ISSN 0956-8549-839

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DISCUSSION PAPER NO 839

PAUL WOOLLEY CENTRE WORKING PAPER No 79

July 2021

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This Draft: March 2021

Abstract

We use granular data covering regulated (brokerage-financed) and unregulated (shadow-financed) margin trading during the 2015 market turmoil in China to provide the first systematic analysis of margin investors' characteristics, leverage management policies, and liquidation choices. We show that leverage constraints induced substantial forced and preemptive sales, and leverage and cash management differed substantially across investor and account types. We explore the relation between margin trading and shock propagation, and show that China's price limit rule led to unintended contagion across stocks. Compared to brokerage investors, shadow investors were closer to their leverage constraints, and played a more significant role in transmitting shocks across stocks.

Keywords: margin trading, leverage management, liquidation policy, contagion

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Abstract

We use granular data covering regulated (brokerage-financed) and unregulated (shadow-financed) margin trading during the 2015 market turmoil in China to provide the first systematic analysis of margin investors' characteristics, leverage management policies, and liquidation choices. We show that leverage constraints induced substantial forced and preemptive sales, and leverage and cash management differed substantially across investor and account types. We explore the relation between margin trading and shock propagation, and show that China's price limit rule led to unintended contagion across stocks. Compared to brokerage investors, shadow investors were closer to their leverage constraints, and played a more significant role in transmitting shocks across stocks.

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1 Introduction

Investors can use margin trading—the practice of borrowing against the securities they hold—to amplify returns. In standard asset pricing models, as well as in practice, investors lend to and borrow from one another to clear both the risk-free and risky securities markets. A well-functioning lending-borrowing market is therefore crucial to a healthy financial system. Despite the apparent importance, there is little empirical evidence on investors' margin trading decisions, mainly due to a lack of granular data. For example, we know little about the characteristics of investors that choose to use margin borrowing, margin investors' leverage- and liquidity-management policies (specifically, how these policies vary with investor demographics and trading experiences, as well as the regulatory environment and advancement of FinTech-driven shadow financing), and finally, the asset pricing implications of margin-induced trading.

In this paper, we provide novel analysis of investor margin trading behavior using detailed account-level data in China that tracks 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.[1] With a total market capitalization of roughly one-third of that of the US, 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.[2]

Individual retail investors are the dominant players in the Chinese stock market and are the main users of margin trading.[3] Our data include two types of margin trading systems: brokerage-financed and shadow-financed margin accounts. Both margin trading systems grew rapidly in popularity in early 2015. The brokerage-financed margin system, which allows retail investors to obtain credit 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.[4]

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

[1]For an informative reading, see Carpenter and Whitelaw (2017) and Allen et al. (2020).

[2]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).

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

[4]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.

generally do not impose restrictions on borrower wealth, trading experience, or financial literacy. There is no regulatory maximum Pingcang Line for shadow-financed margin accounts. Instead, the maximum leverage limits are market outcomes determined by bilateral negotiations between borrowers and lenders. We find that shadow accounts have significantly higher leverage limits and realized leverage than their brokerage counterparts; for example, the average leverage (= assets/equity) is 6.9 for shadow-financed margin accounts and only 1.4 for brokerage-financed accounts.

We begin our analysis by examining the types of investors that are more likely to use margin borrowing (the extensive margin), and have higher initial leverage conditional on using margin (the intensive margin). Consistent with the idea that heterogeneous risk preferences determine margin trading, we find that more leveraged traders are less experienced, more active, male, and take on higher portfolio risk.

We next study the relation between investors' margin borrowing and their trading and cash-management decisions. For each account-date, we compute its "distance-to-margin-call," the difference between the account's leverage (assets/equity) and its Pingcang Line, scaled by the asset volatility. In other words, "distance-to-margin-call" measures the number of standard deviations of downward movements in asset values necessary to push the account's leverage to its Pingcang Line. Similar to distance-to-default measures in Merton-style models, the distance-to-margin-call in our setting 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).

In the theoretical literature, static models such as Brunnermeier and Pedersen (2009) and Geanakoplos (2010) predict that levered investors and their creditors engage in fire sales only when accounts hit the Pingcang Line. However, investors may engage in preemptive selling prior to hitting the Pingcang Line for several reasons. In a dynamic setting such as Garleanu and Pedersen (2011), forward-looking investors sell before hitting the leverage constraint, because they anticipate that the controlling creditor will liquidate stock holdings with some fire-sale cost. Investors' precautionary selling prior to hitting the Pingcang Line can also be explained by runs in financial markets, as illustrated by Bernardo and Welch (2004).[5] Finally, investors may engage in precautionary sales because they fear (rationally or irrationally) that creditors, once they seize control, will sell assets while their prices are temporarily depressed.

We find strong empirical support for both forced and preemptive margin-induced trading in our data. Specifically, after controlling for account- and stock-date- fixed effects, we show that net buying is positively related to the account's distance-to-margin-call (which we label "Z"), and to recent changes in this distance (which we label "Z-shocks" and is driven by recent account returns). For example, margin accounts with $Z \in (0, 1]$ (i.e., accounts that would hit the Pingcang Line after a one standard deviation negative shock) sell 18.4% of their risky holdings on that day, relative to

[5] In Bernardo and Welch (2004), liquidity runs are not caused by liquidity shocks per se, but by the fear of future liquidity shocks. This is in complement to the bank-run mechanism in Diamond and Dybvig (1983), Goldstein and Pauzner (2005) and recently He and Xiong (2012)).

non-levered margin accounts. The coefficients on Z and Z-shocks are larger for female investors and depend on trading restrictions faced by margin investors (to be explained shortly).

It is worth noting that the strong relation between investors' net buying and both the level and change in the distance-to-margin-call can be attributed to two potential mechanisms: (1) leverage constraints, i.e., forced and preemptive sales that occur when account leverage approaches its leverage limit; and (2) a portfolio rebalancing motive that leads risk-averse investors with a target leverage level to adjust leverage after a drop or increase in asset value (which leads to a mechanical increase or decrease in leverage, respectively). Thus, leverage-induced sales in our setting should be viewed as a combination of these two widely-accepted economic forces: one that consists of preemptive and/or forced sales due to tightening leverage constraints and the other driven by a rebalancing motive that would occur even in the absence of Pingcang Lines.

While we believe that both forces play a role in our setting, we provide further evidence for the importance of the leverage constraints channel. First, we compare investors' responses to positive and negative Z-shocks. A simple model of a portfolio rebalancing motive predicts that investors should react to both positive and negative Z-shocks. Instead, we find that investors sell aggressively in response to negative Z-shocks but do not buy significantly in response to positive Z-shocks. This behavior is consistent with the idea that investors face stronger incentives to adjust their risky holdings when the leverage constraint tightens than when it loosens. We also present additional tests in Section 4.3.4 to rule in the role of forced sales and leverage constraints. These tests exploit the granularity of our shadow account data, and use variation in Pingcang Lines across accounts to identify a leverage constraint effect.

Although both brokerage-financed and shadow-financed margin accounts reduce their risky holdings in response to tightening leverage constraints, the two groups behave very differently in their cash and liability management decisions. Brokerage-financed margin accounts use sales proceeds to pay down debt immediately. In contrast, shadow-financed margin accounts keep most of the sales proceeds as cash instead of paying down debt. One possible explanation for this intriguing difference is that the brokerage margin system is more "rule-based," while the shadow system is more "discretion-based." Because brokerage firms allow any account in good standing to increase or reduce leverage at any time, maintaining a cash balance while carrying margin debt is suboptimal given the high interest cost of margin loans. In the shadow margin system, however, each new borrowing request must be approved by the lender. Consequently, despite the higher interest rates for shadow accounts, shadow-financed margin investors worry about future financing needs, and therefore choose to hoard cash today. In other words, frictions in the shadow margin system may lead investors to hoard " borrowed" cash, thereby contributing to the persistently high leverage.

We also uncover an important unintended consequence of trading restrictions imposed by the government. In Chinese markets, a stock cannot be bought or sold if it is suspended from trading, or if the stock hits its daily upper or lower price limit, equal to 110 or 90% of its previous day's closing price, respectively. We find that a stock is sold in larger proportions (in response to changes in distance-to-margin-call) by margin accounts whose *other* holdings cannot be traded due to trading restrictions. Thus, trading restrictions on stocks that have declined in value lead to liquidation of other stocks held by leveraged accounts, resulting in contagion from unhealthy to healthy stocks.

As a natural extension, we also analyze margin investors' liquidation choice more generally, by examining the types of stocks that margin investors are more likely to buy or sell in response to changes in the distance-to-margin-call. Conceptually, liquidation choice can be affected by a number of stock and account characteristics, including riskiness, liquidity, and position size. We conduct panel regressions of investors' trading activity in individual stocks on various stock/position characteristics interacted with account-level distance-to-margin-call shocks. We find that margin investors are more likely to liquidate stocks that are more expensive (relative to book value), larger, and more liquid, when faced with tightening leverage constraints. Brokerage margin investors also exhibit behavior consistent with a disposition effect, in which they are more willing to sell stocks with positive recent returns.

Finally, we study contagion across stocks with common ownership by margin accounts. The idea is that an initial reduction in account value tightens the leverage constraint, leading to additional selling and hence even lower prices. Extending this well-established fire-sale mechanism to a setting with multiple assets, we conjecture that if investors downsize all their holdings—including those that have not gone down in value and thus have little to do with the initial tightening of the leverage constraint—in reaction to negative return shocks, leverage-induced trading can generate contagion across assets that are linked through common ownership by levered investors.

We examine this shock propagation mechanism by constructing a stock-level measure of "margin-account linked portfolio returns" ($MLPR$) based on a theoretically-motivated framework. Specifically, $MLPR$ for a stock is defined as the weighted-average daily return of all margin accounts holding the stock on a particular day, after removing the stock's own contribution to each account's return (so as to isolate the effect of contagion). Importantly, the weights are based on 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 leverage constraint.

We indeed find that $MLPR$ forecasts the corresponding stock's next-day return. While this result is consistent with transmission of shocks via leverage-induced trading, it is also consistent with a key alternative explanation. Margin traders do not choose stock holdings randomly, and they may hold related stocks that move together for other reasons.

We address this potential alternative explanation in several ways. First, we control for observable stock characteristics and past return patterns that could lead to stocks to move together. Second, we show that $MLPR$ only predicts stock returns during downturns. This asymmetric response does not match a simple related holdings story in which related stocks should experience both positive and negative comovement. We also show that selling restrictions transmit negative return shocks from unhealthy stocks (which cannot be sold) to healthier stocks (which are the only stocks that leveraged investors can sell). We construct two $MLPR$ measures for each stock based on accounts with high and low selling restrictions for *other* holdings, and show that $MLPR$ with high selling restrictions is associated with much stronger return predictability.

We also control for a related holdings effect by constructing "non-margin-account linked portfolio returns" ($NMLPR$) using non-margin brokerage accounts that are similar to margin accounts in size and trading volume. Empirically, we find that $NMLPR$ does not predict future returns and controlling for $NMLPR$ does not change the predictive power of $MLPR$. To the extent that matched non-margin accounts choose to hold related stocks in a similar fashion to margin accounts, controlling for $NMLPR$ helps tease out true contagion due to leverage constraints. In a related test, we show that $MLPR$ constructed using only shadow accounts predicts returns more strongly than $MLPR$ constructed using only brokerage accounts, despite brokerage accounts holding substantially greater total asset value. This suggests shadow margin traders played a more significant role in transmitting shocks via the leverage network, in line with the fact that shadow accounts were far more leveraged relative to their leverage limits and thus experienced greater leverage-induced selling. Finally, we show that the return impact of $MLPR$ reverts in approximately one month, consistent with $MLPR$ being a non-fundamental shock.

In summary, our analyses of shock propagation provide evidence of a) an asymmetry between market booms and busts, b) a sharp contrast between the price impact of common holdings of margin and non-margin accounts, and c) a similar contrast between the price impact of common holdings by constrained and unconstrained margin accounts, and d) an initial price effect followed by a gradual return reversal. This set of results on return predictability, when taken as a whole, helps alleviate the concern that our documented contagion pattern is due to correlated fundamental shocks to commonly-held stocks.

Related literature Our paper 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.[6] 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,

[6] 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).

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.[7] Chen et al. (2021) estimates 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 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

[7]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.

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); Chen et al. (2020); and 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, 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. (2020) study the interplay between extrapolative beliefs and the disposition effect using account-level trading records during the same 2014-15 Chinese stock market bubble; they do not, however, analyze the behavior of margin investors during this episode.

2 Institutional Background and Data Sample

2.1 Institutional Background

Our analysis exploits account-level margin trading data in the Chinese stock market covering the period May 1st to July 31st, 2015. We provide details of the institutional background in this section.

2.1.1 Margin trading in the Chinese stock market in 2015

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. It is widely believed that high levels of margin borrowing and the subsequent leverage-induced fire sales played a role in the market run-up and crash.

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.[8] Both systems came into existence in 2010, and thrived after 2014 alongside a surge in the Chinese stock market. Throughout the paper, whenever there is no risk of confusion, we use brokerage (shadow) accounts to refer to brokerage-financed (shadow-financed) margin accounts.

2.1.2 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 Yuan in June 2014, and more than quintupled to 2.2 trillion Yuan after one year.[9] 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 US and other developed markets.

Chinese brokerage firms usually provide margin financing by issuing short-term bonds in the Interbank Market,[10] 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% annualized during our sample period). Brokers then lend these funds to margin borrowers at an annual rate of approximately 8-9% (the left side of Panel A in Figure 1). This margin business offered brokers a much higher profit than trading commissions, which were only about 4 basis points of trading volume.

Almost all brokerage-financed margin accounts are owned by retail investors.[11] The China Securities Regulatory Commission (CSRC) imposes stringent rules to qualify for brokerage-financed margin trading. A qualified investor needs to have a trading account with the broker for at least 18 months, with a total account value exceeding 0.5 million Yuan (or about USD80,000).

The minimum initial margin set by the CSRC is 50%, implying that investors can borrow up to 50% of their own capital when they open their brokerage accounts. More importantly for our analysis, the CSRC also imposes a minimum "maintenance margin," which requires that every brokerage account should have a margin debt level below 1/1.3 of its total asset value. Once the debt-to-asset ratio of a margin account breaches 1/1.3, and the borrower is unable to inject equity by the following day, the account will be taken over by the brokerage firm.

Note that the minimum "maintenance margin" corresponds one-to-one to the maximum leverage that a margin investor can have. Practitioners call this maximum allowable leverage, which equals

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

[9] 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.

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

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

$Asset/Equity = 1.3/(1.3 - 1) = 4.33$, the "Pingcang Line," which means "forced settlement line" in Chinese. Brokerage firms have discretion to set different Pingcang Lines for their customers, as long as they lie below the regulatory maximum of 4.33. In our sample, all brokerage firms adopt the 4.33 Pingcang Line.[12] Once the account leverage exceeds the Pingcang Line, control of the account is transferred to the lender (the brokerage firm), who then has the discretion to sell assets without borrower permission.

2.1.3 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, similar to many financial innovations in the past, existed in a regulatory gray area. Shadow-financing was not initially regulated by the CSRC, and lenders did not require borrowers to have a minimum level of wealth or trading history. In turn, borrowers paid higher interest rates to shadow financing lenders. In a limited subsample where interest rate information is available, we find that the shadow borrowing rate is about 25%, which is approximately 16.5 percentage points higher than the borrowing rate in the brokerage-financed market.

Shadow-financing usually operated through a web-based trading platform that facilitated trading and borrowing.[13] 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 *unlevered* brokerage account, with large asset holdings and trading volume. In reality, the mother account is used by a FinTech platform to transmit the orders submitted by associated child accounts in real time to stock exchanges. As shown, 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

[12] 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.

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

as borrowing from the shadow banking sector. Through this umbrella-style structure, a professional financing company can lend funds to multiple shadow margin traders, while maintaining different leverage limits for each child account.

Similar to the brokerage-financed margin system, a shadow-financed child account had a maximum allowable leverage limit—i.e., the Pingcang Line—beyond which the child account 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, there were no regulations concerning the maximum allowable leverage for each child account. Instead, the creditor (the mother account) and the borrower negotiated an account-specific Pingcang Line that never changes during the life of the account. In our sample, unregulated shadow accounts have much higher Pingcang Lines than their regulated brokerage peers (10 vs. 4.3, median). But, as with their brokerage peers, control rights of the shadow account transfer to the lender (the mother account) once leverage exceeds the Pingcang Line, triggering potential forced liquidation of stock holdings.

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 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 did not know the total size of the shadow margin system, let alone the leverage associated with it. One educated guess of the total debt held by shadow-financed margin system was about 1.0-1.4 trillion Yuan at its peak, consistent with the estimates provided by China Securities Daily on June 12, 2015 (for detailed estimation for each category, see Appendix A.1).

On Friday, June 12, 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 government regulation would require or incentivize shadow lenders to tighten leverage constraints in the future. [14] A month-long stock market crash began the following trading day, Monday, June 15, 2015, wiping out almost 30% of the market index. In response, the Chinese government started to aggressively purchase stocks to support prices on July 6, 2015, and the market stabilized in mid-September 2015.

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

2.1.4 Trading restrictions

The CSRC had several regulatory policies in place during our sample period with the goal of reducing market turbulence. First, listed firms could apply for trading suspensions that can last for a few days up to a few weeks. These applications were actively used by firms that were concerned about precipitous drops in market value, and the CSRC in most instances approved these applications.[15]

Second, the CSRC enforced a daily 10-percent rule (see e.g., Chen et al. (2019) for a detailed analysis). Under this rule, 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. While the stock could technically continue to be traded within the 10% range, in practice, once a stock reaches its daily price limit, its trading volume drops to zero.

The above two trading regulations prevented lenders from timely liquidation. As a result, we observe a significant number of accounts exceeding their Pingcang Lines during the 2015 stock market crash. In our later analysis, we explore whether these trading restrictions have an unintended consequence of exacerbating shock transmission via common ownership by margin traders.

2.2 Data Sample and Summary Statistics

In this subsection, we describe our data samples, define account leverage, and show that leverage is highly counter-cyclical with the market index and exhibits significant cross-account heterogeneity during our sample period.

2.2.1 Data sources and filtering procedures

We use a combination of proprietary and public data from several sources. The first proprietary dataset contains the complete records of equity holdings, cash balances, and trading activity of all accounts from multiple leading brokerage firms in China. These brokers are leading security firms in China, with a total of 5.5% of the market share in the brokerage business in 2015. This sample contains data on nearly five million accounts, over 95% of which are retail accounts. Approximately 77,000 of these accounts are eligible for brokerage-financed margin trading, hereafter referred to as "brokerage-financed margin accounts" or "brokerage accounts." 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 300,000 accounts from a large web-based trading platform in China, i.e., "shadow-financed margin accounts" or "shadow accounts." After

[15] For a thorough analysis for trading suspensions during the Chinese stock market crash in the summer of 2015, see Huang et al. (2018). These "frozen" market prices of these stocks left the leverage of the holding account unchanged, and we exclude these suspended stocks in our stock-level analyses. The CSRC also implemented the controversial market-wide circuit breaker in the first trading week of 2016, but suspended it immediately at the end of that week. For details and a thorough theoretical analysis, see Chen et al. (2018a).

applying the filters detailed in Appendix A.2, we retain a final sample of a little over 106,000 shadow accounts with valid and complete information. The total debt in this sample reached 43 billion Yuan in June 2015. For comparison, recall that Section 2.1.3 estimates that the debt associated with shadow accounts peaked at around 1-1.2 trillion Yuan; in other words, our sample covers a bit over 4% of the shadow-financed margin system.

For all shadow accounts in our sample, we have detailed trading, holding, and leverage information, which form the basis of our account level analysis. For about half of these shadow accounts, we also observe detailed interim cash-flows in and out of the child accounts, and more importantly account-specific Pingcang Lines. For the other half, we do not observe detailed cash-flows, and their Pingcang Lines are fixed at exactly 10 (i.e., a maintenance margin of 10%).[16]

As discussed earlier, a key advantage of our proprietary brokerage and shadow samples is that we observe both the asset and debt of each margin account, and hence its leverage ratio every day. 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 detailed shadow-financed margin trading data), we find a cross-sectional correlation in trading volume of 94% between our brokerage sample and the whole market.[17]

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 in which total investor wealth is unknown.

Finally 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.

2.2.2 Leverage and its patterns

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

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

[16]These two different accounts are based on two distinct FinTech software systems: the former with detailed cash-flows information is called YJ (49.45% of the shadow sample) and the latter without is called QJ (50.55%). A Pingcang Line of 10 is popular in practice because of the daily 10% price limit rule (which gives the lender a false sense of safety since child accounts' asset value can drop by at most 10% in a day). See Appendix A.2 for details.

[17]For each trading day, we calculate the cross-sectional correlation in each stock's trading volume between our brokerage sample and the entire market; we then average across all trading days from May to July in 2015. This exercise includes both margin and non-margin accounts, though our empirical analysis only focuses on the former.

where A_t^j is the total market value of assets held by account j at the start of day t, including stock and cash holdings in RMB value. E_t^j is the equity value held by account j at the start of day t, equal to total assets minus total debt. An account with zero debt has a leverage ratio of 1. All start-of-day values are computed using prices as of the market close on the previous trading day.

