical framework to examine margin investors' trading decisions and how trading aggregates to affect asset prices.

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[24]In the bottom row of Panel B, we construct an alternative measure of lottery stocks following Liu et al. (2022). In our main specification, we measure lottery stocks using the maximum number of *consecutive* days in which a stock hits the upper 10% limit, whereas Liu et al. (2022) does not impose the consecutive requirement. The results are similar with this alternative construction.

3.1 Leverage and Distance-to-Margin-Call Z

We define the leverage of an account j at the start of day t as

$$Lev_t^j \equiv \frac{A_t^j}{E_t^j}, \tag{1}$$

where A_t^j is the total market value of assets held by account j at the start of day t, including stock and cash holdings in RMB value. E_t^j is the equity value held by account j at the start of day t, equal to total assets minus total debt. All start-of-day values are computed using prices as of the market close on the previous trading day.

Theories on optimal portfolios with leverage constraints, such as those of Grossman and Vila (1992) and Garleanu and Pedersen (2011), suggest that an agent's trading strategies are influenced by factors beyond just the level of leverage. In the spirit of the distance-to-default measure in the Merton (1974) credit risk model, we calculate the magnitude of a negative shock to the asset value of an account sufficient to push the account's leverage to its Pingcang Line, thus triggering a control shift from the margin investor to her lender.

Denote by σ_{At}^j the portfolio volatility of account j on day t.[25] For each account-date observation with start-of-day asset value A_t^j, equity value E_t^j, together with account specific Pingcang Line $\overline{Lev}_j$ (which never changes over the life of the account), we define the distance-to-margin-call Z_t^j for account j on date t based on:

$$\frac{A_t^j - A_t^j \sigma_{At}^j Z_t^j}{E_t^j - A_t^j \sigma_{At}^j Z_t^j} = \overline{Lev}_j. \tag{2}$$

In other words, the account's distance-to-margin-call Z_t^j indicates the number of standard deviations of downward movements in asset value necessary to push the account's leverage to its Pingcang Line.

By re-arranging Eq. (2), we can rewrite Z_t^j as a function of current leverage $Lev_t^j = A_t^j/E_t^j$, Pingcang Line $\overline{Lev}_j$, and asset volatility σ_{At}^j:

$$Z_t^j = \underbrace{\frac{\overline{Lev}_j - Lev_t^j}{\overline{Lev}_j - 1}}_{\text{Leverage-to-Pingcang}} \cdot \underbrace{\frac{1}{\sigma_{At}^j}}_{\text{Daily Volatility}} \cdot \underbrace{\frac{1}{Lev_t^j}}_{\text{Amplification}} \cdot \tag{3}$$

Eq. (3) indicates that the account's distance-to-margin-call depends on the account's Leverage-to-Pingcang distance, the volatility of its holdings, and an amplification effect due to the account's current leverage. Specifically, an account has a lower Z (hence, is closer to a margin call), if it

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[25]We calculate σ_{At}^j using account holdings as of market close on the previous trading day, based on the covariance matrix of daily stock returns in the Chinese stock market. To avoid a look-ahead bias, we estimate the covariance matrix from the previous year (5/1/2014 to 4/30/2015). We will come back to this issue when we discuss summary statistics in Section 3.2.

has a lower Leverage-to-Pingcang distance, higher asset portfolio volatility, and/or higher current leverage.

An account's distance-to-margin-call Z is affected by the account return in a highly non-linear way. To see this, from Eq. (3) we have (dropping the time t and account j subscripts for simplicity):

$$Z(R) = \frac{\overline{Lev}\frac{E+AR}{A+AR} - 1}{\overline{Lev} - 1} \frac{1}{\sigma^A}, \tag{4}$$

which allows us to compute the derivative of Z with respect to the account return R evaluated at $R = 0$:

$$Z'(R)\big|_{R=0} = \frac{1 - \frac{1}{Lev}}{1 - \frac{1}{\overline{Lev}}} \cdot \frac{1}{\sigma^A}. \tag{5}$$

In words, the derivative (5) captures how Z, to a first order approximation, responds to the account return R. We highlight that (5) is increasing in account leverage. For a low-leverage account so that $Lev \approx 1$, (5) is close to 0, so the account return barely moves Z. However, for a margin-constrained account $(Lev \to \overline{Lev})$, then (5) is close to $1/\sigma^A$, so a small account return could lead to a substantial change in Z (considering that daily σ_A takes a value of 3-5% in the data).

Finally, for an unlevered investor with $A = E$ (implying that $Lev = 1$), Z is not defined based on Eq. (2),[26] implying that Eq. (3) only applies to the case $Lev \in (1, \overline{Lev}]$. It is also clear from Eq. (5) that with $Lev \to 1$, the impact of account return on Z turns to zero; intuitively, unlevered accounts remain unlevered independent of the account return. As a result, our empirical strategy treats these account-day observations as the omitted benchmark group. Specifically, in subsequent analysis when we control for bins representing the value of Z, unlevered account-day observations with undefined Z are assigned to the omitted category of "NA," and the estimated impact of Z on trading behavior is relative to these unlevered accounts.

3.2 Account Leverage: Summary Statistics

Panel C of Table 1 reports the summary statistics of account leverage, Pingcang Lines, and associated distance-to-margin-call (i.e., Z).

Leverage and Pingcang Lines First, we show that shadow margin investors have much higher leverage and leverage limits compared to brokerage margin investors. Brokerage margin accounts have a uniform Pingcang Line of 4.30, while shadow margin accounts have a wide variation in Pingcang Lines, with a mean of 13.54, a median of 11.00, and a standard deviation of 6.66. Shadow margin accounts also have much higher account leverage ratios: the mean (median) leverage ratio is 6.40 (4.47) and 1.41 (1.32) for shadow and brokerage margin accounts, respectively.[27]

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[26]To see this, the left-hand-side of Eq. (2) always equals 1, while the right-hand-side $(\overline{Lev}_j)$ is always greater than 1, so the two would never equate. Intuitively, for investors without debt, the leverage constraint is never binding.

[27]Recall that the Pingcang Line is the maximum leverage an investor can have before the control of the account is transferred to the lender (who then can start to sell holdings). However, due to trading restrictions in China

Panel A of Figure 2 plots the equity-weighted average account leverage ratios for brokerage and shadow accounts, together with the Shanghai Stock Exchange (SSE) Composite Index. By weighting each account's leverage by the equity of each account, the average leverage ratio is equal to the total assets of all margin accounts divided by their total equity. It is clear from the figure that the leverage of shadow accounts fluctuates much more dramatically than that of brokerage accounts, with a strong negative correlation between both leverage series and the SSE Index (-84% for shadow and -68% for brokerage accounts), suggesting that leverage is highly counter-cyclical.

It is useful to contrast the equity-weighted average leverage ratio with the asset-weighted average leverage ratio. As shown in Panel B of Figure 2, relative to the equity-weighted average, the asset-weighted average leverage is much higher, and increased sharply toward a high of nearly 7-to-1 as the stock market crashed. This suggests that highly levered accounts with little equity owned a growing portion of the market during the market crash.

Distance-to-margin-call Z As defined in Eq. (3), Z reflects how close an account is to its Pingcang Line in terms of account return standard deviations. Despite their higher Pingcang Lines, shadow margin accounts are much closer to their respective Pingcang Lines than brokerage margin accounts: shadow accounts have an average (median) Z of 11.49 (8.32) whereas brokerage accounts have an average (median) Z of 29.72 (26.38). This is also evident in Panels A and B of Figure 3 which plot the distributions of Leverage-to-Pingcang and Z for these two types of margin accounts.

At first glance, it may appear that margin investors in our sample are very far from facing margin calls. For the average shadow account, it would require an return movement equal to 11.49 standard deviations for the account to receive a margin call. However, accounts in our sample are actually much closer to their margin constraints for two reasons. First, to avoid a look-ahead bias, we have estimated Z using data on the covariance matrix of stocks' daily returns in the year *prior* to our sample period (see footnote 25); during our sample period, however, the average daily volatility of stocks more than doubled relative to the prior year. Second, as explained in the discussion of Eq. (5), the derivative of distance-to-margin-call Z with respect to the account return R is highly non-linear. To put these forces into perspective, consider the average shadow margin account in our sample, and how the account return drives the *percentage* change of Z. To this end, one can use (3) to rewrite (5) slightly as

$$\frac{Z'(R)|_{R=0}}{Z} = \frac{\overline{Lev}(Lev-1)}{\overline{Lev}-Lev}. \tag{6}$$

With average leverage $Lev = 6.40$ and average Pingcang Line $\overline{Lev} = 13.54$ for shadow accounts (see Panel C in Table 1), the multiplier in (6) equals 10.18. Therefore, a daily account return of

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(Chen et al., 2019; Huang et al., 2018), it is possible for an account's leverage to exceed its Pingcang Line. We cap leverage at 100 to reduce the influence of outliers; this treatment is innocuous as we will use a flexible non-parametric estimation with respect to the measure of leverage.

−5%—which is about the mean daily volatility of account stock returns during our sample period and which is well within the daily price 10% limit—can reduce Z by as high as 50.4%. In sum, considering the heightened volatility experienced in our sample period, coupled with the significant non-linear nature of leveraged trading, an account starting with the median Z of approximately 10 would quickly reach a Z close to zero after a few negative daily returns.

3.3   Margin Investors' Trading Strategy

We define net buying of stock i by account j on day t as:

$$NetBuy_{it}^{j} \equiv \frac{\text{shares of stock } i \text{ bought by account } j \text{ during day } t}{\text{shares of stock } i \text{ held by account } j \text{ at the beginning of day } t}. \tag{7}$$

$NetBuy_{it}^{j}$ can take both positive (buying) and negative (selling) values, and may depend on stock i's characteristics, account j's distance-to-margin-call Z_{t}^{j}, and shocks to Z_{t}^{j}. Note that $NetBuy_{it}^{j}$ is defined using the number of shares and does not depend on price information. Table 1 Panel C reports the summary statistics of $NetBuy$, which is expressed in percentage points for expositional convenience. We observe that the mean $NetBuy$ for shadow (brokerage) margin accounts is -19.9% (-5.3%), implying that shadow accounts are selling more—presumably due to lower Zs—than the brokerage counterparts during our sample period.

The simple conceptual framework we have in mind is a dynamic portfolio choice problem with leverage constraints, where the distance-to-margin-call Z is the only state variable.[28] $NetBuy_{it}^{j}$, the daily change in optimal holdings, can then be expressed using the following first-order Taylor expansion:

$$NetBuy_{it}^{j} = f\left(Z_{t}^{j}\right) + \underbrace{g\left(Z_{t}^{j}\right) \cdot Z'(R)\big|_{R=0} \cdot R_{t}^{j}}_{Z\text{-shock, denoted by } \Delta Z_{t}^{j}} + \alpha_{j} + \nu_{it}, \tag{8}$$

where $f\left(\cdot\right)$ and $g\left(\cdot\right)$ are general nonlinear functions, Z_{t}^{j} is measured at the start of day t, R_{t}^{j} is the account return over the course of day t based on start-of-day asset holdings, $Z'\left(R\right)$ is the derivative of Z with respect to the account return evaluated at $R = 0$ as in Eq. (5), and ν_{it} are stock-date fixed effects and α_{j} account fixed effects.

Throughout, we refer to the day-t impact of account return R (to its first-order approximation) on the margin investor's position in stock i, i.e., $g\left(Z_{t}^{j}\right) \cdot Z'(0) \cdot R_{t}^{j}$ as Z-Shock, denoted by ΔZ_{t}^{j}. As described previously in the discussion of Eq. (5), $Z'(R)$ is equal to zero for unlevered accounts, and therefore Z-shock equals zero for all observations associated with zero margin borrowing.

By including stock-date fixed effects ν_{it} in Eq. (8), we effectively compare trading of the same

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[28]Our approach is similar to that of Lan et al. (2013), in which a risk-averse hedge fund manager takes a levered position to exploit a profitable trading strategy. In their notation, w_{t} measures the ratio of the fund's assets under management to the fund's high water mark, and serves as the only state variable. The fund is liquidated when w_{t} hits a lower bound. Our measure of distance-to-margin-call Z plays the same role as w_{t}. Other examples include Grossman and Vila (1992) and Panageas and Westerfield (2009).

stock on the same day by margin accounts with different Z's and different Z-Shocks. These fixed effects help alleviate the concern of endogenous matching between investors and stocks. We also note that the additive nature of stock-date fixed effects in Eq. (8) does not allow for stock characteristics to interact with Z and Z-Shocks. In other words, we estimate the *average* trading response (as a percentage of start-of-day holdings) across all stocks held by the account in response to Z-Shocks. In reality, investors may choose to sell more of one stock in their portfolio than another due to beliefs about the stock's future returns or liquidity; we will present more detailed tests exploring how margin investors' trading response to Z-Shocks varies with stock characteristics in Appendix A4. Nevertheless, we prefer to use a proportional sales assumption in our baseline tests to present a parsimonious model of margin investor trading behavior and because employing a proportional sales assumption will allow for improved identification of price impact, as explained in Section 5.

To estimate Eq. (8) empirically, we proxy for $f(\cdot)$ and $g(\cdot)$ using piecewise step functions of Z. Specifically, we sort Z_t^j into K bins indexed by k, and construct dummy variables $I_{kt}^j = 1$ if Z_t^j falls in the kth bin. The bins are $Z > 5$, $Z \in [\tau - 1, \tau)$ for $\tau = 1, 2, 3, 4, 5$ and finally $Z < 0$ (representing accounts with $Lev_t^j > \overline{Lev_j}$ which are possible in practice due to trading restrictions; see Section 4.1.1 and footnote 34 for more details). We also create a $(K+1)^{th}$ group for all unlevered accounts with undefined Z which serve as the control group. We then conduct the following regression to estimate $\{f_k, g_k : k \in \mathbb{K}\}$:

$$NetBuy_{i,t}^j = \sum_{k \in \mathbb{K}} f_k I_{kt}^j + \sum_{k \in \mathbb{K}} I_{kt}^j \cdot \underbrace{g_k \cdot Z'(R)\big|_{R=0} \cdot R_t^j}_{\Delta Z_t^j} + \alpha_j + \nu_{it} + \varepsilon_{it}^j, \tag{9}$$

where $Z'(R)|_{R=0}$ is calculated based on Eq. (5), and $\{f_k, g_k : k \in \mathbb{K}\}$ are estimated non-parametrically. In other words, we rely on observed account level trading data to obtain non-parametric estimates of $\{f_k, g_k\}$, so that the coefficient in front of ΔZ_t^j is normalized to 1:

$$NetBuy_{i,t}^j = \sum_{k \in \mathbb{K}} f_k I_{kt}^j + \Delta Z_t^j + \alpha_j + \nu_{it} + \varepsilon_{it}^j. \tag{10}$$

We report summary statistics of the resulting Z-Shocks in Panel C of Table 1.[29]

Importantly, Eq. (10) also forms the basis of analyzing shock propagation through the network of margin investors' holdings, to which we turn next.

3.4 Z-Shock Transmission in a Leverage Network

When margin investors adjust their holdings in response to Z-Shocks, their trading can transmit shocks across stocks via common holdings by the same margin investor. To estimate the shock

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[29]Since we construct Z-Shock based on its impact on trading (via non-parametric estimators $\{g_k\}$), one cannot simply use the magnitude of Z-Shock to gauge the number of days of negative returns of a certain size that is required for accounts to hit their Pingcang Lines. The answer to this question hinges on the daily return volatility $Z'(R)|_{R=0}$, as we have explained in the discussion following Eq. (6).

transmission, we develop a measure called "margin-account linked portfolio returns" ($MLPR$) that captures the price impact on one stock due to return movements of other stocks that are connected via the leverage network.

Before proceeding to the details of empirical construction, we present a simple example to illustrate the intuition.

