The Drivers and Implications of Retail Margin Trading*

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

This Draft: August 2025

*Bian: University of International Business and Economics, jiangzebian@uibe.edu.cn. Da: University of Notre Dame, zda@nd.edu. He: Stanford Graduate School of Business, hezhg@stanford.edu. Lou: Hong Kong University of Science and Technology, and CEPR, dlou@ust.hk. Shue: Yale University and NBER, kelly.shue@yale.edu. Zhou: PBC School of Finance, Tsinghua University, zhouh@pbcsf.tsinghua.edu.cn. This paper subsumes two previous working papers: "Leverage-Induced Fire Sales and Stock Market Crashes" by Bian, He, Shue and Zhou, and "Leverage Networks and Market Contagion" by Bian, Da, Lou and Zhou. We are grateful to numerous conference discussants and conference and seminar participants. Bian acknowledges financial support from the National Natural Science Foundation of China (Project No. 72073027). He acknowledges financial support from the Fama-Miller Center at the University of Chicago, Booth School of Business. Lou acknowledges funding from the Paul Woolley Center at the London School of Economics. All remaining errors are our own.

The Drivers and Implications of Retail Margin Trading

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 related to their lottery preferences. We then show that margin borrowing 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 to affect asset prices and contributes to shock spillovers across stocks (for example, from lottery stocks to non-lottery 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., 2024) and high borrowing costs, which range from 8% annually 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 affect their trading behavior, and how does margin-induced trading aggregate 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

[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. (2024).

[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% per 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 lottery preferences as a possible driver of retail margin trading. We find that margin investors exhibit significantly stronger lottery preferences compared to non-

[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. (2024) 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.

margin investors, i.e., they have a stronger 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.

While investors' inherent lottery preferences are likely to be a major determinant of their lottery holdings, we show that access to margin and margin constraints can have a direct causal impact on their lottery holdings. Specifically, exploiting a regulatory discontinuity in the eligibility for brokerage margin borrowing as well as plausibly exogenous variation in Pingcang lines of shadow margin accounts, we show that a) just-eligible brokerage-margin accounts hold more lottery stocks than just-ineligible accounts, and b) shadow margin investors closer to the Pingcang line hold more lottery stocks than otherwise identical investors. These results suggest that the act of margin borrowing and the closeness to margin constraints may induce investors to hold more lottery stocks, which offer a way to (hopefully) realize a large gain despite the high borrowing cost and/or gamble for resurrection.

We also find that margin investors' lottery preferences may be partly driven by overconfident beliefs in their information advantage. 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 faster rate than non-margin investors. Finally, margin investors do not outperform the market or non-margin investors in realized portfolio returns. These observations (tendency to hold information-sensitive stocks, high account turnover, but poor average account returns) 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.

Collectively, our results point to lottery preferences, partly driven by overconfident beliefs, as the driver of Chinese retail investors' decisions to engage in expensive margin trading. The data

[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).

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 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 under a leverage constraint (Grossman and Vila, 1992; Garleanu and Pedersen, 2011). Our non-parametic 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 (negative if selling) 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, shadow financed margin accounts with $Z \in (0, 1]$ (i.e., accounts that are close to the Pingcang Line) sell 23.1% of their existing risky holdings on that day, relative to non-levered margin accounts. The difference is 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 in a down market, 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 two tests to identify a causal role of leverage constraints on margin trading behavior (similar to the empirical strategies used earlier to identify the effect of margin borrowing on lottery holdings). In these tests, our goal is not to completely reject alternative explanations of trading. 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). A potential concern with 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—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.

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 = 2.84) 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, consistent with our finding that margin investors tend to sell non-lottery stocks in response to negative portfolio returns, we show that the return spillover effect induced by leverage constraints is weaker for lottery stocks than for non-lottery stocks.

Related literature Our paper is closely related to recent studies on the drivers of retail investors' 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 drivers 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. We extend these results by showing in our unique setting of a bubble-crash episode that lottery preferences, partly driven by overconfident beliefs, drive 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. (2023) 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). 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

[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.

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., 2018b, 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 28^{th}, 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.[11]

2 Institutional Background and Empirical Approach

Our analysis exploits account-level margin trading data in the Chinese stock market covering the period May 1^{st} to July 31^{st}, 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).[12]

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.[13] 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.[14] This amounted to approximately 3-4% 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.

[11] Our paper is also closely related to share pledging in China, where major shareholders use their floating shares as collateral to obtain financing from creditors (and potentially fund their entrepreneurial activities as shown in He et al., 2022). For more on recent progress on China's financial market, see He and Wei (2023).

[12] 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.

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

[14] 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.

Chinese brokerage firms usually provide margin financing by issuing short-term bonds,[15] 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%.[16] 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 (see footnote 7 for more details).

Almost all brokerage-financed margin accounts are owned by retail investors.[17] 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. Our subsequent empirical analyses exploit 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 importantly, 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 translates to "forced settlement line." 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.[18] 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) 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

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

[16] 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.

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

[18] 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.

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 much 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.[19] 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. 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, shadow margin lenders operated in a more "discretionary" manner due to lax regulation, while brokerage margin businesses were more "rule-based." For instance, in the brokerage system, processing of debt 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;

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

typically, each new request for margin financing needed to be reviewed by the mother account in an ad-hoc fashion.

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.[20]

On Friday, June 12^{th}, 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.[21] A stock market crash began the following trading day, Monday, June 15^{th}, 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 1^{st} to July 31^{st}, 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 78,000 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 49.45% and 50.55% of the sample, respectively.[22] Unfortunately, the QJ accounts do not provide

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

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

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

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.[23] 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, we exclude stock-date observations when stocks are suspended from trading (Huang et al., 2018).

[23]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.

2.3 Distance-to-Margin-Call: Z

We introduce in this subsection a simple empirical framework to think about investors' margin constraints—the distance to margin call. To start, 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 of account j at the start of day t, equal to total assets minus total debt. (Throughout the paper, we use account equity to refer to the investor's own capital.) 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 the lender.

Denote by σ_{At}^j the asset portfolio return volatility of account j on day t.[24] For each account-date observation with start-of-day asset value A_t^j, equity value E_t^j, together with the 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 at the start of day 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:

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

Eq. (3) indicates that the account's distance-to-margin-call depends on the account's Leverage-to-

[24] 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 3.3.

Pingcang distance (LP), 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 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 R in a highly nonlinear 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 yields the derivative of Z with respect to account return R evaluated at $R = 0$ is

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

In words, the derivative (5) captures how Z, to a first order approximation, responds to the account return R. Later we will refer to $Z'(R)|_{R=0}\, R$, which is the change of Z in response to account return R, as Z-shock.

We highlight that the non-linearity of $Z(R)$ in (4) as a function of R implies that its derivative (5) increases with account leverage (which is itself affected by account return R). For a low-leverage account, such that $Lev \approx 1$, (5) is close to 0, so the account return has a small effect on Z. However, following a large negative account return so that it is a margin-constrained account ($Lev \to \overline{Lev}$), then (5) is close to $1/\sigma^A$.[25] Considering that daily σ^A takes a value of 3-5% in the data, the marginal impact (5) is about $1/0.04 = 25$. This implies that a small negative return of only 2% would move Z closer to zero by 0.5.

Finally, for an unlevered investor with $A = E$ (implying that $Lev = 1$), Z is not defined based on Eq. (2).[26] In other words, Eq. (3) only applies to the case $Lev \in \left(1, \overline{Lev}\right]$. 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 with zero borrowing 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.

[25]It is proportional the inverse of σ^A because Z in (2) is defined as the number of standard deviations of downward movements in asset value necessary to push the account's leverage to its Pingcang Line.

[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.

3 Investor/Account Characteristics and Lottery Preferences

In this section, we investigate the investor, account, and portfolio characteristics of margin investors in our sample. Our focus will be on their preferences for lottery-like stocks.

3.1 Investor/Account/Portfolio Characteristics

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

We first examine the types of retail investors who 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. (2024). We study three sets of investor and portfolio characteristics. First, in Table 1 Panel A, the first three columns report the average investor and account characteristics corresponding to brokerage margin, shadow margin, and brokerage non-margin accounts. We do not observe investor characteristics for 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 account 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. Non-margin investors stand in the middle and hold 3.4 stocks in their portfolios, which is 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 the three classes of investors have similar Herfindahl indexes (around 0.6); brokerage margin investors have slightly lower Herfindahl index (0.56), consistent with holding a relatively larger number of stocks in their portfolios. Shadow margin investors also have higher portfolio turnover; their average daily portfolio turnover rate is 21.4%, which is much higher than that of brokerage margin investors (11.7%) and non-margin investors (10.6%).

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 (2.2% for brokerage margin accounts and 2.7% for shadow margin accounts vs. 1.7% for non-margin accounts).[27] Interestingly,

[27] 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, albeit with smaller magnitudes as the former is measured based on stock turnover in the prior year (May 2014 to May 2015).

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 and the lotter preferences that we investigae in the next subsection. 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 -17.2 bps daily return for brokerage margin investors and a -64.0 bps daily return for shadow margin investors, and a combined daily return of -26.6 bps for all margin investors—do not outperform non-margin investors (with a daily return of -21.0 bps) 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 from shadow margin financing, despite a far lower average market return, may be that they erroneously believe that they can beat the market.

While reverse causality (that margin trading, with the low average returns during our sample period, led to investor overconfidence) is unlikely, it is possible that some missing factors drive both margin trading and account/holding characteristics. Nevertheless, our evidence is broadly consistent with prior findings using investor survey responses to directly measure overconfidence. For example, by linking Chinese investors' survey responses to their trading activities, Liu et al. (2022) show that perceived information advantage is a main determinant of non-margin retail trading. Similarly, Barber et al. (2022) combine survey information with brokerage trading data to establish a direct link between investor overconfidence and their decisions to use leverage.

3.2 Lottery Preferences

Perhaps more interestingly, we find that margin investors have a 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% 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 the 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 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 2.57 days for brokerage and shadow margin investors respectively, and that of non-margin investors is 2.09 days, so a (statistically significant) difference between margin and non-margin investors of more than 20%.[28]

We also consider alternative definitions of lottery stocks. For instance, in the row labelled "Lottery3 Holding," 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 25%. We obtain similar results if we instead define lottery stocks as those that have had at least two (Lottery2 Holding) or four (Lottery4 Holding) 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 "Reverse Lottery-ness" 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.

Does Margin Borrowing Increase Lottery Holdings? There are several plausible channels that could lead to a positive relation between the choice of leverage and lottery holdings. First and most likely, investors with lottery preferences choose to borrow and lever up – to further amplify extreme payoffs. Second, the act of leverage (or the closeness to leverage constraints) may

[28] 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.

induce investors to hold lottery stocks – to justify the very high borrowing costs or to gamble for resurrection. Third, there could also be other behavioral traits that drive both investors' lottery holdings and their decisions to lever up.

In this subsection, we provide evidence for the second channel. We conduct two identification strategies to this end (which we also use in Section 4.3). Our goal is not to rule out the other two channels, but rather to explore how leverage and leverage constraints can induce investors to hold lottery stocks.