As explained previously, the Pingcang Line is the maximum leverage an investor can have before control of the account is transferred to the lender (either the brokerage firm or the mother account). However, due to trading restrictions in China explained in Section 2.1.4, it is possible for an account's leverage to exceed its Pingcang Line. To reduce the influence of outliers, we cap both leverage and the Pingcang Line at 100 in our analysis; this treatment is mostly innocuous as our main analysis allows for flexible non-parametric estimation with respect to the measure of leverage.

Panel A of Figure 2 plots the equity-weighted average 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 in each account, the resulting average leverage is equal to total margin account assets divided by total margin account equity, for brokerage and shadow accounts, respectively. We see that the leverage of shadow accounts fluctuates more dramatically than that of brokerage accounts, suggesting strong cross-sectional heterogeneity. Further, there is a strong negative correlation between both leverage series and the SSE Index (-84% for shadow accounts and -68% for brokerage accounts), suggesting that leverage is highly counter-cyclical.

We can also contrast the equity-weighted average level of leverage with the asset-weighted average level of leverage in the market. Panel B of Figure 2 shows that, relative to the equity-weighted average, the asset-weighted average leverage is much higher throughout our sample and sharply increased toward a high of almost 7-to-1 as the stock market crashed. This contrast illustrates that highly levered accounts with very little equity owned a growing portion of the market during the market crash.

2.2.3 Summary statistics

Table 1 reports summary statistics for our data sample. We separately report statistics for observations at the account, account-date, and account-stock-date levels. In addition, we report statistics separately for the brokerage- and shadow-financed margin samples. Consistent with Panel A of Figure 2, we find that the average leverage of shadow accounts is almost five times larger than that of brokerage accounts (6.88 vs. 1.41). Shadow accounts also display substantially greater dispersion in leverage, with a standard deviation of 13.73 compared to a standard deviation of 0.48 for brokerage accounts. The average Pingcang Line of shadow accounts (11.8) is almost three times as large as that of brokerage accounts (4.3 as mandated by the CSRC).

3 Empirical Framework

In this section, we outline a simple framework for our empirical analyses. We start by discussing cash management by margin investors, and how it affects account leverage over time. We then study investor responses to leverage shocks. In particular, we examine their trading activity in response to lagged portfolio returns and how their trading helps transmit shocks from one stock to another via the common-ownership network of margin investors.

3.1 Leverage Dynamics and Cash Management: Decomposition

Generally speaking, there are two forces driving the dynamics of leverage, and they are related to how a margin investor manages her assets (cash and risky holdings) and liabilities (equity and debt). The first is a passive valuation effect, which drives leverage up when asset prices fall, leading to counter-cyclical leverage (e.g., He and Krishnamurthy (2013), He et al. (2017)). The second is an active deleveraging effect, where investors respond to negative shocks by selling risky holdings to pay down debt, contributing to pro-cyclical leverage (Geanakoplos (2010) and Adrian and Shin (2014)). We observe a counter-cyclical leverage pattern in Panel A of Figure 2, suggesting that the first valuation effect dominates empirically for individual margin traders.[18]

Thanks to the completeness and granularity of our data, we are able to examine the detailed leverage and cash policies of individual margin accounts. To the best of our knowledge, our paper is the first to study margin investors' cash and leverage management policies, especially during a stock market rally and crash episode.

3.1.1 Decomposition: How does a margin investor manage her account?

All day t variables are measured as of the start of the trading day, using market close prices from $t-1$. All Δ variables refer to changes over the course of the day. For brevity, we omit time subscripts for some variables. We decompose the change in account assets (cash plus risky holdings) in day t as follows:

$$\Delta A \equiv A_{t+1} - A_t = \Delta A_{price} + \Delta A^E_{cash} + \Delta A^D_{cash}. \tag{2}$$

Each of these components can take positive or negative values:

1. ΔA_{price}: Asset value change due to fluctuations in the market value of stock holdings;[19]

2. ΔA^E_{cash}: Cash injection/withdrawal by the margin investor (including interest payments to lenders), which affects the account's equity capital;

[18] Pro-cyclical leverage requires a stronger active deleveraging effect, so much so that the resulting leverage goes down with falling asset prices (e.g., Fostel and Geanakoplos (2008); Geanakoplos (2010), and Adrian and Shin (2014)). He et al. (2017) discuss these two forces in various asset pricing models in detail, and explain why the valuation effect often dominates in general equilibrium and hence counter-cyclical leverage ensues.

[19] This includes gains/losses from within-period trading activities, which are ultimately driven by within-period stock price movements. For a more detailed definition, see Appendix A.4.

3. ΔA^{D}_{cash}: Cash injection/withdrawal by borrowing more or paying down debt.

From the liabilities perspective, the first two components affect the equity value of the margin account, while the third component affects the debt value.[20] This allows us to decompose daily leverage fluctuations into three parts (Δlev_t^{price}, Δlev_t^{E}, and Δlev_t^{D}):

$$\underbrace{\frac{A_{t+1}}{E_{t+1}} - \frac{A_t}{E_t}}_{\Delta lev_t} = \underbrace{\frac{A_t + \Delta A_{price}}{E_t + \Delta A_{price}} - \frac{A_t}{E_t}}_{\Delta lev_t^{price}\text{: gain/loss from price change}} + \underbrace{\frac{A_t + \Delta A_{price} + \Delta A^{E}_{cash}}{E_t + \Delta A_{price} + \Delta A^{E}_{cash}} - \frac{A_t + \Delta A_{price}}{E_t + \Delta A_{price}}}_{\Delta lev_t^{E}\text{: equity injection/withdrawal}}$$
$$+ \underbrace{\frac{A_{t+1}}{E_{t+1}} - \frac{A_t + \Delta A_{price} + \Delta A^{E}_{cash}}{E_t + \Delta A_{price} + \Delta A^{E}_{cash}}}_{\Delta \mathrm{lev}_t^{D}\text{: debt change}}. \tag{3}$$

In a related exercise, we decompose the change in the account's cash holdings in each day into:

$$\Delta C \equiv C_{t+1} - C_t = \Delta C_{trade} + \Delta A^{E}_{cash} + \Delta A^{D}_{cash},$$

where ΔC_{trade} corresponds to a positive (negative) change in cash holdings due to sales (purchases) of stocks. In Section 4.2, we trace out how these three components change in response to portfolio return shocks, by considering daily changes in cash scaled by start-of-day assets ($\Delta cash \equiv {}^{\Delta C}/_{A}$):

$$\Delta cash \equiv \frac{\Delta C_{trade}}{A_t} + \frac{\Delta A^{E}_{cash}}{A_t} + \frac{\Delta A^{D}_{cash}}{A_t} \equiv \underbrace{\triangle cash^{T}}_{\text{Trading}} + \underbrace{\triangle cash^{E}}_{\text{Equity}} + \underbrace{\triangle cash^{D}}_{\text{Debt}}. \tag{4}$$

We emphasize that trading (i.e., the act of buying and selling) does not immediately alter the account's asset value (hence the account leverage), as it simply converts part of the asset value from stock holdings to cash, or vice versa. Of course, trading, by changing the portfolio composition, affects the account's risk and hence its future leverage.

3.1.2 Decomposition: Discussion and examples

For a better understanding of the economics behind our decomposition, let's consider the following examples. First, ΔA_{price} is driven by stock price movements as well as the margin investor's portfolio choice. For instance, imagine an initial holding of one share of a stock in an account; a price drop of the stock leads to a $\Delta A_{price} < 0$.

In the above example, $\Delta C_{trade} = 0$. In other words, $\Delta A_{price} < 0$ has no impact on the account's cash position. Only when the investor sells some of her stock holdings and keeps the cash proceeds—for example, one dollar—in the account, does the cash position change. In such a transaction, $\Delta C_{trade} = 1$ but $\Delta A = 0$ and the account leverage does not change.

[20] Loosely speaking, this statement holds for "book" debt value and "mark-to-market" asset value. When default is possible, the market value of debt will be affected by asset movements (e.g., Merton (1974)).

The next two terms in Eq. (2) capture the margin trader's active liability management. Suppose that the trader withdraws one dollar of cash from her margin account for consumption. Then the equity value goes down by one dollar, together with the cash value, i.e., $\Delta A^E_{cash} = -1$. Because debt remains the same but equity falls, the account leverage rises. That is, cash withdrawal not used to pay down debt translates to increased leverage, $\Delta lev^E_t > 0$, in our leverage decomposition in Eq. (3).

If the investor borrows more (from a brokerage firm or a shadow mother account), so $\Delta A^D_{cash} > 0$, then cash holdings rise, $\triangle cash^D > 0$, and leverage rises as well, $\Delta lev^D_t > 0$. On the other hand, if the investor pays down the debt using cash in the account, then leverage falls, $\Delta A^D_{cash} < 0$.

Finally, suppose the investor—in response to a negative return shock—injects her own money into the margin account. This is similar to the standard practice of cash injection following negative equity shocks, and is captured by $\Delta A^E_{cash} > 0$. Because cash (on the asset side) and equity (on the liability side) move up in tandem, this translates to a reduction in leverage, $\Delta lev^E_t < 0$. In addition, if the investor uses this newly injected cash to pay down debt, $\Delta A^D_{cash} < 0$, then both cash (on the asset side) and debt (on the liability side) go down in tandem, leading to a further reduction in leverage, $\Delta lev^D_t < 0$.

In Section 4.2, we study how margin investors respond to stock price fluctuations. A drop in the market value of an investor's portfolio increases the account leverage through the first component. In response, the investor may delever either by injecting new equity ($\Delta A^E_{cash} > 0$) or by selling stocks and paying back debt ($\Delta C_{trade} > 0$ and $\Delta A^D_{cash} < 0$). Given the completeness and granularity of our data, we are able to examine the degrees to which these two approaches are used by margin investors.

3.2 Distance-to-Margin-Call Z

In this section, we develop a measure for each margin investors' distance to her leverage constraint. 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 that would be enough to push the account's leverage to its Pingcang Line and trigger a control shift from the margin investor to her lender (either a brokerage firm or a shadow mother account).

For each account-date observation with start-of-day asset value A^j_t, equity value E^j_t, and Pingcang Line $\overline{Lev}_j$, we define the account's distance-to-margin-call (denoted by Z) as:

$$\frac{A^j_t - A^j_t \sigma^j_{At} Z^j_t}{E^j_t - A^j_t \sigma^j_{At} Z^j_t} = \overline{Lev}_j, \tag{5}$$

where σ^j_{At} is the portfolio volatility of account j on day t including both cash and stock holdings.[21] In other words, the account's distance-to-margin-call indicates the number of standard deviations

[21] We estimate the variance-covariance matrix based on daily stock returns from the previous year (5/1/2014 to 4/30/2015) in the Chinese stock market.

of downward movements in asset value necessary to push the account's leverage to its Pingcang Line. The Pingcang Line never changes over the life of the account. Hence $\overline{Lev_j}$ has no day-t subscript, and an account's distance-to-margin-call varies over time due to changes in its leverage and asset volatility.

By re-arranging Eq. (5), 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:

$$Z_t^j = \underbrace{\frac{\overline{Lev_j} - Lev_t^j}{\overline{Lev_j} - 1}}_{\text{Leverage-to-Pingcang}} \cdot \underbrace{\frac{1}{\sigma_{At}^j}}_{\text{Daily Volatility}} \cdot \underbrace{\frac{1}{Lev_t^j}}_{\text{Amplification}} . \tag{6}$$

The account's distance-to-margin-call then depends on the account's Leverage-to-Pingcang distance (the first term), the volatility of its holdings (the second term), and an amplification effect due to the account's current leverage (the third term). An account has a low Z and hence is more likely to receive a margin call, if it has lower Leverage-to-Pingcang, higher asset portfolio volatility, and/or higher current leverage.

An account-date observation has $Z_t^j > 0$ if its leverage is below the Pingcang Line, and a smaller Z implies a greater risk of being taken over by the lender. We also observe a number of accounts with leverage ratios exceeding their respective Pingcang Lines, i.e., $Lev_t^j > \overline{Lev_j}$, so $Z_t^j < 0$. As explained in Section 2.2.2, these accounts have been taken over by their lenders who may be unable to liquidate the holdings due to price limit constraints and/or trading suspensions. As shown in Table 1 Panel B, the average Z of the brokerage sample is about 39 (median 33) with a standard deviation of 23, and that of the shadow sample is 13 (median 9), with a standard deviation of 18. In other words, Z is large on average in our sample, suggesting that most margin accounts are far away from receiving margin calls. We also note that some margin accounts keep a large fraction of borrowed money in cash, resulting in very large Z, as their σ_A is close to zero.

3.3 Margin Investors' Trading Strategy

This subsection considers margin investors' trading strategies. Net buying of stock i by account j on day t is defined as:

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

δ_i^j can take both positive (buying) and negative (selling) values, and may depend on stock i's characteristics, account j's distance-to-margin-call Z_t^j, and shocks to Z_t^j. Note that δ_i^j is defined using the number of shares and does not use any price information.

3.3.1 Structural assumptions and discussions

The simple theoretical 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.[22] δ_{it}^{j}, the change in optimal holdings during day t, can then be expressed using the following first-order Taylor expansion:

$$\delta_{it}^{j} = f\left(Z_t^j\right) + \underbrace{g\left(Z_t^j\right) \cdot Z'\left(R\right) \cdot R_t^j}_{\text{capturing shocks to } Z} + \alpha_j + \nu_{it}, \tag{8}$$

where $f(\cdot)$ and $g(\cdot)$ are general nonlinear functions, R_t^j is the account return over the course of day t based on start-of-day asset holdings (if no trading or changes in cash assets occurred), $Z'(R)$ is the derivative of Z with respect to the account return, and ν_{it} are stock-date fixed effects and α_j account fixed effects. Here, as well as in later empirical exercises, Z_t^j is measured at the end of day $t-1$ which gives the account's "distance-to-margin-call" before any shock. Since changes in Z are mainly due to account returns, the second term in Eq. (8) can be interpreted as "Z-shocks." We will give the exact definition of Z-shocks shortly.

By including stock-date fixed effects ν_{it} in Eq. (8), we are effectively comparing 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 account leverage summarized by Z and Z-shocks. In other words, margin investors scale up or down all their positions proportionally in response to Z and Z-shocks.

Note that the proportionality assumption in Eq. (8) allows us to estimate the *average* trading response (as a percentage of start-of-day holdings) across all stocks held by the account in response to variation in leverage constraints. Looking at the average trading response across stock holdings is a simplification that allows us to better focus our later empirical tests on heterogeneity in trading behavior by different types of investors, in response to different types of leverage shocks, and in different market environments. However, we will also show in later sections that investors don't actually sell holdings "pro rata," and we will directly examine liquidation choice and incorporate liquidation choice into our analysis of shock propagation.

3.3.2 Estimation method and Z-shock specification

We estimate Eq. (8) by allowing for flexible nonlinear forms for $f(\cdot)$ and $g(\cdot)$. To do so, 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. We also create a bin 0 for accounts with $Z_t^j < 0$ (i.e., Lev_t^j exceeds $\overline{Lev_j}$). Denote $\mathbb{K} = \{0, 1, 2, \cdots, K\}$.

[22] 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).

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

$$\begin{aligned}
\delta_{i,t}^{j} &= \sum_{k=0}^{K} f_k I_{kt}^{j} + \sum_{k=0}^{K} g_k I_{kt}^{j} \cdot Z'(R) \cdot R_t^{j} + \alpha_j + \nu_{it} + \varepsilon_{it}^{j} && (9)\\
&= \sum_{k=0}^{K} f_k I_{kt}^{j} + \sum_{k=0}^{K} \gamma \cdot I_{kt}^{j} \cdot \underbrace{(g_k/\gamma) \cdot Z'(R) \cdot R_t^{j}}_{\Delta Z_t^j} + \alpha_j + \nu_{it} + \varepsilon_{it}^{j}. && (10)
\end{aligned}$$

As we show shortly in Section 4.3, the estimated $\left\{\widehat{f_k}\right\}$ in Eq. (9) exhibit strong nonlinear patterns, highlighting the importance of employing a non-parametric estimation method. We further simplify regression Eq. (9) in a way that is motivated by theory but disciplined by data. Specifically, as illustrated in Eq. (10), by rewriting Z-shocks ΔZ_t^j, we can replace g_k by a constant γ.

Formally, we define ΔZ as follows:

$$\Delta Z_t^j \equiv \underbrace{\frac{1-\sigma_{At}^j Z_t^j}{Z_t^j \cdot \sigma_{At}^j} \cdot R_t^j}_{\text{percentage shock to } Z,\ Z'(R)/Z \cdot R} \times \underbrace{\left(Z_t^j\right)^{-\theta}}_{\text{nonlinear adjustment}}. \tag{11}$$

We provide a full derivation in Appendix A.5.2. The first term in Eq. (11) is the "percentage shock to Z" due to the account return R_t^j; the second term is the "nonlinear adjustment" so that the γ coefficient in Eq. (10) is roughly constant across all k bins. The functional form of $\left(Z_t^j\right)^{-\theta}$ in the "nonlinear adjustment" is chosen solely for parsimony. We rely on the data to determine θ: as explained in Appendix A.5.2, $\theta = 0.8$ delivers a roughly constant γ across all the k-bins (as shown in Figure A.1).

To recap, our framework also allows for trading to depend on the pre-shock level of Z_t^j in a nonlinear way. Margin investors trade in response to Z-shocks in a linear way, once we measure Z-shocks as in (11). This allows us to drop the k-dependence of $\{g_k\}$ in Eq. (9) and replace them with a common coefficient γ, implying a simple regression specification:

$$\delta_{i,t}^{j} = \sum_{k \in \mathbb{K}} f_k I_{kt}^{j} + \gamma \cdot \Delta Z_t^j + \alpha_j + \nu_{it} + \varepsilon_{it}^{j}. \tag{12}$$

Importantly, Eq. (12) also forms the basis of analyzing shock propagation through the network of margin investor holdings, to which we turn next.

3.4 Z-Shock Transmission in a Leverage Network

When margin investors adjust their holdings in response to Z-shocks, their trading can transmit shocks across stocks via common holdings by the same margin investor. To estimate shock transmission on a daily frequency, we will only consider the effect of Z-shocks in our empirical exercise (as the level of Z is persistent at a daily frequency).

To this end, we develop a measure called "margin-account linked portfolio returns" ($MLPR$) that captures the price impact on one stock due to return movements of other stocks that are connected via the leverage network. Before proceeding to the details of empirical construction, we present a simple example to illustrate the intuition.

3.4.1 An illustrative example

Consider an economy with a single margin investor who holds two stocks, S_1 and S_2. Suppose S_2 experiences a negative return, which pushes the margin investor closer to her Pingcang Line, leading her to sell S_1, hence adding negative price impact for S_1.

The "margin-account linked portfolio returns" ($MLPR$) measures the price impact on S_1 due to return movements in the connected stock S_2. We first translate S_2's return into a Z-shock to reflect how the return movement in S_2 pushes the investor closer to her leverage constraint. We then construct $MLPR$ for S_1 assuming that the investor sells S_1 according to the average relationship between percentage sales and Z-shocks as estimated in Eq. (12). For example, if Eq. (12) predicts that the investor liquidates an average of 5% of all holdings in response to the Z-shock, we would assume that she sells 5% of her holdings of S_1, and translate that sale percentage to a dollar amount using her initial holdings of S_1. Aggregating these dollar sales across all margin investors (in this simple example, there is only one) and scaling these dollar sales by the market cap of S_1, we obtain a measure of S_1's selling pressure stemming from return movements in connected stocks.

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

3.4.2 Constructing $MLPR$

To construct the stock-date level measure $MLPR$, recall that δ_{it}^j denotes the margin investor j's net buying of stock i on day t as a percentage of her initial holdings. Denote:

$$Q_t^j \equiv \left(Z_t^j\right)^{-(1+\theta)} \times \frac{1-\sigma_{At}^j Z_t^j}{\sigma_{At}^j}. \tag{13}$$

We can then rewrite Eq. (11) as $\Delta Z_t^j = Q_t^j R_t^j$. Plugging this into Eq. (12), we can write margin investor j's dollar trading (net buying as denoted by X_{it}^j) in stock i as:

$$X_{it}^j = A_t^j \omega_{it}^j \cdot \gamma Q_t^j R_t^j, \tag{14}$$

where A_t^j is the account value of investor j and ω_{it}^j is the portfolio weight of stock i in account j at the beginning of day t. X_{it}^j captures margin-induced trading in stock i on day t by investor j, assuming that margin investors proportionally scale up or down their positions in response to return shocks. In supplementary analysis in Section 5.2.3, we model margin investors' liquidation choice by allowing X_{it}^j to depend on stock characteristics, and find similar results.