3.4.1 An illustrative example

Consider a margin investor who holds two stocks, S_1 and S_2, and imagine that S_2 experiences a negative return. This negative return pushes the margin investor closer to her Pingcang Line. In response to this negative shock, the investor sells S_1 in addition to S_2, thus pushing down the price of S_1.

The "margin-account linked portfolio returns" ($MLPR$), to be defined in detail shortly, measures the price impact on S_1 due to the returns of stock S_2. We first translate S_2's return into a Z-Shock to reflect how the price movement of S_2 pushes the investor closer to her Pingcang Line. We then construct $MLPR$ for S_1 assuming that the investor sells S_1 according to the average relationship between percentage trading and Z-Shock as estimated in Eq. (4). For example, if Eq. (4) indicates that the investor liquidates an average of 5% of all holdings in response to Z-Shock, we assume that she sells 5% of her holdings of S_1, and then translate the percentage trading to a dollar amount using her initial holding of S_1. Aggregating the dollar sales across all margin investors, which is then scaled by the market value of S_1, we obtain a measure of selling pressure stemming from price movements of connected stocks.

Note that we compute $MLPR$ as though the investor sold S_1 as predicted by the average relation between percentage sales and Z-Shocks in our data. In practice, the investor may choose to sell more or less of S_1 than predicted because she has unobserved beliefs about S_1's future returns or liquidity. If we use her actual liquidation choice in this instance to construct $MLPR$, we may estimate a spurious effect of $MLPR$ on S_1's future return. Instead, we purposely create $MLPR$ under the counterfactual assumption that the investor liquidates assets "pro rata" in response to Z-Shocks, thereby stripping $MLPR$ of omitted variables that could both forecast the stock's future returns and be correlated with liquidation choice. Our use of a counterfactual proportional sales assumption is conceptually similar to the method used in Edmans et al. (2012) and Lou (2012) to study mutual fund flow-induced trading and the resulting price impact.

3.4.2 Constructing $MLPR$

Recall that $NetBuy_{it}^j$ denotes margin investor j's net buying of stock i on day t as a percentage of her initial holdings. Denote $Q_t^j \equiv g_k I_{kt}^j \cdot Z'(R)|_{R=0}$ and plug this into Eq. (4). We can then write margin investor j's dollar trading (denoted by X_{it}^j) in stock i as:

$$X_{it}^j = A_t^j \omega_{it}^j \cdot Q_t^j R_t^j, \tag{11}$$

where A_t^j is investor j's account value, and ω_{it}^j is the portfolio weight of stock i. Aggregating X_{it}^j across all margin traders, we obtain the total margin-induced trading in stock i on day t:

$$X_{it} = \sum_{j=1}^{J} A_t^j \omega_{it}^j \cdot Q_t^j R_t^j. \tag{12}$$

We then scale the dollar amount of trading in each stock by its market capitalization to arrive at a measure of margin-induced price pressure:

$$\frac{1}{MktCap_{it}} \sum_{j=1}^{J} A_t^j \omega_{it}^j \cdot Q_t^j R_t^j. \tag{13}$$

Our results are robust to other scaling variables (e.g., the previous-year trading volume).

In our formal definition of margin-account linked portfolio returns ($MLPR$), it is more convenient to recast (13) to a matrix from. Given N stocks in the market, on each trading day we let r denote an $N \times 1$ vector of stock returns of that day, $\boldsymbol{\Omega}$ a $J \times N$ matrix of beginning-of-day portfolio weights, $\mathbf{diag}(A)$ a $J \times J$ diagonal matrix whose diagonal terms are A_j, $\mathbf{diag}(Q)$ a $J \times J$ diagonal matrix whose diagonal terms are Q_t^j; $\mathbf{diag}(MktCap)$ an $N \times N$ diagonal matrix whose diagonal terms are $MktCap_{it}$. The vector of margin-induced price pressure on all stocks is $\mathbf{T} \times r$, where

$$\mathbf{T} \equiv \mathbf{diag}(MktCap)^{-1} \times \boldsymbol{\Omega}' \times \mathbf{diag}(A) \times \mathbf{diag}(Q) \times \boldsymbol{\Omega}, \tag{14}$$

which governs the transmission of individual stock returns through common ownership by margin investors.

Finally, We isolate the effect of contagion by removing the stock's own return. Let $\mathbf{T}_0 \equiv \mathbf{T} - \mathbf{diag}(\mathbf{T})$; we define margin-account linked portfolio returns ($MLPR$) as $\mathbf{T}_0 \times r$. Intuitively, $MLPR_i$ captures the price impact on stock i stemming from all other stocks that are connected to i via common ownership by margin investors.

4 Trading Behaviors of Margin Investors

In this section, we study the trading activities of margin investors, with an emphasis on their deleveraging behaviors due to leverage constraints.[30]

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[30]Because we are primarily interested in the liquidation behavior of margin investors in relation to distance-to-margin call, we use net-buy as our main dependent variable in this section. Net-buy on day t is only defined for stocks already held by the account at the end of $t - 1$. One may also be interested in how investors initiate new positions. In Appendix Table A1, we examine initial buying of new stocks (not held by the account at the end of day $t - 1$). Similar to net-buy, we find that margin investors are less likely to buy new positions following negative Z-shocks. We also find that margin investors are more likely to buy new stocks when they are far from their Pinggang lines ($Z > 5$) than when they are closer ($Z < 5$). Unlike with net-buy, we do not see sharp non-linear changes in initial buy when accounts move very close to their Pingcang Lines, suggesting that initial buying is less tied to leverage constraints than net-buying (which captures liquidation of holdings). Further, we find that brokerage margin investors that choose to use leverage have significantly greater initial-buying compared to margin investors without any leverage on

4.1 Trading Activity

We now examine margin investors' trading activity as a function of the distance-to-margin-call (captured by Z) as well as changes in distance-to-margin-call (captured by the Z-Shock), using the non-parametric framework described in Section 3.

Formally, we estimate stock-account-date panel regressions as specified in Eq. (10) that include both stock-date and account fixed effects, with standard errors triple-clustered at the account, stock, and date levels. Our study investigates seven Z bins: $Z > 5$, $Z \in [\tau - 1, \tau)$ for $\tau = 1, 2, 3, 4, 5$ and finally $Z < 0$ which corresponds to account-date observations whose leverage is above its Pingcang Line. Unlevered account-day observations form the omitted category and serve as the base group in our regression analyses.[31] More precisely, as explained toward the end of Section 3.1, we have set their Z to "NA" (so they belong to the highest-indexed group $K + 1$) and their ΔZ_t^j to be zero (as the account return has no impact on the margin constraint of an unlevered account); the estimated coefficient for each Z bin (i.e., $\hat{f}_k$ in Eq. (10)) captures the additional trading intensity relative to these non-levered margin accounts.

Recall that Z is measured at the end of trading day $t - 1$, while net buying is measured on trading day t. We measure Z-Shocks contemporaneous to trading; in the next section, we also confirm that shocks during day t continue to affect trading (and returns) in day $t + 1$.

4.1.1 Margin trading: Z and Z-Shocks

The regression results are provided in Table 2. Column (1) shows that brokerage margin accounts facing margin calls ($Z < 0$) sell an additional 22.9% of their current stock holdings, compared to unlevered margin accounts. We also find that selling pressure increases non-linearly as the distance-to-margin-call falls (as Z approaches zero). For instance, the coefficient for a brokerage margin account with Z between 0 and 1 (-10.59, i.e., 10.59% of selling) is about three times that in a brokerage margin account whose Z is greater than 5 (-4.22, i.e., 4.22% of selling).[32] The pattern of intensified liquidation activity as Z approaches zero is robust to looking at the brokerage sample (Column 1), shadow sample (Column 2), and the combined full sample (Column 3), and is consistent with a precautionary motive in theories on leveraged trading (e.g., Garleanu and Pedersen, 2011; He and Krishnamurthy, 2019). The strong non-linear relationship between Z and *NetBuy* as shown in Table 2 is suggestive of the role of leverage constraints rather than merely amplified equity returns, as investors are selling more when they are close to hitting the

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the same day. This difference likely reflects differences in the preferences and beliefs of margin account holders who choose to use leverage on a given day.

[31] In the data, the behavior of accounts that never move across Z-bins will be absorbed by the account fixed effects in our regression. Excluding accounts that always stay in the omitted group throughout the sample period, only 24% of accounts never move across Z bins.

[32] Given our focus on margin accounts that are facing some material risk due to the leverage constraint (i.e., hitting Pingcang Line in a day), we do not further partition accounts whose Z is greater than 5. We confirm that further partitioning these "safe" accounts into more Z-bins does not change our results and selling pressure continues to weaken when Z increases.

Pingcang Line (the leverage constraint). (We will return to this point of leverage constraints shortly in Section 4.2.)

Table 2 also reports a significant and positive coefficient (which we have normalized to 1) on the Z-Shock;[33] this implies that when the margin account experiences a negative shock today that pushes it closer to the Pingcang Line, there is less contemporaneous net buying, or equivalently, more selling. Given the scaling of Z-shock to have a coefficient of 1 in the full sample, a one-standard-deviation negative move in the Z-Shock (equal to 2.19% in the full sample) implies that margin investors in the full sample sell additional stocks over the course of day t that is equal to approximately 2.19% of their stock holdings (recall that $NetBuy$ is expressed in percentage points). It is interesting to observe that the coefficients for brokerage and shadow accounts are also close to 1, when estimated separately in Column 1 and 2.

Note that our estimation implies significant non-linearity. For illustration, compare the bin that is very close to the Pingcang Line $Z \in (0, 1)$, to the one with $Z > 5$ which is far away. In the whole sample estimation reported in Column 3, the estimated $g_k = 4.06$ (unreported) for $Z \in (0, 1)$. Then, together with the mediam $Z'(R)|_{R=0}$ in this bin based on formula (5) in Section 3.1, it implies that our Z-Shock ΔZ_t^j has an amplification factor of—i.e., the coefficient in front of R_t^j—of 194.52. The same amplification factor for $Z > 5$, with estimated $g_k = 0.77$ (unreported), is an order of magnitude smaller, only at 19.63.

Brokerage versus shadow accounts Comparing Column 1 (brokerage accounts) to Column 2 (shadow accounts), we find much stronger precautionary selling by shadow margin investors, especially as their accounts approach the Pingcang Line. For instance, when $Z \in (0, 1]$, the additional selling pressure is 23.2% if the stock appears in a shadow account, compared to 10.6% when it appears in a brokerage account. Interestingly, the selling intensity flips once the account exceeds the Pingcang Line ($Z \leq 0$): the additional selling pressure is 19.9% for shadow accounts, but it rises sharply to 22.9% for brokerage accounts.

These differences can be explained by the institutional background explained in Section 2.1.2. As mentioned, during our sample period, the Chinese brokerage margin system is more rule-based while its shadow margin system is more discretion-based. Brokerage creditors seize control of accounts with $Z \leq 0$ and engage in automated settling. However, due to lack of automated implementation within the shadow system, the selling of stocks in under-water accounts is potentially delayed because of the creditor discretion.[34]

The lack of automated processing of debt financing in the shadow system also implies that each new request for margin financing needed to be reviewed by the mother account in an ad-hoc way. This provides a motivation for shadow margin investors to retain a relatively large cash balance

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[33]Recall that we have scaled our construction of Z-Shock so that the trading response to a one-unit change in Z-Shock in the full sample (Column 3) is equal to one; see footnote 29.

[34]Some margin accounts in our sample have leverage significantly above their Pingcang Lines. These observations likely correspond to cases in which creditors have gained control, but are unable to immediately sell their holdings due to daily price limits (the 10-percent-rule).

in case they cannot secure timely additional financing, while brokerage margin investors tend to quickly pay down margin debt to reduce borrowing costs. Indeed, as shown in Table 1 Panel A, shadow margin investors keep 22% of their portfolio value in cash, and this ratio is less than 10% for brokerage margin investors. By converting risky stock holdings to cash, shadow investors reduce their asset volatility, and thereby increase their distance-to-margin-call Z. However, the same stock sales by a brokerage investor would lead to a greater increase in Z because brokerage investors generally use sales proceeds to pay down debt. Thus, the greater selling intensity by shadow investors (relative to brokerage investors) as Z nears zero is consistent with the fact that shadow investors have to sell more stock to achieve a similar increase in Z.[35]

Trading in up and down markets   In columns (4) and (5) of Table 2, we examine the relation between trading and distance-to-margin-call separately for up and down market periods, defined as the periods before and after June 15th, 2015 (the peak of the market), respectively. This exercise reveals an interesting asymmetry: The extent to which margin investors sell a greater fraction of their holdings as the Z-bins move closer toward zero is approximately two to three times stronger in the down market period than in the up market period. Likewise, the relation between net buying and Z-Shock is approximately 20% stronger in the down market period. A stronger relation between trading behavior and measured Z is expected during the down market period. As explained previously, we measure the account's distance-to-margin-call using data on stock volatility in the year prior to the start of our sample period to avoid a look ahead bias. Average stock volatility more than doubled during our sample period relative to the previous year, and was particularly high during the down-market period. Thus, for a given measured Z, margin accounts were actually closer to their Pingcang Lines, especially during the down market period.

4.1.2   Margin trading of lottery-like stocks

Next, we explore how the impact of distance-to-margin-call (Z) on trading behavior interacts with whether the stock exhibits lottery-like characteristics. As before, we find that investors are significantly more likely to sell their holdings as their distance-to-margin-call shrinks toward zero. In addition, we find that margin investors are more likely to sell non-lottery stocks while continuing to hold lottery stocks. This is especially true during the down-market period. These results are consistent with the view that margin investors buy and hold lottery stocks for their upside potential and as a way to gamble for resurrection when they move closer to distress.

Table 3 reports regressions of *NetBuy* on Z-Shock and its interaction with a measure of the extent to which a stock exhibits lottery-like features, along with controls for Z bins and account and date fixed effects. Recall in Section 2.3.2 we use the variable *Lottery-ness* to represent the maximum number of days that stock i consecutively hit the upper 10% return cap during the one

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[35]In addition, the greater precautionary selling by shadow investors may relate to their anticipation of future regulatory tightening, as we will discuss in Section 4.2.3.

year before our sample period (05/01/2014 to 04/20/2015). Compared to non-lottery stocks, we find that margin investors are significantly less likely to sell lottery stocks after negative Z-Shocks.

To gauge some economics magnitudes, take the full sample result reported in Column (3). For a lottery stock that consecutively hit the upper $+10\%$ daily limit, say four times, in the year prior to our sample period, margin investors are 5.7% ($= 0.015 \times 4/1.045$) less likely to sell a lottery stock compared to a non-lottery stock that never hit the upper daily limit. Comparing Column (1) to Column (2), we find that the difference in selling behavior of lottery and non-lottery stocks is magnified during the down-market period from June 15th to July 31st compared to the up-market period from May 1st to Jun 12th. During the market downturn, margin investors were 10.4% less likely to sell a lottery stock that consecutively hit the upper daily limit four times than a non-lottery stock that never hit the upper daily limit. In contrast, investors sold lottery and non-lottery stocks similarly in response to Z-Shocks in the up-market period (Column 1). The stronger tendency of margin investors to sell non-lottery stocks during the market downturn is consistent with our hypothesis that Chinese margin investors use investments in lottery-stocks for their upside potential, which may be particularly valued during downturns when investors are more distressed.

In Appendix Table A2, we use an alternative measure of lottery stocks following the methods in Liu et al. (2022). In our previous specification, we measured lottery stocks using the maximum number of *consecutive* days in which a stock hits the upper 10% limit, whereas Liu et al. (2022) does not use the consecutive requirement. We find qualitatively similar results with larger effect sizes using the alternative measure; margin investors are significantly more likely to sell lottery stocks than non-lottery stocks in response to negative Z-shocks.

4.1.3 The impact of selling restrictions

Finally, we show that selling pressure from margin investors for a given stock is affected by trading restrictions applying to other stocks held in the margin investor's portfolio. As explain in the institutional background provided in Section 2.2, due to the $\pm 10\%$ trading halt rule, a stock faces significant selling restrictions whenever its price reaches its daily price (lower) limit, which is 90% of the previous closing price. Also, a handful of stocks experienced prolonged trading suspensions during our sample period.