Our first test compares the lottery holdings ("Lottery3 Holding") of brokerage margin investors who just qualified for margin trading and brokerage non-margin investors who just failed to qualify for margin trading. Our test exploits 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. As can be seen from Column (1) of Table 2, just qualified margin investors invest 4.4% more in lottery stocks than just-unqualified non-margin investors. In comparison, the baseline difference between margin and non-margin investors reported in Panel B of Table 1 is 6.4%.

In our second test, we focus on the shadow margin sample where two margin accounts can have the same leverage but different degrees of leverage constraints, thanks to differences in their Pingcang Lines as mentioned in Section 2.2. To further alleviate the concern that Pingcang Lines are endogenously chosen, we use a reduced-form instrument—the average Pingcang Line of peer shadow accounts—for a shadow margin trader's Pingcang Line. This is based on the observation that investors who opened their shadow margin accounts around the same time tend to have similar Pingcang Lines. As shown in Columns (2) and (3) of Table 2, the coefficient on LP (leverage to Pingcang, as defined in Eq. (3)) is statistically negative, indicating that holding constant account leverage, shadow margin investors hold more lottery stocks when they are closer to their leverage constraints.

3.3 Account Leverage and Distance to Margin Call

Finally, 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.[29]

[29] 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 29.73 (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 a 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 calculated Z using data on the covariance matrix of stocks' daily returns in the year *prior* to our sample period 5/1/2015–7/31/2015 (see footnote 24); during our sample period, however, the average daily volatility of stocks more than doubled relative to the prior year 5/1/2014–4/30/2015. This rise of stock level volatility translates to an approximate doubling of the stock portfolio level volatility; as shown in Panel A in Table 1, the stock portfolio volatility (without cash and before leverage adjustment) rose from 2.448% in the prior year to 5.355% in our sample period for shadow margin accounts; the changes are similar for the other two types of accounts.[30]

In Appendix Table A1, we report the distribution of account-day observations across our Z-bins using both the ex-ante and in-sample asset portfolio volatility (including cash). We show that,

(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.

[30]To calculate the stock portfolio volatility in the prior year, we take the covariance matrix of stock returns during the sample period of 5/1/2014–4/30/2015, and calculate the hypothetical stock portfolio return volatility (without cash before leverage adjustment) based on the account holding data in our sample period. This reflects an investor's perceived stock portfolio volatility during the sample period if he/she assumes the volatility does not change from the prior year.

using the higher in-sample estimate of portfolio volatility, a substantially larger cumulative fraction of leveraged margin accounts are close to their leverage constraints: 65.24% and 23.34% of shadow margin accounts have Z less than 5 and 2, respectively. Within the combined sample, 21.20% and 7.03% of accounts have Z less than 5 and 2, respectively.

Second, as explained in the discussion of Eq. (5), the impact of the account return R on the distance-to-margin-call Z increases dramatically when the account leverage edges closer to its Pingcang Line. Because leverage rises following a negative account return, a few consecutive negative returns can cut Z toward zero quickly due to the strong non-linearity in our setting of margin trading with leverage constraints.[31] To put this force into perspective, consider the average shadow margin account in our sample, and how the account return drives the *percentage* change of Z. 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 one standard deviation of (negative) daily account return σ^j_{At} (including cash holdings), which is −4.17% during our sample period and well within the daily price 10% limit, can reduce Z by more than 40%. Considering the heightened volatility experienced in our sample period, coupled with the significant nonlinear 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. Exactly because of this reason, in our sample the frequency of margin accounts that ever hit their Pingcang Lines is quite high, standing at 28.58% for shadow margin accounts and 2.39% for brokerage margin accounts.[32]

4 Trading Behaviors of Margin Investors

In this section, we examine the impact of leverage constraints on the trading behavior of margin investors. We first briefly describe our empirical framework and the baseline results. We then provide causal evidence that leverage constraints exacerbates selling in a down market. Finally, we show that margin investors are more likely to sell non-lottery stocks in such a market.

4.1 Z-Shocks and Margin Trading

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

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

[31] In other words, $Z(R)$ given in (4) is nonlinear in R.

[32] Even the 2.39% default probability for brokerage accounts is non-trivial considering it is measured during a 3 month sample period for our data. In the U.S. corporate bond market, the cumulative default probabilities of 10-year corporate bonds are only 2.1% for Aaa/Aa rated bonds and 3.4% for A rated bonds (Chen et al., 2018a).

$NetBuy^j_{it}$ 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^j_t, and shocks to Z^j_t. Note that $NetBuy^j_{it}$ 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—potentially due to lower Zs—than their 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.[33] $NetBuy^j_{it}$, the daily change in optimal holdings, can then be expressed using the following first-order Taylor expansion:

$$NetBuy^j_{it} = f\left(Z^j_t\right) + g\left(Z^j_t\right) \cdot \underbrace{Z'(R)\big|_{R=0} \cdot R^j_t}_{Z\text{-Shock, denoted by} \Delta Z^j_t} + \alpha_j + \nu_{it}, \tag{8}$$

where Z^j_t is measured at the start of day t, R^j_t is the account return over the course of day t based on start-of-day asset holdings, $Z'(R)$ 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. In (8), $f(\cdot)$ and $g(\cdot)$ are general nonlinear functions; $f(\cdot)$ captures average trading for accounts with a distance-to-margin-call Z, and $g\left(Z^j_t\right)$ captures the trading in response to the changes in Z on that day.

We define Z-Shock, which is denoted by ΔZ^j_t, to be $\Delta Z^j_t \equiv Z'(R)|_{R=0} \cdot R^j_t$. For a given Z-shock, a margin investor may react differently depending on where her Z lies; this potentially nonlinear effect is captured by $g\left(Z^j_t\right)$. Note that as mentioned in the discussion after Eq. (5), $Z'(R)$ is zero for unlevered accounts; this implies that 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 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 A7. Nevertheless, we prefer to use a proportional sales assumption in our baseline tests to present

[33] 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).

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 k^{th} bin at the start of day t; note that the value of I_{kt}^j is fully determined by Z_t^j at the account-date level. 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 footnote 38 for more details). We also create a $(K+1)^{th}$ "NA" bin for all unlevered accounts with undefined Z which serve as the control group. Their ΔZ_t^j are set to zero (as the account return has no impact on the margin constraint of an unlevered account). The estimated coefficient for the other Z bin captures the additional trading intensity relative to these non-levered margin accounts.[34]

We then conduct the following regression to estimate $\{f_k, g_k : k \in \mathbb{K}\}$:

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

where $Z'(R)|_{R=0}$ is calculated based on Eq. (5), and $\{f_k, g_k : k \in \mathbb{K}\}$ are estimated non-parametrically. Once we obtain the coefficients $\{\hat{g}_k\}$ by estimating (9), we take them to be the estimates of $g(Z_t^j)$ in (8) (under the assumption that $g(Z_t^j)$ depends on Z-bin only).

Our non-parametric estimation of $g(Z_t^j)$ has the advantage of allowing the trading response to Z-shocks to depend flexibly on the account's level of Z. A downside of this flexible specification is that we must present many coefficients $\hat{g}_k$, and exposition becomes particularly cumbersome when we are interested in heterogeneity in the trade response, e.g., by stock characteristics. To simplify the exposition, we define the scaled Z-shock as the product between Z-shock and the account-day's relevant $\hat{g}_k$, as estimated in the full sample.[35] Scaled in the way, the coefficient on scaled Z-shock becomes one in the full sample, by construction:

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

We can then interact scaled Z-shock with other variables such as measures of a stock's lotteriness, allowing exploration of heterogeneity in trading behavior in a parsimonious way.

[34]Because we wish to study the behavior of accounts with small Z, we did not choose bins with equal numbers of observations per bin. Nevertheless, we have sufficient statistical power to compare trading behavior across our chosen Z-bins. 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 "NA" group throughout the sample period, only 24% of accounts never move across Z bins.

[35]For example, we estimate $\hat{g}_k = 4.06$ for $Z \in (0, 1)$ and $\hat{g}_k$=0.77 for $Z > 5$. A hypothetical Z-shock = 10 translates to scaled Z-shock of 40.06 and 7.7 for accounts with $Z \in (0, 1)$ and $Z > 5$, respectively.

We report summary statistics of the resulting estimated Z-Shocks and scaled Z-Shocks in Panel C of Table 1.

4.2 Baseline Results

In this subsection, we study the trading activities of margin investors, with an emphasis on their deleveraging behaviors due to leverage constraints.[36]

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 4.1.

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 Appendix Table A3, we also confirm that shocks during day t continue to affect trading (and returns) in day $t+1$.

The regression results are provided in Table 3. Column (1) shows that margin accounts that are very close to margin calls (with Z between 0 and 1) sell an additional 23.95% of their current stock holdings, compared to unlevered margin accounts. We also find that selling pressure increases monotonically as the distance-to-margin-call falls (as Z-bins approach zero). For instance, the coefficient for a margin account with Z between 0 and 1 is almost six times that in a margin account whose Z is greater than 5 (-4.16).[37] The pattern of intensified liquidation activity as Z approaches zero is robust to looking at the full sample of margin accounts (Column 1), brokerage sample (Column 2), and shadow sample (Column 3), and is consistent with a precautionary motive in theories of leveraged trading (e.g., Garleanu and Pedersen, 2011; He and Krishnamurthy, 2019). The nonlinear relationship between Z and *NetBuy* as shown in Table 3 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 Pingcang Line (the leverage constraint). (We will return to this point of leverage constraints shortly in Section 4.3.) Note, we discuss the liquidation behavior of accounts with $Z < 0$, where control has reverted back to the lender, in the next subsection.

Table 3 also reports significant and positive coefficients $\{g_k\}$ on the interaction between Z-bin

[36] 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 A2, 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 nonlinear 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 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.

[37] 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.

indicators and Z-Shock. These positive coefficients imply that when today's account return pushes a margin account closer to its leverage constraint, there is less contemporaneous net buying, or equivalently, more selling. In the full sample (Column 1), we find that $\{g_k\}$ increases as the Z-bins move closer to zero, implying that margin investors are more sensitive to movements in their distance-to-margin call when they are closer to their leverage constraint (again, we will discuss behavior when margin investors lose control of their accounts, $Z < 0$, in the next subsection).

Our estimation further implies that the relation between net buying and account returns is highly non-linear. As shown in Eq. (9), this nonlinear relationship is captured by the coefficient $g_k \cdot Z'(R)|_{R=0}$ in front of the account return R_t^j. Note that $Z'(R)|_{R=0}$ itself increases with leverage as we have discussed after Eq. (5). 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 (1), we estimate $g_k = 4.03$ for $Z \in (0,1)$. Together with the median $Z'(R)|_{R=0}$ of 47.9 in this bin based on Eq. (5) in Section 2.3, it implies that our scaled Z-Shock has an amplification factor of—i.e., the coefficient $g_k \cdot Z'(R)|_{R=0}$ in front of R_t^j—of 194.52. The same amplification factor for $Z > 5$, with estimated $g_k = 0.77$ and median $Z'(R)|_{R=0}$ of 25.49, is an order of magnitude smaller, at only 19.63.