Aggregating X_{it}^j across all J margin traders, we derive the total amount of margin-induced trading in stock i on day t:

$$X_{it} = \sum_{j=1}^{J} A_t^j \omega_{it}^j \cdot \gamma Q_t^j R_t^j. \tag{15}$$

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

$$\frac{1}{MktCap_{it}} \sum_{j=1}^{J} A_t^j \omega_{it}^j \cdot \gamma Q_t^j R_t^j. \tag{16}$$

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

For expositional convenience, we recast everything using matrix algebra and drop the time subscripts. Given N stocks in the market, on each trading day we let R denote an $N \times 1$ vector of stock returns of that day, $\mathbf{\Omega}$ a $J \times N$ matrix of beginning-of-day portfolio weights such that each row sums up to 1 (our holdings include cash), $\mathbf{diag}(A)$ a $J \times J$ diagonal matrix whose diagonal terms are A_j, $\mathbf{diag}(Q)$ a $J \times J$ diagonal matrix whose diagonal terms are Q_t^j; $\mathbf{diag}(MktCap)$ an $N \times N$ diagonal matrix whose diagonal terms are $MktCap_{it}$. The vector of margin-induced price pressure on all stocks can then be written as $\mathbf{T} \times R$, where

$$\mathbf{T} \equiv \mathbf{diag}(MktCap)^{-1} \times \mathbf{\Omega}' \times \mathbf{diag}(A) \times \gamma \times \mathbf{diag}(Q) \times \mathbf{\Omega}. \tag{17}$$

One way of interpreting the transmission matrix, $\mathbf{T}$, is that it governs the transmission of individual stock returns through common ownership by margin investors. The greater the account size (A^j), the smaller the account's distance-to-margin-call (Z^j), the greater the account's weight in the leverage-network-based transmission matrix.

Finally, to isolate the effect of contagion, we remove the stock's own return. We define $\mathbf{T}_0 \equiv \mathbf{T} - \mathbf{diag}(\mathbf{T})$, where $\mathbf{T}_0$ is the $\mathbf{T}$ matrix with all the diagonal terms set to zero. We then define margin-account linked portfolio returns ($MLPR$) as $\mathbf{T}_0 \times R$. Intuitively, $MLPR_i$ captures the price impact on stock i stemming from all other stocks that are connected to i via common ownership by margin investors.

4 Leverage Dynamics, Liability Management and Trading Behavior

Leverage policies and liquidity management are at the core of dynamic portfolio theory, with important implications for other fields of financial economics. It remains largely unknown, however, how margin investors manage their leverage in response to market fluctuations.[23] Our account-level data with detailed financing and trading information allow us to provide the first comprehensive empirical evidence on this important question.

We start our analysis in Section 4.1 by documenting the characteristics of investors who are more likely to use leverage (or, use more leverage). We then analyze and compare the liquidity (cash) and leverage management policies of brokerage- and shadow-financed margin investors in Section 4.2. Finally, we study how margin investors trade as a function of distance-to-margin-call and its shocks in Section 4.3.

4.1 Use of Leverage and Initial leverage

Given the high interest rates charged on margin loans (about 8-9% a year for brokerage-financed loans and 25% for shadow-financed loans), and an annual buy and hold return of merely 1.3% for the Chinese A-share market since 2000, margin trading should be attractive only to investors who strongly believe that they can outperform the market.[24]

This subsection studies investors' leverage decisions and how such decisions vary with investor characteristics and account type, brokerage or shadow. We examine both the extensive margin, i.e., whether an investor uses margin borrowing, and the intensive margin, which includes investors' initial leverage as well as the maximum allowable leverage (the Pingcang Line). Our analysis here focuses on the subset of accounts that were opened during our three-month period (after May 1, 2015) and their account characteristics on the opening day, to alleviate an endogeneity concern related to leverage-induced trading and rebalancing. For example, margin investors may choose to sell more liquid, larger, safer stocks first, thus tilting their remaining holdings to less liquid, smaller, riskier stocks. Detailed discussions of investors' liquidation choice are in Section 4.3.

4.1.1 Brokerage-financed margin accounts

The decision to use margin borrowing Around three quarters of brokerage margin accounts in our sample ever used margin loans during our sample period; the remaining one quarter, although

[23] Due to data limitations, research on hedge funds has mostly focused on long-only funds, with the only exception of Ang et al. (2011) who study the leverage dynamics of the hedge fund sector during the 2007-2009 financial crisis.

[24] Chinese *A*-share market returns are calculated as the geometric average of annual *A*-share market returns reported by RESSET. A similar observation is made by Allen et al. (2020), who contrast the disappointing performance of China's A-share market with China's stellar GDP growth rate in the last two decades.

eligible for margin financing, never took out a margin loan. The latter non-levered group naturally serves as the base group in our regression analyses.

In our first test, we compare the characteristics of brokerage margin investors who borrowed at least once during our sample period with brokerage investors who had margin accounts but never used margin loans. The list of account/investor characteristics includes: account size, percentage of cash holdings, portfolio concentration (proxied by the number of stocks in the portfolio and the Herfindahl Index of portfolio weights), account turnover, experience (account age and investor age), and investor gender. Except for account turnover, which is measured as the average turnover in the entire three-month period, all other account/investor characteristics are measured at account initiation. We also report differences in accounts' weighted-average characteristics of stock holdings (such as the market beta, idiosyncratic volatility, size, book-to-market ratio), where the portfolio weights are computed on the account-open day.

As can be seen in the first three columns of Panel A of Table 2, investors that engage in margin borrowing tend to be more active and less experienced. Compared to non-levered investors, levered investors a) have larger equity capital; b) start with smaller cash holdings (12.8% vs 62.4%); c) invest in a larger number of stocks in their portfolios (5.04 vs. 3.45); d) have higher account turnover (22.5% vs. 6.8%); e) are less experienced (both in terms of account age and investor age); f) are more likely to be male; g) have riskier holdings (measured by both beta and idiosyncratic volatility); h) have more liquid holdings, and finally i) hold stocks that are larger and have better past performance.

Variation in initial leverage We also examine differences in account and stock characteristics between brokerage-financed margin accounts with above-median and below-median leverage ratios measured on the first day of account opening, conditional on using leverage. As mentioned earlier, we focus on the initial leverage and first-day portfolio weights of accounts initiated during our sample period to mitigate the concern that account leverage, past returns, and holding characteristics may be mechanically linked. The results are reported in the last three columns of Panel A. Comparing above- and below-median leverage accounts, we generally find similar patterns to those found earlier when we compared leveraged versus non-leveraged accounts, albeit with weaker statistical significance. One exception is that, conditional on using leverage, accounts with below-median initial leverage have slightly higher account-level turnover.

4.1.2 Shadow-financed margin accounts

Variation in Pingcang Lines. As explained in Section 2.1.3, while the Pingcang Line of brokerage accounts is set to a constant of 4.3 by the CSRC, Pingcang Lines in the shadow margin system can be the market outcomes of bilateral relationships. Consequently, there is substantial variation in observed Pingcang Lines across shadow-financed YJ margin accounts.[25]

In the first three columns of Panel B, Table 2, we compare account and holding characteristics (defined similarly to those examined in Panel A) of shadow-financed YJ margin accounts with above-median vs. below-median Pingcang Lines. Again, we focus solely on shadow margin accounts that are opened during our sample period and their portfolio compositions on the account-open day. Shadow accounts with higher Pingcang Lines a) have less own equity capital and cash holdings; b) hold a smaller number of stocks in the portfolio (2.03 vs. 2.11); c) have higher account turnover; and d) hold stocks with higher idiosyncratic volatility, higher liquidity, and better past performance. The combination of b), c) and d) suggests that shadow accounts with higher Pingcang Lines are less diversified and more active than their peers.

Variation in initial leverage We next compare shadow accounts with above-median initial leverage versus those with below-median initial leverage (measured on the account-open day). The differences in account and holding characteristics between the two subsamples are reported in the last three columns of Panel B. Given the significant cross-sectional correlation between account Pingcang Lines and initial leverage (around 15%), the patterns shown in the last three columns are broadly similar to those in the first three columns: shadow accounts with higher initial leverage tend to be less diversified and more active than their peers.

4.1.3 Brokerage-Financed versus Shadow-Financed Margin Accounts

In our final test, we compare the investor/holding characteristics of brokerage and shadow margin accounts. As shown in Panel C of Table 2, relative to brokerage accounts, shadow margin accounts a) have substantially less own capital, b) hold much more cash (53.9% vs. 12.8%), c) have more concentrated holdings, and d) have much higher account turnover. Combined with the fact that shadow accounts have much higher leverage ratios than brokerage accounts (6.87 vs. 1.41), shadow-financed margin investors are more active and take on more risks compared to their brokerage-financed peers.

4.2 Cash Management and Leverage Dynamics

We now analyze how margin investors manage liquidity (cash) and leverage in response to the distance-to-margin-call Z. For both brokerage- and shadow-financed accounts, we find that investors aggressively sell stock holdings when leverage edges closer to their Pingcang Lines. We also find some intriguing disparities between these two types of accounts and provide a potential explanation for the disparities.

We construct seven Z bins as in regression (12): $Z > 5$, $Z \in [k-1, k)$ for $k = 1, 2, 3, 4, 5$ and finally $Z < 0$. (Recall Z is the number of standard deviations of downward movements in asset

[25] As explained in footnote 16, Pingcang Lines vary across accounts in the YJ sample (49.45% of the shadow accounts).

values necessary to push the account's leverage up to its Pingcang Line; hence there is a negligible risk of receiving margin calls for accounts with $Z > 5$.) Throughout, Z is measured as of the start of trading day t using market close prices from $t-1$, while cash and leverage changes are measured during trading day t. Z-shocks are calculated using start-of-day assets and return movements over the course of day t.

4.2.1 Cash and liability management: Brokerage vs. shadow accounts

Following the framework in Section 3.1, we first investigate margin investors' liquidity management. For each bin, we calculate the change in cash holdings $\Delta cash$ and its three components in Eq. (4): $\Delta cash^T$ (due to trading), $\Delta cash^E$ (equity injection/withdrawal), and $\Delta cash^D$ (debt refinancing/paydown), all scaled by account assets.[26] Since forced sales can take several days to resolve, we use the cumulative cash change for the five days after the account hits the Pingcang Line for the bin representing $Z < 0$.

Figure 3 presents results for brokerage (Panel A) and shadow (Panel B) accounts. Both types of margin accounts sell their stock holdings more aggressively when their accounts edge closer to margin calls (i.e., lower Z). For brokerage accounts, the point estimate ranges from 2% for accounts with $Z > 5$ to about 10% for accounts with Z close to zero (but which have not hit their Pingcang Lines). We will investigate this phenomenon of leverage-induced fire sales in a regression framework in Section 4.3.1.

The cash/liquidity management differ sharply across these two margin systems. As shown in Panel A, brokerage investors use the sales proceeds to pay down their margin debt, i.e., $\Delta cash^T + \Delta cash^D \approx 0$. These traders inject little cash via their own equity ($\Delta cash^E \approx 0$), leading to small changes in total cash $\Delta cash$. Finally, over five trading days after the account hits the Pingcang Line ($Z < 0$), about 26% of the stock holdings are sold to pay down debt (this number barely changes when we extend the horizon further). That creditors do not sell the entire portfolio is likely due to trading restrictions mentioned in Section 2.1; indeed, in our sample, for brokerage accounts, about 81% of stock holdings (in terms of dollars) in the group of $Z < 0$ face selling restrictions.

Turning to shadow accounts in Panel B, for all Z-groups except $Z < 0$, shadow investors keep most of their sales proceeds in cash, i.e., $\Delta cash \approx \Delta cash^T$. As Z approaches zero, shadow investors start paying down debt via equity injection. For accounts with $Z < 0$, shadow investors inject cash to pay down their debt. The lender (mother account) also sells assets, although the change in cash due to trading is only 4%, which is far less than the change in cash of 26% due to trading by the lender for $Z < 0$ in brokerage accounts.

From Figure 3 Panels A and B, it may appear as though shadow investors have smaller $\Delta cash^T$ for very low Z, i.e., that shadow accounts do not sell stocks as aggressively as brokerage investors when they are close to the Pingcang Lines. This visual effect is due to differences in timing:

[26] To minimize the impact of potential outliers, for each day, we first sum up each change in cash component across all accounts in the same Z-bin and divide it by the total assets of these accounts. For each bin, we then compute the average of each cash ratio across all trading days in our sample period.

compared to shadow margin accounts, brokerage margin accounts were more likely to have low Z during the crash period of our sample,[27] when all margin accounts sold more aggressively when close to their Pingcang Lines. In addition, shadow investors also keep a greater proportion of their total assets in cash, so the same stock sale as a fraction of stock holdings translates to a smaller $\Delta cash^T$, which is scaled by total assets.[28] However, we will show in formal regression analysis in Section 4.3.1 that, once we control for stock-date fixed effects, so we are comparing accounts who hold the same stock on the same day, shadow investors actually sell a greater fraction of their stock holdings for a given level of Z close to zero. Further, shadow and brokerage lenders liquidate approximately similar portions of stock holdings once accounts hit their Pingcang Lines and control transfers to the lender.

Overall, the most striking difference between brokerage and shadow accounts' cash and leverage management policies is that shadow accounts maintain a higher level of cash, and keep stock sales proceeds as cash instead of paying down debt as Z approaches zero. Note that leverage ($= assets/equity$) remains constant if shadow investors sell stock and maintain the proceeds as cash, but they are still "delevering" in the sense that they are increasing their distance-to-margin-call Z by converting risky assets to safe assets (because Z is a function of asset volatility). However, the same stock sale translates to a greater increase in Z for brokerage investors, because they use sales proceeds to buy back debt, which directly reduces leverage.

4.2.2 A potential explanation: discretion-based vs. rule-based

What explains the observed differences in liquidity management between these two margin systems? During our sample period, the financing cost of margin debt is about 8% annualized in the brokerage system and 25% in the shadow system, while cash holdings in both systems receive virtually no interest income. Therefore, all else equal, shadow investors have stronger incentives to pay down their debt after selling stocks given their greater opportunity cost of holding cash. We find the exact opposite in the data: shadow investors maintain more cash as a fraction of assets, and, as shown in Figure 3, maintain their stock sales proceeds as cash instead of paying down debt.

We propose a simple explanation relating to discretion- versus rule-based margin systems. Under the disguise of "FinTech" innovation and thanks to lax regulation, shadow margin businesses grew rapidly during the boom period of the Chinese stock market in the first half of 2015. As a result, the shadow margin system is more "discretion-based." It lacks standardized procedures, internal controls, and automated implementation. In contrast, brokerage margin businesses are more "rule-based."

In particular, processing of debt financing is automated in the brokerage system, and margin investors can borrow within the system without delay or cost as long as the account remains in good standing. As a result, it is suboptimal for brokerage investors to maintain a cash balance while

[27] One of the two papers that this article subsumes, Bian et al. (2018), formally documents this result.

[28] As shown earlier in Table 1, brokerage investors keep an average of $314/4042 = 7.8\%$ of their assets in cash; this is far below the average cash-to-assets ratio in the shadow system ($325/1473 = 22\%$).

carrying margin debt given the substantial wedge between the borrowing and lending rates. In contrast, in the shadow margin system, each new request for margin financing needs to be reviewed by the mother account. Consequently, investors have an incentive to hoard cash if they are worried that they may be unable to obtain additional financing in a timely fashion if they pay down the debt today. Consistent with this view, while brokerage-margin investors increase their margin borrowing in 35% of our account-date observations, that number for shadow margin accounts is a mere 3.5%.

As we will discuss in more detail in Section 4.3.5, shadow investors may have also anticipated that increases in debt financing would be more difficult to acquire in the future due to the looming threat of government regulation of the shadow sector. Therefore, shadow investors had an incentive to maintain their current debt instead of paying it down.

Altogether, differences in the processing of debt financing can lead shadow investors to borrow more than brokerage investors. Together with the possibility that shadow investors are more risk tolerant, they help explain the persistently higher leverage ratios observed in the shadow margin system than that in the brokerage system.

4.2.3 Cash changes in response to Z-shocks

Discretion- versus rule-based margin systems can also help explain margin traders' differing cash management strategies in response to Z-shocks. The results are shown in Panels C and D of Figure 3. Specifically, we first sort account-date observations into quintiles based on the daily Z-shocks constructed per Eq. (11), and then plot cash changes for these accounts-date groups, for brokerage and shadow accounts respectively.

For brokerage accounts (Panel C), large negative Z-shocks (first quintile) are associated with aggressive stock sales as well as large debt reductions. Following large positive Z-shocks (the fifth quintile), brokerage margin investors also sell stocks and pay down their margin debt (potentially due to a desire to realize profits and avoid paying high interest rates on debt).

Shadow accounts (Panel D) exhibit similar trading behavior in that they sell stocks after both large negative and positive Z-shocks (first and fifth quintiles). However, these sales do not translate to large reductions in debt. Consistent with the discussion in Section 4.2.1, we again observe $\Delta cash \approx \Delta cash^T$, i.e., shadow investors keep their sale proceeds in cash holdings inside their margin accounts, and do not use the proceeds to pay down debt. We observe a negligible $\Delta cash^D$ even for the accounts with the most negative Z-shocks.

4.2.4 Impact on leverage

Cash and liability management affects the leverage dynamics of margin accounts. Eq. (3) decomposes daily changes in leverage into i) changes in stock holding value, ii) equity injection or withdrawal, and iii) increases or reductions in margin debt; i.e., $\Delta lev_t^j = \Delta lev_t^{j,price} + \Delta lev_t^{j,E} + \Delta lev_t^{j,D}$. This allows us to conduct a variance decomposition exercise for each account j by calculating

$$cov_j^k = \frac{Cov\left(\Delta lev_t^j, \Delta lev_t^{j,k}\right)}{Var\left(\Delta lev_t^j\right)},$$

where $k = price, E$, and D. Each component, cov_j^k, captures its relative contribution to the daily variation in leverage, with $cov_j^{price} + cov_j^E + cov_j^D = 1$. We then take the average cov_j^k across all accounts, separately for the brokerage (subscript "br") and shadow (subscript "sh") systems.

For brokerage accounts, debt management (cov_{br}^D) accounts for 80.24% of the daily variation in account leverage, consistent with our earlier finding that brokerage investors sell their stock holdings to pay down debt. Another 18.45% of daily variation in leverage is due to fluctuations in portfolio value ($cov_{br}^{price} = 18.45\%$). Finally, equity management (cov_{br}^E) contributes little (1.31%) to leverage management.

For shadow accounts, cov_{sh}^{price} is the leading contributor (64.72%) to daily variation in account leverage. This is largely because shadow accounts use much higher leverage than their brokerage peers, which amplifies the impact of changes in stock prices on account leverage. Equity management, cov_{sh}^E, contributes 17.12% to daily variation in account leverage. Strikingly, debt management cov_{sh}^D accounts for only 18.15% of the variation in leverage, which is much lower than that for brokerage accounts. As explained in Section 4.2.2, shadow margin accounts rarely pay down debt before hitting the Pingcang Line, and even when they do, they only pay down a small fraction of the total margin debt.

4.3 Trading Activity

We now examine margin investors' trading activity as a function of the distance-to-margin-call (captured by Z) as well as changes in distance-to-margin-call (captured by the Z-shock). Figure 3 has shown the broad pattern that margin investors sell more of their stock holdings as Z approaches zero or if they suffer a more severe (negative) Z-shock. In this section, we investigate the relationship between distance-to-margin-call and stock sales more formally, controlling for other factors that could affect stock sales. We conduct stock-account-date panel regressions as specified in Eq. (12) that include both stock-date and account fixed effects, with standard errors triple-clustered at account, stock, and date level. We estimate Eq. (12) on the full stock-account-date sample, including stocks that face trading restrictions during part or all of certain trading days, in order to estimate the overall relationship between Z and stock sales during our sample period (we will directly explore the role of trading restrictions in later analysis).

Recall that Z is measured at the end of trading day $t-1$, while net buying is measured over the course of trading day t and Z-shocks are measured based on start of day assets and price changes over the course of trading day t. In this subsection, our analysis of reactions to Z-shocks captures a contemporaneous relation between trading and shocks. In the next section, we also confirm that shocks during day t continue to affect trading (and returns) in day $t + 1$.

As before, we consider seven Z bins: $Z > 5$, $Z \in [k-1, k)$ for $k = 1, 2, 3, 4, 5$ and finally $Z < 0$. Recall that in Section 4.1.1 there exist non-levered (brokerage) margin accounts who never take margin loans during our sample period; throughout our paper these observations form the omitted category and serve as the base group in our regression analyses (for both brokerage and shadow accounts). In other words, the estimated coefficient for each bin captures the additional trading intensity relative to these non-levered margin accounts.

4.3.1 Margin trading: Z and Z-shocks

The regression results are provided in Table 3 Panel A, and Figure 4 plots the regression coefficients on Z bins and the Z-shock. Column (1) shows that brokerage margin accounts facing margin calls ($Z < 0$) sell an additional 18.3% of their current stock holdings, compared to non-levered brokerage margin accounts. We also find that selling pressure increases non-linearly as the distance-to-margin-call falls (as Z approaches zero). For instance, the coefficient for a brokerage margin account with Z between 0 and 1 (-0.0514) is more than 7 times that in a brokerage margin account whose Z is greater than 5 (-0.0067).[29] The observed liquidation activity for accounts with Z close to but exceeding zero is consistent with a precautionary motive (e.g., Garleanu and Pedersen (2011), He and Krishnamurthy (2019)). Column 1 also reports a significant and positive coefficient on the Z-shock. In other words, when the margin account experiences a negative shock today that pushes it closer to the Pingcang Line, there is less contemporaneous net buying, or equivalently, more selling.