Consider stock i held by account j on day t, and suppose that i does not face selling restrictions. Stock i's selling pressure (in response to the same negative Z-Shock) should be higher if other stocks in account j cannot be sold due to selling restrictions. Table 4 tests this prediction by repeating the same exercise as in Table 2 but also including $\%Restriction$ (the fraction of stocks held by the account facing selling restriction and being suspended on that day, excluding stock i itself) and its interaction with Z-Shock. We find a positive and significant coefficient on the interaction between Z-Shock and $\%Restriction$ in all three samples (brokerage, shadow, and combined), which confirms a stronger selling response to the same negative Z-Shock when the account faces selling restrictions in its other holdings.

4.2 Margin Trading: Evidence for Causality

Recall that Table 2 shows that margin investors sell more of their holdings as their distance-to-margin-calls Z shrinks toward zero and after negative Z-Shocks; we argue that this selling behavior is primarily driven by leverage constraints. However, there are two possible alternative explanations for the relation between selling behavior and Z, and the coefficients in our baseline empirical specification in Eq. (4) likely capture all of them. First, distance-to-margin call is correlated with returns on their stock investments, so it is possible that investors sell holdings as a response to poor returns rather than increased leverage constraints that are specific to margin investors. Second, margin investors may target a certain level of leverage, and their trades could be driven by a rebalancing motive unrelated to leverage constraints.

In this section, we present tests to identify a causal role of leverage constraints. In these tests, our goal is not to reject these alternative explanations. Indeed, it would be unreasonable and unrealistic to argue that investors never trade in response to their account levered returns. Rather, our goal is to rule in a large role specific to leverage constraints.

4.2.1 Margin eligibility

In this section, we identify the role of leverage, as distinct from returns, in affecting margin investors' trading behaviors. Our test compares the trading behavior of brokerage margin investors who just qualified for a margin account and brokerage investors who just failed to qualify for a margin account trade. Our tests exploit the fact that, as mentioned in Section 2.1.1, brokerage clients are eligible to open a margin account if assets in their normal (non-margin) account, averaged over the past month (20 trading days), exceeded 500K RMB.

More specifically, we consider how investors react to their "equity returns," which are equal to the levered return for margin investors and unlevered return for non-margin investors. Our tests focus on reactions to equity returns rather than asset returns (i.e., the return delivered by the account's stock holdings), because a simple leverage effect implies that the equity return for a margin investor is an amplified version of her asset return. Thus, it would not be surprising to find that margin investors trade more strongly in response to the same asset return than non-margin investors. Instead, we test whether margin investors react more strongly to the same equity return.

We conduct our analysis in the style of a differences-in-differences comparing how treated and control groups respond to their equity returns. Control observations correspond to non-margin accounts that do not have associated margin accounts, with average assets between 400K and 500K during the first 20 days in the sample period (05/01/2015-05/20/2015). Treated observations correspond to brokerage margin accounts with average assets between 500K and 600K in their associated non-margin accounts in the 20 days before the opening day of the margin account. For margin accounts opened prior to May 20th, 2015, we do not observe account balances for a full 20 days prior to margin account opening. Instead, we use an approximation and categorize these margin accounts as treated if they have total equity between 500K and 600K in their combined

non-margin and margin accounts during the first 20 days of the sample period.

In Table 5 Panel A, we regress *NetBuy* at the account-stock-day level on the account's equity return over the previous day as well as the interaction between the equity return and an indicator for whether the observation belongs in the treatment group (just-eligible margin accounts). Following the standard differences-in-differences approach, we control for date and account fixed effects (which absorb the direct effect of the treatment indicator) in the regression, and the sample is limited to brokerage account observations in the treatment or control groups. In Column (2) we also include indicators for Z bins; for observations in the control group, this indicator is set to the omitted category representing unlevered accounts. We are interested in how treated and control observations trade in response to the equity return, which, as explained previously, equals the levered (unlevered) account return for the treatment (control) group.

In Table 5 Panel A, we find that just-eligible margin investors exhibit approximately double the trading response to the same equity return as just-ineligible investors in the control group. In other words, investors are generally more likely to sell (buy) their holdings following negative (positive) returns, but the trading response to a given return is twice as large for margin investors than for a similar group of brokerage investors who just failed to qualify for margin trading.

To recap, margin traders may react more strongly to the same *asset* return because their equity return is amplified due to leverage. However, Table 5 Panel A identifies an effect that is beyond this traditional leverage amplification channel. We find that margin investors react twice as strongly to the same *equity* return. This difference in response to equity returns is suggestive of a leverage constraints channel which we identify in the next section.

4.2.2 Shadow accounts with heterogeneous leverage constraints

In this test, we focus on the sample of shadow accounts where two accounts can have the same leverage but face different degrees of leverage constraints, thanks to differences in their Pingcang Lines as mentioned in Section 2.2. Instead of regressing net buying on Z-Shock, which is a "structural" object, we take a more reduced-form approach by separately including $LP = \frac{\overline{Lev} - Lev}{Lev - 1}$ (Leverage-to-Pingcang, introduced in Eq. (2)), $Lev \times R$ (levered account return, i.e., equity return), and their interaction $LP \times Lev \times R$.

In Panel B of Table 5, Column (1) with Z-bins and Column (2) without Z-bins as controls, we confirm that the interaction term is significantly negative. In other words, holding constant account leverage and the levered return, a (shadow) margin investor sells more of her holdings in response to the same levered return if her account is closer to its leverage constraint. The significant negative interaction term points to the role of a leverage constraint, and echoes the evidence in the previous Section 4.2.1: there, we showed that just-eligible margin accounts trade differently from just-ineligible brokerage accounts, even with same equity return.

One potential concern with shadow accounts is that their Pingcang Lines are not randomly chosen. To alleviate this concern, we use a reduced-form instrument for a shadow margin trader's

Pingcang Line. We notice that margin traders who opened their accounts in the shadow market around the same time tend to have similar Pingcang Lines. The variation in average shadow Pingcang Lines over time is likely to be driven by aggregate shadow credit supply shocks (as opposed to individual credit demand that causes the above identification concern).

Motivated by this pattern, for each shadow margin account, we define a peer Pingcang Line as the average Pingcang Line of all other shadow accounts opened on the same day (Pingcang Lines are significantly correlated with the corresponding peer Pingcang Lines with p-value < 0.01). In columns (3) and (4) of Panel B, we repeat the same analyses in columns (1) and (2) on our shadow margin accounts, but replace the account's Pingcang Line with the peer Pingcang Line when computing Z and LP (denoted by Z^* and LP^* accordingly). The results are similar, suggesting that it is the leverage constraint (rather than account characteristics that are potentially correlated with investors' risk-aversion) that induces selling activity.

4.2.3   Trading behavior around policy shocks

In this section, we present further evidence to "rule in" a leverage constraints channel by studying how investor trading responds to a policy announcement of regulatory tightening. On Friday, June 12th, 2015, the CSRC banned the creation of new shadow-financed margin accounts. While the regulator did not directly tighten Pingcang Lines for existing shadow accounts, the announcement increased anticipation of future regulatory tightening of shadow leverage. In particular, shadow investors feared that lenders would reduce Pingcang Lines, deny borrowing requests, or sell more aggressively following margin calls (see our discussion in Section 2.1.2).

The June 12th announcement can be viewed as a shock to investor anticipation of future tightening of leverage constraints in shadow accounts. We view the anticipation of government tightening as part of the broader leverage constraints mechanism, as the tightening of margin trading rules effectively pushes investors closer to their Pingcang Lines. Under our framework in which distance-to-margin-call Z acts as the state variable, anticipation of increased leverage constraints contributes to a smaller *effective* Z for a given *measured* Z. In other words, this specific mechanism–that investors sell risky holdings in anticipation of government tightening on shadow margin trading–is broadly consistent with our overall hypothesis that investors liquidate stock in the face of tightening leverage constraints.

The June 12th policy announcement coincided with and may have contributed to the broad market downturn that began on June 15th, 2015. To isolate the impact of tightening leverage constraints on trading behavior, we compare how brokerage and shadow accounts' trading behavior changed around the policy shock. The underlying assumption is that changes in general market conditions had a common effect on brokerage and shadow margin investors, but shadow margin investors were more impacted by the direct threat of regulatory tightening on the shadow sector.

Specifically, we repeat the exercise in Columns (1) and (2) of Table 2 separately for the week before the policy shock (June 8th to June 12th) and the week after (June 15th to June 19th). For

ease of exposition, in Figure 4, we plot the regression coefficients on the Z-bins and the Z-Shock for shadow accounts (Panel A) and brokerage accounts (Panel B).

Panel A presents clear evidence that selling across all Z bins by shadow investors intensified in the week after the policy shock relative to the week before. More importantly, the response to the regulatory shock displays a striking monotone pattern in Z;[36] and for $Z \in (0, 1]$, selling activity intensifies from -17.02% in the week before to -36.67% in the week after, with a 19.34% difference that is statistically significant at 1% level. We also observe a statistically significant policy-induced difference (0.57 percentage points) in Z-Shock responses before and after the regulatory tightening. In sharp contrast, as shown in Panel B, there is no clear change in the relation between trading and Z for brokerage margin investors. In fact, none of the changes (Z-bins and Z-Shock) in the coefficient estimates in response to the policy shock by brokerage investors are statistically significant, despite a larger sample size for our brokerage-financed sample.

The contrasting reactions by shadow and brokerage accounts to the regulatory tightening announcement provide additional support for the perspective that leverage constraints have played an important role in driving margin investors' selling behaviors during the market downturn in our sample period.

5 Price Impact *via* the Leverage Network

As discussed in Section 3.4, when margin investors adjust their holdings in response to Z-Shocks, their trading and the associated price impact may transmit shocks across stocks via common holdings by the same margin investor. Since leverage-induced trading may take more than one day to complete, such leverage-network-based transmission can go beyond the current trading day. In the Appendix, we confirm that negative Z-Shocks on day t significantly predict selling in day $t + 1$ as well. We therefore examine how the leverage network transmits Z-Shocks across stocks and impact future returns. We focus on next-day returns, instead of contemporaneous returns, to alleviate some obvious reverse-causality concerns.

Our main independent variable is the margin-account linked portfolio return ($MLPR$) introduced in Section 3.4. To recap, $MLPR$, which is defined as the weighted-average daily return of all margin accounts holding the stock on a particular day after removing the stock's own contribution to each account's return, measures the buying/selling pressure stemming from changes in the value of *other* stocks that are linked to the one in question through the margin-investor-common-holdings network. Importantly, the weights are based on a function of the distance-to-margin-call for each account (i.e., $Q_t^j = g_k I_{kt}^j \cdot Z'(R)|_{R=0}$ in Eq. (11)) to reflect our earlier finding that leverage-induced selling by margin accounts depends on how close the account is to hitting its leverage constraint. The summary statics of $MLPR$ are provided in Table 1 Panel D.

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[36]The muted response for accounts that have been taken over by creditors ($Z < 0$) is partly due to the discretion-based shadow margin system; see related discussion in Section 4.1.1.

We proceed in this section by first discussing our empirical approach given potential challenges to identification, and then present the empirical results.

5.1 Empirical Design

A contagion story implies that $MLPR$ should positively forecast stock i's next day return. However, these patterns could also reflect an important alternative channel. Margin traders do not choose stock holdings randomly. They may hold related stocks that move together for other reasons. For example, margin traders may select toward large liquid stocks, and these stocks may comove due to common risk exposures or other factors. Before proceeding to detailed results, we summarize how we plan to identify a contagion channel, as distinct from a related-holdings story.

We address the potential alternative explanation in several ways. First, we control for observable stock characteristics and past return patterns that could lead to comovement. Second, consistent with the trading asymmetry shown in Section 4.1.1 that investors are more likely to sell in response to negative shocks than to buy following positive shocks, we document a strong asymmetric effect: $MLPR$ only predicts stock returns during markets downturns. This asymmetric response does not match a simple related-holdings story in which related stocks experience both positive and negative comovement.

Third, we control for related stock holdings by constructing a variable, "non-margin-account linked portfolio returns" or $NMLPR$, using non-margin brokerage accounts that are ineligible for margin trading but are similar to margin accounts in terms of account size and trading volume. To the extent that these matched non-margin accounts choose to hold related stocks in a similar fashion to margin accounts, including $NMLPR$ in the regression will control for comovement due to related holdings. Empirically, we find that $NMLPR$ does not predict return movements in the down market and controlling for $NMLPR$ does not change the predictive power of $MLPR$.

Fourth, we address the possible remaining concern that margin investors hold related stocks with similar downside risk exposure, so they comove more in response to negative common shocks. To better identify true contagion from unhealthy stocks to healthy stocks, we consider transmission of shocks from stocks that face selling restrictions to stock i that is not affected by selling restrictions directly. We sort all margin accounts into two groups based on the account's selling restrictions for *other* stocks holdings, and construct two $MLPR$ measures for each stock i: $MLPR_{High}$ and $MLPR_{Low}$ based on accounts with high and low selling restrictions for other holdings, respectively. We find that $MLPR_{High}$ is associated with much stronger return predictability than $MLPR_{Low}$. These results are consistent with the view that selling restrictions transmit negative return shocks from constrained stocks (which could not be sold) to unconstrained stocks (which were the only stocks that leveraged investors could sell). In a similar spirit, we also examine the difference between lottery vs. non-lottery stocks. Earlier results in Section 4.1.2 suggest that when facing negative Z-Shocks, margin investors sell non-lottery stocks more aggressively. Therefore, we would expect non-lottery stocks to be more exposed to contagion risk. Indeed, we find that $MLPR$ predicts the

return of non-lottery stocks more strongly than that of lottery stocks.

Fifth, we document a return reversal, as expected if the initial $MLPR$ shock is a non-fundamental shock, and prices eventually revert to fundamentals. Slow information diffusion may also explain lead-lag return relations among related stocks, but there should not be a reversal afterwards.

Finally, as discussed in detail in Section 3.4, we construct $MLPR$ as though investors liquidate assets in proportion to their initial holdings according to the average relationship between percentage sales and a given leverage shock. Similar to the approach taken by Edmans et al. (2012) and Lou (2012) in studying mutual fund flow-induced trading and the resulting price impact, we employ this counterfactual proportionality assumption on purpose to strip $MLPR$ of omitted variables that could both forecast a stock's future returns and be correlated with liquidation choice. For completeness, we also relax the proportional sales assumption and incorporate liquidation choice as a function of stock characteristics. We first estimate investors' trading decision as a function of stock characteristics; for instance, the investor liquidates more of a stock if it is more liquid. We then recompute $MLPR$ using predicted sales based on the average relationship between a stock's characteristics and sales in our sample, instead of the investor's actual sales in each specific instance. Doing so purges $MLPR$ of omitted variables that may drive the investor's specific sale decision of each stock and its future returns.

5.2 Shock Propagation

We present the main empirical results in this subsection. We show the regression results with "non-margin-account linked portfolio return" as a control. In addition, we study the role of trading restrictions and lottery holdings in shock transmission via leverage networks.

5.2.1 Baseline regression with $NMLPR$

To examine shock propagation, we estimate the following Fama-MacBeth return forecasting regression:

$$R_{i,t+1} = \alpha + \beta \cdot MLPR_{i,t} + \beta_N \cdot NMLPR_{i,t} + \sum_m \lambda_m \cdot CONTROL_{i,m,t} + \varepsilon_{i,t+1}, \qquad (15)$$

where $R_{i,t+1}$ is the return of stock i on day $t+1$ and $CONTROL_{i,m,t}$ is a set of stock characteristics that are known to forecast future returns.