Brokerage versus shadow accounts Comparing Column (2) (brokerage accounts) to Column (3) (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 23.1% if the stock appears in a shadow account, compared to 11.8% when it appears in a brokerage account. Likewise, selling in shadow accounts is more sensitive to Z-shocks. Interestingly, the selling intensity flips once the account exceeds the Pingcang Line ($Z \leq 0$): the additional selling pressure is 19.6% for shadow accounts, but it rises sharply to 24.5% for brokerage accounts.

These differences can potentially be explained by the institutional background presented 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.[38]

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 in case they cannot secure timely additional financing, while brokerage margin investors tend to

[38] A small fraction of margin accounts in our sample (about 1.11% of account-date observations) have leverage significantly above their Pingcang Lines. They 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) or trading restrictions. In calculating their Z-shocks, we set $Z'(R)|_{R=0} = 1/\sigma^A$, i.e., leverage binds at the Pingcang Line, since leverage itself does not matter any more.

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 below 10% for brokerage 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.

Trading in up and down markets In columns (4) and (5) of Table 3, 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 15^{th}, 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. A stronger relation between trading behavior and 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. We find that average stock volatility and portfolio volatility of margin accounts 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.

In both up and down markets, we continue to find a positive relation between net buying and Z-Shock that increases as Z-bins move closer to zero. Perhaps surprisingly, we do not find that the relation between Z-Shock and net buying is consistently stronger during the down market period compared to the up period. There are two non-exclusive potential explanations for why margin investors do not sell more in response to the same negative Z-Shock during down markets. First, margin investors with Z close to zero are already selling very aggressively (more than 30% of stock holdings in a single day relative to unlevered accounts) even when the account return is zero. At the high level of baseline of sales, their trading may be less sensitive to Z-shocks. Second, during down markets on days with large negative account returns, many stocks could not be sold during part of the day when returns hit the -10% limit.

4.3 Causal Impact of Leverage Constraints

Table 3 shows that margin investors sell more of their holdings as their distance-to-margin-calls Z shrinks toward zero and after negative Z-Shocks. This selling behavior could be driven by leverage constraints. However, there are two possible alternative explanations for the relation between selling behavior and Z. 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 subsection, 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.

4.3.1 Margin eligibility of brokerage accounts

We identify the role of leverage, as distinct from returns, in affecting margin investors' trading behaviors. Similar to the tests in Section 3.2, 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 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 the 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 20^{th}, 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 4 Panel A, we regress *NetBuy* at the account-stock-day level on the account's equity return 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 stock-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 4 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 4 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.

4.3.2 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 $LP = \frac{\overline{Lev} - Lev}{\overline{Lev} - 1}$ (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 4, 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 (i.e., has a smaller Leverage-to-Pingcang). The significant negative interaction term points to the role of a leverage constraint, and echoes the evidence in the previous Section 4.3.1: 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). Using these average Pingcang Lines in Columns (3) and (4), we find very similar results.

4.4 Margin Trading of Lottery 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 5 reports regressions of $NetBuy$ on scaled 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 from the discussion in Secion 4.1 that scaled Z-Shock is calculated as the product of Z-Shock and the account-day's relevant $\hat{g}_k$, as estimated in the full sample. Scaled Z-Shock is scaled to have a coefficient of one in the full sample, allowing us to present heterogeneity results in a parsimonious manner. As described in Section 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 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 scaled 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 6.5% ($= 0.017 \times 4/1.049$) 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 15^{th} to July 31^{st} compared to the up-market period from May 1^{st} to Jun 12^{th}. During the market downturn, margin investors were 11.2% ($= 0.026 \times 4/0.929$) 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 scaled 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 A4, 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 non-lottery stocks than lottery stocks in response to negative scaled Z-shocks.

5 Price Impact *via* the 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 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.

Suppose a margin investor who holds two stocks, S_1 and S_2, and 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 scaled Z-Shock as estimated in Eq. (9). For example, if Eq. (9) 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.

5.1 Constructing $MLPR$

Formally, 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

$$Q_t^j \equiv \sum_{k \in \mathbb{K}} g_k I_{kt}^j \cdot Z'(R)\big|_{R=0}\,, \tag{11}$$

and plug this into Eq. (9). We can then write margin investor j's dollar trading (denoted by X_{it}^j) in stock i as $X_{it}^j = A_t^j \omega_{it}^j \cdot Q_t^j R_t^j$, where A_t^j is investor j's account value and ω_{it}^j is the portfolio weight of stock i, both measured at the beginning of day t. 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 perform several further steps to arrive at the measure of margin-account linked portfolio returns ($MLPR$). First, we scale the dollar amount of trading in each stock by its market capitalization at the start of day t to form the basis for us to construct margin-account linked returns:

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

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

Second, it is more convenient to recast (13) to a matrix from the stock level. Given N stocks in the market, on each trading day we let $\mathbf{R}$ denote an $N \times 1$ vector of stock returns of that day, $\mathbf{\Omega}$ 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-account linked returns on all stocks is $\mathbf{T} \times \mathbf{R}$, where

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

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

Third, we isolate the effect of contagion by removing the stock's own return. We formally define $MLPR$ as

$$MLPR \equiv \mathbf{T}_0 \times \mathbf{R}, \quad \text{where} \quad \mathbf{T}_0 \equiv \mathbf{T} - \mathbf{diag}(\mathbf{T}). \tag{15}$$

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. 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.

5.2 Empirical Design

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 Table A3, 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. Specifically, we estimate the following Fama-MacBeth return forecasting regression:

$$R_{i,t+1} = \alpha + \beta \cdot MLPR_{i,t} + \beta_N \cdot NMLPR_{i,t} + \sum_m \lambda_m \cdot CONTROL_{i,m,t} + \varepsilon_{i,t+1}, \tag{16}$$

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.

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 4.2 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 examine the difference between lottery vs. non-lottery stocks. Earlier results in Section 4.4 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, recall that 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.

5.3 Empirical Results

5.3.1 Baseline regression with $NMLPR$

In Table 6, we estimate the price impact due to return movements of other stocks that are connected via the leverage network, following the framework in Equation (16). Importantly, we 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.[39] $NMLPR$ helps us control for 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.

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 = 2.84), 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 0.745 bps of shares outstanding and 11 bps 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 the absence of the daily limit). This figure is largely in line with the estimates of individual stock demand elasticities

[39] 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.

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 15^{th}, 2015 (the peak of the market), respectively. Consistent with the last two columns reported in Table 3, 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 = 0.10) and 18 bps (t-statistic = 4.83), 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.

To create MLPR, we divide by the stock's market cap because the return impact of a given expected dollar amount of trading on a stock is likely to decline with the stock's market cap. Since the market capitalization ($MktCap$) of a stock enters the denominator in the definition of $MLPR$, as in Eq. (13), one potential concern is that $MLPR$ is driven by (the inverse of) $MktCap$. We present analysis showing that this is not the case. Appendix Table A5 shows that $MLPR$ and $MktCap$ are uncorrelated. In addition, replacing the control variable $MCAP$ in regression Eq. (16) by $MCAP$ decile or its inverse does not change the result qualitatively, as shown in Appendix Table A6.

5.3.2 Lottery vs. non-lottery stocks

Section 4.4 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. If the maximum number of consecutive days of hitting the 10% upper price limit is at least 3, the stock is defined as a lottery stock (our results are also robust to using 2 or 4 days as the cutoff point). We divide our sample into lottery and non-lottery stocks and rerun the return predictive regression in each sub-sample. We 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 7, a one-standard-deviation increase in $MLPR$ predicts a higher next-day return of 19 bps (t-statistic = 4.42) among non-lottery stocks. The corresponding number for lottery stocks is only 13 bps (t-statistic = 4.23) as in Panel A. The two numbers are significantly different at the 10% level.

5.3.3 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 regression in Table 6, but now focus on cumulative stock returns over a longer horizon. Specifically, we use the cumulative returns from $[t+1, t+k]$ for $k = 1, 2, 3, ..., 35$ as the dependent variables. The coefficients on $MLPR$ are plotted graphically in Figure 4. We find that the initial positive significant relation between future returns and $MLPR$ converges toward zero and becomes insignificant within 35 trading days. While our estimates for the cumulative return response to $MLPR$ become noisy as the return horizon expands, the overall pattern is consistent with a full reversal within 35 days.

5.3.4 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 A7, 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 17 bps in the full sample, and 37 bps during the down market, after controlling for other stock characteristics.

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 retail 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 that lottery preferences, partly driven by overconfidence, can help explain why investors 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. Moreover, we find that margin investors are relatively more likely to sell non-lottery stocks as the leverage constraint binds in a down market.

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.

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.

References

Allen, Franklin, Jun "QJ" Qian, Chenyu Shan, and Julie Lei Zhu, 2024, Dissecting the long-term performance of the chinese stock market, Journal of Finance 79, 993–1054.

Amstad, Marlene, and Zhiguo He, 2020, Chinese bond markets and interbank market, in Marlene Amstad, Guofeng Sun, and Wei Xiong, eds., The Handbook of China's Financial System, chapter 6, 105–150 (Princeton University Press, Princeton).

An, Li, Dong Lou, and Donghui Shi, 2022, Wealth redistribution in bubbles and crashes, Journal of Monetary Economics 126, 134–153.

Anton, Miguel, and Christopher Polk, 2014, Connected stocks, The Journal of Finance 69, 1099–1127.

Barber, Brad M, Xing Huang, K Jeremy Ko, and Terrance Odean, 2022, Leveraging overconfidence, Available at SSRN 3445660 .

Basak, Suleyman, and Domenico Cuoco, 1998, An equilibrium model with restricted stock market participation, Review of Financial Studies 11, 309–341.

Brunnermeier, Markus, and Lasse Pedersen, 2009, Market liquidity and funding liquidity, Review of Financial Studies 22, 2201–2238.

Brunnermeier, Markus K., and Yuliy Sannikov, 2014, A macroeconomic model with a financial sector, American Economic Review 104, 379–421.

Campbell, John Y., Stefano Giglio, and Parag Pathak, 2011, Forced sales and house prices, American Economic Review 101, 2108–2131.

Carpenter, Jennifer N, and Robert F Whitelaw, 2017, The development of china's stock market and stakes for the global economy .

Chen, Hui, Zhuo Chen, Zhiguo He, Jinyu Liu, and Rengming Xie, 2023, Pledgeability and asset prices: Evidence from the chinese corporate bond markets, The Journal of Finance 78, 2563–2620.

Chen, Hui, Rui Cui, Zhiguo He, and Konstantin Milbradt, 2018a, Quantifying liquidity and default risks of corporate bonds over the business cycle, The Review of Financial Studies 31, 852–897.

Chen, Kaiji, Jue Ren, and Tao Zha, 2018b, The nexus of monetary policy and shadow banking in China, American Economic Review 108, 3891–3936.

Chen, Ting, Zhenyu Gao, Jibao He, Wenxi Jiang, and Wei Xiong, 2019, Daily price limits and destructive market behavior, Journal of Econometrics 208, 249–264, Special Issue on Financial Engineering and Risk Management.