Comparing Column 1 (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 -0.189 if the stock appears in a shadow account, compared to -0.0514 when it appears in a brokerage account. However, the selling intensity once the account exceeds the Pingcang Line ($Z \leq 0$) is approximately similar for shadow accounts and brokerage accounts (-0.153 vs. -0.183).

As discussed previously, shadow investors generally retain stock sales as cash instead of using sales proceeds to pay down debt when $Z > 0$, so their precautionary selling does not reduce their leverage ($= assets/equity$). 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 shown in Figure 4 is consistent with the fact that shadow investors have to sell more stock to achieve a similar increase in Z. In

[29] 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.

addition, the greater precautionary selling by shadow investors may relate to their anticipation of future regulatory tightening, as we will discuss in Section 4.3.5.

We also estimate a significant positive coefficient on Z-shocks that is quantitatively similar for brokerage and shadow accounts. Column 5 implies that for a one-standard-deviation negative move in the Z-shock (equal to 8.5% in the full sample), margin investors sell additional stocks over the course of day t that is equal to approximately 2.8% of their stock holdings.[30]

In columns (2) and (4) of Table 3, we separately examine reactions to positive and negative Z-shocks. For brokerage accounts in column (2), the coefficients are both positive, implying that brokerage investors buy and sell in response to positive and negative Z-shocks, respectively. The coefficient on negative Z-shocks is much higher than that on positive Z-shocks (0.378 vs. 0.127), highlighting an important asymmetry: investors are more likely to sell in response to negative shocks than to buy following positive shocks. The asymmetric response is even more stark for shadow investors. Column (4) shows that shadow investors sell aggressively in response to negative Z-shocks. Moreover, we estimate a marginally significant negative coefficient on positive Z-shocks, indicating that shadow investors sell even when their accounts experience positive shocks. Finally, columns (5) and (6) repeat the same analyses after combining brokerage and shadow accounts. We again find a strong asymmetric response: investors exhibit a strong sell response to negative Z-shocks but do not respond significantly to positive Z-shocks. The asymmetry between positive and negative Z-shocks is consistent with our theoretical framework laid out in Eq. (8) and (12) in Section 3.3, once we apply our framework to within-day shocks but measure the net buying at the daily level.[31]

4.3.2 The impact of trading restrictions

Selling pressure at the stock level will be affected by trading restrictions at the account level. Selling (rather than buying) restrictions are more relevant to our analysis, and can take two forms as explained in Section 2.1.4. First, in any trading day, a stock cannot be sold below its downward price limit, equal to 90% of its previous closing price. During the bust period of our sample, 15.9% of stocks hit such a limit on a given day. Second, a stock cannot be bought or sold on days that it is suspended from trading. These trading suspensions can last for a few days up to a few weeks during the bust period of our sample period, and 16.2% of stocks experienced trading suspensions on any given day. A stock hence faces "selling" restriction either because it has hit the downward price limit or because its trading has been suspended; because selling restriction is more relevant for our study, we use trading restrictions and selling restrictions interchangeably in this paper.

[30]Regarding the economic magnitude in terms of account returns, for the Z-bin with $Z \in (0, 1]$, a 1% of negative account return leads to 6.5% of net selling; and this number is only 0.09% for the group with $Z > 5$.

[31]To see this, a negative within-day Z-shock caused by a negative within-day account return pushes the account Z downward, and investors who react positively to the account's Z will sell more during the day (relative to a positive within-day account return). In fact, Eq. (8) is general enough to capture all nonlinear (but smooth, as required by the Taylor expansion) response functions of δ^j_{it}.

Consider stock i held by account j on day t, and suppose i does not face direct selling restrictions. Stock i's selling pressure (in response to the same negative Z-shock) should be higher if other stocks in account j cannot be sold due to selling restrictions. Panel B of Table 3 tests this prediction by repeating the same exercise as in Panel A but also including $\%Restriction$ (the fraction of stocks held by the account facing selling restriction on that day, excluding stock i itself) and its interaction with Z-shock. We find a negative and significant coefficient on $\%Restriction$ in all samples, indicating higher selling pressure when a stock is held by an account facing greater selling restriction of its other holdings. In addition, the coefficient on the interaction between Z-shocks and $\%Restriction$ is positive and significant among shadow accounts and in the full sample. This result confirms a stronger selling response to the same negative Z-shock when the account faces selling restrictions in its other holdings.[32]

4.3.3 The role of investor gender and experiences

In this subsection, we examine differences in trading behavior in response to Z and Z-shocks by gender and past trading experience (i.e., the number of years since account opening). We focus on brokerage margin investors, because data on these demographic variables is limited to the brokerage sample. We repeat the exercise in Panel A of Table 3, but interact Z and Z-shocks with these two characteristics.

Column (1) in Panel D shows that female investors respond more strongly to Z and Z-shocks than their male peers. For example, for accounts with $Z \in (0, 1]$, female investors' propensity to liquidate their positions is 33% higher than that of male investors, and the difference is statistically significant at the 5% level. Female investors' response to Z-shocks is also 15% higher than that of male investors (1.44 vs. 1.25).[33] Finally, Column (2) reports the result for more vs. less experienced margin investors. Experienced (inexperienced) margin investors are defined as those who opened their accounts before (after) March 2008, or the median account open date in our sample. Experienced margin investors therefore witnessed the 2007 bubble episode in the Chinese stock market. Nevertheless, we do not find significant differences in trading behaviors between these two investor groups.

In sum, more and less experienced investors respond similarly to leverage constraints. Meanwhile, female margin investors sell risky holdings more aggressively than male investors when approaching their Pingcang Lines. These results are consistent with findings in Barber and Odean (2001) that female investors in a US discount brokerage firm are more risk averse in their investments. Our findings suggest that these gender differences extend to leveraged margin investors.

[32] In unreported results, we also interact $\%Restriction$ with the Z-bin dummies, and find that selling restrictions on other stocks increase the extent to which investors sell stock i as the level of Z approaches zero).

[33] We also estimate that female investors sell 15% more than male investors for the $Z \leq 0$ bin, when control has reverted to the lender. This may occur because we measure Z as of the start of each trading day. Control of the account may revert back to the borrower over the course of the trading day, and female investors may sell more aggressively once they regain control.

4.3.4 Leverage constraints vs. leverage rebalancing

So far, we have shown evidence of selling pressure in reaction to low Z or negative Z-shocks. Such selling behavior can be induced by a leverage constraint effect, i.e., margin investors reduce their account leverage to stay away from their Pingcang Lines, or a portfolio rebalancing effect, i.e., risk-averse margin investors rebalance their portfolios to maintain their account at the target leverage level. The coefficients in our baseline empirical specification in Eq. (12) likely capture both effects.

The fact that we observe a strong asymmetric response to positive and negative Z-shocks already suggests that a leverage constraint effect may be present in addition to a leverage rebalancing motive. A simple rebalancing model predicts that investors should also relever in response to positive Z-shocks, but we see very little relevering after positive Z-shocks. However, we view this evidence as only suggestive, because investors could face asymmetric adjustment costs, leading to an asymmetric response.

To further separate these two channels (leverage constraint vs. leverage rebalancing), 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 2.2.1.[34] More specifically, in column (1) of Panel C, we repeat the same exercise as in column (3) of Panel A in Table 3 using the shadow subsample with heterogeneous Pingcang Lines; the results are qualitatively similar. In column (2), instead of including the Z-shock in the regression, we then separately include $LP = \frac{\overline{Lev}-Lev}{\overline{Lev}-1}$ (Leverage-to-Pingcang, introduced in Eq. (5)), and $Lev \times R$ (levered account return).[35] We find positive and significant coefficients on both components. In other words, even after holding constant the account leverage and account return, a stock is still subject to more selling pressure when the account is closer to its leverage constraint.

One potential concern with shadow accounts is that their Pingcang Lines are not randomly chosen. To alleviate this concern, we use an "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 the aggregate shadow credit supply shocks (as opposed to individual credit demand that causes the above identification concern).

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

[34] This is the sample of the YJ system, as explained in footnote 16 in Section 2.2.1.

[35] In Appendix A.5, we show that Z-shocks defined in Eq. (11) can be decomposed into these two terms.

4.3.5 Trading behavior around policy shocks

Announcements concerning regulatory tightening offer an interesting laboratory to study how margin investors respond to policy shocks. On Friday, June 12, 2015, the CSRC banned the creation of additional shadow-financed margin accounts. While the regulator did not directly tighten shadow leverage constraints for existing accounts, the announcement increased anticipation of future regulatory tightening of shadow leverage. In particular, shadow investors feared that lenders would reduce Pingcang Lines, deny borrowing requests, or sell even more aggressively following margin calls (see our discussion of the more "discretion-based" shadow system in contrast to the "rule-based" brokerage system in Section 4.2.2).

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

We examine how shadow accounts' trading behavior responded to this regulatory announcement. Specifically, we repeat the exercise in Column (3) of Panel A Table 3 separately for the week before the policy shock (June 8 to June 12) and the week after (June 15 to June 19). The policy shock did not directly impact brokerage-financed margin accounts; we conduct the same analysis for these brokerage accounts as a placebo test. For ease of exposition, in Figure 5, we plot the regression coefficients on the Z-bins and the Z-shock for brokerage accounts (Panel A) and shadow accounts (Panel B).

Focusing first on Panel B, we see clear evidence that selling by shadow investors intensified in response to the policy shock, across all Z bins. This is especially true for accounts close to or exceeding their Pingcang Lines ($Z \leq 3$). For example, for Z between 0 and 1, selling activity intensifies from -12.3% in the week before to -31% in the week after. In sharp contrast, as shown in Panel A, there is no clear change in the relation between trading and Z for brokerage margin investors. In fact, none of the changes in the coefficient estimates in response to the policy shock by brokerage investors are statistically significant, despite the similar sample size to the shadow-financed sample.

To the extent that investors, in response to the policy announcement, expected tightening of leverage constraints in the shadow-financed margin system, the contrasting reactions by shadow and brokerage accounts provide additional support for the perspective that it is the leverage constraint, rather than the high realized leverage (due to a declining stock market) that contributed to selling by margin traders.

4.3.6 Liquidation choice at the account-stock level

So far, we have shown that margin investors reduce their risky stock holdings following negative portfolio returns, potentially due to a tightening leverage constraint. In this subsection, we study margin investors' liquidation choice in the cross-section of their holdings in response to Z-shocks.

In Table 4, we present a panel regression of investors' buying/selling activities. Relative to the baseline regression reported in Table 3, which includes Z-bin dummies, Z-shocks, as well as stock-date and account fixed effects, we add a new set of interaction terms between the Z-shock and the following stock characteristics: the stock's market capitalization, overall leverage in the brokerage system (publicly disclosed daily by the CSRC),[36] book-to-market ratio, past returns, share turnover and the daily average of stock's bid-ask spread (both serve as proxies for stock liquidity), market beta and idiosyncratic volatility based on the Fama-French three factor model (both serve as proxies for risk), and the portfolio weight of the stock. We also interact the Z-shock with the stock's portfolio weight within the account, as of the start of day t.[37]

Note that the direct effect of time-varying stock characteristics and returns on trading is absorbed by stock-date fixed effects. We are mainly interested in the coefficients on the interaction terms with Z-shocks, which shows how stock characteristics affect liquidation choice conditional on the account-level Z-shock. Columns (1) and (2) of Table 4 correspond to brokerage and shadow accounts respectively; and Column (3) corresponds to the combined sample. We find a number of noteworthy patterns: a) brokerage accounts are more likely to liquidate smaller positions, stocks with lower risk and larger size, higher liquidity, higher past one-day and one-month returns, and lower book-to-market ratios in response to Z-shocks; b) shadow accounts are more likely to sell stocks with lower past one-day returns, larger size and higher turnover.

In general, both types of margin investors choose to sell more liquid stocks. We also observe an interesting divergent pattern in how investors react to past returns. Earlier, in Panel A of Table Table 3, we documented a positive relation between net buying and Z-shocks that is driven by selling in response to negative Z-shocks. In Table 4, we find that brokerage investors choose to sell stocks with higher past one-day and one-month returns. Given that stocks with higher recent returns are likely to be winners within the investors' portfolio, these results are consistent with brokerage margin investors exhibiting a disposition effect, in which they are more likely to sell winners and hold on to losers. In contrast, shadow investors are more likely to sell stocks with lower recent returns.[38]

[36] For each day, we take the total outstanding margin debt for stock i via the brokerage system from the CSRC website, and then calculate the stock's leverage as the ratio of the stock's market capitalization and the difference between the market capitalization and the above-mentioned total margin debt.

[37] In unreported tables, available upon request, we also add interaction terms between Z-bin dummies with stock characteristics, and find that the estimated coefficients on the Z-shock interaction terms largely unchanged.

[38] While we only find evidence of a disposition effect among brokerage investors, we caution that shadow investors hold very few stocks on average (only two; see Table 1 Panel B). Thus, there may be insufficient heterogeneity within their portfolios for them to hold on to losers while selling winners.

5 Price Impact *via* the Leverage Network

As discussed in Section 3.4, when margin investors adjust their holdings in response to Z and Z-shocks, their trading and the associated price impact may help transmit shocks across stocks via common holdings by the same margin investor. Since leverage-induced trading may take more than one day to complete, such leverage-network-based transmission can go beyond the current trading day.

5.1 Predicting $t+1$ Trading and Liquidation

Before examining shock transmission across stocks, we first show that Z-shocks affect margin investors' next-day trading. In Section 4.3, we examined how Z (measured at the end of day $t-1$), Z-shocks (measured during day t) and selling restrictions (which is measured on day t and is highly persistent) affect net trading and liquidation choices in day t. We now investigate how these variables affect trading in day $t+1$.

Panel A of Table 5 repeats the main analyses in Panels A and B of Table 3, except that the dependent variable is now replaced by net buying in day $t+1$. We find that many contemporaneous patterns continue to hold in the next trading day. For example, Columns (1), (3) and (5) confirm that tighter leverage constraints (smaller Z) on day t predict more selling on day $t+1$ as well. In addition, negative Z-shocks in day t continue to predict selling in day $t+1$. Columns (2), (4) and (6) show that investors respond more strongly to Z-shocks if they face greater selling restrictions on other stock holdings, a result that echoes Panel B in Table 3.

Panel B of Table 5 repeats the analysis of Table 4 on liquidation choice, using the account's net buying in day $t+1$ as the dependent variable. The stock characteristics that matter for $t+1$ liquidation choice in response to Z-shocks on day t include: the book-to-market ratio (both brokerage and shadow margin accounts tend to trade growth stocks) and stock liquidity (brokerage accounts tend to trade stocks with lower bid-ask spreads and shadow accounts trade stocks with higher turnover).

5.2 Return Predictability of $MLPR$

After confirming that Z-shocks on day t also affect trading on day $t+1$, for the rest of this section, we examine how the leverage network transmits Z-shocks across stocks and impact future returns. We focus on next-day returns, instead of contemporaneous returns, to alleviate some obvious reverse-causality concerns.

Our main independent variable is the margin-account linked portfolio return ($MLPR$) introduced in Section 3.4. $MLPR$ measures the buying/selling pressure stemming from changes in the value of *other* stocks that are linked to the one in question through the margin-investor-common-holdings network. It is computed as the weighted-average daily return of all margin accounts holding the stock on a particular day, after removing the stock's own contribution to each account's return.

Importantly, the weights are based on a function of the distance-to-margin-call for each account, to reflect our earlier finding that leverage-induced selling by margin accounts depends on how close the account is to hitting its leverage constraint.

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

5.2.1 Empirical design

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

We address the potential alternative explanation in several ways. First, we control for observable stock characteristics and past return patterns that could lead to comovement. Second, 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. Of course, it remains possible that margin investors hold related stocks with similar downside risk exposure, so they comove more in response to negative common shocks. To better identify true contagion from unhealthy stocks to healthy stocks, we consider stocks i that are not affected by direct selling restrictions. We sort all margin accounts into two groups based on the account's selling restrictions for *other* stocks holdings, and construct two $MLPR$ measures for each stock i: $MLPR_{High}$ and $MLPR_{Low}$ based on accounts with high and low selling restrictions for other holdings, respectively. We find that $MLPR_{High}$ is associated with much stronger return predictability than $MLPR_{Low}$. These results are consistent with the view that selling restrictions transmitted negative return shocks from unhealthy stocks (which could not be sold) to healthier stocks (which were the only stocks that leveraged investors could sell).

In addition, 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 and controlling $NMLPR$ does not change the predictive power of $MLPR$.

In a related test, we show that $MLPR$ constructed using only shadow margin accounts predicts returns more strongly than $MLPR$ constructed using only brokerage margin accounts, despite brokerage margin accounts holding substantially greater total asset value. This makes sense because shadow accounts were far more leveraged relative to their leverage limits and thus experienced greater leverage-induced selling. Finally, we document a return reversal, as expected if the initial $MLPR$ shock is a non-fundamental shock, and prices eventually revert to fundamentals.

5.2.2 Shock propagation

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

$$RET_{i,t+1} = \alpha + \beta \cdot MLPR_{i,t} + \beta_N \cdot NMLPR_{i,t} + \sum_m \lambda_m \cdot CONTROL_{i,m,t} + \varepsilon_{i,t+1}, \tag{18}$$

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

Importantly, we also include the non-margin-account linked portfolio return ($NMLPR$), defined in a similar manner as $MLPR$. We compute $NMLPR$ using 210,000 matched non-margin accounts—i.e., 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 that Q in Eq. (13) is 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.

The results are shown in Table 6 Panel A. 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 12 bps (t-statistic = 3.18), after controlling for the stock's lagged leverage ratio, past returns, and an array of other stock characteristics. This magnitude is moderate, but economically meaningful given that it occurs within a single day, and we shall see that it is substantially larger in certain time periods and subsamples. When interpreting these magnitudes, it is also important to recall that we observe an approximate 5% sample of the full brokerage and shadow margin markets. To the extent that our sample is representative, these results likely represent price pressure from the entire margin sector, rather than only from the accounts within our sample.

Columns (3) and (5) repeat the same exercise, separately for up and down markets. We define up and down markets as the periods before and after June 15, 2015 (the peak of the market), respectively. Note that June 15 is the first trading day (Monday) after the June 12 (Friday) announcement of regulatory tightening on the shadow-financed margin system, as discussed in Section 4.3.5. It is clear from these two columns that the predictive power of $SMLPR$ for returns is present only in market downturns. Specifically, the coefficients on $SMLPR$ for the up and down

[39] We can use any constant here, as it is simply a scalar which becomes irrelevant when we standardize $NMLPR$ in the cross-section of the Fama-MacBeth regressions.

markets are 3 bps (t-statistic = 1.12) and 20 bps (t-statistic = 3.68), respectively. The asymmetry in margin-induced price impact between up and 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.[40] The reverse, however, is not necessarily true for a loosened margin constraint during up markets.

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. In stark contrast to what we see for $SMLPR$, in all specifications, the coefficient on $SNMLPR$, i.e., $\hat{\beta}_N$, is economically small and statistically insignificant; in Columns (2) and (6), it even has the opposite sign. These results suggest that the return predictability of $SMLPR$ is likely due to margin investors' tendency to trade in response to changing margin requirements/conditions.

5.2.3 Liquidation choice

As discussed in detail in Section 3.4, we construct $MLPR$ as though investors liquidated assets in proportion to their initial holdings according to the average relationship between percentage sales and a given leverage shock. 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 now relax the proportional sales assumption and incorporate liquidation choice as a function of stock characteristics. When calculating $MLPR$, we set X_{it}^j in Eq. (14) to the fitted value from Columns (1) and (2) of Table 5 Panel B. This allows us to provide a better fit for the data using our previous analysis of liquidation choice, which would predict, for example, that the investor liquidates more of a stock if it is more liquid. Note that we still use 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.

Repeating the analysis in Panel A in Table 6 but using this liquidation-choice-adjusted $SMLPR$ produces quantitatively similar results. For example, as shown in Panel B, a one-standard-deviation increase in this new $MLPR$ predicts a higher next-day return of 10 bps (vs. 12 bps in Panel A) in the full sample, and 17 bps (instead of 20 bps in Panel A) during the down market, after controlling for other stock characteristics.

[40]One of the two papers that this article subsumes, Bian et al. (2018), zooms in on this episode and offers a more complete descriptive analysis on how this policy shock and the reactions of shadow-financed margin system triggered the month-long stock market crash in China during the summer of 2015.

5.2.4 Brokerage- vs. shadow-financed margin accounts

Since the onset of the stock market crash in early June 2015, practitioners, the media, and regulators have alleged that selling pressure from shadow-financed margin accounts triggered the sudden market collapse. Although it is suggestive that the announcement concerning regulatory tightening of the shadow system exactly precedes the market crash investigated in Section 4.3.5, the above accusation has largely been untested using granular data.

Importantly, whether shadow accounts were more to blame than brokerage accounts is not obvious. While shadow accounts have lower Z on average as shown in Table 1, many estimates suggest that total market assets held within the regulated brokerage-financed system greatly exceeded that in the unregulated shadow-financed system.[41] Although one cannot give a definitive answer, our account-level data allow us to ask the following empirical question: which margin system, brokerage or shadow, offers greater explanatory power in tests of leverage-network-based propagation of shocks during the 2015 stock market crash?