Importantly, we also include the non-margin-account linked portfolio return ($NMLPR$), defined in a similar manner as $MLPR$. We compute $NMLPR$ using 210,000 matched non-margin accounts; they are brokerage normal accounts that are not eligible for margin trading but with similar account size and trading volume (as our full sample of margin accounts). To compute $NMLPR$, we assume Q in Eq. (11) to be a positive constant for all non-margin accounts.[37] $NMLPR$ helps us control for

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[37]This is consistent with zero leverage for these non-margin accounts. In fact, we can use any constant here, as it is simply a scalar which becomes irrelevant when we standardize $NMLPR$ cross-sectionally in the Fama-MacBeth regressions.

stock characteristics that give rise to common investor ownership. We include $NMLPR$ together with $MLPR$ in the same regression to isolate the incremental effect coming from margin traders via leverage networks.

The results are shown in Table 6. We standardize both $MLPR$ and $NMLPR$ in each cross-section and label them $SMLPR$ and $SNMLPR$, respectively, so the coefficients represent the impact of a one-standard-deviation change on (network-amplified) stock returns. Column (1) reports results for the full sample period. We find that a one-standard-deviation increase in $MLPR$ predicts a higher next-day return of 10 bps (t-statistic $= 2.86$), after controlling for the stock's lagged leverage ratio, past returns, and an array of other stock characteristics.

To gauge the economic magnitude of the documented price impact, we note that the standard deviation of $MLPR$ (i.e., aggregate margin-induced trading, as defined in Eq. (11), of all margin investors in our sample) is 0.74bps of shares outstanding and 11bps of the daily volume (the average daily turnover is roughly 6.5% in our sample). Moreover, our sample of margin investors, on an asset-weighted basis, accounts for roughly 4.5% of all margin investors in the market. To the extent that our sample is representative of the population (as discussed in Section 2.2), the standard deviation of aggregate margin-induced trading by all margin investors in the market is 2.44% ($=0.11\%$ / 4.5%) of the daily volume. This is a non-trivial fraction of daily trading volume; combined with a return effect of 10 bps, it implies a price elasticity of demand of 1.64 ($= (0.0074\%/4.5\%)$ / 0.10%). Due to the daily up and down price limits, 1.64 likely serves as an upper bound for the true elasticity (as daily price movements would be larger in absence of the daily limit). This figure is largely in line with the estimates of individual stock demand elasticities in the U.S. For example, Lou (2012) estimates an elasticity of 1.2 using mutual fund flow-induced trading.

Columns (3) and (5) repeat the same exercise, separately for up and down markets, defined as the periods before and after June 15th, 2015 (the peak of the market), respectively. Consistent with the last two columns reported in Table 2, these two columns show that the predictive power of $SMLPR$ for returns is present only in market downturns. Specifically, the coefficients on $SMLPR$ for the up and down markets are 0 bps (t-statistic $= 0.11$) and 18 bps (t-statistic $= 4.93$), respectively. The asymmetry in margin-induced price impact between the up and the down markets is consistent with the notion that, when the shadow-financed margin system faced regulatory tightening, investors chose to scale down their holdings, leading to a significant price effect. The reverse, however, is not necessarily true for a loosened margin constraint during the up market.

In Columns (2), (4) and (6), we conduct similar regressions as those reported in Columns (1), (3) and (5), except that we also control for the non-margin-account linked portfolio returns ($SNMLPR$). To the extent that matched non-margin accounts choose to hold related stocks in a similar fashion to margin accounts, controlling for $SNMLPR$ allows us to isolate the incremental impact from common ownership by margin investors. Column (2) shows an insignificant coefficient on $SNMLPR$ for the full sample period. Examining the up and the down markets separately, we

find the coefficient on $SNMLPR$ to be positive and significant only in the up market. The stark difference between $SMLPR$ and $SNMLPR$ suggests that the return predictability of $SMLPR$ is likely due to margin investors' tendency to trade in response to changing margin requirements and market conditions.

5.2.2 Trading restrictions

We first exploit the variation in account-level trading restrictions faced by margin investors. For each stock-day, we create two groups of accounts: $High$ and Low, based on whether the fraction of *other* stock holdings with selling restrictions is in the top 30% or the bottom 30% of the cross-sectional distribution, respectively, at the end of the previous day. For each stock in our sample, we construct two $MLPR$ measures: $MLPR_{High}$ and $MLPR_{Low}$, using only the subsamples of $High$ accounts and Low accounts, respectively. Since selling pressure is higher for stocks held by $High$ accounts, $MLPR_{High}$ should be associated with stronger return predictability than $MLPR_{Low}$. In Table 7, we analyze the price impact associated with $MLPR_{High}$ and $MLPR_{Low}$. For ease of interpretation, we standardize both variables in the regression. In columns (5) and (6) where we focus on the down market, the coefficients on $SMLPR_{High}$ are significantly larger than those on $SMLPR_{Low}$. In fact, the coefficients on $SMLPR_{Low}$ are statistically insignificant in these two columns. In other words, as leverage-induced selling intensifies for stocks held by margin accounts that cannot sell other holdings, this leads to a greater price impact for connected stocks.

5.3 Lottery vs. Non-lottery Stocks

Section 4.1.2 shows that when facing negative Z-Shocks, margin investors sell non-lottery stocks more aggressively, tilting their remaining portfolios towards lottery stocks. Such trading behavior suggests that non-lottery stocks are more exposed to contagion risk. When we divide our sample into lottery and non-lottery stocks and rerun the return predictive regression in each sub-sample, we indeed find $MLPR$'s return predictive power to be stronger among non-lottery stocks during the down market. Specifically, as shown in Column (5) of Panel B in Table 8, a one-standard-deviation increase in $MLPR$ predicts a higher next-day return of 19 bps (t-statistic $= 4.64$) among non-lottery stocks. The corresponding number for lottery stocks is only 13 bps (t-statistic $= 2.94$) as in Panel A.

5.4 Other Results

Liquidation-choice-adjusted $MLPR$ Recall that we have constructed $MLPR$ as though investors liquidate assets in proportion to their initial holdings according to the average relationship between percentage sales and a given leverage shock. For completeness, we now relax the proportional sales assumption and incorporate liquidation choice as a function of stock characteristics. As explained in Appendix Table A4, repeating the analysis in Table 6 but using this liquidation-choice-adjusted

$SMLPR$ produces even stronger results. For example, a one-standard-deviation increase in this new $SMLPR$ predicts a higher next-day return of 14 bps in the full sample, and 33 bps during the down market, after controlling for other stock characteristics.

Return reversal   Finally, if the return effect associated with $MLPR$ reflects price pressure from leverage networks that is unrelated to the fundamental value of stocks, we expect the temporary return reaction on day $t + 1$ to eventually revert. To test this, we repeat the same regression as in Column 2 of Table 6, but now focus on cumulative stock returns over a longer horizon. Specifically, we use the cumulative returns from $[t + 1, t + h]$ for $h = 5, 10, 15, 20, 25, 30$ and 35 as the dependent variables. The coefficients on $SMLPR$ are plotted graphically in Figure 5. We find that the initial positive significant relation between future returns and $SMLPR$ converges toward zero and becomes insignificant within 35 trading days. While our estimates for the cumulative return response to $SMLPR$ become noisy as the return horizon expands, the overall pattern is consistent with a full reversal within 35 days.

6   Conclusion

Taking advantage of unique and granular data of margin investors' leverage and trading activities during the 2015 market turmoil in China, we conduct the first systematic study of the characteristics of margin traders and how their margin constraints affect their trading and asset prices. Our data cover both regulated brokerage-financed margin traders and unregulated shadow-financed margin traders.

We find that margin traders tend to hold stocks with more scope for "informed trading" and lottery-like features, though they do not outperform their unlevered counterparts. Our results thus suggest overconfidence and lottery preferences as two important drivers of retail margin trading. They erroneously believe that they can beat the market and therefore are willing to pay an annual interest rate of up to 25% in order to lever up.

Both shadow and brokerage margin investors heavily sell their holdings when their account-level leverage edges toward their Pingcang Lines (the maximum leverage limit, or maintenance margin), controlling for stock-date and account fixed effects. In other words, we find strong empirical support for both forced and preemptive margin-induced trading. The fact that investors react asymmetrically to positive and negative return shocks suggests a leverage constraint channel in addition to a rebalancing motive. We exploit the discontinuity around the eligibility of brokerage margin trading and the variation in Pingcang Lines across certain shadow accounts to provide unique evidence that leverage constraints induce selling. An event study around the regulatory tightening of shadow margin constraints provides further support.

Aggregating trading behavior across margin investors, we find a significant return spillover in the near future: a stock's return can be strongly forecasted by a portfolio of stocks with which it shares common margin-investor ownership. This pattern is subsequently reversed, and is present

only in market downturns. We also show that China's price limit rule led to unintended contagion across stocks.

Our results have important implications for academics, policy makers, and practitioners who are interested in the effect of margin trading on asset return dynamics. While margin lending and borrowing is an integral part of a well-functioning financial system, it can also lead to contagion across assets. In addition, our analysis of unique shadow margin data offers insight into how investors behave when new financial innovations relax leverage constraints ahead of regulation.

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Figure 1
Structure and Funding Sources of Margin Systems in the Chinese Stock Market

Panel A depicts the funding sources of both the brokerage- and shadow-financed margin systems in the Chinese stock market. Panel B depicts the structure of the shadow-financed margin system. Each mother account appears to the brokerage firm as a normal, unlevered, brokerage account with a large quantity of assets and high trading activity. In reality, the mother account is managed by a shadow financing company and linked via FinTech software to multiple child accounts. Orders submitted by child accounts are automatically routed through the mother account to the brokerage firm in real time.

Panel A: Funding Sources of Margin Systems
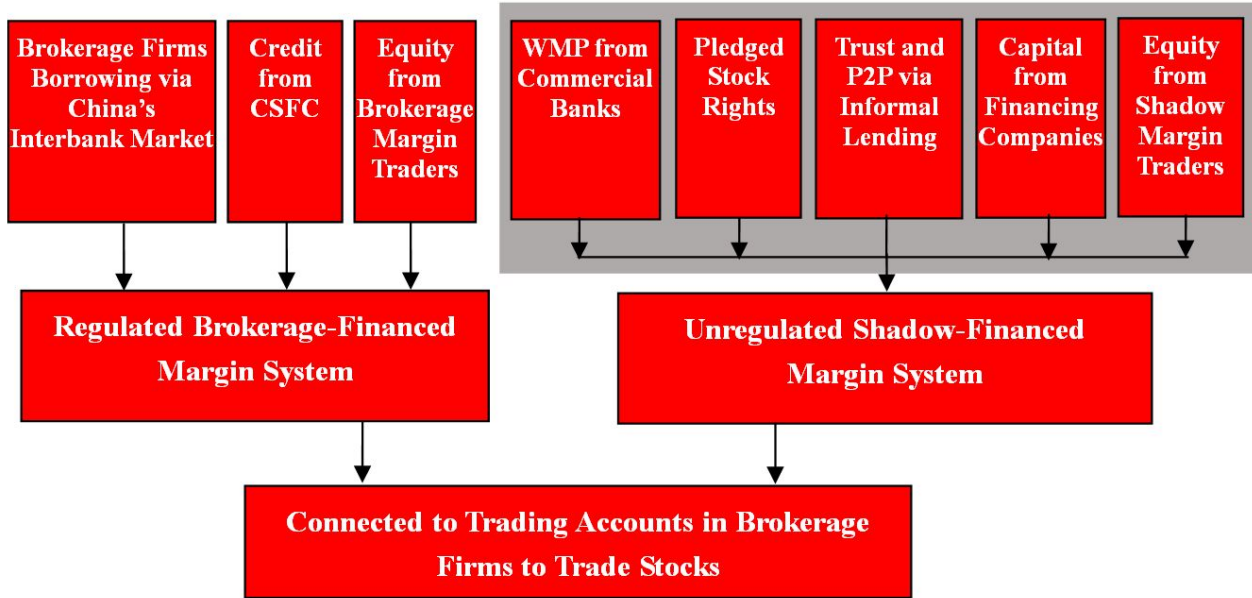
Panel B: Structure of the Shadow-Financed Margin System
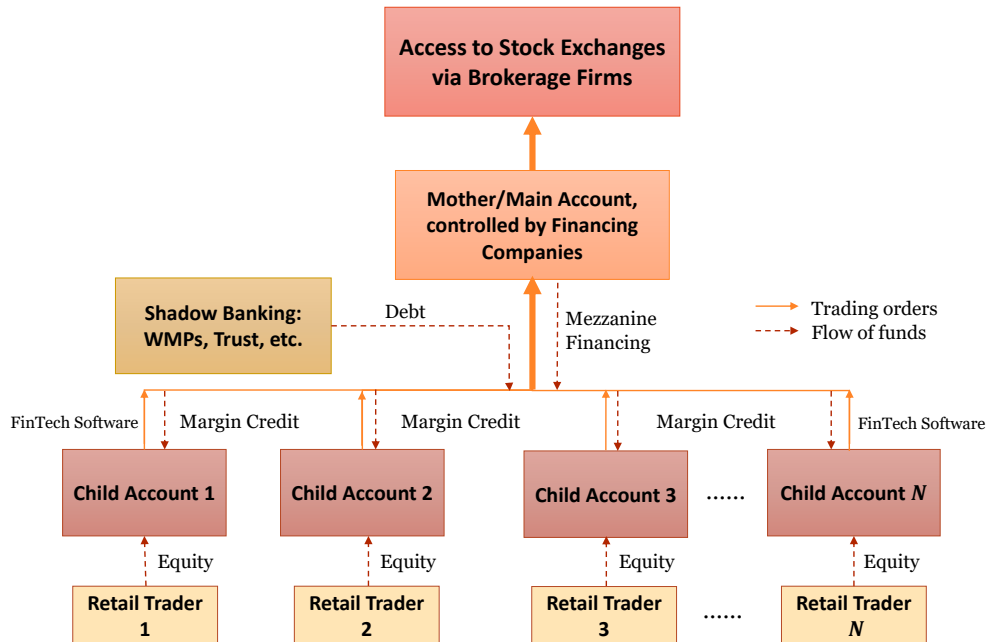
Figure 2
Leverage of Brokerage and Shadow Margin Accounts

Panel A shows the Shanghai Stock Exchange (SSE) composite index (the dashed blue line), the average leverage ratio of shadow margin accounts (the solid red line), and the average leverage ratio of brokerage margin accounts (the dashed-dotted red line) for the period May to July, 2015. Average leverage ratios are weighted by the equity amount of each account; in other words, the average leverage equals the total debt divided by total equity in the margin system. Panel B presents the asset-weighted (the solid red line) and equity-weighted (the dashed-dotted red line) average leverage for the combined sample of brokerage and shadow margin accounts for the period May to July, 2015.