Chen, Zhuo, Zhiguo He, and Chun Liu, 2020, The financing of local government in china: Stimulus loan wanes and shadow banking waxes, Journal of Financial Economics 137, 42–71.

Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, Journal of Financial Economics 86, 479–512.

Danielsson, Jon, Jean-Pierre Zigrand, and Hyun Song Shin, 2002, Asset price dynamics with value-at-risk constrained traders, Working Paper .

Dinc, Serdar, Isil Erel, and Rose Liao, 2017, Fire sale discount: Evidence from the sale of minority equity stakes, Journal of Financial Economics 125, 475–490.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2012, The real effects of financial markets: The impact of prices on takeovers, The Journal of Finance 67, 933–971.

Ellul, Andrew, Chotibhak Jotikasthira, and Christian T. Lundblad, 2011, Regulatory pressure and fire sales in the corporate bond market, Journal of Financial Economics 101, 596–620.

Fostel, Ana, and John Geanakoplos, 2008, Leverage cycles and the anxious economy, American Economic Review 98, 1211–1244.

Frazzini, Andrea, and Lasse Heje Pedersen, 2014, Betting against beta, Journal of financial economics 111, 1–25.

Galbraith, J. Kenneth, 2009, The Great Crash 1929 (Houghton Mifflin, New York, NY).

Gambacorta, Leonardo, Yiping Huang, Zhenhua Li, Han Qiu, and Shu Chen, 2020, Data vs collateral, Working Paper .

Garleanu, Nicolae, and Lasse Pedersen, 2011, Margin-based asset pricing and deviations from the law of one price, Review of Financial Studies 24, 1980–2022.

Geanakoplos, John, 2010, The leverage cycles, NBER Macroeconomics Annual 24, 1–66.

Greenwood, Robin, and David Thesmar, 2011, Stock price fragility, Journal of Financial Economics 102, 471–490.

Gromb, Denis, and Dimitri Vayanos, 2002, Equilibrium and welfare in markets with financially constrained arbitrageurs, Journal of Financial Economics 66, 361–407.

Grossman, Sanford J., and Jean-Luc Vila, 1992, Optimal dynamic trading with leverage constraints, The Journal of Financial and Quantitative Analysis 27, 151–168.

Hansman, Christoper, Harrison Hong, Wenxi Jiang, Jane Liu, and Juanjuan Meng, 2018, Riding the credit boom, Technical report, Columbia University.

Hardouvelis, G. A., 1990, Margin requirements, volatility, and the transitory component of stock prices, American Economic Review 80, 736–762.

Hardouvelis, Gikas A., and Panayiotis Theodossiou, 2002, The asymmetric relation between initial margin requirements and stock market volatility across bull and bear markets, Review of Financial Studies 15, 1525–1559.

Hardouvelis, Gikas A., and Panayiotis Theodossiou, 2015, The Asymmetric Relation Between Initial Margin Requirements and Stock Market Volatility Across Bull and Bear Markets, The Review of Financial Studies 15, 1525–1559.

He, Zhiguo, and Arvind Krishnamurthy, 2013, Intermediary asset pricing, American Economic Review 103, 732–770.

He, Zhiguo, and Arvind Krishnamurthy, 2019, A macroeconomic framework for quantifying systemic risk, American Economic Journal: Macroeconomics 11, 1–37.

He, Zhiguo, Bibo Liu, and Feifei Zhu, 2022, Share pledging in china: funding listed firms or funding entrepreneurship?, Technical report, National Bureau of Economic Research.

He, Zhiguo, and Wei Wei, 2023, China's financial system and economy: a review, Annual Review of Economics 15, 451–483.

Heimer, Rawley Z, and Alex Imas, 2022, Biased by Choice: How Financial Constraints Can Reduce Financial Mistakes, The Review of Financial Studies 35, 1643–1681.

Hu, Conghui, Yu-Jane Liu, and Ning Zhu, 2021, Deleveraging commonality, Journal of Financial Markets 53, 100582.

Huang, Jennifer, Donghui Shi, Zhongzhi Song, and Bin Zhao, 2018, Discretionary stock trading suspension .

Ivković, Zoran, Clemens Sialm, and Scott Weisbenner, 2008, Portfolio concentration and the performance of individual investors, Journal of Financial and Quantitative Analysis 43, 613–655.

Kahraman, Bige, and Heather E. Tookes, 2017, Trader leverage and liquidity, The Journal of Finance 72, 1567–1610.

Khandani, Amir E., and Andrew Lo, 2011, What happened to the quants in august 2007? evidence from factors and transactions data, Journal of Financial Markets 14, 1–46.

Koijen, Ralph SJ, and Motohiro Yogo, 2019, A demand system approach to asset pricing, Journal of Political Economy 127, 1475–1515.

Kumar, Alok, 2009, Who gambles in the stock market?, The Journal of Finance 64, 1889–1933.

Kyle, Albert S, and Wei Xiong, 2001, Contagion as a wealth effect, Journal of Finance 56, 1401–1440.

Lan, Yingcong, Neng Wang, and Jinqiang Yang, 2013, The economics of hedge funds, Journal of Financial Economics 110, 300–323.

Liao, Jingchi, Cameron Peng, and Ning Zhu, 2022, Extrapolative bubbles and trading volume, The Review of Financial Studies 35, 1682–1722.

Liu, Hongqi, Cameron Peng, Wei A. Xiong, and Wei Xiong, 2022, Taming the bias zoo, Journal of Financial Economics 143, 716â741.

Lou, Dong, 2012, A flow-based explanation for return predictability, The Review of Financial Studies 25, 3457–3489.

Merrill, Craig B., Taylor D. Nadauld, Rene M. Stulz, and Shane M. Sherlund, 2016, Were there fire sales in the rmbs market?, Technical report, Ohio State University.

Merton, Robert, 1974, On the pricing of corporate debt: The risk structure of interest rates, The Journal of Finance 29, 449–470.

Mian, Atif, Kamalesh Rao, and Amir Sufi, 2013, Household balance sheets, consumption, and the economic slump, The Quarterly Journal of Economics 128, 1687–1726.

Mitchell, Mark, Lasse Pedersen, and Todd Pulvino, 2007, Slow moving capital, American Economic Review, Papers and Proceedings 97, 215–220.

Panageas, Stavros, and Mark M. Westerfield, 2009, High-water marks: High risk appetites? convex compensation, long horizons, and portfolio choice, The Journal of Finance 64, 1–36.

Pulvino, Todd, 1998, Do asset fire sales exist? an empirical investigation of commercial aircraft transactions, Journal of Finance 53, 939–978.

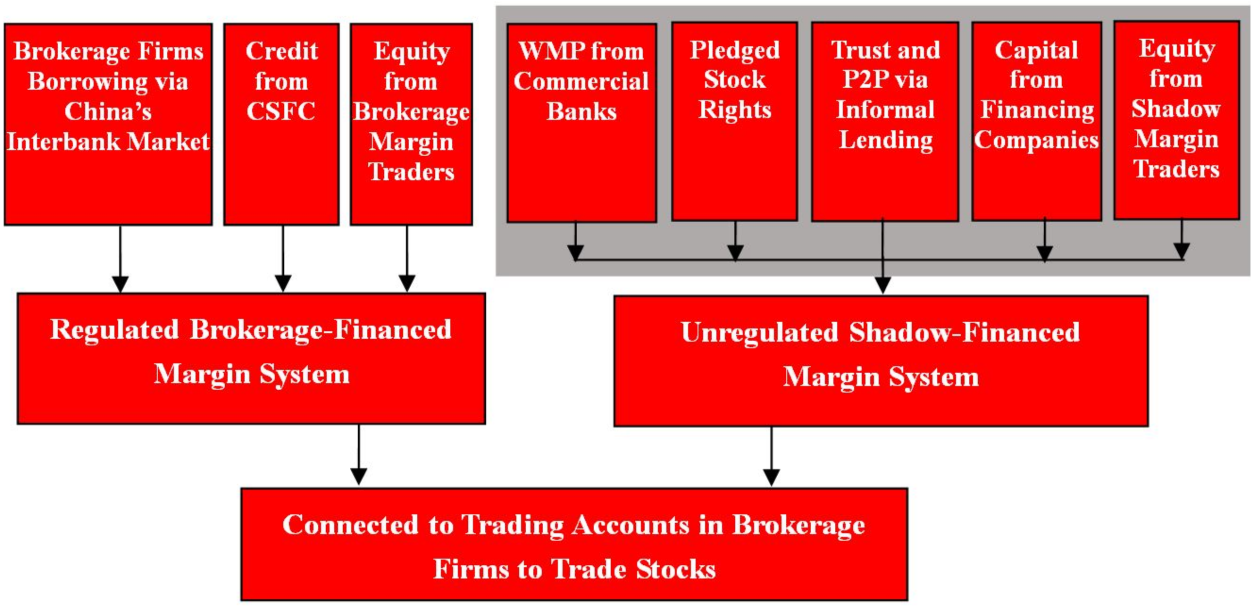
Schwert, G. William, 1989, Margin requirements and stock volatility, Journal of Financial Services Research 3, 153–164.

Shleifer, Andrei, and Robert Vishny, 1992, Liquidation values and debt capacity: a market equilibrium approach, Journal of Finance 47, 1343–1366.

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

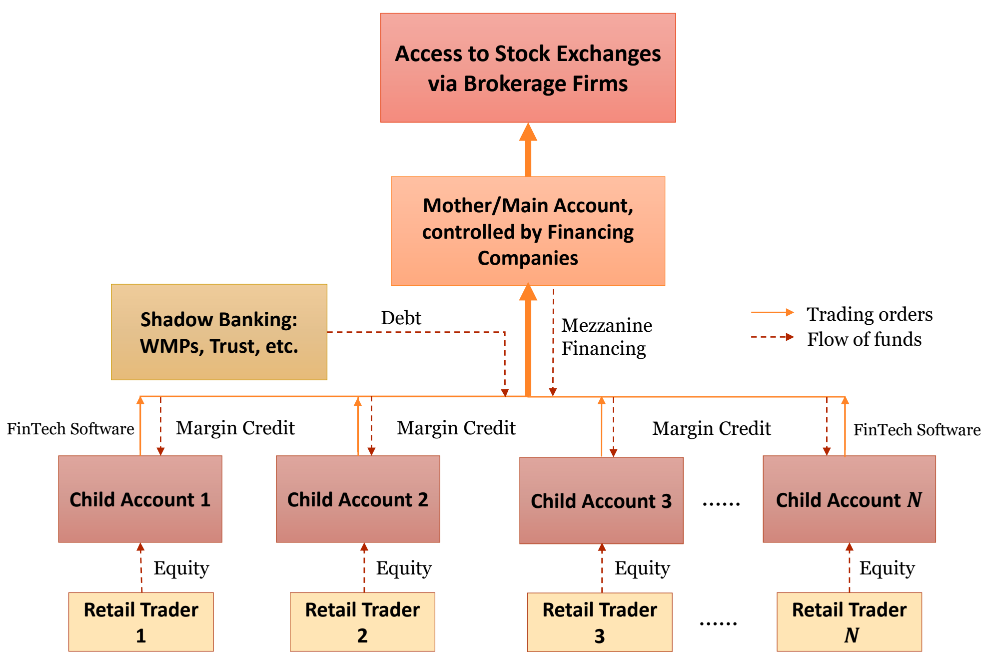
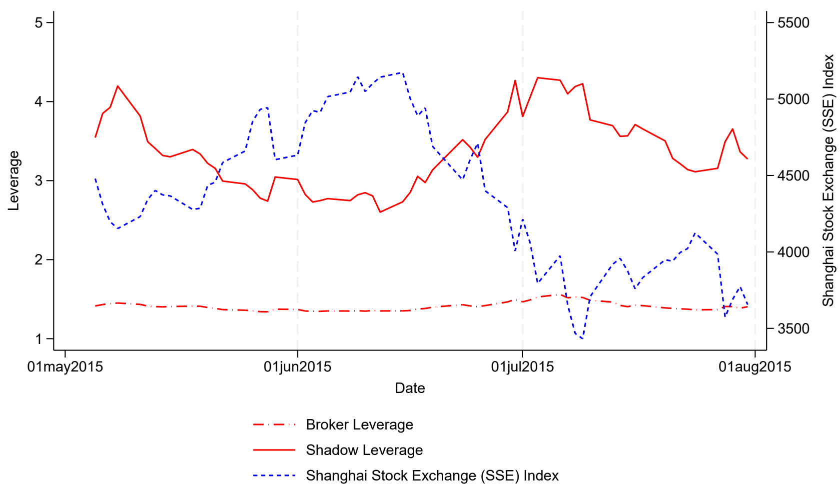