We repeat the same exercise as in Panel A Table 6 (without $SNMLPR$), but construct two standardized $MLPR$ measures, $SMLPR_{br}$ and $SMLPR_{sh}$ based on the brokerage leverage network and shadow leverage network, respectively. As shown in Panel C Table 6, we find the coefficients on $SMLPR_{sh}$ (shadow network) to be much greater in magnitude with higher statistical significance than the coefficients on $SMLPR_{br}$ (brokerage network). These patterns hold in both up and down markets, although as before, the impact of $SMLPR_{sh}$ is much larger during down markets. This evidence lends support to the view that shadow-financed margin trading played a relatively more important role in transmitting shocks during the Chinese stock market crash in the summer of 2015.

5.2.5 Trading restrictions

Panel A of Table 5 confirms that account-level selling restrictions on other stocks in day t continue to predict selling in day $t+1$ of stock i. This is because both forms of selling restriction are persistent: if a stock hits the down price limit today, it will hit the same limit again tomorrow with a 48% likelihood in our sample period; similarly, trading suspensions can last for a few days up to a few weeks during the bust period of our sample period.

We now exploit the variation in account-level trading restrictions faced by margin investors. For each day, we create two groups of accounts: $High$ and Low, based on whether the fraction of holdings with selling restrictions is in the top 30% or the bottom 30% of the cross-sectional

[41] We estimate the total asset holdings of all brokerage-financed margin accounts during the peak of our sample period to be approximately RMB 8.76 trillion; this is the product of the total debt of brokerage accounts (2.26 trillion published on stock exchanges) and the asset-to-debt ratio in brokerage account sample of about 3.87 in the week of June 8-12, 2015. We estimate the total asset holdings of all shadow-financed margin accounts during the peak of our sample period to be approximately RMB 1.93 trillion, which is the product of the estimated total debt of shadow accounts in Section 2.1.3 (about 1.2 trillion in its peak time) and the asset-to-debt ratio in the shadow account sample of about 1.61 in the week of June 8-12, 2015. These two numbers imply that the asset holdings of shadow accounts are approximately 22% that of brokerage accounts. In our sample, this ratio is about 19%.

distribution, respectively, at the end of the previous day. For each stock (that is free from trading suspensions so we observe its daily return), we construct two $MLPR$ measures: $MLPR_{High}$ and $MLPR_{Low}$, using only the subsamples of $High$ accounts and Low accounts, respectively. Since selling pressure is higher for stocks held by $High$ accounts, $MLPR_{High}$ should be associated with stronger return predictability than $MLPR_{Low}$. In Panel D of Table 6, we analyze the price impact associated with $MLPR_{High}$ and $MLPR_{Low}$. For ease of interpretation, we standardize all these four variables in the regression. As shown in Panel D, the coefficient on $SMLPR_{High}$ is significantly larger than that on $SMLPR_{Low}$ (in fact, the coefficient on $SMLPR_{Low}$ is statistically insignificant in all specifications). In other words, as leverage-induced selling intensifies for stocks held by margin accounts that cannot sell other holdings, this leads to a greater price impact for connected stocks.

5.2.6 Return reversal

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

6 Conclusion

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

We examine how margin traders manage their cash holdings and liability in response to price shocks and how such actions impact their leverage, and document an interesting distinction between brokerage-financed and shadow-financed margin traders. In response to a negative return shock, brokerage traders raise cash by selling stocks or injecting new capital, and then use the cash to pay down debt and reduce leverage. In contrast, while shadow traders also raise cash by selling stocks, they "hoard" the cash instead of paying down their debt (so their leverage remains high), possibly due to different lending frictions in these markets. These findings are consistent with that brokerage margin system being more "rule-based" and the shadow margin system being more "discretion-based;" the shadow system's lack of standardized procedures and automated implementation incentivized shadow investors to maintain high leverage.

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 variation in Pingcang Lines across certain shadow accounts to separate a leverage rebalancing motive from a leverage constraints channel, and provide unique evidence that leverage constraints induce selling. An event study around the regulatory tightening of shadow margin constraints provides further support. Our granular data further allow us to examine the liquidation choice of margin traders.

Aggregating trading behavior across margin investors, we find a significant return spillover in the near future: a stock's return can be strongly forecasted by a portfolio of stocks with which it shares common margin-investor ownership. This pattern is subsequently reversed, and is present only in market downturns. We find that shadow investors were closer to their leverage constraints than brokerage investors, and played a much bigger role in transmitting shocks across stocks. We also show that China's price limit rule led to unintended contagion across stocks.

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

Appendix

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

As we mentioned in Section 2.1.3, 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 5th, 2015 which was just before the stock market collapse in June 2015, borrowing from WMP peaked at around 600 billion Yuan and Peer-to-Peer (P2P) informal lending peaked at about 200 billion Yuan. (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 a 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 Yuan 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 Yuan as a reasonable estimate.

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

A.2 Details of Shadow-Financed Margin Accounts

We adopt the following data cleaning and filtering procedures on our account-level data from the online trading platform. First, we keep only the accounts with the maintenance margin (Pingcang Line) less than the initial margin. Second, we require the initial leverage ratio to be less than 100, but above one, and eliminate accounts with too high or too low initial leverage ratios; this is because those accounts with extremely high initial leverage ratios are usually marketed as some "teaser" accounts to attract investors with little own capital. Third, for each (child) account, we require the first cash-flow record, before any reported trading activities, to be a cash inflow from the mother account (instead of from the child accounts to the mother account). Finally, we exclude accounts that do not have any cash inflows from the mother accounts.

After applying the above filters, we end up with a sample of over 106K (shadow) margin accounts. As mentioned in the discussion in Section 2.2.1 and footnote 16, there are two kinds of shadow accounts:

- For the YJ sample, which contains 49.45% of our shadow accounts sample, the platform provides detailed descriptions of each cash flow, indicating whether the cash flows are for a new loan, an interest payment, or a loan repayment. With this information, we can calculate each account's daily outstanding debt and leverage ratio.
- For the QJ sample, which contains 50.55% of our shadow accounts sample, all Pingcang Lines are set and recorded as 10. We observe detailed cash flows from and to their mother accounts, but without detailed payment descriptions. To calculate daily leverage, we use daily stock price information and assume that cash flows to (from) the mother account exceeding 20% of the current margin debt in the child account reflects a payment of existing debt (additional borrowing). Using other cutoffs (e.g., 15% or 5%) has virtually no impact on our results.

A.3 Data Filtering and Winsorization

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%. For the leverage change variance decomposition analysis in Section 4.2.4, we further drop account-day observations for shadow accounts with leverage change variance in the bottom 2% (to avoid having close-to-zero denominators).

After data filtering, we winsorize the following main variables at the 1% and 99% levels prior to estimating regressions: account turnover, Δlev_t^{price}, Δlev_t^E, Δlev_t^D, Δlev_t, Z, Z-shock, LP (leverage-to-Pingcang), and $Lev \times R$ (levered account return).

A.4 Asset Change Decomposition

At the start of day t, the asset side A_t of each margin account consists of cash holdings C_t and a stock holdings row vector S_t. Its liability side consists of debt D_t and equity E_t. Within the period $[t, t+1]$, the account can trade stocks as well as inject cash via either equity or debt. We denote holdings by $H_t \equiv (C_t, S_t)$ and their corresponding prices by $P_t \equiv (1; p_t)$ where p_t is the price vector for stock holdings. By setting the cash price to 1, we ignore the accrual of interest rate for cash savings (this is negligible given the short time period in our study (daily). We denote the borrowing interest rate as r.

The account asset value at (the end of) day t is $A_t = H_t P_t$. Our goal is to decompose the daily change of asset holdings into the following three parts:

$$
\begin{aligned}
A_{t+1} - A_t =& H_{t+1}P_{t+1} + \int_t^{t+1} H_s d\hat{P}_s - rD_t - \int_t^{t+1} H_s d\hat{P}_s + rD_t - H_t P_t \\
=& \underbrace{\int_t^{t+1} H_s d\hat{P}_s - rD_t}_{\substack{\text{trading gains/losses} \\ \Delta A_{price}}} + \underbrace{H_{t+1}P_{t+1} - \underbrace{\left(H_t P_t + \int_t^{t+1} H_s d\hat{P}_s - rD_t \right)}_{\text{account value w/o cash injection/withdrawal}}}_{\text{change due to cash injection/withdrawal, } \Delta A_{cash}}
\end{aligned} \tag{A1}
$$

Here, rD_t is the (daily) interest expense, and $d\hat{P}_s \equiv dP_s + div_s$ includes both capital gain and dividend income. Without any cash infusion or withdrawal, the end-of-day account market value should be $H_t P_t + \int_t^{t+1} H_s d\hat{P}_s - rD_t$ (see the topic on self-financing portfolio, page 123 in Duffie (2010)). Intuitively, self-financing portfolio's value change must come from trading gains/losses $\int_t^{t+1} H_s d\hat{P}_s$ and the interest expenses, which we denote by ΔA_{price}.

The margin trader may inject/withdraw some cash to/from the account, which is the second component in (A1) denoted by ΔA_{cash}. To study the investor's active liability management, we further decompose cash injection/withdrawal ΔA_{cash} to two parts ΔA^D_{cash} and ΔA^E_{cash}, so that

$$
\Delta A_{cash} = \Delta A^D_{cash} + \Delta A^E_{cash}, \text{ with } \Delta A^E_{cash} \equiv E_{t+1} - (E_t + \Delta A_{trading}). \tag{A2}
$$

In the above decomposition, ΔA^E_{cash} captures the part of equity change that cannot be explained by trading gains/losses, and $\Delta A^D_{cash} = \Delta A_{cash} - \Delta A^E_{cash}$ must come from debt changes.

A.5 Z-Shock Derivation and Construction

We provide details on how we construct Z-shocks in Eq. (11) and Q^j_t in Eq. (13).

A.5.1 Analytical derivation of Z-shock

We first explain the first term in Eq. (11). An account's distance-to-margin-call Z can be viewed as a function of its return R. Because $E(R) = E + AR$ and $A(R) = A + AR$, from Eq. (6) we have

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

with $Z(0) = Z$. For a sufficiently small account return R, the first order expansion has

$$
Z(R) = Z + \frac{\overline{Lev} - \frac{\overline{Lev}}{Lev}}{\overline{Lev} - 1} \frac{1}{\sigma^A} \cdot R + O\left(R^2\right).
$$

As a result, we have

$$\frac{\overline{Lev} - \frac{\overline{Lev}}{Lev}}{\overline{Lev} - 1} \frac{1}{\sigma^A} \cdot R = \underbrace{\left(1 - \sigma^A Z\right)}_{>0} \cdot \frac{R}{\sigma^A}$$

Therefore, the "percentage shock to Z," i.e., the first-order effect on Z due to return R_t^j can be written as:

$$\frac{Z'(R) \cdot R_t^j}{Z_t^j} = \frac{\overbrace{1 - \sigma_{At}^j Z_t^j}^{>0,\text{ as } \overline{Lev}^j > Lev_t^j}}{Z_t^j \cdot \sigma_{At}^j} R_t^j. \tag{A3}$$

Finally, in Section 4.3.4 we decompose the account's Z-shock into further Leverage-to-Pingcang (LP) and levered return. This is because (recall Eq. (5))

$$\Delta Z_t^j = \frac{1 - \sigma_{At}^j Z_t^j}{\sigma_{At}^j Z_t^j} \cdot R_t^j \times \left(Z_t^j\right)^{-\theta} = \underbrace{\left(Z_t^j\right)^{-\theta} \left(1 - \sigma_{At}^j Z_t^j\right)}_{\text{Function of } Z} \times \underbrace{\frac{\overline{Lev}^j - 1}{\overline{Lev}^j - Lev_t^j}}_{1/LP} \times \underbrace{Lev_t^j \cdot R_t^j}_{\text{Levered Return}} \tag{A4}$$

A.5.2 Z-shock construction

Now we turn to our Z-shock construction and regression specification. Section 3.3 explains that we allow for nonlinear adjustment in Eq. (11) (including the functional form as well as the power parameter θ) to deliver a desired feature where margin traders react to their account Z-shocks in a homogeneous way. Specifically, we let the data to speak and pick θ so that empirically, margin traders respond to Z-shocks linearly with a constant coefficient γ across various Z bins (so we can drop the k-dependence of $\{g_k\}$ in Eq. (9) and replace them with one common coefficient γ). This is an important step in justifying the regression specification in Eq. (12) that we adopt in this paper.

We first construct Z-shocks at the account-date level based on Eq. (11). For any choice of θ, we then estimate the regression (12) with flexible coefficients γ_k's. As shown in Figure A.1, when we set $\theta = 0.8$, we find γ_k's are roughly constant across all Z-bins. Note, for the group with $Z < 0$, i.e., the group $k = 0$, the account Z should not matter (creditors take the control); hence we simply scale their Z-shocks by an appropriate chosen constant (which is 14), so that the estimated γ_0 takes a similar value as other γ_k's. The similar adjustment applies to the construction of Q_t^j in Eq. (13) for that group.

References

Adrian, Tobias, and Hyun Song Shin, 2014, Procyclical leverage and value-at-risk, *Review of Financial Studies* 27, 373–403.

Allen, Franklin, Jun "QJ" Qian, Chenyu Shan, and Julie Lei Zhu, 2020, Dissecting the long-term performance of the chinese stock market, *Working Paper* .

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).

Ang, Andrew, Sergiy Gorovyy, and Gregory B. van Inwegen, 2011, Hedge fund leverage, *Journal of Financial Economics* 102, 102–126.

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

Barber, Brad M, and Terrance Odean, 2001, Boys will be boys: Gender, overconfidence, and common stock investment, *Quarterly Journal of Economics* 116, 261–292.

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

Bernardo, Antonio E., and Ivo Welch, 2004, Liquidity and financial market runs, *The Quarterly Journal of Economics* 119, 135–158.

Bian, Jiangze, Zhiguo He, Kelly Shu, and Hao Zhou, 2018, Leverage-induced fire sales and stock market crashes, Technical report, University of Chicago.

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, Anton Petukhov, and Jiang Wang, 2018a, The dark side of circuit breakers, Technical report, Working Paper, MIT.

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, Hui Chen, Zhiguo He, Jinyu Liu, and Rengming Xie, 2021, Pledgeability and asset prices: Evidence from the chinese corporate bond markets, Technical report, University of Chicago.

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* .

Diamond, Douglas W., and Philip H. Dybvig, 1983, Bank runs, deposit insurance, and liquidity, *Journal of Political Economy* 91, 401–419.

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.

Duffie, D., 2010, *Dynamic Asset Pricing Theory: Third Edition*, Princeton Series in Finance (Princeton University Press).

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.

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.

Goldstein, Itay, and Ady Pauzner, 2005, Demand deposit contracts and the probability of bank runs, *The Journal of Finance* 60, 1293–1327.

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, Bryan Kelly, and Asaf Manela, 2017, Intermediary asset pricing: New evidence from many asset classes, *Journal of Financial Economics* 126, 1–35.

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, and Wei Xiong, 2012, Dynamic debt runs, *The Review of Financial Studies* 25, 1799–1843.

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

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.

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, 2020, Price and volume dynamics in bubbles, *Working Paper* .

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.

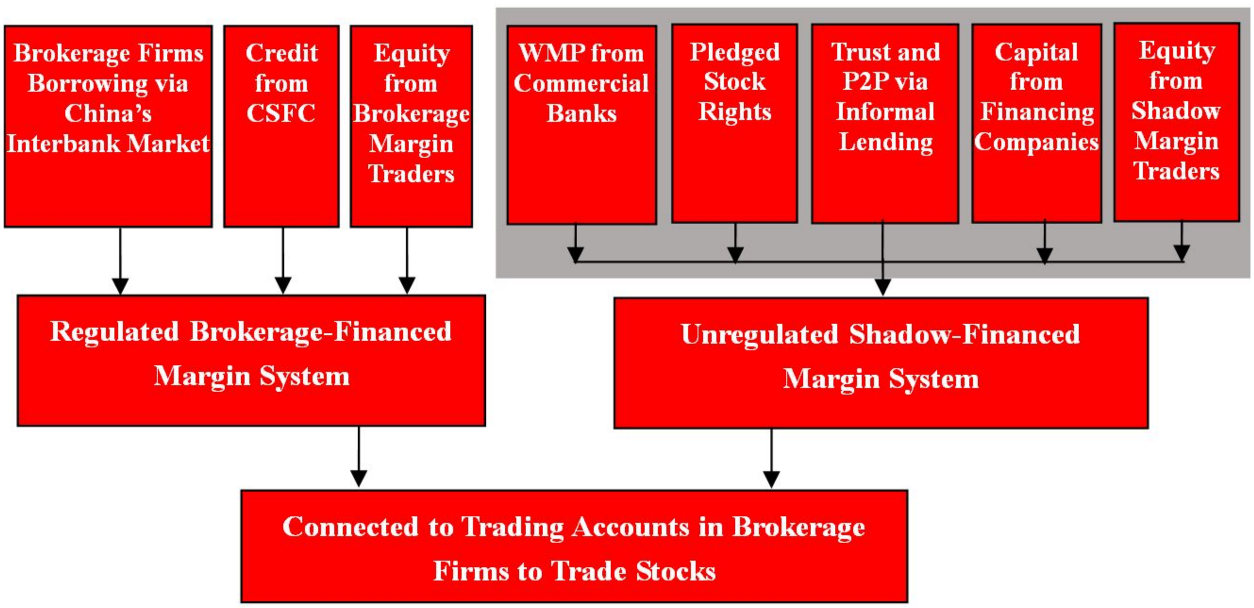
Schwert, G. William, 1989, Margin requirements and stock volatility, *Journal of Financial Services Research* 3, 153–164.

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 for 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 via the software system through the mother account to the brokerage firm in real time.

Panel A: Funding Sources



Panel B: Structure of Shadow-Financed Margin System

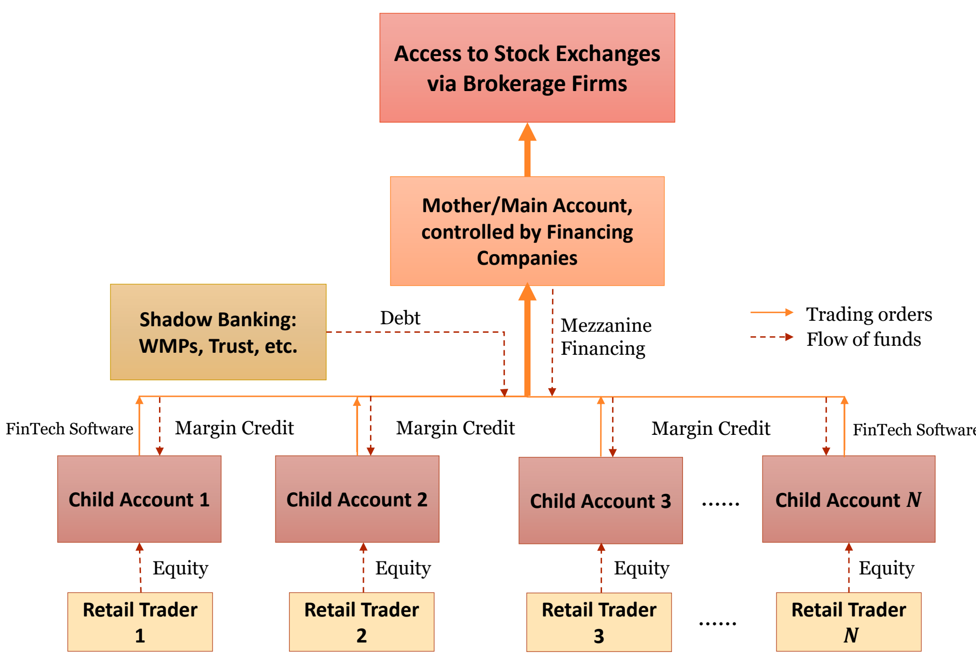
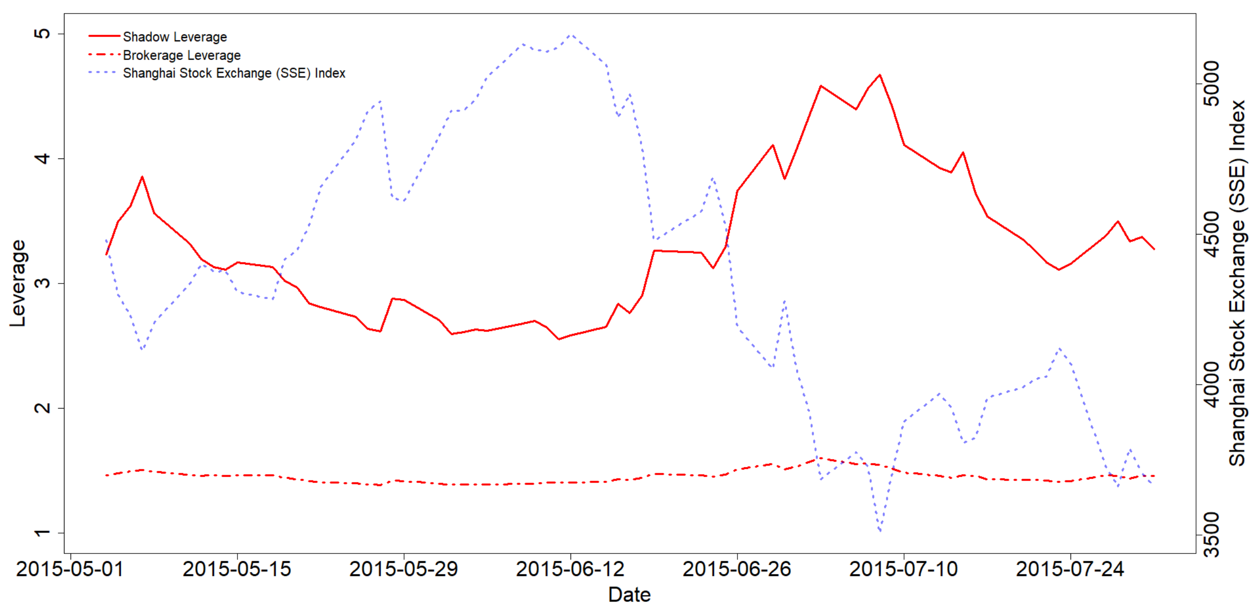


Figure 2
Leverage in Brokerage and Shadow Margin Accounts

Panel A depicts the Shanghai Stock Exchange (SSE) composite index (the dashed blue line), the average leverage for shadow margin accounts (the solid red line), and the average leverage for brokerage margin accounts (the dashed-dotted red line), weighted by the equity size of each account, at the start of each day from May to July, 2015. To compute the average, we weight each account's leverage by the equity in each account. Weighted in this manner, average leverage equals total debt scaled by total equity. 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 all brokerage and shadow margin accounts at the start of each day from May to July, 2015.