Panel A: Equity-weighted Leverage, Brokerage vs. Shadow Margin Accounts
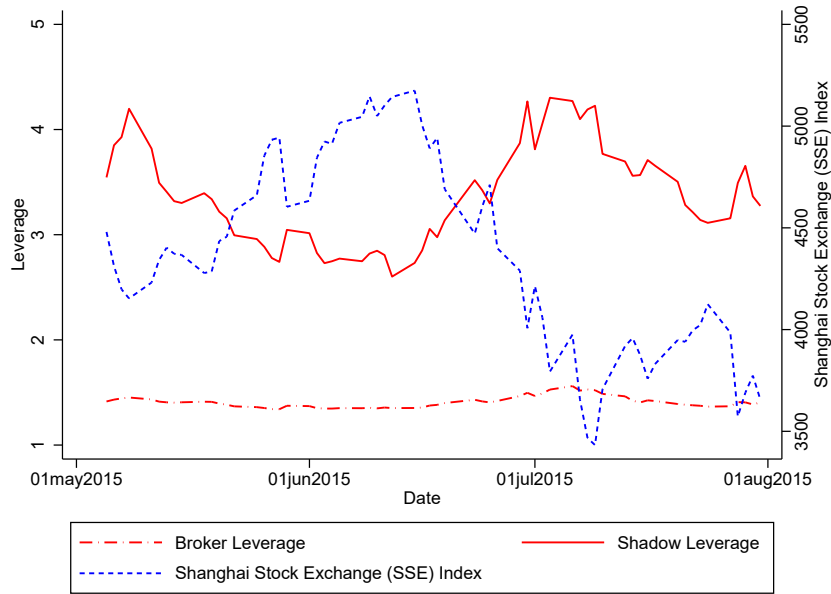
Panel B: Asset-weighted vs. Equity-weighted Leverage, Combined Sample

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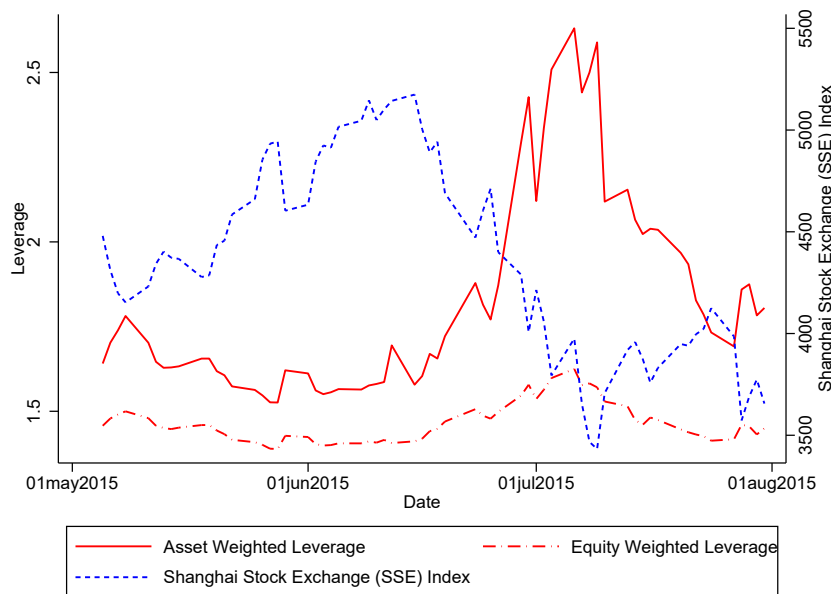
Figure 3
Distributions of Leverage

Panel A shows the distribution of leverage to Pingcang line, $\frac{\overline{Lev_j} - Lev_{j,t}}{\overline{Lev_j} - 1}$, and Panel B shows the distribution of Z (winsorized at the 99th percentile), for both brokerage and shadow margin accounts. We exclude accounts with no leverage ($Lev_{j,t} = 1$) as well as accounts whose leverage exceeds the Pingcang line ($Lev_{j,t} > \overline{Lev_j}$, i.e., accounts that are controlled by the lender).

Panel A: Distribution of Leverage to the Pingcang Line
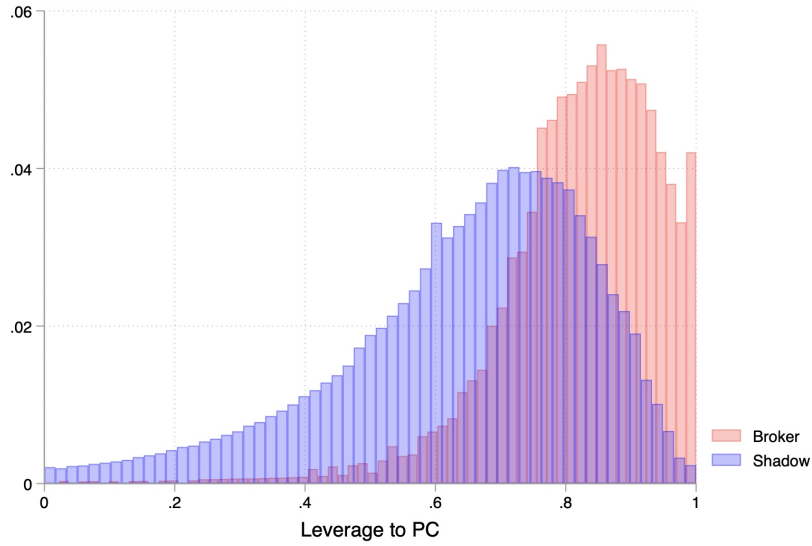
Panel B: Distribution of Z

43
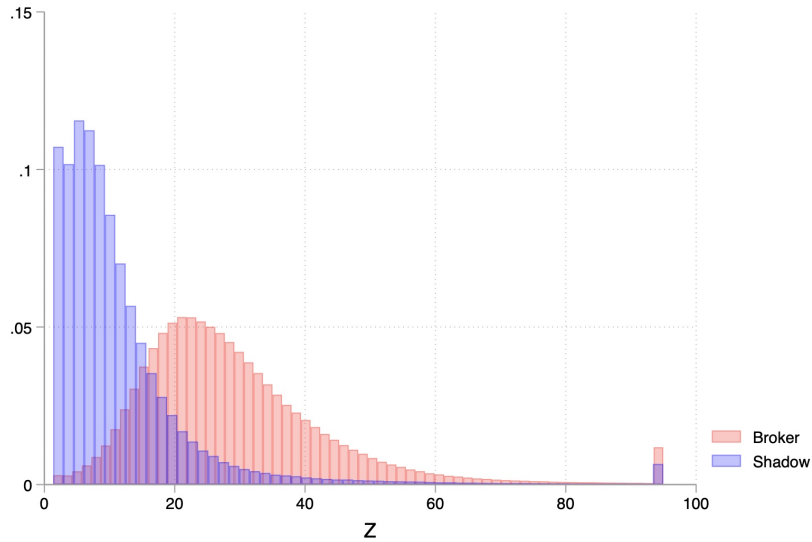
Figure 4
A Policy Shock

We plot the coefficients and their corresponding 90% confidence interval in the following regression:

$$NetBuy_{i,t}^j = \sum_{k\in\mathbb{K}} \alpha_{k,before} I_{kt}^j \mathbf{1}_{t,before} + \sum_{k\in\mathbb{K}} \alpha_{k,after} I_{kt}^j \mathbf{1}_{t,after} + \gamma_{before}\Delta Z_t^j \mathbf{1}_{t,before} + \gamma_{after}\Delta Z_t^j \mathbf{1}_{t,after} + \alpha_j + \nu_{it} + \varepsilon_{it}^j,$$

where $NetBuy_{i,t}^j$ is the netbuying of stock i by account j on day t, I_{kt}^j is an indicator for whether account j is in Z bin k at the start of day t, $\mathbf{1}_{t,before}$ is an indicator for whether day t falls in the week immediately before the June 12 CSRC announcement, $\mathbf{1}_{t,after}$ is an indicator if day t falls in the week immediately after the June 12 CSRC announcement, ν_{it} is an account-fixed effect, and ε_{it}^j is stock-date fixed effect. The red circles and lines show the point estimates and confidence intervals of the coefficients on $I_{kt}^j \mathbf{1}_{t,before}$, the blue diamonds and lines show the point estimates and confidence intervals of the coefficients on $I_{kt}^j \mathbf{1}_{t,after}$, and the grey squares and lines shows the point estimates and confidence intervals of the difference between the coefficients on $I_{kt}^j \mathbf{1}_{t,before}$ and $I_{kt}^j \mathbf{1}_{t,after}$. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are triple-clustered at the account, stock, and date level and are reported in parentheses.

Panel A: Shadow Accounts
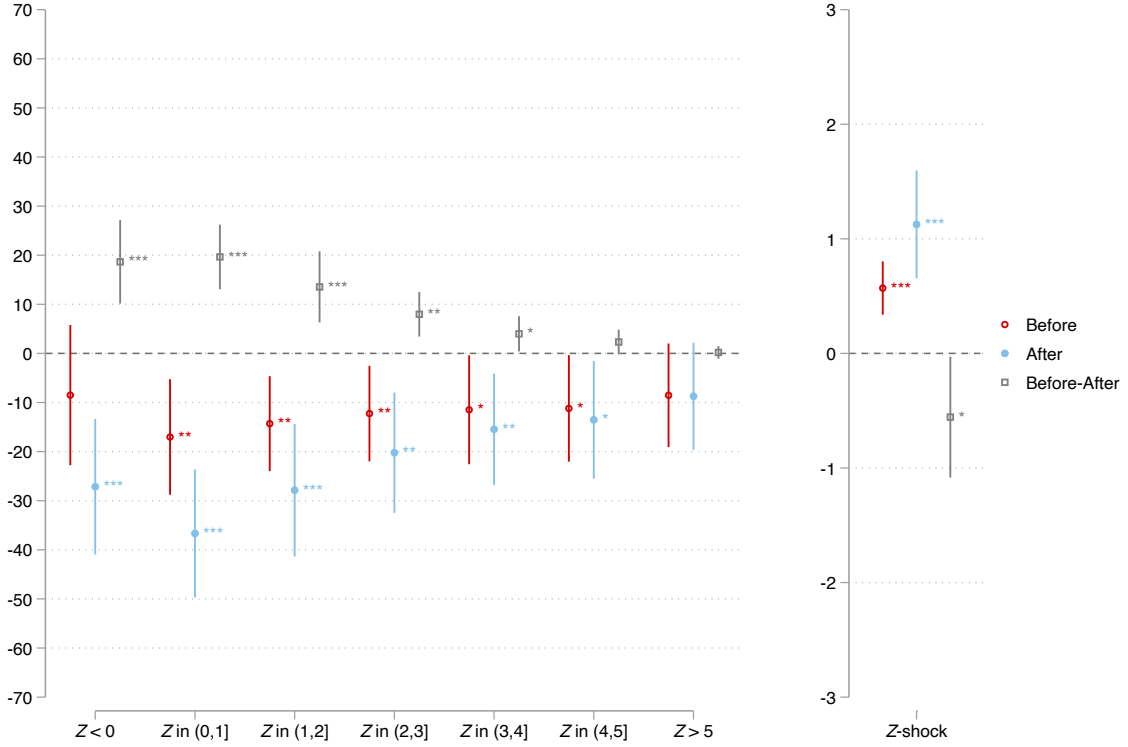
Figure 4
A Policy Shock

Panel B: Brokerage Accounts
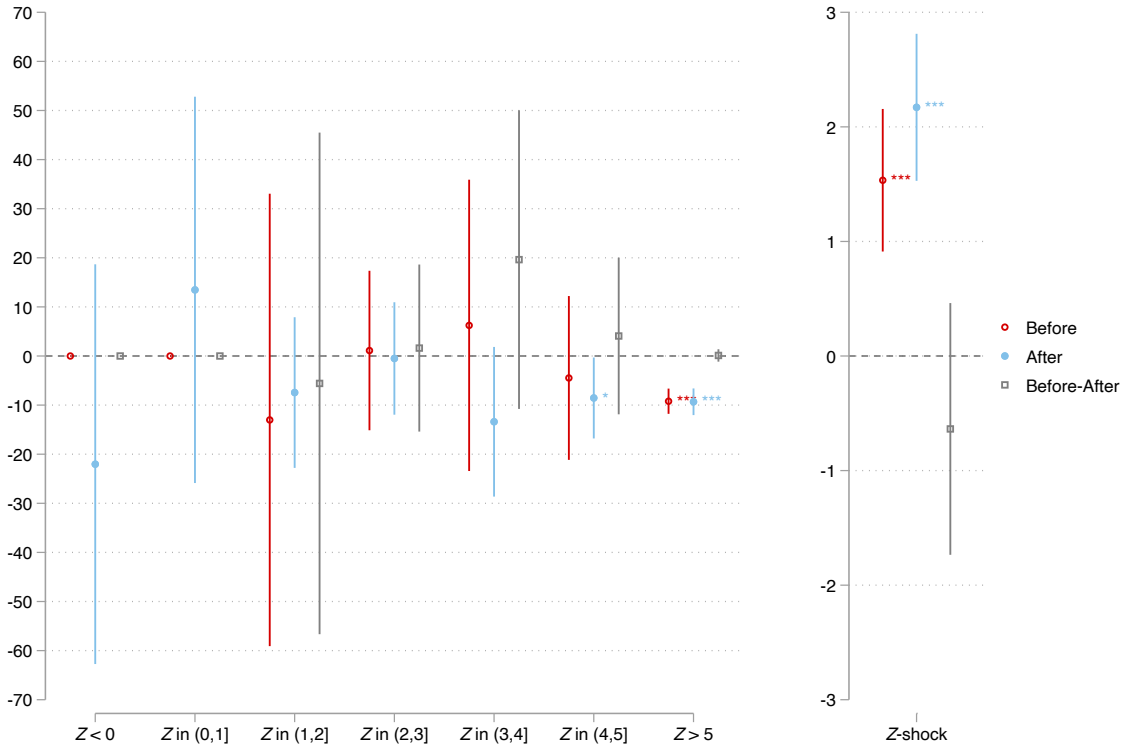
Figure 5
Long-term Return Predictability of $MLPR$

This figure plots the coefficients on $SMLPR$ in the following Fama-MacBeth return predictive regressions:

$$CumRet_{i,t+1,t+k} = \alpha + \beta \cdot SMLPR_{i,t} + \beta_N \cdot SNMLPR_{i,t} + \sum_m \lambda_m \cdot CONTROL_{i,m,t} + \varepsilon_{i,t+1},$$

where $CumRet_{i,t+1,t+k}$ is cumulative return from $t+1$ to $t+k$ for stock i. All independent variables are defined in Table 6. The x-axis plots $k \in \{0, 1, ..., 25\}$ which is the number of trading days forward. We set the coefficient for $k = 0$ to be 0. Dashed lines are the upper and lower bounds of the 90% confidence interval.
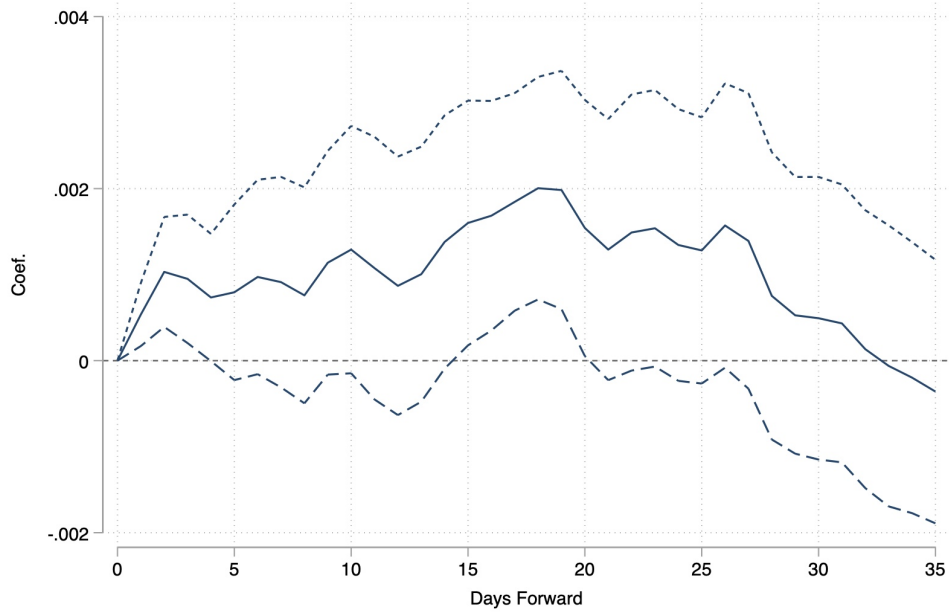
Table 1
Summary Statistics

This table reports the summary statistics of brokerage margin, shadow margin, and brokerage normal accounts for the period May to July 2015. ***, **, and * denote statistical significance of the differences at the 1%, 5%, and 10% levels, respectively.

Panel A reports account-level characteristics, including demographics (age and gender), portfolio allocations (total assets, cash holdings, stock holdings), account performance (average returns and volatility of the stock holdings in the portfolio), portfolio concentration (number of stocks, the Herfindahl index), and account turnover. The first three columns report the means of the three types of accounts, and the next three columns report the statistical significance of differences across the three types of accounts (based on standard errors clustered by account and date).