Figure 2
Average Leverage of Brokerage and Shadow Margin Accounts

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

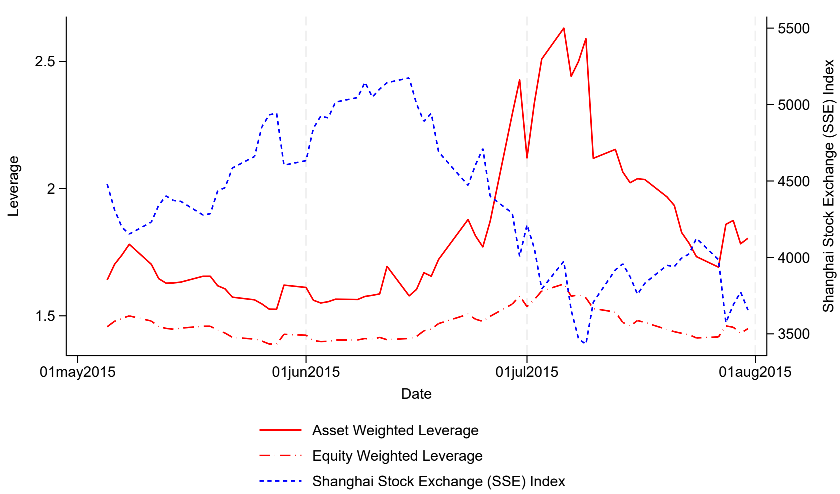
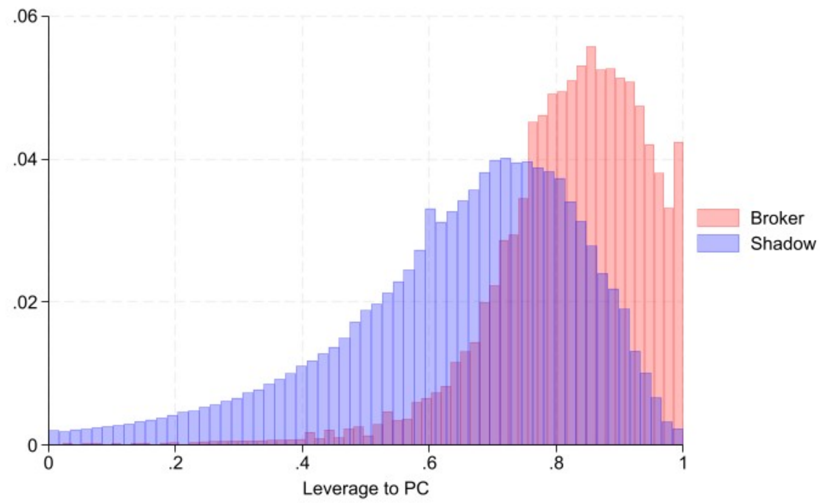


Figure 3
Distributions of Leverage

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

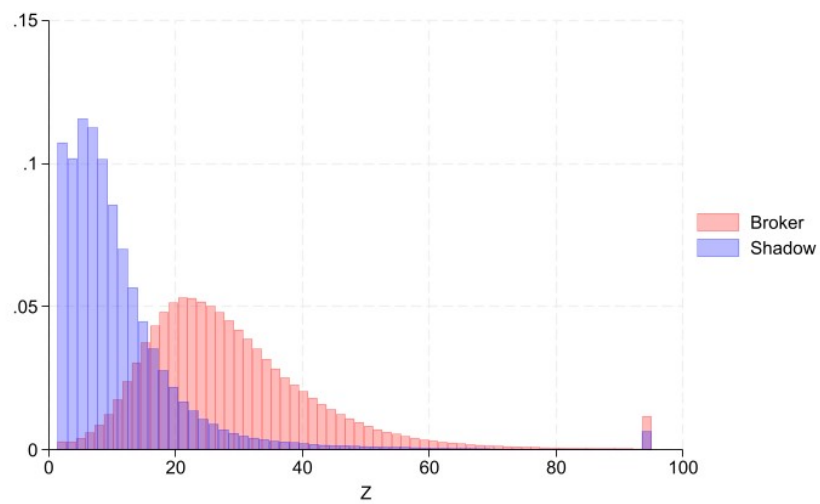


Figure 4
Long-term Return Predictability of $MLPR$

This figure plots the coefficients on $MLPR$ in forecasting $CumRet_{i,t+1,t+k}$, where $CumRet_{i,t+1,t+k}$ is the cumulative return from $t+1$ to $t+k$ for stock i. All independent variables are defined in Table 6. The x-axis plots $k \in \{0, 1, ..., 35\}$ 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.

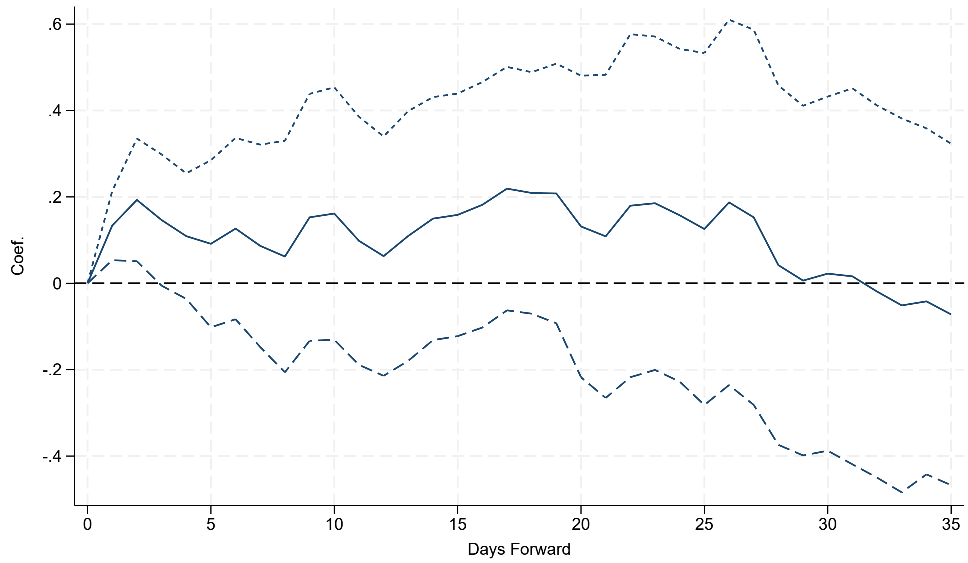


Table 1
Summary Statistics

This table reports the summary statistics of brokerage margin, shadow margin, and brokerage normal (non-margin) 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 (Stock Portfolio Return, which is the average return of the account's stock portfolio excluding cash before leverage adjustment; and Stock Portfolio Return Volatility, which is the return volatility of account's stock portfolio excluding cash and before leverage adjustment, both in our sample period 5/1/2014–7/30/2015) and ex ante (5/1/2014–4/30/2015), portfolio concentration (number of stocks in the account, and the Herfindahl index of the stock holdings in the account), 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-ness in the table is the portfolio average lottery-ness, measured in number of days. Similarly, Reverse Lottery-ness is the portfolio-average maximum number of consecutive days in which a stock hits the −10% price limit over the past year. Lottery2 Holding, Lottery3 Holding, Lottery4 Holding 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). Z-shock and scaled Z-shock are defined in Eq. (9). 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).

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)	5,599.574	1,512.517	1,354.181	***	***	
Cash Holdings (in 1000s)	372.717	345.366	55.926		***	***
Stock Holdings (in 1000s)	5,226.857	1,167.151	1,298.254	***	***	
% of Cash Holdings	0.098	0.221	0.167	***	***	***
% of Stock Holdings	0.902	0.779	0.833	***	***	***
% of Restricted Stocks	0.180	0.206	0.268	*	***	***
Stock Portfolio Return (daily in %)	-0.172	-0.640	-0.210	**		**
Stock Portfolio Return Volatility (daily in %, in sample)	5.104	5.355	5.054	***	***	***
Stock Portfolio Return Volatility (daily in %, ex ante)	2.325	2.448	2.328	***		***
Number of Stocks	4.547	2.807	3.360	***	***	***
Herfindahl Index	0.555	0.596	0.620	***	***	***
Account Turnover	0.117	0.214	0.106	***	***	***

Panel B: Stock Characteristics of the holdings

	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	0.895	***	***	***
IDVOL	0.067	0.074	0.062	***	***	***
Illiquidity	0.002	0.002	0.002		***	***
Momentum Short	0.002	0.001	0.001			
Momentum Medium	0.106	0.159	0.090	**		
Momentum Long	0.627	0.672	0.676	*		
Log MCAP	23.853	23.161	24.760	***	***	***
BM Ratio	0.437	0.414	0.707	***	***	***
Turnover	0.022	0.027	0.017	***	***	***
Lottery-ness	2.434	2.568	2.085	***	***	***
Reverse Lottery-ness	1.087	1.112	1.106	*		
Lottery2 Holding	0.582	0.624	0.497	***	***	***
Lottery3 Holding	0.344	0.344	0.280		***	***
Lottery4 Holding	0.200	0.206	0.170	**	***	***
LotteryAlt	0.485	0.504	0.395	*	***	***