Panel A: Equity-weighted Leverage, Brokerage vs. Shadow Samples



Panel B: Asset-weighted vs. Equity-weighted Leverage, Combined Sample

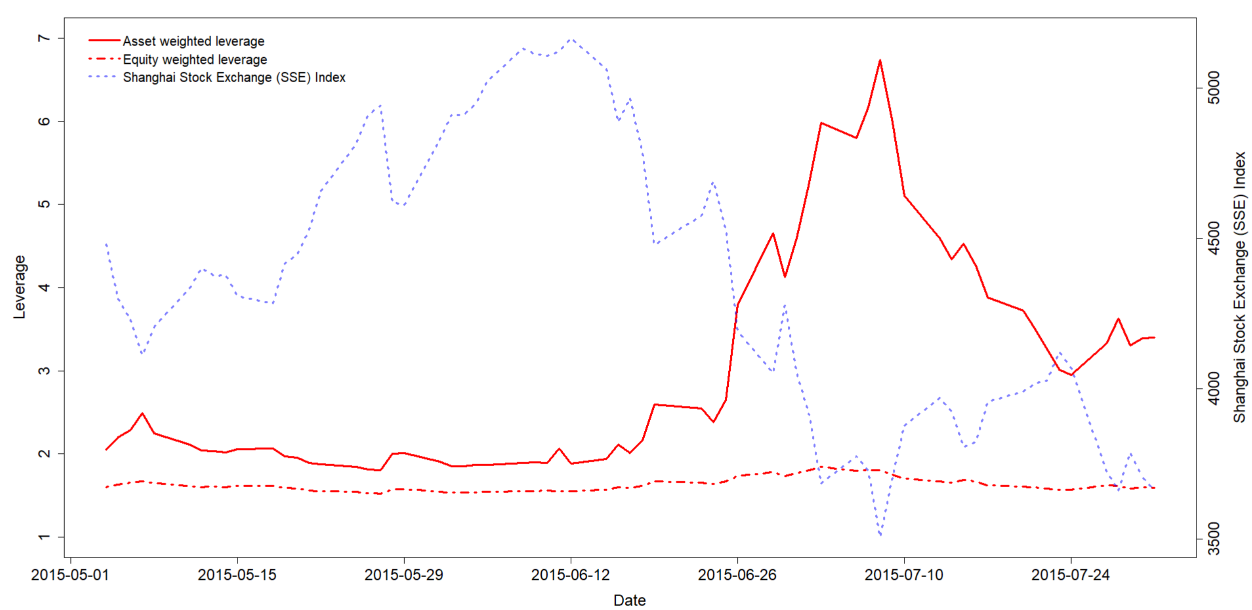
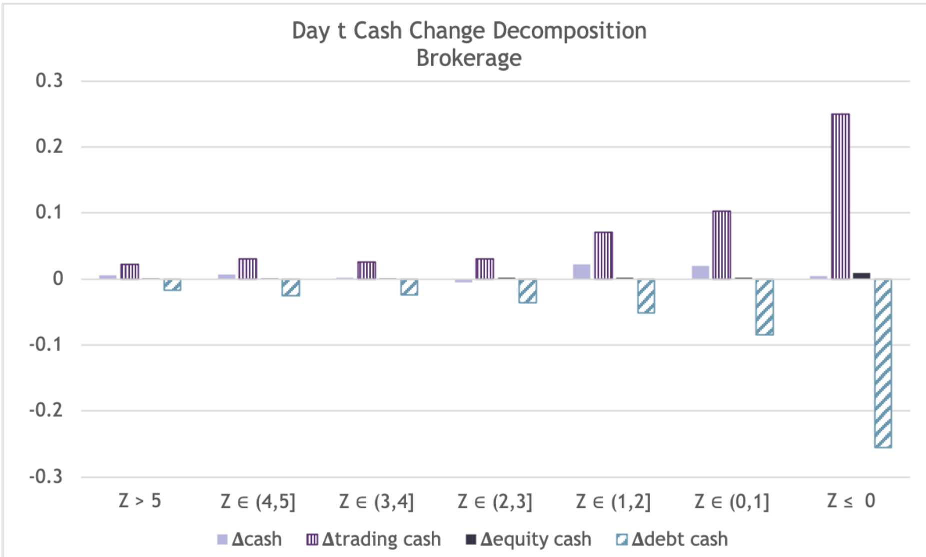


Figure 3
Cash Decomposition

These figures show the cash decomposition grouped by Z bins (Panels A and B) and by Z-shock quintiles (lowest group being quintile 1, Panels C and D). In Panels A and B, we use the cumulative cash change in the next 5 days for accounts that enter the negative Z bin.

Panel A: Z bin Brokerage Account



Panel B: Z bin Shadow Account

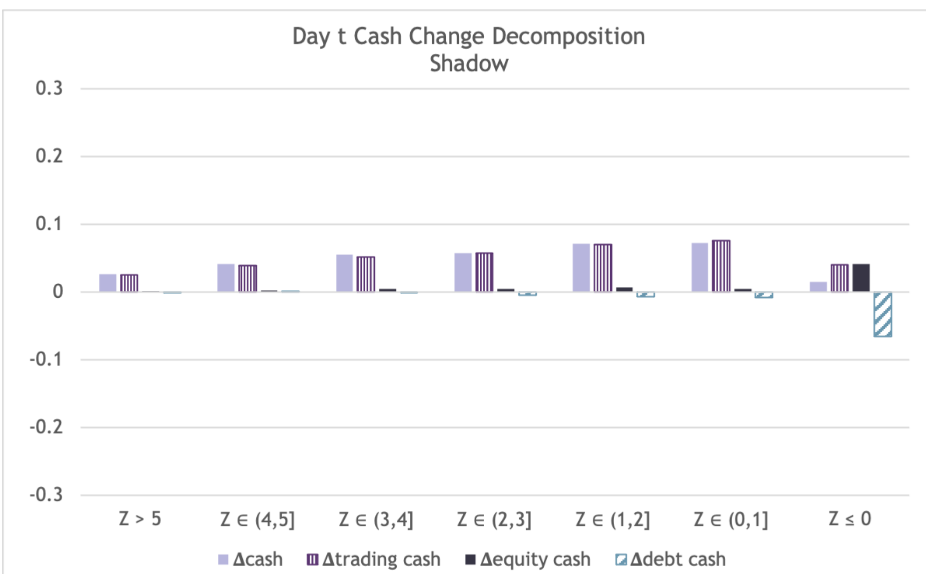
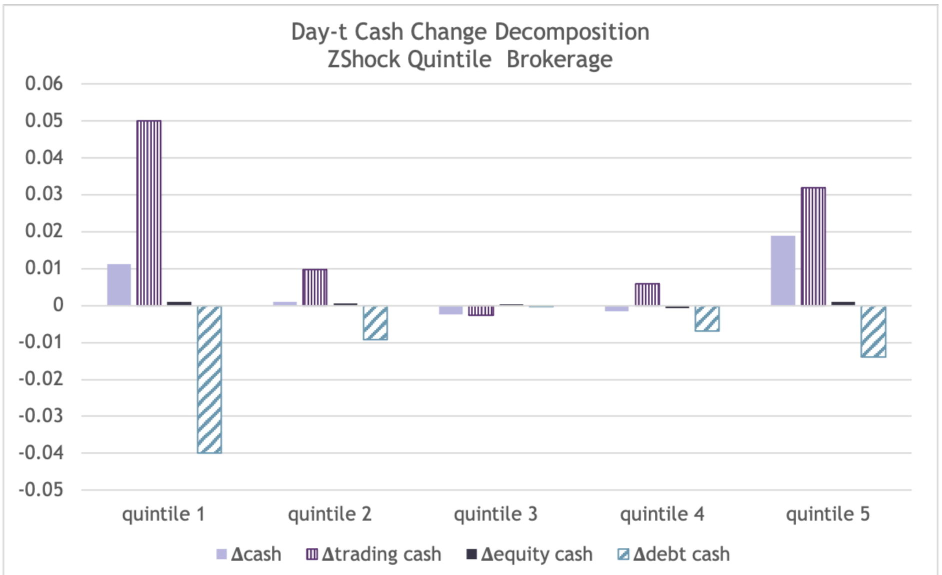


Figure 3
Cash Decomposition: Continued
Panel C: Z-shock Brokerage Account



Panel D: Z-shock Shadow Account

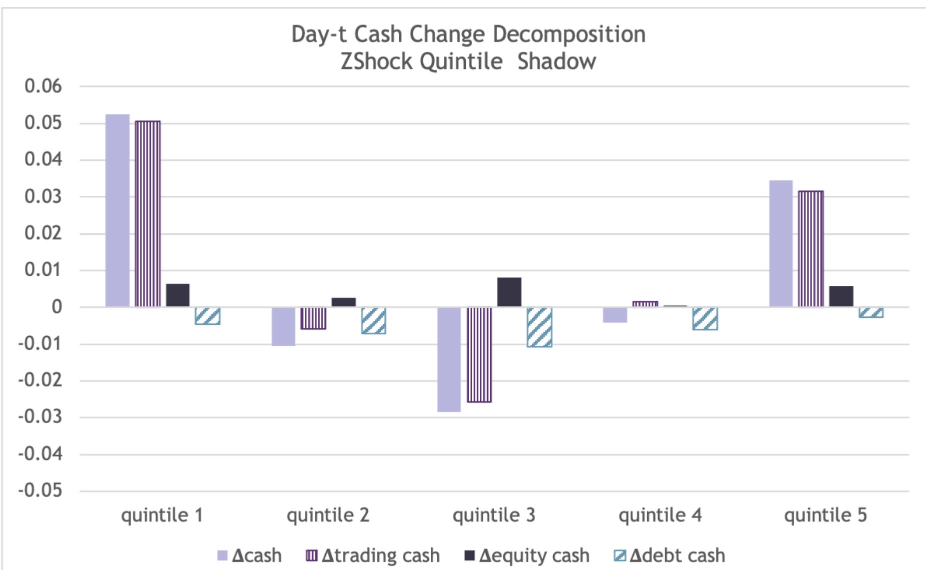


Figure 4
Trading by Z-bins and in Response to Z-Shocks

This figure shows the estimated coefficients on Z-bin dummies and Z-shocks for brokerage-financed and shadow-financed margin accounts, as reported in Columns (1) and (3) in Table 3 Panel A. All regressions include account fixed effects and stock-date fixed effects.

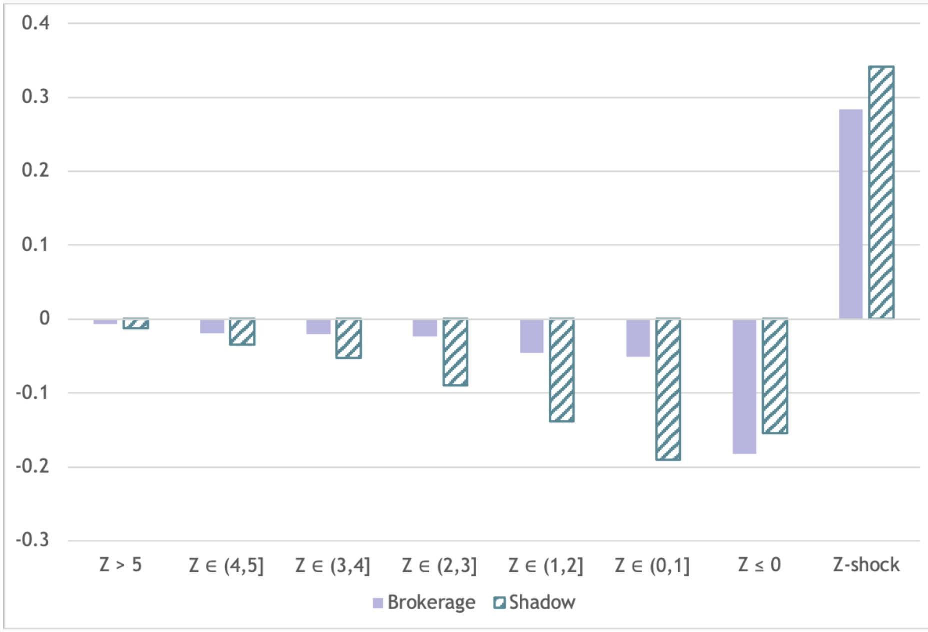
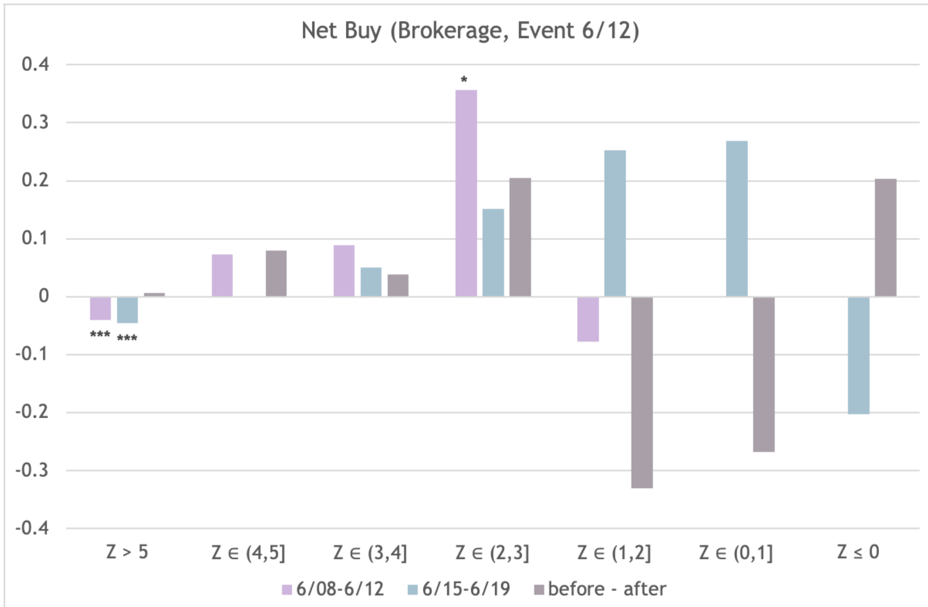


Figure 5
Event Study

These figures show net buying by brokerage-financed and shadow-financed margin accounts across Z bins, in the week before and after the June 12 CSRC announcement. All regressions include account fixed effects and stock-date fixed effects. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Brokerage Account



Panel B: Shadow Account

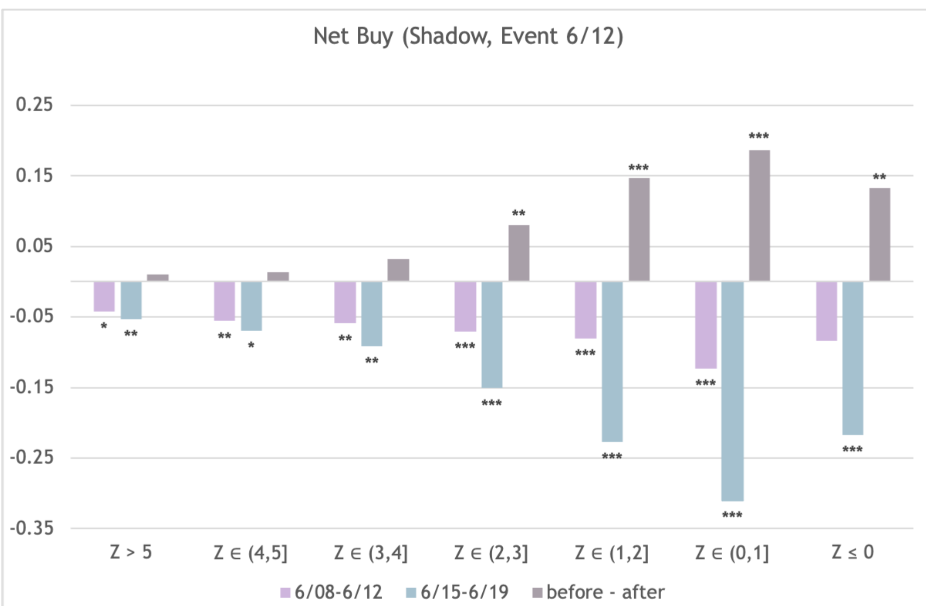


Figure 6
Return Reversal

This figure shows the returns reversal associated with $MLPR$. The y-axis shows the coefficients of $SMLPR$ in regressions reported in Table 6, with dependent variables being cumulative returns from $t+1$ to $t+k$. (These coefficients are reported in Table 6 Panel A Column 1 and Panel E). The x-axis plots $k \in \{0, 1, ..., 25\}$ which is the number of trading days forward. $MLPR$ is measured on day t and we set the coefficient on day t, i.e., $k = 0$ to be 0. Dashed lines are upper and lower bounds of the 90% confidence interval.

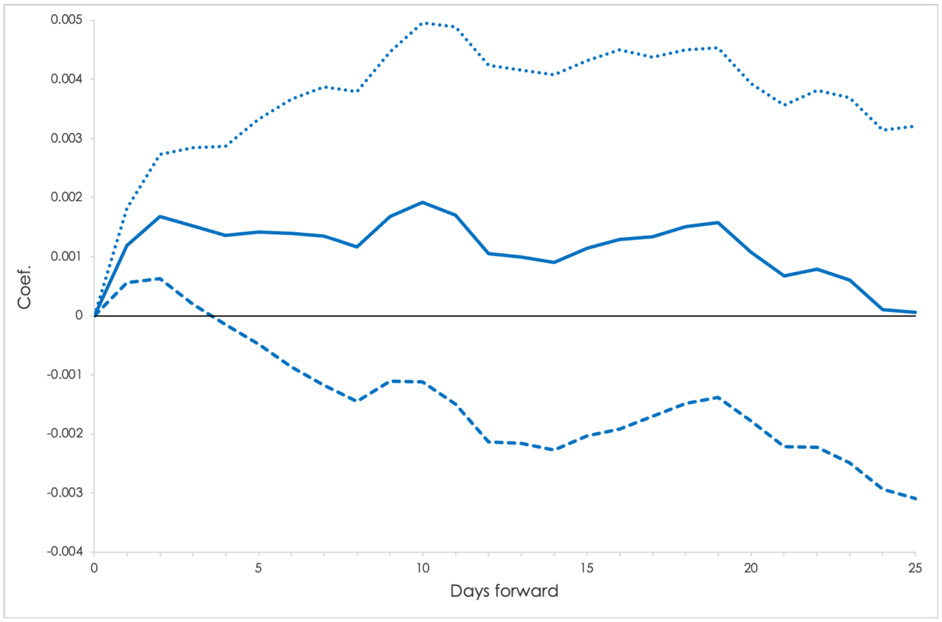


Figure A.1
Constant λ

This figure shows the nonlinear adjustment of Z-shocks (ΔZ_t^j). The y-axis is the coefficient γ in Eq. (10), where we set $\theta = 0.8$ when constructing ΔZ_t^j as in Eq. (11). For the group with $Z < 0$ ($k = 0$), the account Z should not matter (creditors take the control) and we choose to scale Z-shocks by 14 so that the estimated γ_0 takes a similar value as other γ_k's.