Panel B reports the average stock characteristics in the portfolio, including stock leverage (a measure of margin buying of the stock), market beta, idiosyncratic volatility, illiquidity (measured by the bid-ask spread), the log of market capitalization, the book-to-market ratio, cumulative returns in the past day, month, and six months, and turnover. We measure each stock's lottery-ness by the maximum number of consecutive days in which a stock hits the $+10\%$ price limit over the past year. Lottery Holding is the portfolio average lottery-ness, measured in number of days. Similarly, Lottery Reverse Holding is the portfolio-average maximum number of consecutive days in which a stock hits the -10% price limit over the past year. Lottery Holding 2, Lottery Holding 3, Lottery Holding 4 are the portfolio weights in stocks whose lottery-ness measure is at least two, three, and four days, respectively. Following Liu, Peng, Xiong, and Xiong (2022), we also measure a stock's lottery-ness by the total number of days in which the stock hits the $+10\%$ price limit over the past year. LotteryAlt is the portfolio weight in stocks whose alternative lottery-ness measure is above the sample median. The first three columns report average stock characteristics of different account types, which are asset-value-weighted across accounts and then averaged over time. The next three columns report the statistical significance of differences across the three types of accounts (based on standard errors with Newey-West adjustments.)

Panel C reports the mean/median/standard-deviation of margin trading characteristics of margin accounts. Pingcang Line is the maximum leverage allowed before the account is taken control of by the lender. Account Leverage is the asset-to-equity ratio at the start of each trading day. Z is the distance-to-margin-call defined in Eq. (3) and Z-shock is defined in Eq. (7). NetBuy is the daily percentage change of a position (multiplied by 100).

Panel D shows the mean/median/standard-deviation of Margin-Linked-Portfolio-Returns (MLPR, multiplied by 1000). MLPR high and MLPR low are calculated using accounts in the top and bottom 30%, respectively, in terms of the fraction of stocks in the portfolio with trading restrictions in each trading day.

Table 1
Summary Statistics

Panel A: Basic Account Characteristics

	Brokerage Margin (1)	Shadow Margin (2)	Brokerage Normal (3)	t-stat. of equality (1) vs. (2)	t-stat. of equality (1) vs. (3)	t-stat. of equality (2) vs. (3)
Account Age	7.975		6.972		***	
Investor Age	44.505		43.045		***	
Female	0.356		0.458		***	
Assets (in 1000s)	5,597.244	1,512.547	1,352.831	***	***	
Cash Holdings (in 1000s)	372.711	345.373	55.026		***	***
Stock Holdings (in 1000s)	5,224.532	1,167.174	1,297.805	***	***	
% of Cash Holdings	0.098	0.221	0.166	***	***	***
% of Stock Holdings	0.902	0.779	0.834	***	***	***
% of Restricted Stocks	0.180	0.206	0.267	*	***	***
Stock Portfolio Return (daily in %)	-0.165	-0.639	-0.258	**		*
Stock Portfolio Return Volatility (daily in %)	5.104	5.355	5.052	***	***	***
Number of Stocks	4.547	2.806	3.368	***	***	***
Herfindahl Index	0.555	0.596	0.617	***	***	***
Account Turnover	0.117	0.214	0.107	***	***	***

Panel B: Stock Characteristics in the Portfolio

	Brokerage Margin (1)	Shadow Margin (2)	Brokerage Normal (3)	t-stat. of equality (1) vs. (2)	t-stat. of equality (1) vs. (3)	t-stat. of equality (2) vs. (3)
Leverage	1.055	1.038	1.028	***	***	***
MKT Beta	0.719	0.535	0.896	***	***	***
IDVOL	0.067	0.074	0.062	***	***	***
Illiquidity	0.002	0.002	0.002		***	***
Momentum Short	0.002	0.001	0.001			
Momentum Medium	0.103	0.158	0.091	**		
Momentum Long	0.627	0.672	0.670	*		
Log MCAP	23.853	23.161	24.766	***	***	***
BM Ratio	0.437	0.414	0.708	***	***	***
Turnover	0.024	0.028	0.019	***	***	***
Lottery Holding	2.427	2.553	2.073	***	***	***
Lottery Inverse Holding	1.117	1.151	1.118	**		
Lottery2 Holding	0.584	0.626	0.495	***	***	***
Lottery3 Holding	0.344	0.344	0.279		***	***
Lottery4 Holding	0.200	0.205	0.169	*	***	***
LotteryAlt	0.492	0.473	0.448	***	***	***

Table 1
Summary Statistics

Panel C: Margin Trading Characteristics

	Brokerage Margin			Shadow Margin			All Margin		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Account									
Pingcang Line	4.300	4.300	0.000	13.543	11.001	6.661	8.083	4.300	6.230
N	77,891			53,972			131,863		
Account-Day									
Account Leverage	1.409	1.321	0.471	6.399	4.469	11.158	2.476	1.500	5.566
Z	29.717	26.376	16.419	11.488	8.323	16.427	24.615	21.980	18.347
Z-Shock	-0.040	0.000	0.975	-0.607	0.000	4.329	-0.161	0.000	2.193
N	3,853,513			1,047,766			4,901,279		
Account-Stock-Day									
NetBuy	-5.273	0.000	42.089	-19.884	0.000	52.845	-7.373	0.000	44.096
N	17,520,508			2,940,244			20,460,752		

Panel D: Margin-Linked-Portfolio-Returns (MLPR)

	Mean	Median	Std
MLPR	-0.694	0.166	7.453
MLPR High	-0.417	0.002	3.268
MLPR Low	-0.135	0.000	0.896
N	148,959		

Table 2
Trading Activity and Distance-to-Margin-Call

This table reports regressions of net buying (negative if selling) on the level of and change in distance-to-margin-call. The dependent variable is the net buying of stock i by each account j on day t. The main independent variables are indicators for Z-bins at the end of $t-1$ and a continuous variable for Z-shocks on day t. Columns (1), (2), and (3) conduct the regressions over the whole sample period from May 1st to July 31st, 2015 within brokerage-financed margin accounts, shadow-financed margin accounts, and all margin accounts, separately. Column (4) includes the subsample from May 1st to June 12th, 2015 (Up Market) for all accounts, while column (5) includes the subsample of June 15th to July 31st, 2015 (Down Market) for all accounts. Account fixed effects and stock-date fixed effects are included in all regressions. Standard errors are triple-clustered at the account, stock, and date level and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. var.: $NetBuy_{i,t}^{j}$	(1) Broker Whole	(2) Shadow Whole	(3) All Whole	(4) All Up	(5) All Down
$Z < 0$	-22.853***	-19.863***	-22.856***	-8.771**	-31.603***
	(3.624)	(2.969)	(2.939)	(3.866)	(2.877)
Z in $(0,1]$	-10.588***	-23.209***	-23.954***	-15.634***	-31.427***
	(2.274)	(2.494)	(2.447)	(2.593)	(2.816)
Z in $(1,2]$	-10.135***	-16.998***	-18.470***	-11.631***	-26.207***
	(2.633)	(2.109)	(2.023)	(1.354)	(2.502)
Z in $(2,3]$	-6.822***	-11.680***	-13.299***	-8.208***	-20.490***
	(1.982)	(1.623)	(1.454)	(0.885)	(1.826)
Z in $(3,4]$	-6.886***	-7.850***	-9.763***	-6.822***	-15.808***
	(1.248)	(1.266)	(1.039)	(0.705)	(1.397)
Z in $(4,5]$	-7.261***	-5.636***	-7.842***	-6.502***	-12.929***
	(1.102)	(1.019)	(0.754)	(0.522)	(1.072)
$Z > 5$	-4.216***	-1.644**	-4.166***	-5.746***	-6.668***
	(0.278)	(0.810)	(0.276)	(0.422)	(0.582)
Z-Shock	1.081***	1.022***	1.000***	0.720***	0.858***
	(0.141)	(0.153)	(0.142)	(0.065)	(0.156)
Account FE	Yes	Yes	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes	Yes	Yes
Obs	17,552,457	6,983,143	20,456,448	9,822,647	10,632,716
R^2	0.074	0.153	0.097	0.104	0.113

Table 3
Trading Activity and Lottery Preferences

This table reports regressions of net buying (negative if selling) on Z-shock and its interaction with stock lottery characteristics. The dependent variable $NetBuy_{it}^{j}$ is the net buying of stock i by account j on day t. The main independent variables are indicators for Z-bins at the end of $t-1$, a continuous variable for Z-shocks on day t, and their interaction with stock lottery characteristic $Lottery$. $Lottery$ is the maximum number of days that stock i consecutively hit the upper 10% return cap over the one-year period before the start of our full sample. Column (1) includes the subsample from May 1st to June 12th, 2015 (Up Market). Column (2) includes the subsample of June 15th to July 31st, 2015 (Down Market). Column (3) includes the whole sample from May 1st to July 31st, 2015. Account fixed effects and stock-date fixed effects are included in all regressions. Standard errors are triple-clustered at the account, stock, and date level and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. var.: $NetBuy_{i,t}^{j}$	(1)	(2)	(3)
	Up	Down	Whole
$Z < 0$	-8.873**	-31.903***	-22.953***
	(3.876)	(2.912)	(2.962)
Z in $(0,1]$	-15.730***	-31.866***	-24.151***
	(2.609)	(2.844)	(2.470)
Z in $(1,2]$	-11.716***	-26.591***	-18.620***
	(1.352)	(2.524)	(2.036)
Z in $(2,3]$	-8.304***	-20.847***	-13.441***
	(0.887)	(1.848)	(1.466)
Z in $(3,4]$	-6.888***	-16.145***	-9.889***
	(0.705)	(1.416)	(1.049)
Z in $(4,5]$	-6.558***	-13.212***	-7.947***
	(0.519)	(1.086)	(0.761)
$Z > 5$	-5.792***	-6.887***	-4.256***
	(0.423)	(0.588)	(0.282)
Z-Shock	0.671***	0.925***	1.045***
	(0.069)	(0.163)	(0.153)
Z-Shock $\times Lottery$	0.017	-0.024***	-0.015**
	(0.011)	(0.006)	(0.007)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
Obs	9,621,826	10,190,533	19,813,469
R^2	0.104	0.113	0.097

Table 4
Trading Activity and Trading Restrictions

This table repeats the analyses of Table 2 but adds trading restrictions in the regressions. The dependent variable $NetBuy_{it}^{j}$ is the net buying (negative if selling) of stock i by account j on day t. The independent variables are indicators for Z-bins at the end of $t-1$, a continuous variable for Z-shocks on day t, trading restrictions $\%Restriction$ on day t, and an interaction term between Z-Shock and $\%Restriction$. $\%Restriction$ is measured by the fraction of other stocks in the account (excluding stock i itself) facing trading suspensions or hitting the downward price limit on day t. Account fixed effects and stock-date fixed effects are included in all regressions. Standard errors are triple-clustered at the account, stock, and date level and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. var.: $NetBuy_{i,t}^{j}$	(1) Broker	(2) Shadow	(3) All
$Z < 0$	-21.775***	-18.013***	-21.201***
	(3.844)	(3.051)	(3.001)
Z in $(0,1]$	-9.122***	-20.477***	-21.530***
	(2.483)	(2.796)	(2.636)
Z in $(1,2]$	-8.471***	-14.522***	-16.223***
	(2.615)	(2.340)	(2.165)
Z in $(2,3]$	-5.589**	-9.895***	-11.701***
	(2.155)	(1.755)	(1.548)
Z in $(3,4]$	-6.088***	-6.628***	-8.702***
	(1.311)	(1.338)	(1.078)
Z in $(4,5]$	-6.747***	-4.839***	-7.181***
	(1.072)	(1.064)	(0.771)
$Z > 5$	-4.169***	-1.430*	-4.084***
	(0.274)	(0.818)	(0.275)
Z-Shock	0.779***	0.506***	0.524***
	(0.142)	(0.125)	(0.109)
$\%Restriction$	-0.317	-0.471	-0.297
	(0.417)	(0.533)	(0.433)
Z-Shock $\times$ $\%Restriction$	0.497***	0.923***	0.838***
	(0.161)	(0.172)	(0.175)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
Obs	17,552,457	6,983,143	20,456,448
R^2	0.074	0.153	0.097

Table 5
Identification Tests for Trading Activity

This table estimates the causal impact of leverage constraints on margin trading activity. The dependent variable $NetBuy_{it}^j$ is the net buying (negative if selling) of stock i by account j on day t. Within the brokerage sample, Panel A compares the trading activity of margin accounts that just qualified for margin borrowing (treatment group) with that of non-margin accounts that just failed to qualify (control group). For the detailed definition of treatment and control groups, see Section 4.2.1. The independent variables include indicators for Z-bins, Lev (account leverage) $\times$ R (account returns) on day t, and its interaction with the treatment group dummy. Within the shadow account sample, we conduct similar tests in Panel B but exploit variations in Pingcang Line across shadow accounts. We decompose Z-shock into LP (Leverage-to-Pingcang, measured at the end of $t-1$), $Lev \times R$, and $LP \times Lev \times R$. In Columns (1) and (2), we use the account's own Pingcang Line to obtain Z measures. In Columns (3) and (4), we use the peer Pingcang Line (the average Pingcang Line of all other shadow accounts opened on the same day) as a reduced-form instrument for the account's own Pingcang Line. Account fixed effects and stock-date fixed effects are included in all regressions. Standard errors are triple-clustered at the account, stock, and date level and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Trading Behavior of Just-Eligible Margin Brokerage Accounts versus Just-Ineligible Normal Brokerage Accounts

Dep. var.: $NetBuy_{i,t}^j$	(1)	(2)
$Z < 0$		-0.431***
		(0.040)
Z in $(0,1]$		0.000
		(0.000)
Z in $(1,2]$		-0.123
		(0.115)
Z in $(2,3]$		0.000
		(0.000)
Z in $(3,4]$		-0.083*
		(0.046)
Z in $(4,5]$		-0.107
		(0.122)
$Z > 5$		-0.050***
		(0.009)
$Lev \times R$	0.150***	0.150***
	(0.021)	(0.021)
$Lev \times R \times Treat$	0.147***	0.138**
	(0.055)	(0.053)
Account FE	Yes	Yes
Stock-Date FE	Yes	Yes
Obs	7,785,565	7,785,556
R^2	0.260	0.260

Table 5
Identification Tests for Trading Activity

Panel B: Shadow Accounts with Heterogeneous Pingcang Lines

Dep. var.: $NetBuy_{i,t}^{j}$	(1)	(2)	(3)	(4)
	Z	Z	Z^*, LP^*	Z^*, LP^*
$Z < 0$	-20.105***		-18.013***	
	(2.670)		(2.825)	
Z in $(0, 1]$	-26.127***		-25.646***	
	(2.408)		(2.606)	
Z in $(1, 2]$	-19.782***		-19.635***	
	(2.114)		(2.174)	
Z in $(2, 3]$	-13.409***		-14.071***	
	(1.621)		(1.785)	
Z in $(3, 4]$	-8.928***		-10.406***	
	(1.242)		(1.412)	
Z in $(4, 5]$	-6.311***		-7.938***	
	(0.975)		(1.195)	
$Z > 5$	-1.801**		-2.375***	
	(0.801)		(0.803)	
LP	0.593	9.676***	3.028**	12.993***
	(0.759)	(1.846)	(1.273)	(2.255)
$Lev \times R$	2.002***	2.370***	1.910***	2.101***
	(0.481)	(0.539)	(0.466)	(0.474)
$LP \times Lev \times R$	4.158***	3.579***	7.475***	7.445***
	(1.113)	(1.177)	(1.434)	(1.548)
Account FE	Yes	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes	Yes
Obs	6,983,143	6,983,143	6,983,143	6,983,143
R^2	0.151	0.149	0.150	0.149