Table 1
Summary Statistics

Panel C: Margin Account Characteristics

	Brokerage Margin			Shadow Margin			All Margin		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Account									
Pingcang Line	4.300	4.300	0.0000	13.543	11.001	6.6610	8.083	4.300	6.2301
N	77,891			53,972			131,863		
Account-Day									
Account Leverage	1.409	1.321	0.4710	6.399	4.469	11.1600	2.476	1.500	5.5663
Z	29.727	26.380	16.4315	11.489	8.323	16.4290	24.624	21.985	18.3577
Z-Shock	-0.047	0.000	0.9860	-0.318	-0.000	2.3310	-0.104	0.000	1.3922
Scaled Z-Shock	-0.041	0.000	0.9813	-0.605	-0.000	4.3221	-0.162	0.000	2.1918
N	3,853,717			1,047,798			4,901,515		
Account-Stock-Day									
NetBuy	-5.273	0.000	42.0770	-19.882	0.000	52.8363	-7.373	0.000	44.0849
N	17,524,686			2,940,760			20,465,446		

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

	Mean	Median	Std
MLPR	-0.692	0.165	7.4143
N	141,108		

Table 2
The Effect of Margin Borrowing on Lottery Holdings

This table estimates the causal impact of leverage constraints on lottery holdings. The dependent variable $Lottery3Holding_t^j$ is the portfolio weight by account j on day t of lottery stocks, defined as those that have had at least three consecutive days of hitting the +10% price limit in the year prior to the start of our sample period. Column (1) reports the brokerage sample result. Within the brokerage sample, the table compares the stock holding status 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 4.3.1. Columns (2) and (3) report shadow accounts results. We decompose Z-shock into LP (Leverage-to-Pingcang, measured at the end of $t-1$), $Leverage$, and $Volatility$. In Columns (2) and (3), 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, and calculate LP^* similarly as LP. Date fixed effects are included in all the columns and Account fixed effects are included in Column (3). Standard errors are clustered at the date level and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. var.: $Lottery3Holding_t^j$	(1) Brokerage	(2) Shadow LP*	(3) Shadow LP*
Treat	0.044***		
	(0.006)		
Volatility		10.732***	7.448***
		(0.218)	(0.218)
Leverage		-0.008***	-0.003**
		(0.001)	(0.001)
*LP**		-0.104***	-0.036**
		(0.013)	(0.017)
Account FE	No	No	Yes
Date FE	Yes	Yes	Yes
Obs	1,068,687	635,599	631,965
R^2	0.0027	0.0890	0.4135

Table 3
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, as described in Equation (9). 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 the interactions between Z-bins and Z-shocks on day t. Coefficients g represent the net buying response to Z-shocks within each Z-bin. Columns (1), (2), and (3) conduct the regressions over the whole sample period from May 1st to July 31st, 2015 within all margin accounts, brokerage-financed margin accounts, and shadow-financed margin accounts, respectively. Column (4) includes the subsample from May 1st to June 12th, 2015 (Up) for all accounts, while column (5) includes the subsample of June 15th to July 31st, 2015 (Down) 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.: $NetBuy^j_{i,t}$	(1) All Whole	(2) Broker Whole	(3) Shadow Whole	(4) All Up	(5) All Down
$Z < 0$	-22.850***	-24.523***	-19.633***	-9.054**	-31.930***
	(3.218)	(1.951)	(3.217)	(4.100)	(3.080)
Z in $(0, 1]$	-23.946***	-11.750***	-23.066***	-16.475***	-31.690***
	(2.535)	(0.825)	(2.648)	(2.344)	(2.802)
Z in $(1, 2]$	-18.466***	-11.109***	-16.919***	-11.901***	-26.395***
	(2.095)	(1.739)	(2.180)	(1.290)	(2.556)
Z in $(2, 3]$	-13.293***	-8.502***	-11.516***	-8.044***	-20.495***
	(1.460)	(0.780)	(1.603)	(0.889)	(1.836)
Z in $(3, 4]$	-9.751***	-7.474***	-7.747***	-6.417***	-15.555***
	(1.017)	(0.648)	(1.225)	(0.685)	(1.391)
Z in $(4, 5]$	-7.829***	-7.424***	-5.588***	-6.190***	-12.714***
	(0.740)	(0.943)	(0.999)	(0.537)	(1.079)
$Z > 5$	-4.156***	-4.190***	-1.736**	-5.732***	-6.650***
	(0.275)	(0.276)	(0.807)	(0.426)	(0.578)
g ($Z < 0$)	2.639***	0.996*	2.885***	2.425**	2.017**
	(0.815)	(0.581)	(0.795)	(1.002)	(0.756)
g (Z in $(0, 1]$)	4.034***	2.659***	4.207***	5.288***	3.294***
	(0.627)	(0.326)	(0.634)	(0.552)	(0.613)
g (Z in $(1, 2]$)	4.430***	3.739***	4.546***	4.457***	3.686***
	(0.675)	(1.052)	(0.672)	(0.522)	(0.717)
g (Z in $(2, 3]$)	3.660***	2.006***	3.935***	2.455***	3.157***
	(0.489)	(0.308)	(0.498)	(0.282)	(0.526)
g (Z in $(3, 4]$)	2.858***	1.751***	3.056***	1.121***	2.701***
	(0.402)	(0.236)	(0.408)	(0.167)	(0.433)
g (Z in $(4, 5]$)	2.056***	1.828***	2.144***	0.730***	1.981***
	(0.298)	(0.388)	(0.294)	(0.217)	(0.343)
g ($Z > 5$)	0.770***	1.113***	0.486***	0.532***	0.681***
	(0.095)	(0.107)	(0.156)	(0.077)	(0.131)
Account FE	Yes	Yes	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes	Yes	Yes
Obs	20,460,681	17,556,387	6,981,248	9,823,991	10,635,611
R^2	0.0969	0.0738	0.1526	0.1037	0.1127

Table 4
The Effect of Margin Borrowing on 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 4.3.1. The independent variables include indicators for Z-bins, the equity return calculated as Lev (account leverage, equal to 1 for unlevered accounts) $\times$ 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 variation in Pingcang Line across shadow accounts. LP is the Leverage-to-Pingcang, measured at the end of $t-1$. $Lev \times R$ is the account's levered return (equity return). 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 and calculate Z^* and LP^* similarly to Z and LP. 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 vs. Just-Ineligible Brokerage Accounts

Dep. var.: $NetBuy_{i,t}^{j}$	(1)	(2)
$Z < 0$		-0.430***
		(0.041)
Z in $(0, 1]$		0.000
		(0.000)
Z in $(1, 2]$		-0.121
		(0.114)
Z in $(2, 3]$		0.000
		(0.000)
Z in $(3, 4]$		-0.082*
		(0.046)
Z in $(4, 5]$		-0.152
		(0.110)
$Z > 5$		-0.049***
		(0.009)
$Lev \times R$	0.146***	0.146***
	(0.020)	(0.020)
$Lev \times R \times Treat$	0.146***	0.139***
	(0.052)	(0.050)
Account FE	Yes	Yes
Stock-Date FE	Yes	Yes
Obs	7,699,246	7,699,237
R^2	0.2660	0.2661

Table 4
The Effect of Margin Borrowing on Trading Activity

Panel B: Shadow Accounts with Heterogeneous Pingcang Lines

Dep. var.: $NetBuy^j_{i,t}$	(1) Z	(2) Z	(3) Z*, LP*	(4) Z*, LP*
$Z < 0$	-20.240***		-18.641***	
	(2.612)		(2.597)	
Z in $(0, 1]$	-27.042***		-26.877***	
	(2.453)		(2.643)	
Z in $(1, 2]$	-21.659***		-22.132***	
	(2.227)		(2.238)	
Z in $(2, 3]$	-15.877***		-16.734***	
	(1.801)		(1.946)	
Z in $(3, 4]$	-11.647***		-12.702***	
	(1.473)		(1.652)	
Z in $(4, 5]$	-9.057***		-10.146***	
	(1.220)		(1.396)	
$Z > 5$	-4.769***		-5.176***	
	(0.965)		(0.997)	
LP	-1.525***	6.231***	0.317	9.417***
	(0.434)	(1.270)	(0.737)	(1.658)
$Lev \times R$	1.070***	1.300***	1.040***	1.155***
	(0.280)	(0.290)	(0.270)	(0.262)
$LP \times Lev \times R$	-4.736***	-5.487***	-2.529*	-2.606*
	(1.258)	(1.447)	(1.419)	(1.491)
Account FE	Yes	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes	Yes
Obs	2,933,036	2,933,036	2,933,036	2,933,036
R^2	0.1770	0.1736	0.1765	0.1743

Table 5
Trading of Lottery Stocks

This table reports regressions of net buying (negative if selling) on scaled 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 scaled Z-shocks on day t, and their interaction with stock lottery characteristic *Lottery-ness*. Following Equation (10), scaled Z-shock is the product between Z-shock and the account-day's relevant $\hat{g}_k$, as estimated in Table 3 Column (1). *Lottery-ness* is the maximum number of days that stock i consecutively hits 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). Column (2) includes the subsample of June 15th to July 31st, 2015 (Down). 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) Up	(2) Down	(3) Whole
$Z < 0$	-8.965**	-31.952***	-23.029***
	(3.853)	(2.910)	(2.955)
Z in $(0, 1]$	-15.713***	-31.931***	-24.211***
	(2.635)	(2.851)	(2.481)
Z in $(1, 2]$	-11.744***	-26.665***	-18.701***
	(1.354)	(2.522)	(2.041)
Z in $(2, 3]$	-8.354***	-20.880***	-13.485***
	(0.886)	(1.851)	(1.472)
Z in $(3, 4]$	-6.962***	-16.162***	-9.928***
	(0.706)	(1.415)	(1.052)
Z in $(4, 5]$	-6.599***	-13.227***	-7.975***
	(0.528)	(1.087)	(0.766)
$Z > 5$	-5.897***	-6.895***	-4.302***
	(0.434)	(0.591)	(0.285)
scaled Z-Shock	0.677***	0.929***	1.049***
	(0.068)	(0.163)	(0.153)
scaled Z-Shock $\times$*Lottery-ness*	0.012	-0.026***	-0.017**
	(0.010)	(0.006)	(0.006)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
Obs	9,459,035	10,126,080	19,586,245
R^2	0.1044	0.1124	0.0968

Table 6
Baseline $MLPR$ Return-Forecasting 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, 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, $[t-30, t-1]$, 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	0.097***	0.085**	-0.002	-0.009	0.179***	0.162***
	(0.034)	(0.032)	(0.020)	(0.016)	(0.037)	(0.036)
SNMLPR		0.021		0.058**		-0.010
		(0.042)		(0.024)		(0.071)
LEVERAGE	-1.241	-1.307	-3.167***	-3.029***	0.345	0.111
	(0.889)	(0.826)	(0.752)	(0.745)	(1.163)	(1.074)
BETA	-0.046***	-0.046***	-0.037	-0.035	-0.054**	-0.055**
	(0.017)	(0.017)	(0.028)	(0.028)	(0.021)	(0.021)
IDVOL	-0.811	-0.834	-1.115	-0.959	-0.560	-0.731
	(0.781)	(0.772)	(1.460)	(1.424)	(0.712)	(0.743)
ILLIQUIDITY	9.475*	9.255*	7.223	6.854	11.330	11.233
	(5.439)	(5.432)	(6.669)	(6.659)	(8.184)	(8.159)
MOM SHORT	24.568***	24.499***	16.352***	16.339***	31.334***	31.219***
	(3.438)	(3.410)	(2.122)	(2.105)	(4.506)	(4.468)
MOM MEDIUM	-1.118**	-1.112**	-0.316	-0.329	-1.778**	-1.758**
	(0.455)	(0.450)	(0.289)	(0.290)	(0.710)	(0.704)
MOM LONG	-0.116**	-0.116**	-0.126	-0.125	-0.107**	-0.109**
	(0.050)	(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	-0.029	-0.038	-0.404	-0.386	0.281	0.249
	(0.232)	(0.229)	(0.368)	(0.365)	(0.262)	(0.259)
TURNOVER	1.050	1.056	2.998	3.062	-0.555	-0.597
	(1.177)	(1.174)	(1.973)	(1.951)	(1.170)	(1.160)
p-value (SMLPR > SNMLPPR)	.	0.1150	.	0.9822	.	0.0211
Obs	130,914	130,914	62,886	62,886	68,028	68,028
R^2	0.1664	0.1691	0.1161	0.1175	0.2079	0.2116