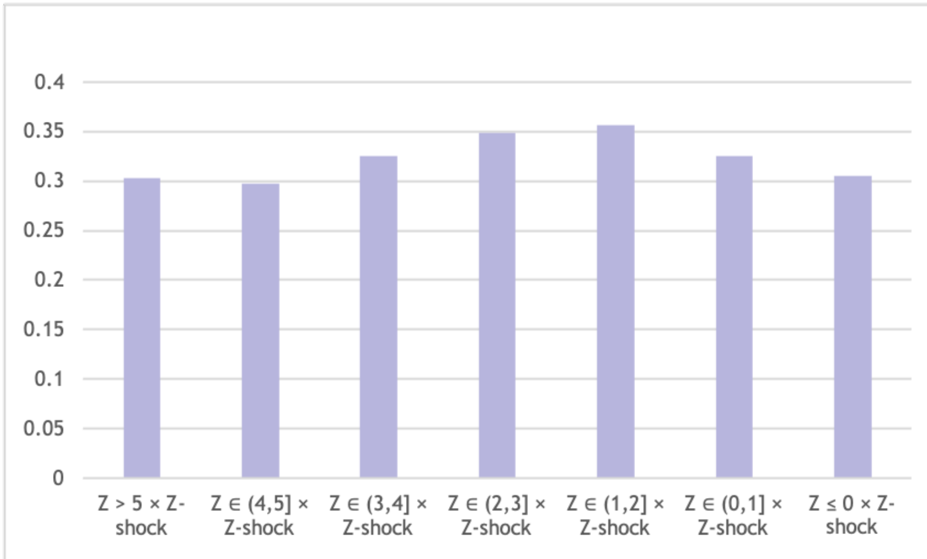


Table 1
Summary Statistics

This table reports summary statistics of account and stock characteristics for our sample from May to July 2015. Panels A, B, and C report summary statistics for observations at the account, account-day, and account-stock-day levels, respectively. All beginning-of-day-t values are calculated based on closing prices as of trading day $t-1$. The Pingcang Line is the account-specific maximum level of leverage. Account Leverage is defined as the assets-to-equity ratio at the start of each trading day, where equity is equal to assets minus debt. Account Return is the daily return of each margin account based on daily opening stock holdings, and Account Return Std is the standard deviation of daily returns. Z is the Distance-to-Margin-Call defined by Eq. (6) and Z-shock is defined by Eq. (11). Net Buying is buying minus selling of stock i by account j, normalized by account j's holding of stock i at the beginning of the day.

	Brokerage			Shadow			Full		
	mean	median	std	mean	median	std	mean	median	std
Panel A: Account									
Pingcang Line	4.3	4.3	0	11.79	10	5.053	8.646	10	5.336
Observations		77267			106900			184167	
Panel B: Account-Day									
Asset (in 1000s)	4042	947	33313	1473	217	6132	3131	633	27036
Cash holdings (in 1000s)	314	1.999	6228	325	7.484	2352	318	2.827	5195
Stock holdings (in 1000s)	3729	835	30840	1149	134	5098	2813	520	24989
Account Leverage	1.411	1.323	0.477	6.874	4.177	13.73	3.349	1.662	8.593
Account Return (daily, in %)	-0.216	0.0754	4.30	-0.354	-0.000448	3.83	-0.265	0.0291	4.14
Account Return Std (daily, in %)	2.02	1.99	0.699	1.85	1.88	0.793	1.96	1.95	0.738
Z	38.75	32.94	22.84	13.46	9.129	18.02	29.77	24.27	24.46
Z-shock (in %)	-0.0651	0	2.49	-1.83	0	13.8	-0.691	0	8.51
Observations		3804540			2096439			5900979	
Panel C: Account-Stock-Day									
Net Buying	-.0854	0	0.331	-.228	0	0.457	-.121	0	0.372
Observations		17212669			5706826			22919495	

Table 2
Determinants of Leverage Ratios

This table examines how account characteristics vary with leverage choice. We focus on the subset of accounts that were opened during our three-month period and their account characteristics on the opening day. Panel A focuses on brokerage-financed margin accounts. The first three columns compare margin accounts that have ever used leverage with those that have not. The last three columns compare accounts with above-median and below-median leverage as of the account open day, among the set of accounts that have ever used leverage. Panel B focuses on YJ shadow-financed margin accounts. The first three columns compare accounts with above-median and below-median Pingcang Lines. The last three columns compare accounts with above-median and below-median leverage as of the account open day. Panel C compares the characteristics of brokerage-financed and shadow-financed margin accounts (both QJ and YJ). We begin with a list of account characteristics. Equity size is the amount of own capital in RMB. % of Cash Holding is the fraction of portfolio value in cash. # of stocks is the number of stocks in the portfolio, and Herfindahl Index is calculated from portfolio weights. Account Turnover is the ratio of daily trading volume to the average open and close account value. Account age and investor age are reported in years. Except for account turnover, which is measured as the average turnover in the entire three-month period, all other account characteristics are measured at the opening of account. We also report a set of account average stock characteristics, using a) portfolio weights at the beginning of the sample and b) stock characteristics measured prior to our sample period. Market BETA and IDVOL are measured using daily stock returns in the previous year. LEVERAGE is the stock's overall leverage in the brokerage system, defined as MCAP/(MCAP-BDEBT) where BDEBT (publicly disclosed) is the total outstanding margin debt for stock i in the brokerage system. ILLIQUIDITY is the bid-ask spread in the past month. MOMENTUM SHORT/MEDIUM/LONG are past cumulative returns of three non-overlapping horizons: $t-1$, $[t-2, t-30]$, and $[t-31, t-180]$. MCAP is the market capitalization at the end of previous month. BMRATIO is the book-to-market ratio in the previous fiscal year. TURNOVER is average daily trading volume divided by the number of tradeable shares in the previous 120 trading days. We also report the statistical significance of the differences between groups. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Brokerage Accounts

	Levered	Non-Levered	Diff	High Initial Lev	Low Initial Lev	Diff
Log Equity Size	13.16	7.082	***	13.74	12.58	***
% of Cash Holding	0.128	0.624	***	0.0398	0.216	***
# of Stocks	5.035	3.451	***	5.668	4.390	***
Herfindahl Index	0.520	0.657	***	0.471	0.571	***
Account Turnover	0.225	0.0679	***	0.215	0.235	***
Account Years	8.286	8.844	***	8.192	8.379	*
Age in Years	44.97	46.60	***	44.65	45.30	**
Female	0.340	0.391	***	0.334	0.347	***
LEVERAGE	1.060	1.048	***	1.065	1.055	***
MKT BETA	0.772	0.732	***	0.802	0.741	***
IDVOL	0.0254	0.0248	***	0.0256	0.0252	
ILLIQUIDITY	0.0421	0.0488	***	0.0360	0.0486	
MOMENTUM SHORT	0.0154	0.0143	***	0.0153	0.0155	
MOMENTUM MEDIUM	0.188	0.179	***	0.189	0.187	
MOMENTUM LONG	0.710	0.683	***	0.714	0.706	*
MCAP	23.91	23.72	***	24.02	23.79	***
BMRATIO	0.675	0.681		0.689	0.662	***
TURNOVER	0.0381	0.0381		0.0376	0.0387	***
Observations	9142	1558		4572	4570	

Table 2
Determinants of Leverage Ratios (Continued)

Panel B: Shadow Margin Accounts

	High PC	Low PC	Diff	High Initial Lev	Low Initial Lev	Diff
Log Equity Size	9.218	9.982	***	9.343	9.857	*
% of Cash Holding	0.504	0.639	***	0.500	0.642	***
# of Stocks	2.030	2.109	***	2.019	2.125	***
Herfindahl Index	0.708	0.694	**	0.710	0.692	**
Account Turnover	0.621	0.517	***	0.649	0.489	***
Peer Average Pingcang	13.59	13.39	***	13.50	13.47	
LEVERAGE	1.044	1.045	**	1.044	1.045	
MKT BETA	0.705	0.737	***	0.711	0.732	***
IDVOL	0.0281	0.0275	***	0.0280	0.0275	***
ILLIQUIDITY	0.0436	0.0492		0.0431	0.0500	
MOMENTUM SHORT	0.00927	0.00811		0.0102	0.00700	
MOMENTUM MEDIUM	0.240	0.162	***	0.225	0.175	***
MOMENTUM LONG	0.883	0.865		0.890	0.857	**
MCAP	23.71	23.89	***	23.74	23.87	***
BMRATIO	0.586	0.683	***	0.610	0.661	**
TURNOVER	0.0435	0.0409	***	0.0430	0.0412	***
Observations	21829	21828		21829	21828	

Panel C: Brokerage vs. Shadow Margin Accounts

	Brokerage	Shadow	Diff
Log Equity Size	13.18	9.702	***
% of Cash Holding	0.128	0.539	***
# of Stocks	5.075	2.080	***
Herfindahl Index	0.520	0.692	***
Account Turnover	0.224	0.597	***
LEVERAGE	1.060	1.045	***
MKT BETA	0.772	0.719	***
IDVOL	0.0254	0.0280	***
ILLIQUIDITY	0.0422	0.0507	***
MOMENTUM SHORT	0.0154	0.00773	***
MOMENTUM MEDIUM	0.188	0.192	**
MOMENTUM LONG	0.710	0.892	***
MCAP	23.91	23.78	***
BMRATIO	0.675	0.625	***
TURNOVER	0.0381	0.0427	***
Observations	9223	76269	

Table 3
Trading Activities and Distance-to-Margin-Call

This table reports regressions of net buying on the level of and change in distance-to-margin-call. The dependent variable is the net buying of each stock by each account on day t. The main independent variables are indicators for Z-bins measured as of the end of $t-1$, and a continuous variable for Z-shocks measured on day t. Panel A reports the baseline results for brokerage-financed margin accounts, shadow-financed margin accounts, and all margin accounts. Panel B adds controls for the interaction between Z-shocks and trading restrictions on day t, as measured by the fraction of *other* stocks in the portfolio that experience trading suspensions or hit the downward price limit. Panel C uses only the shadow account sample. We further decompose Z-shocks into LP (leverage-to-Pingcang) and Lev (account leverage) $\times$ R (account returns), all of which are measured on day t. In Columns 3 and 4, we use peer Pingcang Line (the average Pingcang Line of all other shadow accounts opened in the same day) as an instrument for the account's own Pingcang Line. Panel D compares female versus male investors and experienced versus inexperienced; we classify experienced and inexperienced investors based on the median account age (the median cutoff account open date is March 2008). For all regressions, the omitted category is non-levered margin accounts (18,628 accounts), which explains why the sum of the number of observations in the brokerage and shadow regressions exceeds that of full regression. Account fixed effects and stock-date fixed effects are included in all regressions. Standard errors are triple clustered at account, stock, and date level and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Z and Z-Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Brokerage	Brokerage	Shadow	Shadow	Full	Full
$Z > 5$	-0.00670***	-0.00645***	-0.0125**	-0.00951	-0.00617***	-0.00547***
	(0.00165)	(0.00164)	(0.00607)	(0.00606)	(0.00159)	(0.00158)
$Z \in (4, 5]$	-0.0192***	-0.00421	-0.0341***	-0.00717	-0.0283***	-0.00307
	(0.00667)	(0.00558)	(0.00804)	(0.00794)	(0.00557)	(0.00526)
$Z \in (3, 4]$	-0.0209**	-0.000457	-0.0523***	-0.00935	-0.0470***	-0.00665
	(0.00862)	(0.00917)	(0.0105)	(0.00973)	(0.00925)	(0.00836)
$Z \in (2, 3]$	-0.0234**	0.00171	-0.0893***	-0.0293**	-0.0843***	-0.0282**
	(0.0114)	(0.0116)	(0.0147)	(0.0137)	(0.0142)	(0.0132)
$Z \in (1, 2]$	-0.0464***	-0.0191*	-0.138***	-0.0646***	-0.134***	-0.0656***
	(0.0112)	(0.0107)	(0.0195)	(0.0178)	(0.0195)	(0.0179)
$Z \in (0, 1]$	-0.0514***	-0.0216*	-0.189***	-0.109***	-0.184***	-0.109***
	(0.00912)	(0.0108)	(0.0229)	(0.0219)	(0.0235)	(0.0226)
$Z \leq 0$	-0.183***	-0.163***	-0.153***	-0.111***	-0.164***	-0.125***
	(0.0238)	(0.0220)	(0.0239)	(0.0216)	(0.0253)	(0.0227)
Z-shock	0.284***		0.342***		0.328***	
	(0.0332)		(0.0489)		(0.0512)	
Z-shock(≥ 0)		0.127*		-0.130*		-0.113
		(0.0691)		(0.0681)		(0.0713)
Z-shock(< 0)		0.378***		0.596***		0.567***
		(0.0338)		(0.0534)		(0.0564)
Observations	17,283,231	17,283,231	9,682,568	9,682,568	22,902,942	22,902,942
R-squared	0.153	0.153	0.214	0.215	0.186	0.187
Accout FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3

Trading Activities and Distance-to-margin-calls (Continued)

Panel B: Account-Level Trading Restrictions (interacting with Z-shock)

VARIABLES	(1) Brokerage	(2) Shadow	(3) Full
$Z > 5$	-0.0202***	-0.00170	-0.0199***
	(0.00108)	(0.00273)	(0.00107)
$Z \in (4, 5]$	-0.0272***	-0.0194***	-0.0362***
	(0.00449)	(0.00318)	(0.00183)
$Z \in (3, 4]$	-0.0253***	-0.0226***	-0.0392***
	(0.00536)	(0.00349)	(0.00242)
$Z \in (2, 3]$	-0.0264***	-0.0266***	-0.0433***
	(0.00774)	(0.00378)	(0.00312)
$Z \in (1, 2]$	-0.0292***	-0.0332***	-0.0497***
	(0.00762)	(0.00475)	(0.00405)
$Z \in (0, 1]$	-0.0387***	-0.0328***	-0.0503***
	(0.00855)	(0.00521)	(0.00465)
$Z \leq 0$	-0.0717***	-0.0185***	-0.0375***
	(0.0112)	(0.00489)	(0.00460)
Z-shock	0.145***	0.0730***	0.0680***
	(0.0257)	(0.00713)	(0.00750)
$\%Restriction$	-0.00778***	-0.00582***	-0.00705***
	(0.00108)	(0.00122)	(0.00112)
Z-shock$\times\%Restriction$	0.0164	0.0604***	0.0567***
	(0.0349)	(0.0208)	(0.0196)
Observations	15,365,270	7,460,730	19,400,474
R-squared	0.040	0.071	0.042
Account FE	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes

Table 3
Trading Activities and Distance-to-Margin-Calls (Continued)

Panel C: Shadow Accounts with Heterogeneous Pingcang Lines

	(1)	(2)	(3)	(4)
VARIABLES	Z	Z	Z^*	Z^*, LP^*
$Z > 5$	-0.00969	0.00673	-0.0152	0.0116
	(0.0147)	(0.0161)	(0.0148)	(0.0163)
$Z \in (4, 5]$	-0.0344**	-0.0153	-0.0533***	-0.0196
	(0.0160)	(0.0156)	(0.0170)	(0.0155)
$Z \in (3, 4]$	-0.0518***	-0.0355**	-0.0741***	-0.0399**
	(0.0174)	(0.0154)	(0.0195)	(0.0157)
$Z \in (2, 3]$	-0.0897***	-0.0766***	-0.115***	-0.0788***
	(0.0206)	(0.0161)	(0.0233)	(0.0164)
$Z \in (1, 2]$	-0.139***	-0.128***	-0.163***	-0.120***
	(0.0243)	(0.0173)	(0.0275)	(0.0183)
$Z \in (0, 1]$	-0.197***	-0.181***	-0.221***	-0.168***
	(0.0273)	(0.0195)	(0.0320)	(0.0212)
$Z \leq 0$	-0.178***	-0.134***	-0.182***	-0.110***
	(0.0303)	(0.0197)	(0.0325)	(0.0228)
Z-shock	0.372***		0.509***	
	(0.0536)		(0.0765)	
LP		0.0521**		0.109***
		(0.0251)		(0.0372)
$Lev \times R$		0.232***		0.234***
		(0.0326)		(0.0331)
Observations	6,887,619	6,887,619	6,885,666	6,885,666
R-squared	0.215	0.214	0.215	0.214
Accout FE	Yes	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes	Yes

Table 3
Trading Activities and Distance-to-Margin-Calls (Continued)

Panel D: Gender and Experience

VARIABLES	(1) Gender	VARIABLES	(2) Experience
$Z > 5$	-0.00699***	$Z > 5$	-0.00636***
	(0.00179)		(0.00186)
$\times Female$	0.00120	$\times Experienced$	-0.000361
	(0.00154)		(0.00161)
$Z \in (4, 5]$	-0.0155***	$Z \in (4, 5]$	-0.0257***
	(0.00471)		(0.00689)
$\times Female$	-0.0225**	$\times Experienced$	0.00606
	(0.00921)		(0.00770)
$Z \in (3, 4]$	-0.0273***	$Z \in (3, 4]$	-0.0377***
	(0.00431)		(0.00712)
$\times Female$	-0.0195**	$\times Experienced$	0.00915
	(0.00840)		(0.00800)
$Z \in (2, 3]$	-0.0430***	$Z \in (2, 3]$	-0.0544***
	(0.00704)		(0.0102)
$\times Female$	-0.00931	$\times Experienced$	0.0170
	(0.00922)		(0.0115)
$Z \in (1, 2]$	-0.0645***	$Z \in (1, 2]$	-0.0715***
	(0.0104)		(0.0205)
$\times Female$	-0.0238	$\times Experienced$	-0.00380
	(0.0215)		(0.0226)
$Z \in (0, 1]$	-0.0729***	$Z \in (0, 1]$	-0.0797***
	(0.0128)		(0.0122)
$\times Female$	-0.0242**	$\times Experienced$	-0.000308
	(0.0116)		(0.0123)
$Z \leq 0$	-0.185***	$Z \leq 0$	-0.210***
	(0.0150)		(0.0222)
$\times Female$	-0.0284**	$\times Experienced$	0.0330
	(0.0131)		(0.0247)
Z-shock	1.249***	Z-shock	1.252***
	(0.109)		(0.125)
$\times Female$	0.191**	$\times Experienced$	0.124
	(0.0919)		(0.0797)
Observations	17,173,429		17,173,429
R-squared	0.152		0.152
Account FE	Yes		Yes
Stock-Date FE	Yes		Yes

Table 4
Investors' Liquidation Choice

This table examines investors' liquidation choice as a function of lagged stock characteristics. The dependent variable is the net buying of a stock by each account on day t. The main independent variables include the account's Z-shock measured on day t, and its interactions with various stock characteristics measured at the end of day t-1 or averaged across the whole sample. The set of stock characteristics includes: the portfolio weight of the stock (WEIGHT); the stock's overall leverage (LEVERAGE) in the brokerage system on day t-1, defined as MCAP/(MCAP-BDEBT) where BDEBT (publicly disclosed) is the total outstanding margin debt for stock i in the brokerage system; market beta (BETA); idiosyncratic volatility (IDVOL); bid-ask spread (ILLIQUIDITY); past cumulative returns of three non-overlapping horizons: $t-1$, $[t-2, t-30]$, and $[t-31, t-180]$ days (MOMENTUM SHORT/MEDIUM/LONG); market capitalization (MCAP); book-to-market ratio (BMRATIO) and share turnover (TURNOVER). Columns (1), (2), and (3) correspond to brokerage accounts, shadow accounts, and all accounts, respectively. For all regressions, the omitted category is non-levered margin accounts (18,628 accounts), which explains why the sum of the number of observations in brokerage and shadow regressions exceeds that of full regression. Z-bin dummies are included in all regressions. Stock-date and account fixed effects are included in all regressions. Standard errors are triple clustered at account, stock, and date level and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Brokerage	(2) Shadow	(3) Full
Z-shock×WEIGHT	-0.146***	0.00811	-0.0150
	(0.0413)	(0.0253)	(0.0283)
Z-shock×LEVERAGE	0.120	0.151	0.0308
	(0.168)	(0.102)	(0.0831)
Z-shock×BETA	-0.0580*	-0.0182	-0.0268
	(0.0325)	(0.0166)	(0.0166)
Z-shock×IDVOL	-4.371*	-0.468	-0.582
	(2.574)	(1.737)	(1.837)
Z-shock×ILLIQUIDITY	-0.979***	-0.0304	-0.142
	(0.261)	(0.142)	(0.161)
Z-shock×MOMENTUM SHORT	0.876*	-1.591**	-1.443**
	(0.457)	(0.618)	(0.673)
Z-shock×MOMENTUM MEDIUM	0.387***	-0.0292	-0.0107
	(0.142)	(0.0502)	(0.0509)
Z-shock×MOMENTUM LONG	0.0162	-0.0154	-0.0159
	(0.0186)	(0.0107)	(0.0118)
Z-shock×MCAP	0.0177	0.0126*	0.0165**
	(0.0143)	(0.00729)	(0.00824)
Z-shock×BMRATIO	-0.0542**	-0.00734	-0.0112
	(0.0271)	(0.0117)	(0.0131)
Z-shock×TURNOVER	0.0564	0.310*	0.394**
	(0.435)	(0.185)	(0.197)
Z-shock	0.256	-0.111	-0.0596
	(0.401)	(0.167)	(0.169)
Observations	12,379,749	8,134,547	17,449,201
R-squared	0.156	0.218	0.191
Z-bin Dummies	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
Account FE	Yes	Yes	Yes