Table 6
Baseline $MLPR$ Regressions

This table reports results from Fama-MacBeth return predictive regressions. The dependent variable is stock i's return (in percentage) on day $t+1$. The main independent variable is $SMLPR$, the standardized margin-account-linked portfolio return in day t, calculated as the weighted average return of all other stocks connected to stock i through common ownership by margin investors. $SNMLPR$ is defined similarly but uses common ownership of matched non-margin accounts (matched by account size and trading volume). The set of stock characteristics includes: the stock's overall leverage ($LEVERAGE$) in the brokerage system on the day t-1, defined as $MCAP/(MCAP-BDEBT)$ where $BDEBT$ (publicly disclosed) is the total outstanding margin debt for stock i in the brokerage system; market beta ($BETA$); idiosyncratic volatility ($IDVOL$); bid-ask spread ($ILLIQUIDITY$); past cumulative returns of three non-overlapping horizons: $t-1$, $[t-30, t-2]$, and $[t-180, t-31]$ days ($MOM\ SHORT/MEDIUM/LONG$); market capitalization ($MCAP$); book-to-market ratio ($BMRATIO$) and share turnover ($TURNOVER$). All the stock characteristics are measured on day t. Columns (1) and (2) include the whole sample from May 1st to July 31st, 2015. Columns (3) and (4) include the subsample of May 1st to June 12th, 2015 (Up Market), and Columns (5) and (6) include the subsample of June 15th to July 31st, 2015 (Down Market). Standard errors, with Newey-West adjustments of four lags, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. var.: $R_{i,t+1}$	(1) Whole	(2) Whole	(3) Up	(4) Up	(5) Down	(6) Down
SMLPR	0.098***	0.088***	-0.002	-0.008	0.181***	0.166***
	(0.034)	(0.032)	(0.020)	(0.017)	(0.037)	(0.035)
SNMLPR		0.009		0.056**		-0.030
		(0.044)		(0.020)		(0.077)
LEVERAGE	-1.213	-1.286	-3.081***	-2.991***	0.326	0.119
	(0.877)	(0.819)	(0.780)	(0.772)	(1.142)	(1.047)
BETA	-0.048***	-0.048***	-0.041	-0.040	-0.053**	-0.054**
	(0.017)	(0.017)	(0.028)	(0.028)	(0.021)	(0.021)
IDVOL	-0.931	-0.953	-1.289	-1.164	-0.636	-0.779
	(0.747)	(0.745)	(1.360)	(1.339)	(0.715)	(0.752)
ILLIQUIDITY	9.705*	9.562*	6.719	6.732	12.164	11.892
	(5.434)	(5.402)	(6.667)	(6.641)	(8.131)	(8.079)
MOM SHORT	24.471***	24.390***	16.364***	16.320***	31.147***	31.036***
	(3.463)	(3.438)	(2.103)	(2.085)	(4.615)	(4.578)
MOM MEDIUM	-1.108**	-1.108**	-0.263	-0.270	-1.804***	-1.797***
	(0.421)	(0.418)	(0.279)	(0.278)	(0.628)	(0.625)
MOM LONG	-0.112**	-0.113**	-0.118	-0.118	-0.107**	-0.108**
	(0.049)	(0.049)	(0.098)	(0.098)	(0.042)	(0.042)
MCAP	0.000	0.000	-0.000***	-0.000***	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BMRATIO	-0.023	-0.029	-0.400	-0.381	0.288	0.260
	(0.236)	(0.233)	(0.375)	(0.372)	(0.267)	(0.266)
TURNOVER	1.293	1.291	3.129	3.167	-0.219	-0.254
	(1.191)	(1.191)	(2.086)	(2.074)	(1.113)	(1.106)
p-value (SMLPR > SNMLPPR)	.	0.0779	.	0.9858	.	0.0149
Obs	130,914	130,914	62,886	62,886	68,028	68,028
R^2	0.165	0.168	0.115	0.116	0.206	0.210

Table 7
$MLPR$ **Regressions: with Trading Restrictions**

This table reports results from Fama-MacBeth return predictive regressions, using $MLPR$ that incorporates information about account holdings with trading restrictions. The dependent variable is stock i's return (in percentage) on day $t + 1$. The main independent variables are $SMLPR_{High}$ and $SMLPR_{Low}$, which are calculated using the accounts in the top and bottom 30%, respectively, in terms of the fraction of stocks in the portfolio with trading restrictions in each trading day. $SMLPR_{High}$ and $SMLPR_{Low}$ are standardized to have a standard deviation of one and a mean of 0 each day. $SNMLPR$ and other stock characteristics are defined in Table 6. Columns (1) and (2) include the whole sample from May 1st to July 31st, 2015. Columns (3) and (4) include the subsample of May 1st to June 12th, 2015 (Up Market), and Columns (5) and (6) include the subsample of June 15th to July 31st, 2015 (Down Market). Standard errors, with Newey-West adjustments of four lags, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. var.: $R_{i,t+1}$	(1) Whole	(2) Whole	(3) Up	(4) Up	(5) Down	(6) Down
$SMLPR_{High}$	0.101***	0.091***	0.024	0.019	0.164***	0.150***
	(0.034)	(0.031)	(0.023)	(0.022)	(0.046)	(0.041)
$SMLPR_{Low}$	-0.052***	-0.055***	-0.074***	-0.075***	-0.034	-0.039
	(0.016)	(0.015)	(0.016)	(0.016)	(0.023)	(0.023)
SNMLPR		0.012		0.058***		-0.025
		(0.043)		(0.019)		(0.075)
LEVERAGE	-1.131	-1.204	-2.958***	-2.880***	0.373	0.176
	(0.825)	(0.771)	(0.787)	(0.781)	(1.021)	(0.930)
BETA	-0.048***	-0.048***	-0.040	-0.039	-0.055**	-0.056**
	(0.017)	(0.017)	(0.028)	(0.028)	(0.021)	(0.021)
IDVOL	-0.963	-0.984	-1.300	-1.171	-0.685	-0.831
	(0.756)	(0.755)	(1.368)	(1.348)	(0.743)	(0.777)
ILLIQUIDITY	9.451*	9.297*	6.977	6.981	11.488	11.204
	(5.544)	(5.508)	(6.725)	(6.696)	(8.367)	(8.310)
MOM SHORT	24.583***	24.507***	16.530***	16.483***	31.215***	31.115***
	(3.425)	(3.405)	(2.031)	(2.014)	(4.584)	(4.557)
MOM MEDIUM	-1.097**	-1.097**	-0.262	-0.269	-1.786***	-1.778***
	(0.417)	(0.415)	(0.279)	(0.279)	(0.623)	(0.621)
MOM LONG	-0.110**	-0.110**	-0.117	-0.117	-0.104**	-0.105**
	(0.049)	(0.049)	(0.098)	(0.097)	(0.042)	(0.042)
MCAP	0.000	0.000	-0.000***	-0.000***	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BMRATIO	-0.034	-0.040	-0.408	-0.388	0.274	0.246
	(0.236)	(0.233)	(0.373)	(0.370)	(0.270)	(0.269)
TURNOVER	1.336	1.339	3.157	3.204	-0.164	-0.197
	(1.197)	(1.195)	(2.089)	(2.074)	(1.134)	(1.125)
p-value (High > Low)	0.0001	0.0001	0.0018	0.0018	0.0004	0.0004
Obs	130,914	130,914	62,886	62,886	68,028	68,028
R^2	0.167	0.170	0.116	0.117	0.209	0.214

Table 8
$MLPR$ Regressions: Lottery vs. Non-lottery Stocks

This table reports results from Fama-MacBeth return predictive regressions within the lottery (Panel A) and non-lottery (Panel B) stock subsamples. Lottery stocks are stocks that hit the 10% daily limit in three or more consecutive days (i.e., *Lottery Holding 3*) during the one-year period prior to the start of our sample. The dependent variable is stock i's return (in percentage) on the day $t+1$. $SMLPR$, $SNMLPR$ and other stock characteristics are defined in Table 6. Columns (1) and (2) include the whole sample from May 1st to July 31st, 2015. Columns (3) and (4) include the subsample of May 1st to June 12th, 2015 (Up Market), and Columns (5) and (6) include the subsample of June 15th to July 31st, 2015 (Down Market). Standard errors, with Newey-West adjustments of four lags, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Lottery Stocks

Dep. var.: $R_{i,t+1}$	(1) Whole	(2) Whole	(3) Up	(4) Up	(5) Down	(6) Down
SMLPR	0.079**	0.067**	0.017	0.007	0.129***	0.116***
	(0.033)	(0.030)	(0.035)	(0.031)	(0.044)	(0.039)
SNMLPR		0.034		0.076		-0.010
		(0.052)		(0.047)		(0.085)
LEVERAGE	-0.567	-0.582	-1.853*	-1.816*	0.660	0.595
	(0.823)	(0.786)	(0.947)	(0.959)	(1.230)	(1.140)
BETA	-0.014	-0.015	-0.006	-0.007	-0.023	-0.023
	(0.015)	(0.015)	(0.020)	(0.020)	(0.023)	(0.024)
IDVOL	0.678	0.719	-0.089	-0.001	1.654**	1.645**
	(0.893)	(0.886)	(1.761)	(1.762)	(0.681)	(0.661)
ILLIQUIDITY	13.412**	13.454**	2.247	2.431	21.333***	21.256***
	(5.543)	(5.549)	(6.517)	(6.435)	(7.184)	(7.301)
MOM SHORT	24.656***	24.631***	16.237***	16.196***	32.010***	31.997***
	(3.391)	(3.402)	(2.526)	(2.537)	(4.060)	(4.075)
MOM MEDIUM	-1.457**	-1.449**	-0.264	-0.269	-2.453***	-2.433***
	(0.553)	(0.553)	(0.256)	(0.253)	(0.846)	(0.851)
MOM LONG	-0.090**	-0.089**	-0.081	-0.079	-0.092**	-0.093**
	(0.042)	(0.042)	(0.084)	(0.084)	(0.039)	(0.039)
MCAP	-0.000	-0.000	-0.000***	-0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BMRATIO	0.325	0.324	-0.306	-0.295	0.723**	0.710**
	(0.301)	(0.299)	(0.504)	(0.500)	(0.281)	(0.283)
TURNOVER	1.443	1.469	1.647	1.895	1.469	1.277
	(1.459)	(1.439)	(2.773)	(2.713)	(1.367)	(1.374)
p-value (SMLPR > SNMLPPR)	.	0.2914	.	0.8819	.	0.0987
Obs	25,350	25,350	12,260	12,260	12,672	12,672
R^2	0.212	0.216	0.179	0.183	0.239	0.243

Table 8
$MLPR$ Regressions: Lottery vs. Non-lottery Stocks

Panel B: Non-Lottery Stocks

Dep. var.: $R_{i,t+1}$	(1) Whole	(2) Whole	(3) Up	(4) Up	(5) Down	(6) Down
SMLPR	0.096**	0.088**	-0.010	-0.015	0.186***	0.175***
	(0.036)	(0.035)	(0.017)	(0.015)	(0.040)	(0.038)
SNMLPR		0.005		0.057***		-0.047
		(0.041)		(0.016)		(0.071)
LEVERAGE	-1.138	-1.198*	-2.491***	-2.429***	0.239	0.068
	(0.722)	(0.685)	(0.727)	(0.723)	(0.846)	(0.785)
BETA	-0.149	-0.152	-0.461***	-0.448***	0.093	0.075
	(0.147)	(0.143)	(0.144)	(0.142)	(0.211)	(0.207)
IDVOL	-2.621	-2.612	0.174	0.141	-4.997	-4.949*
	(2.013)	(1.982)	(2.532)	(2.500)	(2.917)	(2.860)
ILLIQUIDITY	10.904	11.056	47.807	47.148	-23.989	-22.935
	(23.548)	(23.201)	(32.994)	(32.872)	(25.904)	(25.333)
MOM SHORT	24.147***	24.097***	15.909***	15.881***	31.172***	31.098***
	(3.573)	(3.551)	(2.004)	(1.985)	(4.965)	(4.931)
MOM MEDIUM	-0.993**	-0.995**	-0.106	-0.112	-1.719***	-1.718***
	(0.403)	(0.402)	(0.380)	(0.377)	(0.550)	(0.550)
MOM LONG	-0.161**	-0.162**	-0.159	-0.162	-0.143	-0.143*
	(0.074)	(0.073)	(0.128)	(0.128)	(0.084)	(0.082)
MCAP	0.000	0.000	-0.000***	-0.000***	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BMRATIO	-0.035	-0.037	-0.132	-0.125	-0.031	-0.041
	(0.146)	(0.145)	(0.278)	(0.275)	(0.116)	(0.114)
TURNOVER	0.986	0.978	4.302**	4.268**	-1.418	-1.405
	(1.557)	(1.548)	(1.826)	(1.819)	(2.100)	(2.086)
p-value (SMLPR > SNMLPPR)	.	0.0623	.	0.9973	.	0.0063
Obs	105,564	105,564	50,626	50,626	53,174	53,174
R^2	0.167	0.170	0.103	0.104	0.223	0.227

Online Appendix

A.1   China's Shadow Banking Sector: Funding Sources of Shadow Margin System

As we mentioned in Section 2.1.2, funding for shadow-financed margin accounts came from a broader set of sources that are directly, or indirectly, linked to the shadow banking system in China. The right hand side of Figure 1 Panel A lists three major funding sources: Wealth Management Products (WMP) raised from depositors via commercial banks, Trust and Peer-to-Peer (P2P) inform al lending, and borrowing through pledged stock rights.

As suggested by the gray color on the right hand side of Figure 1 Panel A, the shadow-financed margin system operated in the "shadow." Regulators do not know the detailed breakdown of the shadow funding sources and therefore do not know the exact leverage ratio associated with this system, let alone the total size of the shadow-financing market.

For the first two sources, according to a research report issued by Huatai Securities on July 5th, 2015 which was just before the stock market collapse in June 2015, borrowing from WMP peaked at around 600 billion RMB and Peer-to-Peer (P2P) informal lending peaked at about 200 billion RMB. (See Figure 1, https://wenku.baidu.com/view/565390bd43323968001c9234?pcf=2.)

For pledged stock rights, there is much less agreement on how much borrowing through pledged stock rights flowed back to the stock market. A pledge of stock rights in China is an agreement in which the borrower pledges the stocks as collateral to obtain credit, often from commercial banks or security firms, for real investment or consumption use. It is illegal to use borrowed funds to invest in the stock market. However, during the first half of 2015, it was reported that some borrowers lent these borrowed funds to professional lending firms who then lent them out to shadow-financed margin traders to purchase stocks. Given the total borrowing of 2.5 trillion RMB through pledged stock rights in early June 2015, we estimate that about 10-15% of the borrowing flowed back to the stock market. This suggests that 250-350 billion RMB is a reasonable estimate.

Summing up, the estimated total debt held by shadow-financed margin accounts was about 1.0-1.2 trillion RMB at its peak, consistent with the estimates provided by China Securities Daily on June 12th, 2015.

A.2   Details of Data Filtering and Winsorization

We adopt the following data cleaning and filtering procedures on our account-level data from the online trading platform.

First, we keep only the accounts with the maintenance margin (Pingcang Line) less than the initial margin. Second, we require the initial leverage ratio to be less than 100, but above one, and eliminate accounts with too high or too low initial leverage ratios; this is because those accounts with extremely high initial leverage ratios are usually marketed as some "teaser" accounts to attract investors with little own capital. Third, for each (child) account, we require the first cash-flow record, before any reported trading activities, to be a cash inflow from the mother account (instead

of from the child accounts to the mother account). Finally, we exclude accounts that do not have any cash inflows from the mother accounts. After applying the above filters, we end up with a sample of over 54K shadow margin accounts.

We adopt further general data filtering procedures on our account-day level data for both brokerage and shadow-financed margin accounts. First, we drop observations with negative close assets, close total stock holdings, or close cash holdings. Second, we drop observations that have cash holdings percentages larger than 100%.