Table 7

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. We 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." A stock is a lottery stock if *Lottery-ness*>= 3. It is a non-lottery stock otherwise. 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	0.084***	0.067***	0.029	0.019	0.127***	0.105***
	(0.026)	(0.023)	(0.032)	(0.030)	(0.030)	(0.026)
SNMLPR		0.059		0.111**		0.007
		(0.049)		(0.046)		(0.079)
LEVERAGE	-1.061	-1.103	-2.705***	-2.615***	0.550	0.380
	(0.917)	(0.835)	(0.884)	(0.881)	(1.313)	(1.139)
BETA	-0.024	-0.023	-0.015	-0.015	-0.034	-0.033
	(0.015)	(0.015)	(0.023)	(0.023)	(0.021)	(0.021)
IDVOL	0.360	0.359	-0.351	-0.257	1.253	1.157
	(0.963)	(0.945)	(1.836)	(1.803)	(0.882)	(0.883)
ILLIQUIDITY	9.791*	9.763*	-1.897	-1.755	18.158**	17.967**
	(5.732)	(5.776)	(6.655)	(6.775)	(7.352)	(7.450)
MOM SHORT	23.749***	23.683***	14.689***	14.611***	31.672***	31.624***
	(3.389)	(3.386)	(2.353)	(2.352)	(3.757)	(3.737)
MOM MEDIUM	-1.416**	-1.412**	-0.294	-0.302	-2.350**	-2.333**
	(0.645)	(0.644)	(0.261)	(0.260)	(1.066)	(1.066)
MOM LONG	-0.109**	-0.109**	-0.115	-0.115	-0.096**	-0.096**
	(0.045)	(0.045)	(0.091)	(0.090)	(0.039)	(0.038)
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	0.099	0.093	-0.439	-0.409	0.448	0.410
	(0.276)	(0.271)	(0.444)	(0.438)	(0.294)	(0.295)
TURNOVER	0.841	0.887	1.442	1.785	0.615	0.375
	(1.395)	(1.379)	(2.579)	(2.537)	(1.383)	(1.374)
p-value (SMLPR > SNMLPPR)	.	0.4401	.	0.9405	.	0.1263
Obs	40,268	40,268	19,482	19,482	20,118	20,118
R^2	0.1965	0.1997	0.1534	0.1561	0.2327	0.2361

Table 7

***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	0.095**	0.086**	-0.018	-0.022	0.190***	0.178***
	(0.039)	(0.037)	(0.018)	(0.015)	(0.043)	(0.042)
SNMLPR		0.003		0.039*		-0.033
		(0.039)		(0.020)		(0.067)
LEVERAGE	-1.151	-1.217*	-2.563***	-2.479***	0.243	0.042
	(0.700)	(0.661)	(0.646)	(0.644)	(0.836)	(0.787)
BETA	-0.123	-0.127	-0.424***	-0.407***	0.121	0.096
	(0.146)	(0.143)	(0.138)	(0.137)	(0.212)	(0.211)
IDVOL	-2.777	-2.720	-0.237	-0.253	-4.832	-4.710
	(2.078)	(2.052)	(2.697)	(2.686)	(3.029)	(2.977)
ILLIQUIDITY	20.989	21.441	76.163*	74.841*	-29.588	-27.303
	(29.565)	(28.776)	(39.509)	(39.371)	(30.856)	(29.405)
MOM SHORT	24.552***	24.547***	16.674***	16.694***	31.229***	31.202***
	(3.548)	(3.534)	(2.149)	(2.137)	(5.033)	(5.016)
MOM MEDIUM	-1.016**	-1.015**	-0.262	-0.275	-1.638***	-1.623**
	(0.396)	(0.393)	(0.378)	(0.379)	(0.576)	(0.573)
MOM LONG	-0.162**	-0.162**	-0.148	-0.147	-0.159*	-0.160*
	(0.076)	(0.076)	(0.130)	(0.131)	(0.091)	(0.090)
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	-0.057	-0.062	-0.151	-0.153	-0.058	-0.067
	(0.141)	(0.139)	(0.266)	(0.263)	(0.108)	(0.105)
TURNOVER	1.486	1.481	5.071***	4.977***	-1.238	-1.168
	(1.624)	(1.605)	(1.568)	(1.548)	(2.273)	(2.261)
p-value (SMLPR > SNMLPPR)	.	0.0645	.	0.9860	.	0.0075
Obs	90,646	90,646	43,404	43,404	45,728	45,728
R^2	0.1695	0.1722	0.1048	0.1060	0.2261	0.2300

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) informal 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 5^{th}, 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 12^{th}, 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 about 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
Z-bin Distribution

This table reports the distribution of Z at the account-day level for the period May to July 2015. We use the asset portfolio return volatility (including cash), σ^j_{At}, of account j on day t to calculate Z for Panel A and Panel B. In Panel A, we use the ex-ante σ^j_{At} estimated in the year prior to our sample (5/1/2014 to 4/30/2015) to calculate Z while in Panel B we use the in-sample σ^j_{At} (5/1/2015 to 7/31/2015). To compute the distribution reported in this table, we restrict the sample to account-days with non-zero leverage (excluding accounts in the control group of unleveraged margin accounts, with Z set to NA). Columns (1) and (2) show the distribution of Z for brokerage-financed margin accounts, columns (3) and (4) show the distribution of Z for shadow-financed margin accounts, and columns (5) and (6) show the distribution for the combined sample.

Panel A: Z-bin Distribution using Ex-ante Volatility

	Brokerage Margin		Shadow Margin		All Margin	
	Percent(%)	Cumulative(%)	Percent(%)	Cumulative(%)	Percent(%)	Cumulative(%)
$Z < 0$	0.09	0.09	5.06	5.06	1.48	1.48
Z in $(0, 1]$	0.08	0.17	2.09	7.14	0.64	2.12
Z in $(1, 2]$	0.10	0.28	3.47	10.61	1.04	3.17
Z in $(2, 3]$	0.14	0.41	4.79	15.40	1.44	4.61
Z in $(3, 4]$	0.19	0.61	5.85	21.25	1.78	6.39
Z in $(4, 5]$	0.25	0.86	6.59	27.85	2.03	8.41
$Z > 5$	99.14	100.00	72.15	100.00	91.59	100.00

Panel B: Z-bin Distribution using In-sample Volatility

	Brokerage Margin		Shadow Margin		All Margin	
	Percent(%)	Cumulative(%)	Percent(%)	Cumulative(%)	Percent(%)	Cumulative(%)
$Z < 0$	0.09	0.09	5.08	5.08	1.49	1.49
Z in $(0, 1]$	0.20	0.29	6.02	11.10	1.84	3.32
Z in $(1, 2]$	0.37	0.67	12.24	23.34	3.70	7.03
Z in $(2, 3]$	0.63	1.29	15.79	39.13	4.88	11.91
Z in $(3, 4]$	1.05	2.34	14.59	53.71	4.84	16.75
Z in $(4, 5]$	1.69	4.03	11.53	65.24	4.45	21.20
$Z > 5$	95.97	100.00	34.76	100.00	78.80	100.00

Table A2
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 scaled 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
$Z < 0$	-0.177***	-0.770***	-0.240***	-0.152	-0.283***
	(0.012)	(0.096)	(0.020)	(0.100)	(0.015)
Z in $(0, 1]$	-0.168***	-0.801***	-0.265***	-0.281***	-0.292***
	(0.009)	(0.092)	(0.009)	(0.019)	(0.015)
Z in $(1, 2]$	-0.166***	-0.787***	-0.254***	-0.262***	-0.285***
	(0.011)	(0.092)	(0.008)	(0.013)	(0.015)
Z in $(2, 3]$	-0.167***	-0.768***	-0.237***	-0.247***	-0.269***
	(0.009)	(0.092)	(0.008)	(0.010)	(0.015)
Z in $(3, 4]$	-0.169***	-0.750***	-0.220***	-0.229***	-0.255***
	(0.009)	(0.092)	(0.007)	(0.008)	(0.014)
Z in $(4, 5]$	-0.164***	-0.736***	-0.207***	-0.219***	-0.235***
	(0.008)	(0.091)	(0.007)	(0.008)	(0.013)
$Z > 5$	-0.130***	-0.661***	-0.136***	-0.151***	-0.158***
	(0.004)	(0.090)	(0.005)	(0.006)	(0.009)
scaled Z-Shock	0.001	0.006***	0.005***	0.002	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Account FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Obs	3,926,310	2,341,077	5,006,007	2,310,360	2,693,657
R^2	0.1025	0.1407	0.1052	0.1579	0.1211

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 scaled 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.: $NetBuy^{j}_{i,t+1}$	(1) Broker	(2) Shadow	(3) All
$Z < 0$	-23.176***	-19.382***	-22.592***
	(3.522)	(3.004)	(3.024)
Z in $(0,1]$	-10.961***	-22.675***	-23.316***
	(2.057)	(2.710)	(2.657)
Z in $(1,2]$	-9.740***	-16.499***	-17.907***
	(2.291)	(2.277)	(2.204)
Z in $(2,3]$	-7.430***	-11.250***	-12.972***
	(1.859)	(1.697)	(1.567)
Z in $(3,4]$	-6.962***	-7.578***	-9.599***
	(1.221)	(1.333)	(1.136)
Z in $(4,5]$	-6.941***	-5.136***	-7.503***
	(0.957)	(1.039)	(0.789)
$Z > 5$	-4.307***	-1.507*	-4.274***
	(0.285)	(0.847)	(0.282)
scaled Z-Shock	0.963***	1.002***	0.973***
	(0.138)	(0.166)	(0.151)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
Obs	15,642,129	5,764,909	17,841,800
R^2	0.0535	0.1357	0.0733