Table 5
Predicting Next-Day Trading Activity

This table reports forecasting regressions of investors' net buying on lagged Z-shocks and its interactions with trading restrictions (Panel A) and stock characteristics (Panels B). The dependent variable is the net buying of a stock by each account on day $t+1$. The main independent variables include the account's Z-shock measured on day t, and its interactions with trading restrictions measured on day t and/or stock characteristics measured as of the market close on day $t-1$. In Panel A, trading restrictions capture the fraction of *other* stocks in each account that either hit the downward price limit or experience trading suspensions on day t. Columns (1)-(2), (3)-(4), and (5)-(6) correspond to brokerage accounts, shadow accounts, and all accounts, respectively. In panel B, stock characteristics are as defined in Table 4 and Z-bin dummies are included in all specifications. For all regressions, the omitted category is non-levered margin accounts (18,628 accounts), which explains why the sum of the number of observations in brokerage and shadow regressions exceeds that of full regression. Stock-date and account fixed effects are included in all regressions. Standard errors are triple clustered at account, stock, and date level and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Account-Level Trading Restrictions (interacting with Z-shock)

VARIABLES	(1) Brokerage	(2) Brokerage	(3) Shadow	(4) Shadow	(5) Full	(6) Full
$Z > 5$	-0.0102***	-0.00902***	-0.0190***	-0.00627	-0.00985***	-0.00843***
	(0.00159)	(0.00160)	(0.00687)	(0.00871)	(0.00156)	(0.00157)
$Z \in (4,5]$	-0.0292***	-0.0228***	-0.0497***	-0.0309**	-0.0403***	-0.0321***
	(0.00738)	(0.00702)	(0.00990)	(0.0117)	(0.00696)	(0.00770)
$Z \in (3,4]$	-0.0258***	-0.0164*	-0.0552***	-0.0324**	-0.0452***	-0.0325***
	(0.00862)	(0.00822)	(0.0102)	(0.0128)	(0.00762)	(0.00949)
$Z \in (2,3]$	-0.0293***	-0.0202**	-0.0535***	-0.0289**	-0.0444***	-0.0300***
	(0.00910)	(0.00895)	(0.0104)	(0.0133)	(0.00806)	(0.0104)
$Z \in (1,2]$	-0.0376***	-0.0270***	-0.0478***	-0.0209	-0.0399***	-0.0229**
	(0.00981)	(0.00957)	(0.0107)	(0.0134)	(0.00842)	(0.0103)
$Z \in (0,1]$	-0.0395***	-0.0281***	-0.0504***	-0.0217	-0.0433***	-0.0240*
	(0.00817)	(0.0105)	(0.0124)	(0.0145)	(0.0105)	(0.0123)
$Z \leq 0$	-0.103***	-0.0940***	-0.0526***	-0.0252*	-0.0558***	-0.0384***
	(0.0269)	(0.0267)	(0.0114)	(0.0140)	(0.0103)	(0.0115)
Z-shock	0.285***	0.127***	0.426***	0.250***	0.443***	0.251***
	(0.0383)	(0.0366)	(0.0585)	(0.0691)	(0.0612)	(0.0727)
%*Restriction*		0.00120		0.00398		0.00182
		(0.00313)		(0.00433)		(0.00356)
Z-shock×%*Restriction*		0.240**		0.402***		0.411***
		(0.0916)		(0.103)		(0.117)
Observations	15,024,956	14,590,003	7,678,772	7,115,399	19,235,572	18,494,675
R-squared	0.104	0.105	0.179	0.179	0.140	0.138
Account FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5
Predicting Next-Day Trading Activity (Continued)

Panel B: Stock Characteristics (interacting with Z-shock)

VARIABLES	(1) Brokerage	(2) Shadow	(3) Full
Z-shock×WEIGHT	-0.110	-0.0171	-0.0281
	(0.0736)	(0.0291)	(0.0338)
Z-shock×LEVERAGE	0.403***	0.183	0.118
	(0.101)	(0.110)	(0.113)
Z-shock×BETA	-0.0968***	-0.00593	-0.0169
	(0.0293)	(0.0194)	(0.0189)
Z-shock×IDVOL	-8.347***	-1.844	-2.309
	(2.662)	(2.208)	(2.371)
Z-shock×ILLIQUIDITY	-0.483**	0.165	0.106
	(0.239)	(0.193)	(0.215)
Z-shock×MOMENTUM SHORT	0.0788	-0.362	-0.436
	(0.391)	(0.657)	(0.671)
Z-shock×MOMENTUM MEDIUM	0.123	-0.0924	-0.0507
	(0.146)	(0.0645)	(0.0697)
Z-shock×MOMENTUM LONG	0.0362	-0.00721	-0.00221
	(0.0247)	(0.0148)	(0.0159)
Z-shock×MCAP	0.00390	-0.00200	-0.000233
	(0.0193)	(0.0101)	(0.0108)
Z-shock×BMRATIO	-0.0361*	-0.0384**	-0.0467***
	(0.0206)	(0.0152)	(0.0163)
Z-shock×TURNOVER	-0.287	0.522*	0.520*
	(0.388)	(0.274)	(0.276)
Z-shock	0.242	0.340	0.421*
	(0.408)	(0.221)	(0.246)
Observations	10,798,298	6,420,000	14,583,861
R-squared	0.111	0.184	0.146
Z-bin Dummies	Yes	Yes	Yes
Stock-Date FE	Yes	Yes	Yes
Account FE	Yes	Yes	Yes

Table 6
Return Predictability of $MLPR$

This table reports Fama-MacBeth forecasting regressions of future returns. The dependent variable is stock i's return on day $t+1$ for Panels A to D. The main independent variable is $SMLPR$, the margin-account-linked portfolio return in day t, calculated as the weighted average return of all other stocks that are connected to stock i through common ownership by margin investors (see Section 3.4 for a detailed explanation). $SMLPR$ is standardized to have a standard deviation of one. $SNMLPR$ is defined similarly but uses common ownership of matched non-margin accounts (matching is based on account size and trading volume). Other controls are as described in Table 4 but measured on day t. In Panel A, the construction of $SMLPR$ assumes proportional scaling of portfolio positions. In Panel B, we incorporate liquidation choice into the construction of $SMLPR$ using fitted values from Column (3) of Panel A, Table 5. Panel C shows regressions separately for the brokerage and shadow samples, where $SMLPR$ is constructed using only the brokerage and shadow samples, respectively. Panel D shows the return response associated with $SMLPR_{High}$ and $SMLPR_{Low}$, which are calculated using subsamples with top and bottom 30% percentile selling restrictions of each trading day (as defined in Section 5.2.5), respectively. For $SMLPR_{Low}$, if for some trading day there are more than 30% accounts with a selling restriction rate of 0, we choose the 30% accounts with the smallest total stock holdings. In Panels A to D, Columns (1) and (2) include the whole sample of May 1st to July 31st, 2015. We then split the sample based on the general market trend: 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). In panel E, the dependent variable is the cumulative return of a stock from $t+1$ to $t+k$, where $k = 5, 10, 15, 20$ and 25, and the independent variables are the same as other panels. 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: $MLPR$ Assuming Proportional Scaling

VARIABLES	(1) Whole	(2) Whole	(3) Up	(4) Up	(5) Down	(6) Down
SMLPR	0.00119***	0.00115***	0.000284	0.000275	0.00198***	0.00193***
	(0.000374)	(0.000351)	(0.000254)	(0.000218)	(0.000538)	(0.000500)
SNMLPR		-4.96e-05		0.000198		-0.000314
		(0.000359)		(0.000381)		(0.000580)
LEVERAGE	-0.00271	-0.00295	-0.00577	-0.00583	0.000909	0.000515
	(0.00468)	(0.00463)	(0.00593)	(0.00592)	(0.00687)	(0.00679)
BETA	-0.00187	-0.00188	-0.00146	-0.00144	-0.00279*	-0.00285*
	(0.00138)	(0.00137)	(0.00219)	(0.00218)	(0.00164)	(0.00163)
IDVOL	-0.205**	-0.209**	-0.310**	-0.310**	-0.0708	-0.0792
	(0.100)	(0.0976)	(0.125)	(0.124)	(0.135)	(0.130)
ILLIQUIDITY	0.0653***	0.0655***	0.114***	0.114***	0.0228	0.0231
	(0.0149)	(0.0148)	(0.00809)	(0.00811)	(0.0169)	(0.0167)
MOMENTUM SHORT	0.197***	0.196***	0.137***	0.136***	0.247***	0.246***
	(0.0259)	(0.0258)	(0.0229)	(0.0226)	(0.0374)	(0.0374)
MOMENTUM MEDIUM	-0.0184***	-0.0184***	-0.00980**	-0.00978**	-0.0258**	-0.0256**
	(0.00671)	(0.00665)	(0.00433)	(0.00432)	(0.0116)	(0.0115)
MOMENTUM LONG	-0.00102**	-0.00102**	-0.000179	-0.000188	-0.00169***	-0.00168***
	(0.000483)	(0.000483)	(0.000715)	(0.000717)	(0.000603)	(0.000604)
MCAP	-0.000436	-0.000459	-0.00278***	-0.00276***	0.00161	0.00154
	(0.000873)	(0.000855)	(0.000638)	(0.000624)	(0.00119)	(0.00116)
BMRATIO	4.54e-05**	4.42e-05**	2.57e-06	2.97e-06	8.52e-05**	8.24e-05**
	(2.24e-05)	(2.20e-05)	(1.72e-05)	(1.72e-05)	(3.55e-05)	(3.51e-05)
TURNOVER	-0.00226	-0.00223	-0.0131	-0.0125	0.00878	0.00813
	(0.0209)	(0.0204)	(0.0295)	(0.0289)	(0.0302)	(0.0295)
p-value (SMLPR>SNMLPR)		.0198		.8616		.0062
Observations	128,512	128,512	59,959	59,959	66,423	66,423
R-squared	0.184	0.187	0.158	0.159	0.208	0.211
Number of groups	62	62	28	28	33	33

Table 6
Return Predictability of $MLPR$ (Continued)

Panel B: $MLPR$ with Liquidation Choice

VARIABLES	(1) Whole	(2) Whole	(3) Up	(4) Up	(5) Down	(6) Down
SMLPR	0.00104***	0.00101***	0.000310	0.000303*	0.00170***	0.00164***
	(0.000324)	(0.000303)	(0.000199)	(0.000168)	(0.000482)	(0.000448)
SNMLPR		-1.31e-05		0.000216		-0.000262
		(0.000365)		(0.000400)		(0.000588)
LEVERAGE	-0.00368	-0.00386	-0.00603	-0.00612	-0.000716	-0.000964
	(0.00494)	(0.00488)	(0.00602)	(0.00597)	(0.00753)	(0.00743)
BETA	-0.00192	-0.00194	-0.00149	-0.00147	-0.00286*	-0.00292*
	(0.00138)	(0.00138)	(0.00220)	(0.00219)	(0.00165)	(0.00164)
IDVOL	-0.207**	-0.212**	-0.312**	-0.312**	-0.0730	-0.0821
	(0.100)	(0.0977)	(0.125)	(0.124)	(0.135)	(0.130)
ILLIQUIDITY	0.0651***	0.0653***	0.114***	0.114***	0.0224	0.0228
	(0.0151)	(0.0149)	(0.00814)	(0.00816)	(0.0172)	(0.0169)
MOMENTUM SHORT	0.198***	0.197***	0.138***	0.137***	0.248***	0.248***
	(0.0261)	(0.0260)	(0.0230)	(0.0227)	(0.0376)	(0.0375)
MOMENTUM MEDIUM	-0.0184***	-0.0184***	-0.00979**	-0.00977**	-0.0257**	-0.0256**
	(0.00675)	(0.00669)	(0.00434)	(0.00433)	(0.0117)	(0.0116)
MOMENTUM LONG	-0.00102**	-0.00101**	-0.000172	-0.000179	-0.00168***	-0.00167***
	(0.000485)	(0.000485)	(0.000715)	(0.000718)	(0.000608)	(0.000608)
MCAP	-0.000464	-0.000487	-0.00278***	-0.00276***	0.00156	0.00149
	(0.000860)	(0.000843)	(0.000637)	(0.000622)	(0.00117)	(0.00114)
BMRATIO	4.72e-05**	4.58e-05**	3.42e-06	3.79e-06	8.79e-05**	8.47e-05**
	(2.27e-05)	(2.23e-05)	(1.70e-05)	(1.71e-05)	(3.61e-05)	(3.56e-05)
TURNOVER	-0.00380	-0.00372	-0.0138	-0.0132	0.00645	0.00591
	(0.0207)	(0.0203)	(0.0296)	(0.0290)	(0.0298)	(0.0291)
p-value (SMLPR>SNMLPR)		.0357		.8431		.0149
Observations	128,512	128,512	59,959	59,959	66,423	66,423
R-squared	0.184	0.186	0.157	0.158	0.207	0.210
Number of groups	62	62	28	28	33	33

Table 6
Return Predictability of $MLPR$ (Continued)

Panel C: Brokerage and Shadow

	Brokerage			Shadow		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Whole	Up	Down	Whole	Up	Down
SMLPR	0.000395	-0.000172	0.000881**	0.00115***	0.000430*	0.00179***
	(0.000253)	(0.000222)	(0.000363)	(0.000331)	(0.000214)	(0.000503)
LEVERAGE	-0.00508	-0.00613	-0.00320	-0.00592	-0.00817	-0.00301
	(0.00445)	(0.00577)	(0.00664)	(0.00506)	(0.00599)	(0.00782)
BETA	-0.00215	-0.00158	-0.00323*	-0.00237*	-0.00212	-0.00317*
	(0.00142)	(0.00223)	(0.00171)	(0.00137)	(0.00215)	(0.00168)
IDVOL	-0.209**	-0.312**	-0.0753	-0.188*	-0.276**	-0.0672
	(0.101)	(0.124)	(0.138)	(0.0949)	(0.120)	(0.125)
ILLIQUIDITY	0.0647***	0.114***	0.0219	0.0695***	0.122***	0.0235
	(0.0151)	(0.00818)	(0.0173)	(0.0163)	(0.00856)	(0.0189)
MOMENTUM SHORT	0.201***	0.139***	0.253***	0.190***	0.129***	0.241***
	(0.0267)	(0.0229)	(0.0386)	(0.0263)	(0.0225)	(0.0382)
MOMENTUM MEDIUM	-0.0184***	-0.00977**	-0.0257**	-0.0195***	-0.0123**	-0.0255**
	(0.00668)	(0.00433)	(0.0115)	(0.00688)	(0.00482)	(0.0120)
MOMENTUM LONG	-0.00101**	-0.000166	-0.00168**	-0.00119**	-0.000505	-0.00172**
	(0.000495)	(0.000732)	(0.000625)	(0.000487)	(0.000721)	(0.000642)
MCAP	-0.000416	-0.00278***	0.00165	-0.000371	-0.00269***	0.00165
	(0.000877)	(0.000643)	(0.00119)	(0.000867)	(0.000652)	(0.00118)
BMRATIO	5.02e-05**	3.88e-06	9.31e-05**	4.61e-05**	1.85e-06	8.72e-05**
	(2.33e-05)	(1.69e-05)	(3.68e-05)	(2.27e-05)	(1.66e-05)	(3.60e-05)
TURNOVER	-0.00688	-0.0144	0.00114	-0.000589	-0.0101	0.00924
	(0.0205)	(0.0295)	(0.0295)	(0.0214)	(0.0303)	(0.0309)
Observations	127,770	59,640	66,014	127,316	59,488	65,710
R-squared	0.183	0.158	0.204	0.184	0.154	0.209
Number of groups	62	28	33	62	28	33

Table 6
Return Predictability of $MLPR$ (Continued)

Panel D: Selling Restrictions

VARIABLES	(1) Whole	(2) Whole	(3) Up	(4) Up	(5) Down	(6) Down
SMLPR_HIGH	0.000959**	0.000917**	-4.57e-05	-4.37e-05	0.00182***	0.00175***
	(0.000400)	(0.000375)	(0.000296)	(0.000261)	(0.000560)	(0.000520)
SMLPR_LOW	0.000103	9.86e-05	0.000229	0.000228	-4.32e-05	-4.99e-05
	(0.000178)	(0.000176)	(0.000279)	(0.000268)	(0.000221)	(0.000224)
SNMLPR		-3.07e-05		0.000206		-0.000295
		(0.000365)		(0.000410)		(0.000580)
LEVERAGE	-0.00466	-0.00491	-0.00479	-0.00497	-0.00355	-0.00385
	(0.00417)	(0.00412)	(0.00590)	(0.00588)	(0.00590)	(0.00579)
BETA	-0.00179	-0.00182	-0.00142	-0.00140	-0.00275	-0.00282
	(0.00141)	(0.00141)	(0.00224)	(0.00223)	(0.00167)	(0.00167)
IDVOL	-0.211**	-0.214**	-0.267**	-0.267**	-0.123	-0.130
	(0.0877)	(0.0853)	(0.128)	(0.127)	(0.110)	(0.105)
ILLIQUIDITY	0.0631***	0.0632***	0.108***	0.108***	0.0246	0.0249
	(0.0145)	(0.0144)	(0.00835)	(0.00836)	(0.0180)	(0.0178)
MOMENTUM SHORT	0.211***	0.210***	0.140***	0.139***	0.270***	0.269***
	(0.0261)	(0.0261)	(0.0229)	(0.0226)	(0.0341)	(0.0342)
MOMENTUM MEDIUM	-0.0160***	-0.0160***	-0.00953**	-0.00953**	-0.0216**	-0.0215**
	(0.00567)	(0.00564)	(0.00433)	(0.00432)	(0.00971)	(0.00965)
MOMENTUM LONG	-0.00104**	-0.00104**	-0.000404	-0.000421	-0.00153***	-0.00151***
	(0.000444)	(0.000444)	(0.000713)	(0.000715)	(0.000535)	(0.000534)
MCAP	-0.000238	-0.000256	-0.00281***	-0.00277***	0.00200*	0.00193*
	(0.000862)	(0.000845)	(0.000635)	(0.000616)	(0.00107)	(0.00105)
BMRATIO	5.17e-05**	5.08e-05**	2.02e-06	2.74e-06	9.76e-05***	9.50e-05***
	(2.30e-05)	(2.25e-05)	(1.68e-05)	(1.69e-05)	(3.53e-05)	(3.47e-05)
TURNOVER	-9.26e-05	-5.06e-05	-0.0149	-0.0142	0.0146	0.0138
	(0.0189)	(0.0185)	(0.0295)	(0.0289)	(0.0246)	(0.0241)
p-value (High>Low)	.0554	.0526	.5045	.4734	.0041	.0033
p-value (High>SNMLPR)		.0748		.6106		.0133
Observations	124,184	124,184	58,913	58,913	63,169	63,169
R-squared	0.190	0.192	0.156	0.157	0.219	0.222
Number of groups	62	62	28	28	33	33

Table 6
Return Predictability of $MLPR$ (Continued)

Panel E: Returns Reversal

VARIABLES	(1) $k = 5$	(2) $k = 10$	(3) $k = 15$	(4) $k = 20$	(5) $k = 25$
SMLPR	0.00142	0.00192	0.00114	0.00107	5.77e-05
	(0.00114)	(0.00182)	(0.00190)	(0.00171)	(0.00189)
LEVERAGE	-0.0246	-0.0630*	-0.0860*	-0.117*	-0.165***
	(0.0209)	(0.0361)	(0.0504)	(0.0590)	(0.0619)
BETA	-0.00538	-0.00357	0.00137	0.00343	0.00276
	(0.00515)	(0.00657)	(0.00836)	(0.00984)	(0.00994)
IDVOL	-1.224**	-2.317***	-3.137***	-3.899***	-4.384***
	(0.462)	(0.707)	(0.805)	(0.808)	(0.770)
ILLIQUIDITY	0.352***	0.609***	0.738***	0.772***	0.744***
	(0.0679)	(0.118)	(0.141)	(0.143)	(0.134)
MOMENTUM SHORT	0.144**	0.0193	-0.0807	-0.141**	-0.180***
	(0.0701)	(0.0914)	(0.0704)	(0.0676)	(0.0629)
MOMENTUM MEDIUM	-0.105***	-0.181***	-0.223***	-0.249***	-0.259***
	(0.0305)	(0.0453)	(0.0408)	(0.0469)	(0.0596)
MOMENTUM LONG	-0.00528***	-0.00897***	-0.0117***	-0.0117***	-0.0136***
	(0.00184)	(0.00243)	(0.00271)	(0.00353)	(0.00376)
MCAP	-0.00267	-0.00536	-0.00767	-0.00615	-0.00167
	(0.00424)	(0.00668)	(0.00838)	(0.00909)	(0.00913)
BMRATIO	0.000232**	0.000387**	0.000506***	0.000658***	0.000856***
	(9.22e-05)	(0.000147)	(0.000179)	(0.000189)	(0.000188)
TURNOVER	-0.00757	0.0173	0.0388	0.0255	0.0799
	(0.0755)	(0.0940)	(0.0961)	(0.0910)	(0.103)
Observations	134,160	137,460	139,414	140,972	142,202
R-squared	0.215	0.247	0.247	0.234	0.222
Number of groups	62	62	62	62	62