After data filtering, we winsorize the following main variables at the 1% and 99% levels prior to estimating regressions: $NetBuy_{it}^{j}$, Z-Shock, $MLPR$ (we standardize $MLPR$ to $SMLPR$ after the winsorization of $MLPR$), and $NMLPR$ (we standardize $NMLPR$ to $SNMLPR$ after the winsorization of $NMLPR$).

Table A1
Initial Buys

This table reports regressions of initial buying on the level of and change in distance-to-margin-call. Observations are at the account-date level. Initial buy is the total buying of new stocks (not already held by the account at the end of day $t-1$) by account j on day t scaled by account assets at the start of day t. The main independent variables are indicators for Z-bins at the end of $t-1$ and a continuous variable for Z-shocks on day t. Columns (1), (2), and (3) conduct the regressions over the whole sample period from May 1st to July 31st, 2015 within brokerage-financed margin accounts, shadow-financed margin accounts, and all margin accounts, separately. Column (4) includes the subsample from May 1st to June 12th, 2015 (Up Market) for all accounts, while column (5) includes the subsample of June 15th to July 31st, 2015 (Down Market) for all accounts. Account and date fixed effects are included in all regressions. Standard errors are double-clustered at the account and date level and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. var.: $InitialBuy_t^j$	(1) Broker Whole	(2) Shadow Whole	(3) All Whole	(4) All Up	(5) All Down
$Z < 0$	-0.176***	-0.747***	-0.193***	-0.091	-0.232***
	(0.012)	(0.095)	(0.021)	(0.096)	(0.013)
Z in $(0,1]$	-0.166***	-0.773***	-0.214***	-0.217***	-0.240***
	(0.009)	(0.092)	(0.007)	(0.018)	(0.012)
Z in $(1,2]$	-0.164***	-0.759***	-0.202***	-0.200***	-0.233***
	(0.011)	(0.092)	(0.007)	(0.012)	(0.012)
Z in $(2,3]$	-0.166***	-0.743***	-0.187***	-0.190***	-0.218***
	(0.009)	(0.092)	(0.007)	(0.009)	(0.012)
Z in $(3,4]$	-0.167***	-0.729***	-0.174***	-0.179***	-0.207***
	(0.008)	(0.092)	(0.006)	(0.008)	(0.011)
Z in $(4,5]$	-0.131***	-0.694***	-0.138***	-0.152***	-0.161***
	(0.004)	(0.091)	(0.005)	(0.006)	(0.009)
$Z > 5$	0.686***	-0.126	0.456***	0.455***	0.423***
	(0.030)	(0.101)	(0.033)	(0.057)	(0.039)
Z-Shock	0.001	0.004***	0.004***	0.004***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Account FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Obs	3,926,099	2,341,970	5,005,764	2,310,266	2,693,509
R^2	0.107	0.157	0.121	0.175	0.135

Table A2
An Alternative Definition of Lottery Stocks

This table reports regressions of net buying (negative if selling) on Z-shock and its interaction with stock alternative lottery characteristics. The dependent variable $NetBuy_{it}^j$ is the net buying of stock i by account j on day t. The main independent variables are indicators for Z-bins at the end of $t-1$, a continuous variable for Z-shocks on day t, and their interaction with stock lottery characteristic $LotteryAlt$. $LotteryAlt$ is a dummy that equals one if the number of days that stock i hits the $+10\%$ price limit over the one-year period (2014) before the start of our full sample is larger than the sample median. Column (1) examines the subsample from May 1st to June 12th, 2015 (Up Market). Column (2) examines the subsample of June 15th to July 31st, 2015 (Down Market). Column (3) includes the whole sample from May 1st to July 31st, 2015. Account fixed effects and stock-date fixed effects are included in all regressions. Standard errors are triple-clustered at the account, stock, and date level and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. var.: $NetBuy_{i,t}^j$	(1)	(2)	(3)
	Up	Down	Whole
$Z < 0$	-8.976**	-31.978***	-23.044***
	(3.855)	(2.910)	(2.955)
Z in $(0,1]$	-15.717***	-31.969***	-24.237***
	(2.636)	(2.847)	(2.476)
Z in $(1,2]$	-11.751***	-26.688***	-18.715***
	(1.355)	(2.521)	(2.038)
Z in $(2,3]$	-8.363***	-20.894***	-13.497***
	(0.887)	(1.851)	(1.469)
Z in $(3,4]$	-6.973***	-16.181***	-9.942***
	(0.705)	(1.413)	(1.051)
Z in $(4,5]$	-6.610***	-13.247***	-7.989***
	(0.527)	(1.086)	(0.765)
$Z > 5$	-5.907***	-6.909***	-4.312***
	(0.433)	(0.591)	(0.285)
Z-Shock	0.681***	0.952***	1.065***
	(0.071)	(0.167)	(0.155)
Z-Shock $\times$ $LotteryAlt$	0.048	-0.173***	-0.119**
	(0.046)	(0.047)	(0.045)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
Obs	9,459,035	10,126,082	19,586,247
R^2	0.104	0.112	0.097

Table A3
Trading Activity and Distance-to-Margin-Call: $t+1$ Results

This table reports regressions of net buying (negative if selling) on the level of and change in distance-to-margin-call. The dependent variable is the net buying of stock i by each account j on day $t+1$. The main independent variables are indicators for Z-bins at the end of $t-1$ and a continuous variable for Z-shocks on day t. Columns (1), (2), and (3) conduct the regressions over the whole sample period from May 1st to July 31st, 2015 within brokerage-financed margin accounts, shadow-financed margin accounts, and all margin accounts, separately. Account fixed effects and stock-date fixed effects are included in all regressions. Standard errors are triple-clustered at the account, stock, and date level and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. var.: $NetBuy_{i,t+1}^{j}$	(1)	(2)	(3)
	Broker	Shadow	All
$Z < 0$	-23.195***	-19.393***	-22.599***
	(3.489)	(3.003)	(3.022)
Z in $(0,1]$	-10.999***	-22.681***	-23.325***
	(2.014)	(2.710)	(2.653)
Z in $(1,2]$	-9.738***	-16.508***	-17.913***
	(2.275)	(2.276)	(2.199)
Z in $(2,3]$	-7.444***	-11.257***	-12.979***
	(1.838)	(1.695)	(1.562)
Z in $(3,4]$	-7.016***	-7.586***	-9.613***
	(1.200)	(1.332)	(1.132)
Z in $(4,5]$	-6.962***	-5.149***	-7.516***
	(0.947)	(1.039)	(0.786)
$Z > 5$	-4.316***	-1.519*	-4.284***
	(0.285)	(0.848)	(0.282)
Z-Shock	0.970***	1.001***	0.973***
	(0.138)	(0.165)	(0.151)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
Obs	15,637,080	5,765,910	17,836,370
R^2	0.054	0.136	0.073

Table A4
$MLPR$ Regressions: with Liquidation Choice

This table reports results from Fama-MacBeth return predictive regressions where we construct $SMLPR$ allowing for endogenous liquidation choice. Specifically, instead of assuming proportional trading, we use the fitted values of $NetBuy_{it}^{j}$ from the following regression:

$$NetBuy_{it}^{j} = \sum_{k \in \mathbb{K}} I_{kt}^{j} + \Delta Z_{t}^{j} + \Delta Z_{t}^{j} \times StockCharacteristics$$

where $NetBuy_{it}^{j}$ is the netbuying of stock i by account j on day t, I_{kt}^{j} is an indicator for whether account j is in Z bin k at the start of day t. The dependent variable is stock i's return (in percentage) on day $t + 1$. $SNMLPR$ and other stock characteristics are defined in Table 6. Columns (1) and (2) include the whole sample from May 1st to July 31st, 2015. Columns (3) and (4) include the subsample of May 1st to June 12th, 2015 (Up Market), while Columns (5) and (6) include the subsample of June 15th to July 31st, 2015 (Down Market). Standard errors, with Newey-West adjustments of four lags, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. var.: $R_{i,t+1}$	(1) Whole	(2) Whole	(3) Up	(4) Up	(5) Down	(6) Down
SMLPR	0.136	0.136	-0.077	-0.062	0.334***	0.321***
	(0.088)	(0.085)	(0.071)	(0.069)	(0.103)	(0.103)
SNMLPR		-0.006		0.037*		-0.048
		(0.038)		(0.021)		(0.067)
LEVERAGE	-0.325	-0.377	-3.408***	-3.299***	2.597*	2.392*
	(1.202)	(1.148)	(0.891)	(0.873)	(1.352)	(1.280)
BETA	-0.040**	-0.040**	-0.042	-0.041	-0.043*	-0.045*
	(0.017)	(0.017)	(0.028)	(0.028)	(0.024)	(0.023)
IDVOL	-1.258*	-1.245	-1.223	-1.112	-1.160	-1.239
	(0.744)	(0.748)	(1.360)	(1.339)	(0.725)	(0.768)
ILLIQUIDITY	9.504*	9.377*	6.828	6.771	9.621	9.461
	(5.369)	(5.346)	(6.618)	(6.606)	(8.064)	(8.017)
MOM SHORT	24.155***	24.096***	16.444***	16.345***	30.686***	30.667***
	(3.289)	(3.283)	(1.971)	(1.973)	(4.494)	(4.458)
MOM MEDIUM	-1.233**	-1.229**	-0.260	-0.270	-2.040***	-2.024***
	(0.464)	(0.459)	(0.270)	(0.268)	(0.711)	(0.704)
MOM LONG	-0.123**	-0.123**	-0.114	-0.115	-0.123**	-0.123**
	(0.048)	(0.048)	(0.095)	(0.095)	(0.047)	(0.047)
MCAP	0.000	0.000	-0.000***	-0.000***	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BMRATIO	0.015	0.009	-0.416	-0.396	0.296	0.267
	(0.244)	(0.240)	(0.367)	(0.363)	(0.289)	(0.286)
TURNOVER	2.190*	2.179*	2.866	2.978	2.048**	1.914**
	(1.164)	(1.150)	(2.361)	(2.334)	(0.888)	(0.869)
p-value (SMLPR > SNMLPPR)	.	0.0673	.	0.9061	.	0.0035
Obs	130,914	130,914	62,886	62,886	65,846	65,846
R^2	0.173	0.175	0.119	0.120	0.219	0.223

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Table A5

MLPR **Regressions: with Alternative Size Controls**

This table reports results from Fama-MacBeth return predictive regressions using alternative size controls. Instead of *MCAP*, we use the market cap decile (*MCAP_BIN*) in Panel A and the inverse of *MCAP* (*MCAP_INV*) in Panel B. The dependent variable is stock i's return (in percentage) on day $t+1$. *SMLPR*, *SNMLPR* and other stock characteristics are defined in Table 6. Columns (1) and (2) include the whole sample from May 1st to July 31st, 2015. Columns (3) and (4) include the subsample of May 1st to June 12th, 2015 (Up Market), and Columns (5) and (6) include the subsample of June 15th to July 31st, 2015 (Down Market). Standard errors, with Newey-West adjustments of four lags, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Baseline *MLPR* (*MCAP* Bin)

Dep. var.: $R_{i,t+1}$	(1) Whole	(2) Whole	(3) Up	(4) Up	(5) Down	(6) Down
SMLPR	0.102***	0.090***	0.001	-0.006	0.185***	0.168***
	(0.034)	(0.032)	(0.020)	(0.017)	(0.037)	(0.035)
SNMLPR		0.015		0.060***		-0.023
		(0.046)		(0.020)		(0.081)
LEVERAGE	-1.212	-1.286	-3.080***	-2.979***	0.327	0.108
	(0.881)	(0.819)	(0.779)	(0.770)	(1.153)	(1.055)
BETA	-0.047***	-0.047***	-0.044	-0.043	-0.050**	-0.051**
	(0.017)	(0.017)	(0.028)	(0.028)	(0.021)	(0.021)
IDVOL	-0.948	-0.971	-1.399	-1.258	-0.576	-0.734
	(0.752)	(0.746)	(1.360)	(1.339)	(0.722)	(0.750)
ILLIQUIDITY	10.087*	9.899*	4.301	4.417	14.852*	14.414*
	(5.611)	(5.575)	(6.769)	(6.744)	(8.225)	(8.191)
MOM SHORT	24.804***	24.715***	16.511***	16.460***	31.634***	31.513***
	(3.601)	(3.578)	(2.123)	(2.105)	(4.874)	(4.842)
MOM MEDIUM	-1.113**	-1.112**	-0.242	-0.251	-1.830***	-1.822***
	(0.422)	(0.420)	(0.277)	(0.276)	(0.622)	(0.621)
MOM LONG	-0.113**	-0.114**	-0.115	-0.116	-0.111**	-0.112**
	(0.049)	(0.049)	(0.097)	(0.097)	(0.042)	(0.042)
MCAP_BIN	0.871	1.035	4.246***	3.633***	-1.909	-1.105
	(1.213)	(1.071)	(0.851)	(0.893)	(1.382)	(1.357)
BMRATIO	-0.011	-0.018	-0.479	-0.455	0.375	0.342
	(0.252)	(0.247)	(0.375)	(0.372)	(0.290)	(0.286)
TURNOVER	1.291	1.289	3.324	3.359	-0.383	-0.415
	(1.228)	(1.229)	(2.090)	(2.079)	(1.169)	(1.165)
p-value (SMLPR > SNMLPPR)	.	0.0952	.	0.9887	.	0.0207
Obs	130,914	130,914	62,886	62,886	68,028	68,028
R^2	0.153	0.156	0.112	0.113	0.187	0.192

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Table A5
$MLPR$ **Regressions: with Alternative Size Controls**

Panel B: Baseline $MLPR$ (Inverse of $MCAP$)

Dep. var.: $R_{i,t+1}$	(1) Whole	(2) Whole	(3) Up	(4) Up	(5) Down	(6) Down
SMLPR	0.058**	0.056**	-0.028	-0.027*	0.129***	0.124***
	(0.029)	(0.028)	(0.017)	(0.015)	(0.029)	(0.029)
SNMLPR		-0.028		0.017		-0.066
		(0.038)		(0.020)		(0.065)
LEVERAGE	-0.688	-0.718*	-0.534	-0.546	-0.814	-0.859
	(0.440)	(0.419)	(0.544)	(0.544)	(0.632)	(0.580)
BETA	-0.047***	-0.047***	-0.040	-0.040	-0.052**	-0.053**
	(0.017)	(0.017)	(0.028)	(0.028)	(0.022)	(0.022)
IDVOL	-0.735	-0.758	-0.430	-0.403	-0.987*	-1.049*
	(0.707)	(0.714)	(1.361)	(1.350)	(0.559)	(0.601)
ILLIQUIDITY	8.750	8.493	-1.358	-1.266	17.075*	16.529*
	(6.274)	(6.223)	(6.955)	(6.966)	(8.879)	(8.827)
MOM SHORT	24.322***	24.277***	16.111***	16.056***	31.083***	31.047***
	(3.524)	(3.517)	(2.156)	(2.137)	(4.712)	(4.701)
MOM MEDIUM	-1.115***	-1.113***	-0.350	-0.350	-1.745***	-1.741***
	(0.396)	(0.394)	(0.291)	(0.289)	(0.592)	(0.589)
MOM LONG	-0.102**	-0.103**	-0.091	-0.092	-0.112**	-0.113**
	(0.048)	(0.048)	(0.096)	(0.096)	(0.042)	(0.042)
MCAP_INV	0.030	0.034	0.213***	0.210***	-0.120	-0.111
	(0.071)	(0.068)	(0.038)	(0.036)	(0.092)	(0.090)
BMRATIO	-0.007	-0.014	-0.385	-0.378	0.304	0.286
	(0.230)	(0.229)	(0.373)	(0.370)	(0.249)	(0.251)
TURNOVER	1.023	0.985	1.344	1.393	0.758	0.648
	(1.116)	(1.101)	(2.135)	(2.114)	(1.062)	(1.036)
p-value (SMLPR > SNMLPPR)	.	0.0401	.	0.9559	.	0.0071
Obs	130,914	130,914	62,886	62,886	68,028	68,028
R^2	0.163	0.166	0.120	0.121	0.199	0.203