Table A4
An Alternative Definition of Lottery Stocks

This table reports regressions of net buying (negative if selling) on Z-shock and its interaction with an alternative definition of lottery stocks. 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 scaled 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) Up	(2) Down	(3) Whole
$Z < 0$	-8.967**	-31.971***	-23.040***
	(3.853)	(2.910)	(2.956)
Z in $(0, 1]$	-15.710***	-31.969***	-24.234***
	(2.634)	(2.849)	(2.479)
Z in $(1, 2]$	-11.743***	-26.690***	-18.714***
	(1.354)	(2.522)	(2.041)
Z in $(2, 3]$	-8.354***	-20.893***	-13.492***
	(0.886)	(1.854)	(1.472)
Z in $(3, 4]$	-6.964***	-16.169***	-9.932***
	(0.706)	(1.416)	(1.053)
Z in $(4, 5]$	-6.601***	-13.236***	-7.978***
	(0.528)	(1.088)	(0.766)
$Z > 5$	-5.897***	-6.894***	-4.302***
	(0.434)	(0.591)	(0.285)
scaled Z-Shock	0.683***	0.953***	1.067***
	(0.072)	(0.166)	(0.155)
scaled Z-Shock × $LotteryAlt$	0.051	-0.174***	-0.119***
	(0.047)	(0.046)	(0.044)
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
Obs	9,459,035	10,126,080	19,586,245
R^2	0.1044	0.1124	0.0968

Table A5
$MLPR$ and Firm Size Controls

This table reports how much of the variation in MLPR is driven by size. The dependent 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. The independent variable is market capitalization ($MCAP$) or log of ($log(MCAP)$). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. var.: $MLPR_{i,t}$	(1)	(2)
MCAP	-0.000	
	(0.000)	
ln(MCAP)		-0.016
		(0.012)
Date FE	Yes	Yes
Obs	137,532	137,532
R^2	0.0006	0.0006

MLPR-Size

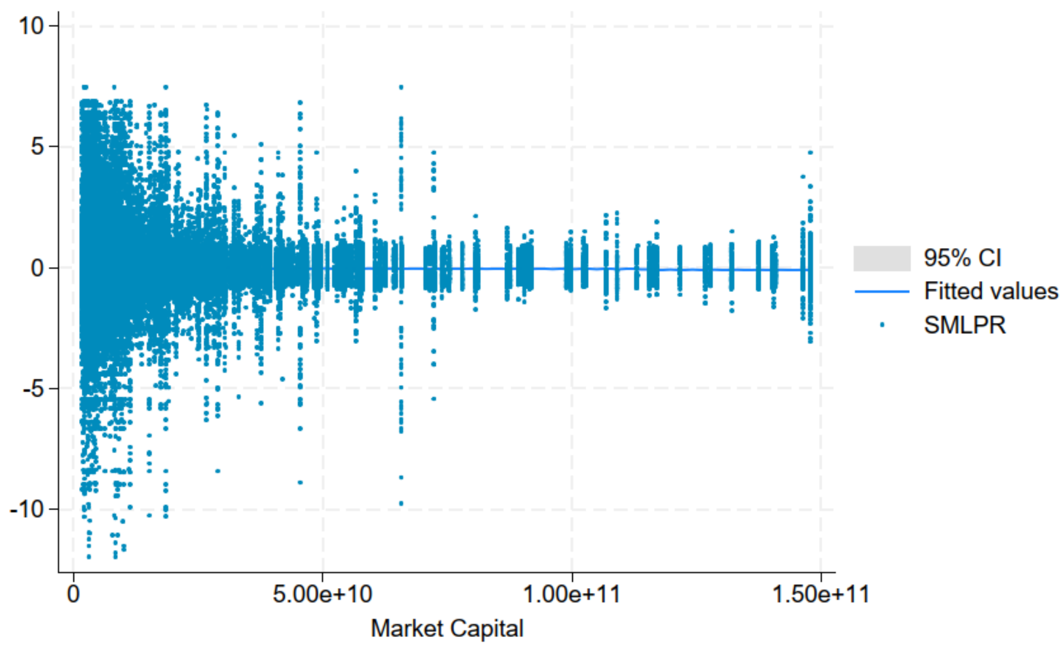


Table A6
$MLPR$ Regressions: with Alternative Size Controls

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	0.101***	0.086***	0.001	-0.007	0.183***	0.164***
	(0.034)	(0.032)	(0.020)	(0.016)	(0.037)	(0.036)
SNMLPR		0.028		0.064**		-0.002
		(0.044)		(0.024)		(0.076)
LEVERAGE	-1.243	-1.310	-3.162***	-3.010***	0.337	0.090
	(0.893)	(0.826)	(0.751)	(0.742)	(1.178)	(1.085)
BETA	-0.046***	-0.046***	-0.040	-0.038	-0.051**	-0.052**
	(0.017)	(0.017)	(0.028)	(0.028)	(0.021)	(0.021)
IDVOL	-0.830	-0.855	-1.209	-1.035	-0.519	-0.707
	(0.783)	(0.770)	(1.459)	(1.421)	(0.716)	(0.739)
ILLIQUIDITY	9.891*	9.659*	4.737	4.453	14.135*	13.947
	(5.557)	(5.574)	(6.750)	(6.763)	(8.196)	(8.206)
MOM SHORT	24.897***	24.819***	16.495***	16.474***	31.816***	31.692***
	(3.579)	(3.552)	(2.141)	(2.124)	(4.774)	(4.740)
MOM MEDIUM	-1.135**	-1.129**	-0.295	-0.311	-1.826**	-1.803**
	(0.464)	(0.459)	(0.287)	(0.287)	(0.721)	(0.715)
MOM LONG	-0.117**	-0.117**	-0.123	-0.122	-0.111**	-0.113**
	(0.049)	(0.049)	(0.098)	(0.097)	(0.042)	(0.042)
MCAP BIN	1.143	1.156	4.323***	4.177***	-1.894	-1.248
	(1.245)	(1.194)	(0.713)	(0.772)	(1.398)	(1.330)
BMRATIO	-0.018	-0.027	-0.485	-0.460	0.367	0.329
	(0.248)	(0.242)	(0.366)	(0.364)	(0.284)	(0.279)
TURNOVER	1.047	1.054	3.163	3.229	-0.696	-0.738
	(1.209)	(1.208)	(1.980)	(1.959)	(1.210)	(1.204)
p-value (SMLPR > SNMLPPR)	.	0.1434	.	0.9873	.	0.0307
Obs	130,914	130,914	62,886	62,886	68,028	68,028
R^2	0.1549	0.1578	0.1127	0.1143	0.1897	0.1937

Table A6
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**	0.057**	-0.028	-0.026*	0.128***	0.125***
	(0.029)	(0.028)	(0.017)	(0.014)	(0.029)	(0.030)
SNMLPR		-0.027		0.011		-0.059
		(0.035)		(0.025)		(0.058)
LEVERAGE	-0.709	-0.734*	-0.583	-0.603	-0.812	-0.841
	(0.435)	(0.416)	(0.524)	(0.522)	(0.635)	(0.588)
BETA	-0.046**	-0.046**	-0.037	-0.037	-0.053**	-0.053**
	(0.017)	(0.017)	(0.028)	(0.028)	(0.022)	(0.022)
IDVOL	-0.618	-0.640	-0.320	-0.291	-0.863	-0.928
	(0.752)	(0.754)	(1.466)	(1.446)	(0.575)	(0.614)
ILLIQUIDITY	8.587	8.286	-0.937	-0.900	16.431*	15.851*
	(6.164)	(6.144)	(6.900)	(6.940)	(8.769)	(8.763)
MOM SHORT	24.406***	24.388***	16.119***	16.095***	31.230***	31.218***
	(3.490)	(3.486)	(2.177)	(2.160)	(4.593)	(4.591)
MOM MEDIUM	-1.147**	-1.136**	-0.407	-0.408	-1.757**	-1.735**
	(0.443)	(0.436)	(0.301)	(0.300)	(0.696)	(0.685)
MOM LONG	-0.106**	-0.106**	-0.097	-0.097	-0.113**	-0.115**
	(0.048)	(0.048)	(0.096)	(0.096)	(0.042)	(0.041)
MCAP INV	0.032	0.036	0.217***	0.213***	-0.121	-0.110
	(0.072)	(0.069)	(0.038)	(0.035)	(0.092)	(0.091)
BMRATIO	-0.014	-0.023	-0.391	-0.388	0.297	0.277
	(0.226)	(0.225)	(0.367)	(0.364)	(0.244)	(0.247)
TURNOVER	0.772	0.747	1.273	1.339	0.360	0.259
	(1.093)	(1.074)	(1.999)	(1.963)	(1.140)	(1.116)
p-value (SMLPR > SNMLPPR)	.	0.0343	.	0.8963	.	0.0053
Obs	130,914	130,914	62,886	62,886	68,028	68,028
R^2	0.1651	0.1670	0.1208	0.1217	0.2015	0.2044

Table A7

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:

$$NetBuy_{i,t}^j = \sum_{k \in \mathbb{K}} f_k I_{kt}^j + \text{scaled } \Delta Z_t^j + \text{scaled } \Delta Z_t^j \times \text{StockCharacteristics} + \alpha_j + \nu_{it} + \varepsilon_{it}^j$$

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	0.169*	0.167**	-0.047	-0.030	0.369***	0.349***
	(0.088)	(0.083)	(0.056)	(0.054)	(0.108)	(0.104)
SNMLPR		-0.000		0.036		-0.036
		(0.035)		(0.026)		(0.058)
LEVERAGE	-0.397	-0.411	-3.486***	-3.294***	2.526*	2.319*
	(1.200)	(1.138)	(0.881)	(0.866)	(1.347)	(1.273)
BETA	-0.039**	-0.038**	-0.038	-0.036	-0.043*	-0.044*
	(0.017)	(0.017)	(0.028)	(0.028)	(0.023)	(0.023)
IDVOL	-1.091	-1.065	-1.081	-0.939	-0.945	-1.029
	(0.777)	(0.773)	(1.463)	(1.428)	(0.699)	(0.739)
ILLIQUIDITY	9.208*	8.917	7.347	6.872	8.674	8.565
	(5.392)	(5.393)	(6.634)	(6.643)	(8.151)	(8.140)
MOM SHORT	24.317***	24.270***	16.437***	16.343***	30.989***	30.992***
	(3.289)	(3.286)	(1.995)	(1.995)	(4.416)	(4.385)
MOM MEDIUM	-1.230**	-1.222**	-0.312	-0.327	-1.995**	-1.965**
	(0.482)	(0.474)	(0.281)	(0.280)	(0.763)	(0.754)
MOM LONG	-0.126**	-0.126**	-0.121	-0.121	-0.124**	-0.123**
	(0.048)	(0.048)	(0.095)	(0.095)	(0.046)	(0.046)
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	0.011	0.005	-0.419	-0.398	0.292	0.260
	(0.241)	(0.237)	(0.360)	(0.356)	(0.284)	(0.281)
TURNOVER	1.913	1.928*	2.773	2.939	1.584	1.452
	(1.143)	(1.121)	(2.217)	(2.176)	(0.998)	(0.965)
p-value (SMLPR > SNMLPPR)	.	0.0341	.	0.8533	.	0.0021
Obs	130,914	130,914	62,886	62,886	65,846	65,846
R^2	0.1738	0.1762	0.1193	0.1207	0.2205	0.2239